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Scour Prediction in Long Contractions Using ANFIS and SVM

Mohammad Najafzadeh[1*], Amir Etemad-Shahidi[2], Siow-Yong Lim[3]

[1]Assistant Professor, Department of Civil Engineering, Graduate University of Advanced Technology-Kerman, P.O.BOX 76315-116, Kerman, Iran. Email:moha.najafzadeh@gmail.com.

[2]Senior Lecturer, Griffith School of Engineering, Griffith University, Southport, Queensland, Australia. Email: a.etemadshhaidi@griffith.edu.au

[3]Associate Professor, School of Civil and Environmental Engineering, Nanyang Technological University, Singapore 639798. Email: csylim@ntu.edu.sg.

Abstract

Protection of the channel bed in waterways against scour phenomena in long contractions is a very significant issue in channels design. Several field and experimental investigations were carried out to produce a relationship between the scour depth due to the contracted channels width and the governing variables. However, existing empirical equations do not always provide accurate scour prediction due to the complexity of the scour process. This paper investigates local scour depth in long contractions of rectangular channels using the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machines (SVM). For modeling of ANFIS and SVM, the input parameters that affect the scour phenomena are average flow velocity, critical threshold velocity of sediment movement, flow depth, median particle diameter, geometric standard deviation, un-contracted and contracted channel widths. Training and testing stages of the models are carried out using experimental data collected from different literature. The performances of the developed models are compared with those calculated using existing scour prediction equations. The results show that the developed ANFIS model can predict scour depth more accurately than SVM and the existing equations. A sensitivity analysis is also performed to determine the most important parameter in predicting the scour depth in long contractions.

Keywords: Adaptive Neuro-Fuzzy Inference System; Support Vector Machines; Long Contraction; Rectangular Channel; Scour Depth; Traditional Equations

Introduction

Occasionally, local scour occurs in waterways, riverbanks, barrages, cofferdam, weirs, and bridge abutments due to a reduction in width of the channel cross section. The width reduction increases the flow velocity and caused an increase in the shear stress in the contraction zone. When the bed sediment shear stress is larger than critical shear stress for sediment entrainment, erosion in the contracted zone occurs. The channel contraction can be divided into two types: long and short contractions. For long contractions, the ratio of contraction length to the approaching channel width is more than one or two (Komura, 1966; Webby, 1984; Raikar, 2004).

A large number of experimental investigations have been performed to find the scour mechanism in channel contraction (Straub, 1934; Komura, 1966; Gill, 1981; Webby; 1984; Lim, 1993; Lim and Cheng, 1998; Raikar, 2004; Dey and Raikar, 2005). Empirical equations obtained by experimental observations are not accurate enough to predict the scour depth. This is mainly due to the complexity of the phenomena. Recently, different artificial intelligence approaches such as Artificial Neural Networks (ANNs), Genetic Programming (GP), Gene-Expression Programming (GEP), Model Tree (MT), and Group Method of Data Handling (GMDH) have been used to solve scour problem around hydraulic structures (e.g., Bateni et al., 2007a; Lee et al., 2007; Guven and Gunal, 2008a; Ayoubloo et al., 2010; Azamathulla et al., 2010; Etemad-Shahidi and Ghaemi, 2011; Najafzadeh and Barani, 2011; Azamathulla, 2012a&b; Pal et al., 2012; Najafzadeh et al., 2013).
From the predictive techniques, the Support Vector Machines (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) model were successfully utilized for solving different scour problems (e.g., Bateni and Jeng, 2007; Bateni et al., 2007b; Zounemat-Kermani et al., 2009; Azamathulla et al., 2009; Muzzammil and Ayyub, 2010; Firat, 2010; Muzzamil, 2010; Kaya, 2010; Pal et al., 2011;

Ghazanfari-Hashemi et al., 2011; Hong et al., 2012; Pal et al., 2014; Akib et al., 2014). However, the performing of the SVM and ANFIS based methods for predicting the local scour depth in channels bed due to contracted cross section has not been investigated yet.

In this study due to considerably complicated process of scour in long contractions, the ANFIS and SVM models are developed to predict the scour depth which occurred in bed of rectangular channels. The performances of the proposed ANFIS and SVM models are compared with several empirical equations to predict the maximum scour depth in long contractions.

Review on the Investigations of Scour in Long Contractions

Traditional methods involved the measurements of scour depths at existing bridge sites, sharp bends, and contractions or, other locations where the natural channel configuration is comparable to that expected at the bridges site. Since 1934 , many laboratory tests have been proposed to measure the scour depth experimentally and its prediction in long contractions. Several empirical equations have been proposed to predict the scour depth in long contraction. Straub (1934) initiated investigations of sediment transportation for prediction of scour depth in contractions and un-contracted widths of channels. He presented an empirical equation based on the Manning and Du Boy equations (Lim and Cheng, 1998). Later, Laursen (1963) proposed a formula based on the total sediment transport in a compound channel by assuming that effects of the flow rate over the flood plains is negligible:

$$\frac{d_s}{h_1} + 1 = \left(\frac{b_2}{b_1}\right)^{-0.75} \qquad (1)$$

where d_s, h_1, b_1, and b_2 are the scour depth, flow depth, un-contracted channel width, and contracted channel width, respectively.

Komura (1966) carried out experiments to investigate influences of sediment particles grading on scour depth. He suggested an explicit equation based on characterizations of upstream flow conditions, bed sediment size, and channel geometry as,

$$\frac{d_s}{h_1}+1=1.6Fr_C^{0.2}(\sigma_g)^{-0.5}(\frac{b_2}{b_1})^{-0.67} \tag{2}$$

in which, d_{50}, Fr_C, and σ_g are the median particle diameter, Froude number due to the approaching flow velocity required to initiate sediment motion within un-contracted cross section of channel, and geometric standard deviation, respectively. The Fr_C is expressed as follows:

$$Fr_C=\frac{U_C}{\sqrt{g.h_1}} \tag{3}$$

where U_C and g are the critical velocity of sediments and gravitational acceleration, respectively.

Gill (1981) presented a formula by assuming that sediment rate is proportional to the bed and critical shear stress:

$$\frac{d_s}{h_1}+1=1.58(\frac{b_2}{b_1})^{-0.857} \tag{4}$$

Lim (1993) proposed an empirical equation of equilibrium scour depth in long contractions for both clear-water and live-bed scour conditions.

$$\frac{d_s}{h_1}+1=1.545Fr_0^{0.75}(\frac{d_{50}}{h_1})^{0.25}(\frac{b_2}{b_1})^{-0.75} \tag{5}$$

where Fr_0 is the densimetric flow Froude number defined as,

$$Fr_0=\frac{U_1}{\sqrt{g.\left(\frac{\rho_S}{\rho_w}-1\right)d_{50}}} \tag{6}$$

in which U_1, ρ_S, and ρ_w are the average flow velocity, mass density of sediments and water, respectively.

Lim and Cheng (1998) also presented a theory based on the continuity condition between flow and sediment transport. In case of field studies, it was sufficiently accurate for most practical purposes. Li (2002) carried out local scour experiments for contractions in cohesive bed soils. He found that the scour depth due to the contracted cross sections was linearly dependent on the Froude number. Dey and Raikar (2005) carried out extensive investigations of scour in long contractions at a rectangular channel. They proposed a new empirical equation for the maximum scour depth under clear-water condition.

