Evaluation Of Sediment Transport Equations And ANFIS-Based Models For Computing Total Load In The Elbe River

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Abstract

Computation of sediment transport rates in natural rivers is necessary for successful implementation of sustainable projects in hydraulic engineering. There are many equations available which are derived based on probabilistic, deterministic and regression approaches. Prediction errors of the existing equations are usually very high for practical applications, and show significant discrepancy from observed transport rates. There is a very large degree of uncertainty and fuzziness associated with the prediction of sediment transport. A data-driven fuzzy logic approach is a powerful alternative to model complicated processes, where computation of sediment transport is a focus area.

This paper focuses on assessing the applicability of data-driven adaptive neuro-fuzzy modelling technique for predicting total sediment transport rate in the Elbe river. Flow depth, velocity, energy slope and median size of sediment particles are selected as dominant parameters influencing the amount of sediment transport. After data analysis and exclusion of extreme values, a total of 320 datasets are selected for the final model development. Two thirds of the datasets are used for training and one third for testing. The initial fuzzy model is obtained by grid partitioning of the input variables and a neuro-fuzzy system is used for optimizing the model. A sensitivity analysis for the combination of input parameters as well as number and type of membership functions is performed to determine the significance of the parameters on model performance.

The accuracy of the ANFIS model is compared with the results computed by the equations of Yang (1973), Ackers and White (1973), Engelund and Hansen (1972), Bagnold (1966), and van Rijn (1984). From the results of the investigation it can be concluded that the ANFIS model performs significantly better than the selected transport equations. The values predicted by the equations show a large deviation from measured transport rate.

Introduction

In natural rivers, flow is able to transport sediment particles when it exceeds the critical condition required for the initiation of motion. This critical condition is called incipient motion and its criteria can be expressed using critical bed shear stress (Shields, 1936), critical velocity, or stream power as characteristic parameters. If this condition is satisfied and the flow is able to exert enough force or energy, sediment particles start moving. The motion of sediment particles can be as bed load or suspended load. Different factors determine whether a sediment particle is transported as bed load or suspended load including particle size, flow velocity, flow depth. Understanding the process of sediment transport in rivers and prediction of the amount of transported sediment is essential for the design of hydraulic structures and a sustainable management of water resources. Sediment transport plays a key role in channel morphology changes, reservoir sedimentation, maintenance of navigation channels, design of intake structures for hydropower, habitat modelling, river aesthetic, and environmental impact assessment. One, two, or three dimensional numerical hydraulic models are usually used to simulate the process of sediment transport and the resulting short and long term river morphology changes so that appropriate mitigation measures can be implemented based on the results of the simulation. The sum of the amount of bed load and suspended load is called *total load*. Wash load is usually fine and mainly moves in suspension (Xiaoqing, 2003). The wash load does not play an active role for river morphology changes, thus the portion of wash load should be subtracted from the total sediment load to determine the morphologically active bed-material load (Yang, 1996).

Sediment transport modelling and river morphology change analysis are fields which are in the main focus of research in hydraulic engineering, and different approaches are utilized for deriving sediment transport equations. This paper presents the application of a data-driven adaptive neuro-fuzzy modelling approach for computing sediment transport for the Elbe river. The estimation accuracy of the adaptive neuro-fuzzy model is compared to that of other well known sediment transport equations.

Sediment Transport Modelling Approaches

The basic approaches used in the derivation of sediment transport functions are: regression, probabilistic, and deterministic approaches (Yang, 2006).

Regression approaches

The regression approach uses a non-linear multiple regression analysis to derive the relationship between sediment transport and input variables. Equations of Shen and Hung (1972), Karim and Kennedy (1990), Rottner (1959) are derived by regression. Sediment transport equations derived by regression analysis should be applied to conditions within the range of datasets used for the formulation of the equations.

Probabilistic approaches

Einstein (1950) introduced the derivation of sediment transport equations from a probabilistic approach. He observed the stochastic nature of sediment transport and combined probability and statistics with modern fluid mechanics to derive his sediment transport equation. Detailed analysis of Einstein's probabilistic approach can be found in Yang (1996), and Chien and Wan (1999). Equations of Colby (1964) and Toffaleti (1969) are based on Einstein's probabilistic approach.

