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Prediction of Afflux (backwater) Caused by a Single Spur Dike Using Artificial Neural Network

Hamed Sarveram and Hamed Ebrahimkhani

Department of Civil Engineering,
Zanjan Branch, Islamic Azad University, Zanjan, Iran (IRAN)
E-mail: h.sarveram@iauz.ac.ir, hamed.ebrahimkhani@yahoo.com

ABSTRACT

Construction of the spur dikes in the river leads to rise of the water level in upstream and may increase flood zones in the region. Most of the proposed methods for prediction of afflux caused by spur dike were presented based on energy and momentum equations. In this study, a model is presented for prediction of afflux due to submerged spur based on spur dike blockage ratio (L/B), spur dike length to width ratio (P/L), submergence ratio of the spur dike (h_2/P) and downstream Froude number (Fr_2) using multi-layer perceptron artificial neural network and its results are compared with the regression and multi-functional models proposed by other researchers. In order for analysis using an artificial neural network in hidden layer of perceptron neural network, the hyperbolic tangent sigmoid stimulus function is used and back propagation network of this function is of sigmoid type. Results revealed that the accuracy of artificial neural network model was very high with the mean absolute error of 3.2%, providing the lowest error in prediction of afflux due to spur dike.

Keywords: afflux, spur dike, artificial neural network

INTRODUCTION

Spur dikes are hydraulic structures that project from the bank of a stream at some angle to the main flow direction. They are principally used for two purposes, namely river training and erosion protection of a riverbank. Main purposes of river training involve improving the navigability of a river by increasing the flow depth and straightening the channel alignment, and increasing the sediment transport rate through the improved reach. The latter feature results in reduced costs for channel dredging. In the case of bank protection, spur dikes can be used to protect the bank against erosion. Despite their useful features, however, there is some concern that spur dikes may be responsible for increased flooding due to the associated backwater effect. These increases in flood stage often endanger buildings, infrastructure (roadways, cables, bridges, etc.), farmland, hydraulic structures (pump stations, intakes, etc.), and people who live near the river. Therefore, prediction of the backwater effect due to spur dikes can be helpful in understanding this phenomenon toward flood management.

Any obstacle located within a flow field exerts a drag force on the flow, which invariably results in some type of energy loss. In free surface flow, such as the flow in a river, the drag force is overcome by a rise in the upstream water level, herein termed the backwater effect (δh) which is shown in figure 1.