Analysis of Effective Parameters on the Scour Depth in Long Contractions

In experimental or field studies of the scour depth in long contractions, the main parameters affecting the process are the characteristics of bed sediments, approaching flow conditions, geometry of contracted and un-contracted cross sections (Straub, 1934; Komura, 1966; Gill, 1981; Webby, 1984; Lim, 1993; Lim and Cheng, 1998; Li, 2002; Raikar, 2004; Dey and Raikar, 2005). In this way, the functional relationship between the scour depth and effective parameters can be expressed as follows:

$$d_s = f(d_{50}, U_1, U_c, \nu, g, \sigma_g, h_1, b_1, b_2, \rho_w, \rho_s) \tag{7}$$

where ν is the kinematic viscosity of water. Studies have found that artificial intelligence approaches based on non-dimensional parameters produced better prediction than those obtained using dimensional parameters (e.g., Bateni and Jeng, 2007; Bateni et al., 2007a&b; Azamathulla et al., 2009; Kazeminezhad et al., 2010; Pal et al., 2012; Hong et al., 2012; Pal et al., 2014). Therefore, dimensional analysis is carried out for Eq. (7) using the Buckingham π theorem. The scour depth, d_s, is normalized with b_1 and the following function is obtained:

$$d_s / b_1 = f(d_{50} / b_1, h_1 / b_1, b_2 / b_1, \sigma_g, U_1 / U_c, Fr_0) \tag{8}$$

The non-dimensional parameters in Eq. (8) were used as input and output parameters in modeling of the ANFIS and SVM models in this study. We used 204 data sets for developments of scour modeling , and these data were collected from the Komura (1966), Gill (1981), Webby (1984), Lim (1993), Dey and Raikar (2005), and Lim (2013) (unpublished data sets). The data sets obtained are for the long contractions scour tests in rectangular channels under clear-water conditions $(U_1 / U_c \leq 1)$. Out of the 204 data set, about 67% and 33% were selected randomly to perform training and testing stages, respectively. The ranges of parameters used for the scour depth modeling are presented in Table 1. The schematic sketch of a rectangular channel contraction is shown in Figs.1a and 1b. For evaluating the scour depth in long contractions, four traditional equations proposed by Laursen (1963), Komura (1966), Gill (1981), and Lim (1993) were also used for comparison.

Model Descriptions

Fuzzy Inference System

Fuzzy logic initiates with the fuzzy set theory. Principle of fuzzy set was developed for definition of physical behavior for high-order complex systems in uncertain and imprecise environments. A fuzzy set is an extension of a classical set whose elements may partially belong to that set. Suppose X is the universe of discourse (input space) and its elements are defined by X, then a fuzzy set A in X is expressed as a set of ordered pairs in form of:

$$A = \{x, \mu_{A(x)} | x \in X\} \quad (9)$$

where $\mu_{A(x)}$ is the membership function (MF) of X in A. MF is a function that expresses how each element x in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

Through the context of fuzzy set theory to deal with nonlinear, but ill-defined, mapping of input variables to some output ones, one of the most useful features is known as Fuzzy Inference System (FIS). From the framework of FIS, the behavior of a given system can be simulated as IF-

THEN rules through knowledge extraction of experts or past available data of the systems with high-order complexity. Also, this process indicated that fuzzy logic can be applied to map a set of given input variables to an output variable using. A fuzzy inference system is included of five functional blocks as follows:

1. A rule base containing a number of fuzzy IF–THEN rules.

2. A database which defines the membership functions of the fuzzy sets used in the fuzzy rules.

3. A decision making unit which performs the inference operations on the rules.

4. A fuzzification inference which transforms the crisp inputs into the degree of match with linguistic values.

5. A defuzzification interface which transforms the fuzzy results of the inference into a crisp output.

Occasionally, the rule base and the database are compromisingly referred to as the knowledge base (Lee, 1995). Fundamentally, a fuzzy IF-THEN rule includes main two parts. The first is IF part and the second is THEN part which are known premise and consequent, respectively. The general form of a fuzzy IF-THEN rule can be expressed as follows:

Rule 1: If X is A_1 and Y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If X is A_2 and Y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

where p_i, q_i, and r_i are the consequent parameters of ith rule. A_i and B_i are the linguistic labels which are represented by fuzzy sets (Sugeno, 1985).

The so called firing strength or degree of fulfillment of a pair (x, y) to rule i, which measures the degree to which that pair belongs to rule i, can be defined as follows:

$$w_i = \mu_{A_i(x)} \wedge \mu_{B_i(x)}, \qquad i = 1,2 \tag{10}$$

where $\mu_{A_i(x)}$ and $\mu_{B_i(x)}$ are membership functions of x and y in fuzzy sets A_i and B_i. '$\wedge$' denotes a fuzzy T-norm operator which is a function that describes a superset of fuzzy intersection (AND) operators, including minimum or algebraic product. In this study algebraic product was used as a T-norm operator. The final output of the system is the weighted-average of all rules outputs as follows:

$$Ultimate \quad Output = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i} \tag{11}$$

There is no systematic way to know what type and shape of membership functions of premise variables have the best performance in a defined FIS. An efficient way for performing this process is that, using an artificial neural networks (ANNs) model trained by input-output database (Kazeminezhad et al., 2005).

Combining neural nets and FIS

An Adaptive-Network-Based Fuzzy Inference System (ANFIS) (Jang, 1993) is a Sugeno type FIS in which the problem of fine-tuning membership functions of premise variables is carried out by a feed-forward neural network. ANFIS combines the advantages of both neural networks (e.g. learning capabilities, optimization capabilities, and connectionist structures) and fuzzy inference systems (e.g. human like 'IF-THEN' rule thinking and ease of incorporating expert knowledge). The basic idea behind these neuro-adaptive learning techniques is very simple. They provide a methodology for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated FIS to track the given input-output data. ANFIS is based on the premise of mapping a FIS into a neural network structure so that the membership functions and consequent part parameters are optimized using a hybrid learning algorithm. In this algorithm, parameters of the membership functions are determined by a neural network back-propagation learning algorithm while the consequent parameters by the least square method. Figure 2 shows the structure of ANFIS including two inputs x (wind speed), y (fetch length), and one output f (significant wave height or peak spectral period) and two rules which were described in previous part. The first step is the fuzzifying layer in which A_i and B_i are the linguistic labels. The output of this layer is the membership functions of these linguistic labels. In other words, in this step, the premise parameters are calculated. The second step calculates the firing strength for each rule. The output of this step is the algebraic product of the input signals as can be seen in Eq. (12). The third step is the normalized layer. Every node in this layer calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strength as:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \tag{12}$$

The output of every node in fourth layer is

$$w_i f_i = w_i (p_i x + q_i y + r_i) \tag{13}$$

The fifth layer computes the overall output as the summation of all incoming signals, which represents the results of significant wave height or peak spectral period as can be seen in Eq.(13).

From development of ANFIS model for the scour problems in long contractions, six inputs and one output parameters are considered. In addition, corresponding fuzzy IF-THEN rules for improving the structure of ANFIS model are given in Table 2.

Development of SVM Model

The Support vector machines, similar to artificial neural networks, are a kind of data-mining approach. SVM has been successfully applied to a number of applications in water resources (Bateni and Jeng, 2007; Bateni et al., 2007a&b; Kazeminezhad et al., 2010; Pal et al., 2012; Hong et al., 2012; Pal et al., 2014). The classification problem is used to investigate the basic concepts behind SVM and to examine their strengths and weaknesses from a data-mining perspective (Campbell 2000).

In support vector regression, the objective is to find a function $f(x)$ which has at most ε deviation from the actually obtained targets y_i for all the training data $\{(x_1, y_1),...,(x_i, y_i)\}$ and at the same time is as flat as possible. In other words, errors are negligible as long as they are less than ε and any deviation larger than this is not accepted. $f(x)$ can be expressed as (Smola and Scholkopf, 2004):

$$f(x) = (\omega, x) + b, \omega \in X \quad , b \in R \tag{14}$$

where ω is a weight vector $(\omega \in R^n)$; b is additive noise $(b \in R)$ and (ω, x) denote dot points in X. Flatness of the regression function $f(x)$ can be achieved by smaller values of ω. One way to ensure this is to minimize the Euclidean norm as defined by $\|\omega\|^2 = (\omega, \omega)$ (Vapnik, 1995; Smola and Scholkopf, 2004). Nonlinear support vector regressions can be used in complex and nonlinear problems by introducing kernel functions (Vapnik, 1995). Solving nonlinear problems can be achieved by mapping the data into a higher-dimensional feature space with the help of kernel functions. To develop SVM for each process, two main parameters of SVM namely regularization parameter (C) and the type of kernel (Polynomial or Gaussian Radial Basis Function) should be determined. In this study, the radial basis function kernel was used to minimize training error for scour data sets. The regularization parameter, C, and the size of error in sensitive zone parameters control the complexity of prediction. Also, RBF kernel has two variables of γ and σ that were determined through simplex optimization method. The values of γ and σ parameters were fixed 14.109 and 3.59, respectively. The other details of SVM algorithm are presented in literatures (Vapnik, 1995; Smola and Scholkopf, 2004).

