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Support vector regression based modeling of pier scour using field data

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ABSTRACT

This paper investigates the potential of support vector machines based regression approach to model the local scour around bridge piers using field data. A dataset of consisting of 232 pier scour measurements taken from BSDMS were used for this analysis. Results obtained by using radial basis function and polynomial kernel based Support vector regression were compared with four empirical relation as well as with a backpropagation neural network and generalized regression neural network. A total of 154 data were used for training different algorithms whereas remaining 78 data were used to test the created model. A coefficient of determination value of 0.897 (root mean square error=0.356) was achieved by radial basis kernel based support vector regression in comparison to 0.880 and 0.835 (root mean square error=0.388 and 0.438) by backpropagation neural and generalized regression neural network. Comparisons of results with four predictive equations suggest an improved performance by support vector regression. Results with dimensionless data using all three algorithms suggest a better performance by dimensional data with this dataset. Sensitivity analysis suggests the importance of depth of flow and pier width in predicting the scour depth when using support vector regression based modeling approach.

1. Introduction

Scour is a natural phenomenon caused by the removal of sediments near the structures by the action of turbulent flow. The scour reduces the bed elevation near the piers and abutments thus exposing the foundations of a bridge, which may results in structural collapse as well as loss of life and property. The amount of this reduction below an assumed natured level is termed scour depth. Failure of bridges due to scour at abutments and piers is a common occurrence. Bridge scour is a function of flow energy, sediment-transport characteristics, and bridge characteristics.

Richardson and Davis (2001) suggested that total scour at a bridge can be divided into aggradation or degradation, contraction scour and local scour. Local scour is defined as the removal of bed material from around piers, abutments, spurs, and embankments. Local scour can either be clear-water or live-bed. Local scour at piers is caused by the formation of vortices known as the horseshoe vortex at their base. The horseshoe vortex is caused by the accumulation of water on the upstream surface of the obstruction resulting in increased shear stress and hence an increase in sediment transport capacity of the flow. This acceleration in sediment transport capacity of flow removes bed material from around the base of the pier. Thus, the amount of the sediments carried away from the base region is greater than the amount being brought into the region, consequently, causing a scour hole around the bridge pier. The temporal variation of scour and the maximum depth of scour at bridge pier mainly depend on the characteristics of flow, pier and river-bed material. Accurate estimation of equilibrium depths of local scour around bridge piers is a vital issue in the hydraulic design of bridges.

Accurate measurement of equilibrium depths of local scour around bridge piers is a vital issue in the design of bridges concerned to the hydraulics engineering. Equilibrium scour occurs when the scour depth does not change appreciably with time or scouring rate becomes insignificant. Equilibrium between the erosive capability of the flow and the resistance to motion of the bed materials is progressively attained through erosion of the flow boundary. The physical process of scour around bridge piers is quite complicated which makes the development of methodology for predicting scour at bridge piers difficult.

Most of the researches in the field of local scour at bridge piers are based on dimensional analysis using small-scale laboratory experiments with non-cohesive and cohesive uniform bed material under steady-flow conditions (Kandasamy and Melville, 1998; Ansari et al., 2002). A number of equations are proposed to estimate local scour at bridges by carrying out laboratory experiments (McIntosh, 1989; Mueller and Wagner, 2005). The equations developed using laboratory research have not been adequately verified by using field data and the scour prediction methods developed based on laboratory data did not always produce good results for field conditions (Melville, 1975; Dargahi, 1990; Jones,

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1984). Owing to scale effect, laboratory settings oversimplify or ignore the complexities of natural rivers and majority of researches are conducted with uniform flow, a constant depth of flow and non-cohesive bed materials, thus the scour-depth equations based on laboratory flume data were found to overestimate scour depth measured at bridge piers (Mueller and Wagner, 2005).

Soft computing technique, like artificial neural network is being used in prediction of scour (Trent et al., 1993, 1999; Kambekar and Deo, 2003; Choi and Cheong, 2006; Azmathullah et al., 2006; Bateni et al., 2007a, 2007b; Ayoubloo et al., 2010; Kaya, 2010) and their performance was compared with different empirical equations. Most of these studies suggest that neural network approach works well in comparison to the empirical relations. A neural network based modeling algorithm requires setting up of different learning parameters (like learning rate and momentum), the optimal number of nodes in the hidden layer and the number of hidden layers. A large number of training iterations may force a neural network to overtrain, which may affect the predicting capabilities of the model. Further, presence of local minima is another problem with the use of a backpropagation neural network. Recent studies by Guven and Gunal (2008), Guven et al. (2009) and Azamathulla et al. (2010) suggest the usefulness of genetic algorithm to find the optimal architecture of a neural network for scour prediction.