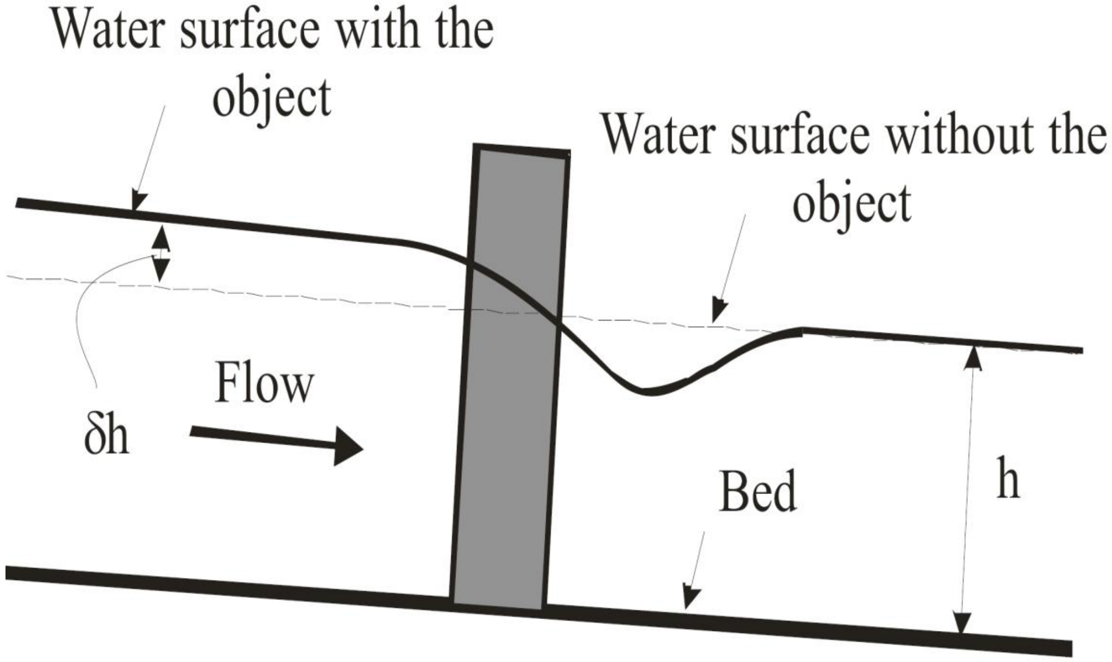


Fig. 1. Backwater effect due to a spur dike in an open channel (1)

The analysis of the backwater effect due to a spur dike in an open channel can be done using either an energy approach or a momentum approach. Application of momentum equation, determines the coefficient of the drag, while the use of the energy equation will reveal the coefficient of energy loss. In some studies, backwater is directly related with flow conditions and dike properties using empirical equations developed from laboratory studies (2).

An experimental study was done by Oak to determine afflux caused by a single spur dike for both submerged and unsubmerged test conditions. The studied spur dikes have a very thin (2D) rectangular shape, a triangular cross section and a rounded nose (3). Based on Oak's experiments, Smith used regression analysis to develop two empirical relationships for the prediction of the backwater effect due to 2D spur dikes for both submerged and unsubmerged conditions (4), viz.

$$\frac{h_1}{h_2} = 1 + 20\ \ 1 - e_r\ \ ^{1.8} Fr_2^{1.8} \qquad h_1/P \le 1 \tag{1}$$

$$\frac{h_1}{h_2} = 1 + C_p\ \ 1 - e_r\ \ ^{1.6} Fr_2^{1.5} \qquad h_1/P \ge 1 \tag{2}$$

where h_1 and h_2 are upstream and downstream depth of flow, respectively; Fr_2 is the Froude number of flow in downstream and e_r is the opening ratio that for the channel and rectangular spur dike is defined as (B-L)/B. Also, L and P are respectively the length and height of the spur dike and B is the width of the rectangular channel. In Eq. [2], the effects of the submergence are shown by the coefficient C_p, which is determined to be

$$C_p = 3.9\left(\frac{h_2}{p}\right)^{-2.4} \tag{3}$$

In another experiment, with the assumption of spur dike placement within a uniform flow field and establishment of hydrostatic pressure distribution, Azinfar had presented the following formula using the momentum equation along with the continuity equation and the drag force (1-5):

$$2Fr_1^2\left(\frac{h_1}{h_2}\right)^3 - \ \ 2Fr_1^2 - C_D A_r Fr_1^2 + 1\ \left(\frac{h_1}{h_2}\right)^2 + 1 = 0 \tag{4}$$

Where A_r is blockage ratio that for unsubmerged spur dike is L/B and for submerged spur dike is LP/(Bh_1). C_D is the drag coefficient that for submerged and unsubmerged spur dikes, based on Azinfar experiments, will be as follows(1-5):

$$C_D = 1.62\ \ 1 - A_r\ \ ^{-2.40}\left(\frac{P}{L}\right)^{-0.19}\left(\frac{h_1}{P}\right)^{-0.19} \tag{5}$$

$$C_D = 2.02\left(1 - \frac{L}{B}\right)^{-3.83}\left(\frac{h_1}{L}\right)^{0.40} \tag{6}$$

Based on experimental findings of Azinfar, to account for the underestimate, the backwater effect calculated from those equations must be increased by about 25%. Likewise, determining the drag coefficient using 540 experimental data from Oak's submerged spur dike (3), and applying multiple variable regression analysis to the data set resulted in

$$C_D = 4.00\ \ P/L\ \ ^{-0.431}\ \ 1 - L/B\ \ ^{-0.849}\left(\frac{h_1}{P}\right)^{-1.676}\ \ Fr_1\ \ ^{-0.221} \tag{7}$$