Implementations and Results

The results of ANFIS and SVM models were presented in this section. correlation coefficient (R), root mean square error (RMSE), mean absolute percentage of error (MAPE), scatter index (SI), and BIAS, and were used to evaluate the performances of models. The formulations of these statistical parameters have been given in literature (Ayoubloo et al., 2010; Najafzadeh and Barani, 2011).

The statistical results of proposed ANFIS and SVM models for training and testing stages are presented in Table 3. Error measures of the training phase indicated that SVM model predicted the scour depth better than ANFIS model. The statistical error parameter obtained from training stage indicated that SVM model produced relatively lower error (RMSE=0.023 and MAPE=29.72) and higher correlation coefficient (R=0.92) than those provided using the ANFIS model (RMSE=0.0263, MAPE=42.76, and R=0.9). In addition, SI parameters for ANFIS and SVM were yielded 0.236 and 0.263, respectively.

In the testing phase, it can be said that the ANFIS and SVM models predicted the scour depth with nearly the same accuracy in term of RMSE and MAPE values. In addition, the correlation coefficients of ANFIS (0.88) and SVM (0.89) model were approximately the same. From the SI value for ANFIS model, it was found that ANFIS model produced predictions better than those of the SVM model. Scatter plots between predicted and observed scour depth values for both training and testing phases by the ANFIS and SVM models were illustrated in Figures 3 and 4, respectively. Empirical equations were also applied to predict the local scour depth at long contractions in rectangular channels. In fact, empirical equations were evaluated using the testing datasets.

Statistical results of empirical equations were given in Table 4. From the Table 4, it can be said that Eq.(1) given by Laursen (1963) provided relatively lower errors (RMSE=0.0543 and MAPE=60.24) for the scour depth prediction than the other traditional equations. Eq.(4) developed by the Gill (1981) observations was found to yield the worse results. RMSE and MAPE values from Eq.(4) were 0.201 and 258.55, respectively. Also, Komura equation predicted the scour depth relatively accurate (RMSE=0.083 and MAPE=101.01) in comparison with Lim's equation. From the experimental procedures, the lack of validation for traditional methods was related to the limitation of effective parameters range, which commonly can not present the accurate feature for physical behavior of scour process (e.g., Guven and Gunal, 2008; Azamathulla et al., 2010; Najafzadeh et al., 2011). Scatter plots between predicted and observed scour depth values for evaluating the models given by ANFIS, SVM, and traditional equations were given in Figure 5.

Sensitivity Analysis

Through the data analysis, process of sensitivity analysis was to quantify how much model output values were affected by variations in the input values. To determine the importance of each input variable on the scour depth, the ANFIS was applied to perform a sensitivity analysis. The analysis was conducted such that, one parameter of Eq.(8) was eliminated each time to evaluate the effect of that particular input on output. Results of the analysis indicated that U/U_C (R=0.91, RMSE=0.0244, MAPE=27.1, and SI=0.224) was the most effective parameter on the scour depth whereas the b_2/b_1 (R=0.6, RMSE=0.0488, MAPE=59.21, and SI=0.493) has the least influence on scour depth for the ANFIS model, respectively. The other effective parameters on the d_s/b_1 were $d_{50}/b_1, Fr_0, h_1/b_1$, and σ_g ranked from higher to lower values, respectively. Statistical error parameters yielded from the sensitivity analysis were given in Table 5. In this study, influences of d_{50}/b_1, h_1/b_1 and Fr_0 parameters on the d_s/b_1 values were investigated. Fig.6 illustrated variations of d_s/b_1 variable versus h_1/b_1 for $b_2/b_1 = 0.4-0.7$. From Fig.6, it can be seen that the scour depth increased linearly with an increase of h_1/b_1 for b_2/b_1 parameter equals to 0.4, 0.5, and 0.66-0.7 because shear stress induced by the boundary layer within the contraction changes with approaching flow depth. Also, for $b_2/b_1 = 0.6$, the scour depth in long contraction generally decreased with an increase of h_1/b_1 values. This finding has opposite trend in Fig.6 due to the computational errors of the ANFIS models.

Fig.7 indicated variations of the scour depth versus d_{50}/b_1 values. For b_2/b_1 between 0.4 and 0.5, the scour depth decreased with an increase of d_{50}/b_1 parameter. Meantime, d_s/b_1 values had an increasing trend with variations of d_{50}/b_1 variable for b_2/b_1 between 0.6 and 0.77. Different trends of the non-dimensional scour depth for b_2/b_1 values between 0.4-0.77 is due to the transitional properties of the Shields diagram, where the bed shear stress required for the motion of sand particles is relatively less than that critical shear stress. For gravels, the fundamental increase of U_1 to fix the status of U_1/U_c increases the bed shear stress within the contracted zone to a great extent, boost the scour process potential which yields in increase of d_s/b_1 ratio at a constant rate.

Fig.8 indicated variations of the scour depth versus densimetric Froude number. For $b_2/b_1 = 0.6$, scour depth values decreased with increase of Fr_0 because the mobility of the sediment particles decreases with an increase in sediment sizes of sands and gravels. In addition, for other opening ratios, this pattern is opposite because of contraction severity.

Parametric Study

As aforesaid in the sensitivity analysis section, dimensionless parameter of b_2/b_1 was known as the most effective input variable on the scour depth prediction in long contraction. Effects of models output on the variations of b_2/b_1 parameter were investigated in this research. In this way, the discrepancy ratio (DR), known as the ratio of predicted and observed values, was utilized to quantify the sensitivity of the proposed models to b_2/b_1 parameter. A DR value of 1 shows a promisingly perfect agreement, while values greater (or smaller) than 1 indicate over (or under) prediction of the scour depth. Variations of DR values were plotted versus the logarithm of b_2/b_1.

The result of the ANFIS model was illustrated in Figure 9. The minimum, mean, and maximum DR values for the ANFIS model were obtained -3.14, 0.987, and 3.81, respectively. For

0.316 $< b_2/b_1 <$0.63, DR values decreased to around 1. Also, it indicated that ANFIS model provided well agreement with observed scour depth. Figure 9 illustrated that the ANFIS model had over predicted the scour depth for DR=0.381. Furthermore, for b_2/b_1=0.657, the ANFIS model had relatively under predicted the scour depth.

The results of SVM model were shown in Figure 10. The DR values were yielded between -1.25 and 3.79. In addition, mean value of DR was 1.04. For 0.324$< b_2/b_1 <$0.7, values of several points including b_2/b_1=0.324 and 0.657 indicated that over (or under) predictions of the scour depth were met. For 1.875 $< b_2/b_1 <$4.05, SVM model produced more accurate scour depth prediction because the scour depth values were trend to 1.

Figure 11 illustrated the results from the Eq. (1) proposed by Laursen (1963). The minimum, mean, and maximum DR values of this model were obtained -4.55, 0.75, and 1.83, respectively. For the b_2/b_1 values between 0.324 and 0.7, Eq.(1) produced relatively good agreement with observed scour depth. With increase in b_2/b_1 values from 1.875 to 4.06, Eq. (1) produces high under predictions of scour depth. Also, Figure 12 showed the results from the Eq. (2) given by Komura (1966). The DR values of this model were between -1.28 and 7.62. Also, mean value of DR was 1.67. With an increase in b_2/b_1 values between 0.324 and 0.7, at first scour depth decreased thereafter increases. For this range of b_2/b_1, Eq.(2) provided the scour depth with very much over predictions.

With increase in b_2/b_1 values from 1.875 to 4.06, Eq.(2) produced high under predictions of scour depth. Results of the Eq.(4) were illustrated in Figure 13. The minimum, mean, and maximum DR values of this model were obtained -1.25, 3.3, and 12.3, respectively. For the b_2/b_1 values between 0.324 and 0.7, Eq.(4) produced remarkable over prediction of scour depth. Also, b_2/b_1 values from 1.875 to 4.06, Eq.(4) produced high under predictions of scour depth. In addition, Figure 14 showed the results from the Eq.(5) presented by Lim (1993). The DR values of this model were yielded between -1.27 and 10.34. Also, mean value of DR was 3.3. With an increase in b_2/b_1 values from 0.324 to 0.7, scour depth predicted by Eq.(5) increased. For this range of b_2/b_1, Eq. (5) provided significantly high over predictions. Also, b_2/b_1 values from 1.875 to 4.06, Eq. (5) produced high under predictions of scour depth. b_2/b_1 values from 1.875 to 4.06, Eq. (5) significantly predicted the scour depth.