Deterministic approaches

The deterministic approach is based on the assumption that sediment transport can be estimated by using one or more dominant hydraulic parameters (Yang, 2006). The most commonly used parameters are flow velocity, sediment particle diameter, slope, water depth, shear stress, stream power, unit stream power, etc. Equations of Meyer-Peter and Müller (1948), and Laursen (1958) are based on the assumption that the amount of sediment transport is proportional to the excess of bed shear stress. Bagnold (1966) introduced the stream power approach for estimating sediment transport based on general physics. He assumed that the rate of dissipation of energy is proportional to the amount of material transported. Bagnold defined stream power as the power per unit bed area which can be used to transport sediment. Stream power is considered to be the product of shear stress (τ) and flow velocity (V). Sediment transport equations of Engelund and Hansen (1972), and Ackers and White (1973) are derived based on Bagnold's concept of stream power. Yang (1973) derived his sediment transport equation based on the unit stream power approach. He defined unit stream power as the product of velocity and slope.

There are many equations provided by different authors for computing the amount of sediment under transport. Most of the equations are derived using data from laboratory flumes or limited field data, and the calculated results of the equations show considerable discrepancies from the measured transport rate (Yang, 2006). Estimation of the amount and composition of sediment transport is one of the challenging tasks facing engineers up to date and there is not any equation which is universally acceptable under varying site condition. The existence of so many governing variables creates uncertainty and makes the formulation of a single equation for accurately predicting sediment transport quite challenging. For such complicated processes, data-driven fuzzy logic is an alternative modelling approach. Fuzzy logic which is introduced by Zadeh (1965) is capable of incorporating uncertainty and imprecision in the modelling process.

Application of ANFIS for Sediment Transport

Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang (1993), is usually utilized for optimizing data-driven fuzzy models. ANFIS is a network structure consisting of a number of nodes and layers connected through directional links. The ANFIS-based technique is used for predicting the desired parameters of a fuzzy system when measured training data is provided. The data for training should include enough historical data representing the process. ANFIS has been successfully applied to solve a number of problems in water resources. Some of the applications include: estimation of suspended sediment transport (Kisi, 2005; Kisi et al., 2008), long shore sediment transport (Bakhtyar et al., 2008), modelling of hydrological time series (Nayak et al., 2004), and stream flow reconstruction (Chang et al., 2001).

In this study, the ANFIS-based modelling for sediment transport computation is accomplished by following three general steps. The first step is the identification of input and output variables and data preparation which includes: selection of input and output variables, collection of sufficient data, data analysis and filtering, and preparation of training and test datasets. The second step is the generation of initial membership functions, model optimization using ANFIS and performing a sensitivity analysis for the different parameters of the model. The final step is the model validation and testing using additional datasets. Model validation can also be performed by comparing the results of the ANFIS model with results of other commonly applied models.

Input variables

The main parameters needed to estimate sediment transport rate are related to the properties of flow conditions and sediment mixture (Chien & Wan, 1999). There are several flow variables which are relevant for the motion of sediment and the three important variables describing the flow condition are depth, velocity, and slope. These variables are important factors needed for the computation of shear stress, unit stream power or stream power which are used as dominant parameters in many sediment transport equations. For initiation of motion of sediment particles, resistance force should be balanced by drag force. The drag force is the shear stress which is exerted on the sediment particle and it is a function of slope and depth. The resistance to movement depends on the physical properties of the particle of which size is the most important. Particle size determines the criteria for incipient motion whether it is based on critical shear stress or critical stream power, or critical unit stream power. Most of the parameters used in many sediment transport equations are functions of four fundamental parameters: bed or energy slope (S), mean flow velocity (V), water depth (D), and the median particle diameter (d_{50}). These parameters are selected as the main important variables governing the process of sediment transport to develop the ANFIS model. Additionally, the four basic variables are selected because they can be measured as primary data and their physical meaning is obvious for practical applications.

