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Prediction of Bed Load Transport in Heterogeneous sand bed Channel Using Artificial Neural Networks (ANN)

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Abstract

The study and estimation of river bed load transport fluctuation is very complex for supplementing existing sediment transport theory. Fluctuation of bed load depends on several scales, including individual particle motion, the development of bed forms, the presence of bed load sheets, and waves of stored sediment. The essential characteristic of a river channel is to percolate the water in terms of downward seepage because of the permeability of sandy materials. Further, the problem of seepage is crucial for the sustainability of hydraulic structures because of its interaction with groundwater. In the present work, we consider the seepage effect on bedload transport across a heterogeneous (non-uniform) sand bed channel based on the importance of downward seepage. The dimension of the channels is 17.20 m in length, 1 m in width and 0.22m in depth. The fact that the bedload transfer rate increases fast and then plateaus is an important finding. The use of neural network modelling, which is particularly beneficial in modelling processes, is described here as a supplement to modelling bed material load transport. In comparison to other traditional methods based on different statistical criteria, the proposed model outperformed them. The significance of the various input characteristics has been investigated in this study to better understand their impact on the transport process.

Keywords: Bed load, Seepage, Input parameters, Neural Network

1. Introduction

Sediment transport knowledge in alluvial channels is essential for sediment analysis and engineering research. The bed material load is calculated by adding the bed and suspended loads together. When analysing the bed load transfer, two major assumptions are consider: (1) No sediment transport occurs until the bed shear stress surpasses its critical value, and (2) after the incipient motion occurs, the transport rate increases according to the size of the bed shear stress. The second method is to directly calculate the bed material load. The Shield’s number is determined by shear stress, fluid and particle density, gravity acceleration and particle diameter.

The initiation of sediment transport is observed if the Shield’s number, θ is greater than the threshold value, θ_c:

$$\theta = \frac{\tau}{(\rho_s - \rho) g d} \qquad \theta_c = \frac{\tau_c}{(\rho_s - \rho) g d}$$

where τ and τ_c represent shear stress and critical shear stress respectively.

Critical shear stress (CSS) is found to vary linearly with grain size in sand-gravel mixes, with CSS increasing proportionally with the size of the gravel fraction. The sand-gravel composition in the heterogeneous sediment impacts the total transport rate under laboratory settings, according to experimental investigations. Because of the increased sediment supply to the bed channel, gravel fraction transport in channel beds is greater, which might result in bed degradation and sediment migration from the channel bed. Frostick ran flume tests to see how fine materials affected coarse sand movement. They hypothesised that fine particulates cause gravel movement, resulting in the formation of various bed shapes. To construct a bed load transport model for non-uniform sediment, Elhakeem and Imran (2016) used a model based on the density function of the bed material movement.
Artificial Neural Networks (ANN) continues to be the pinnacle of this supplementary modeling technique. We are able to analyse numerous hydrological and hydraulic phenomena, including water quality, stream flows, rainfall, runoff, sediment transport, and infilling missing data, using Neural network techniques.

In previous papers, it is found that already bed load transport has been computed for several channels using experimental data. So, using these methods, various results were found out regarding the parameters of bedload transport based on variations. Very less study happened about bed load transport in heterogenous channels with different models, as a result, This study focused on solve this problem using ANN.

The fundamental goal of this study is predict the bed load transport in heterogenous channels using method of Artificial Neural Networks (ANN) and find out which parameters affect the bedload transport under seepage conditions also compare the effectiveness of ANN model in comparison to other models

2. Methodology

2.1 Bed load calculation

The hydrodynamic forces acting on the debris are greater than the critical value, incipient movement of bed materials sitting on a wall boundary in a sand bed channel occurs. Due to sediment degradation on the corresponding phase, bed shear forces are better within the flume's upstream stop. As a result, the degraded material is deposited on the channel surface during the next phase downstream, as well as transferring downstream along the entire channel. As a result, large amounts of damaged soil are conveyed as a bed load across the bed in such a way that the materials slide over one another. For a seepage-affected channel, the functional form of bed load transfer (q_b) is:

$\boldsymbol{q_b = f(P, L, h, Q, S_f, d, \rho_s, \rho, g, q_s)}$

The above equation can be rewritten as follows by converting discharge into characteristic velocity:

$\boldsymbol{q_b = f(h, u, S_f, d, \rho_s, \rho, g, V_s)}$ where u denotes the rate of flow

The seepage velocity V_s is calculated as:

$$V_s = \frac{q_s}{PL}$$

The following variables were utilised to characterize the bed material load transport: –
Channel geometry: P (channel wetted perimeter), L (seepage zone length), h (flow depth)
Dynamic properties: Q (channel discharge), S_f (friction/energy slope)
Sediment properties: d (mean size of sediment), q_s (sediment discharge), ρ_s (density of sand)
Fluid properties: ρ (density of water), g (acceleration due to gravity)

In this study, three dimensionless statistics, namely Froude's Number (Fr), the roughness Reynold's number (Re*) andthe seepage Reynold's number (Re_s)are used to derive an empirical formula for bed load conveyance. Equation for the non-dimensional bed load transport (Φ) is given below:
The value of θ_c is calculated in this study using Paphitis' equation:

$$\theta_c = \frac{0.273}{1+1.2d*} + 0.046\left(1 - 0.576\exp^{-0.05d*}\right)r)^{7.83} \left(\mathrm{Re}\, d_* = d\left[g\left(\frac{\rho_s}{\rho} - 1\right)\middle/ \upsilon^2\right]\right.$$

Data for Calculation are collected from Sharma and Kumar (2018) based on various parameters.

2.2 ANN Training

Complex associations can be learned from a set of connected input–output vectors using artificial neural networks and a suitable learning method. Back-propagation is the most adaptable learning algorithm for the feed-forward multilayer network. The knowledge in a neural network is stored in the connectivity weights between neurons and the network's topology. As a result, one of the most crucial aspects of a neural network is the learning process, which involves presenting representative samples of the knowledge to be learned to the network so that it can integrate it into its structure. As a result, the learning process entails establishing the weight matrices that yield the greatest match of projected outputs across the whole training data set. The new point is determined by the Levenberg-Marquardt method, which strikes a balance between the step in the steepest descent direction and the previously described jump.

The following are the formulae for altering the weights during training in the Levenberg-

Marquardt method:

$$\Delta W = J^T J + \mu I^{-1} J^T e$$

Where J is the Jacobian matrix connecting each error to each weight's derivative, μ is a scalar and e is an error vector.

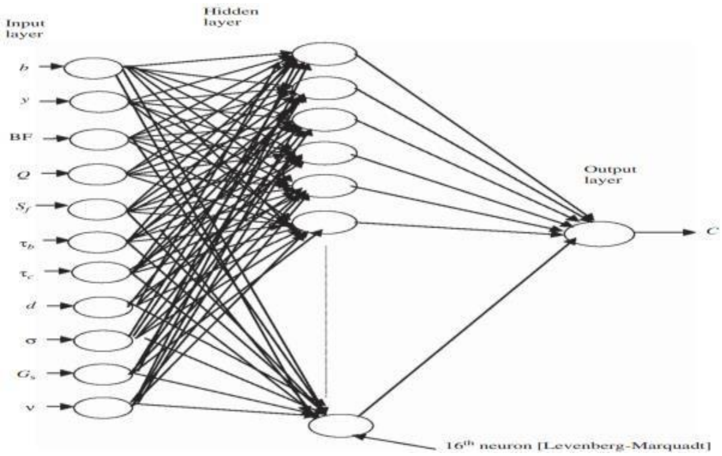

Figure 1: Neural network architecture

3. Results and Discussions

The neural modeling results are displayed in Fig. 2, which clearly illustrates that the linear coefficient of correlation between observed data and values predicted by neural nets is extremely high. In training and testing, the values were 0.997 and 0.992 respectively. Overall, the linear correlation coefficient is 0.995. (Fig.2).