From empirical equations, it was found that Eq.(4) had more over prediction of scour depth in long contractions compared to the other empirical equations. Eq.(1) given by Laursen (1963) provided very much under prediction of scour depth.

Summary and Conclusions

In this paper, adaptive neuro-fuzzy inference system and support vector machines were developed to predict the scour depth in long contractions at rectangular channel bed. Furthermore, traditional equations given by Laursen (1963), Komura (1966), Gill (1981), and Lim (1993) were used for comparisons. Data sets for performing the training and testing stages were collected from literatures. Six inputs and one output parameter were defined through the dimensional analysis for scour depth modeling. Performing the proposed models for training stage indicated that SVM model produced relatively lower error (RMSE=0.023 and MAPE=29.72) and higher correlation coefficient (R=0.92) compared to those obtained using the ANFIS model. Through the testing stage, ANFIS model yielded better results with relatively lower error (SI=0.28) rather than that obtained using performing the SVM.

Between the traditional equations, Eq.(1) proposed by Laursen (1963) had a relatively lower error (RMSE=0.0543 and MAPE=60.24) for the scour depth prediction , compared to other ones. Results of sensitivity analysis indicated that b_2/b_1 is the most important parameter in modeling of scour depth by the ANFIS model. In addition, parametric study indicated that shear stress due to motion of bed sediments at contracted zone played an important factor to illustrate effects of input parameters on the scour depth in long contractions.

Application of ANFIS and SVM approaches proven which these methods were used successfully as soft computing tools for prediction of the scour depth in long contraction at rectangular channels.

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Table 1. Ranges of grouped input and output parameters for scour depth modeling

Parameters	Training	Testing
d_{50}/b_1	0.000875-0.0237	0.000875-0.2375
h_1/b_1	0.0509-0.442	0.0360-0.32
b_2/b_1	0.25-4.062	0.33-4.062
Fr_0	0.878-3.504	1.08-3.28
U_1/U_c	0.321-1	0.431-1
σ_g	1.065-3.61	1.065-3.61
ρ_s/ρ_w	2.65	2.65
d_s/b_1	0.00131-0.29	0.0118-0.256

Table 2. IF-THEN rules for ANFIS model

Rules ANFIS	
1	If (d_{50}/b_1 is d_{50}/b_1 mf1) and (h_1/b_1 is h_1/b_1 mf1) and (Fr_0 is Fr_0 mf1) and (b_2/b_1 is b_2/b_1 mf1) and (U_1/Uc is U_1/Uc mf1) and (σ_g is σ_g mf1) Then (d_s/b_1 is d_s/b_1 mf1)
2	If (d_{50}/b_1 is d_{50}/b_1 mf2) and (h_1/b_1 is h_1/b_1 mf2) and (Fr_0 is Fr_0 mf2) and (b_2/b_1 is b_2/b_1 mf2) and (U_1/Uc is U_1/Uc mf2) and (σ_g is σ_g mf2) Then (d_s/b_1 is d_s/b_1 mf2)

Table 3. Statistical parameters of the training and testing data set for difference models.

Training Stage					
Technique	R	RMSE	MAPE	BIAS	SI
SVM	0.92	0.023	29.72	0.00	0.236
ANFIS	0.9	0.0263	42.76	0.00	0.263
Testing Stage					
SVM	0.88	0.028	36.35	0.0039	0.279
ANFIS	0.89	0.0281	27.54	-0.0035	0.279

Table 4. Statistical parameters of the testing data set for difference models.

Technique	Source	R	RMSE	MAPE	BIAS	SI
SVM	Developed by Data Sets	0.88	0.028	36.35	0.0039	0.279
ANFIS	Developed by Data Sets	0.89	0.0281	27.54	-0.0035	0.279
Eq.(1)	Laursen (1963)	0.68	0.0543	60.24	-0.0107	0.534
Eq.(2)	Komura (1966)	0.75	0.083	101.01	0.0455	0.699
Eq.(4)	Gill (1981)	0.69	0.69	258.55	0.155	1.27
Eq.(5)	Lim (1993)	0.72	0.112	161.58	0.096	0.942

Table 5. Sensitivity analysis for independent parameters of the testing data set by ANFIS model.

Input parameters	R	RMSE	MAPE	BIAS	SI
$d_s/b_1 = f(h_1/b_1, b_2/b_1, \sigma_g, Fr_0, U_1/U_c)$	0.84	0.0336	34.56	0.0034	0.307
$d_s/b_1 = f(d_{50}/b_1, b_2/b_1, \sigma_g, Fr_0, U_1/U_c)$	0.6	0.0488	59.21	0.0017	0.493
$d_s/b_1 = f(d_{50}/b_1, h_1/b_1, \sigma_g, Fr_0, U_1/U_c)$	0.84	0.0375	32.77	-0.0093	0.357
$d_s/b_1 = f(d_{50}/b_1, h_1/b_1, b_2/b_1, Fr_0, U_1/U_c)$	0.85	0.0298	55.6	-0.0012	0.308
$d_s/b_1 = f(d_{50}/b_1, h_1/b_1, b_2/b_1, \sigma_g, U_1/U_c)$	0.85	0.0299	28.84	-0.0053	0.27
$d_s/b_1 = f(d_{50}/b_1, h_1/b_1, b_2/b_1, \sigma_g, Fr_0)$	0.91	0.0244	27.1	0.0026	0.224

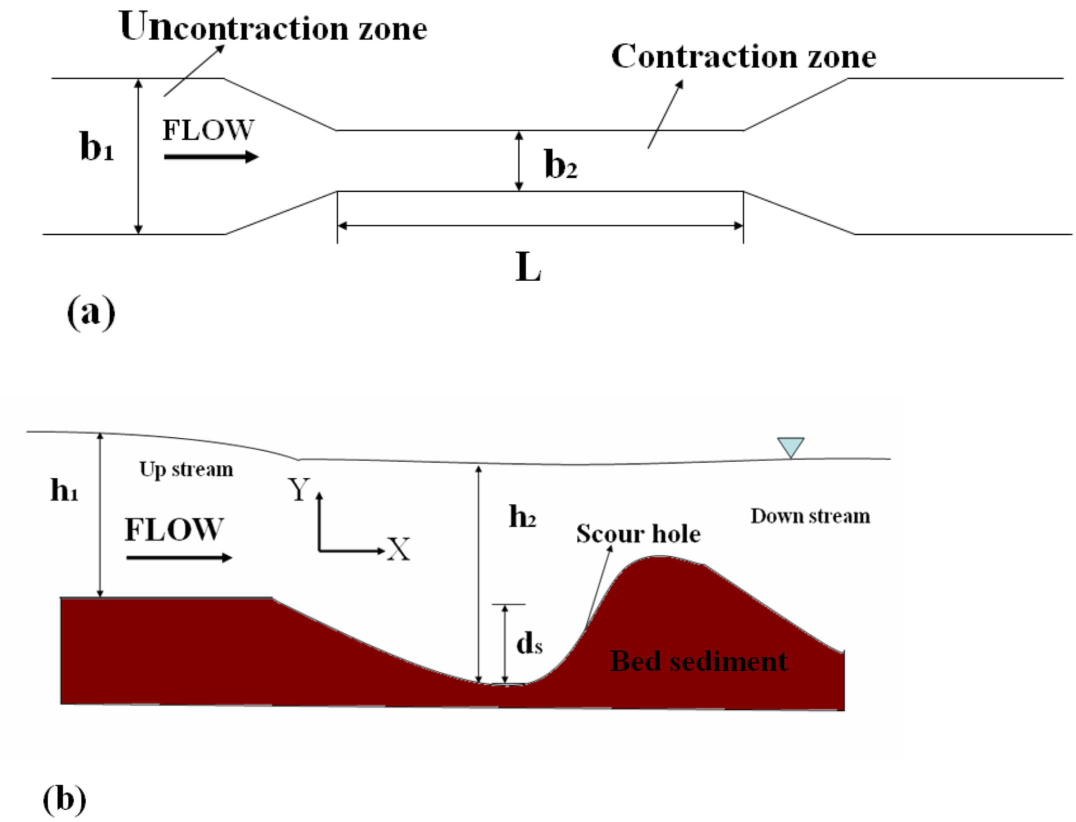

Figure1. Schematic of a long rectangular channel contraction at equilibrium scour condition: (a) top view; and (b) side view.