Study area: the Elbe river

The Elbe river is the third largest river of Central Europe. It flows from the Krkonose Mountains (Czech Republic) to the North Sea covering a total distance of 1091 km and a catchment area of 148,268 km^2. The Elbe river basin spans four countries: two third of the basin lies in Germany, one third in the Czech Republic, and less than 1% in Austria and Poland. The mean annual discharge into the North Sea is 877 m^3/s. A comprehensive dataset for the Elbe river is provided by the German Federal Institute of Hydrology (BfG). Measured values of mean velocity, water surface slope, river bed width, median particle size (d_{50}), water depth, and total bed-material transport are available. The data obtained from the BfG covers the German part of the river. Measured parameters are available for 20 stations, on a total length of more than 500 km. The Elbe is a sandy river where most sediment particles are transported as suspended load. The data is analysed in detail where extreme values are removed and wash load is excluded. This results in a total of 321 datasets for final analysis. The data is categorized into two groups: training and testing. The training datasets are used to train the model and obtain best fitting parameters by implementing optimization algorithms (Solomatine & Ostfeld, 2008). The test datasets are utilized to validate the model and avoid overtraining. In this study, two third of the available datasets are selected for training and one third for testing. The ranges of input and output parameters applied to develop total bed-material load ANFIS models are indicated in Table 1.

Table 1: Ranges of parameters implemented to develop total bed-material ANFIS models for the Elbe river.

Parameters	Range
velocity (m/s)	0.08 – 3.89
depth (m)	0.38 – 5.07
bed slope (mm/m)	0.13 – 0.35
d_{50} (mm)	0.50 – 8.53
total bed-material transport (g/s.m)	20 – 600

Optimization and sensitivity analysis

The initial Takagi-Sugeno fuzzy model (Takagi & Sugeno, 1985) is generated by grid partitioning and equally shaped and equally spaced membership functions are defined for each of the input variables based on the ranges of measured data. The adaptive neuro-fuzzy inference system which implements neural network learning algorithms to optimize fuzzy models is implemented for optimizing the parameters of the fuzzy model. The hybrid learning algorithm in ANFIS is the combination of the gradient descent and least-squares methods. The gradient descent method is employed to tune premise non-linear parameters, while the least-squares method is applied to identify consequent linear parameters. A detailed analysis of ANFIS and the hybrid optimization algorithm can be found in (Jang, 1993; Jang et al., 1997). During the optimization process, great care should be taken to ensure that the model will not be over-trained.

A sensitivity analysis for the combination of input parameters, and number and type of membership functions for each input parameter is also performed. In order to determine the relative importance of each of the four primary input parameters (D, S, V, and d_{50}) on the accuracy of the model results, a sensitivity analysis is performed with one of the parameters removed at a time. The different architectures of the models tried are ANFIS (D V S d_{50}), ANFIS (V S d_{50}), ANFIS (D S d_{50}), ANFIS (D V d_{50}), and ANFIS (D V S). Other possible combinations of the variables including dimensionless parameters as used in some sediment transport equations can be defined as alternative inputs. Furthermore, a sensitivity analysis is performed for the number (2 to 5) and type (triangular, trapezoidal, generalized bell-shaped, Gaussian) of membership functions to achieve an optimized model. Finally three generalized bell-shaped membership functions are selected for each input variable based on the results of the sensitivity analysis.

The selection of an appropriate statistical model performance evaluation criterion is necessary during model optimization and for comparison of the accuracy of different models. Correlation coefficient (r), root mean squared error (RMSE), average absolute relative error (AARE) and discrepancy ratio (Dr = computed/measured) are selected as model performance evaluation criteria. The absolute relative error (ARE) is the prediction error expressed in percentage of the observed transport rate.

Model results

Table 2 shows the accuracy of different total load ANFIS models developed for the Elbe river. The ANFIS model with four input parameters (D, V, S, d_{50}) is found to be having the best performance with AARE values of 52.3% and 50.4%, average discrepancy of 1.29 and 1.22 for the training and test datasets respectively. Around 70% of the total data lie in the discrepancy ratio range of 0.5 - 1.5 and less than 15% of the total data have a computational error greater than 100%. This is a good performance for estimating sediment transport in large rivers like the Elbe. From the results of the sensitivity analysis, depth and flow velocity are found to be the most important parameters influencing the model performance. As most of the sediment load in the Elbe river contains relatively uniform sand and is transported as suspended load (the Elbe is a sandy bed river), the effect of excluding the sediment particle size from the input parameters is not quite significant. The fuzzy model with three input parameters D, V, and S shows a comparable accuracy as that with four input parameters, with AARE 54.1% for the training datasets and 45.5% for the test datasets. Additionally, average discrepancy ratios of 1.30 and 1.20, correlation coefficients 0.8 and 0.6 are obtained for the training and test datasets respectively. Around 80% of the total data lie within discrepancy ratio of 0.25 - 1.75. The RMSE values are 57.4 and 82.9 g/s.m, and the percent of data with ARE > 100% are 13.6% and 15.2% for the training and test datasets respectively.

