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Artificial Neural Network Model for Predicting the Impact of Changing Water Structures' Locations on the Hydraulic Performance of Branched Open Channel System

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Artificial Neural Network **(ANN)** has been widely utilized in the past ten years in civil engineering applications for the simulation and prediction of the different physical phenomena and has proven its capabilities in the different fields. The existence of hydraulic structures in α branched open channel system urges the need for considering the gradually varied flow criterion in evaluating the different hydraulic characteristics in this type of open channel system. Computations of hydraulic characteristics such as flow rates and water surface profiles in branched open channel system with hydraulic structures require tremendous numerical effort especially when the flow cannot be assumed uniform. The present study aims towards introducing the use of **ANN** technique to model and predict the impact of changing water structures' locations on the hydraulic performance of branched open channel system. Specifically the current paper investigates α branched open channel system that consists of main channel supplies water to two branch channels with water structures such as clear over fall weirs and sluice gates. The results of this study showed that **ANN** technique was capable, with small computational effort and high accuracy, of predicting the impact of changing the locations of two types of water structures on the hydraulic performance of branched open channel system.

Keywords: neural network, water supply.

1. Introduction

Computations of hydraulic characteristics in branched open channel system cannot be performed using the uniform flow criterion. Therefore, the utilization of the gradually varied flow concept in these channels is a must. In addition, the existence of hydraulic structures in this branched channel system adds more complexity to the computational effort required to evaluate the different hydraulic characteristics such as flow rates and water surface profiles upstream the hydraulic structures.

Regarding branched channel system, Wylie [13] discussed the island-type flow, which occurs when the discharge is carried in two or more separate channels as it flows around one or more islands. This procedure was an iterative procedure consisting of dividing the network into reaches and calculating the specific energy at each node. Later Chaudhry *et al.* [3] developed a numerical technique to compute water surface profile in a junction of channels and the channel networks. They indicated that any form of channel's junction or channel networks could be divided into small reaches for the water surface profile computations. Their solution method was based on developing an algorithm for solving the specific energy and continuity equations simultaneously at each node according to their designed increment.

On the other hand, in Delft Hydraulic Research [4], they developed a one-dimensional mathematical model called WENDY. WENDY consists of a basic module for the simulation of water flow in open channel networks. This water flow module can be used for the simulation of discharge distribution, water levels, flow velocities, and so on.

Later Ibrahim [5] used the same technique of Chaudhry *et al.* [3] to evaluate the different hydraulic characteristics in junction of open channels utilizing gradually varied flow. In his study, each branch channel had a water structure that controls the flow. Specifically he developed a numerical computer model to solve the different governing flow equations simultaneously considering gradually varied flow through this Junction of channels. As a continuation for his study, Ibrahim *et al.* [6] modified the previous model to explore the impact of water structure's position in branched channel system on its overall hydraulic efficiency.

It is quite clear from the literature mentioned previously the amount of numerical effort required to accurately determine the different hydraulic characteristics of branched open channel system that has different hydraulic structures in the branched channels. This fact urged the need for utilizing new technology and techniques to facilitate these comprehensive numerical computations and at the same time preserving high accuracy. Artificial intelligence has proven its capability in simulating and predicting the behavior of the different physical phenomena in most of the engineering fields.