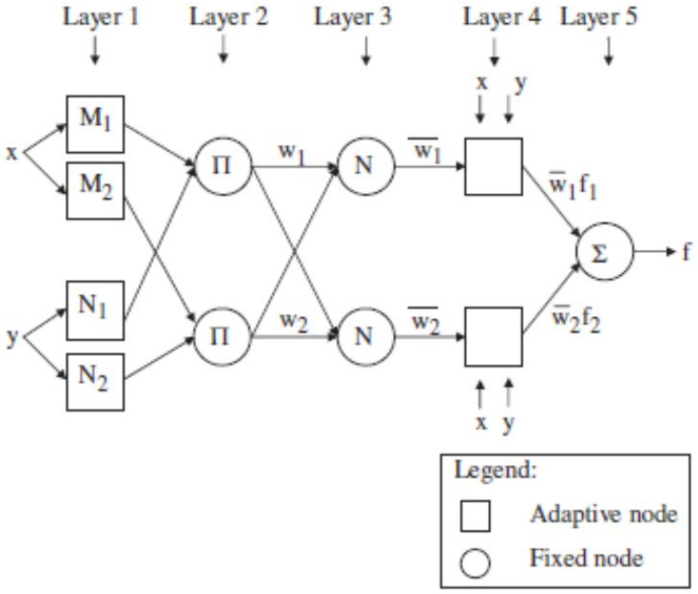

Figure 2. General architecture for ANFIS model (Jang, 1993)

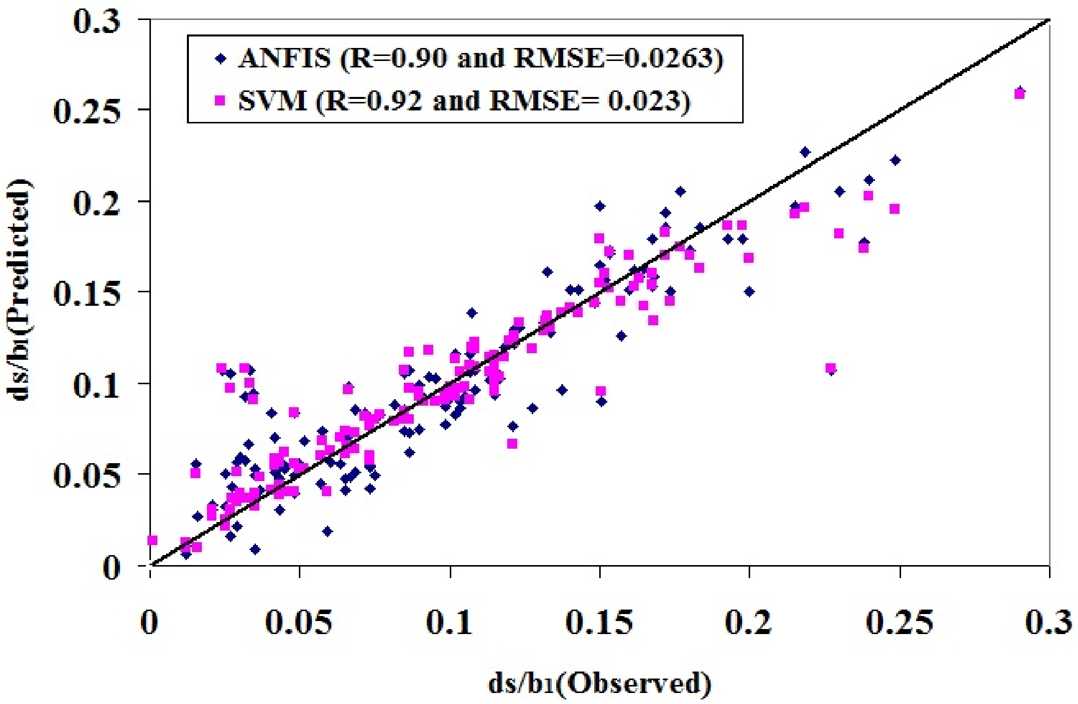

Figure 3. Scatter plot of observed and predicted scour depth for training stages of NFIS and SVM models

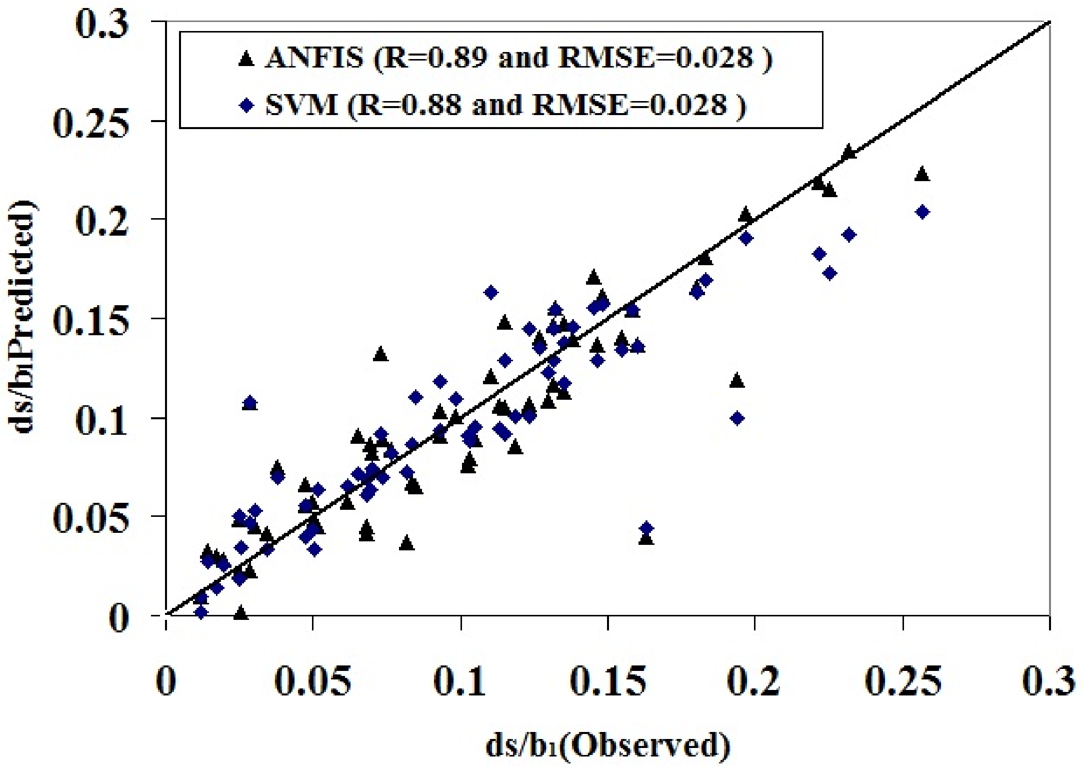

Figure 4. Scatter plot of observed and predicted scour depth for testing stages of ANFIS and SVM models

