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Artificial Neural Network (ANN) Model for End Depth Computations

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Abstract

In this paper a feed-forward back-propagation type of neural network as well as the multi nonlinear regression model using statistical programming were used to determine the critical depth and discharge passing over the end-depth model, free overfall. This was achieved by training and validating (215) experimental data. The results of the trained verified and tested for neural network model are compared to the experimental measurements. There were well agreements with the measured values.

Keywords: Artificial neural network; Free overfall; Nonlinear regression

Notations

B: Bed width; C1, C2: Constants; Cd: Discharge coefficient; Fr: Froude number; G: Acceleration due to gravity; K: Channel bed roughness; Q: Discharge per unit depth; Re: Reynolds number; So: Channel bed slope; yb: Brink depth; yc: Critical depth; yn: Uniform flow depth; μ: Viscosity of water; ρ: Density of water

Abbreviations

ANN: Artificial neural network; ARE: Absolute relative error; FFBP: Feed forward back propagation; MSE: Mean square error; NLR: Nonlinear regression; R^2: Determination coefficient; SPSS: Statistical package for the social sciences

Introduction

A free overfall which means end depth drop refers to the downstream portion of a rectangular channel horizontal or sloping terminating abruptly at its lower end. If it is not submerged in the tail water, it is referred to as the free overfall [1].

In Figure 1 for rectangular channel of bed width is (b), y_b=brink depth (end depth); Q=discharge; y_n=uniform flow depth; y_c= critical depth; k=channel bed roughness and S_o=channel bed slope. If the slope of the upstream channel is steep the flow will be super critical and determined by the upstream conditions, while if the channel slope is mild, horizontal or adversely, the flow will be critical [2].

Because of this, it can be used as a measuring device, author's deal with studying free overfall experimentally and theoretically. Rajaratnam et al. [1] and Davis et al. [3] investigated the effect of slopes and roughness on the brink depth. They found that the influence of roughness is negligible, but the ratio of brink depth to critical depth was affected by the ratio of bed slope to critical slope. Where analytical solutions for circular overfall based on the momentum equation and the simulation of a free overfall with a sharp-crested weir were given by Dey [4] considering the streamline inclination and curvature. The solutions of momentum and extended energy equations were put forward by Hager [5]. Another analytical approach, termed conidial wave theory, was reported by Marchi [6] to solve the two-dimensional free overfall. Anastasiadou-Partheniou and Hatzigiannakis [7] and Ferro [8] simulated the free overfall with a sharp-crested weir. The effect of bottom roughness on rectangular overfalls was studied by Dey [9].

Literature Review

Dey [10,11] studied free overfalls in circular channels with flat base, inverted semicircular channels, respectively. Ahmed et al. [12] studied two models of free overfall, straight vertical and skewed end lip, and found the relationship between brink and critical depth, discharge equation for two models, and showed that the discharge for the skewed lip model was greater 13% than straight vertical. Ahmed Y.M. [13] presented an experimental study and analysis for effect of channel slope on straight vertical and skew free overfall for a rectangular channel with different slopes and find the discharge over skewed model is greater by (21%) from straight vertical. Ahmed Y.M. [14] studied the behavior of free surface flow on a rectangular free overfall which has a triangular shape, the results prevail, that the ratio of brink depth to critical depth at center line for falls inclined with flow direction was greater by (3%) than that falls in the opposite direction, this value increased to (27%) when Froud number increased. Most of the ANNs applications were related to the fields of water engineering and were presented in Negm et al. [15] and Nakhaei [16] for estimating the saturated hydraulic conductivity of granular material.

The main goal of this study is to make an artificial neural network ANN model for flow over free overfall using feed-forward back-propagation (FFBP), as well as nonlinear regression model NLR model and compared the experimental data with these two models. The experimental data presented by Mowafaq et al. [17], Mowafaq et al. [18] and Ahmed Y.M. [19], was used to train and validate the ANN and compared with the results of regression equations that were developed to estimate the critical depth and discharge.

Artificial Neural Networks (ANN)

Artificial neural networks ANNs are classified based on the number of layers: single layer, multilayer, and based on the direction of information flow and processing feed forward. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. Of the many ANN paradigms, the multi-layer back propagation network (MLP) is by far the most popular [20,21]. Mathematically, an ANN is often used as a universal approximate. The ability of identifying a relationship from giving patterns makes it possible for ANNs to solve large-scale complex problems such as pattern recognition, nonlinear modeling, classification, association and control [22]. A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function [23].

