J. Agr. Sci. Tech. (2015) Vol. 17: 859-868

Estimation of River Bedform Dimension Using Artificial Neural Network (ANN) and Support Vector Machine (SVM)

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ABSTRACT

Movement of sediment in the river causes many changes in the river bed. These changes are called bedform. River bedform has significant and direct effects on bed roughness, flow resistance, and water surface profile. Thus, having adequate knowledge of the bedform is of special importance in river engineering. Several methods have been developed by researchers for estimation of bed form dimensions. In this investigation, bedform has been estimated using Artificial Neural Network (ANN) and Support Vector Machine (SVM) methods. The results obtained from these two methods were compared with empirical formulas of Van Rijn. The accuracy of the model was evaluated using (RMSE), (MSRE), (CE), (R^2) and (RB) statistical parameters. Higher values of statistical parameters indicated that the SVM model with RBF kernel function predicted the bedform more accurately than the other method. The values calculated for R^2, RMSE, MSRE, CE and RB parameters were 0.79, 0.024, 0.066, 0.786, -0.081, respectively. Comparison of the results of the SVM model with RBF kernel with other models indicated that SVM had a higher capability for estimating and simulating height of the bedform than Artificial Neural Networks.

Keywords: Bed roughness, RBF kernel function, River engineering.

[DOR: 20.1001.1.16807073.2015.17.4.10.7]

INTRODUCTION

Rivers are one of the most important resources of water supply and have played an important role in the development of human societies. A river is a dynamic system governed by hydraulic and sediment transport processes. Over time, the river responds to changes in channel cross section, longitudinal profile, flow regime, general shape, and increased or decreased sediment carrying capacity, all of which affect bank stability and river morphology. Important changes in rivers caused by sediment transportation consist of erosion and sedimentation (Azamathulla *et al*., 2008).

Bedform in a river is created due to flow movement and has a significant effect on bed roughness and resistance to flow and water surface profile. Therefore, computation of the river stage and flow velocity relies on the determination of bedform roughness, therefore, knowledge of the bedform is very important (Chang, 1988). The accurate prediction of the geometric characteristics of bed forms is an essential component for estimating the flow resistance and the consequent flow conditions (Karamisheva *et al*., 2005). Water surface elevation is the main factor in the determination of flood plains boundaries and in the design of important river structures such as flood control structures, diversion dams, power plant projects, and bridges. This elevation is closely related to the resistance of erodible fluvial beds against water flow (Talebbeydokhti *et al*., 2006). The prediction of water level during floods depends primarily on hydraulic roughness caused by the dimension of

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bedforms such as dunes and ripples. In turn, the length and height of the dunes is viewed as a complex function of hydraulic and sediment parameters pertaining to sediment motion in alluvial rivers (Julien, 1992). The mutual interaction between the flow and the erodible bed through sediment transport phenomena in a sand-bed channel causes a variety of bed forms, starting with ripples, and gradually increases shear stress or water velocity, dunes, washed out the dunes, flat bed, anti-dunes, and standing waves (Talebbeydokhti *et al*., 2006).

Ripples are known to occur for "small" values of the grain size Reynolds number $X = \vartheta_{*}D/_{V}(X <\approx 5.5.)$: dunes. On the other hand, they are known to occur for "large" values of X (X >≈ 30). For "intermediate" values of X (5.5 ≈< X <≈ 30), both ripples and dunes occur, in the form of ripples superimposed on the dunes Figure 1 shows the existence of regions of ripples and dunes, as determined by X (Zhang, 1999).

Different approaches have been used to find bedform dimensions by a lot of researchers. Their results differ drastically from each other and from field observations. The difference between laboratory and field conditions, lack of a reliable method for the estimation of bedform dimensions, the 3D nature of the bedform development, practical difficulties in measuring bedform dimensions, especially in the field, the role of suspended sediment in bed form creation, and the lack of knowledge about turbulence at the interface between flow and bed are among the reasons of differences in the results. Thus, the complexity of this problem indicates the need for additional research (Talebbeydokhti *et al*., 2006).

