SEDIMENT MODEL FOR NATURAL AND MAN-MADE CHANNELS USING GENERAL REGRESSION NEURAL NETWORK

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ABSTRACT

This paper presents a new sediment transport model using general regression neural network (GRNN) that are applicable for both natural and man-made channels. GRNN is a supervised network that trains quickly sparse data sets. The network architecture responses very well with data that is spasmodic in nature than back propagation algorithm. Field data (499 data) extracted from rivers in Selangor, Perak and Kedah are used in the training and testing phases. The model is further tested using hydraulics and sediment data from rivers in the United States namely Sacremento, Atchafalaya, Colorado, Mississippi, Middle Loup, Mountain Creek, Niobrara, Saskatchewan, Oak Creek, Red, Rio Grande rivers and Chop Irrigation Canal. Four independent variables, namely, relative roughness on the bed (R/d_{50}), ratio of shear velocity and fall velocity (U^*/W_s), ratio of shear velocity and average velocity (U^*/V) and the Froude Number ($V/\sqrt{gy}$) are used as input variables in the input layer and the total sediment load Q_T as the output variable. The proposed GRNN sediment model had accurately predicted 89% of the river data sets (local and foreign rivers) with 90% of the predicted values lie in the discrepancy ratio of 0.5 – 2.0. For the sake of illustrations, accuracy of the derived sediment transport model is also measured using smaller range of discrepancy ratios.

Keywords: *General Regression Neural Network, Man-made Channels, Natural Channels, Sediment Transport*

1.0 INTRODUCTION

Attempts to develop sediment transport equations have started more than a decade but until today there is no one universal equation that can best predict sediment transport satisfactorily. Studies were extensively carried out by several researchers to model sediment transport rate. This is evident from Figure 1 that illustrates the various sediment transport models derived using different conventional approaches. Regression method is the most commonly used by investigators in comparison to other methods such as graphical solutions, probability concept, stream power concept and multimode characteristics method. However, in dealing with data that are spasmodic in nature, regression may not give favourable results. This has resulted in researchers opting for alternative approaches to conventional approaches for model development. Artificial neural network (ANN) have proven to be a better alternative for modeling complex and non linear processes [1]. He indicated that one of the distinct features in ANN is their ability to extract the relationship between the input and the output without the physics being explicitly provided to them. It provides a mapping from one multivariate space to another, given a set of data that represents the mapping. Even if data are noisy and contaminated with errors, ANN is able to identify the underlying mechanism. ANN is suited to problems on estimation and prediction in hydrology [2].

Figure 2 illustrates the wide ranging applications of ANN in different fields of engineering. From the figure, it is evident that ANN is most commonly applied in the field of hydrology namely rainfall and runoff. In the field of sediment transport engineering, research on sheet sediment transport to quantify the sediment yield through sheet erosion has been conducted [3]. Some researchers focused on the development of suspended sediment concentration [4]. Neural network sediment model with six parameters namely dimensionless tractive shear stress ψ, dimensionless suspended sediment parameter ω_0/u^*, water depth ratio h/d_{50} , Froude number F, Reynolds number R* and width scale ratio, h/B forming the input layer with total load concentration, C_s in the output layer has been proposed [5]. The model was tested on five rivers in the United States.

Analysis on the performance of some of the sediment transport equations are shown in Table 1.

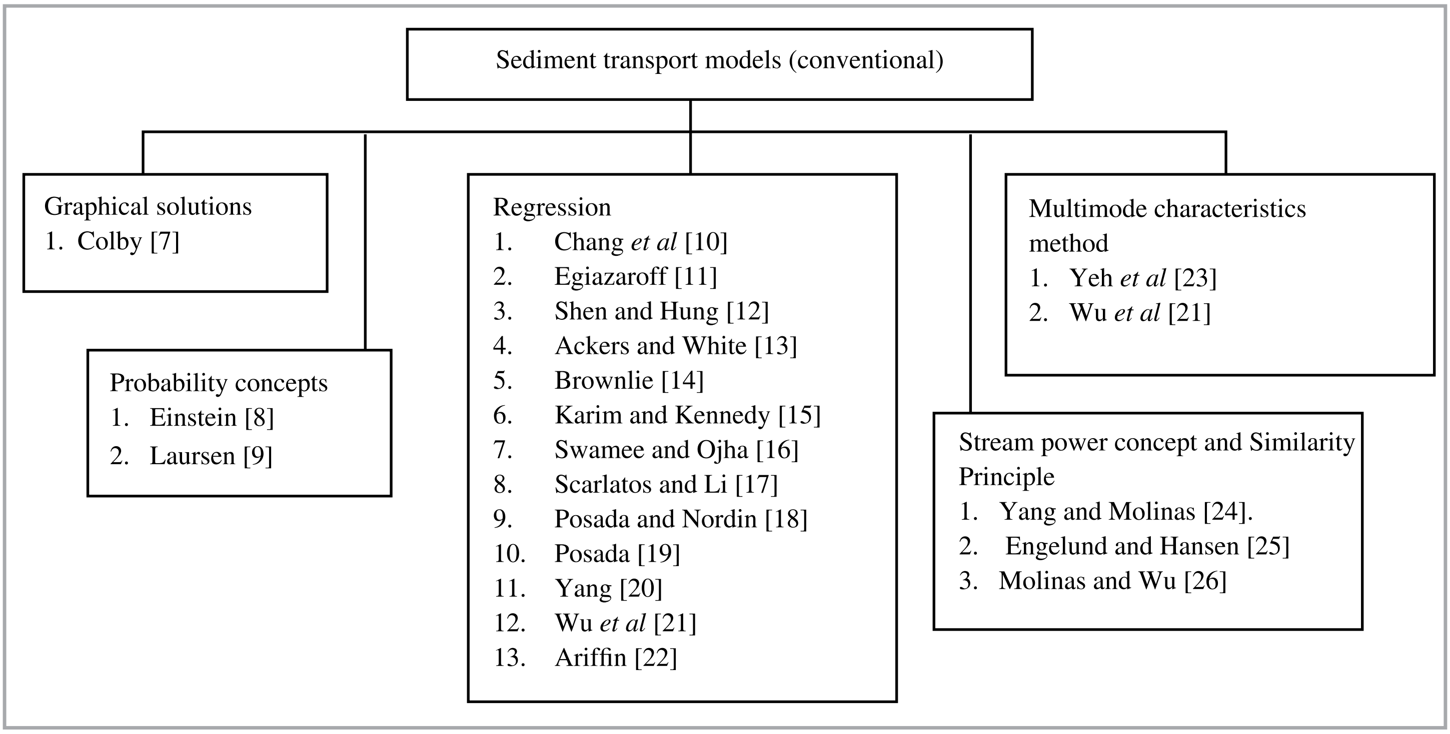


Figure 1: Sediment transport models developed using conventional approaches [6]