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Neural network structure

In the FFBP used in training, the input variables determine the number of input nodes in the input layer, the number of nodes in the middle called hidden layer, the output layer is processed and sent to an external source. The number of hidden layer nodes in the hidden layer is determined by trial and error procedure until the error is minimized. The number of neurons in the hidden layer influences the performance of a network, so, too few and too many nodes in the hidden layer lead the network to poor performance thus to avoid failing of convergence, it is recommended that the total number of hidden layer nodes is at least three times of the total number of input layer nodes [24].

The parameters considered in this study are; b, S_o, y_b, y_n, k, y_c and Q. The parameters; b, So, y_b, y_n and k was used as inputs to the ANN for the estimation of y_C and Q respectively, depend on 215 experimental data, in this study, 15% of data series was selected for cross validation (30 data), 15% data series was selected for testing (30 data) and 70% data series was selected for training (155 data) (Figure 2). The model results were evaluated using the absolute relative error (ARE) and determination coefficient (R^2) statistics.

In the Figure 2 the size of the network is 5 nodes in the input layer representing the input to the network (b, S_o, y_b, y_n and k); 15 nodes in the hidden layers and 2 nodes in the output layers (y_c and Q).

For this network architecture, Figure 3 shows the results variation of mean squared error (MSE) for training, validation and tested considering the critical depth and discharge. The figure gives the best validation performance ($1.89e^{-006}$).

ANN and NLR analysis

For a rectangular free overfall the following variables are affecting of the brink depth: yb= Brink Depth (L); q= Discharge per Unit Depth (L^2/T); yn= Uniform Flow Depth (L); b=Channel Width (L); So= Channel Bed Slope (-); g= The acceleration due to gravity (L/T^2); μ= Viscosity of water (M/LT); ρ= Density of water (M/L^3); k= depth Roughness (L), the dimensional equation parameter can be written as:

$$Yb = f(q, yn, b, So, g, \mu, \rho, k) \tag{1}$$

Using dimensional analysis, the functional relationship can be obtained:

$$\frac{y_b}{y_c} = f\left(R_e, F_r, \frac{y_n}{b}, S_o, \frac{k}{b}\right) \tag{2}$$

Where;

R_e (Reynolds number) = $\frac{q\rho}{\mu}$, and F_r (Froude number) = $\frac{q}{y_n\sqrt{gy_n}}$

From experimental data shown in Table 1, the (NLR) statistical analysis was used to estimate a relationship for brink to critical depth calculation, this will be achieved by using Statistical Package for the Social Sciences (SPSS, V.17) programming and the following equations detected after neglecting parameters Re because its little affecting in open channel and $\frac{b}{y_n}$ in wide open channels:

$$\frac{y_b}{y_c} = C_1 + C_2\sqrt{\frac{kS_o}{b}} \tag{3}$$

Where; C1 and C2 are constants.

For rectangular flume the critical depth can be calculated using:

$$y_c = \frac{q^{2/3}}{g^{1/3}} \tag{4}$$

Eq. 3 can be rewritten by replacing y_c in Eq. 3 with Eq. 4 such that:

$$q = \frac{y_b^{3/2} g^{1/2}}{\left(C_1 + C_2\sqrt{\frac{kS_o}{b}}\right)^{3/2}} \tag{5}$$

