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ANN Model for Predicting the Impact of Submerged Aquatic Weeds Existence on the Hydraulic Performance of Branched Open Channel System Accompanied by Water Structures

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Abstract

The existence of hydraulic structures in a 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. In addition, the existence of submerged aquatic weeds in this branched open channel system adds to the complexity of the evaluation of the different hydraulic characteristics for this system. However, this existence of aquatic weeds can not be neglected since it is very common in Egyptian open channel systems.

Artificial Neural Network (ANN) has been widely utilized in the past decade in civil engineering applications for the simulation and prediction of the different physical phenomena and has proven its capabilities in the different fields. The present study aims towards introducing the use of ANN technique to model and predict the impact of submerged aquatic weeds existence on the hydraulic performance of branched open channel system. Specifically the current paper investigates a branched open channel system that consists of main channel supplies water to two branch channels that are infested by submerged aquatic weeds and have 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 different infestation percentage for submerged aquatic weeds on the hydraulic performance of branched open channel system with two different hydraulic structures.

Keywords: Artificial neural network; Open channel hydraulics modeling; Vegetated open channels; Hydraulic structures

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 and infestation of submerged aquatic weeds in this branched channel system add 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 (1972) 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

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specific energy at each node. Later Chaudhry and Chulte (1987) developed a numerical technique to compute water surface profile in a junction of channels and 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 (1992), 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 (1997) used the same technique of Chaudhry and Chulte (1987) 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*. (2000) modified the previous model to explore the impact of water structure's position in branched channel system on its overall hydraulic efficiency.

Regarding modeling studies of open channels' infested by aquatic weeds, Ibrahim *et al.* (1999) developed a finite difference model for investigating the impact of vegetation on water distribution system accompanied by water structures. During Ibrahim *et al.* (1999) study, the water distribution system consisted of a main channel and two branch channels that have water structures. These two branch channels were infested by aquatic weeds. Ibrahim *et al.* (1999) could successfully develop a finite difference model for evaluating the hydraulic characteristics of their open channel junction. However, during their study, Ibrahim *et al.* (1999) commented on the tremendous amount of numerical computations required to solve this problem. In addition, several assumptions had to be adopted for their study so the developed numerical model could actually produce correct results and the numerical errors could be minimized.

It is quit clear from the literature mentioned previously that few modeling studies were performed to simulate the hydraulic behavior of open channels infested by submerged aquatic weeds for various weeds densities and distributions. On the other hand, it was also clear from the mentioned literature the huge amount of numerical efforts and computations required to actually determine the different hydraulic characteristics of branched open channel system that has different hydraulic structures with weeds infestation. These facts urged the need for utilizing new technology and techniques to facilitate these comprehensive numerical computations and at the same time preserve high accuracy regarding the branched channel system.

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 have been incorporated in various scientific disciplines. Tahk and Shin (2002) presented a study on the fault diagnosis of Roller-Shape using frequency analysis of tension signals and Artificial Neural Networks (ANN) based approach in a web transport system. Specifically, the authors suggested a new diagnosis algorithm to detect the effective rollers based on the frequency analysis of web tension signals. Throughout their study, the authors utilized the characteristics features of tension signals (RMS, Peak value, and Power spectral density) to train an ANN that classified the roller condition into three groups (normal, warning, and faulty conditions). The results of this study showed that the suggested diagnosis algorithm could be successfully used to identify the effective rollers as well as to diagnose the degree of the defect of those rollers. Park and Seo (2003) explored a new Life Cycle Assessment (LCA) methodology for the product concepts by grouping products according to their environmental characteristics and by mapping product attributes into environmental impact driver (EID) index. The relationship is statistically verified by investigating the correlation between total impact indicator and energy impact category. Thereafter, the authors developed an ANN model with back propagation to predict an approximate LCA of grouping products in conceptual design. The results of the ANN model were compared with those of multiple regression analysis. Finally the authors stated that the proposed approach did not replace the full LCA but it would give some useful guidelines for the design of environmentally conscious products in conceptual design phase.