Also, Azinfar presented the following equation for drag coefficient by applying a multiple function model (1-5):

$$C_D = \left[1.8\left(1-P/L\right)^{3.7}+1.2\right]\left(1-L/B\right)^{-0.85}\left[\frac{3.2}{\left(h_1/P\right)^{3}}+1\right]\left[1.1\left(1-Fr_1\right)^{15}+1.4\right] \qquad [8]$$

Where Fr_1 is the Froude number of flow in upstream and the rest of parameters are the same as the previous relations and in accordance with the figure 2. One of the problems in the relations proposed by Azinfar (4) is their inability to explicitly determine the (h_1 - h_2) afflux. This problem has been solved in present study by replacing the downstream parameters instead of upstream ones as the input for artificial neural network model.

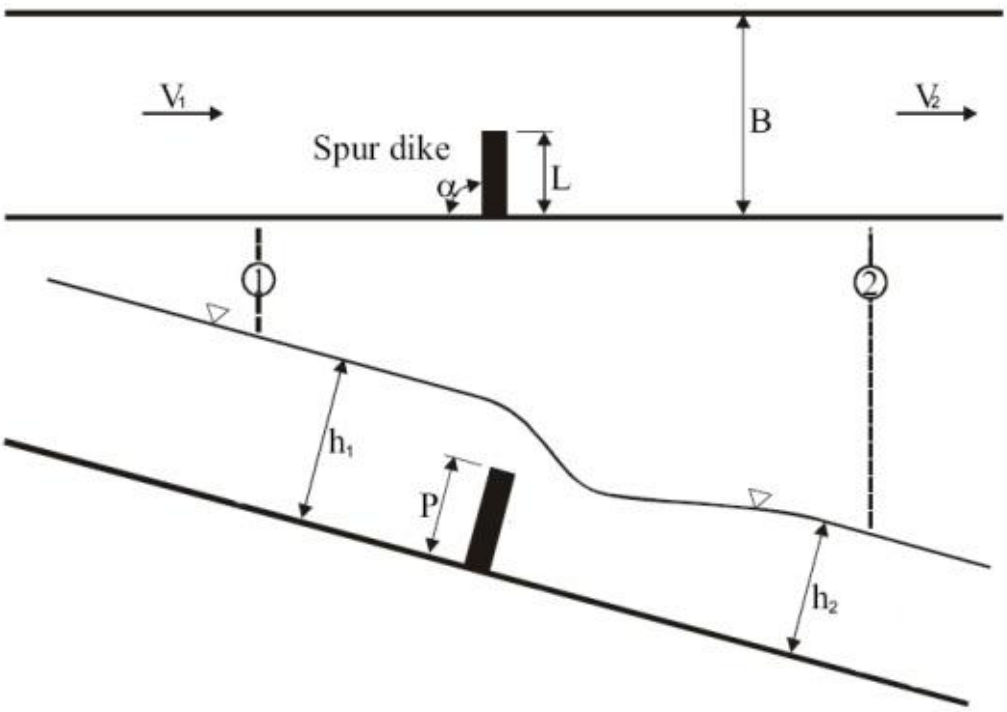


Fig. 2. Schematic (plan and profile) of a spur dike (1)

Here, by taking the advantages of artificial neural network model, we predict the afflux (backwater) caused by a spur dike and then compared the results with the relations presented by other researchers (1-4-5).

