PREDICTION OF THE CHARACTERISTCS OF FREE RADIAL HYDRAULIC B-JUMPS FORMED AT SUDDEN DROP USING ANNS

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ABSTRACT

Pure theoretical models seeking for the length of jump is extremely difficult (if not impossible). For this reason, empirical prediction equations are normally developed using statistical multiple line regression (MLR). These models may be satisfactory enough for few numbers of variables but may predict unrealistic values when many variables are involved. Fortunately, the recently developed computational tool, the artificial neural networks, can be used to develop computational models to predict the length of jump more accurately than MLR can do. In this research paper, the ANN was used to develop a prediction model to predict the length of free hydraulic B-jumps formed at sudden drop in radial stilling basins provided with end sills. The data needed for modeling were collected from large series of experiments conducted in a laboratory flume under wide variety of test conditions. Results from both MLR and ANN for the length of jump were compared with the experimental data. Also, the available MLR and theoretical models for the depth ratio and the energy loss ratio were compared to similar ANN model developed for the same ratios. It is concluded that the ANN is more efficient than other prediction models in most of the cases.

Keywords: Hydraulic jumps, Radial stilling basins, Prediction models, Artificial neural networks (ANN), Multiple linear regression.

1. INTRODUCTION

The hydraulic jump is a well known hydraulic phenomenon for the hydraulic engineers and it could be used in many situations, Chow [1]. Basic information on different types of hydraulic jumps could be found in Hager [2]. Review of the previous works indicated that extensive investigation were made to cover the different aspects of free and submerged hydraulic jumps in rectangular channels. However, only few studies were dealt with the hydraulic jumps in non-prismatic channels as diverging channels with a bottom drop, Negm et al. [3,4,5] or when a sill is existed at the end of divergence as the case of diverging stilling basins, Habib et al. [6] or when both a bottom drop and end sill is existed, Abdel-Aal et al. [7]. Negm et al. [3] provided the following theoretical verified equation for predicting the depth ratio of B-jump formed at a sudden drop in radial stilling basin:

$$d_o^3(2r_o^2+r_o r)-d_o^2[(d+Z)(r_o^2-r_o r)]-d_o r_o[2+Z^2(2r+r_o)+ Z(4rd+2r_o d)+d^2(r_o-1)+d(r-1)+r]-6F_1^2(d_o r_o-1)=0.0, \tag{1}$$

in which $d_o=d_2/d_1$ is the relative depth of jump, $d=d_3/d_1$ is the depth at the end of the step, $r_o=r_2/r_1$ is the radii ratio of the jump, $r=r_3/r_1$ is the radial distance to the end of the step, $Z=z/d_1$ is the relative height of the step, and F_1 is the initial Froude number.

Negm et al. [4] provided the following statistical prediction models for depth ratio d_2/d_1, length of jump ratio L_j/d_1 and energy loss ratio E_L/E_1 of the B-jump formed at sudden drop in radial stilling basins.

$$d_2/d_1= -3.231+1.115\ F_1+2.529\ r+1.143\ z/ \tag{2}$$

$$L_j/d_1 = -0.135+5.525\ F_1-4.407\ r+3.274\ z/d_1 \tag{3}$$

$$E_L/E_1= -0.818-0.175\ F_1+1.122\ F_1^{0.5} -0.195\ r-0.037\ z/d_1 \tag{4}$$

While the following statistical equations were provided for predicting the characteristics of B-jump formed at sudden drop in the radial basin provided with end sill, Habib [9]:

$$d_2/d_1= -5.713+1.068\ F_1+4.909\ r+1.331\ z/d_1-0.027s/d_1 \tag{5}$$

$$L_j/d_1 = 17.435+5.405F_1-18.703r+2.289z/d_1 -0.812z/d_1 \tag{6}$$

$$E_L/E_1= -5.320-0.140\ F_1+1.001\ F_1^{0.5} -0.356\ r-0.056\ z/d_1 -0.002s/d_1 \tag{7}$$

Moreover, Abdel-Aal et al. [8] provided the following theoretical model for $d_o=d_2/d_1$ of B-jump formed at sudden drop in the radial basin provided with end sill:

$$d_o^2 r_s (d_s+S)(r-r_s)-d_o r_s (d_s+S)\left[(d+Z)(r_o-r)+(d_s+S)(r_s-r_o)\right]+r_s (d_s+S). \left[\begin{matrix}3r_s d_s^2-3-3rZ(2d+Z)+3r_s (Sd_{s*}+Sd_s+S^2)-(1+d+d^2).\\(r-1)-(d+Z)^2 (r_o-r)-(d_s+S)^2 (r_s-r_o)\end{matrix}\right]-6F_1^2 [r_s (d_s+S)-1]=0.0 \tag{8}$$

in which d_s and d_{s*} are relative depths related to the end sill and r_s is the radial distance to the end of sill.

