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Predicting the impact of vegetations in open channels with different distributaries' operations on water surface profile using artificial neural networks

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Abstract

Most of the open water irrigation channels in Egypt suffer from the infestation of aquatic weeds, especially the submerged ones that cause numerous hydraulic problems for the open channels themselves and their water distributaries such as increasing water losses, obstructing water flow, and reducing channels' water distribution efficiencies. Accurate simulation and prediction of flow behavior in such channels is very essential for water distribution decision makers. Artificial neural networks (ANN) have proven to be very successful in the simulation of several physical phenomena, in general, and in the water research field in particular. Therefore, the current study aims towards introducing the utilization of ANN in simulating the impact of vegetation in main open channel, which supplies water to different distributaries, on the water surface profile in this main channel. Specifically, the study, presented in the current paper utilizes ANN technique for the development of various models to simulate the impact of different submerged weeds' densities, different flow discharges, and different distributaries operation scheduling on the water surface profile in an experimental main open channel that supplies water to different distributaries. In the investigated experiment, the submerged weeds were simulated as branched flexible elements. The investigated experiment was considered as an example for implementing the same methodology and technique in a real open channel system. The results showed that the ANN technique is very successful in simulating the flow behavior of the pre-mentioned open channel experiment with the existence of the submerged weeds. In addition, the developed ANN models were capable of predicting the open channel flow behavior in all the submerged weeds' cases that were considered in the ANN development process

Keywords: Artificial neural network; Open channel hydraulics modeling; Open channel infested by submerged weeds

1. Introduction

Open channels are still the major conveyers to deliver water to agricultural lands in Egypt where 33,000 km length of canals supplies irrigation water to the cultivated lands. The main task and responsibility of the irrigation engineers is to operate these channels at the highest possible efficiency. However, the presence of aquatic weeds in irrigation channels causes many problems such as water velocity reduction, water level rising, preventing water from reaching canals' ends, decrease water flow, in-efficient water distribution, etc.

Several researchers have investigated the hydraulic efficiency of open channels infested by aquatic weeds. The research community in this field divides the studies according to the type of weeds (or their simulators) and their impact on the roughness as rigid or flexible roughness studies. [1] presented a study for the development of ANN model for simulating the flow behavior in one main open channel infested by submerged aquatic weeds. Throughout this study, [1] presented a very profound literature review for the investigation of the hydraulic efficiency of open channels that are infested by aquatic weeds. The re-

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sults of this literature review, presented by [1], revealed that many experimental studies had been conducted in this research area; however, modeling and simulation efforts were still very limited.

On the other hand, 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 various scientific disciplines. [2] 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. [3] 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.