Regarding water engineering field area, several researchers have incorporated ANN technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. Chandramouli and Raman (2001) 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 (2001) 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 (1998) 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.* (1997) showed the applicability of using the ANN technique for modeling rating curves with hysteresis sensitive criterion. Ramanitharan and Li (1996) 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 (1996) 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. Solomatine and Toorres (1996) 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 quit clear from the previously presented literature that ANN technique showed its applicability in simulating and predicting the behavior of different hydraulic problems. Therefore, the current study is aimed towards utilizing the ANN technique in investigating the hydraulics' impact of different submerged aquatic weeds infestation patterns in a branched open channel system associated with different hydraulic structures on the overall system 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 is divided into two prismatic branch channels. The main channel upstream the channel's junction supplies two branch channels as shown in Fig. 1. 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 two branch channels are infested by submerged aquatic weeds. The flow in this kind of open channel system cannot be assumed uniform. Therefore, the gradually varied flow concept has to be adopted in any computations for the evaluation of this problem flow characteristics. Ibrahim *et al.* (1999) solved this problem numerically with lots of computational effort. Throughout Ibrahim *et al.* (1999) study, the first branch channel was assumed to be infested by a constant 5% of submerged aquatic weeds and the authors utilized the empirical equation developed by Bakry (1996) to estimate its manning roughness coefficient (n) to be equal to 0.03. On the other hand, the percentage of aquatic weeds infestation within the second branch channel was assumed to vary from 5% to 63%, with n values vary from 0.03 to 0.1 using Bakry's (1996) empirical formula, to investigate the impact of different levels of weeds infestation on the hydraulic characteristics of this branched channel system associated with hydraulic structures.

The authors of this study commented about the tremendous amount of numerical computations required for the solution of this problem. Therefore, the current study utilizes the ANN technique and develops neural network models to simulate and predict the flow behavior of the study of Ibrahim *et al*. (1999) utilizing the basic raw data that would be collected in any real field problem. This means that the percentages of submerged aquatic weeds infestation were the one used as inputs to the model and not the manning n values. This is done to avoid carrying out any errors from either empirical or numerical computations within the ANN models.

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 were reported by Ibrahim *et al*. (1999). On the other hand, if field 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. Neural network structure

Neural networks are models of biological neural structures. Abdeen (2001) 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 Fig. 2. 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 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 as a collector of the features detected and the producer of the response.

4. Neural network operation

It is quit important for the reader to understand how the neural network operates to simulate different physical problems. As described by Abdeen (2001) the output of each neuron is a function of its inputs (X_i). In more details, the output (Y_j) of the j^{th} neuron in any layer is described by two sets of equations as follows:

$$U_j = \Sigma\left(X_i * w_{ij}\right) \tag{1}$$

and

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

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 Fig. 3. 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 (1994), was used.

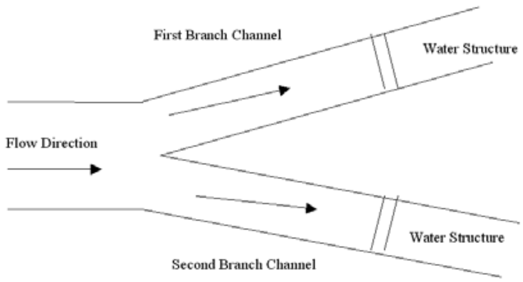

Fig. 1. Schematic diagram for the investigated channel's junction.

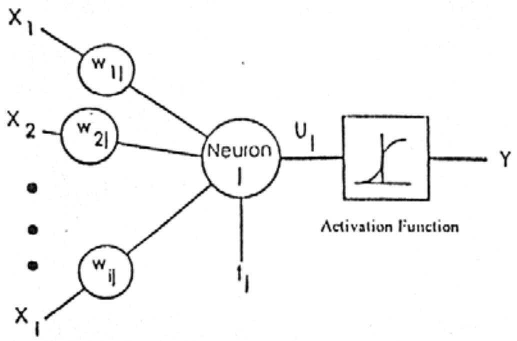

Fig. 2. Typical picture of a model neuron that exists in every neural network.