In this research paper, relatively more accurate prediction models using the artificial neural networks were developed to predict the basic characteristics of the B-jump formed at sudden drop in radial stilling basin provided with end sill. The results of the ANN were compared with the previously statistical and theoretical models of the same jump type.

2. INTRODUCING THE ARTIFICIAL NEURAL NETWORKS

2.1. BACKGROUND

Artificial neural networks (ANNs) are massively parallel-distributed information processing system that has certain performance and characteristics resembling biological neural networks of the human, Schalkoff [9]. The human brain is made up of many neurons, each of which is connected to many others in a network, that adapt and change as the brain learns. In neural computing, processing elements or nodes replace the neurons and this nodes are linked together to form neural networks. Each node performs a simple task. It is the connection between the nodes that give neural network the ability to learn patterns and interrelationships in data. By producing systems that learn the relationships between data and results, neural networks avoid many of the problems of conventional computing. Given new unseen data, a neural network can make a decision or prediction based upon its experience as a human.

Signals are passed between nodes through connection links; each connection link has an associated weight that represents its connection strength. Each node applies a nonlinear transformation called an activation function to its input to determine its output signal. ANNs can be classified according to the direction of information flow and processing. In a feed-forward network that is used in this research, the nodes are generally arranged in layers starting from the first input layer, and ending at the final output layer. There may be one or more hidden layers, each hidden layer having one or more nodes. The number of hidden layers and their nodes are usually determined by trail and error.

Information passes from the input to the output side. The nodes in one layer are connected to those in the next, but not to those in the same layer. Thus the output of a node in a layer is only dependent on the input it receives from previous layers and its associated weights. A typical feedforward artificial neural network of three layers is presented in Figure 1. The first layer is consisted of n neurons, the second is consisted of j neurons and the third is consisted of p neurons.

2.2. MATHEMATICAL ASPECTS

The inputs to a jth node (Figure 2) coming from other nodes form an input vector $X=(x_1,\ldots.., x_n)$. The sequence of weights leading to the node form a weight vector W_t $=(w_{1j},\ldots\ldots\ldots, w_{nj})$,where w_{nj} represents the connection weight from the nth node in the preceding layer to this node. The output of node j, considered as Y_j, is obtained by computing the value of activation function (tansh function in this case) with respect to the inner product of vector X, and W_t minus b_j, where b_j is the bais, associated with this node, ASCE Task Committee [10], as follow:

$$Y_i = \frac{e^{(X.W_t - b_j)} - e^{-(X.W_t - b_j)}}{e^{(X.W_t - b_j)} + e^{-(X.W_t - b_j)}} \tag{9}$$

This type of function is normally chosen because the learning algorithm requires smooth nonlinear functions with a continuous, single-value first derivative. Its functional form determines the response of a node to the total input signal it receives.