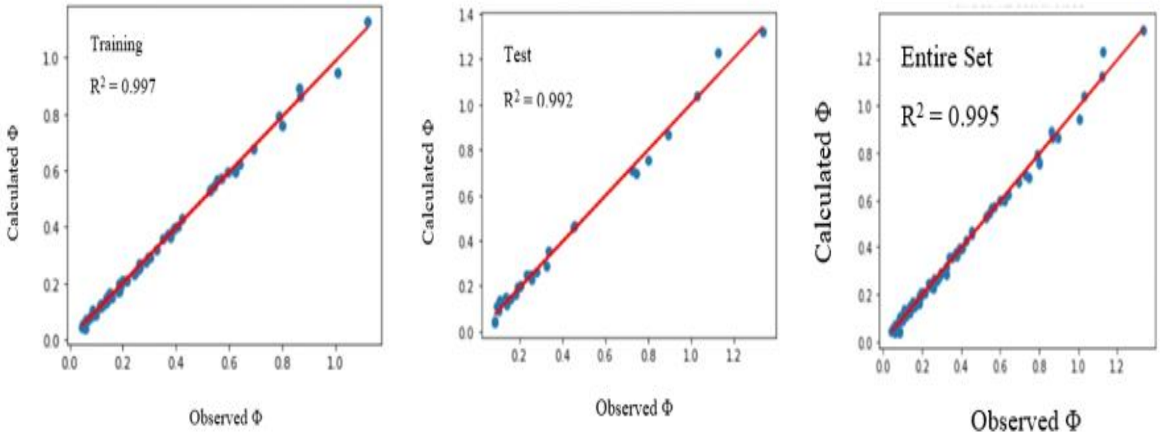

Figure 2: ANN Model results: (a) for training sets (b) for test sets (c) for entire sets

Model performance is nearly identical in all three cases: training, testing and overall, indicating that the model is more universal. As a result, the current model may be used to predict total bed material load both in flumes and in the field.

Performance of Bedload Transport Formula (Validation)

Despite the fact that there are numerous bedload transport equations in the literature, there are numerous disagreements on their effectiveness. Experimentally recorded bedload values are compared to the equivalent values predicted by various existing bedload transport formulae in order to determine the efficiency of bedload equations.

Meyer-Peter and Miller (1948), Engelund and Fredsee (1976), Ashida and Michiue (1972), Madsen (1991), Nielsen (1992) and Van Rijn (1993) were the six bedload equations studied to determine their efficiency for the experimental observations.

Table 1: Selected sediment transport formulae

Author	Equation
Meyer-Peter and Miller (1948)	$\phi = 8(\theta - \theta_c)^{1.5}$
Ashida and Michiue (1972)	$\phi = 17(\theta - \theta_c)(\theta^{0.5} - \theta_c{}^{0.5})$
Engelund and Fredsee (1976)	$\phi = 18.74(\theta - \theta_c)(\theta^{0.5} - 0.7\theta_c{}^{0.5})$
Madsen (1991)	$\phi = (\theta - \theta_c)(\theta^{0.5} - 0.7\theta_c{}^{0.5})$
Nielsen (1992)	$\phi = 12\theta^{0.5}(\theta - \theta_c)$
Van Rijn (1993)	$\phi = \frac{0.053}{d_*{}^{0.3}}\left(\frac{\theta}{\theta_c} - 1\right)^{2.1}$

The prediction of R^2 values corresponding to Calculated Bedload for each equation versus Observed Bedload and found several results.