Table 2: Performances of different total load ANFIS models for the Elbe river.

	Training data					Test data				
Combination of inputs	Avg. Dr	AARE (%)	RMSE (g/s.m)	r	Percent of ARE >100%	Avg. Dr	AARE (%)	RMSE (g/s.m)	r	Percent of ARE>100%
D V S d_{50}	1.29	52.3	56.7	0.80	14.1	1.22	50.4	80.7	0.56	13.9
V S d_{50}	1.37	62.5	67.8	0.69	18.6	1.19	53.2	76.2	0.53	13.9
D S d_{50}	1.38	61.2	67.5	0.69	19.5	1.22	48.6	82.5	0.62	10.9
D V d_{50}	1.33	55.8	60.0	0.78	17.7	1.29	54.8	84.3	0.54	13.9
D V S	1.30	54.1	57.4	0.79	13.6	1.20	45.5	82.9	0.59	15.2

Model Comparison

Comparison of accuracy of the total load ANFIS model with four input parameters, ANFIS (D V S d_{50}), on the training and test datasets with the results computed by the total load equations of Yang (1973), Ackers and White (1973), Engelund and Hansen (1972), Bagnold (1966), and van Rijn (1984a,b) is shown in Figure 1 below. The range of datasets chosen for the use in developing the equations and the corresponding application guidelines recommended by the authors are considered while selecting the equations for comparison.

From the scatter plots of measured total load transport rate per width (g/s.m) versus computed total load transport rates, it can be clearly observed that the data-driven adaptive neuro-fuzzy model performs significantly better than the selected sediment transport equations. The transport equations result in large scatter form the observed values. The ANFIS model is selected as the best model with the lowest AARE of 51.7%, RMSE of 65 g/s.m, and the highest correlation coefficient of r = 0.72. The average discrepancy ratio of the data-driven model is 1.27 and 68.7% of the computed values lie within the discrepancy range of 0.5 - 1.5. The AARE values for Yang (1973), Engelund and Hanson (1967), Ackers and White (1973), Bagnold (1966) and van Rijn (1984) are 121.6%, 116.8%, 85.9%, 167.2%, and 165.1% respectively.