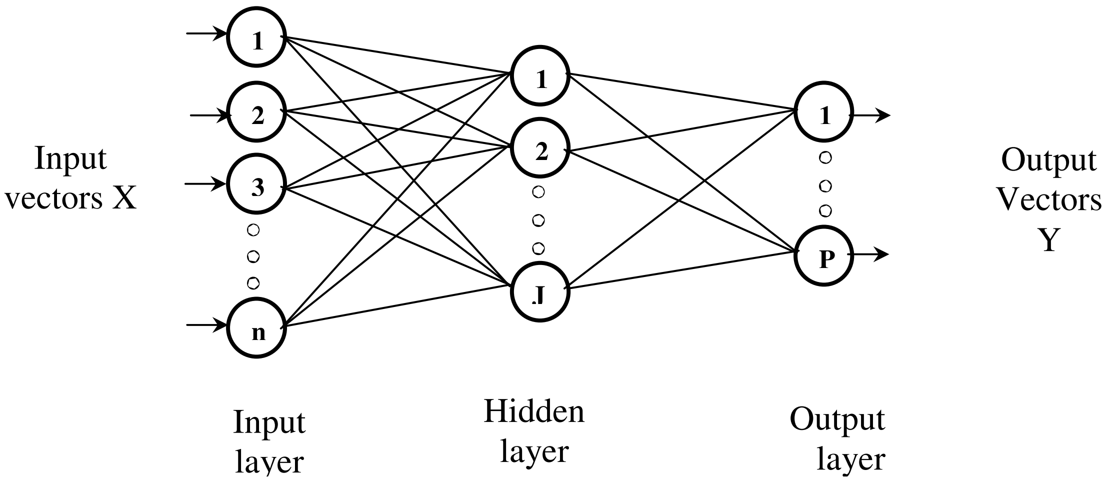

Figure 1. General Configuration of feedforward ANN of three layers n-j-p

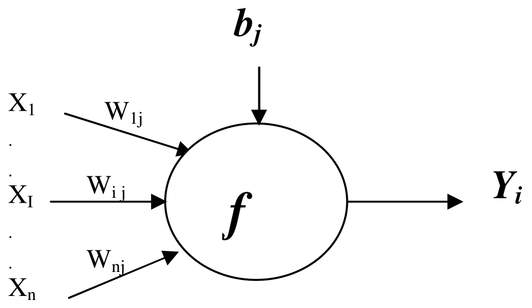

Figure 2. A schematic diagram of a typical *j*th node showing inputs and output of the node (f stands for the activation function)

2.3. TRAINING OF THE NETWORK IN GENERL

In order for an ANN to generate an output vector $Y=(y_1,\ldots, y_i,\ldots, y_n)$. that is as close as possible to the target vector $T = (t_1,t_2,\ldots\ t_p)$, a training process, also called learning, is employed to find optimal weight matrices W and bias vectors V, that minimize a predetermined error function that usually has the form, ASCE Task Committee [10].

$$E = \sum_{P} \sum_{p} (y_i - t_i)^2 \qquad (10)$$

in which t_i is a component of the desired output T; y = corresponding ANN output; p = number of output nodes; and P = number of training patterns. Training is a process by which the connection weights of an ANN are adapted through a continuous process of stimulation by the environment in which the network is embedded. This typically implies that a large number of examples (or patterns) of inputs and outputs are required for training. The inputs are cause variables of a system and the outputs are the effect variables. This training procedure involves the iterative adjustment and optimization of connection weights and threshold values for each of nodes. The primary goal of training is to minimize the error function by searching for a set of connection strengths and threshold values that cause the ANN to produce outputs that are equal or close to targets. After training has been accomplished, it is hoped the ANN is then capable of generating reasonable results given new inputs.

3. COLLECTION AND PREPARATION OF TRAINING DATA

The experimental work of this study was conducted using a re-circulating adjustable flume of 15.0 m long, 45 cm deep and 30 cm wide. The experimental setup and test procedure were explained in Negm et al. [3] and Abdel-Aal et al. [7] in the same conference proceedings. The range of the experimental data were as follows: Froude numbers (2.0-7.0), r_o (1.2-1.4), relative position of the drop, r (1-1.133), relative height of the drop, z/d_1 (0.6 – 1.9), and relative height of end sill, s/d_1 (0.0-3.4). A total number of observations is 217.

3.1 NORMALIZATION OF DATA

Normalization of input data is needed because it makes each input contributes equally in the prediction made by the network. Without normalization the large numbers input data will be more significant than the small numbers data. A method of normalization is to determine the mean and the standard deviation (S.D.) for each field. Each field is then normalized where the mean value of the field becomes (0.0), and the values of standard deviation are mapped onto (+/- 1). This method is known as zero mean unit standard deviation normalization, Neural Connection [11]. Table 1 presents the normalization factors of the variables associated with the present application

Table 1. Normalization factors for the present application

Factor	F_1	r	$S=s/d_1$	$Z=z/d_1$	d_2/d_1	L_j/d_1	E_L/E_1
Mean	4.596	1.106	1.232	1.143	6.039	23.365	0.500
S.D.	1.078	0.104	1.067	0.443	1.708	6.898	0.089

3.2. ALLOCATION OF INPUT DATA

The input data that is used in development of an ANN model are classified into three sets as follow:

Training data: it represents the major percentage of the total data, in which the neural techniques are trained to map the inputs with their outputs. This set of data represents 70% of the total data (151 observations).

Validation data: which is used to monitor the neural network performance during training process and represents 15% of the total data (33 observations)

Test data: which is used to measure the performance of a trained ANN model and represents 15% of the total data (33 observations).