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)	20	m
First Branch Channel Bed Width (B_2)	18	m
Second Branch Channel Bed Width (B_3)	18	m
First Branch Channel Bed Slope (S_{o2})	0.0001	-
Second Branch Channel Bed Slope (S_{o3})	0.0001	-
Main Channel Side Slope (m_1)	1	-
First Branch Channel Side Slope (m_2)	1	-
Second Branch Channel Side Slope (m_3)	1	-
Percentage of Weeds infestation in First Branch Channel (I_2)	5%	-
Variable Percentage of Weeds in Second Branch Channel (I_3)	5 – 63 %	-
First Branch Channel Weir Height (H_{w2})	2.5	m
Second Branch Channel Weir Height (H_{w3})	2.5	m
First Branch Channel Gate Height from Bed Level (Y_{G2})	0.4	m
Second Branch Channel Gate Height from Bed Level (Y_{G3})	0.4	m
Acceleration of Gravity (g)	9.81	m^2/sec
Distance between water structure in first branch channel and the junction (L_2)	5000	m
Distance between water structure in second branch channel and the junction (L_3)	5000	m

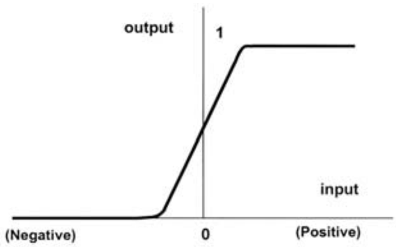

Fig. 3. The sigmoid activation function used in the designed networks.

5. Neural network training

The next step in neural network procedure as described by Kheireldin (1998) 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,

$$e_j = Y_j * \left(1 - Y_j\right) * \left(d_j - Y_j\right) \tag{4}$$

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 ouput, and d_j is the desired output.

6. 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, and bed slopes. However, the percentage of weeds infestation in the first branch channel is fixed to 5 %, as mentioned earlier, and this percentage varies from 5 – 63 % in the second branch channel. 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 a*l. (1999). In addition to these two simulation cases, the current study investigates the impact of different percentage of submerged aquatic weeds in the second branch channel utilizing the ANN technique through two sub-simulation cases within each hydraulic structure case mentioned earlier. The two sub-simulation cases within each hydraulic structure case considers both the interpolation and extrapolation range for the available weeds infestation data within the second branch channel in developing the different robust ANN models. As a summary, the current study investigates two main hydraulic structures cases (clear over fall weirs and sluice gates) through developing ANN models for both interpolation and extrapolation scenarios in each case. These two interpolation and extrapolation scenarios are called in the following discussions as two sub-simulation cases.

7. Neural network design

To develop a neural network in order to simulate the impact of the existence of different percentages of submerged aquatic weeds infestation in the two branch channels that are associated with hydraulic structures in branched open channel system application as it is shown in Fig. 1 and described previously, first step is to determine the input and output variables. 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 were a field experiment. The basic 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_1 : Flow rate in the main channel
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

To clearly specify the key input variables for each neural network simulation case and their associated outputs, Table 2 is designed to summarize all neural network key input and outputs variables for these two simulation cases. It is worth mentioning here that all data presented in Table 1 is also considered basic inputs for every ANN model developed in the current study.

Table 2. Key input and outputs variables for the two neural network simulation cases.