Methods

Artificial neural network is a branch of Artificial Intelligence that transmits the regulation behind the data to network structure by processing the experimental data. That is why it is called the intelligent system (6). These networks are made of simple operating elements in parallel that inspired by biologically neural systems. In the nature, structure of neural networks will be determined by the method of connection between components and by adjusting values for each connection as the connection weight, the communication between its components is determined. The network establishes a logical relationship between data by analysis of inputs and their corresponding results which may be nonlinear and uncertain; then, using this logical relationship, simulation is done for the same issues (6). Neurons are the small elements of the data processing. Model calibration is performed by minimizing the mean square error (MSE) and maximizing the correlation coefficient values (8). Distributed processing of data reduces the sensitivity of the network to MSE. Since a large number of neurons are involved simultaneously, the contribution of each neuron is not so important; therefore, existence of an error in one of them or their results does not affect other computational units (9). these networks are made of three types of input, intermediate and output layers that are able to reduce differences between output and real values by adjusting the weights. Each network is composed of inputs, weights, transfer functions, and outputs. Inputs can be either the output of other layers or raw amounts in the first layer. Weights determines the extent of input effect on the output and in multi-neuron networks, summation junction specifies the activity of neuron j in the inner layers. In this research, hyperbolic tangent sigmoid transfer function (Eq. [9]) was used in hidden and output layers. Training algorithm selection was adjusted based on parameters of problem (weights) and the output is answer to the problem.

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{9}$$

Elements of the input vector (P) multiplied by weight vectors (W) plus bias (b) results in *n* net input, which can be formulated as follows:

$$n = \sum_{i=1}^{i=R} P_i W_{1,i} + b = WP + b \tag{10}$$

Net input of *N* provides *a* output after applying to the function *F*. The output is applied as the input to the next layer and this process will continue until the last layer. To assess the accuracy of prediction methods, various criteria have already been proposed. In this study, several methods including mean absolute error, root mean square error and correlation coefficient were used.

Data must be normalized before entering to the network because raw data will reduce accuracy and speed of the network. Likewise, since each parameter has its own division, normalization of data is done to equalize their range to prevent the network weights from too much shrinkage (10). In this study, equation 11 was used to normalize data between -1 and 1:

$$N_i = 2 \times \left(\frac{X_i - X_{min}}{X_{max} - X_{min}} \right) - 1 \tag{11}$$

Where N_i is normalized data, X_i represents the original data, and X_{min} and X_{max} correspond to the minimum and maximum values among the original training data.

The purpose of this study is to simulate and predict the afflux (backwater) caused by a spur dike using artificial neural networks using experimental data of Oak and Azinfar (1-3-5) in order for training and verification of neural network model.

Since the most important cause of afflux due to spur dike is the drag coefficient, the parameters that affecting this coefficient were chosen as the input for neural network model. Given that all of the investigated spur dikes are rectangular and perpendicular to the main flow direction, based on dimensional analysis, dimensionless parameters affecting the drag coefficient by assuming negligible impact of water viscosity are Fr_1, L/B, P/L, and h_1/P. Since the amount of afflux is not clear, h_1 and Fr_1 are not computable explicitly and hence, h_2 and Fr_2 have replaced them as the input for neural network model.

Table 1- Range of parameters used for training and verification of neural network model

Spur dike height, P (mm)	50, 75, 100, 150,200
Spur dike length, L (mm)	100, 150, 200, 250, 320, 400, 480, 800
Channel width, B (mm)	800
Channel slope, So (m/m)	0, 0.000975
Downstream depth, h_2 (mm)	28.0 – 333.0
Downstream Froude number, Fr_2	0.038 – 0.608
Discharge, Q (L/s)	5.1-149.1

In order for homogeneity and sufficiency statistical data, homogeneity and reverse data test were applied. The results showed that the data are statistically homogeneous and the number of data is sufficient for research. Data with the combination of 80 to 20 were used as training and predicting data. Using raw data in modeling did not reveal suitable results. Accordingly, the data using equation [11] have normalized in the range of (1, -1).