Artificial Neural Network **(ANN)** is one of the artificial intelligence techniques that has been utilized in civil engineering in general and in the water field area specifically. Several researchers have incorporated **ANN** technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. Chandramouli *et al.* [2] developed a dynamic programming-based neural network model for optimal multi-reservoir operation. In this developed model, the multi-reservoir operating rules were derived using a feed-forward neural network from the results of three state variables' dynamic programming algorithm. The authors applied the multi-reservoir system called Parambikulam Aliyar Project in their study. Comparison between the developed model against first the regression-based approach used for deriving the multi-reservoir operating rules from optimization results; and second the single-reservoir dynamic programming neural network model approach showed an improved operating performance. Abdeen [1] developed a neural network model for predicting flow characteristics in irregular open channels: The developed model proved that **ANN** technique was capable with small computational effort and high accuracy of predicting flow depths and average flow velocities along the channel reach when the geometrical properties of the channel cross sections were measured or vice versa. Kheireldin [7] presented a study to model the hydraulic characteristics of severe contractions in open channels using **ANN** technique. The successful results of his study showed the applicability of using the **ANN** approach in determining relationship between different parameters with multiple input/output problems. Tawfik *et al.* [12] showed the applicability of using the **ANN** technique for modeling rating curves with hysteresis sensitive criterion. Ramanitharan *et al.* [9] utilized **ANN** with back-propagation algorithm for modeling ocean waves which were represented by wave height and period. This study showed the applicability of forecasting the ocean waves with different neural networks for wave height and period. Minns [8] investigated the general application of **ANN** in modeling rainfall runoff process. The results of the numerical experiments reported in his study indicated that **ANN** was capable of identifying usable relationships between runoff discharges and antecedent rainfall depts. Solomatne *et al.* [11] presented a study of using **ANN** in the optimization loop for the hydrodynamic modeling of reservoir operation in Venezuela. The authors stated that the **ANN** representation of the hydrodynamic/hydrologic model could easily allow the incorporation of the various modeling components into the optimization routines.

It is quite clear from the previously presented literature that **ANN** technique showed its applicability in simulating and predicting the behavior of different hydraulic problems. Therefore, the presented study is aimed towards utilizing the **ANN** technique in investigating the impact of changing the water structures' position in a branched open channel system on its different hydraulic characteristics.

2. Problem Description

The current paper investigates the problem of a junction of open channels that consists of a main prismatic channel that divides into two prismatic branch channels. The main channel upstream the channel's junction supplies two branch channels as shown in Figure 1.

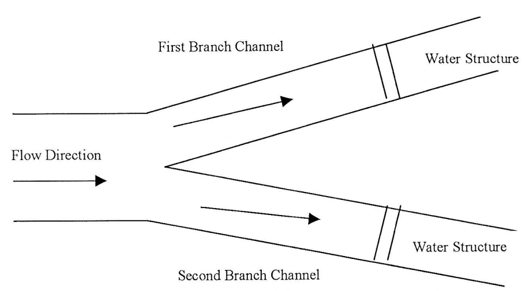

Figure 1 Schematic diagram for the investigated channels junction

It is shown that the main channel's flow, Q_1, is the upstream control flow in the channel's junction. Downstream the junction, there is a water structure at each branch channel that controls the flow. The flow in this kind of open channel system cannot be assumed uniform. Therefore, the gradually varied flow concept has to be

Table 1 Hydraulic and Geometric Parameters for the two investigated cases

Parameter	Value	Unit
Main Channel Discharge Q_1	70	m^3/sec
Main Channel Bed Width B_1	18	m
1. Branch Channel Bed Width B_2	16	m
2. Branch Channel Bed Width B_3	16	m
1. Branch Channel Bed Slope S_{o2}	0.00013	-
2. Branch Channel Bed Slope S_{o3}	0.00013	-
Main Channel Side Slope m_1	1	-
1. Branch Channel Side Slope m_2	1	-
2. Branch Channel Side Slope m_3	1	-
1. Branch Channel Roughness Coefficient n_2	0.014	-
2. Branch Channel Roughness Coefficient n_3	0.014	-
1. Branch Channel Weir Height H_{w2}	2.5	m
2. Branch Channel Weir Height H_{w3}	2.5	m
1. Branch Channel Gate Height from Bed Level Y_{G2}	0.4	m
2. Branch Channel Gate Height from Bed Level Y_{G3}	0.4	m
Acceleration of Gravity g	9.81	m^2/sec
Dist. between water struct. in 1. branch chann. and junction L_2	5000	m
Dist. between water struct. in 2. branch chann. and junction L_3	100	m

