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Prediction of Critical Submergence for Horizontal Intakes

Arun Goel

Abstract— Accurate prediction of the critical submergence for intakes in open channels has been mainly based on experimental studies and theoretical equations developed are empirical in nature. In the present study, estimation of critical submergence for 90^o horizontal intakes have been attempted by using empirical equations, multi linear regression, back propagation ANN and M5 model tree based modeling. The horizontal intakes have been tested experimentally for two different locations of intake from the channel bed-one with clearance from the bottom equal to zero (c = 0) and the other having half the intake diameter (c = di/2). The data set has intake pipes of diameter equal to 4.25, 6.25 and 10.16 mm for the critical submergence under a wide range of flow conditions in a flume for 90^o horizontal intakes. The study shows that the soft computing technique namely Back propagation ANN and M5 model tree have emerged as alternate to the analytical equations as suggested by previous investigators on the present data.

Keywords- Critical submergence, intake, modeling, prediction, ANN and M5 model tree.

I. INTRODUCTION

FLOW through hydraulic intakes is one of the most complicated types of flow that occurs in nature and industry. Vortices are formed at the intakes when water is drawn from the reservoirs, rivers or sea. Vortices are formed at the intakes when water is drawn from the reservoirs, rivers or sea. Thus causes additional head loss, drawdown of floating debris and reduced efficiency of hydraulic machinery [1]. The vortex inception and prediction of critical condition at intakes is of interest for engineering applications in water quality management [1, 2]. Intakes in the form of pipes are employed for withdrawing water from river, lake, reservoir for different purposes. Insufficient depth of water above intake could result in the formation of the air entraining free surface vortices. Formation of air entraining vortices in front of intake may cause operational problems, noise, corrosion and ultimately reduction in the discharge. Air entraining vortices have been observed frequently at many installations such as Hirfanli Dam in Turkey, Harspranget Dam in Sweden, Kariba Dam in Zambia etc [3]. The vertical distance between the water level and upper level of intake is generally called submergence. Due to insufficient submergence of the intake, air enters the intake pipe and reduction in discharge takes place. The submergence depth at which incipient air entrainment takes place at the pipe intake is called critical submergence. The velocity of intake pipe, diameter of intake, position of intake (bottom clearance) and roughness of the bottom are some of the most effective air entraining problem. There are several methods of avoiding air entrainment i.e. providing sufficient submergence at the intake entrance by restoring to physical studies. However, in some situations physical modeling may not be economical due to time and financial constraints. Hence in the present paper, an attempt has been made to predict critical submergence of an intake in water flow by using soft computing techniques ANN and M5 model tree on the experimental data taken from a study [3].

Arun Goel is with Department of Civil Engineering at National Institute of Technology, Kurukshetra, Haryana, India.
Email: drarun_goel@yahoo.co.in, FAX: +91 1744 238050

Several empirical relationships and charts are available in literature [1, 4-10] for the prediction of critical submergence for intakes. These relationships relate the critical submergence as a function of Froude number, Reynolds number, the vertical height of intake, Weber number, circulation and some more additional parameters. Recently, authors in [11] also proposed the predictors for the critical submergence for both flat and bell mouth shaped vertical intakes. They reported that Froude number is the predominant parameter which affects the critical submergence. For the same Froude number, the values of critical submergence for flat and bell mouth vertical intakes are different. However, some investigators [12, 13] have applied soft computing techniques like RBF based ANN for prediction of submergence intake in water flow. In ref. [14] authors investigated the critical submergence in still water and open channel flow for permeable and impermeable bottom by using ANN and compared the results with the linear regression. The present study, however, deals with the determination of critical submergence for a lateral (90^o) horizontal intake from an open channel flow by using soft computing modeling techniques like multi linear regression, and Back propagation ANN and M5 model tree.

