ARTICLE IN PRESS

Alexandria Engineering Journal (2017) xxx, xxx–xxx

HOSTED BY

ELSEVIER

Alexandria University

Alexandria Engineering Journal

www.elsevier.com/locate/aej
www.sciencedirect.com

ORIGINAL ARTICLE

A new hybrid decision tree method based on two artificial neural networks for predicting sediment transport in clean pipes

Isa Ebtehaj, Hossein Bonakdari *, Amir Hossein Zaji

Department of Civil Engineering, Razi University, Kermanshah, Iran
Water and Wastewater Research Center, Razi University, Kermanshah, Iran

Received 1 February 2016; revised 13 May 2017; accepted 22 May 2017

KEYWORDS

Artificial Neural Network (ANN);
Decision Tree (DT);
Hybrid model;
Multilayer Perceptron (MLP);
Radial Basis Function (RBF);
Sediment transport

Abstract A new hybrid decision tree (DT) technique based on two artificial neural networks (ANN), namely multilayer perceptron (MLP) and radial basis function (RBF), is proposed to predict sediment transport in clean pipes (i.e. without deposition). The parameters affecting densimetric Froude number (*Fr*) prediction were extracted from the literature in order to build the model proposed in this study. The effect of each parameter is first examined using MLP and RBF and a sensitivity analysis. According to the sensitivity analysis, the optimal model indicates that using the volumetric sediment concentration (C_V), median diameter of particle size distribution to pipe diameter (d/D) and ratio of median diameter of particle size distribution to hydraulic radius (d/R) parameters yield the best *Fr* prediction results. Subsequently, the hybrid DT-MLP and DT-RBF model results are compared with MLP and RBF. According to the results, MLP with all models predicted *Fr* more accurately than RBF, and DT-MLP exhibited the best performance ($R^2 = 0.975$, $MARE = 0.063$, $RMSE = 0.328$, $SI = 00.081$, $BIAS = -0.01$). Moreover, the comparison between DT-MLP and existing regression-based equations indicates that the models presented in the current study are superior.

1. Introduction

For many years engineers have focused on using pipe channels for storm water transfer. The inflow to a pipe channel frequently contains suspended solid substances. Such substances will deposit on the channel bed if the velocity of flow passing through the channel is insufficient or at a certain slope. Sedimentation increases channel bed roughness and decreases the cross-sectional flow area. As a result, the channel's transmission capacity and sediment transport capacity decrease. Consequently, methods of estimating the minimum velocity in a channel to prevent sediment deposition are required.

A traditional method of determining the minimum velocity is to use constant shear stress and velocity [1–3]. This method mostly under or overestimates since the hydraulic conditions

* Corresponding author. Fax: +98 833 428 3264.
E-mail address: bonakdari@yahoo.com (H. Bonakdari).

Peer review under responsibility of Faculty of Engineering, Alexandria University.

http://dx.doi.org/10.1016/j.aej.2017.05.021
1110-0168 © 2017 Faculty of Engineering, Alexandria University. Production and hosting by Elsevier B.V.

Nomenclature

A	cross-sectional area of flow
c	function's center in the nonlinear radial basis function (Eq. (7))
C_V	volumetric sediment concentration
d	median diameter of particle size distribution
D	pipe diameter
Fr	densimetric Froude number
g	gravitational acceleration
k	number of classes in decision tree
p	number of decision tree input variables
R	hydraulic radius
s	specific gravity of sediment ($=\rho_s/\rho$)
S_0	pipe slope
V	flow velocity
V_t	velocity required for the incipient motion of sediment (Eq. (2))
x	input variable in the nonlinear radial basis function (Eq. (7))
y	flow depth
Greek symbols	
λ_c	clear water friction factor
λ_s	overall friction factor with sediment
ρ	water density
ρ_s	sediment density

of the flow and channel are not considered [4]. Therefore, numerous researchers have examined the factors affecting minimum velocity determination and presented various equations through experimentation and analyses for estimating sediment transport in clean pipes [5–15]. The clean pipe concept entails sediment transport in a pipe channel without sedimentation occurring on the channel bed.