The phenomenon of bedforms in alluvial rivers was perhaps first described in the classic research of Gilbert in 1914. Brooks in 1958 showed that the flow-induced roughness did not always increase with the velocity, since it might also decrease as the velocity increases. Forms of bed roughness observed in the flumes and in alluvial streams are illustrated by Simons and Richardson in 1961. Based on similarities in form, resistance to flow, and sediment transport, these bedforms are divided into categories of lower flow regime, transition zone, and upper flow regime in the order of increasing velocity (Chang, 1988). In 1961, Engelund and hansen illustrated the results of his study on resistance of different bedforms. Based on this graph, one could determine the type of bed form with Froude number, Flow velocity, and shear velocity (Julien, 1992). Richards (1980) predicted the maximum velocity growth of turbulent flow with a combination of bed's effective roughness and one dimensional turbulent model in analysis of resistance for two types of bedforms, dunes (under the effect of flow depth), and ripples (independence of flow depth). Karim (1995) concluded that dune height is a function of the rate of shear velocity to fall velocity. Coleman and Melville (1996) studied two types of sediment with uniform grading and mean diameters of 0.2 and 0.82 mm. The sand waves developing started with getting a

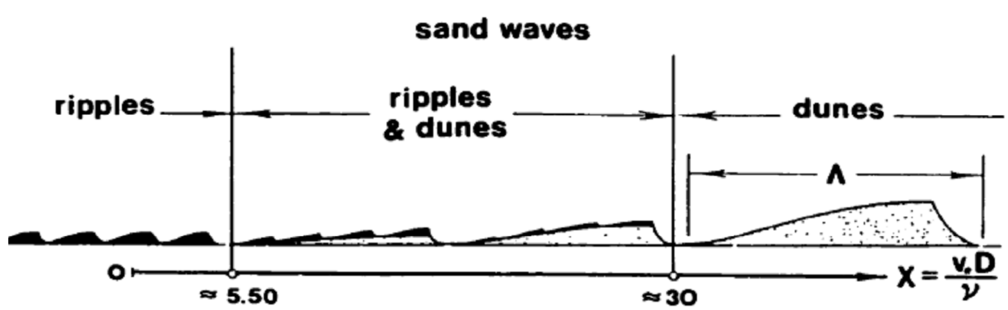

Figure 1. General form of bed form in Regimes of turbulent flow

random mass of sediments, that frequently the more amount of sediment adds to this mass and they become two dimensional rapidly. The wave lengths of sands depend on the amount of bed shear stress and it is mainly a function of sediment grain size. The results of Coleman and Melville (1996) are similar to Richards (1980) unstable flow analyses. Karamisheve *et al*. (2005) compared between prediction formulas of bedform height in the straight channels and meandering channels. Talebbeydokhti *et al.* (2006) found that length of dune depends on combination of three parameters consisting of Froude number (Fr), energy gradient line slope, and the ratio of sediment mean diameter to flow depth (D_{50}/H). Tuijnder *et al*. (2008) concluded that bed form would be limited when the amount of sediment movement is less than the required volume for its formation. The results of Singh *et al*. (2011) showed that flow ratio and compounds of bed sediment had a significant effect on multi scale dynamic, nonlinear degree and the complexity of bedform evolution. Van Rijn (1984) developed a method based on the analysis of experimental data and a limited number of field data. In van Rijn approach, the classification of bed form is assumed to be controlled mainly by bed-load transport. Van Rijn method is one of the most commonly used methods for prediction of bedform dimensions which has been investigated by many researchers. Dunes height and length parameters in Van Rijn method are given below:

$$\frac{\Delta}{h} = 0.11\left(\frac{D_{50}}{h}\right)^{0.3}(1-e^{0.5T})(25-T) \quad (1)$$

$$\frac{\Delta}{\lambda} = 0.015\left(\frac{D_{50}}{h}\right)^{0.3}(1-e^{-0.5T})(25-T) \quad (2)$$

Where, $\frac{\Delta}{\lambda}$ is ratio of bedform height to wave length, $\frac{D_{50}}{h}$ is the ratio of sediment mean diameter to flow depth, and T is the bed shear stress parameter.