adopted in any computations for the evaluation of this problem flow characteristics. Ibrahim [5] solved this problem numerically with lots of computational effort. Later Ibrahim *et al.* [6] modified the previous numerical solution to investigate the effect of changing the location of the different water structures in each branch on the overall flow characteristics. However, the authors of this study commented about the tremendous amount of numerical computations required for the solution of their problem. Therefore, the current study utilizes the **ANN** technique and develops α neural network model to simulate and predict the flow behavior of the study of Ibrahim *et al.* [6]. The main objective of the current study was to use new technology such as **ANN** to facilitate the understanding of the hydraulic behavior of the previously mentioned application with minimum numerical computational effort but with high accuracy. The mathematical and hydraulic parameters for the studied application can be shown in Table 1 as they are reported by Ibrahim *et al.* [6]. On the other hand, if filed data were available for the same problem, the **ANN** approach and its methodology, described in this study, can be utilized to simulate this real case.

3. Artificial Neural Network (ANN)

Artificial Neural Network is a mathematical technique that simulates the behavior of the human's brain in understanding and learning from previous experience the physical nature of a given problem. As stated by Abdeen [1], generally **ANN** consists of layers of processing units (representing biological neurons) where each processing unit (neuron) in each layer is connected to all processing units in the adjacent layers. At least three layers have to be implemented to simulate any proposed problem. The first layer is the input layer where all the inputs to the problem are represented. The third layer is the output layer where all the target outputs are stored. The second layer is a non-visible one and it is called hidden layer. The number of hidden layers varies according to the problem. Each of the three types of layers consists of several neurons according to the task of this layer. The first layer (input layer) consists of several neurons each one of them represents one input for the studied problem. On the other hand, the output layer consists of several neurons each one of them represents an output for the problem. While the hidden layers are structured based on the problem needs so that the whole network can understand and simulate the physical behavior of the problem.

3.1. *Neural Network Structure*

Neural networks are models of biological neural structures. Abdeen [1] described in a very detailed fashion the structure of any neural network. Briefly, the starting point for most networks is a model neuron as shown in Figure 2.

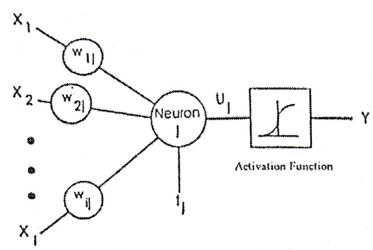

Figure 2 Typical picture of a model neuron that exists in every neural network

This neuron is connected to multiple inputs and produces a single output. Each input is modified by a weighting value (w). The neuron will combine these weighted inputs and, with reference to a threshold value and an activation function, will determine its output. This behavior follows closely the real neurons work of the human's brain. In the network structure, the input layer is considered a distributor of the signals from the external world while hidden layers are considered to be feature detectors of such signals. On the other hand, the output layer is considered a collector of the features detected and the producer of the response.

3.2. *Neural Network Operation*

It is quite important for the reader to understand how the neural network operates to simulate different physical problems. As described by Abdeen [1] the output of each neuron is a function of its inputs (X_i). In more details, the output (Y_i) of the j^{th} neuron in any layer is described by two sets of equations as follows:

$$U_j = \sum (X_i * w_{ij}) \ , \tag{1}$$

and

$$Y_j = F_{th} (U_j + t_j) \ . \tag{2}$$

For every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th}. This activation function can take several forms but the most commonly used one is the Sigmoid function which has an input to output mapping as shown in Figure 3.

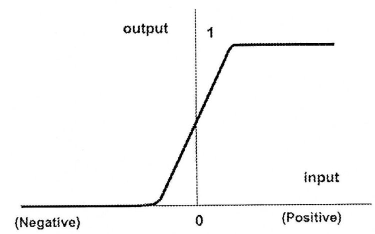

Figure 3 The Sigmoid activation function used in designed networks

The resulting output, Y_j, is an input to the next layer or it is a response of the neural network if it is the last layer. There are some other activation functions that are commonly used by the researchers in this field such as *Step, Linear, Hyperbolic*, and *Gaussian* functions. In applying the Neural Network technique in this study Neuralyst Software, Shin [10], was used.