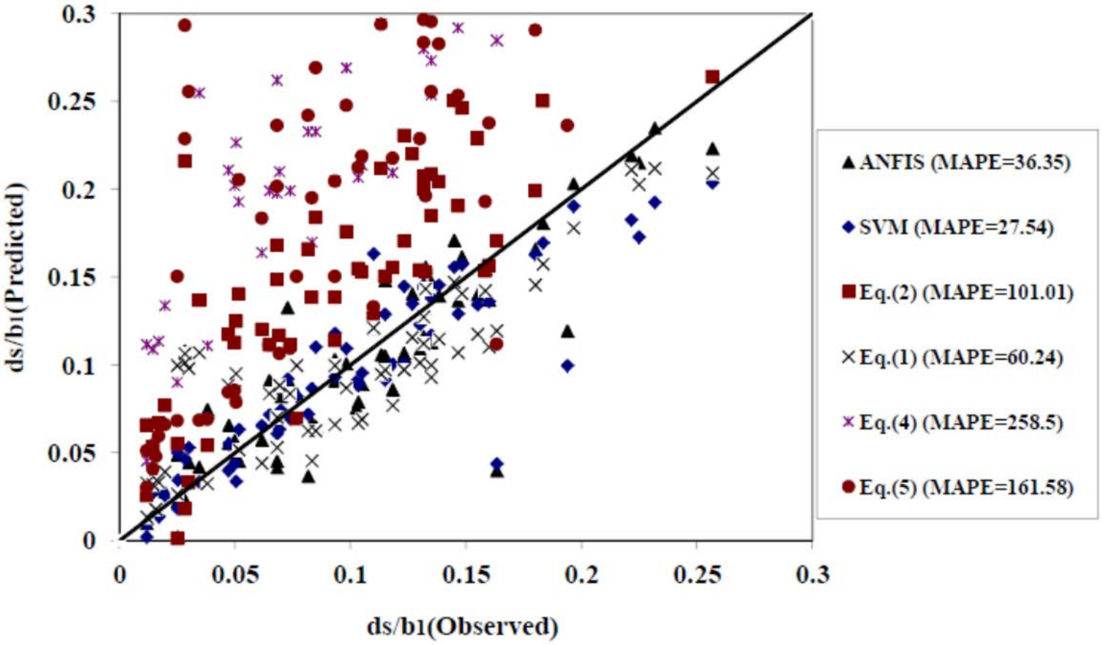

Figure 5. Scatter plot of observed and predicted scour depth for the ANFIS, SVM, and traditional equations

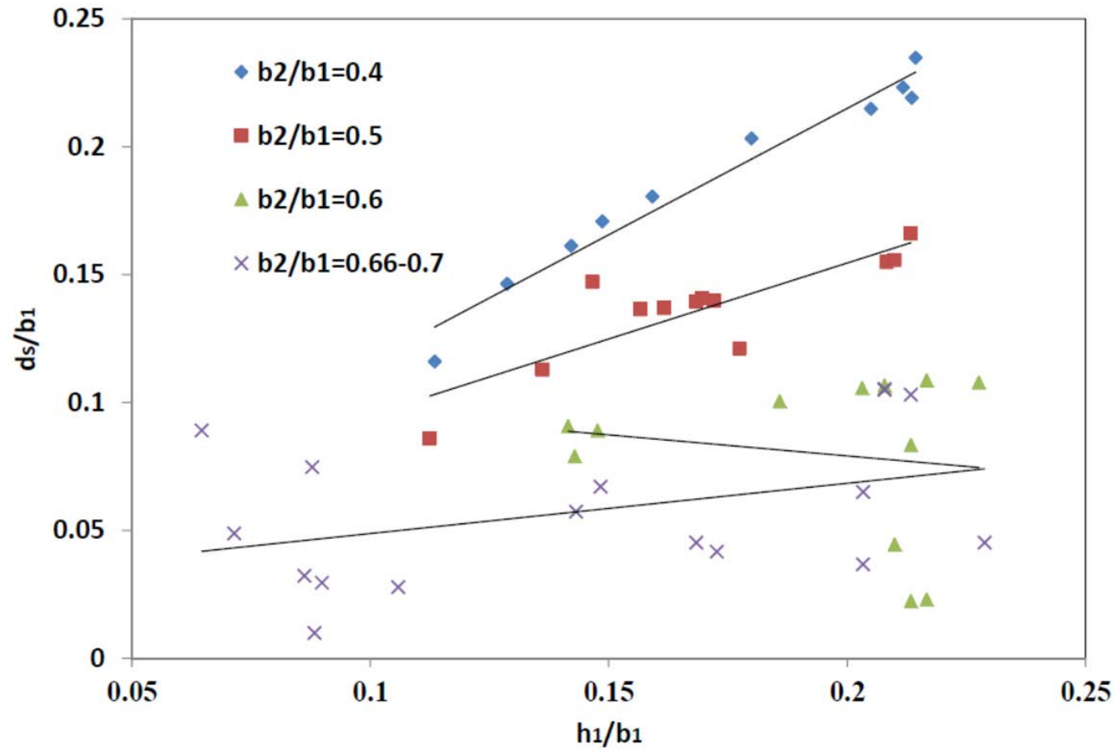

Figure 6. Variations of d_s / b_1 variable versus h_1 / b_1 for different ratio of b_2 / b_1

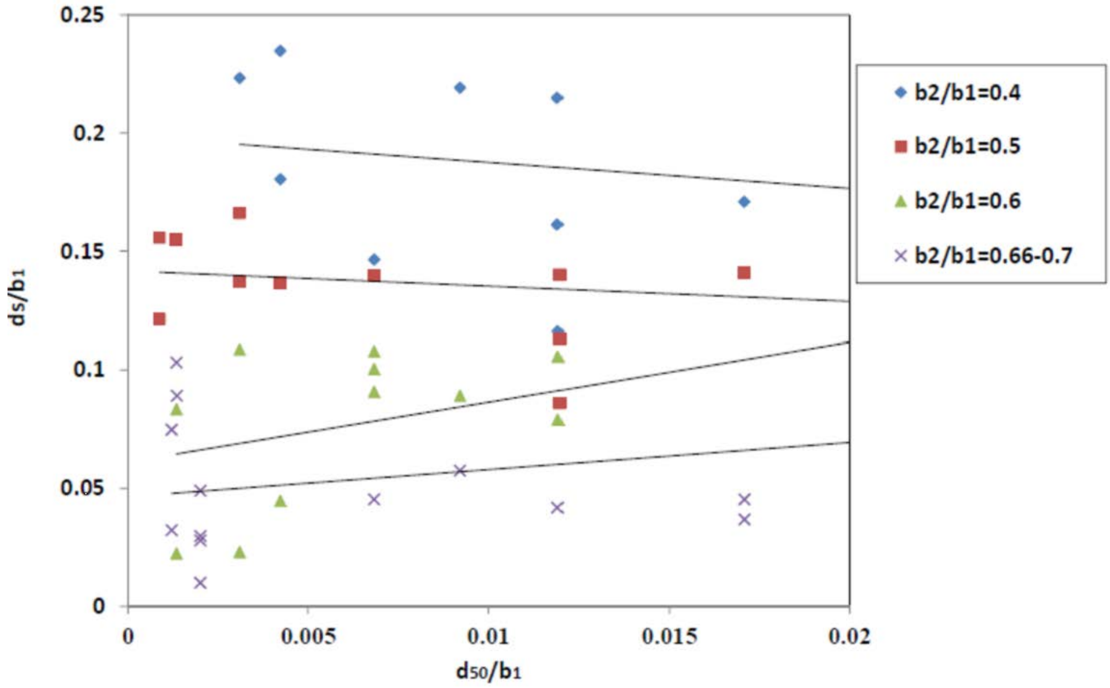

Figure 7. Variations of d_s/b_1 variable versus d_{50}/b_1 for different ratio of b_2/b_1