Case No.	Simulation Case (based on type of hydraulic structures)	Key Input Variables		Key Output Variables	
First Case	Over fall Weirs	Q_1	I_3	Q_2/Q_1	H_{u3}/H_{u2}
Second Case	Sluice Gates	Q_1	I_3	Q_2/Q_1	Y_{u3}/Y_{u2}

The hydraulic data for simulating the impact of different percentage of submerged aquatic weeds infestation within the second branch channel for the open channel junction system reported by Ibrahim *et al*. (1999) 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 and their sub-simulation cases that can be thereafter used in predicting the different output variables for any input data set similar (in its type not values) 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.

Specifically, the interpolation sub-simulation case within each of the two investigated cases considers the full range of I_3 (percentage of weeds infestation in the second branch channel) within the training process; and hide few intermediate records from this process (I_3 = 0.3, 0.38, and 0.46) as well as their hydraulic associated data and use them in the testing process. On the other hand, the extrapolation sub-simulation case within each of the two investigated cases considers portion of the full range of I_3 (percentage of weeds infestation in the second branch channel) within the training process; and hide few external records outside the training range from this process (I_3 = 0.46, 0.55, and 0.63) as well as their hydraulic associated data and use them in the testing

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

Weeds Infestation within the first Branch Channel)I_2	Weeds Infestation within the second Branch Channel)I_3	Q_2/Q_1	Q_3/Q_1	H_{u3}/H_{u2}
0.05	0.05	0.5	0.5	1.0
0.05	0.13	0.538	0.462	0.97
0.05	0.22	0.574	0.426	0.942
0.05	0.30	0.607	0.393	0.918
0.05	0.38	0.635	0.365	0.897
0.05	0.46	0.661	0.339	0.878
0.05	0.55	0.683	0.317	0.862
0.05	0.63	0.703	0.297	0.848

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

Weeds Infestation within the first Branch Channel)I_2	Weeds Infestation within the second Branch Channel)I_3	Q_2/Q_1	Q_3/Q_1	Y_{u3}/Y_{u2}
0.05	0.05	0.5	0.5	1.0
0.05	0.13	0.509	0.491	0.936
0.05	0.22	0.519	0.481	0.866
0.05	0.30	0.530	0.470	0.797
0.05	0.38	0.541	0.459	0.734
0.05	0.46	0.552	0.448	0.676
0.05	0.55	0.565	0.435	0.615
0.05	0.63	0.585	0.415	0.527

process.

However, if the ANN models were to be applied to a field experiment, the type of basic input data needs to be collected would be the same as they are listed in table 1. Similarly, the first set of key input and 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 basic input variables conditions as they are identified in Table 2.

Several neural network architectures are tested for each of the two simulated cases and their interpolation and extrapolation sub-simulation cases investigated in this study. These networks were tested to determine the best network to simulate, very accurately, the impact of different submerged aquatic weeds infestation, within the second branch channel, on the hydraulic characteristics of the branched channel system based on minimizing the Root Mean Square Error (RMS-Error). Table 5 shows the complete design of the finally developed ANN models for the two simulated cases and their sub-simulation cases. In addition, Fig. 4 shows a schematic diagram for a generic neural network.

Table 5. The developed neural network models for all the simulated cases.

Simulation case	Sub-simulation case	Activation Function	No. of layers	No. of neurons in the different layers			
				Input	1st hidden	2nd hidden	Output
Over fall weirs	Interpolation	Sigmoid	3	3	4	-	3
	Extrapolation	Sigmoid	4	3	4	3	3
Sluice Gate	Interpolation	Sigmoid	4	3	3	3	3
	Extrapolation	Hyperbolic	3	3	6	-	3

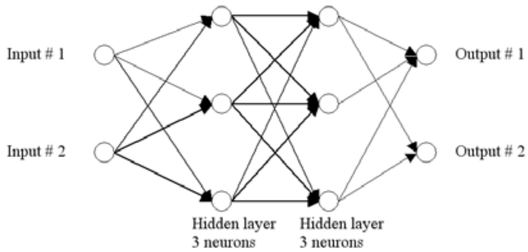

Fig. 4. General schematic diagram of a simple generic neural network.