Although Van Rijn method is based on experimental data, Julien and Klaassen in 1995 investigated the capability of this method for prediction of bedform dimensions in large rivers in flood condition and with high values of Shields parameter or movement parameter. These researchers found better results than Van Rijn method by definition of dune height and length parameters for prediction of wide bedforms dimensions.

$$\Delta = \beta h\left(\frac{d_{50}}{h}\right)^{0.3} \quad (3)$$

$$\lambda = \alpha\Delta\left(\frac{h}{d_{50}}\right)^{0.3} \quad (4)$$

Where, β and $\alpha = 2.5$. Since $\lambda = \alpha\beta h$ can be obtained from relationships (3) and (4), so $\lambda \cong 6.25h$. In the above relationships, α and β are dune coefficients of height and length. The results show that the average height parameter of dune has good agreement with the average depth of flow. Opposite of van Rijn diagram, the height of the dune for T>10 will not decrease with discharge and those not change to T>40, (Julien et al., 2002).

Support Vector Machine (SVM) is one of intelligent data-driven approaches which was introduced in 1995 by Vapnik. It is an effective method for data modeling. SVM makes an integrated space for most models by increasing the dimensions of problems and using kernel function. Botsis *et al.* (2011) compared the performance of support vector regression (SVR) and multilayer feed-forward neural network (MFNN) in the prediction of rainfall and runoff. Kakaei Lafdani *et al.* (2013) predicted daily suspended sediment load using SVM and ANN. Moharrampour *et al.* (2012) used SVM method for prediction of daily flow of Ghara-Soo river in north of Iran.

The aim of this study was the estimation of bedform dimensions using SVM and ANN, using statistical software with three types of kernel function for data simulation with SVM model. Also, the aim was to develop a model based on ANN in Matlab with MLP trained with a back propagation algorithm to estimate the bed form height.

[DOR: 20.1001.1.16807073.2015.17.4.10.7]

MATERIALS AND METHODS

Artificial Neural Network

The ANN technology is an alternate computational approach inspired by studies of the brain and nervous systems. The beginning of the artificial neural network theory belongs to the 1940s, when Mcculloch, the famous psychologist, and Walter Pitts, a mathematician, founded it in 1943 and then Rosenblatt in 1962s proposed the idea of perceptron (Kakaei Lafdani *et al*., 2013). The main theme of ANN research focuses on modeling of the brain as a parallel computational device for various computational tasks that are performed poorly by traditional serial computers. ANNs have a number of interconnected processing elements (PEs) that usually operate in parallel and are configured in regular architectures. The collective behavior of ANN, like a human brain, demonstrates the ability to learn, recall, and generalize from training patterns or data. The advantage of neural networks is that they are capable of modeling linear and nonlinear systems (Riad and Mania, 2003). In the present study, after training of neural networks with different number of neurons in the middle layer, it was observed that the structure of a neural network with a hidden layer and six neurons in the middle layer and MLP trained with a back propagation algorithm had the best performance among the other neural networks.

Support Vector Machines

In recent years, a modern tool regarding artificial intelligence, called a support vector machine (SVM), has had many applications in learning method machines. This method successfully has been used in information categorization and, lately, in regression problems. Mathematically, SVM is placed in classification and regression algorithms range which is formulated using the principles of statistical learning theory by Vapnik in 1995 (Botsis *et al*., 2011). This model was used for water resources management firstly by Sivapragasam and Liong (2000), Dibike *et al*. (2001), and Han and Yang (2001) and its new model is called reference vector machines used by Han *et al*. (2002).

SVM is a classification and regression method, which has been derived from statistical learning theory. 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 minimization. Thus, the selected hyper plane will be the one that leaves the maximum margin between the two classes, where margin is defined as the sum of the distances of the hyper plane from the closest point of the two classes. The SVM can also be applied to regression problems. Goel *et al*., 2012).