3.3. *Neural Network Training*

The next step in neural network procedure as described by Kheireldn [7] and Abdeen [1] is the training operation. The main purpose of this operation is to tune up the network to what it should produce as a response. From the difference between the desired response and the actual response, the error is determined and a portion of it is back propagated through the network. At each neuron in the network, the error is used to adjust the weights and the threshold value of this neuron. Consequently, the error in the network will be less for the same inputs at the next iteration. This corrective procedure is applied continuously and repetitively for each set of inputs and corresponding set of outputs. This procedure will decrease the individual or total error in the responses to reach a desired tolerance. Once the network reduces the total error to the satisfied limit, the training process may stop. The error propagation in the network starts at the output layer with the following equations:

$$w_{ij} = w'_{ij} + LR * e_j * X_i \, , \tag{3}$$

and

$$e_j = Y_j * (1 - Y_j) * (d_j - Y_j) \; , \tag{4}$$

where, w_{ij} is the corrected weight, w'_{ij} is the previous weight value, LR is the learning rate, e_j is the error term, X_i is the i^{th} input value, Y_j is the output, and d_j is the desired output.

4. Simulation Cases

Two open channel junction systems are investigated in the current manuscript using the **ANN** technique. The first one studies a junction that consists of a main channel that supplies water to two branch channels. Two over fall weirs exist in these two branch channels. The two branch channels are identical in geometrical characteristics, weirs' heights, bed slopes, and channel roughness. The position of the first clear over fall weir in the first branch channel is fixed, however the position of the second weir is varied throughout the second branch channel length. On the other hand, the second case investigated in the current paper is similar in its hydraulic description to the first one except the hydraulic structures in the two branch channels are sluice gates instead of weirs. The different hydraulic and geometric parameters that associated with the two investigated cases are shown in Table 1 as they are reported by Ibrahim *et al.* [6].

5. Neural Network Design

To develop a neural network in order to simulate the impact of changing water structure's position in branched open channel system application as it is shown in Figure 1 and described previously, first input and output variables have to be determined. Input variables are chosen according to the nature of the problem and the type of data that would be collected in the field if this was a field experiment. The input variables for the two investigated simulation cases are the ones shown in Table 1. On the other hand, the output variables for the first simulated case are Q_2/Q_1, Q_3/Q_1, and H_{u3}/H_{u2}, and for the second simulated case are Q_2/Q_1, Q_3/Q_1, and Y_{u3}/Y_{u2}, where:

Q_2: Flow rate in the first branch channel,

Q_3: Flow rate in the second branch channel,

H_{u2}: Water depth upstream the clear over fall weir in the first branch channel,

H_{u3}: Water depth upstream the clear over fall weir in the second branch channel,

Y_{u2}: Water depth upstream the sluice gate in the first branch channel,

Y_{u3}: Water depth upstream the sluice gate in the second branch channel.

The hydraulic data for simulating the impact of changing the location of the water structure on the hydraulic performance of the open channel junction system reported by Ibrahim *et al.* [6] and used in the current study for developing the **ANN** models for the two investigated cases mentioned earlier are shown in Tables 3 and 4, respectively. The **ANN** technique needs one set of inputs and one set of outputs to train the network and develop the full **ANN** model for any of the two investigated cases that can be thereafter used in predicting the different output variables for any input data set similar to the ones used in its training procedure. Part of the data presented in Tables 3 and 4 are used for training the neural networks and the remaining portion is used for testing the accuracy of the prediction power of the two developed **ANN** models.

However, if the **ANN** model was to be applied to a field experiment, the type of input data needs to be collected would be the same as they are listed in Table 1. Similarly, the first set of output variables required for the training of the **ANN** would also need to be collected and reported as they were measured in the field corresponding to their input variables conditions.

Several neural network architectures are tested for each of the two simulated cases investigated in this study to finally determine the best network to simulate, very accurately, the impact of changing the water structure's location on the hydraulic characteristics of a branched channel system based on minimizing the Root Mean Square Error (RMS-Error). Figure 4 shows a schematic diagram for a generic neural network.