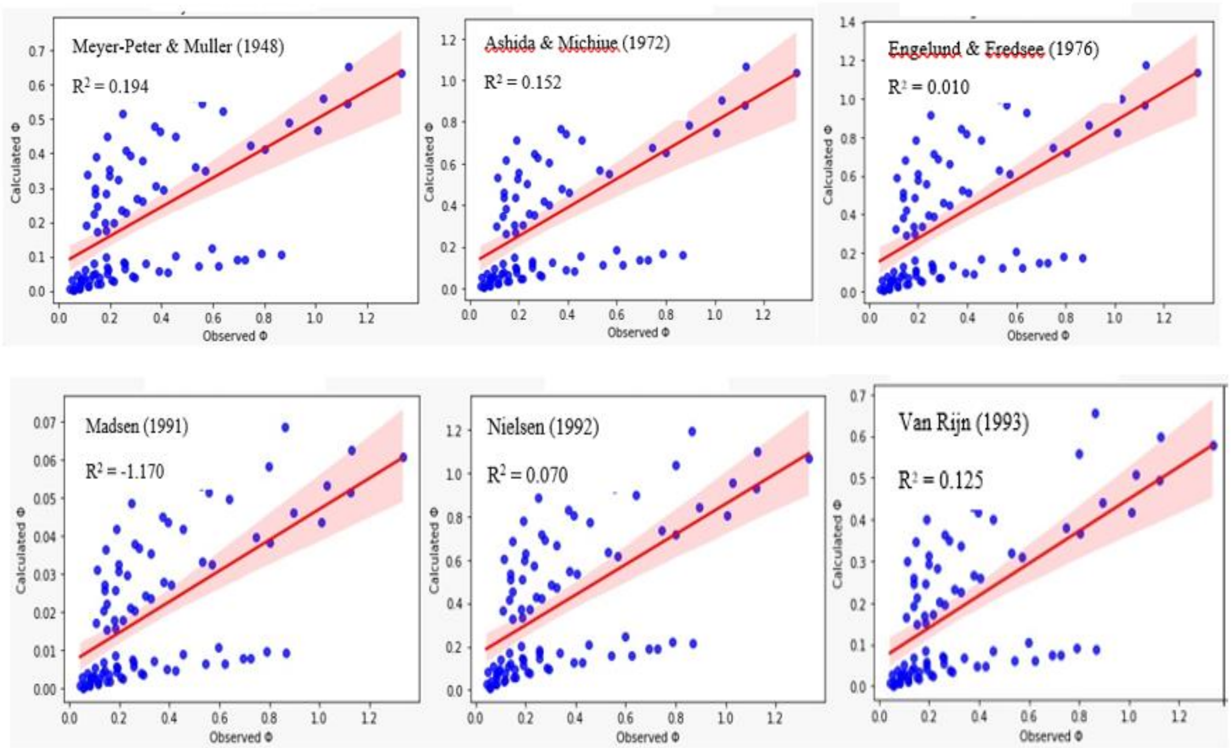

Figure 3: Performance analyses of bed material load formulas

From the graphs, we see that Mayer and Miller Equation fits the best because of its highest R^2 value while in comparison to other equations. Another reason for this type of deviation is because of consideration of seepage conditions in bed load transport. In these above 6 equations, only no seepage condition is considered where as in our ANN model, both seepage and no seepage conditions are taken for which reason, our model suits the best of all.
For better understanding of the model, the value of R^2 of all the corresponding equations used in this experiment is given below in the table.

Table 2: Statistical performance of bed material load transport formulas

MODEL	R^2
ANN Training	0.997
ANN Testing	0.992
ANN Overall	0.995
Meyer-Peter and Miller (1948)	0.194
Engelund and Fredsee (1976)	0.152
Ashida and Michiue (1972)	0.010
Madsen (1991)	-1.170
Nielsen (1992)	0.070
Van Rijn (1993)	0.125

The connection weights between neurons in a neural network represent the linkages between the network's input and output, and hence the problem and solution. Estimating the contribution of predictor factors to the outcome can be done using a number of different ways. For input significance testing, the current study employs the Garson's Algorithm. In order to identify the relative relevance of each input variable in the network, Garson devised a method for dividing neural network connection weights.

Table 3: Relative Ranking of Input Parameters

Variables	Garson's Algorithm	Ranking
Fr	1.4564	1
u_s	1.4256	2
Q	1.3384	3
S_f	1.3091	4
θ	1.2324	5
Re_*	1.1734	6
Re_s	1.1549	7
h	1.1356	8
θ_c	1.0631	9
V_s	0.9583	10

Along with the relative ranking of the input parameters, the graphs between required parameters versus observed bed load are also plotted to know the behavioral changes.