Typical architecture of artificial neural networks consisting of three layers: the input layer which distribute data in the network, the hidden layer that processes the data, and the output layer which extract the results for the specified inputs. A network may have several hidden layers but theoretical researches in this field have shown that a hidden layer for this kind of models can approximately obtain any complex and non-linear function (11-12-13). Empirical and scientific results confirm this issue, as well (13-14-15). Based on conducted researches, 90% of artificial neural networks which have been used in water issues are of propagation algorithms (16-17).Therefore, in this study, a laminated Perceptron Neural Network with one hidden layer is used to predict the afflux due to spur dike. Artificial neural network architecture of this research is shown in Figure 3.

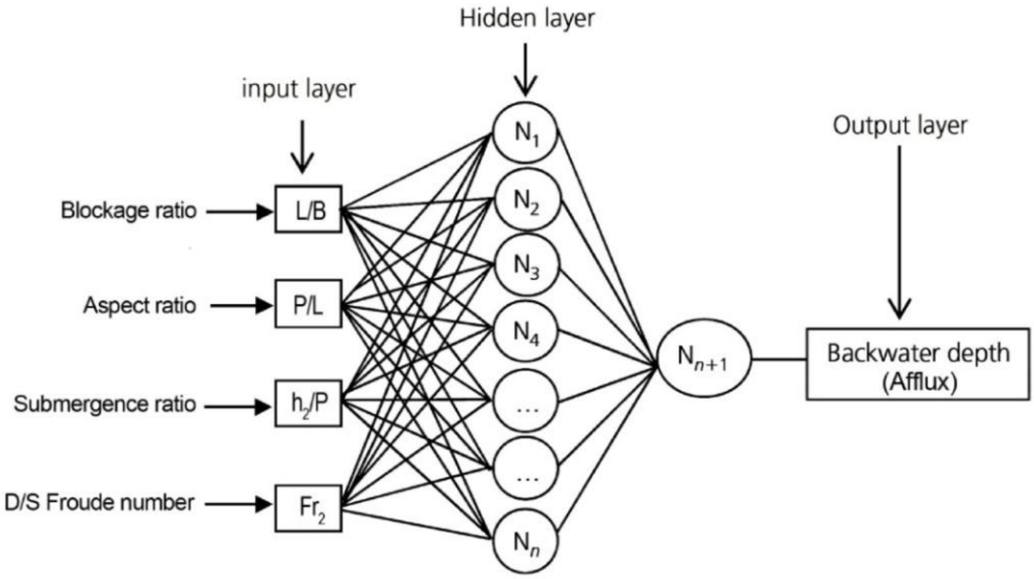


Fig. 3. Artificial neural network architecture of this research

Discussion and Data Analysis

In this study, multilayer perceptron and also back propagation networks were used to simulate and predict afflux caused by spur dike. The efficiency function model in all networks was the mean square error. In order to use artificial neural network MATLAB R2013a software was used. After establishing several models, the following model was selected:

Table 2. Selected neural network model

Training Method	Stimulus Function	Number of neurons	Number of layers	Proportion of data	scale
Tansig	hyperbolic tangent sigmoid	1-5--15 20-30	5	20 to 80	)1 & 1(

Hyperbolic tangent sigmoid stimulus function was applied in hidden layers of perceptron neural network and back propagation network of this function is of sigmoid type. Levenberg–Marquardt training algorithm and slope reduction with momentum were used in perceptron and back propagation networks. Using learning function along with training algorithm increases the accuracy of model in this network. Figure 4 shows results of the prediction of this model in different scenarios.