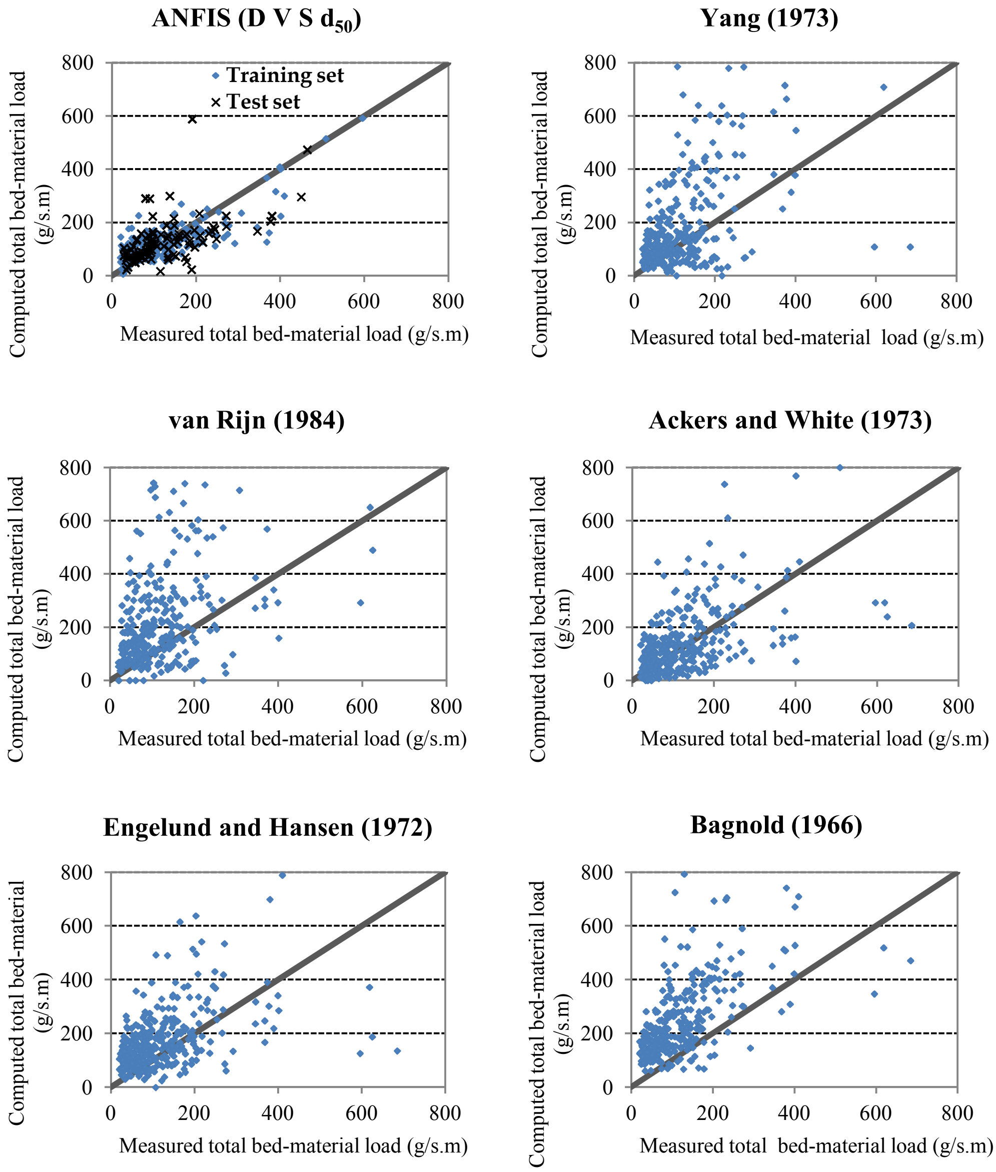

Figure 1: Scatter plots of measured versus computed total load transport rates per width by using ANFIS model and selected sediment transport equations for the Elbe river.

The results of AARE of all equations, except the Ackers and White, is greater than 100% and the deviations from the line of perfect agreement are significant. Bagnold's equation is the least accurate with 56.1% of the computed values having absolute relative error greater than 100%. The Ackers and White equation performs relatively better than the other equations with average discrepancy ratio of 1.46 and 40.8% of the values lying between 0.5 - 1.5 times the observed transport rate.

These results strengthen the complexity of computing sediment transport rate in large rivers like the Elbe where a great deal of factors plays a significant role and the uncertainty is very high. The results from the data-driven model are fairly accurate and provide better estimation of the total load. The ANFIS model is quite simple to apply and results are promising. But like any regression and data-driven model, the ANFIS model developed for estimating total load in the Elbe captures the hidden relationship between the input variables and the total load transport rate for the river. This relationship can be different for other rivers and the model developed for the Elbe cannot be directly applied to river reaches with different characteristics. But the sediment transport equations are supposed to be generally applicable.

Conclusions

The results of this research are promising and prove the potential applicability of a data-driven adaptive neuro-fuzzy modelling for estimation of total load transport rate for the Elbe river. The model results show that the data-driven adaptive neuro-fuzzy modelling approach can be used for reasonably accurate estimation of sediment transport rates. The ANFIS model is found to be performing better than selected sediment transport equations. Furthermore, the results of the sensitivity analysis show which parameters are more important in influencing the amount of sediment transport depending on the ranges of input data and river characteristics. The relatively simple ANFIS model is a powerful tool where the physical processes are too complicated to be expressed mathematically. Sediment transport is definitely one of the focus areas in this regard as proved in this study. However, it needs to be pointed out that data-driven models do not consider mathematical expressions describing the physical processes, and they are developed and optimized based on the analysis of available measured data. The models developed are usually data specific. They require collection of sufficient data with good quality capturing the process under consideration. To assess the general ability of the ANFIS model in successfully estimating sediment transport for different rivers under varying conditions accurately, more training datasets from additional rivers should be included in the analysis.

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