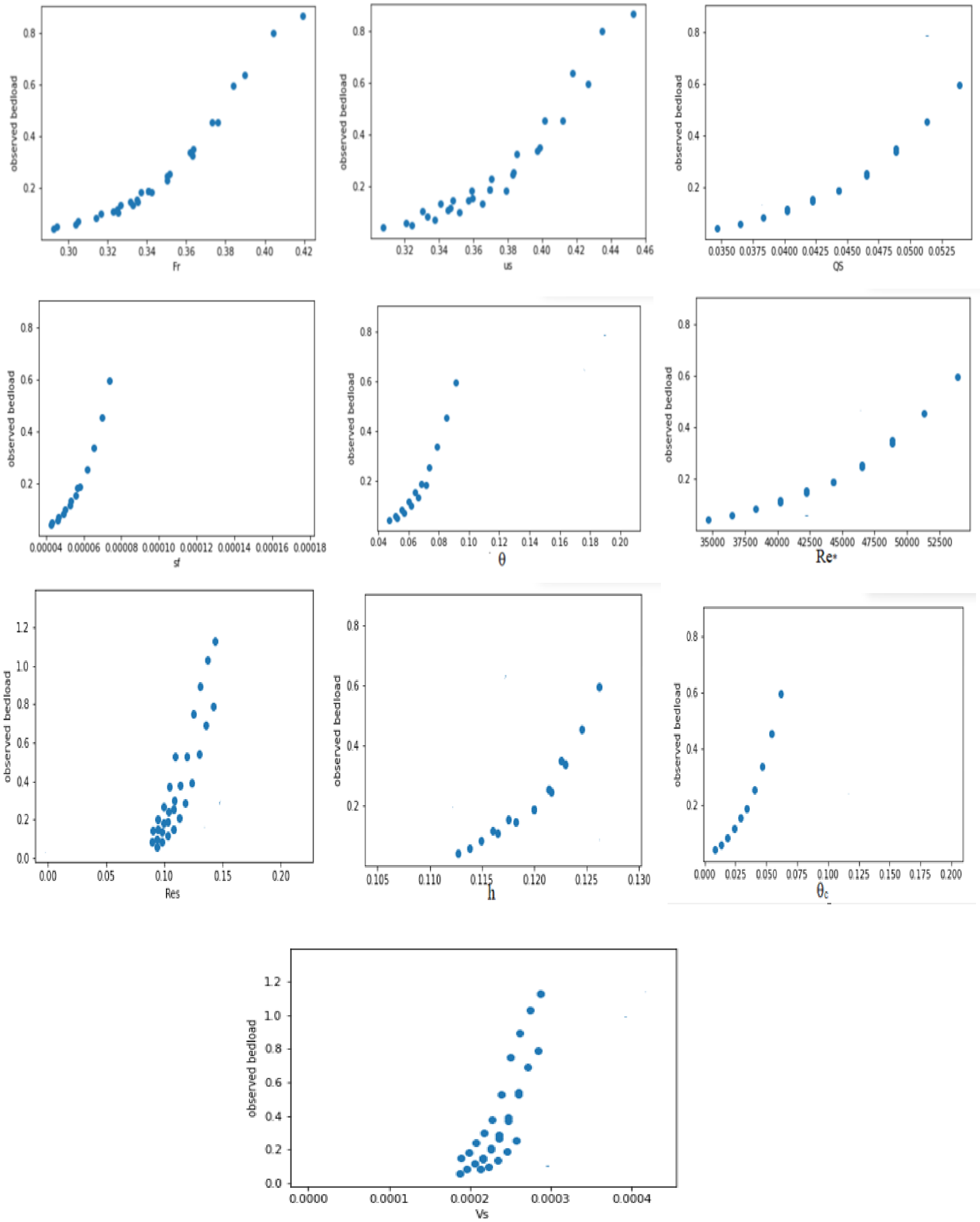

Figure 4: Behavioral changes of input parameters with observed bed load

4. Conclusions

The rate of sediment transport in a river is measured by bed material load. The bed load transfer in an experimental seepage-affected sand bed channel formed of a sediment mixture was studied in this study. Because

i. The models of bed material load transport are frequently complex, relying on semi-empirical or empirical equilibrium transport equations to link sediment fluxes to physical parameters.
ii. Froude's number has shown the maximum impact on bed load transport, followed by shear velocity, hydraulic radius, friction slope, flow depth and least given by seepage velocity.
iii. The current study demonstrates that more accurate hydraulic parameter calculation is required for accurate prediction of bed material load transmission.
iv. The ANN Model gives better results than Experimental observation.

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