II. DETERMINATION OF CRITICAL SUBMERGENCE

A. Analytical Solution

An analytical equation for the critical submergence can be obtained by considering the flow as potential flow with pipe intake as point sink and superposition of point sink and uniform flow [15]. The Rankine half-body of revolution divides flow into two regions namely flow area entering and not entering the intake. Until the upper boundary of the Rankine half body of revolution reaches the free surface, the surface water just above the centre of the intake cannot enter the intake. At critical condition, water surface level above the intake is almost matching the upper surface of the Rankine half-body of revolution which is also called critical spherical sink surface (CSSS). Thus, the vertical distance between any point on the upper portion of the Rankine half-body of revolution and the intake level may approximately be taken as equal to the critical submergence. After analysis of the flow, the critical submergence in horizontal intake may be calculated by using the following equation:

$$S_c = r - \frac{d_i}{2} = \frac{-\left(c + d_i/2\right) + \sqrt{\left(c + d_i/2\right)^2 + 2\left(U_i/U_\infty\right) d_i^{\,2}}}{2} - \frac{d_i}{2} \qquad (1)$$

Where Sc is critical submergence, r is radius of critical spherical sink surface, c is bottom clearance, di is intake pipe diameter, Ui is velocity of flow in intake, U_∞ is velocity of flow in flume.

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B. Dimensional Analysis [3]

This critical submergence can also be obtained by dimensional analysis of variables affecting it. Various pertinent variables influencing the critical at a horizontal intake pipe are d_i, U_i, U_∞, c, width of the channel b, circulation Γ, mass density ρ, dynamic viscosity μ, surface tension σ, and acceleration due to gravity g. The functional relationship for the critical submergence S_c can be written as:

$$S_C = f(d_i, b, U_i, U_\infty, \Gamma, c, \rho, \mu, \sigma, g) \qquad (2)$$

Where, F = intake Froude number; R = intake Reynolds number; and W = Weber number. Effect of width of the channel may be neglected for critical submergence $S_C < b$. After dimensional analysis following equations as proposed by [3] are:

(a) Predictor for S_C/d_i for c = 0

$$\frac{S_C}{d_i} = 0.36\left(\frac{U_i}{\sqrt{gd_i}}\right)^{0.80}\left(\frac{U_\infty}{\sqrt{gd_i}}\right)^{-0.90} \qquad (3)$$

(b) Predictor for S_C/d_i for $c = d_i/2$

$$\frac{S_C}{d_i} = 0.29\left(\frac{U_i}{\sqrt{gd_i}}\right)\left(\frac{U_\infty}{\sqrt{gd_i}}\right)^{-1} = 0.29\left(\frac{U_i}{U_\infty}\right) \qquad (4)$$

The proposed relationships for S_c/d_i, i.e., Equation (3) and equation (4) are validated for prediction of S_c/d_i for c = 0 and $c = d_i/2$. It was found that for c = 0 predictions is within $\pm$ 20% error of observed values and for $c = d_i/2$, within $\pm$ 15% error. The same equations have been used in the present study in order to make a comparison with soft computing techniques. The equations namely Sc/di = 1.5 + F [16] and Sc/di = 1 + F [17] are also used in the present study on the same data set and the results are compared with the soft computing techniques.

C. Prediction Methods of Critical Submergence

Here the author has used 165 data sets taken from the experimental study by [3] for training and model verification to predict the critical submergence of horizontal intake. The ANN, M5 model tree and linear regression approaches are used to predict the critical submergence for the horizontal intake at two different positions for c = 0 and c = di/2. The results obtained are also compared with analytical equations [3, 16, 17].

III. ARTIFICIAL NEURAL NETWORKS

A neural network is an artificial intelligence technique that mimics a function of the human brain. Neural networks are general-purpose computing tools that can solve complex non-linear problems in the field of pattern recognition, classification, speech, vision and control systems. The network comprises a large number of simple processing elements linked to each other by weighted connections according to a specified architecture. A neuron consists of multiple inputs and a single output. The number of neurons in the input and output layers are fixed by the problem being modelled as the number of input variables equals number of input neurons and number of output variables equal number of output neurons. The determination of optimal number of hidden layers and hidden neurons is usually cumbersome, as no general methodology is available for their determination. These networks learn from the training data by adjusting the connection weights. There is a range of artificial neural network architectures designed and used in various fields of hydrology and hydraulics. Most of the studies employing neural networks for water resource problems have used back propagation & radial basis function types of neural networks. In this study, a feed-forward neural network with back propagation learning algorithm is applied. The basic element of a back-propagation neural network is processing node and structure of commonly used back propagation neural network (Figure 1). A three layer feed forward ANN has been shown in Fig1, which consists of three layers known as input, hidden and output layers. Input layer neuron are called as x_1, x_2, x_3; hidden layers neurons are h_1, h_2, h_3 and output layers neurons are O_1,O_2,O_3. The output of a neuron is decided by an activation function, which can be step, sigmoid, threshold and linear etc.