From experimental data shown in Table 1, the (NLR) statistical

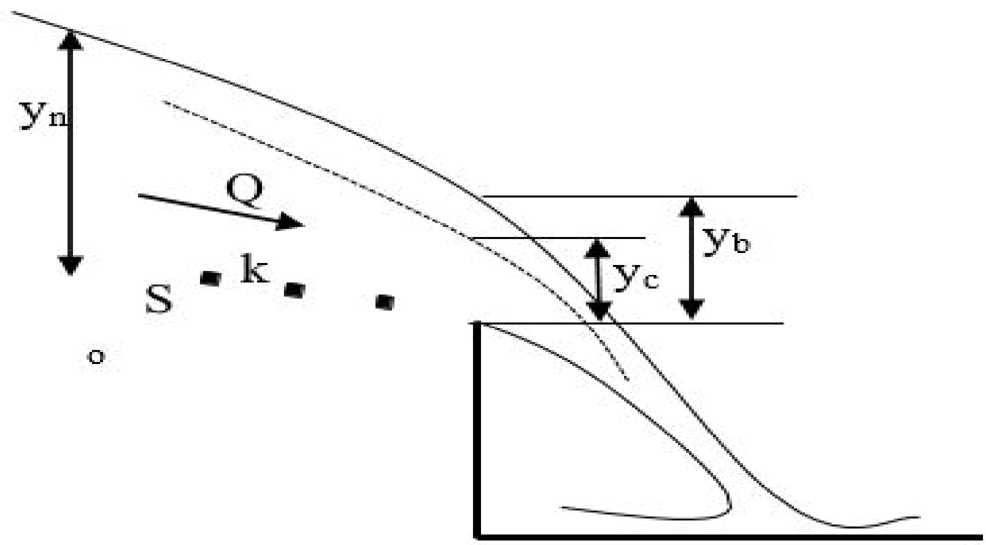

Figure 1: Definition sketch of free overfall.

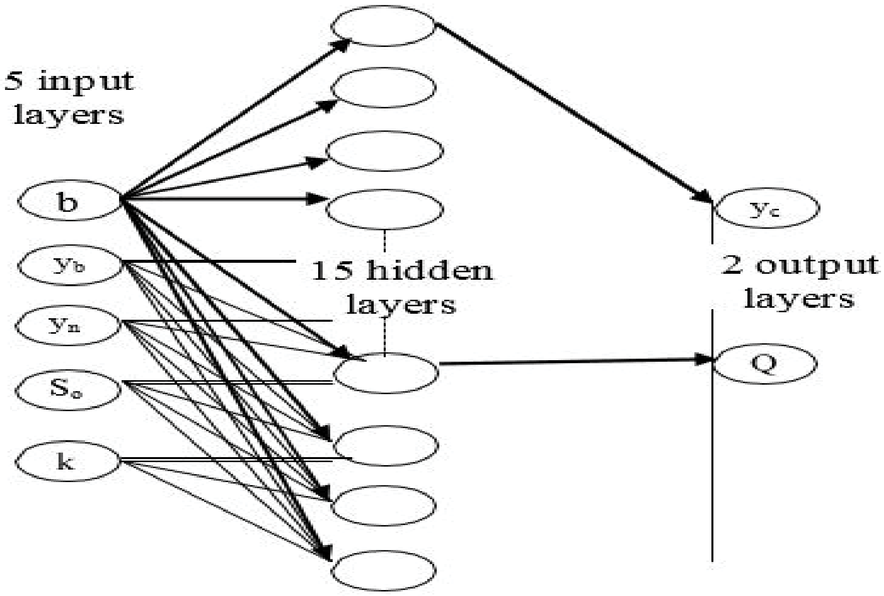

Figure 2: The neural network architecture.

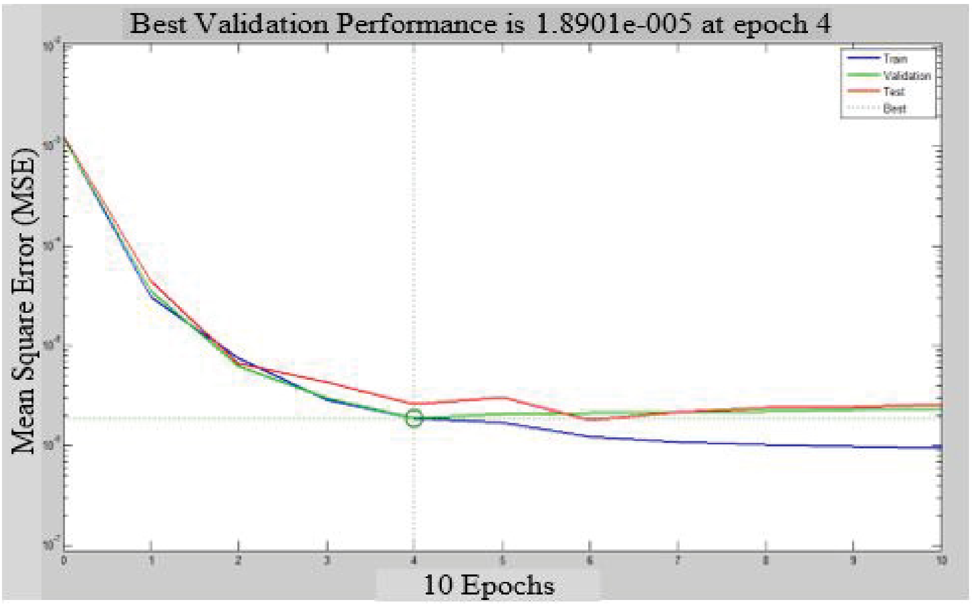

Figure 3: ANN system runs for (5-15-2) architecture.