May et al. [16] carried out 332 tests with 7 experiment sets obtained from Ackers et al. [17] and presented the following semi-experimental equations:

$$C_V = 3.03 \times 10^{-2}\left(\frac{D^2}{A}\right)\left(\frac{d}{D}\right)^{0.6}\left(\frac{V^2}{g(s-1)D}\right)^{1.5}\left(1-\frac{V_t}{V}\right)^4 \tag{1}$$

$$V_t = 0.125[g(s-1)D]^{0.5}\left(\frac{y}{d}\right)^{0.47} \tag{2}$$

where D is the pipe diameter, g is the gravitational acceleration, s is the specific gravity of sediment ($=\rho_s/\rho$), d is the median diameter of particle size distribution, V is the flow velocity, A is the cross-sectional area of flow, C_V is the volumetric sediment concentration, y is the flow depth and V_t is the velocity required for the incipient motion of sediments (Eq. (2)).

Azamathulla et al. [18] employed Ab Ghani [6] and Vongvisessomjai et al.'s [19] datasets to modify Ab Ghani's [6] equation as follows:

$$Fr = \frac{V}{\sqrt{g(s-1)d}} = 0.22C_V^{0.16}D_{gr}^{-0.14}\left(\frac{d}{R}\right)^{-0.29}\lambda_s^{-0.51} \tag{3}$$

where λ_s is the overall friction factor ($\lambda_s = 0.851{\lambda_c}^{0.86}{C_V}^{0.04}$-$\lambda_s = 0.851{\lambda_c}^{0.86}{C_V}^{0.04}{D_{gr}}^{0.03}$, λ_c = *clear water friction factor*).

Ebtehaj et al. [20] performed a wide range of experiments using three experimental datasets [6,19,21] and presented an equation for predicting the densimetric Froude number (Fr). The equation is dependent on the volumetric sediment concentration (C_V) and ratio of median diameter of particle size distribution to hydraulic radius (d/R) as follows:

$$Fr = \frac{V}{\sqrt{g(s-1)d}} = 4.49C_V^{0.21}\left(\frac{d}{R}\right)^{-0.54} \tag{4}$$

Because regression-based equations produce different results in different hydraulic conditions, and they are not sufficiently flexible for application in certain hydraulic conditions [14]. Artificial intelligence methods are an alternative means of reducing the inaccuracies of regression-based models and have consequently been widely utilized in diverse engineering sciences, such as hydrology and hydraulic engineering [13,22–27].

Han et al. [28] applied support vector machines (SVMs) in flood forecasting. The authors indicated that the optimum selection of various input combinations is an actual challenge in SVM modeling. Bhattacharya et al. [29] used machine learning methods, artificial neural networks and model trees for bed load and total load modeling using measured data. They compared their model results with existing methods. According to the results, machine learning methods lead to superior modeling accuracy over existing methods. Tirelli and Pessani [30] applied ANN and decision trees to model the presence/absence of telestes muticellus in Northwest Italy. El-Baroudy et al. [31] compared three data-driven methods (evolutionary polynomial regression (EPR), genetic programming (GP) and artificial neural networks (ANN)) in evapotranspiration process modeling. The results demonstrated that EPR is a simpler method with more accurate results than GP and ANN. Senthil Kumar et al. [32] applied different soft computing methods including ANN with backpropagation (BP), radial basis function (RBF), decision trees (DT) such as the REP tree and M5, and fuzzy logic (FL) to predict the suspended sediment concentration upstream of the Bhakra reservoir in North India. Their results indicated that the M5 tree model is more accurate than the other methods. This model also presents decision-makers with a better outlook compared with the rest of the models and offers engineers explicit expressions for practical use. Ebtehaj and Bonakdari [33] examined the performance of two evolutionary algorithms, i.e. the imperialist competitive algorithm (ICA) and genetic algorithm (GA) in predicting the bed load in a clean pipe. These two algorithms were employed to optimize the MLP neural network weights. The results signified that both algorithms predict sediment transport well, although ICA is more accurate than GA. Ebtehaj et al. [34] examined PSO algorithm performance in radial basis function (RBF) neural network (RBF-PSO) training and compared the results with the backpropagation (BP) algorithm. According to their results, prediction accuracy is greater with RBF-PSO than RBF-BP.

In this study, the minimum velocity required to prevent sediment deposition, which is expressed as the densimetric Froude

Please cite this article in press as: I. Ebtehaj et al., A new hybrid decision tree method based on two artificial neural networks for predicting sediment transport in clean pipes, Alexandria Eng. J. (2017), http://dx.doi.org/10.1016/j.aej.2017.05.021