Vapnik in 1995 proposed Support Vector Regression (SVR) by introducing an alternative: the Insensitive Loss Function. This loss function allows the concept of margin to be used for regression problems. SVR differs from conventional regression in that it maps input data into a high dimensional reproducing kernel Hilbert space and uses an ε-insensitive loss function. As a result, SVR has a sparse representation of solutions, and hence is relatively fast in training/testing. For a given training data with k number of samples, represented by $(x_1,y_1),\ldots\ldots,(x_k,y_k)$, a linear decision function can be represented by:

$$f(x,a) = \langle w,x \rangle + b \qquad (5)$$

Where, $w \in R^N$ and $b \in R \langle w,x \rangle$ represents the dot product in space R^N. A smaller value of w indicates the flatness of Equation 5, which can be achieved by minimizing the Euclidean norm as defined by $\|W\|^2$. Thus, an optimization problem in regression can be written as:

$Minimise\ \frac{1}{2}||w||^2$ Subject to $\begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon \\ \langle w, x_i \rangle + b - y_i \le \varepsilon \end{cases}$ (6)

The optimization problem in Equation 6 is based on the assumption that there exists a function that provides an error on all training pairs which is less than ε. In real life problems, there may be a situation like the one defined for classification. So, to allow some more error, slack variables $\boldsymbol{\xi_i}, \boldsymbol{\grave{\xi}_i}$ can be introduced and the optimization problem defined in Equation 6 can be written as:

$Minimise\ \frac{1}{2}||w||^2 + c\sum_{i=1}^{k}(\xi_i + \grave{\xi}_i)$

Subject to $\begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \le \varepsilon + \grave{\xi}_i \end{cases}$ (7)

Where, $\boldsymbol{\xi_i}, \boldsymbol{\grave{\xi}_i} \ge \mathbf{0}$ for all i=1,2,…. k. Parameter C is determined by the user and it decide the tradeoff between the flatness of the function and the amount by which the deviations to the error more than ε can be tolerated. The optimization problem in Equation 7 can be solved by replacing the inequalities with a simpler form determined by transforming the problem to a dual space representation using Lagrangian multipliers. The prediction problem in Equation 5 can now be written as: $f(x,b) = \sum_{i=1}^{k}(\acute{\lambda}_i - \lambda_i)\langle(x_i, x)\rangle + b$ (8)

Where, λ_i, λ_i' are positive Lagrange multipliers. The techniques discussed above can be extended to allow for non-linear support vector regression by introducing the concept of the kernel function. This is achieved by mapping the data into a higher dimensional feature space, thus performing linear regression in feature space. The regression problem in feature space can be written by replacing $x_i . x_j$ with $\Phi(x_i) * \Phi(x_j)$. Where, $k(x_i, x_j) \equiv \Phi(x_i) * \Phi(x_j)$ (9) Regression function in this case can now be written as (Botsis *et al*., 2011): $f(x,b) = \sum_{i=1}^{k}(\acute{\lambda}_i - \lambda_i)k(x_i, x) + b$ (10)

The general structure of these models is shown in Figure 2.

Data Set

In this study, the parameters given below were used as input variables for evaluating the performance of SVM and ANN models for estimating bedform height:

- Shields parameter $\theta = \frac{\tau_\cdot}{\gamma d(s-1)}$
- Bed shear stress parameter $T = \frac{\tau_0 - \tau_c}{\tau_c}$
- Particle parameter $D^* = d(\frac{g(s-1)}{\vartheta^2})^{1/3}$

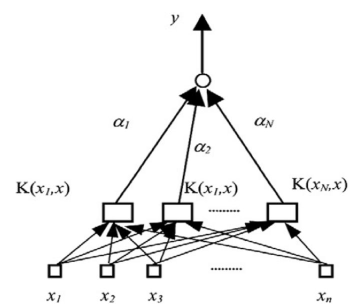

Figure 2. Structure of SVM model.

- Suspension parameter $z = \frac{\omega}{ku_*}$

The ratio of bedform height to flow depth ($\frac{\Delta}{h}$) is used as output variable. Each set of data consisted of 257 data. The data set was collected from Julien study at Rhine and Meuse rivers (Julien, 1992). In both models, 85 percent of data set was used for network training and 15 percent of the data set was used for network testing. The statistical parameters of a data set are shown in Tables 1, 2, and 3 and consist of minimum, maximum, mean, standard deviation, and coefficient of variation.