The input and output layers represent the key input and output variables described previously for each sub-simulation case. It is very important to mention here that most of the developed models incorporated the sigmoid activation function presented in Fig. 3, while one model utilized the Hyperbolic activation function as shown from Table 5. The choice for any activation function, in the different models' development, was based on the power of the function in simulating the real nature of the problem in each case. The Sigmoid 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 (1994). The Sigmoid function can be expressed mathematically as follows:

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

It is quite clear from Eq. (5) that the Sigmoid function value (f(x)) lies between 0 and 1. On the other hand, the Hyperbolic function is shaped exactly as the Sigmoid one with the same mathematical representation but it ranges from –1 to +1 rather than from 0 to 1. Thus it has the interesting property that there is inhibition near 0, but values at either extreme will be excited to full level, but in opposite sense. In addition, the Hyperbolic function can be considered as a switch with an intermediate range where it can be discriminating, Shin (1994).

The training parameters of the four networks designed for the simulated cases are chosen to minimize the overall RMSE for both the training and testing processes. These parameters are different from each of the four developed ANN models as shown from Table 6. for clarity purposes, 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 "life time" of a correction term as the training process takes place.

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 a 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.

Table 6. List of different ANN models' parameters.

Network Parameter	Parameter Value			
	Over fall Weir (Interpolation case)	Over fall Weir (Extrapolation case)	Sluice Gate (Interpolation case)	Sluice Gate (Extrapolation case)
Learning Rate	1.0	1.0	1.0	1.0
Momentum	0.9	0.9	0.9	0.9
Training Tolerance	0.01	0.007	0.01	0.003
Testing Tolerance	0.005	0.007	0.01	0.003
Input Noise	0	0	0	0
Function Gain	1.0	1.0	1.0	1.0
Scaling Margin	0.1	0.1	0.1	0.1
Calculation Method	Fixed	Fixed	Fixed	Float

Scaling Margin: Adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst Software, Shin (1994), in preparing data for the neural network or interpreting data from the neural network.

8. Results and discussion

As mentioned earlier, the current study investigates the impact of submerged aquatic weeds infestation in a branched open channel system that has water structure in each of the branch channels, as presented in Fig. 1, on the overall hydraulic performance of this system using the ANN technique. Two cases for the hydraulic structures are investigated; (1) clear over fall weir and (2) sluice gate. Four ANN models were developed in the current study; two for each hydraulic structure case to accommodate for the interpolation and extrapolation sub- simulation cases, as presented in Table 5. The results of this study and the outputs of the developed models can be presented as follows:

8.1 First case: Clear over fall weir water structure

Clear over fall weirs exits in the two branches of the open channel system described in Fig. 1. The locations of the weirs in the two branch channels (L_2 and L_3) from the junction are fixed and equal to 5000 m as shown in Table 1. As described in Sec. 7 of this paper, two ANN models are designed and developed for interpolation and extrapolation sub-simulation cases regarding the I_3 (percentage of weeds infestation) values. Several results are produced within the current study case and they can not be all presented in figures' format. Therefore sample of the results will be presented in figure format and all the results will be presented in table format. 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*. (1999) for the interpolation case in the output Q_2/Q_1. This figure shows how accurate the developed ANN could simulate the impact of different weeds infestation in the second branch channel on the ratio between Q_2 and Q_1 since the maximum relative error was 0.215 %. Regarding testing the prediction power of the developed ANN model for this specific sub-simulation case, Fig. 6 shows the percentage relative error between the testing results of the developed ANN model and the original data reported by Ibrahim *et al*. (1999) for the interpolation case in the output

Table 7. Maximum percentage relative errors for training and testing processes for different outputs of the two simulation cases.