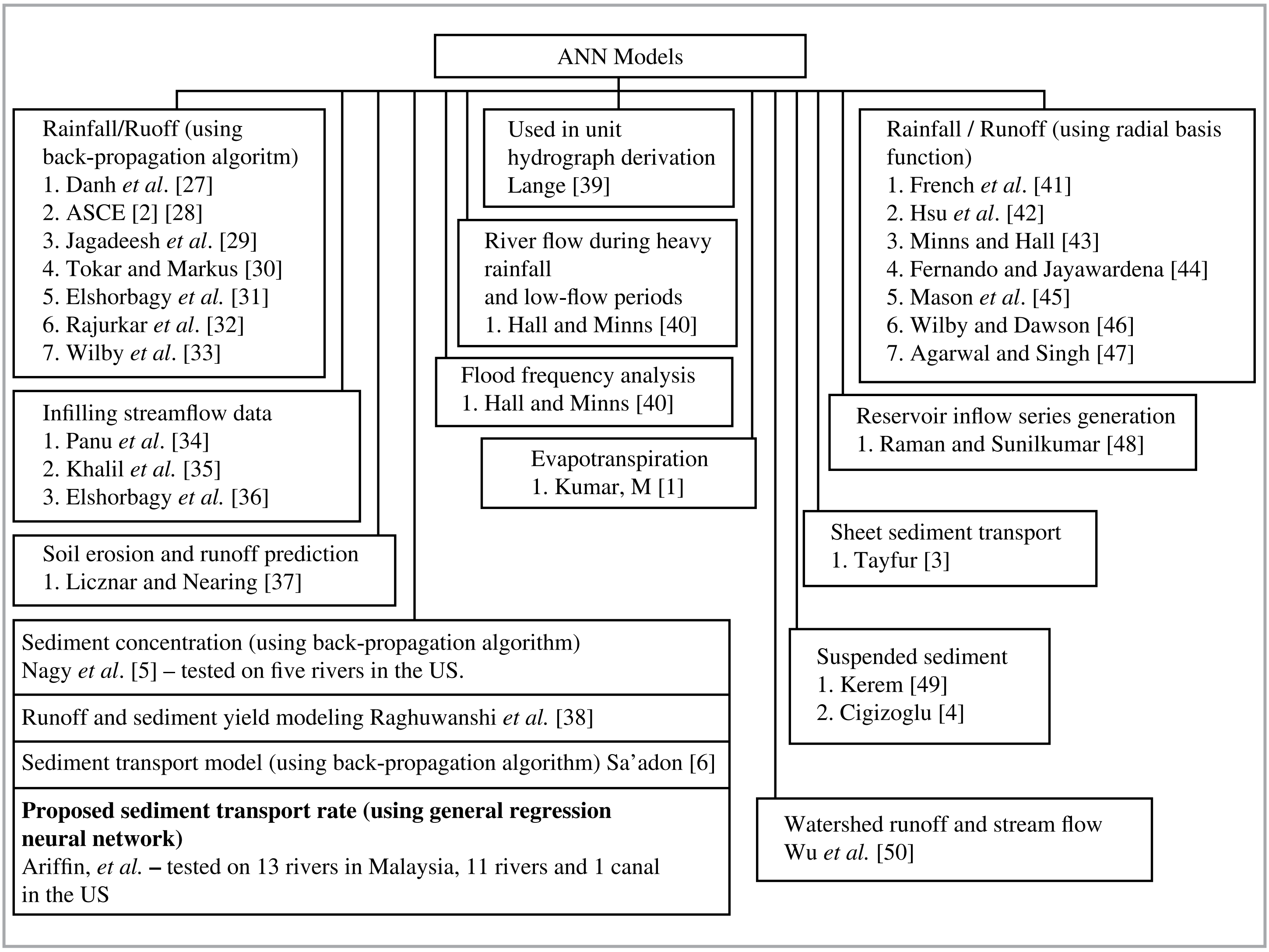


Figure 2: ANN models

Table 1: Performance of different sediment transport Equations [22]

Investigator	Equations	Discrepancy ratio (0.5 – 2.0)		Total data / rivers
		No. of data	Percentage (%)	
Alonso [51]	Ackers and White	35	87.8	40 (3 US rivers)
	Engelund and Hansen	33	82.9	
	Laursen	22	56.1	
	MPME*	23	58.5	
	Yang	37	92.7	
	Bagnold	13	32.0	
	Meyer-Peter-Muller	0	0.00	
	Yalin	19	46.3	
Abu Hassan [52]	Yang	6	54.6	11 (3 Malaysian rivers)
	Engelund and Hansen	3	27.3	
	Ackers and White	5	45.5	
	Graf	5	45.5	
Yahaya [53]	Yang	39	65.0	60 (3 Malaysian rivers)
	Ackers and White	2	3.3	
	Graf	37	61.7	
Wu *et al.* [21]	Ackers and White	NA	82.4	Not available
	Yang	NA	76.6	
	Engelund and Hansen	NA	77.0	
	Wu *et al.*	NA	81.3	
Molinas and Wu [26]	Molinas and Wu	323	78.0	414 (US large rivers)
	Engelund and Hansen	242	58.4	
	Ackers and White	257	62.1	
	Yang	112	27.1	
	Toffaleti	297	71.7	
Molinas and Wu [26]	Molinas and Wu	336	62.9	534 (US medium rivers)
	Engelund and Hansen	300	56.2	
	Ackers and White	219	41.0	
	Yang	161	30.2	
	Toffaleti	112	21.0	
Ariffin *et al.* [54]	Yang	6	10.7	56 * (3 Malaysian rivers)
	Engelund and Hansen	3	5.4	
	Ackers - White	13	23.2	
	Wu *et al.*	9	34.6	
Ibrahim [55]	Einstein	0	0.0	108 (5 Malaysian rivers)
	Yang	30	28.0	
	Engelund and Hansen	19	18.0	
	Ackers and White	22	20.0	
	Graf	29	27.0	

** In Wu et al.'s Equation [21] only 26 data sets were used*

They are from the works of both local and foreign investigators. Evaluation of these equations proved that an equation that performs well for one river may not give satisfactory results when tested on other rivers. Based on the above analyses, this paper aims at proposing a new sediment transport equation for use in both natural and man-made channels. General regression neural network (GRNN) algorithm is used in the analyses. Development and validation of the model used hydraulics and sediment data from 13 rivers in Malaysia and 11 rivers and one irrigation canal in Pakistan.

2.0 GENERAL REGRESSION NEURAL NETWORK

General Regression Neural Network (GRNN) is a three-layer network where there are no training parameters such as learning rate and momentum as in back-propagation network, but there is a smoothing factor which is applied after the network is trained. In GRNN networks, a smoothing factor is required which has effects on the output. The smoothing factor must be greater than 0 and usually range from 0.01 to 1.

Data needs to be trained to determine which smoothing factor is most appropriate. At the end of training, the individual smoothing factors may be used as a sensitivity analysis tool: the larger the factor for a given input, the more important that input is to the model at least as far as the test set is concerned. GRNN are known for their ability to train quickly sparse data sets and it is a type of supervised network. Its applications are able to produce continuous valued outputs and study had proved that GRNN responded much better than back-propagation to many types of problems. It is especially useful for continuous function approximation with options for multi-dimensional inputs.

Table 2: Summary of the sediment discharge variables by the investigators

Author	Sediment discharge variables
Engelund and Hansen [25]	$\frac{S_s}{S_s - 1}, \frac{VS_0}{\sqrt{g(S_s - 1)d_{50}}}, \frac{(S_s - 1)d_{50}}{RS_0}$
Ackers and White [13]	$\sigma, \frac{d_{50}}{y}, \frac{(S_s - 1)d_{50}}{RS_0}, \frac{V}{U_*}$
Yang [20]	$\frac{VS_0}{W_s}, \frac{V}{U_*}, \frac{W_s d_{50}}{\upsilon}$
Nagy [5]	$\psi, \frac{W_s}{U_*}, F, R_*, \frac{y}{B}$
Ariffin [22]	$\frac{R}{d_{50}}, \frac{U^*}{\omega}, \frac{U^*}{V}, F$

The meanings of each symbol are presented in Appendix I

3.0 DATA COLLECTION

Total of 499 hydraulics and sediment field data extracted from thirteen rivers in Malaysia between the year of 2000 and 2007, 1978 data from rivers in the United States namely Sacremento, Atchafalaya, Colorado, Mississippi, Middle Loup, Mountain Creek, Niobrara, Saskatchewan, Oak Creek, Red, Rio Grande rivers as well as data from Chop Irrigation Canal, Pakistan were used in model development, testing and validation phases.

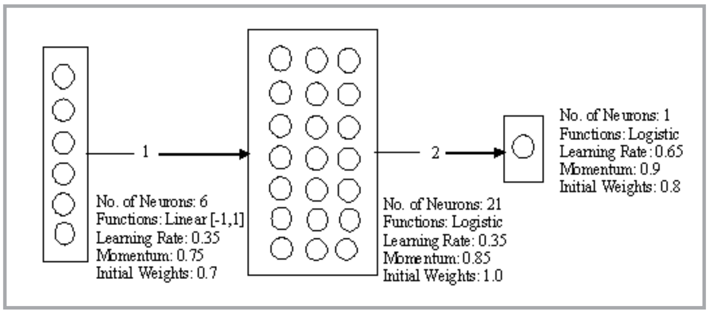
4.0 SELECTION OF SEDIMENT DISCHARGE VARIABLES

Development of the proposed equation takes into consideration the common discharge variables as summarized in Table 2. From the summary, the common variables used by these investigators have been identified. The selected variables are the hydraulic radius R, mean size of sediment d_{50}, shear velocity U^*, fall velocity of the sediment W_s, average velocity of flow V and the Froude Number. The dependent and the independent variables are in the form of dimensionless parameters consisting of the selected variables. Several analyses were done to check on the dependency of single and combination of the independent variables with the dependent variable Q_T which is the total sediment transport rate. The range of hydraulics and sediment data of the Malaysian rivers used in analyses and model development is as shown in Table 3.

5.0 EVALUATION OF THE EQUATIONS

Attempts were made to evaluate selected sediment transport equations as listed in Table 2. Nagy *et al.* sediment model was test run using three network architectures with their proposed variables namely the dimensionless tractive shear stress ψ, dimensionless suspended sediment parameter ω_0/u^*, water depth ratio h/d_{50}, Froude number F, Reynolds number R* and width scale ratio, h/B forming the input layer with total load concentration, C_s in the output layer. These equations were tested on 346 Malaysian river data. Accuracy of each equation was measured using the discrepancy ratios 0.5-2.0, 0.75-1.25, 0.5-1.5 and 0.25-1.75. Discrepancy ratio is the ratio of the calculated to observed sediment discharge. Figure 3 illustrate the various network architectures used to evaluate Nagy *et al.* equation. They suggested the use of back-propagation algorithm for use in their model.