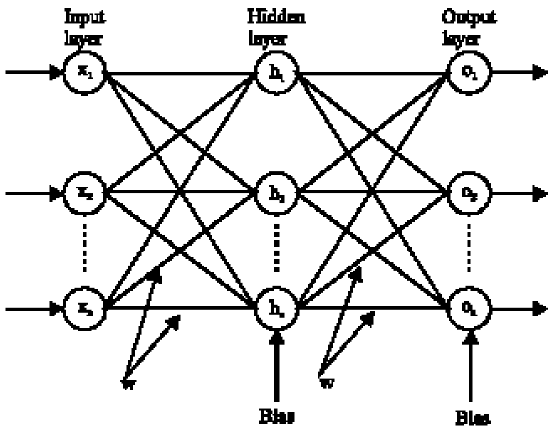

Figure 1 Three layer feed forward neural network

In a back propagation neural network, generally, there is an input layer that acts as a distribution structure for the data being presented to the network. This layer is not used for any type of processing. After this layer, one or more processing layers follow, called the hidden layers. The final processing layer is called the output layer in a network. This process is repeated until the error rate is minimized or reaches to an acceptable level, or until a specified number of iterations have been accomplished. Gradient descent method can be used to adjust the interconnecting weights to achieve minimal overall training error in multi-layer networks. The generalized delta rule, or back-propagation is one of the most commonly used methods [18] in which the first derivative of the total error with respect to a weight determines the extent to which that weight is adjusted. A neural network based modelling approach requires setting up several user-defined parameters like learning rate, momentum, optimal number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a better generalization capability.

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IV. M5 MODEL TREE

One of the popular ways of classifying of a particular input is a decision tree. It consists of leaf or answer nodes that indicate a class and decision nodes that contain an attribute name and branches to other decision tress. There are many efficient algorithms for building decision trees such as ID3 and C4.5 as proposed in [19]. The structure of M5 model tree follows the decision trees and has multivariate regression model at leaf nodes. Thus M5 is a combination of piecewise linear models, each of which is suitable for a particular domain of input space as shown in Fig. 2. The algorithms of model tree (MT) break the input space of training data through nodes to assign a linear model suitable to sub area of input space. The continuous splitting often results in a too complex tree that needs to be reduced to a simpler tree to improve the generalized capacity. The value predicted by model at the leaf is adjusted by smoothing operation to reflect the predicted values at the nodes along the path from root to that of leaf. The overall global model is the collection of these linear models, wherein optimal splitting of input space is done automatically. Model tree can learn efficiently and tackle tasks of high dimensionality with hundred of attributes as mentioned [20, 21, 22, 23].

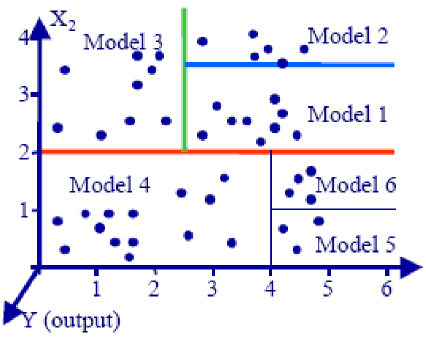

Figure 2 Splitting the input space X1.X2 by M5 model tree algorithm & each model is linear regression model.

V. PERFORMANCE EVALUATION CRITERION

The data sets mentioned in the study by [3] are used in the present study for model building and validation to assess the potential of the empirical equations, linear regression, Back propagation ANN and M5 modelling techniques in predicting the critical submergence for horizontal intake. The correlation coefficient (CC) and Root Mean Square Error (RMSE) values are used as shown in equation (5) and (6) mainly for the performance evaluation of models and comparison of the results for prediction of critical submergence. A higher value of a correlation coefficient and a smaller value RMSE means a better performance of the model. Further, measured values were plotted against the computed values of critical submergence obtained with empirical equations, linear regression, Back propagation ANN and M5 model tree algorithms. To study the scatter of line of perfect agreement (a line at 45°) was plotted for the data set along with 15% error line.