Simulation case	Sub-simulation case	Maximum Percentage Relative Error for Training and Testing Processes for the different outputs					
		Training Process			Testing Process		
		Q_2/Q_1	Q_3/Q_1	H_{u3}/H_{u2} or Y_{u3}/Y_{u2}	Q_2/Q_1	Q_3/Q_1	H_{u3}/H_{u2} or Y_{u3}/Y_{u2}
Over fall weirs	Interpolation	0.215	0.6	0.15	2.74	3.5	1.35
	Extrapolation	0.23	0.36	0.12	3.4	8.4	2.1
Sluice Gate	Interpolation	0.58	0.95	3.2	1.3	1.04	2.7
	Extrapolation	0.06	0.08	0.26	2.7	3.6	11.7

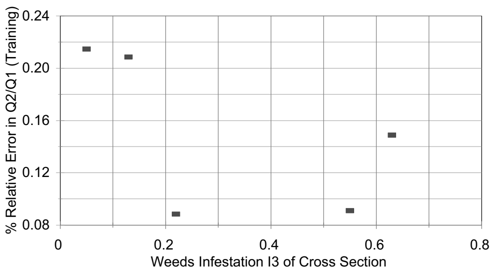

Fig. 5. Percentage relative error in simulating Q_2/Q_1 for the interpolation of the first investigated case for the training process.

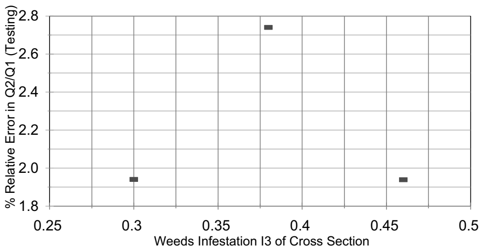

Fig. 6. Percentage relative error in simulating Q_2/Q_1 for the interpolation of the first investigated case for the testing process.

Q_2/Q_1. This figure shows that the developed ANN model is very successful in predicting the impact of different aquatic weeds infestation in the second branch channel on the ratio between Q_2 and Q_1 since the maximum relative error was 2.74 %. All results produced in this first case and its sub-simulation cases are presented in Table 7.

The ANN testing results presented in Table 7 for the first case including its sub-simulation cases show that the maximum percentage relative error was 8.4 % in the extrapolation sub-simulation case of the output Q_3/Q_1. This small error in the testing process especially in the current investigated study where the training process was performed using only 5 records can be considered a real success for the developed ANN models in predicting the impact of submerged aquatic weeds infestation on the hydraulic characteristics of the branched open channel system accompanied by clear over fall weirs in its two branches. Finally these results show that ANN technique was capable in simulating the hydraulic behavior of branched open channel system associated with weirs water structures and infested by submerged aquatic weeds. These results can be further utilized in providing the irrigation engineer with useful information regarding his water ways behavior that has similar nature.

8.2 Second case: Sluice gate water structure

In this case, sluice gate structure exits in each of the two branches of the open channel system described in Fig. 1. The locations of the gates in the two branch channels (L_2 and L_3) from the junction are fixed and equal to 5000 m as shown in Table 1. As described in Sec. 7 of this paper, two ANN models are designed and developed for interpolation and extrapolation sub-simulation cases regarding the I_3 (percentage of weeds infestation) values. Similar to the first case, several results are produced within the current study case and they can not be all presented in figures' format. Therefore sample of the results will be presented in figure format and all the results will be presented in table format. Figure 7 shows the percentage relative error between the training results of the developed ANN model and the original data reported by Ibrahim *et al*. (1999) for the interpolation case in the output Y_{u3}/Y_{u2}. This figure shows how accurate the developed ANN could simulate the impact of different weeds infestation in the second branch channel on the ratio between Y_{u3} and Y_{u2} since the maximum relative error was 3.2 %. Regarding testing the prediction power of the developed ANN model for this specific sub-simulation case, Fig. 8 shows the percentage relative error between the testing results of the developed ANN model and the original data reported by Ibrahim *et al*. (1999) for the interpolation case in the output Y_{u3}/Y_{u2}. This figure shows that the developed ANN model is very successful in predicting the impact of different aquatic weeds infestation in the second branch channel on the ratio between Y_{u3} and Y_{u2} since the maximum relative error was 2.7 %. All results produced in this second case and its sub-simulation cases are presented in Table 7.