analysis was used to estimate a relationship for discharge calculation, from the following equation:

$$Q = C_d y_b^{3/2} b \quad (6)$$

Where Q: discharge and

$$C_d = \frac{g^{1/2}}{\left(C_1 + C_2\sqrt{\frac{kS_o}{b}}\right)^{3/2}}$$

A program code including neural network toolbox was written in Matlab language ver. R2010a for the ANN simulations.

The measured critical depth y_c as well as discharge Q is computed with those obtained by the ANN and NLR technique. The ARE statistics of the measured and computed Q and y_c values using ANN and NLR are given in Table 1.

It can be obviously seen from Table 1 that the ANN approximates measured Q and y_c values with high accuracy. The mean ARE of ANN and NLR are 3.8% and 10.1% respectively for Q while these values reach to 2.0% and 6.8% respectively for y_c. The measured and computed Q and y_c using ANN and NLR technique are compared in Figures 4 and 5.

It can be seen from the fit line equations (assume that the equation is y=ax) for the ANN with higher R^2 values (0.986 and 0.988 for Q and y_c respectively) while these values are (0.8491 and 0.8688 respectively) for NLR. The ANN seems to be much better than the NLR based on ARE statistics confirms that the ANN seems to be much better than the NLR as shown in Table 1.

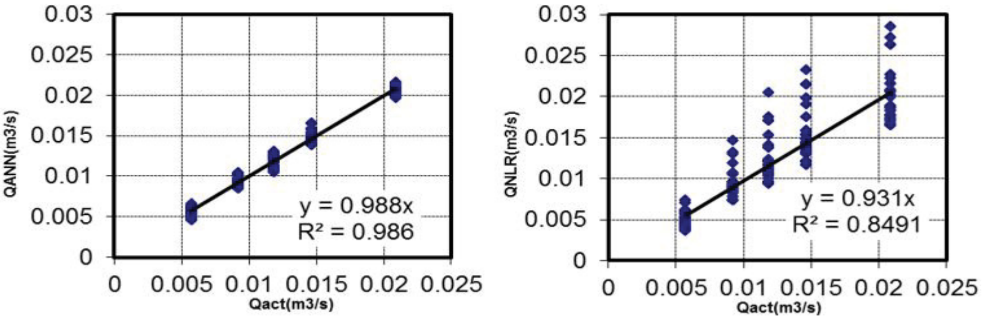

Figure 4: Comparison of measured and computed discharge (Q) using the ANN and NLR techniques.

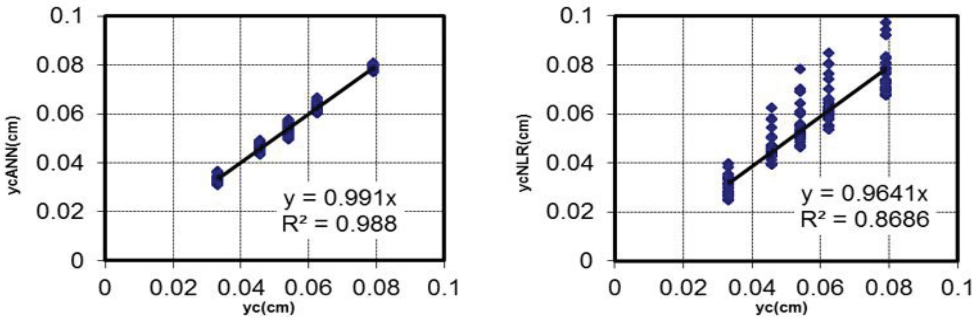

Figure 5: Comparison of measured and computed critical depth (y_C) using the ANN and NLR techniques.