(a) Network architecture with 1 hidden layer



(b) Network architecture with 2 hidden layers

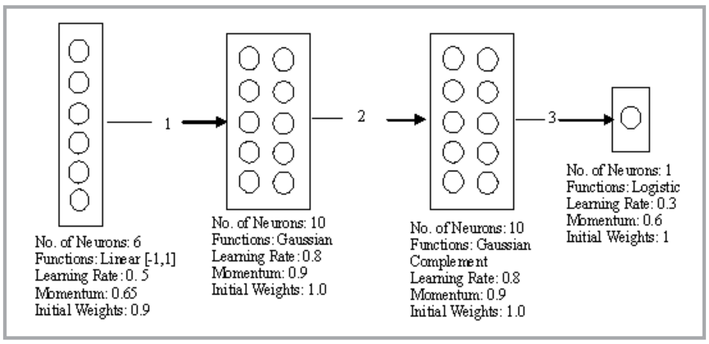


Table 3: Range of hydraulics and sediment data used in analyses and model development [6, 22, 55]

River	Location	No of data	Flow Q (m^3/s)	Velocity V (m/s)	Depth y_o (m)	Mean size d_{50} (mm)	Total Load Q_T (kg/s)	Slope S_o	Data source
Pari	Manjoi	20	9.7 - 47.9	0.7 - 1.3	0.69 - 1.87	1.70 - 3.00	1.2 – 18.0	0.0011	DID (2003)
	Buntong	20	9.7 - 17.0	0.7 – 1.0	0.68 - 0.89	0.85 -1.20	1.0 - 4.9	0.0012	
Raia	Kg. Tanjung	20	3.6 - 8.5	0.5 - 0. 8	0.24 - 0.49	0.60 -1.60	0.6 - 2.0	0.0036	Ibrahim (2002)
	Batu Gajah	21	4.4 - 17.4	0.5 - 0.8	0.41 - 1.76	0.50 - 0.85	0.4 - 2.7	0.0017	DID (2003)
Kampar	Km 34	21	8.0 – 18.0	0.6 - 0.7	0.55 - 1.28	0.85 - 1.10	0.5 - 2.5	0.001	
Kinta	Ipoh	20	3.8 - 9.7	0.4 - 0.7	0.32 - 0.57	0.40 - 1.00	0.2 - 12.8	0.0011	Ibrahim (2002)
Kerayong	Kuala Lumpur	27	0.9 - 6.0	0.2 - 0.6	0.54 - 1.30	2.00 - 3.10	0.4 - 15.8	0.00125	
Kulim	Kedah	16	1.4 - 11.0	0.30 - 0.9	0.31 - 0.84	3.00 - 4.00	0.3 - 7.1	0.001	
Pari	T. Merdeka	16	5.3 - 24.4	0.4 - 1.1	0.54 - 1.30	2.00 -3.10	0.4 - 15.8	0.00125	
Langat	Kajang	20	3.8– 39.6	0.5 – 1.4	0.45 – 1.39	0.37 – 2.13	0.7 – 77.9	0.0043 – 0.0051	Ariffin (2004)
	Dengkil	3	33.5 – 87.8	0.5 – 0.9	1.90 – 3.23	0.52 – 0.95	19.0 – 119.0	0.0167	
Lui	Kg Lui	92	0.7 – 17.2	0.2 – 1.0	0.23– 0.99	0.50 – 1.74	0.2 – 6.2	0.0003 – 0.0093	
Semenyih	Kg. Rinching	50	2.6 – 8.0	0.4 – 0.9	0.36 – 0.82	0.88 – 2.29	1.0 – 12.0	0.0023 – 0.015	
Bernam	Tg. Malim	55	2.0 – 90.0	0.2 – 6.7	0.60 – 1.30	0.50 – 2.50	0.03 – 47.0	0.0005 – 0.06	Ariffin *et al.* (2007)
Selangor	K.Kubu	98	0.6 – 2.0	0.2 – 0.5	0.20 – 0.55	0.70 – 1.50	0.06 – 21.0	0.001 – 0.01	

(c) Network architecture with 3 hidden layers

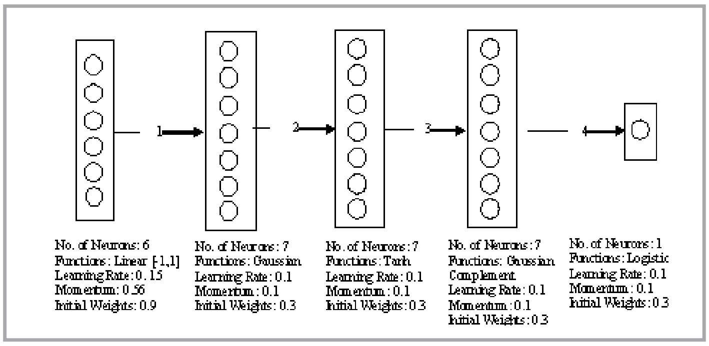


Figure 3: Various network architectures used to evaluate Nagy et al. [5] sediment model

Nagy *et al.* had proposed back-propagation algorithm for sediment transport prediction. Graphs of predicted versus measured sediment values are shown in Figures 4-9. Results of analysis have indicated the viability to develop a new sediment transport equation. Engelund and Hansen, Ackers and White and Yang equations gave prediction accuracies of 22%, 28% and 24% respectively in the discrepancy ratio of 0.5-2.0. Ackers and White's equation over-predicts sediment load while Yang's equation under-predicts the sediment load. Both Engelund and Hansen and Yang equations show a similar trend with large scatter. From analysis, it is evident that there are significant deviations of calculated values from the measured values for Engelund and Hansen, Ackers and White and Yang equations. Three network architectures were tried on Nagy *et al.* using their proposed input variables. The network architecture with 3 hidden layers (Figure 3c) gave a slightly reasonable estimate in comparison to the other two network architectures. Nevertheless the estimation holds true for sediment load greater than 1 kg/s. A summary on the accuracy of the equations in the discrepancy ratios of 0.25-1.75 and 0.5-2.0 with the respective statistical parameters is as shown in Table 4.

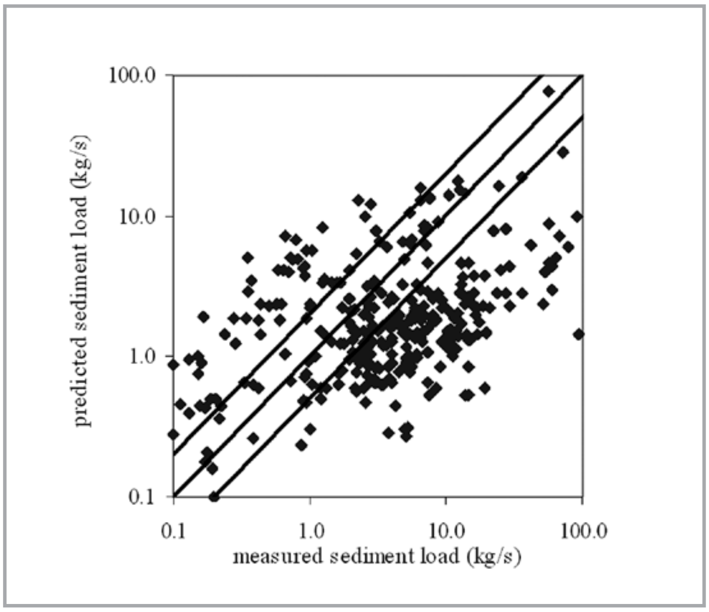


Figure 4: Predicted against measured sediment load using Engelund and Hansen [25] equation