Within last decade, several studies reported the use of generalized regression neural network and support vector machines in civil engineering (Abu Keifa, 1998; Nawari et al., 1999; Dibike et al., 2001; Pal and Mather, 2003; Cigizoglu, 2005; Kurup and Griffin, 2006; Gill et al., 2006; Pal and Goel, 2006; Pal, 2006; Pal and Deswal, 2008; Firat and Gungor, 2009; Goel and Pal, 2009; Pal and Singh, 2010) and found them working well in comparison to a backpropagation neural network approach. The advantage of using a generalized regression neural network and support vector machines is that both of these approaches require few user-defined parameters and do not face the problem of local minima.

Keeping in view the improved performance by support vector machine based regression approach in civil engineering problems; this study compare its performance with four empirical relations, a backpropagation neural network and a generalized regression neural network in modeling pier scour. A study by Mueller and Wagner (2005) suggests that out of 26 equations used in their study no single equation is conclusively better than the rest. Thus, four empirical relations (HEC-18, HEC-18/Mueller equation (Froehlich, 1988), Froehlich Design, 1988) were used to compare their performance with support vector machines based regression.

2. Dataset

Of the total 493 pier scour measurements available in the bridge scour data management system (Mueller and Wagner, 2005), 232 data for upstream scour were selected for this study. The time required for scour to reach its maximum depth in cohesive material is considerably longer than in non-cohesive material. Therefore, observations with scour in cohesive material (a total of 5 data out of 493 measurements) were removed from this analysis. Data sets with pier type "group", "unknown bed material", "missing value of any input variable" and having "zero scour" (a total of six data for zero scour with non-cohesive material) were also removed from the total dataset. Furthermore, data sets with scour measurements at the downstream side of piers were also removed. The effect of debris on the scour depth was also provided in the dataset and grouped in four categories (i.e. unknown, insignificant, moderate and substantial). Debris accumulation near a pier often makes measurement of maximum scour impossible and may increase the scour near the pier due to a larger obstruction to flow (Song et al., 1989). Thus, all scour measurements with "substantial" and "moderate" effect of debris (a total of 40 data, having 14 data with scour measurement at the downstream side and 3 data with pier type group) were removed from the dataset. Finally, the remaining dataset was divided randomly in a way such that 154 data were used for training purposes and the remaining 78 data to test the models.

Seven input parameters namely pier shape factor (P_s), pier width (P_w), skew of the pier to approach flow (skew), velocity of the flow (V), depth of flow (h), D_{50} (i.e. the grain size of bed material in mm for which 50 percent is finer) and gradation of bed material (σ) were used to predict the scour depth. Minimum, maximum, mean and standard deviation values of all input and output parameters used in this study are shown in Table 1.

3. Support vector machines (SVM)

Support vector machines are classification and regression methods which have been derived from statistical learning theory (Vapnik, 1995). The SVM classification methods are based on the principle of optimal separation of classes. If the classes are separable, this method selects, from among the infinite number of linear classifiers, the one that minimizes the generalization error or at least an upper bound on this error, derived from structural risk

Table 1
Characteristics of the train and test data used in this study.

Input parameter	Train data				Test data			
	Min	Max	Mean	St. dev.	Min	Max	Mean	St. dev.
Dimensioned data								
P_s	0.7	1.3	0.973	0.210	0.7	1.3	0.988	0.202
P_w	0.3	5.5	1.558	1.156	0.3	5.5	1.397	1.151
skew	0	85	9.260	18.629	0	65	9.897	18.373
V	0.2	4.5	1.639	0.891	0	3.2	1.301	0.675
h	0.3	22.5	4.552	4.019	0	22.4	3.796	3.579
D_{50}	0.12	95	18.978	26.758	0.15	95	19.473	25.097
σ	1.2	20.3	3.650	3.294	1.2	21.8	3.605	2.901
Scour	0.1	7.1	1.121	1.272	0.1	6.2	0.938	1.059
Non-dimensioned data								
V/gh	0.046	0.784	0.288	0.144	0	0.607	0.257	0.133
h/P_w	0.333	10.444	2.998	1.826	0.4	11	2.937	1.774
D_{50}/P_w	0	0.12	0.02	0.03	0	0.12	0.02	0.03
$Scour/P_w$	0.091	2	0.738	0.455	0.108	2.333	0.74	0.491

The unit of measurements for P_w, h and scour depth is in meter (m), velocity of flow is in meter/second (m/s), D_{50} is in mm and skew is measured in degrees (°).

P_s=1.3 for square nosed piers, 1.0 for round-nosed piers and 0.7 for sharp-nosed piers.