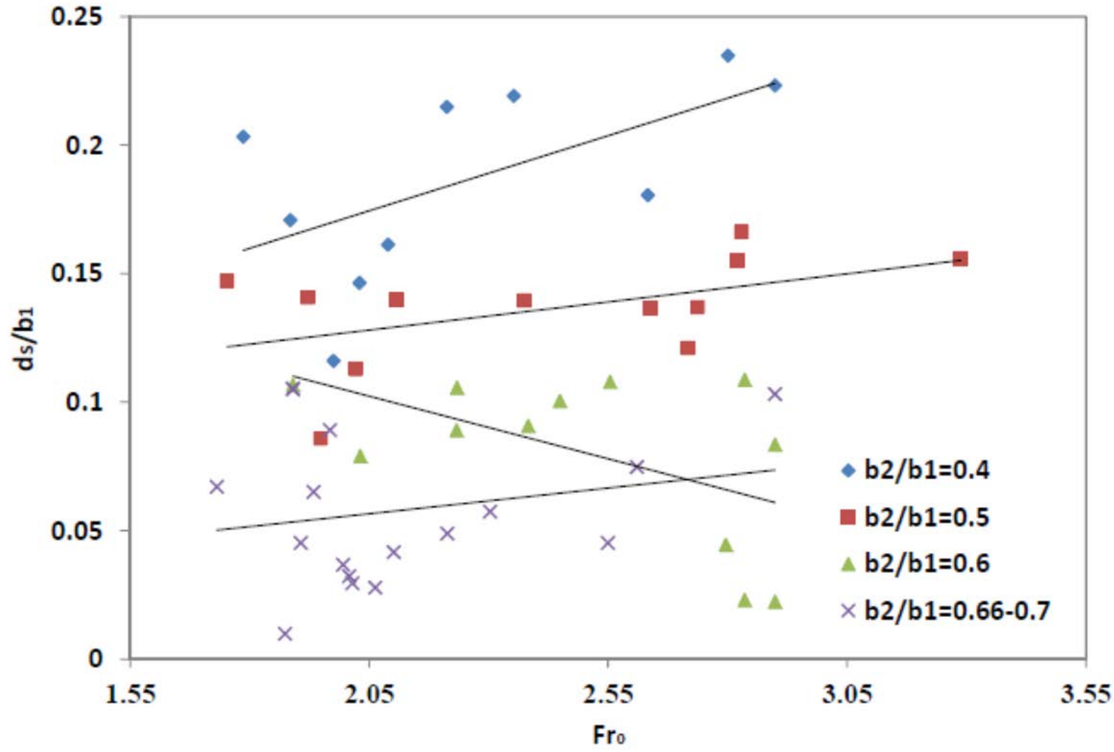

Figure 8. Variations of d_s/b_1 variable versus Fr_0 for different ratio of b_2/b_1

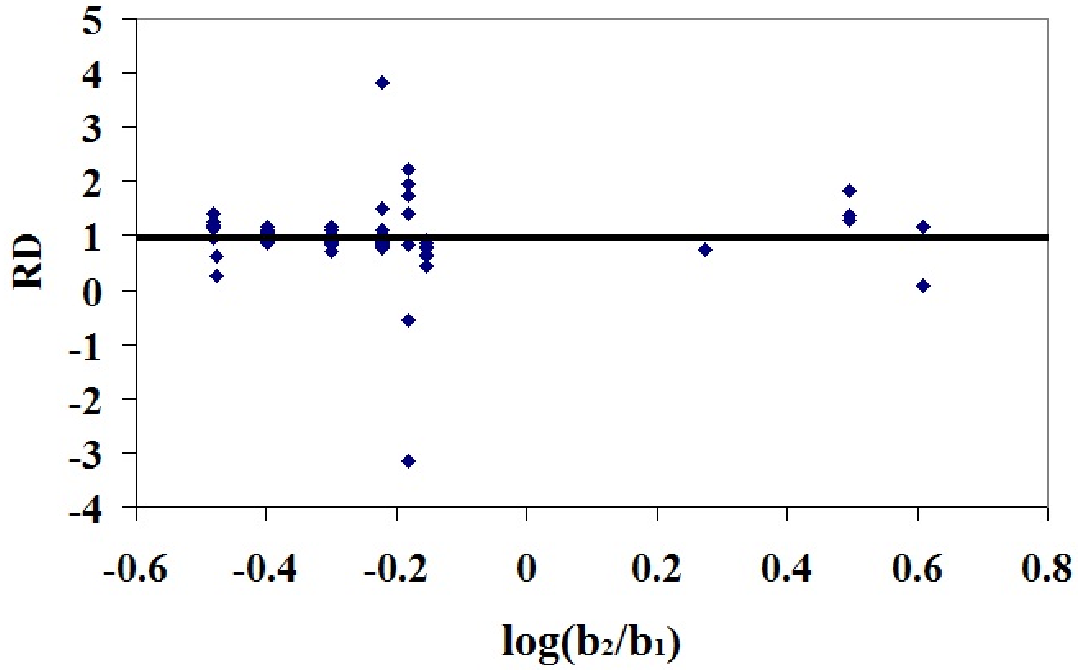

Figure 9. Variation of DR with log (b_2/b_1) for ANFIS model

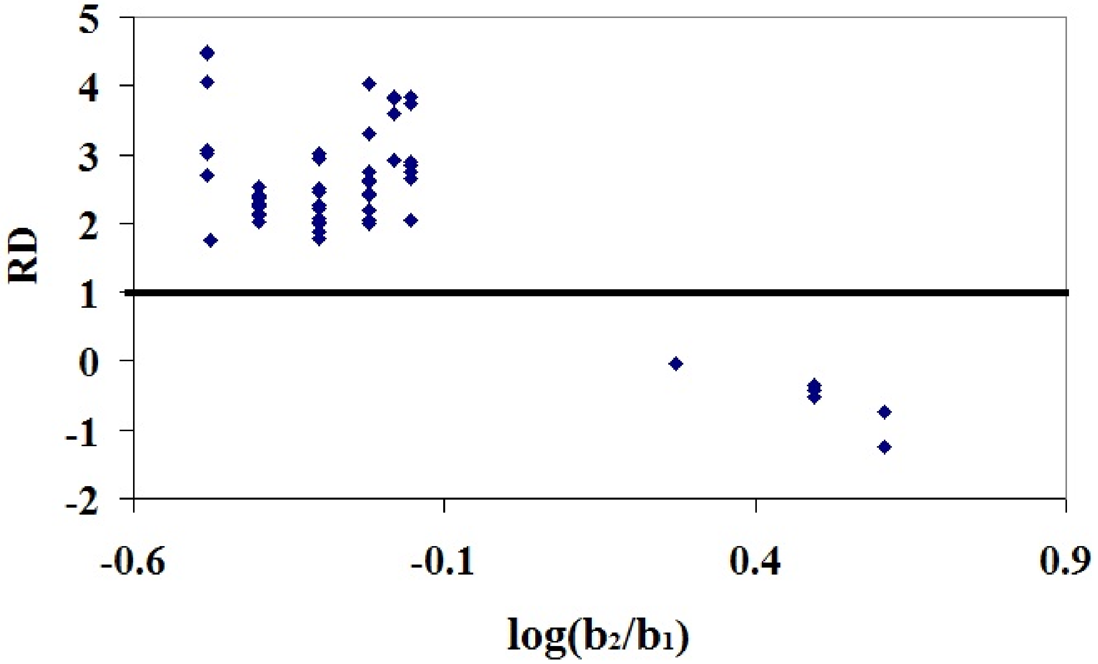

Figure 10. Variation of DR with log (b_2/b_1) for SVM model

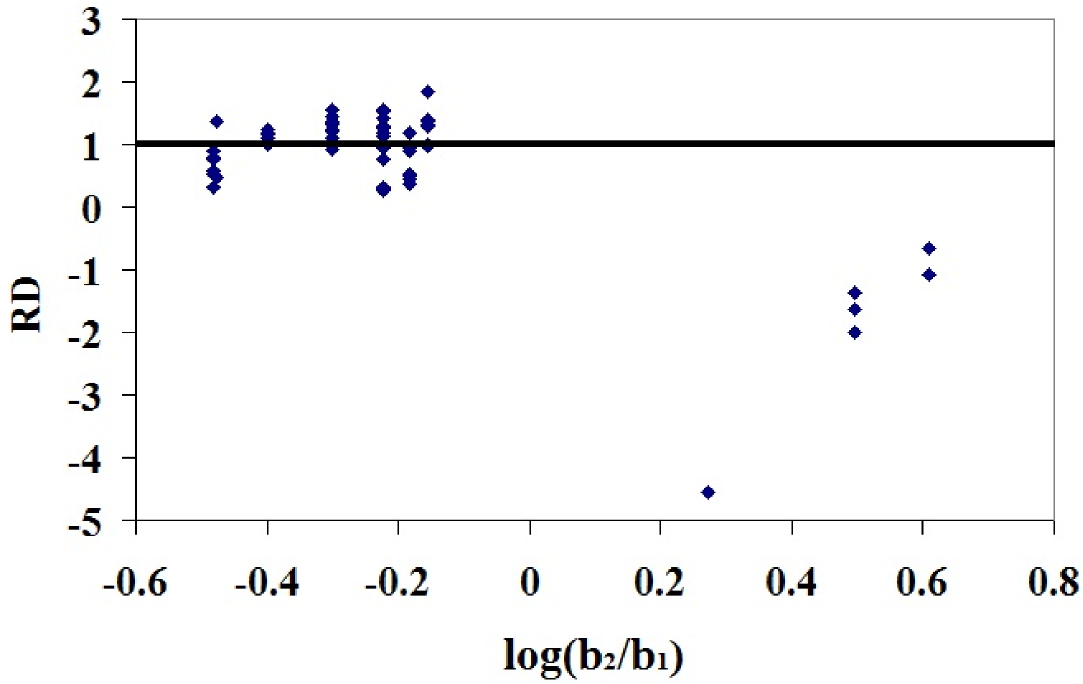

Figure 11. Variation of DR with log (b_2/b_1) for Eq.(1)