Regarding the water engineering field, several researchers have incorporated ANN technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. [1] presented a study for the development of ANN models to simulate flow behavior in open channel infested by submerged aquatic weeds. The study presented by [1] is considered the first of its kind that tackles modeling such a problem. Specifically, the author utilized the ANN technique in predicting the flow behavior in an experiment of an open channel infested by submerged aquatic weeds. The results of this study showed that ANN was quite successful in simulating this flow behavior in such an open channel experiment. In addition, this study could be considered as an added value to the modeling research efforts in the area of hydraulics of open channels that are infested by submerged aquatic weeds. [4] presented a study for estimating the scour characteristics downstream of a ski-jump bucket using neural networks (NN). Specifically, the authors developed NN structure as well as its connection weights and functions to predict the depth, location of maximum scour, and the width of scour hole. Thereafter, the authors compared this NN prediction with the results of traditional statistical schemes. Finally, the authors concluded that simple NN with feed forward back propagation produced similar reliable results as the more advanced NN schemes, compared with the traditional statistical techniques, even though the simple one took a very long time for the training. In addition, the authors reported that the use of causative variables in grouped forms was more rewarding than that of their raw forms, probably due to lesser scaling effect. [5] presented a study for investigating water distribution systems using ANN. Specifically, the authors presented a modified network analysis program where nodal outflows were developed as a function of pressure and secondary network characteristics. The outflow was estimated by using ANN that had been trained with extensive data on pressure, flows, and secondary network characteristics. Thereafter, the ANN was incorporated into a network analysis model and the network was solved by numerical differentiation. After the development process, the authors tested their model on several networks and found it to be performing well. On the other hand, [6] presented a study for predicting the impact of subsurface heterogeneous hydraulic conductivity on the stochastic behavior of well draw down in a confined aquifer using artificial neural networks. Several ANN models were developed in this study to predict the unsteady two-dimensional well draw down and its stochastic characteristics in a confined aquifer. The results of the [6] study showed that the ANN method with less computational effort was very efficiently capable of simulating and predicting the stochastic behavior of the well draw down resulting from the continuous constant pumping in the middle of a confined aquifer with subsurface heterogeneous hydraulic conductivity. [7] developed a dynamic programming-based neural network model for optimal multi-reservoir operation. [8] 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. [9] presented a study to model the hydraulic characteristics of severe contractions in open channels using ANN technique. [10] showed the applicability of using the ANN technique for modeling rating curves with hysteresis sensitive criterion. [11] utilized ANN with back-propagation algorithm for modeling ocean waves that 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. [12] investigated the general application of ANN in modeling the 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. [13] 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 the ANN technique showed its applicability in simulating and predicting the behavior of different hydraulic problems. In addition, the modeling research area of hydraulics of open channel that is infested by submerged aquatic weeds is still quite limited to few studies that cannot allow field engineers to adopt these models in their water planning and distribution works. Therefore, the presented study is aimed towards enriching this area of research and consequently helps field engineers to adopt ANN hydraulics modeling for their water planning and distribution work. Specifically, the current study is directed towards utilizing the ANN technique in modeling and simulating the water surface profile in vegetated channel that supplies water to different distributaries.

2. Problem description

The current paper investigates the problem of the existence of submerged aquatic weeds in open channels and their impact on the flow behavior in these channels and their distributaries. Specifically, the current study utilizes the ANN technique in developing simulation and prediction models for the flow behavior in open channel infested by submerged aquatic weeds and supplies water to six distributaries with different operation schedule. Since the utilization of the ANN approach in open channels infested by submerged aquatic weeds is considered relatively new, the current study develops the ANN model for an experimental data as a proof of concept that can be generalized later for field application. The experimental data used in the current study for developing the ANN model is the one reported by [14] in his Master's thesis. Detailed description about this experimental work is presented in the following section.

2.1 Experimental work

The experimental work performed by [14] for his Master's thesis work was carried out in the hydraulics laboratory of the Channel Maintenance Research Institute within the National Water Research Center – El-Kanater El-Khairiah–Egypt. The flume used in the experimental work is a reinforced concrete flume with a total length of 22.10 m. The operating system of this flume is re-circulated through an underground reservoir, with dimensions (24.10 m long, 1.75 m wide, and 1.5 m height) to supply the flume with water. The layout of the flume and all the hydraulic structures within the experiment can be shown from Fig. 1 as they were presented in the Master's thesis. On the other hand, the underground reservoir and the cross section of the experimental fume are shown in Fig. 2. The inlet part of the flume and the basin are shown in Fig. 3. The dimensions of the inlet part are 4.52 m long, 1.63 m wide, and 1.16 m height with two vertical reinforced concrete walls to dissipate any excessive energy diffusion of the jets in the possible shortest distance. The two walls are in a basin with the dimensions of 3.0 m long, 1.63 m wide, and 1.21 m height. However, the inlet bed has a ramp with 3:1 slope and is located downstream the two vertical walls. On the other hand, the dimensions of the horizontal trapezoidal part of the flume are 16.22 m long, 0.6 m wide, 0.42 m maximum depth, and 1:1 side slope. Fig. 4 shows the trapezoidal cross section while the flume is covered by 3 mm plastic sheets representing the submerged aquatic weeds. This experimental flume was designed, as mentioned previously, to simulate most of the Egyptian canals infested by weeds as stated by Abd Elhalim. The reader can refer to the study [14] presented in 2005 for complete details about all experiment's description, materials, and measuring tools.