4. APPLICATIONS OF ANNS

Artificial neural networks were applied in many branches of engineering sciences. In Hydraulic Engineering, they were applied by Grubert [13] in studying the stability analysis of stratified flow, by Dibike and Abbott to simulate 2-D flow et al. [13], by Negm [14] to predict the different parameters needed for the hydraulic design of sudden expanding stilling basin when a forced hydraulic jump is formed in the basin. The length of the hydraulic jump formed over artificially roughened beds was predicted effectively and better other models, Negm [15]. Recently, Negm et al. [16] developed an ANN model to predict suspended sediment transport in river flow. In the field of scour downstream stilling basins, Negm et al. [17] developed an ANN to predict the maximum scour depth downstream sudden expanding stilling basins with and without a central sill of limited width. A brief review of the related applications in the field of Water Resources Engineering could be found in Negm [14] and in Habib [8].

5. BUILDING THE NETWORK

All the developed network models in this research paper have single output either d_2/d_1, or L_j/d_1, or E_L/E_1 because a single output model produces more satisfactory results than a network with a multi-output using the same inputs. The following steps were followed to develop each ANN network model (refer to Figure 3).

1- The data were prepared in a suitable format; the general topology of the network was specified using the special tools of the Neural Connection Software [11]. The data was then allocated using the input tool.
2- The multi-layer perceptron (MLP) tool was used to specify the following parameters (a) the normalization method of the input field (zero mean unit standard deviation); (b) the activation function obtained (by trails); (c) the normalization method of the target fields (zero mean unit standard deviation); (d) the range of the initial weights (by trials); (e) the learning algorithm (the conjugate gradient), and (f) the maximum number of iterations (by trials).
3- The network was allowed to train and the validation system error is observed to stop training at the minimum validation error. The output tool was used to save the output results for training, validation, and test sets in three files, which in turn were transferred to another software to enable the computations of performance criteria such as the correlation coefficient (R) between the target and the output of the developed ANN model, and the mean absolute relative error (MRE).
4- An iterative procedure was used to obtain the best range of the weights, the best activation function, the best number of neurons of the hidden layer, and the best number of iterations.
5- The output of step 4 was combined together in a single network which was trained with fine adjustment to obtain the best network.
6- The best network was allowed to train several times with different starting point to obtain the network that could provide a global solution. The results from that network were compared.

The flowchart presented in Figure 3 summarized the basic steps needed to build a network model for the present application using the Neural Connection Software [10].