Error Measure Criteria:
1. Correlation coefficient (r)

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{5}$$

here x = X - X', y = Y - Y' where X = observed critical submergence values; X' = mean of X, Y = predicted critical submergence values, Y' = mean of Y.

2. Root mean square error

$$RMSE = \left[\frac{\sum (X - Y)^2}{n} \right]^{0.5} \tag{6}$$

VI. MATERIAL USED AND METHODS

In this paper modeling techniques like ANN, M5 model tree and linear regression are being applied to the problems in prediction of critical submergence of the horizontal intake. The ANN and M5 model tree require setting up of the optimum values of the parameters and the size of the error-insensitive zone ε need to be determined. To select user-defined parameters i.e. (no of iterations, learning rate, hidden layers, biases, weights etc.), a large number of trials were carried out by using different combination of these parameters on each of the data sets (Table 1). To reach at a suitable choice of these parameters, the correlation coefficients (CC) and Root Mean Square Error (RMSE) were compared and a combination of parameters providing smallest value of RMSE and the highest value of correlation coefficient was selected for the final results. Similarly, a number of trials were also carried out to find a suitable value of ε (error-insensitive zone) with a fixed value of technique specific parameters. Variation in the error-insensitive zone ε has no effect on the predicted critical submergence, so a value of 0.0010 was chosen for all the experiments.

Due to the availability of small data sets, a cross validation was used to train and test the performance of the linear, ANN and M5 model tree based regression techniques using WEKA software[24]. The cross-validation is a method of estimating the accuracy of a classification or regression model. The input data set is divided into several parts (a number defined by the user), with each part in turn used to test a model fitted to the remaining parts. In this study, the data sets of the laboratory were used for both creating and testing the models. For quantitative comparison of results, an error measure, a correlation coefficient (r) and RMSE, which presents the degree of linear regression association between predicted and true values has been considered, which is preferred to, in many iterative prediction and optimization scheme.

VII. PREDICTION OF CRITICAL SUBMERGENCE

Use of empirical equations in prediction of critical submergence for horizontal intake has been studied by [3]. The first set of analysis was carried out by using data from the study [3] predicting the critical submergence for horizontal intake. Various pertinent variables influencing the critical at a horizontal intake pipe are intake pipe diameter di, velocity of flow in intake Ui, velocity of flow in flume U_∞, bottom clearance c, critical submergence Sc, intake discharge Qi, width of the channel b, circulation Γ, mass density ρ, dynamic viscosity μ, surface tension σ, and acceleration due to gravity g, Froude number F, Reynold Number, and weber number. However, di, Qi U_∞, were used to predict Sc/di for c = 0 and di, Qi, D, U_∞ were used to predict Sc/di for c = di/2. The values of Sc/di were calculated by analytical equations (3) and (4) as suggested by [3]. A number of trials were carried out to reach at the maximum correlation coefficient based on various user-defined parameters required for the ANN, M5 model tree and linear regression based algorithms by using WEKA software by a method of cross validation. Table 2 provides the values of correlation coefficients and RMSE for the data set. The results obtained for critical submergence by equations (3) & (4) as suggested by [3] and soft computing techniques linear regression, ANN and M5 model tree are plotted shown in Fig.3 to Fig. 6.

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For c = 0, a correlation coefficient and RMSE for ANN (0.9882, 0.1518), M5 tree (0.9947, 0.1034), Ahmad (0.9639, 0.3082) are obtained in comparison to a value of 0.7692 (RMSE = 0.6313) by using linear regression based modeling (Table 2). Further, it is evident from Figure 3 that more number of points are lying on or close to the 45^o line when ANN and M5 model tree and Ahmad equation based models were used to predict the critical submergence in comparison to linear regression.