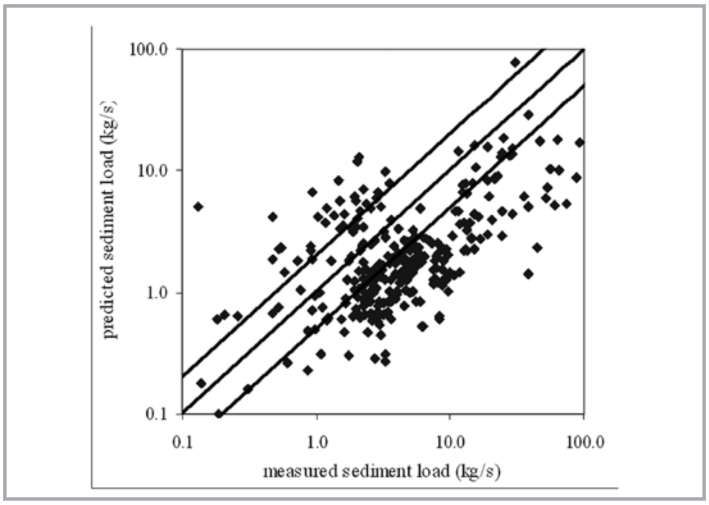


Figure 5: Predicted against measured sediment load using Yang [20] equation

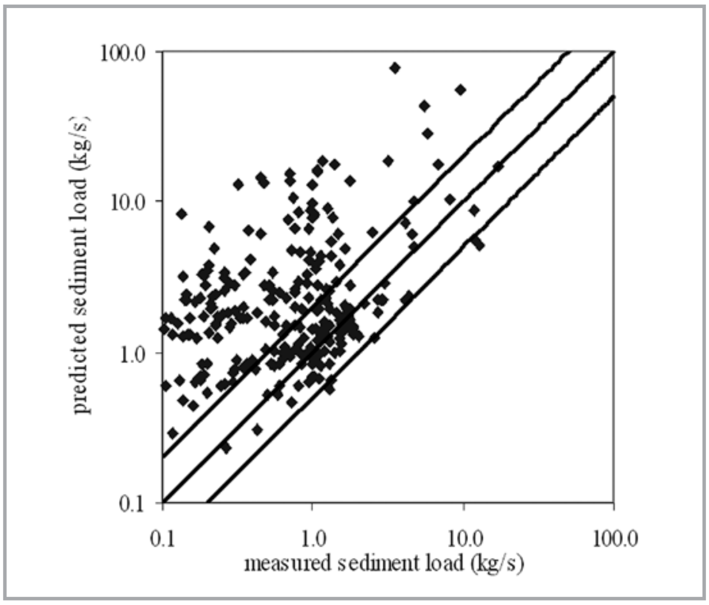


Figure 6: Predicted against measured sediment load using Ackers and White [13] equation

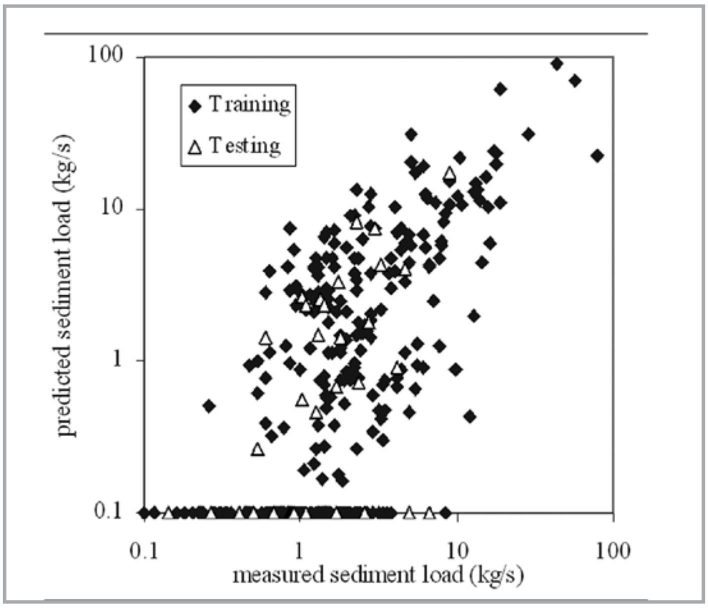


Figure 7: Predicted against measured sediment load using Nagy et al. [5] sediment model (with 1 hidden layer)

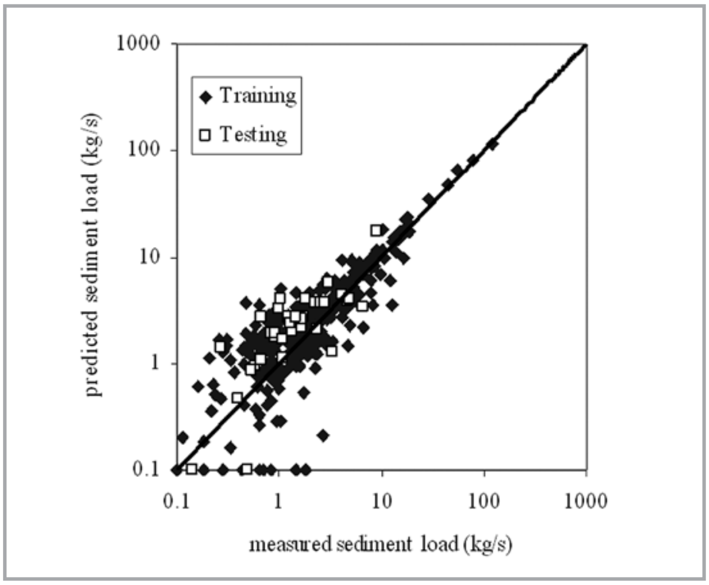


Figure 8: Predicted against measured sediment load using Nagy et al. [5] sediment model (with 2 hidden layers)

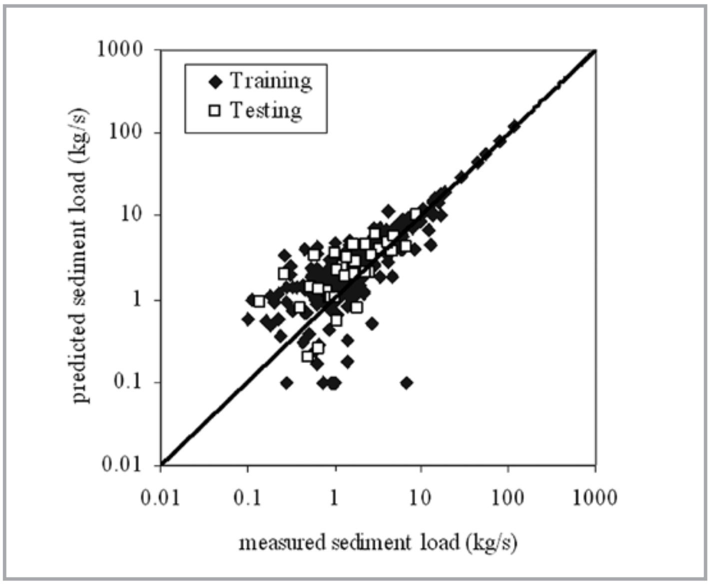


Figure 9: Predicted against measured sediment load using Nagy et al. [5] sediment model (with 3 hidden layers)

Table 4: Accuracy of established equations for sediment transport [53]

Equation / Model	Network Architec-ture	No. of data	Discrepancy ratio						
			Mean	Median	Standard deviation	Percent of data in range			
						0.25 – 1.75		0.5 – 2.0	
						Training	Testing	Training	Testing
Nagy *et al.* [5]	1 hidden layer	346	0.89	0.45	0.96	45	41	39	35
	2 hidden layer		1.74	1.58	1.03	77	59	80	71
	3 hidden layer		1.89	1.34	1.61	68	62	76	65
Engelund and Hansen [25]	-	346	4.63	2.52	8.26	27		22	
Ackers and White [13]	-	346	0.49	0.28	0.50	41		28	

6.0 PROPOSED SEDIMENT TRANSPORT MODEL

The proposed sediment transport model uses general regression neural network (GRNN) that are applicable for both natural and man-made channels. GRNN is a supervised network that trains quickly sparse data sets [56]. The network architecture responses very well with data that is spasmodic in nature than back propagation algorithm. Four independent dimensionless variables, namely, relative roughness on the bed (R/d_{50}), ratio of shear velocity and fall velocity (U^*/W_s), ratio of shear velocity and average velocity (U^*/V) and the Froude Number ($V/\sqrt{gy}$) were used as inputs and the total sediment load Q_T in kg/s as the output variable.

The proposed network architecture GRNN is a three-layer network with one hidden neuron for each training pattern. There are no training parameters such as learning rate and momentum as in back-propagation network, but there is a smoothing factor which is applied after the network is trained. The range for the smoothing factor is between 0.01 and 1. Data needs to be tested to determine which smoothing factor is most appropriate for the data set. No retraining is required to change the smoothing factors, as the value is specified when the network is applied. Smoothing factors of 0.01 and 0.0138824 are used for Malaysian and US rivers respectively. Figures 10 through 17 show graphs of predicted against measured sediment load using the proposed sediment transport model. Figure 18 show the overall performance of the proposed model on all 13 rivers in Malaysia. The model gave very good prediction in both the training and testing phases where all data lie in line of perfect agreement. The model gave an equally good performance when tested on hydraulics and sediment data of 11 rivers in the United States and data from a canal in Pakistan. This is evident from graphs shown in Figures 19 through 29. Figure 30 gives the overall performance of the model on all foreign rivers. Table 5 illustrates the performance of the proposed model in the discrepancy ratios of 0.5-2.0, 0.75-1.25, 0.25-1.75 and 0.75-2.0. Smaller discrepancy ratio of 0.75-1.25 was used to illustrate the accuracy of the model. Nevertheless discrepancy ratio of 0.5-2.0 is acceptable for field data. Mean, median and standard deviations of the predicted values are in the range of 0.93-1.23, 0.84-1.09 and 0.26-1.84 respectively.