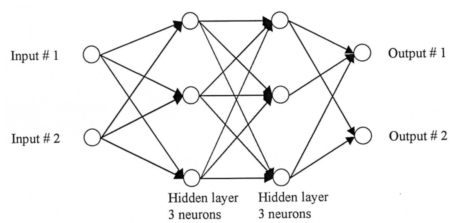

Figure 4 General schematic diagram of a simple generic neural network

In our two simulated cases, one neural network structure could successfully simulate both cases. This structure consists of 4 layers including the input and the output ones. The input layer consists of 3 neurons representing L_2, L_3, and Q_1 main input variables to the problem while the other input variables were held constant all over the application. On the other hand, the output layer consists of 3 neurons representing the three output variables mentioned earlier for each simulated cases. The chosen network consists of 2 intermediate hidden layers besides the input and the output layers. The first and second hidden layers consist of 3 and 2 neurons respectively. The Sigmoid function, presented in Figure 3, is used as the activation function for all of the neurons in the chosen design. This particular function typically has a narrow region about zero wherein the output will be roughly proportional to the input, but outside this region the Sigmoid function will limit to full inhibition or full excitation, Shin [10]. The Sigmoid function can be expressed mathematically as follows:

$$f(x) = \frac{1}{1+e^{-x}}\,. \tag{5}$$

From Eq.(5), it is clear that the function value $f(x)$ lies between 0 and 1. The training parameters of the two networks chosen for the two simulated cases are presented in Table 2. These parameters can be described with their tasks as follows:

Learning Rate: determines the magnitude of the correction term applied to adjust each neuron's weights during training process.

Momentum: determines the "lifetime" of a correction term as the training process takes place.

Table 2 List of network parameters

Network Parameter	Value
Learning Rate	1.0
Momentum	0.9
Training Tolerance	0.025
Testing Tolerance	0.01
Input Noise	0.0
Function Gain	1.0
Scaling Margin	0.1
Calculation Method	Fixed point

Training Tolerance: defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process. Testing Tolerance: it is similar to Training Tolerance, but it is applied to the neural network outputs and the target values only for the test data.

Input Noise: provides α slight random variation to each input value for every training epoch.

Function Gain: allows a change in the scaling or width of the selected function.

Scaling Margin: adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst Software [10] in preparing data for the neural network or interpreting data from the neural network.

6. Results and Discussion

As mentioned earlier, the current study investigates the impact of changing the location of water structure in a branched open channel system that is presented in Figure 1, on the overall hydraulic performance of this system using the **ANN** technique. Two cases for the hydraulic structures are investigates;

(1) clear over fall weir, and,

(2) sluice gate.

Two **ANN** models are developed, one for each case, to achieve this objective. The results of this study and the developed models can be presented as follows:

6.1. *First Case: Clear over fall weir water structure*

Clear over fall weirs exits in the two branches of the open channel system described in Figure 1. The location of the weir in the first branch channel (L_2) from the junction is fixed and the location of the second weir in the second branch channel (L_3) is changing from 100 m to 5000 m. The designed and developed **ANN** model mentioned in the previous section is used to simulate the overall hydraulic performance of the open channel system. Part of the date presented in Table 3 is used for training the **ANN**. Figure 5 shows the percentage relative error between the training results of the developed **ANN** model and the original data reported by Ibrahim *et al.* [6].

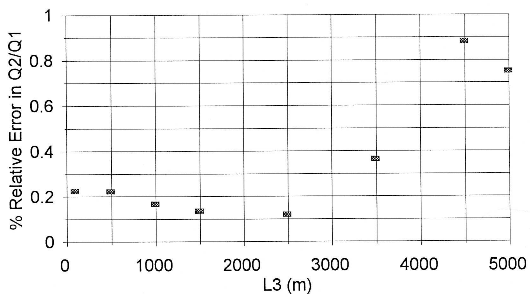

Figure 5 Percentage relative error in simulating Q_2/Q_1 for the first investigated case

This figure shows how accurate the developed **ANN** could simulate the impact of changing the location of the weir in the second branch channel on the ratio between Q_2 and Q_1 since the maximum relative error was 0.9 %.