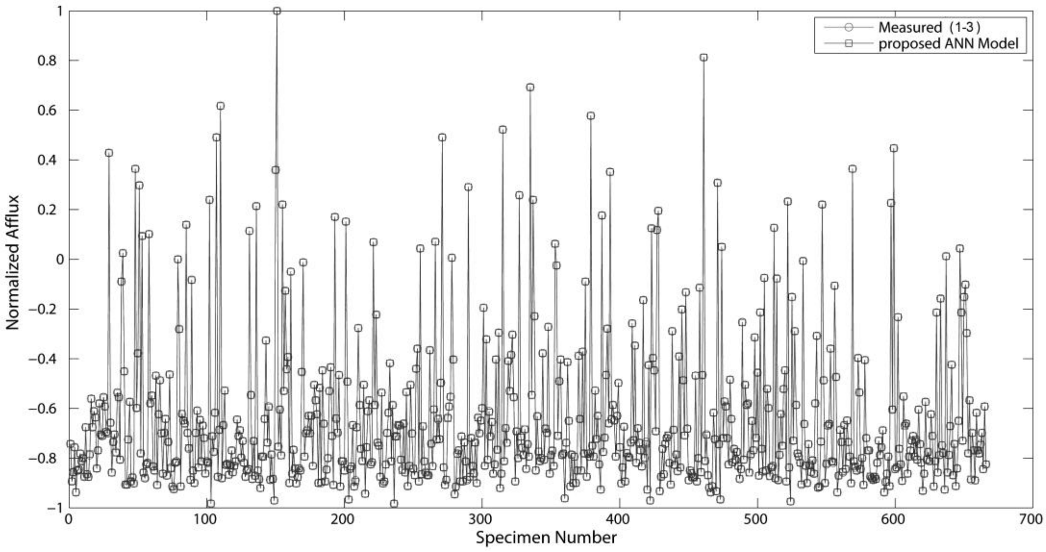
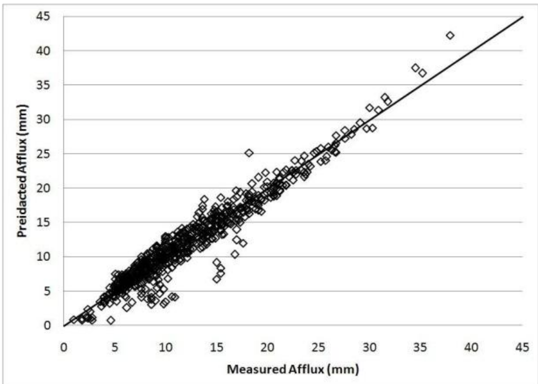


Fig. 4. Comparison of normalized afflux and neural network model

In order for validation of the neural network model, the remaining 80% of data were used and its results were compared to results of experimental data of afflux. Figure 4 shows the normalized results of this comparison.



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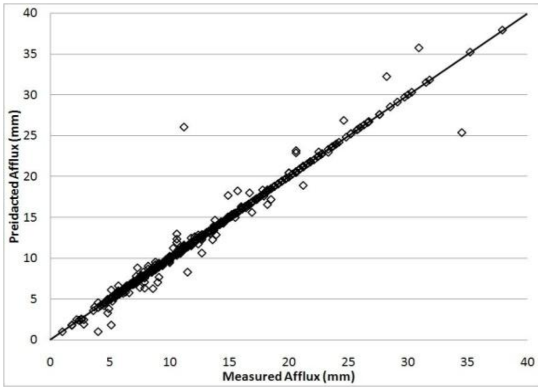

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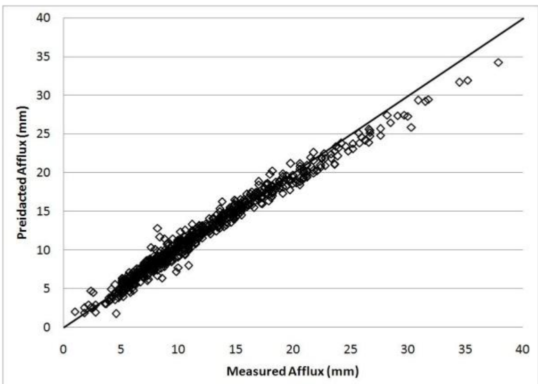