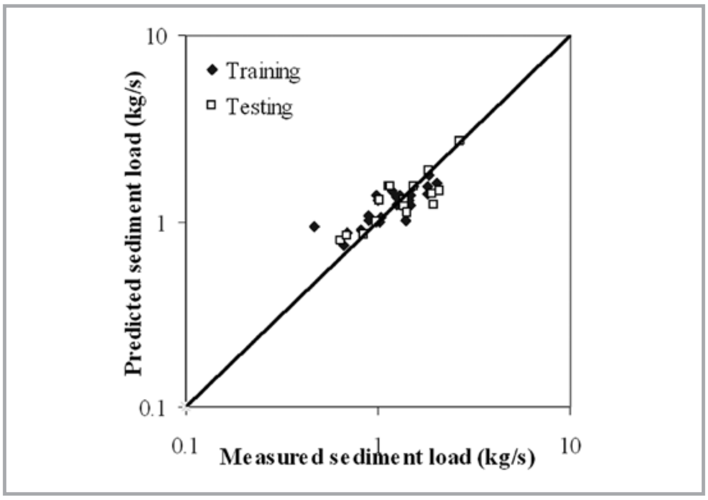


Figure 12: Predicted against measured sediment load using the derived model on Sungai Pari @ Manjoi, Buntong and Taman Merdeka (56 data)

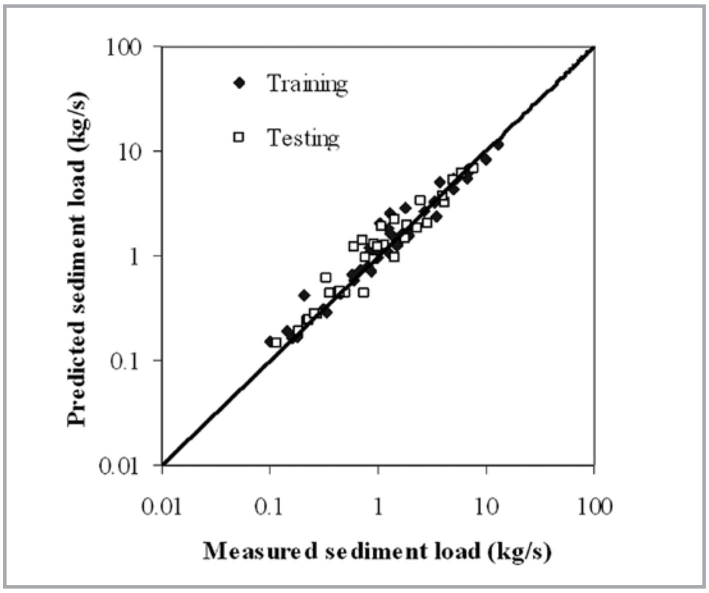


Figure 10: Predicted against measured sediment load using the derived model on Sungai Kinta, Kerayong, Kulim and Kampar (84 data)

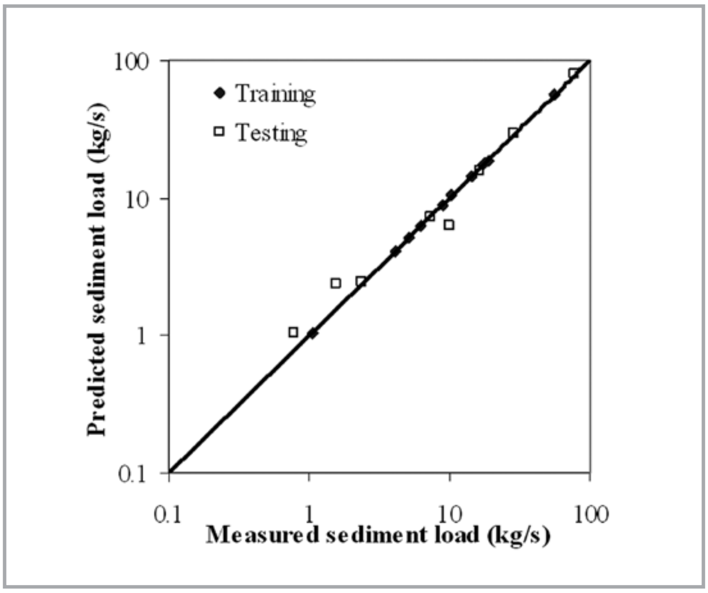


Figure 13: Predicted against measured sediment load using the derived model on Sungai Langat @ Kajang and Dengkil (23 data)

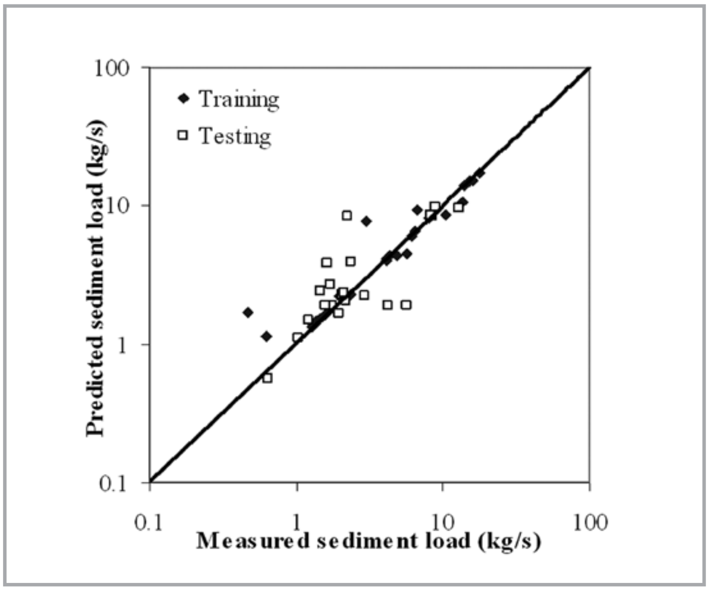


Figure 11: Predicted against measured sediment load using the derived model on Sungai Raia @ Kg Tanjung and Batu Gajah (41 data)

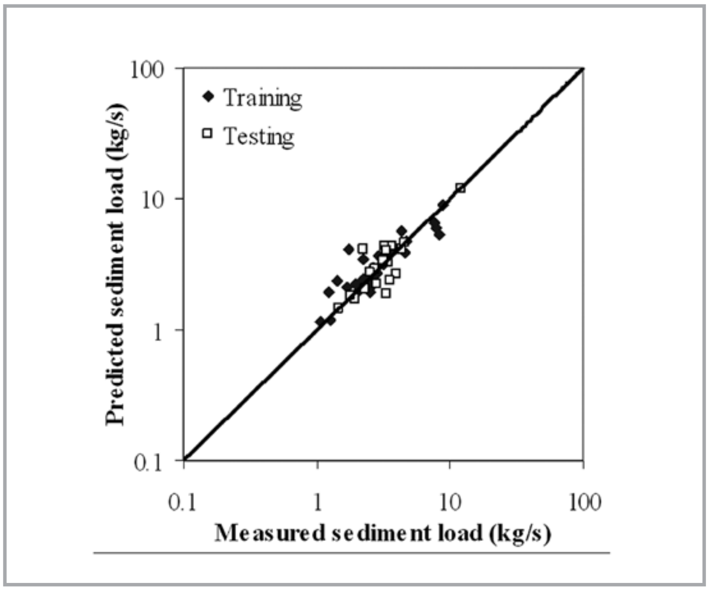


Figure 14: Predicted against measured sediment load using the derived model on Sungai Semenyih (50 data)

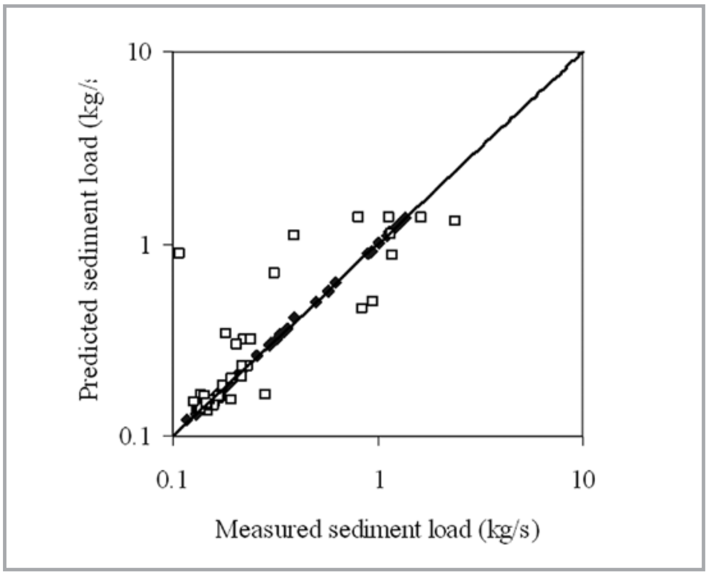


Figure 15: Predicted against measured sediment load using the derived model on Sungai Selangor, Gerachi and Luit (98 data)