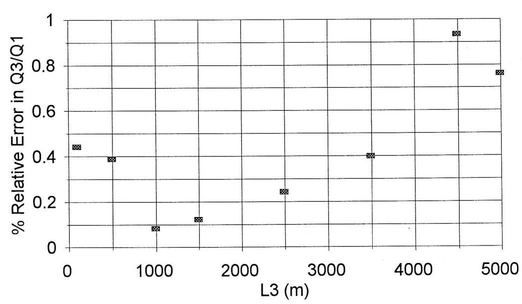

Figure 6 Percentage relative error in simulating Q_3/Q_1 for the first investigated case

On the other hand, Figure 6 and 7 show the relative error for simulating the ratio between Q_3 and Q_1; and H_{u3} and H_{u2}; respectively. The results shown in these two figures confirmed the perfect accuracy of the developed **ANN** in simulating the overall hydraulic behavior of the studied open channel system.

Thereafter, the developed **ANN** model is used for predicting this behavior for part of the data that was not included in the training process. The prediction results for the **ANN** model is presented in Table 5 which show the accuracy power of the developed **ANN** model in predicting the flow behavior in the studied open channel system since the maximum relative error was 1.8 %.

6.2. *Second Case: Sluice gate water structure*

In this case Sluice gate exists in the two branches of the open channel system described in Figure 1. The location of the gate in the first branch channel (L_2) from the junction is fixed and the location of the second gate in the second branch

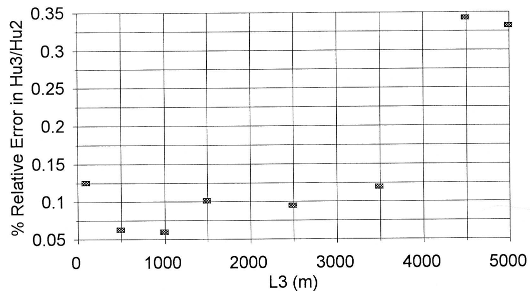

Figure 7 Percentage relative error in simulating H_{u3}/H_{u2} for the first investigated case

Table 3 Hydraulic parameters used for developing the ANN model for case (1)

L_2	L_3	Q_2/Q_1	Q_3/Q_1	H_{u3}/H_{u2}
5000	100	0.6660	0.3340	0.8680
5000	500	0.6510	0.3490	0.8790
5000	1000	0.6340	0.3670	0.8930
5000	1500	0.6160	0.3840	0.9070
5000	2000	0.5980	0.4020	0.9200
5000	2500	0.5810	0.4190	0.9340
5000	3000	0.5640	0.4360	0.9470
5000	3500	0.5360	0.4640	0.9700
5000	4000	0.5320	0.4690	0.9740
5000	4500	0.5160	0.4840	0.9870
5000	5000	0.5000	0.5000	1.0000

Table 4 Hydraulic parameters used for developing the ANN model for case (2)

L_2	L_3	Q_2/Q_1	Q_3/Q_1	H_{u3}/H_{u2}
5000	100	0.5180	0.4820	0.8700
5000	500	0.5170	0.4830	0.8800
5000	1000	0.5150	0.4850	0.8900
5000	1500	0.5130	0.4870	0.9060
5000	2000	0.5110	0.4890	0.9190
5000	2500	0.5090	0.4910	0.9320
5000	3000	0.5070	0.4930	0.9450
5000	3500	0.5060	0.4940	0.9590
5000	4000	0.5040	0.4960	0.9720
5000	4500	0.5020	0.4980	0.9860
5000	5000	0.5000	0.5000	1.0000

Table 5 Prediction results for the first investigated case

L_3 [m]	Q_1 [m^3/s]	error in predicting Q_2/Q_1 [%]	error in predicting Q_3/Q_1 [%]	error in predicting H_{u3}/H_{u2} [%]
2000	70	0.4650	0.598	0.143
3000	70	1.1070	1.482	0.622
4000	70	1.7565	1.784	0.744

Table 6 Prediction results for the second investigated case

L_3 [m]	Q_1 [m^3/s]	error in predicting Q_2/Q_1 [%]	error in predicting Q_3/Q_1 [%]	error in predicting Y_{u3}/Y_{u2} [%]
2000	70	0.0460	0.055	0.268
3000	70	0.1370	0.136	0.162
4000	70	0.0510	0.046	0.161

channel (L_3) is changing from 100 m to 5000 m. The designed and developed **ANN** model mentioned in the previous section is used to simulate the overall hydraulic performance of the open channel system for this particular case. Part of the date presented in Table 4 is used for training the **ANN**.