Inputs					Measured		Computed				ARE(%)			
b(m)	S_o	y_b (m)	yn(m)	k(m)	y_c (m)	Q (m^3/s)	y_c(m) ANN	Q(m^3/s) ANN	Q(m^3/s) NLR	y_c(m) NLR	Q ANN	y_c ANN	Q NLR	y_c NLR
0.3	0	0.046	0.099	0.002	0.0791	0.021	0.08	0.0215	0.021	0.079	2.7092	0.6348	0	1.25
0.3	0	0.039	0.075	0.002	0.0625	0.015	0.062	0.0146	0.016	0.064	0.2434	0.4034	6.667	3.226
0.3	0	0.03	0.067	0.002	0.0541	0.012	0.049	0.0105	0.012	0.051	11.393	8.6003	0	4.082
0.3	0	0.028	0.057	0.002	0.0458	0.009	0.045	0.0089	0.01	0.046	3.2096	2.4235	11.111	2.222
0.3	0	0.018	0.05	0.002	0.0333	0.006	0.033	0.0055	0.005	0.031	4.4734	1.6438	16.667	6.061
0.3	0.01	0.045	0.094	0	0.0791	0.021	0.08	0.0211	0.022	0.077	0.7547	1.3008	4.762	3.75
0.3	0.01	0.035	0.077	0	0.0625	0.015	0.06	0.0139	0.015	0.061	5.4231	3.7277	0	1.667
0.3	0.01	0.03	0.069	0	0.0541	0.012	0.054	0.0117	0.011	0.052	1.1979	1.0876	8.333	3.704
0.3	0.01	0.027	0.059	0	0.0458	0.009	0.046	0.0096	0.01	0.046	4.5764	1.1599	11.111	0
0.3	0.01	0.017	0.046	0	0.0333	0.006	0.034	0.006	0.006	0.03	4.5252	1.2	0	11.765
0.3	0.005	0.047	0.095	0	0.0791	0.021	0.08	0.0209	0.022	0.079	0.1175	0.6505	4.762	1.25
0.3	0.005	0.037	0.078	0	0.0625	0.015	0.062	0.0141	0.016	0.062	3.5225	1.0689	6.667	0
0.3	0.005	0.033	0.07	0	0.0541	0.012	0.054	0.0117	0.013	0.056	1.2922	0.163	8.333	3.704
0.3	0.005	0.029	0.06	0	0.0458	0.009	0.046	0.0094	0.01	0.047	2.6093	0.7367	11.111	2.174
0.3	0.005	0.017	0.047	0	0.0333	0.006	0.033	0.0057	0.005	0.029	0.3747	1.2297	16.667	12.121
0.3	0	0.05	0.096	0	0.0791	0.021	0.079	0.021	0.023	0.081	0.2323	0.4936	9.524	2.532
0.3	0	0.04	0.079	0	0.0625	0.015	0.061	0.0143	0.017	0.065	2.6149	1.5849	13.333	6.557
0.3	0	0.035	0.071	0	0.0541	0.012	0.052	0.0112	0.013	0.059	5.4564	4.062	8.333	13.462
0.3	0	0.032	0.061	0	0.0458	0.009	0.047	0.0097	0.011	0.052	5.328	2.9946	22.222	10.638
0.3	0	0.02	0.048	0	0.0333	0.006	0.034	0.0059	0.006	0.034	2.795	1.5351	0	0
0.3	0.01	0.04	0.097	0.006	0.0791	0.021	0.079	0.0203	0.019	0.069	3.1044	0.2115	9.524	12.658
0.3	0.01	0.03	0.08	0.006	0.0625	0.015	0.063	0.0148	0.014	0.059	1.2232	0.8858	6.667	6.349
0.3	0.01	0.026	0.066	0.006	0.0541	0.012	0.051	0.0108	0.01	0.048	8.657	6.1255	16.667	5.882
0.3	0.01	0.022	0.062	0.006	0.0458	0.009	0.046	0.0093	0.007	0.039	0.5207	0.1242	22.222	15.217
0.3	0.01	0.014	0.049	0.006	0.0333	0.006	0.032	0.0057	0.004	0.028	0.1908	2.5487	33.333	12.5
0.3	0.005	0.043	0.097	0.006	0.0791	0.021	0.078	0.0203	0.02	0.075	2.9807	0.852	4.762	3.846
0.3	0.005	0.032	0.08	0.006	0.0625	0.015	0.063	0.0149	0.013	0.059	1.914	1.4768	13.333	6.349
0.3	0.005	0.028	0.066	0.006	0.0541	0.012	0.051	0.011	0.011	0.047	6.8251	5.3312	8.333	7.843