For c = di/2, a correlation coefficient and RMSE for ANN (0.999, 0.023), M5 tree (0.9969, 0.1130), Ahmad eq (0.9705, 0.0013) are obtained in comparison to a value of 0.9693 (RMSE = 0.3355) by using linear regression based modeling (Table 2). Further, it can be seen from Figure 4 that more number of points are lying on or closer to the 45^o line when ANN, M5 model tree and Ahmad equation [3] as compared to the linear regression.

The variation of actual critical submergence versus predicted critical submergence for the values of c = 0 and c = d/2 by Ahmad eq (2008), Swroop eq [16] and Reddy & Pickard equation [17] have been plotted in Fig. 5 and Fig. 6 respectively. For c = 0, a correlation coefficient and RMSE by Swroop equation [16] (0.7112, 2.7121), by Reddy & Pickford [17] (0.7112, 2.2910) are obtained. For c = di/2, a correlation coefficient and RMSE by Swroop equation [16] (0.8781, 0.03780), by Reddy & Pickford [17] (0.8781, 0.02565) are obtained. The results are better in case of c = di/2 as indicated by the Table 2. The perusal of these two figures indicates that the results are closer to the line of perfect agreement by Ahmad equation [3] as compared to Swroop equation [16] and Reddy & Pickard equation [17]. The predictor by [16, 17] shows that predicted values for c = 0 and c = di/2 are greater that the observed values. It may be due to the fact that the predictor by [16, 17] do not consider the approach velocity and relate critical submergence only with Froude number of the intake.

However, a critical examination of Fig.3 to Fig.6 indicates that relatively less used ANN and M5 model tree techniques have emerged as an alternate to the analytical equations suggested by Ahmad eq [3] for the prediction critical submergence of the horizontal intake successfully.

TABLE II

COMPARISON OF RESULTS

S No	Intake position	Type of technique	Correlation coefficient (r)	Root mean squared error (RMSE)
1	c = 0	ANN	0.9882	0.1518
2	c = 0	M5	0.9947	0.1034
3	c = 0	Linear	0.7692	0.6313
4	c = 0	Ahmad	0.9639	0.3082
5	c = 0	Swroop	0.7112	2.7121
6	c = 0	Reddy & Pickford	0.7112	2.2910
7	c = di/2	ANN	0.9993	0.0230
8	c = di/2	M5	0.9969	0.1130
9	c = di/2	Linear	0.9693	0.3355
10	c = di/2	Ahmad	0.9705	0.0013
11	c = di/2	Swroop	0.8781	0.03780
12	c = di/2	Reddy & Pickford	0.8781	0.02565

TABLE I

VALUES OF SPECIFIC PARAMETERS OF ANN MODELING

S.No	Intake position	Type of parameter			
		Momen tum	Learning rate	No of nodes	iteratio n
1	c = 0	0.3	0.2	1	500
2	c = di/2	0.3	0.2	1	500

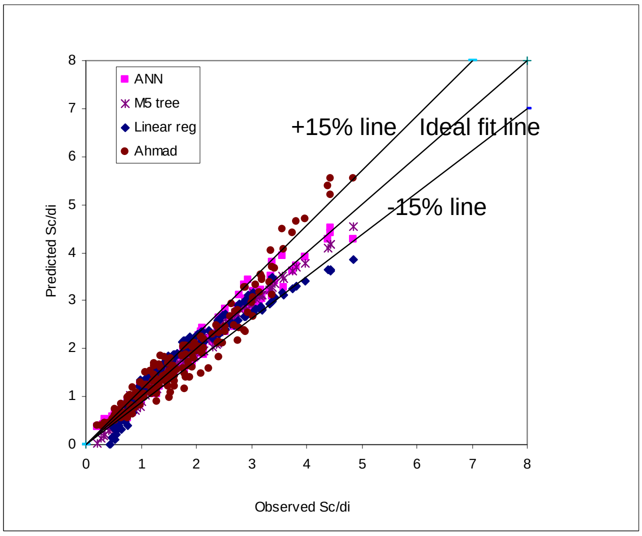

Fig.3 Variation of actual critical submergence with predicted critical submergence for c = 0