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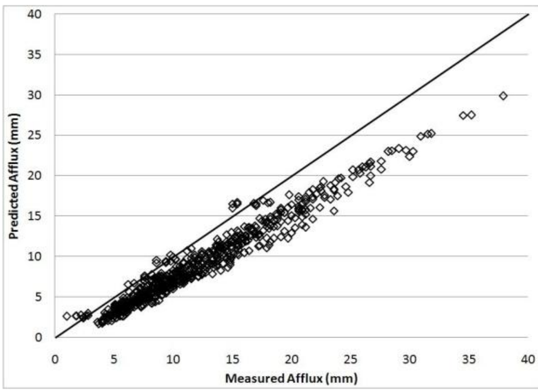

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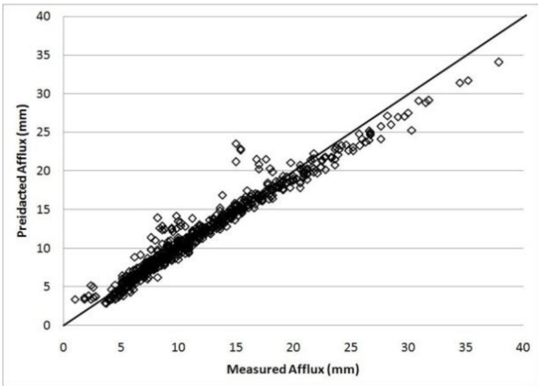

e

Fig. 5. comparison of results of afflux measurement with results of prediction by (A) neural network model, (B) Smith regression model (4), (C) regression model based on Azinfar experimental data (1), (D) regression model based on Oak experimental data (1-5), and (E) multifunctional model based on Oak experimental data (1-5).

Table 3 shows a statistical comparison of the results of artificial neural network models and relationships provided by Azinfar (1-5) and Smith (4). As can be seen in the table, Artificial Neural Network Model with correlation coefficient of 0.989 and mean absolute error of 2.3 provides the best prediction for the afflux.

Table 3. Statistical results of different models of predicting afflux caused by a single spur dike

	Based on Oak and Azinfar experiments (1-3)	Based on Azinfar experiments (1)	Based on Oak experiments (3)		
	ANN model (proposed)	egression Model (1-5)	regression Model (4)	regression Model (1-5)	multiple function model (1-5)
MSE*	0.8	11.9	2.8	1.0	1.8
MAPE**	2.3	27.5	11.6	7.3	9.0
Minimum Absolute percentage Error	0.0004	0.0082	0.0096	0.0020	0.0071
Maximum Absolute Error percentage	132.54	163.13	84.48	105.36	238.28
Correlation Coefficient (r)	0.989	0.976	0.964	0.988	0.977

** Mean Square Error*
*** Mean absolute percentage error*

Figure 4 shows afflux rates obtained from different relationships using laboratory data. Therefore, it is obvious that the closer the data distribution to the 45 degree line, the higher accuracy of model will be. These shapes can clearly show that the distribution of data in the neural network model was much closer than the other models to the 45^o line.

Studies have shown that the regression equations developed by Smith (4) and Azinfar (1-5) in the range of data obtained from it, provided good results but considering the rest of the data, it is less accurate. Neural Network Model, however, is an exception and could be used with more confidence for predicting the afflux.

Conclusion

In this study, artificial neural network was used in order for prediction of afflux caused by a single spur dike using affecting parameters including the blockage ratio of the spur dike (L/B), the aspect ratio of the submerged spur dike (P/L), the spur dike submergence ratio (h_2/P) and Froude number of the downstream flow (Fr_2). Comparisons between optimum model of neural network and the regression and multi-functional models presented by other researchers show that the neural network model presents more accurate prediction for afflux caused by a single spur dike. In this regard, the accuracy of neural network model is 4 times better than the best regression model. Also, the relationship proposed by Azinfar (1-5) could not be clearly solved and requires the process of trial and error, but a proper model of neural networks has solved this problem and afflux rates is explicitly determinable.

Analytical prediction of afflux due to a single spur dike is a difficult issue; however, a well-trained neural network model can effectively predict this behavior with high accuracy. Therefore, it is suggested to use artificial neural network model instead of usual statistical methods to provide a model for predicting of afflux.

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