0.3	0.005	0.023	0.062	0.006	0.0458	0.009	0.044	0.0088	0.008	0.039	3.9659	3.4329	11.111	11.364
0.3	0.005	0.016	0.049	0.006	0.0333	0.006	0.033	0.0056	0.005	0.028	1.7366	0.6598	16.667	15.152
0.3	0	0.045	0.098	0.006	0.0791	0.021	0.08	0.0208	0.021	0.076	0.6436	0.6927	0	5
0.3	0	0.034	0.081	0.006	0.0625	0.015	0.062	0.0145	0.014	0.058	1.2481	0.4526	6.667	6.452
0.3	0	0.03	0.067	0.006	0.0541	0.012	0.05	0.0107	0.012	0.051	9.6089	6.9285	0	2
0.3	0	0.025	0.063	0.006	0.0458	0.009	0.043	0.0085	0.009	0.044	7.907	5.0365	0	2.326
0.3	0	0.018	0.05	0.006	0.0333	0.006	0.034	0.0054	0.005	0.03	4.6102	0.9833	16.667	11.765
0.3	0.01	0.042	0.091	0.002	0.0791	0.021	0.081	0.0212	0.02	0.071	1.4441	1.8425	4.762	12.346
0.3	0.01	0.033	0.074	0.002	0.0625	0.015	0.061	0.0144	0.013	0.056	1.8373	1.7811	13.333	8.197
0.3	0.01	0.028	0.069	0.002	0.0541	0.012	0.055	0.0123	0.011	0.049	4.3695	2.0231	8.333	10.909
0.3	0.01	0.025	0.062	0.002	0.0458	0.009	0.049	0.0104	0.009	0.042	13.288	6.8256	0	14.286
0.3	0.01	0.015	0.046	0.002	0.0333	0.006	0.032	0.0053	0.005	0.028	6.4539	4.4908	16.667	12.5
0.3	0.005	0.04	0.092	0.002	0.0791	0.021	0.077	0.0202	0.019	0.068	3.3987	2.1637	9.524	11.688
0.3	0.005	0.037	0.075	0.002	0.0625	0.015	0.064	0.0152	0.016	0.063	3.3972	2.2062	6.667	1.563
0.3	0.005	0.032	0.07	0.002	0.0541	0.012	0.057	0.0128	0.013	0.054	8.0188	5.1303	8.333	5.263
0.3	0.005	0.027	0.063	0.002	0.0458	0.009	0.048	0.0101	0.01	0.046	9.9589	5.29	11.111	4.167
0.3	0.005	0.017	0.047	0.002	0.0333	0.006	0.032	0.0052	0.005	0.029	8.1446	4.0091	16.667	9.375
0.3	0	0.043	0.093	0.002	0.0791	0.021	0.077	0.0202	0.02	0.073	3.5303	2.0797	4.762	5.195
0.3	0	0.04	0.076	0.002	0.0625	0.015	0.064	0.0152	0.017	0.068	3.63	2.2776	13.333	6.25
0.3	0	0.035	0.071	0.002	0.0541	0.012	0.056	0.0125	0.015	0.059	5.6783	3.1941	25	5.357
0.3	0	0.03	0.064	0.002	0.0458	0.009	0.048	0.0101	0.011	0.051	9.7641	5.7453	22.222	6.25
0.3	0	0.02	0.048	0.002	0.0333	0.006	0.034	0.0058	0.006	0.034	1.0069	2.055	0	0

Table 1: The ARE percentage for computed Q and y_c using ANN and NLR models (sample computations).

Discussion and Conclusions

In this study, multilayer feed forward artificial neural network with back propagation learning algorithm (FFBP) is used to model the end depth drop, as well as NLR is developed to determine the discharge and critical depth of the free overfall. The results of the models were compared to each other with 215 experimental data. A network of size of 5-15-2 is found suitable for this purpose. The determination coefficient (R2) and mean absolute, relative error (ARE) of predicted outputs were 0.986 & 3.849 for Q and 0.988 & 2.022 for yc for this optimum configuration. The results of the trained, verified and tested ANN model compare to the experimental measurements. These values were in close agreement with those obtained by systematic investigation by Mowafaq et al. [17], Mowafaq et al. [18] and Ahmed Y.M. [19]. It was found that the artificial neural network models could be successfully used in computation of discharge and critical depth and powerful tools for modeling of hydraulic characteristics of flow over free overfall.

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