In order to assess the accuracy of the models, various statistics have been developed and used, of which the best known and most widely used will be presented in the following. These statistics were appropriately used in the calibration phase to determine the parameters and structures.

1. Root Mean Square Errors (RSME)
2. The correlation between predicted and actual values (R^2)

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3. Mean Square Relative Error(MSRE)
4. Coefficient of Efficiency (CE)
5. Relative Bias (RB)

Normalized using the equation: $x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}}$ (11)

Where, x_{min} and x_{max} are the maximum and minimum values at the time i, respectively.

RESULTS AND DISCUSSION

In this study, a model was developed for simulating the bedform height in rivers using Artificial Neural Network ANN and SVM Support Vector Machine. Statistical values of the test period for ANN and SVM methods and Van Rijn empirical formula are given in Table4. Statistical criteria show that support vector machine with the RBF kernel function has better results than a support vector machine with the polynomial kernel function, Artificial Neural Network and empirical formula Van Rijn for estimating of the bedform height of the river.

The comparison of observed and estimated ratio of the bedform height to flow depth by SVM and ANN models in test period are shown in Figure 3 to 6 in the form of hydrography and scatter plot. It is seen from the fit line equations and R^2 values in scatter plots that the SVM (RBF kernel) estimates are closer to the observed values than the other models. The SVM (RBF kernel) performs much better than the other models. It can be obviously seen from the fit line equations that the estimates of the SVM (RBF kernel) are much closer to the exact fit, in line with a higher R^2 value of 0.79, than the support vector machine with the polynomial kernel function, Artificial Neural

Table 1. Statistical parameters of all data set.

Statistical Parameters	All data set				
	θ	z	T	D^*	Δ/h
Min	0	0	0	0	0
Max	1	1	1	1	1
Mean	0.139	0.277	0.276	0.458	0.131
Sd	0.1996	0.247	0.201	0.254	0.088
Cv=Sd/Mean	1.435	0.892	0.728	0.553	0.670

Table 2. Statistical parameters of Train data set.

Statistical Parameters	Train data set				
	θ	z	T	D^*	Δ/h
Min	0	0	0	0	0
Max	1	1	1	1	1
Mean	0.134	0.284	0.268	0.464	0.133
Sd	0.195	0.253	0.198	0.258	0.092
Cv=Sd/Mean	1.460	0.891	0.741	0.557	0.690

Table 3. Statistical parameters of Test data set.

Statistical Parameters	test data set				
	θ	z	T	D^*	Δ/h
Min	0.008	0.002	0.064	0.019	0.056
Max	0.899	0.700	0.811	0.810	0.290
Mean	0.173	0.235	0.324	0.425	0.117
Sd	0.222	0.205	0.208	0.219	0.053
Cv=Sd/Mean	1.285	0.871	0.642	0.515	0.454

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Table4. Statistical values of the test period for ANN and SVM methods and empirical formula of Van Rijn.

Best Indices	SVM [a]			Van Rijn	ANN [g]
	RBF C=10, ε = 0.1 GAMMA=0.25	Polynomial C=10, ε =0.1, degree=2 GAMMA=0.25	Polynomial C=10, ε =0.1, degree=2 GAMMA=0.25		
MSRE [b]	0.066	0.07	0.097	8.93	0.164
RMSE [c]	0.024	0.772	0.681	-71.35	0.490
CE [d]	0.786	-0.078	-0.091	-2.323	-0.250
RB [e]	0.081	0.0253	0.030	0.230	0.038
R^2	0.79	0.77	0.71	0.11	0.66

[a] Support Vector Machine, [b] Mean Square Relative Error; [c] Root Mean Square Errors; [d] Coefficient of Efficiency; [e] Relative Bias; [f] The Correlation between predicted and actual values; [g] Artificial Neural Network.

Network and empirical formula of Van Rijn.