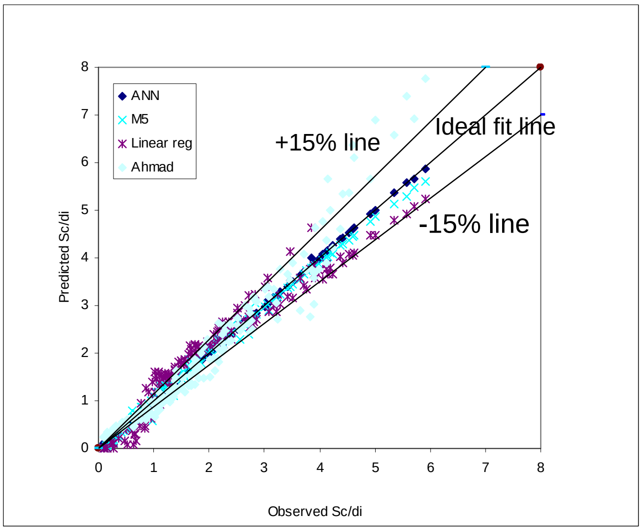

Fig.4 Variation of actual critical submergence with predicted critical submergence for c = di/2

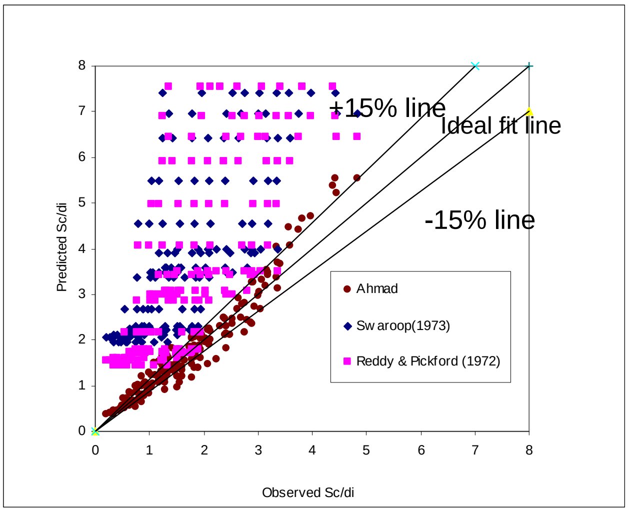

Fig.5 Variation of actual critical submergence with predicted critical submergence for c = 0 by Ahmad et al. (2008), Swroop (1973) and Reddy & Pickard (1972).

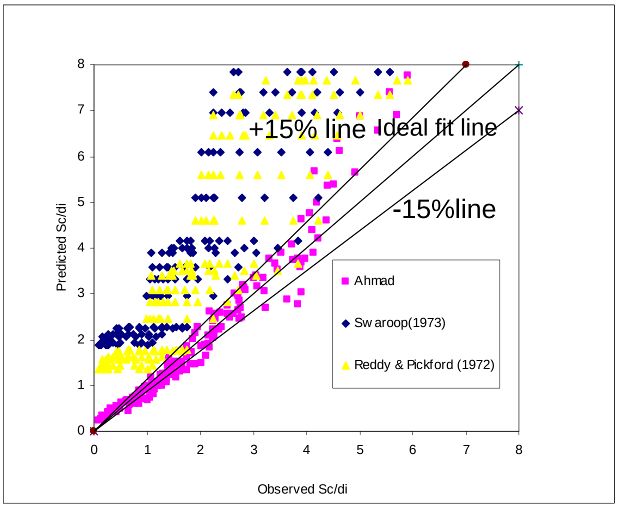

Fig.6 Variation of actual critical submergence with predicted critical submergence for c = di/2 by Ahmad et al. (2008), Swroop (1973) and Reddy & Pickard (1972).

VIII. CONCLUSIONS

This study was carried out to judge the potential and suitability of soft computing techniques like Back propagation ANN and M5 model tree regression based modelling in the prediction of critical submergence for horizontal intakes in comparison to empirical equations by Ahmad et al. [3] and the linear regression. The outcome of this study encourages the application of back propagation ANN and M5 model tree approach in predicting the critical submergence for horizontal intakes as an alternative approach to empirical relations and the linear regression. The study also concludes that the results obtained are parameter specific and data sensitive.

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