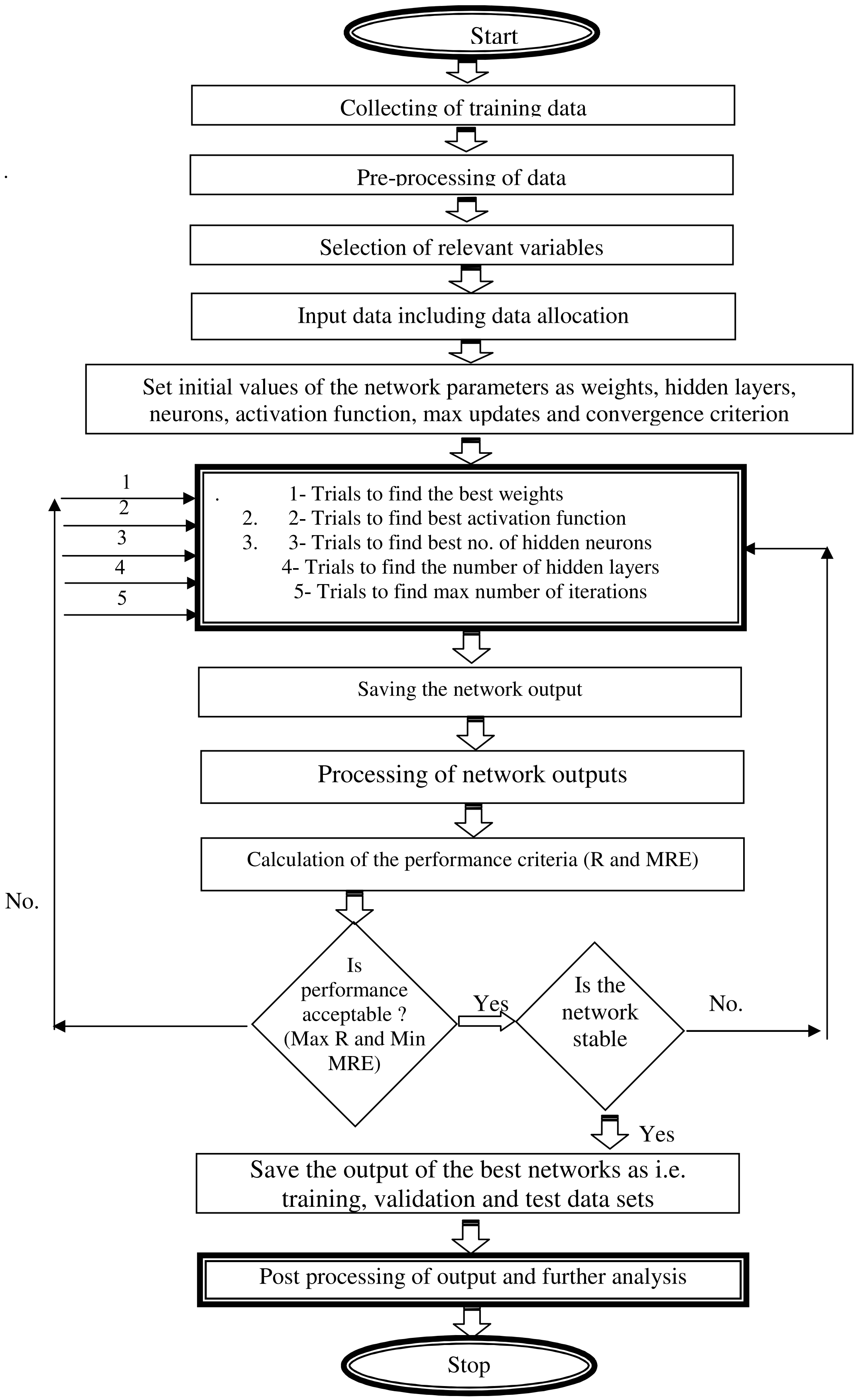

Figure 3. Flowchart showing the basic steps of building a neural network model for the present application

6. RESULTS OF THE DEVELOPED ANNs MODELS

Based on the above explained network building procedure, the results indicated in Table 2 were obtained.

Table 2. Basic features of the developed ANN models

n-j-p.	Output	Training		Validation		Test		Average	
		R^2	MRE	R^2	MRE	R^2	MRE	R^2	MRE
4-3-1	d_2/d_1	0.992	0.011	0.99	0.023	0.99	0.019	0.992	0.021
4-3-1	L_j/d_1	0.974	0.041	0.948	0.048	0.959	0.052	0.969	0.044
4-3-1	E_L/E_1	0.984	0.019	0.980	0.019	0.986	0.019	0.984	0.019

The results of each network were compared to the measured data in four figures, one for training results, the second one for validation, the third figure for test and the fourth one for the variation of the residuals with the predicted values of the ANN model. Typical figures for the relative length of jump, L_j/d_1 are shown in Figure 4a, 4b, 4c and 4d. Figures 4a to 4c indicate good agreement while Figure 4d show reasonable distribution of uncorrelated residuals proving the validity of the prediction model.

7. COMPARISON WITH OTHER DEVELOPED MODELS

The results of previously developed theoretical and multiple linear regression (MLR) models [3,4,6,7] and those of those of present developed ANN models were compared with the experimental results. The results of different models are presented in Table 3. Based on R^2 and MRE, it is clear that ANN models show the best results in most of the cases.

Table 3. Overall comparison between results of ANN, MLR, theoretical models and all measured data

Target	ANN		MLR		Theo.	
	R^2	MRE	R^2	MRE	R^2	MRE
d_2/d_1	0.992	0.021	0.960	0.021	0.951	0.048
L_j/d_1	0.969	0.044	0.922	0.049	-	-
E_L/E_1	0.984	0.019	0.952	0.021	0.924	0.035

The results of the ANN models were compared to those of MLR results and theoretical for typical experimental data sets as shown in Figures 5a and 5b for d_2/d_1, in Figures 6a and 6b for L_j/d_1 and in Figures 7a and 7b for E_L/E_1. Figures 5a, 6a and 7a are for negative B-jump in radial basin without end sill (r=1, z/d_1=1.15 and s/d_1=0.0) while Figure 5b, 6b and 7b are for the same but when an end sill was existed in the basin (r=1, z/d_1=1.15 and s/d_1=1.35). These figures show the relationships between each of relative depth, relative length, and relative energy loss of the jump and the initial Froude number for different prediction models. The figures showed that the results of the ANN models are almost better than those of the statistical and theoretical models (MLR) compared with the experimental measurements.