The ANN testing results presented in Table 7 for the second case, including its sub-simulation cases, show that the maximum percentage relative error was 11.7 % in the extrapolation sub-simulation case of the output Y_{u3}/Y_{u2}. This small error in the testing process especially in the current investigated study where the training process was performed using only 5 records can be considered a real success for the developed ANN models in predicting the impact of submerged aquatic weeds infestation on the hydraulic characteristics of the branched open channel system accompanied by sluice gates water structures in its two branches. Finally these results show that ANN technique was capable in simulating the hydraulic behavior of branched open channel system associated with sluice gates water structures and infested by

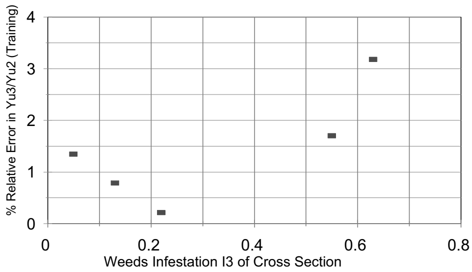

Fig. 7. Percentage relative error in simulating Y_{u3}/Y_{u2} for the Interpolation of the second investigated case for the training process.

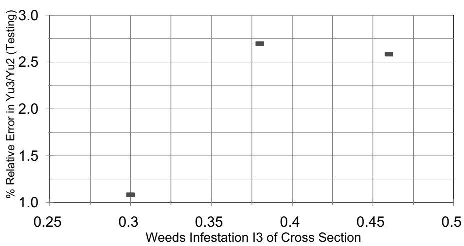

Fig. 8. Percentage relative error in simulating Y_{u3}/Y_{u2} for the interpolation of the second investigated case for the testing process.

submerged aquatic weeds. These results can be further utilized in providing the irrigation engineers with useful information regarding their water ways behavior that have similar nature.

8.3 ANN versus conventional statistical methods

The current study adopted the utilization of the ANN technique as mentioned previously and not any other conventional statistical methods such as least square technique. Several reasons were behind this adaptation and selection and they can be listed as follows:

Introducing new techniques from Artificial Intelligence such as ANN in the hydraulics area of open channel infested by aquatic weeds and accompanied by different water structures.

The current study is considered the first from its kind that explores the adaptation of ANN in this area of research.

ANN is a multi-inputs multi-outputs process that can fit the nature of the investigated problem.

Conventional statistical methods do not produce as high accurate predictions as ANN in most of the water related problems with little computational efforts as ANN does.

According to these reasons, the current study was aimed towards presenting if the ANN technique would be capable of simulating the investigated problem or not. Once ANN proved its capabilities, as it is shown from the results of the current study, research in this area can be extended for more complex problems that can benefit the irrigation engineers as well as the scientific and research communities.

9. 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 submerged aquatic weeds infestation in two branch channels that are associated with two different water structures within 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*. (1999).

Two simulation cases were considered in the current study; the first one considered the existence of clear over fall weirs in the two branched open channels and the second one considered the existence of sluice gates in the same branched open channels. The aquatic weeds infestation was assumed constant in the first branch channel and it varied in the second one. Interpolation and extrapolation sub-simulation cases were considered in the current investigated study regarding the various percentages of weeds infestation in the second branch channel.

Several ANN model were developed for each of the two investigated cases and their two sub-simulation 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 prediction accuracy and power 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 models developed and presented in this study were very successful in simulating the impact of different submerged aquatic weeds infestation on the overall hydraulic behavior of open channel junction system that has two types of water structures with very high accuracy. This conclusion opens the door for the irrigation engineers in utilizing the ANN technique in acquiring future knowledge and predict the behavior of their water ways that have similar nature.

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