To evaluate the accuracy of the developed model, the maximum and minimum values of observed and estimated bedform height was investigated. Relative errors for all estimated values were calculated and absolute errors were added. Based on total absolute values, the best model with lowest error was chosen. It is clear from Table 4 that the RBF estimates are closer to the corresponding peak of bedform height values than the Polynomial Degree2, Polynomial Degree3, ANN, and Van Rijn. The RBF, Polynomial Degree2, Polynomial Degree3, ANN and Van Rijn predict the maximum peak at 0.276, 0.255, 0.218, 0.319 and 0.314 instead of the measured 0.290, with underestimations of -5%, -12%, -25%, and overestimation of 10% and 8%, respectively. The RBF estimation is almost equal to the observed values. In Table4, C, ε, and GAMMA are kernel functions constant parameters. Table 5 compares the accuracy of the SVM model with RBF, Polynomial Degree2 and Polynomial Degree3 kernel, ANN and Van Rijn models in the estimation of the peak of bedform height with

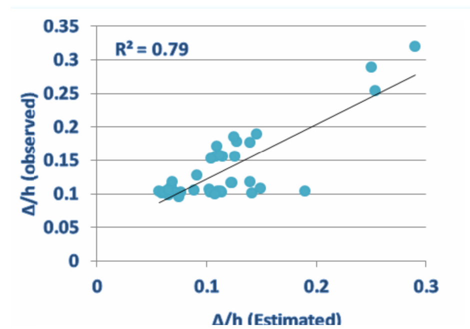

Figure 3. Scatter plot of observed and estimated data for test period from SVM model (RBF kernel).

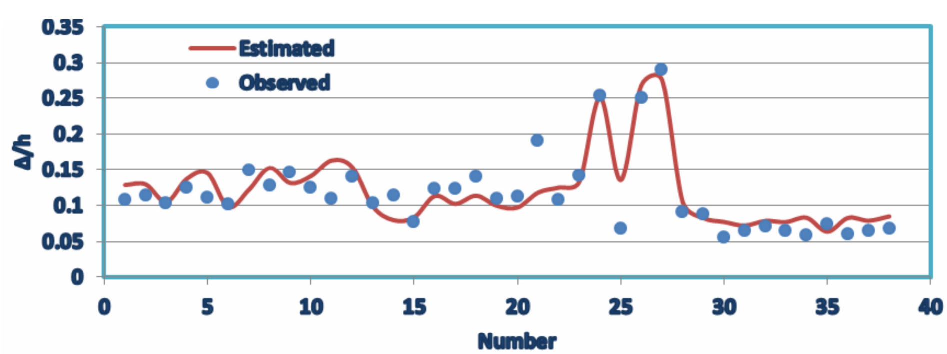

Figure 4. A comparison of observed and estimated data for a test period curve by SVM (RBFkernel).

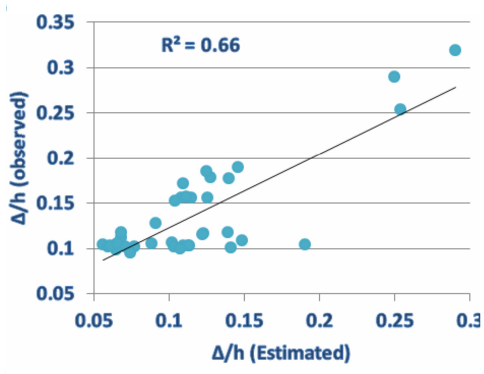

Figure 5. Scatter plot of observed and estimated data for test period of ANN mode.

dimensionless values.

CONCLUSION

In this study, a model for simulating the bedform height in rivers was developed using the methods of Artificial Neural Network (ANN) and Support Vector Machine (SVM). In bedform modeling by using ANN and SVM models, there are not limitations like empirical methods such as sediment grain size, flow conditions, etc. It was also observed that the kernel function selection in the case of SVR had a significant effect on the performance of the model. In particular, this investigation concludes that the RBF kernel function has the best performance in simulation of bedform height. The accuracy of the results demonstrates high performance of developing an SVM model with RBF kernel function and the values calculated for R^2, RMSE, MSRE, CE and RB parameters are 0.79, 0.024, 0.066, 0.786, and -0.081, respectively. Results of the comparison of SVM model with RBF kernel with other models indicated that SVM had a higher capability for estimating and simulating