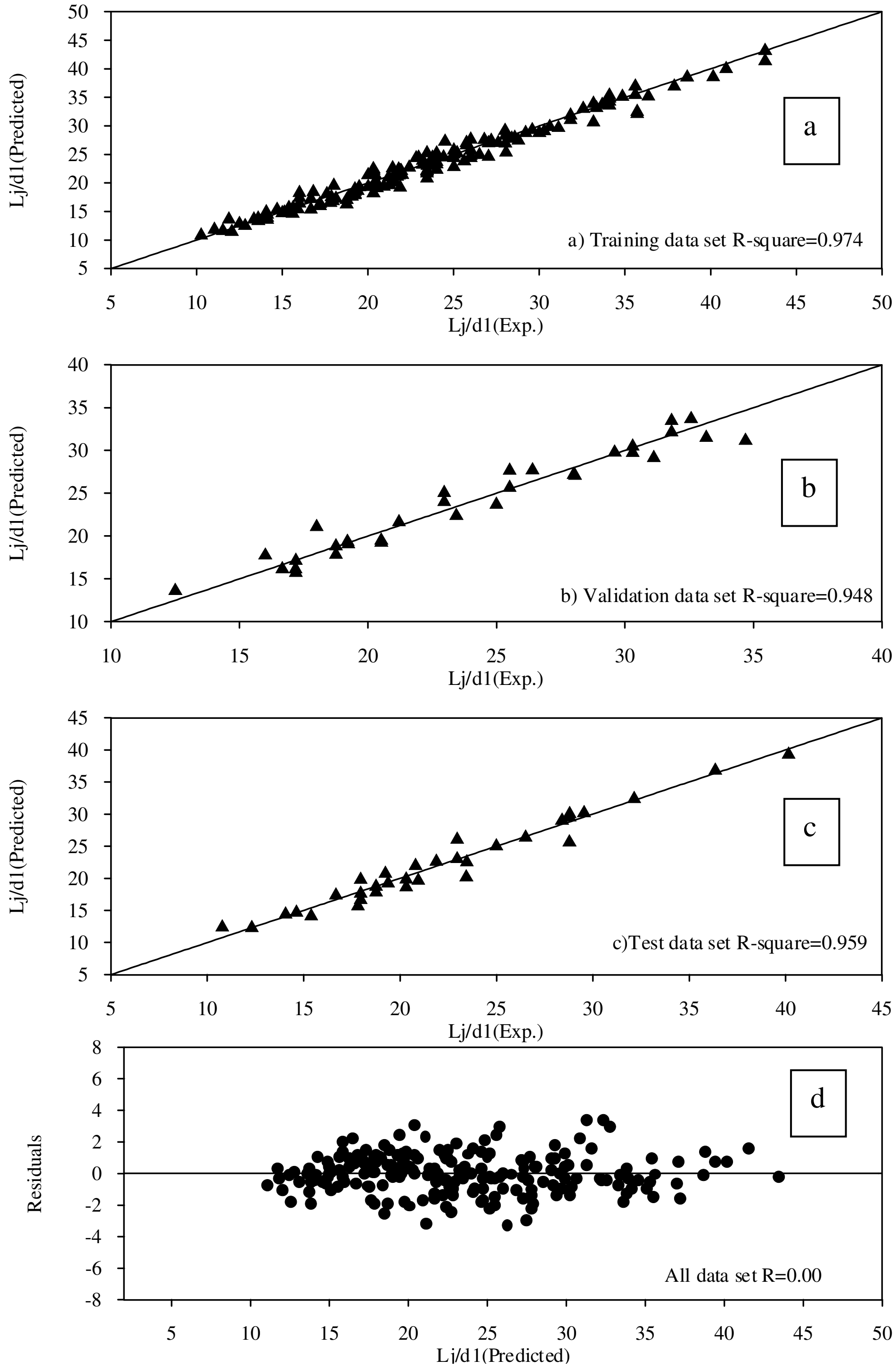

Figure 4. Typical results of one ANN model for the L_j/d_1 showing ANN predictions versus measurements for (a) training data, (b) validation data (c) test data and (d) variations of the residuals with the predicted values

Table 4 summarizes the results of comparison in terms of R^2 and MRE for each model compared to the experimental data. Well inspection of values in Table 4 confirmed the above discussions.