As reported by [14], the water depth in the flume is controlled by means of a revolving gate at the end of the flume as shown in Fig. 5. The gate is pivoted around a horizontal axis passing through its lower edge; two chains, one at each end of the gate, are used to operate it. Using the connected handle, the level of the tailgate upper edge is controlled and consequently the water level in the flume.

For the purpose of experimentally simulating the distributaries from the main canal, six pipes, 2-inch diameter (D1, D2, D3, D4, D5, and D6) are connected to both sides of the trapezoidal flume (3 in each side). Both D1 and D4 are on the same cross sectional axis upstream weed zone, D2 and D5 are on the same cross sectional axis inside weed zone, and finally D3 and D6 are on the same cross sectional axis downstream weed zone. The spacing between any two adjacent axes is 4.0 m apart. All pipes' openings are leveled in the trapezoidal flume (pipe's internal lower point is 5.0 cm above flume bed). A control valve is fixed on each pipe to control the flow of the

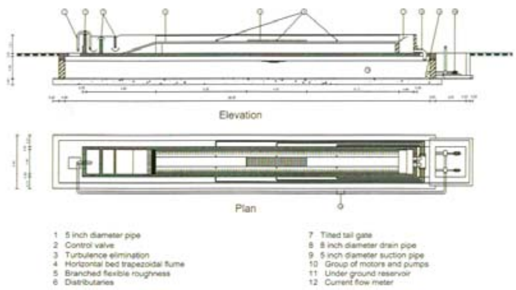

Fig. 1. Layout of the experimental flume with all its hydraulic structures.

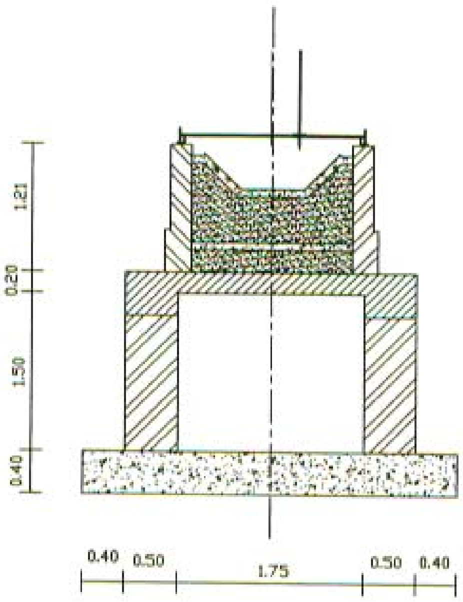

Fig. 2. Underground reservoir for the experimental flume.

Fig. 3. The inlet part of the flume and the basin.

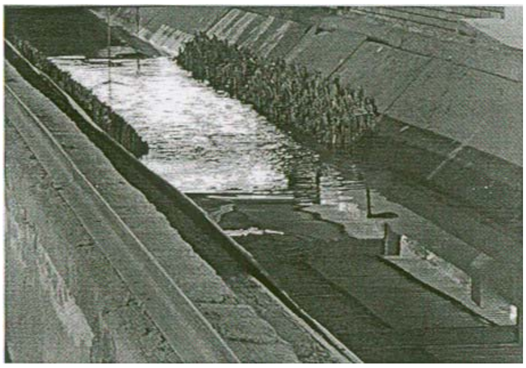

Fig. 4. The flume trapezoidal cross section covered by the plastic sheets.

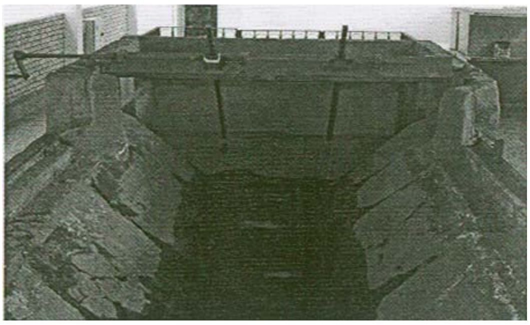

Fig. 5. Tilted tail gate.