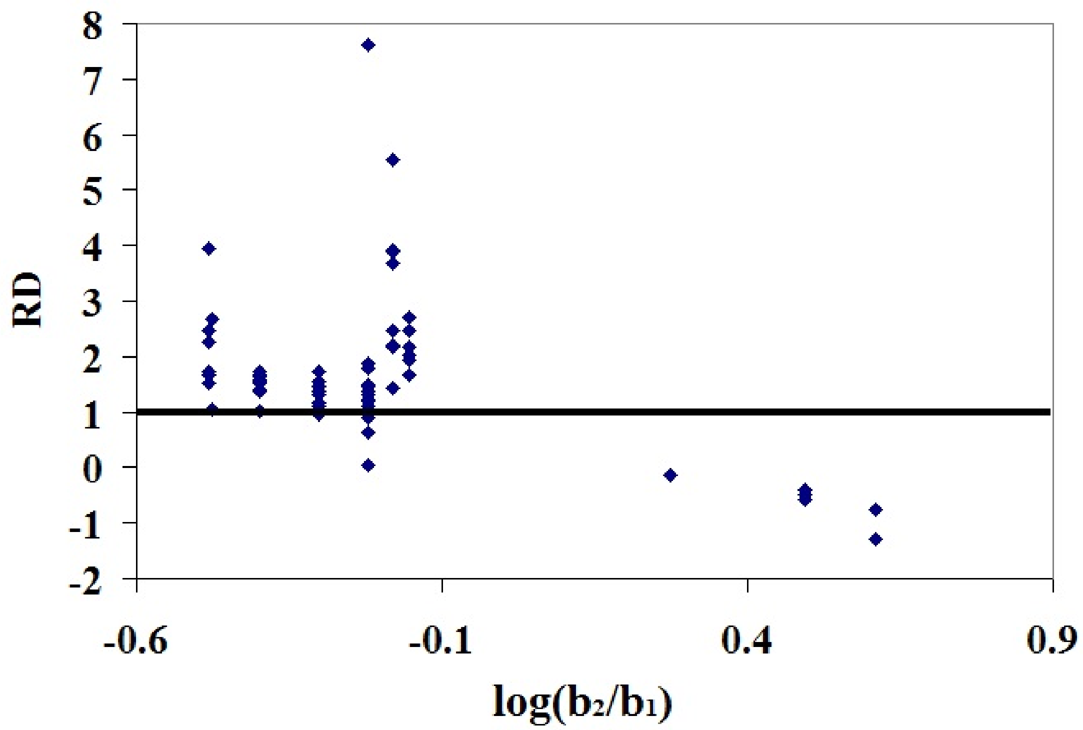

Figure 12. Variation of DR with log (b_2/b_1) for Eq.(2)

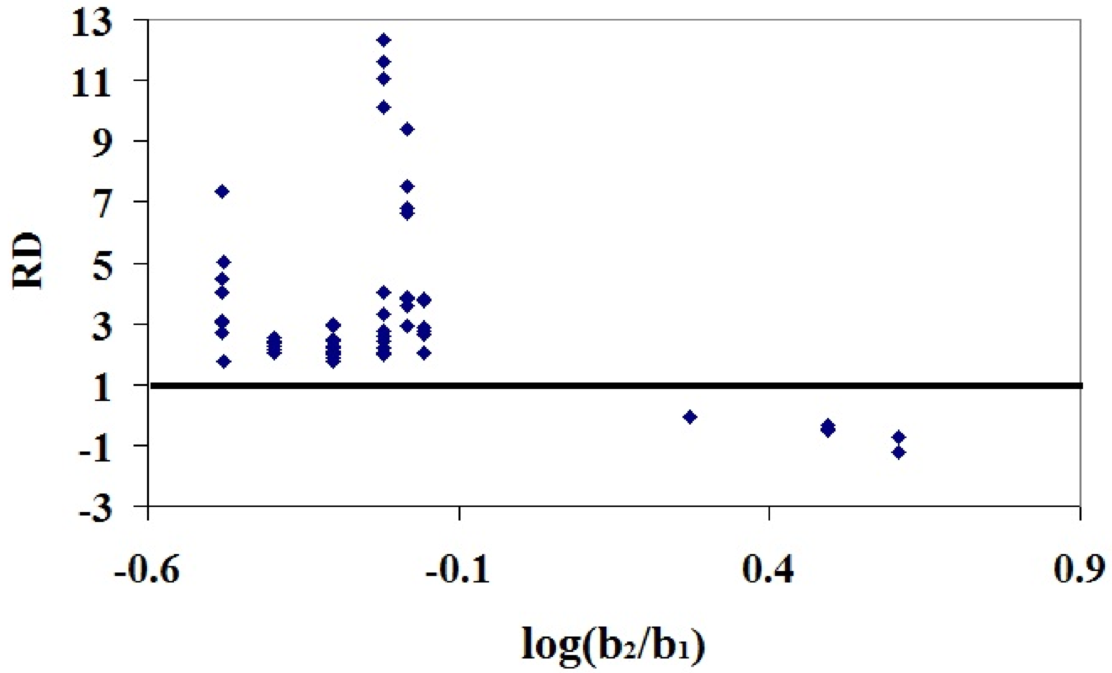

Figure 13. Variation of DR with log (b_2/b_1) for Eq.(4)

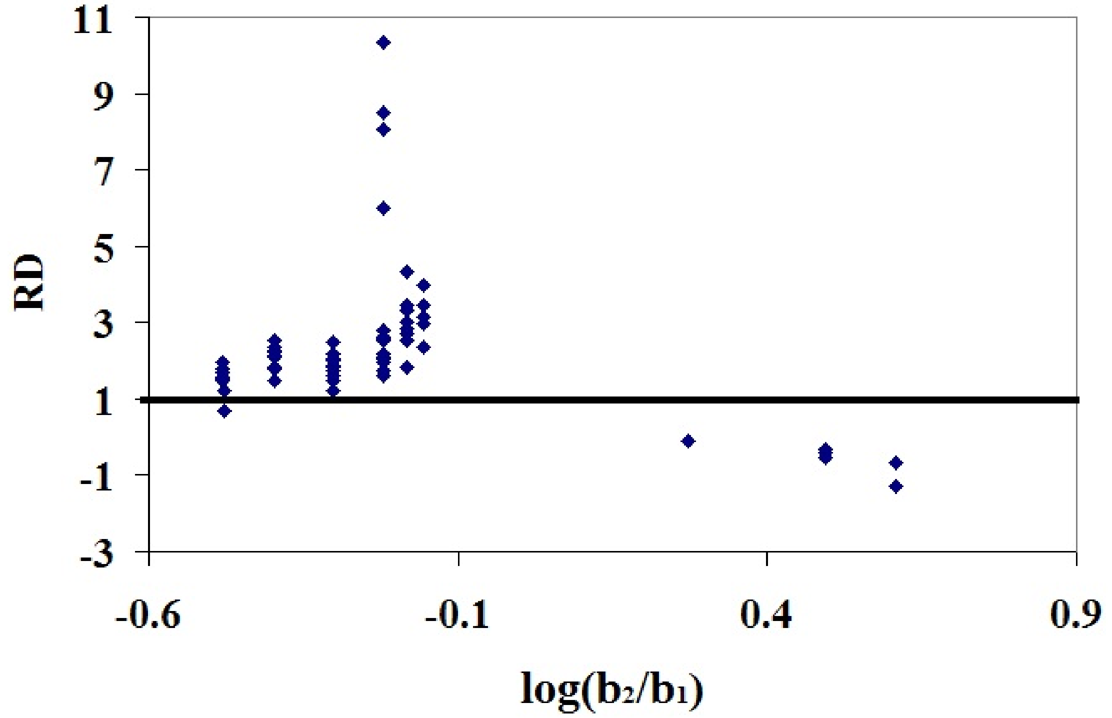

Figure 14. Variation of DR with log (b_2/b_1) for Eq.(5)