Table 4. Comparison between ANN, MLR, and theoretical models, with the experimental data for typical data sets

Target	s/d_1	z/d_1	r	Exp. & ANN		Exp. & MLR		Exp. & Theo.	
				R^2	MRE	R^2	MRE	R^2	MRE
d_2/d_1	0.0	1.15	1.00	0.979	0.018	0.965	0.022	0.989	0.060
d_2/d_1	1.35	1.15	1.00	0.979	0.024	0.986	0.020	0.946	0.034
L_j/d_1	0.0	1.15	1.00	0.995	0.012	0.995	0.025	-	-
Lj/d_1	1.35	1.15	1.00	0.953	0.050	0.941	0.070	-	-
E_L/E_1	0.0	1.15	1.00	0.966	0.017	0.968	0.018	0.991	0.047
E_L/E_1	1.35	1.15	1.00	0.967	0.020	0.980	0.025	0.899	0.023

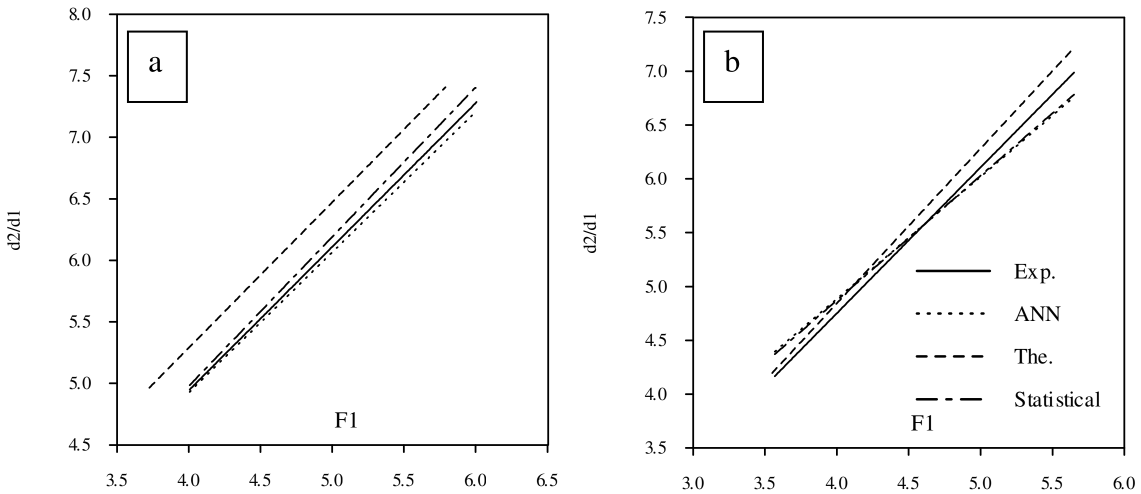

Figure 5. Comparisons of results of different prediction models of d_2/d_1 for typical data sets, (a) r=1.0, z/d_1=1.15 & s/d_1=0.0 and (b) r=1.0, z/d_1=1.15 & s/d_1=1.35.

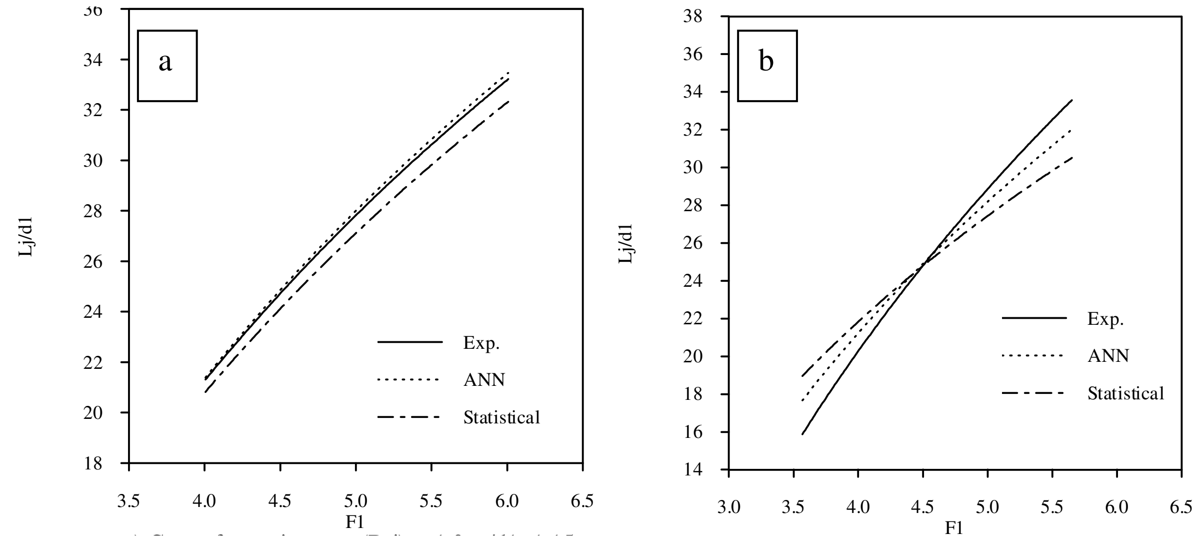

Figure 6. Comparisons of results of different prediction models of L_j/d_1 for typical data sets, (a) r=1.0, z/d_1=1.15 & s/d_1=0.0 and (b) r=1.0, z/d_1=1.15 & s/d_1=1.35.