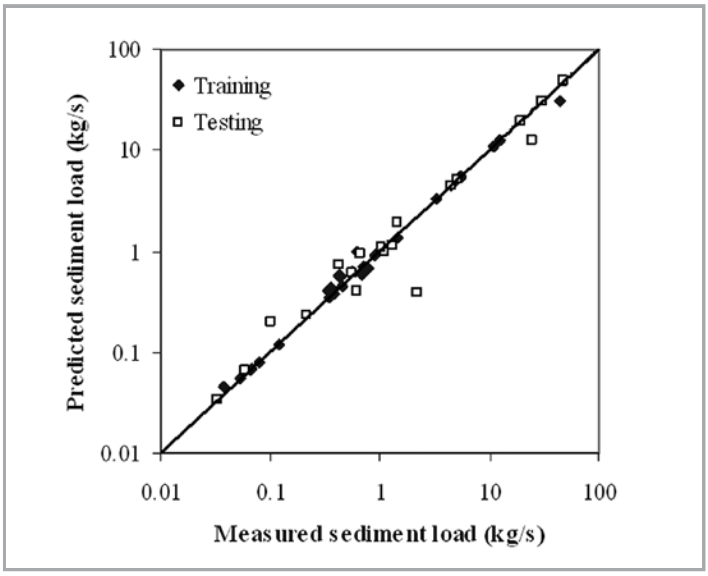


Figure 16: Predicted against measured sediment load using the derived model on Sungai Bernam (55 data)

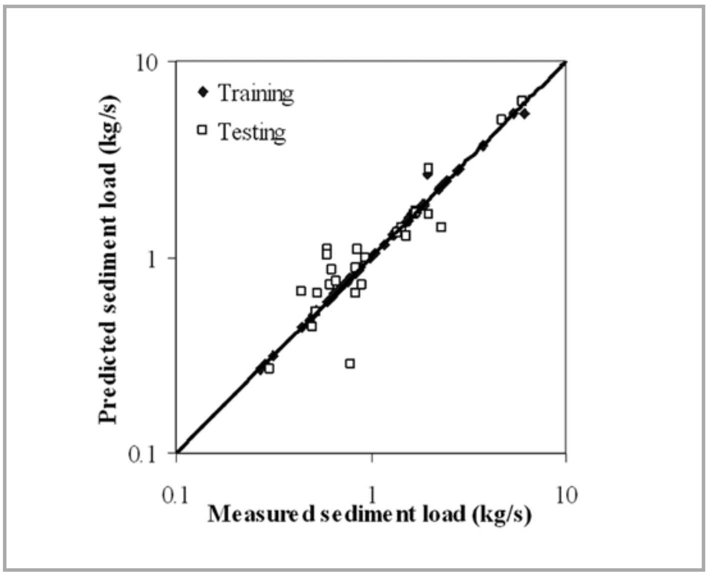


Figure 17: Predicted against measured sediment load using the derived model on Sungai Lui (92 data)

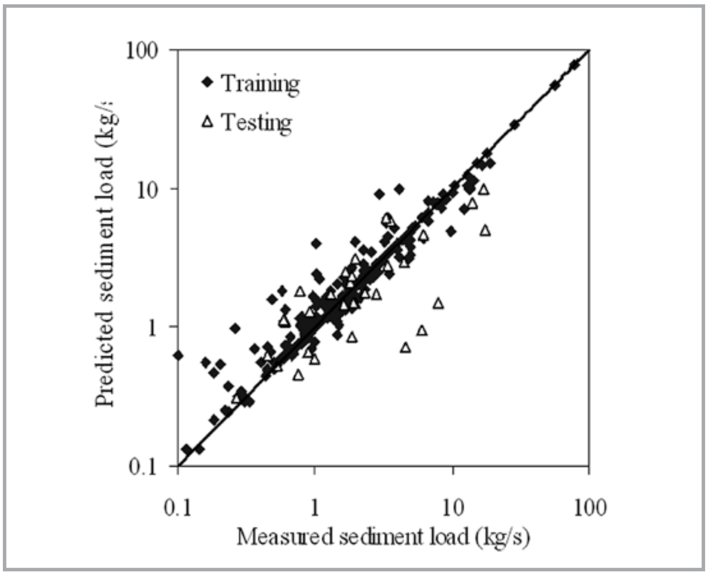


Figure 18: Overall performance on Malaysian rivers using the derived model

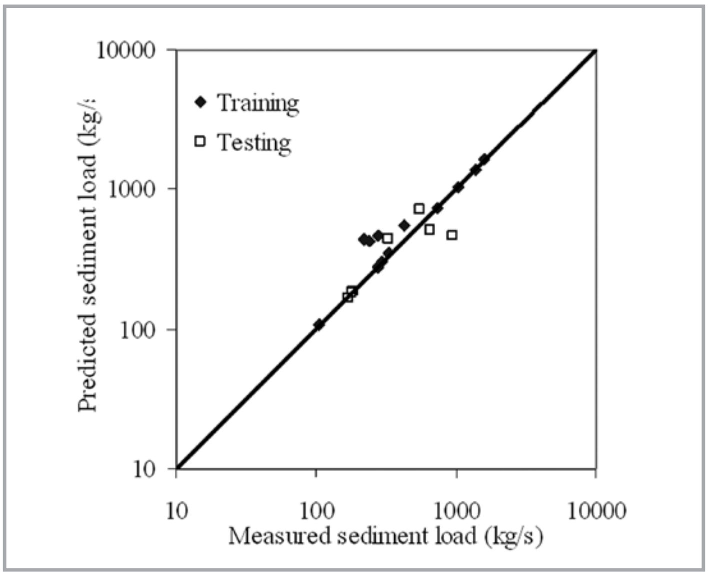


Figure 19: Predicted against measured sediment load using the derived model on Chop Irrigation Canal (19 data)

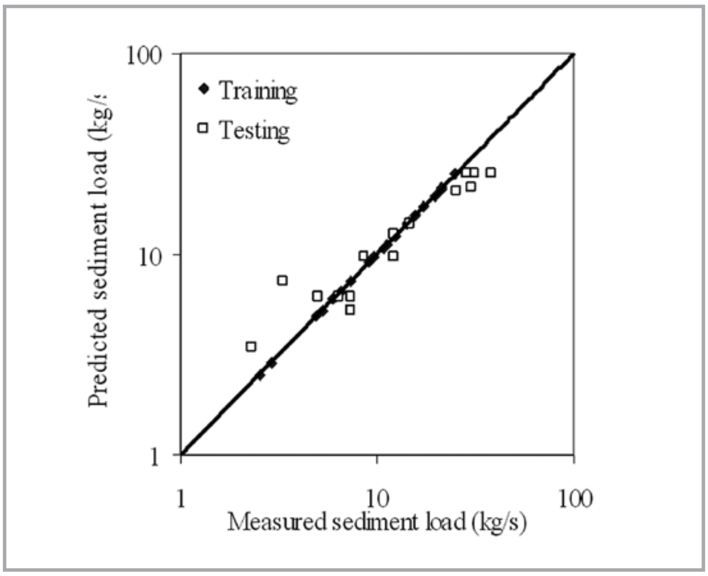


Figure 20: Predicted against measured sediment load using the derived model on Niobrara River (39 data)

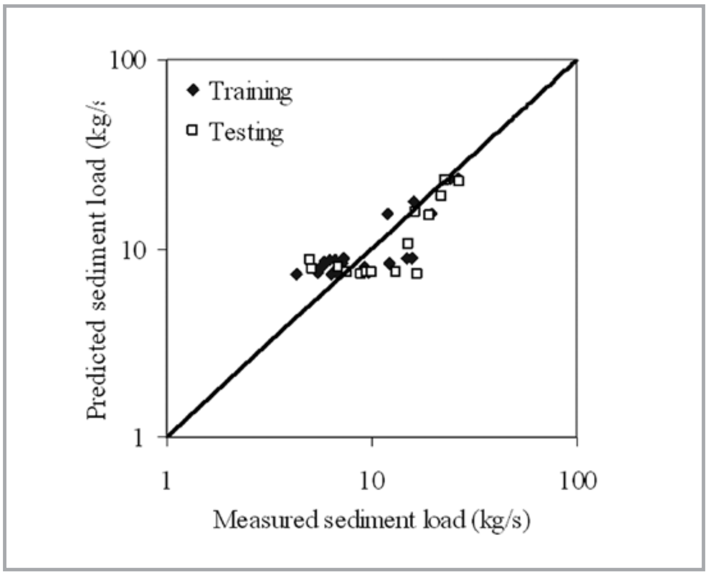


Figure 21: Predicted against measured sediment load using the derived model on Middle Loup River (38 data)