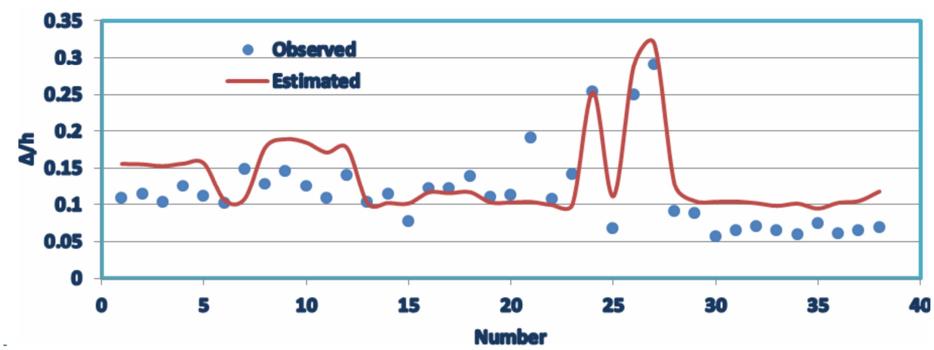

Figure 6. A comparison of observed and estimated data for a test period curve by ANN.

Table 5. Comparison of SVM with different kernel functions, ANN, and Van Rijn results for peak estimation for test period.

Relative error (%)					Van Rijn	ANN	Pol. Deg. 3	Pol. Deg. 2	RBF	Observed height bed form peaks
Van Rijn	ANN [a]	Pol. Deg. [a] 3	Pol. Deg. 2	RBF [b]						
8	10	-25	-12	-5	0.314	0.319	0.218	0.255	0.276	0.290
41	16	-15	-1	8	0.352	0.289	0.212	0.247	0.269	0.249
65	-1	-1	0	-1	0.420	0.253	0.253	0.254	0.251	0.254
26	-45	-46	-44	-38	0.240	0.104	0.103	0.106	0.118	0.190
140	72	87	57	52	Total absolute					

[a] Artificial Neural Network; [b] Radius Basis Function.

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bedform height than artificial neural networks.

It can be concluded that SVR can replace some of the neural network models for bedform height estimation applications, but it is clear that there are still many knowledge gaps in applying SVR to bedform height. The generalization capability of the SVR and ANN models is the biggest open question in bedform height estimation. It is essential to test these models in a variety of different regions in order to improve the understanding of this potentially powerful tool for the machine learning community.

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پیش بینی ارتفاع فرم بستر رودخانه با استفاده از شبکه عصبی مصنوعی(ANN) و ماشین بردار پشتیبان(SVM)

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چکیده

حرکت رسوبات در بستر رودخانه باعث ایجاد تغییرات زیادی در بستر رودخانه می‌گردد. این تغییرات تحت عنوان فرم‌بستر رودخانه مورد بررسی قرار می‌گیرد. فرم‌بستر تاثیر مستقیم و مهمی روی زبری بستر، مقاومت در مقابل جریان و پروفیل سطح آب دارد. بنابراین شناخت هرچه بیشتر فرم‌بستر از اهمیت خاصی در مهندسی رودخانه برخوردار است. روش های متعددی توسط محققان برای برآورد ابعاد فرم-بستر توسعه داده شده است. در این تحقیق پیش‌بینی ابعاد فرم‌بستر رودخانه با استفاده از شبکه‌های عصبی مصنوعی(ANN) و ماشین بردار پشتیبان(SVM) و فرمول تجربی فن‌راین انجام شده است. ارزیابی نتایج بدست آمده با استفاده از معیارهای آماری R^2، RMSE، MSRE، CE و RB انجام شده است. روش SVM با تابع کرنل RBF با مقادیر آماری R^2، RMSE، MSRE، CE و RB ۰/۷۹، ۰/۰۲۴، ۰/۰۶۶، ۰/۷۸۶، ۰/۰۸۱– نسبت به سایر مدل‌های SVM و شبکه عصبی مصنوعی از دقت بالایی در پیش‌بینی ارتفاع فرم‌بستر در رودخانه‌ها برخوردار است.