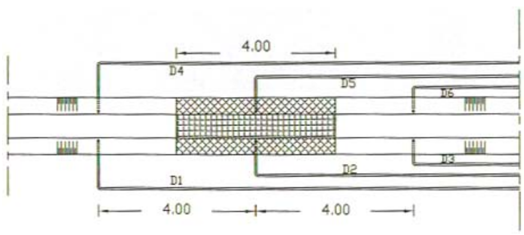

Fig. 6. The Flume and its connected distributaries.

distributaries (on–off). The main flume and its connected distributaries are shown in Fig. 6.

Throughout the experimental program, [14], ran his experiment, first, for the smooth case without any weeds infestation. Thereafter, he passed the same flow discharges as the smooth case and consequently the upstream water depth increased compared to the smooth case due to the presence of vegetation. The ANN models developed in the current study investigate the water surface profile prediction pattern for this particular case when the upstream water depths in the main vegetated channel are higher than the smooth channel water depths for the same flow rates. In addition, a specific ANN model is developed in the current study for each of the six distributaries' operation and opening cases investigated by [14] and will be described in the following section.

2.2 Data categories utilized for the ANN

As stated by [14] for investigating the impact of submerged weeds presence with different densities on the discharge of distributaries, five main channel discharges were selected to pass through the flume (25, 30, 35, 40, and 45 l/s). Two flexible roughness element densities were used in the experimental program (0.25 and 0.0625 No. of stem/cm^2). During the experimental work, six cases of distributaries operation were investigated (D1 open, D2 open, D3 open, D1&D4 open, D2&D5 open, and D3&D6 open). Throughout the experimental works, the water surface profile depths, in the main vegetated channel, were measured along the entire flume length for various parameters (five flow discharges, six distributaries operation cases, and two weeds densities) as mentioned previously. These water depths' realizations are the main outputs' type for the several developed ANN models within the current presented study.

3. Neural network structure

Neural networks are models of biological neural structures. [8] 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. 7. 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

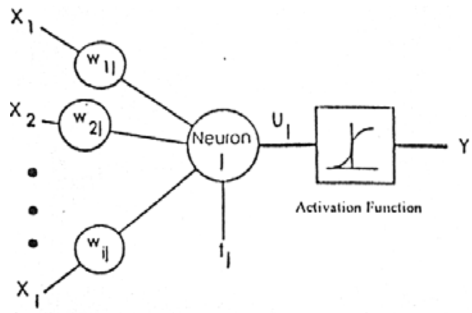

Fig. 7. Typical picture of a model neuron that exists in every neural network.

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 quite important for the reader to understand how the neural network operates to simulate different physical problems. As described by [8] the output of each neuron is a function of its inputs (X_i). In more detail, the output (Y_j) of the jth 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. 8. 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. On the other hand, other activation functions are commonly used by the re-

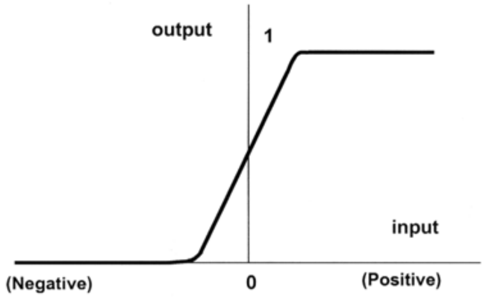

Fig. 8. The Sigmoid activation function used in some of the designed networks.

searchers in this field such as step, linear, hyperbolic, and Gaussian functions. In applying the neural network technique, in this study, Neuralyst Software, [15], was used.