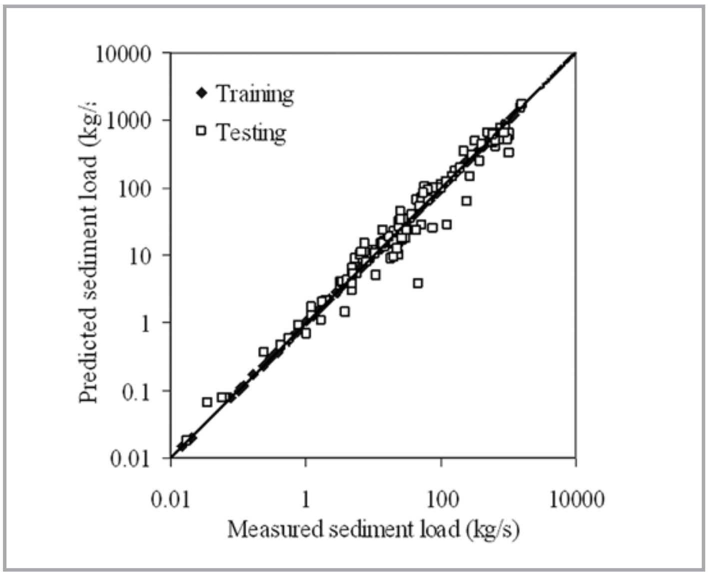


Figure 22: Predicted against measured sediment load using the derived model on Rio Grande River (314 data)

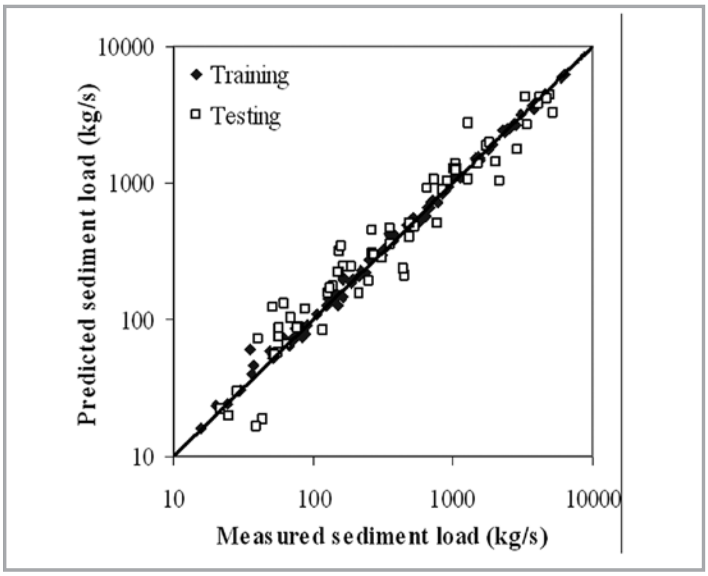


Figure 23: Predicted against measured sediment load using the derived model on Mississippi River (164 data)

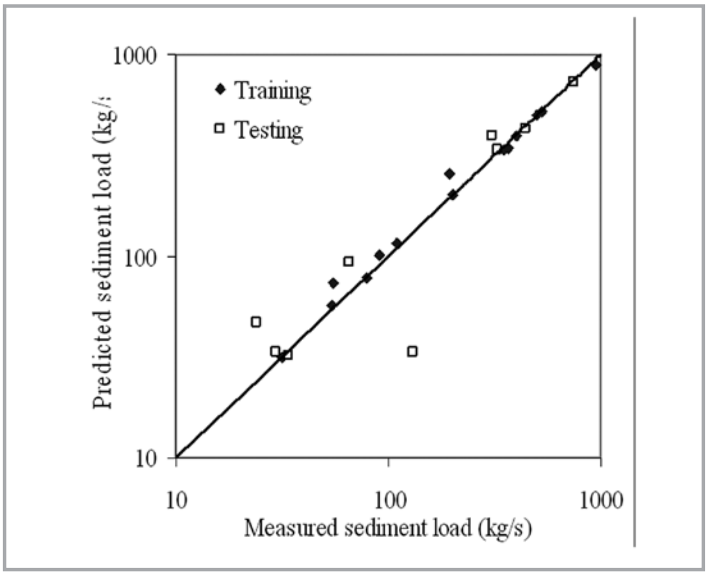


Figure 24: Predicted against measured sediment load using the derived model on Sacremento River (23 data)

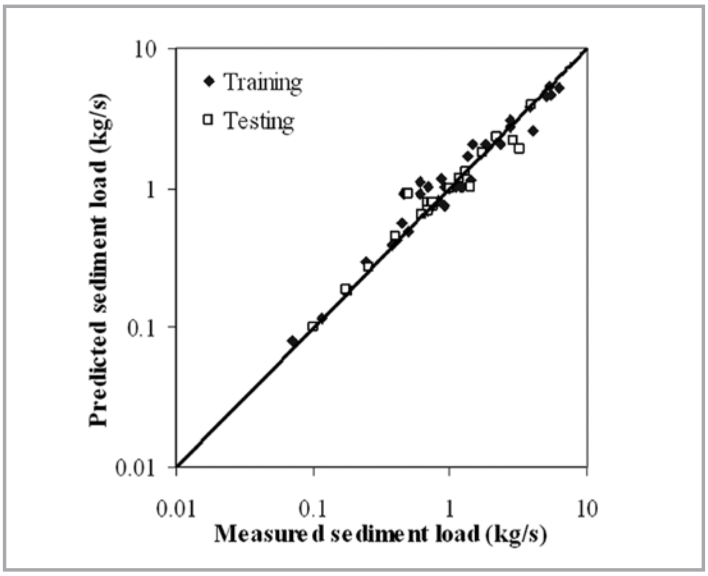


Figure 25: Predicted against measured sediment load using the derived model on Sasketchewan River (55 data)

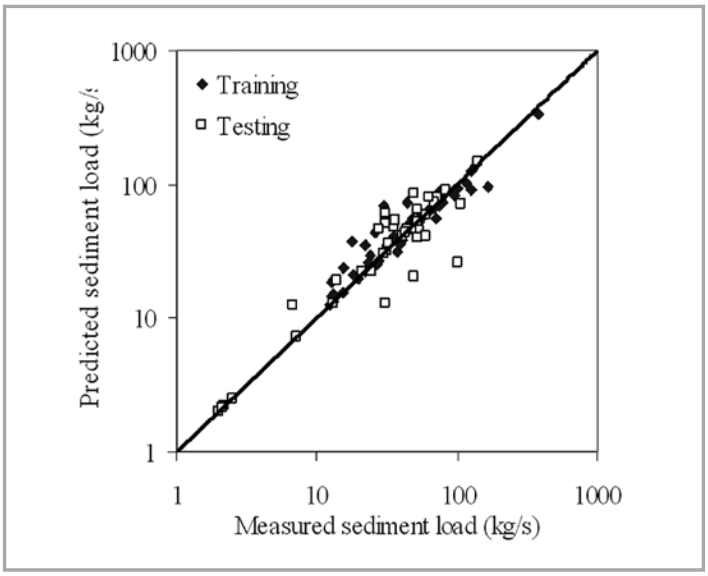


Figure 26: Predicted against measured sediment load using the derived model on Colorado River (100 data)

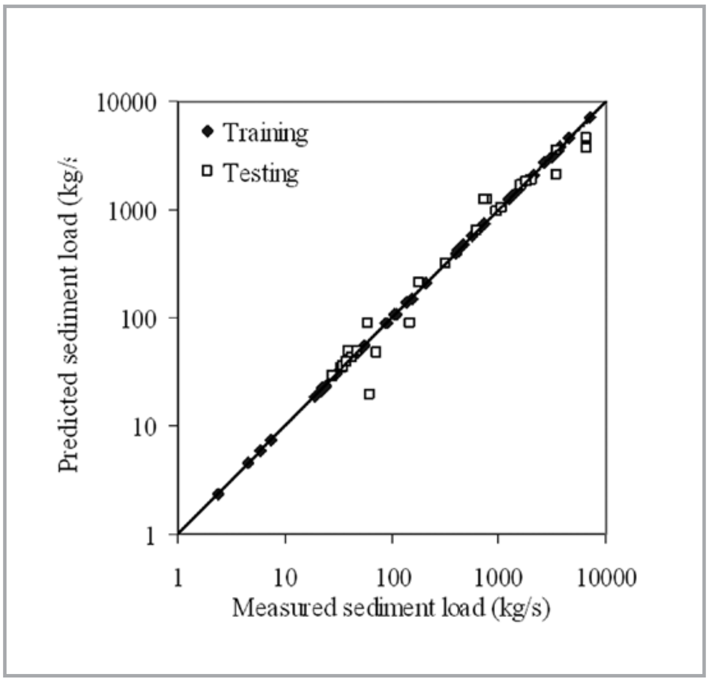


Figure 27: Predicted against measured sediment load using the derived model on Atchafalaya River (67 data)