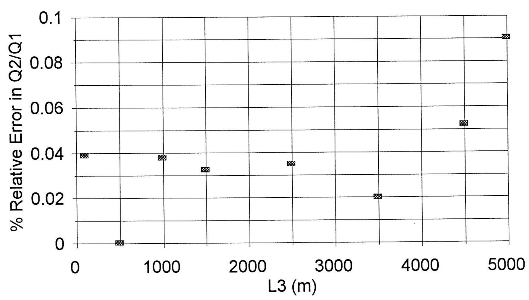

Figure 8 Percentage relative error in simulating Q_2/Q_1 for the second investigated case

Figure 8 shows the percentage relative error between the training results of the developed **ANN** model and the original data reported by Ibrahim *et al.* [6]. This figure shows how accurate the developed **ANN** could simulate the impact of changing the location of the gate in the second branch channel on the ratio between Q_2 and Q_1 since the maximum relative error was 0.09 %. On the other hand, Figure 9 and 10 show the relative error for simulating the ratio between Q_3 and Q_1 and Y_{u3} and Y_{u2}, respectively. The results shown in these two figures confirmed the perfect accuracy of the developed **ANN** in simulating the overall hydraulic behavior of the studied open channel system.

Thereafter, the developed **ANN** model is used for predicting this behavior for part of the data that was not included in the training process. The prediction results for the **ANN** model is presented in Table 6 which show the accuracy power of the developed **ANN** model in predicting the flow behavior in the studied open channel system since the maximum relative error was 0.161 %.

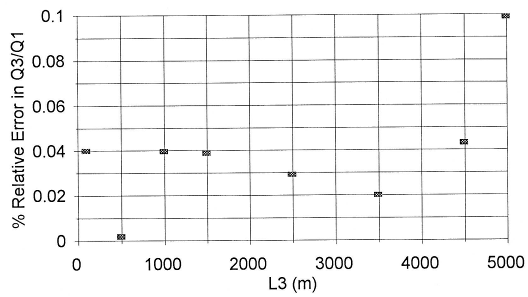

Figure 9 Percentage relative error in simulating Q_3/Q_1 for the second investigated case

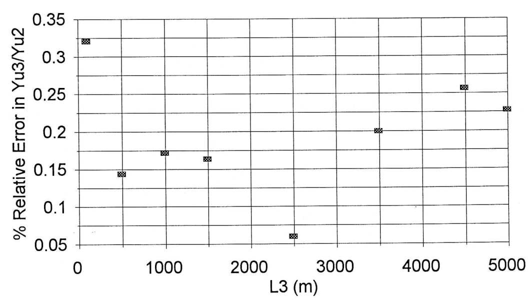

Figure 10 Percentage relative error in simulating Y_{u3}/Y_{u2} for the second investigated case

7. Summary and Conclusion

The current study was aimed towards investigating the applicability of using the artificial neural network **(ANN)** technique in simulating, with little computational effort, the impact of changing the location of water structure in a junction of open channel system on the overall hydraulic performance of this channel system. The data used in the current study was the same data reported by Ibrahim *et al.* [6].

Two simulation cases were considered in the current study; the first one investigate the existence of clear over fall weirs in the two branched open channels and the second one investigates the existence of sluice gates in the same branched open channels. **ANN** model was developed for each of the two investigated cases to simulate the overall hydraulic behavior of the studied open channel junction system. The developed **ANN** models were first trained using part of the available data and their accuracy was tested against the remaining parts. The results of implementing the **ANN** technique in this study showed that this approach was capable of identifying relationship between different uncertain parameters with multiple input/output criterions. The **ANN** presented in this study was very successful in simulating the impact of changing the location of two types water structures in a junction system of three open channels on the overall hydraulic behavior of this system with very high accuracy.

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