5. Neural network training

The next step in neural network procedure as described by [9] is the training operation. The main purpose of this operation is to tune 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:

$$w_{ij} = w_{ij}^{'} + LR\left(e_j X_i\right) \tag{3}$$

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

To investigate and model the water surface profile in main open channels infested by aquatic weeds and supply water to different distributaries using ANN technique, the experimental work of [14] was utilized in the current study representing the Egyptian open channels. To fully understand how the water surface profile in open channels infested by aquatic weeds can be affected by the weeds' density, flow discharges, and different distributaries operation system, several simulation cases are considered in this study. These simulation cases can be divided into two main groups. The first group simulates and models the impact of the different flow discharge values on the water surface profile in the experimental flume infested by weeds. Specifically, this group of simulations predicts the water surface profile for one extra flow discharge that was not included in the ANN training process along the entire flume length for all distributaries operation cases mentioned previously and for the two weeds densities. The first simulation cases group will be called "different flow discharges group" in the following sections. The second simulation cases group assumes that water surface profile measurements are available only for two-thirds of the flume length for all flow discharges and predicts the water surface profile along the remaining one-third of the flume length for all distributaries operation cases and for the two weeds densities. This second simulation cases group will be called "different depths measurements locations group" in the following sections.

7. Neural network design

To develop a neural network model to simulate any physical phenomenon such as the impact of the aquatic weeds on the water surface profile in open channel that supplies water to different distributaries within the experimental flume mentioned 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 were a real field experiment. To clearly specify the key input variables for each neural network simulation groups and their associated outputs, table 1 is designed to summarize all neural network key input variables and outputs for these two groups.

As mentioned previously, two weed densities have been utilized for the development of the different ANN models for all distributaries' operational cases in the current research. Regarding the different flow discharges group, the ANN models consider the neural network training for Q = 25, 30, 35, and 40 (l/s), and the prediction and testing processes for the developed models are for Q = 45 (l/s). For the training process, the water surface profile measurements along the entire flume length are utilized. On the other hand, the testing process for Q = 45 l/s predicts the water surface profile along the entire flume length.

Regarding the water depth measurement locations simulation group, the ANN models consider the network training for water depths along the flume length from the beginning until 8.0 m for all flow discharges and distributaries operational cases. Whereas, the testing process for the developed models predicts the water surface profile along the flume length from 8.1–12.0 m for all flow discharges and distributaries operational cases.

It is worth mentioning that one specific ANN model is developed for each distributary's operational case for each weed density within the two simulation groups described previously.

Table 1. Key input and outputs variables for the two neural network simulation groups.

Groups No.	Simulation Case	Input Variables				Output Variable
First Group	Different Flow Discharges	Flow Discharge (l/s)	Distance along the flume (m)	Weed's density	Distributaries' operation	Water Depth along the main flume (cm)
Second Group	Water depths measurements locations	Flow Discharge (l/s)	Distance along the flume (m)	Weed's density	Distributaries' operation	Water Depth along the main flume (cm)

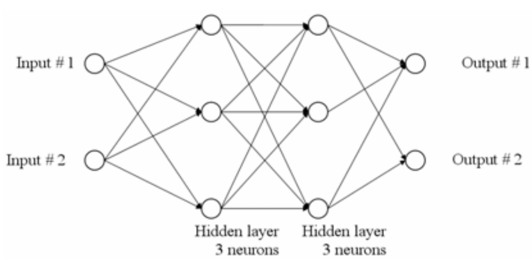

Fig. 9. General schematic diagram of a simple generic neural network.

On the other hand, if the ANN models were to be applied to a similar field application, not laboratory experiment, the type of input data that needs to be collected would be the same as they are listed in table 1. Similarly, the 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 designed and tested for each of the sub-simulated cases investigated in the current study to finally determine the best network model to simulate, very accurately, the water surface profile in the pre-described open channel setup based on minimizing the root mean square error (RMS-Error). Fig. 9 shows a schematic diagram for a generic neural network.

Due to the extreme difficulty of the investigated problem in the current presented study, one specific neural network is designed and developed for each sub-simulation case (distributaries' operational case) within the two simulation groups. Table 2 shows the final neural network models for each sub-simulation case and their associated number of neurons.