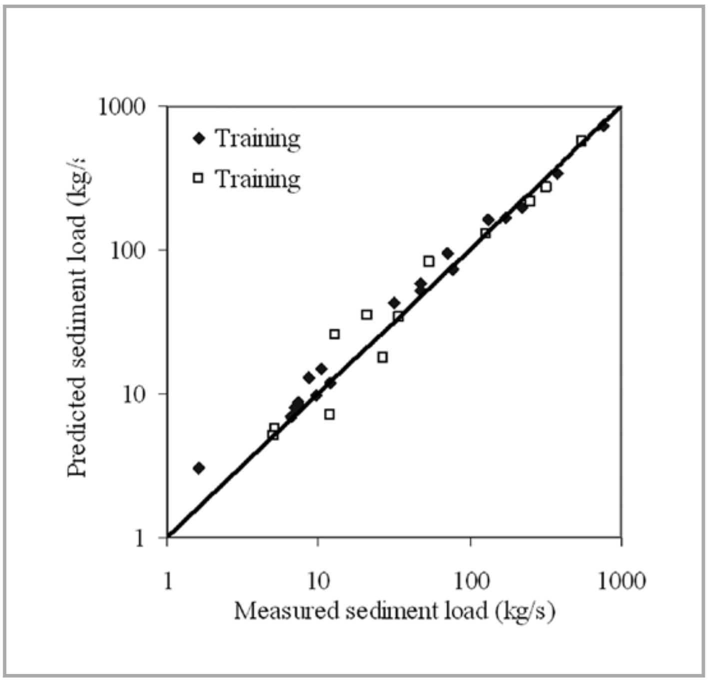


Figure 29: Predicted against measured sediment load using the derived model on Red River (30 data)

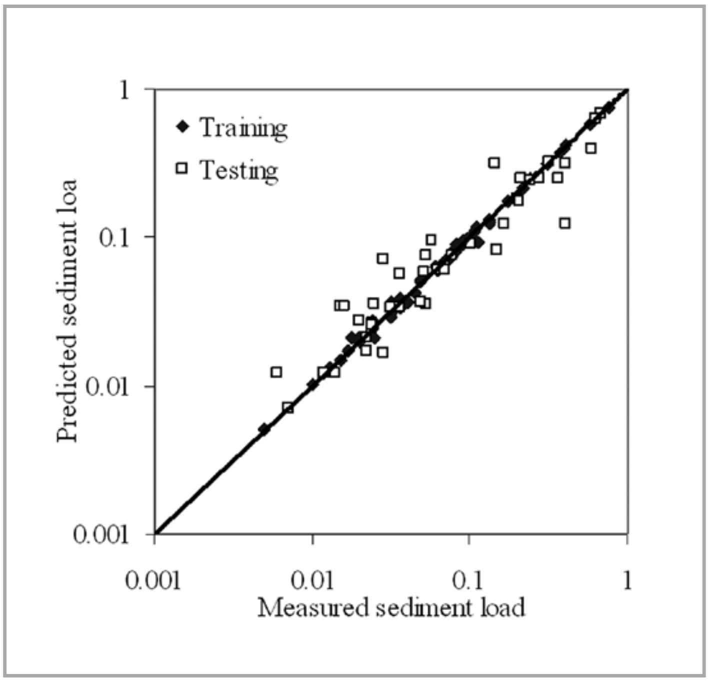


Figure 28: Predicted against measured sediment load using the derived model on Mountain Creek and Oak Creek (116 data)

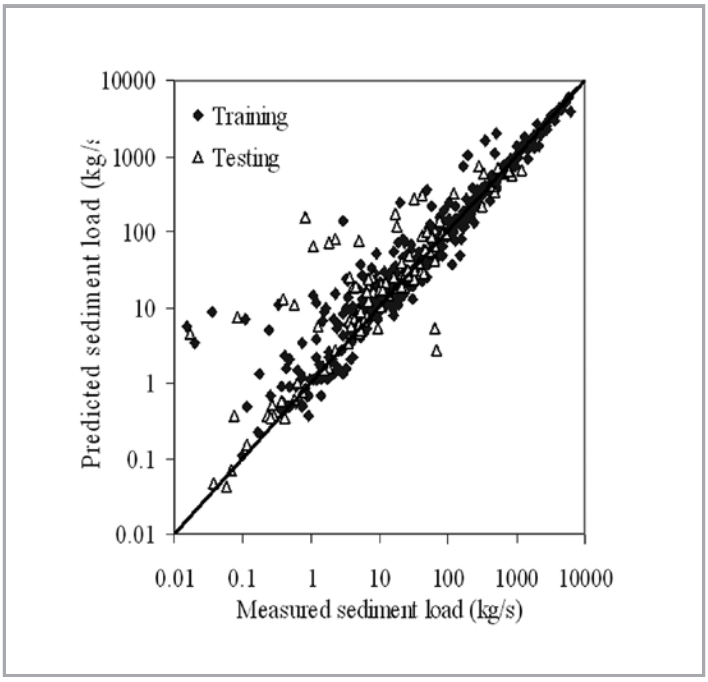


Figure 30: Overall performance on US rivers using the derived model

7.0 CONCLUSION

The proposed sediment model which uses general regression neural network had shown to response better to back-propagation algorithm. This kind of network accommodates data that are sparse and spasmodic in nature. The results of the analysis (both physical and graphical) have indicated that the proposed sediment transport model predicts more accurately sediment transport for both local and foreign rivers then presently available methods in the literature which is proven physically and graphically. This gives a very clear indication on the robustness of the model for use in sediment prediction for rivers with different hydraulics and sediment characteristics. The proposed sediment model can thus be used in the estimation of sediments in dams and sediment transport rates in rivers.

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Table 5: Accuracy of the proposed model tested on Malaysian rivers and rivers in US and Pakistan

Rivers	Country	No. of data	Mean	Median	Standard deviation	Discrepancy ratio							
						0.5-2.0		0.75-1.25		0.25-1.75		0.75-2.0	
						Training	Testing	Training	Testing	Training	Testing	Training	Testing
Sungai Kinta, Kerayong, Kulim and Kampar		84	1.133	1.052	0.357	100	100	79	73	94	91	98	94
Sungai Raia		41	1.002	1.005	0.224	100	100	88	75	96	100	100	81
Sungai Pari		56	1.229	1.092	0.703	94	82	94	73	94	91	94	82
Sungai Langat @ Kajang and Dengkil	Malaysia	23	1.061	1.015	0.260	100	100	100	88	100	100	100	100
Sungai Semenyih		50	1.014	1.003	0.274	97	100	83	75	97	90	97	90
Sungai Lui		92	1.067	1.010	0.314	100	96	99	82	100	96	100	96
Sungai Bernam		55	1.046	1.027	0.370	100	95	100	67	100	95	100	86
Sungai Selangor, Luit and Gerachi		98	1.504	1.014	1.844	100	90	100	69	100	87	100	77
Chop Irrigation Canal	Pakistan	19	0.981	1.000	0.286	100	100	83	86	83	100	100	86
Mid Middle Loup		38	0.926	0.843	0.333	100	93	74	73	100	100	96	87
Mississippi		164	1.126	1.054	0.429	100	89	99	65	100	91	100	83
Niobrara	United States	39	1.020	0.876	0.399	100	93	100	73	100	93	100	73
Rio Grande		314	0.987	1.006	0.353	100	96	100	70	100	98	100	78
Sacremento		23	1.103	1.032	0.452	100	78	86	67	100	89	100	78
Sasketchewan		55	1.069	1.021	0.293	100	100	85	81	94	95	94	91
Atchafalaya		67	0.990	1.007	0.305	100	96	100	77	100	100	100	77
Colorado	United States	100	1.079	1.015	0.360	97	95	83	73	97	98	93	78
Mountain Creek and Oak Creek		116	1.097	0.993	0.470	100	91	100	70	100	91	100	78
Red		30	1.097	1.007	0.399	100	100	94	80	100	90	100	90

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APPENDIX I: NOTATIONS

The following symbols are used in this paper.

Symbol	Description
A	Flow area (m^2)
C_s, C_V	Volumetric concentration of sediment (ppm)
C	Total load concentration
d_{50}	Sediment diameter where 50% of bed material is finer
g	Acceleration due to gravity (9.812 m/s^2)
R	Hydraulics radius
S	Energy slope
U_*,U^*	Shear stress = $\sqrt{gRS}$ or $\sqrt{gDS}$ or shear velocity
V	Average flow velocity (m/s)
W_s	Fall velocity of sediment particles (m/s)
y	Depth of flow in m
γ	Specific weight of water (N/m^3)
γ_s	Specific weight of sediment (N/m^3)
σ	Geometric standard deviation of discrepancy ratio
ν	Kinematic viscosity
D	Flow depth (m)
Q_T	Total sediment load (kg/s)