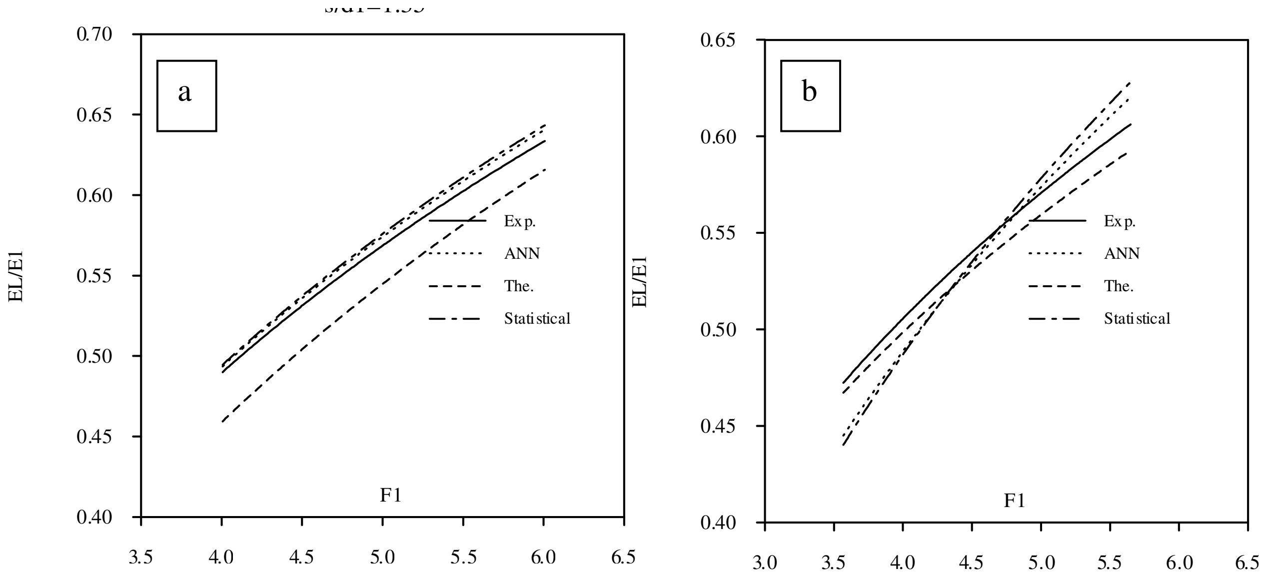

Figure 7. Comparisons of results of different prediction models of E_L/E_1 for typical data sets, (a) r=1.0, z/d_1=1.15 & s/d_1=0.0 and (b) r=1.0, z/d_1=1.15 & s/d_1=1.35.

8. CONCLUSIONS

Accurate prediction models using ANNs were developed to predict the basic characteristics of the free hydraulic B-jump formed at sudden drop in radial stilling basin provided with end sill. The basic inputs to the network were the initial Froude number, the relative position of the drop, the relative height of the drop and relative height of end sill. The network output was the relative depth, the relative length or the relative energy loss of the jump. The predictions of the developed ANN models were compared with those of the previously developed prediction statistical and theoretical models. It was concluded that well designed and well trained ANN model provided better predictions than other models in most of the cases.

NOTATIONS

d_1 = water depth at vena contracta downstream the gate;
d_2 = sequent water depth;
d_4 = water depth over end sill;
d_5 = water depth just downstream the end sill over end sill;
d_6 = water depth just upstream the end sill over end sill;
d_o = the relative water depth, d_2/d_1;
d_3 = depth of water above the step;
d = the ratio of d_3 to d_1;
d_s = the ratio of $d_4$to d_1;
d_{s*} =the ratio of d_6 to d_1;
F_1 = Froude's number at the initial depth;
L_j = the length of the hydraulic jump;
L_b= the length of the stilling basin;
r_1 = radius at the beginning of the jump;
r_2 = radius at the end of the jump;
r_o = the ratio of r_2 to r_1;
r_3 = radius at the end of the step;
r_4 = radius at the end sill;
r = the ratio of r_3 to r_1;
R^2= the coefficient of determination;
s = the sill height;
S= the ratio of s to d_1;
z = the drop height;
Z= the ratio of z to d_1;

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