The input and output layers represent the key input and output variables described previously for each sub-simulation case. It is probably worth mentioning here, as shown from Table 2, that all input layers have 3 neurons representing 3 input variables, while, table 1 shows 4 input variables. This difference between the two tables is addressed through the development of separate ANN model for each distributaries' operation case. Therefore, for each ANN model for each distributaries' operation case, there were three input variables.

Regarding the adopted activation function within the current developed ANN models, it is important to mention here that some of the developed models incorporated the sigmoid activation function presented in Fig. 8, while other models utilized the hyperbolic activation function. The choice for any activation function, in the different models' development, was based on the power of this function in simulating the real nature of the water surface profile 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 [15]. The Sigmoid function can be expressed mathematically as follows:

Table 2. The design of the developed neural network models for all the simulated cases.

Simulation case	Sub-simulation case	Weeds density (stem/cm^2)	No. of layers	No. of neurons in each layer				
				Input	1st hidden	2nd hidden	3rd hidden	Output
Different Flow Discharges	D1 Open	0.25	4	3	4	2		1
	D1 Open	0.0625	4	3	4	2		1
	D2 Open	0.25	4	3	4	4		1
	D2 Open	0.0625	4	3	4	4		1
	D3 Open	0.25	4	3	4	3		1
	D3 Open	0.0625	4	3	4	3		1
	D1 & D4 Open	0.25	4	3	4	3		1
	D1 & D4 Open	0.0625	4	3	4	3		1
	D2 & D5 Open	0.25	4	3	4	3		1
	D2 & D5 Open	0.0625	4	3	4	4		1
	D3 & D6 Open	0.25	4	3	4	3		1
	D3 & D6 Open	0.0625	4	3	4	2		1
Water depths measurements locations	D1 Open	0.25	5	3	4	3	2	1
	D1 Open	0.0625	4	3	4	3		1
	D2 Open	0.25	4	3	4	3		1
	D2 Open	0.0625	4	3	4	3		1
	D3 Open	0.25	4	3	5	4		1
	D3 Open	0.0625	4	3	4	3		1
	D1 & D4 Open	0.25	4	3	4	3		1
	D1 & D4 Open	0.0625	4	3	4	4		1
	D2 & D5 Open	0.25	4	3	4	3		1
	D2 & D5 Open	0.0625	4	3	4	4		1
	D3 & D6 Open	0.25	4	3	4	4		1
	D3 & D6 Open	0.0625	4	3	4	2		1

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

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, 1996).

The training parameters of the various network models developed in the current study for the different sub-simulation cases can be described according to their tasks as well as their values for the different developed ANN models as follows:

Learning Rate (LR): determines the magnitude of the correction term applied to adjust each neuron's weights during the training process. LR = 0.5 for all developed ANN models.

Momentum (M): determines the "life time" of a correction term as the training process takes place. M = 0.7 for all developed ANN models.

Training Tolerance (TRT): defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process. TRT = 0.01 for all developed ANN models.

Testing Tolerance (TST): it is similar to training tolerance, but it is applied to the neural network outputs and the target values only for the test data. TST = 0.03 for all developed ANN models.

Input Noise (IN): provides a slight random variation to each input value for every training epoch. IN = 0 for all developed ANN models.

Function Gain (FG): allows a change in the scaling or width of the selected function. FG = 1 for all developed ANN models.

Scaling Margin (SM): adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst Software (Shin, 1996), in preparing data for the neural network or interpreting data from the neural network. SM = 0.1 for all developed ANN models.

8. Results and discussion

As described previously, several ANN models were developed for all the simulated cases investigated within the current study; their modeling design was presented in Table 2. The results and the prediction power of the developed ANN models in simulating the water surface profile in the studied flume that is infested by aquatic weeds and supplies water to different distributaries are presented in a detailed fashion in the following sections according to their simulation group.

8.1 Different flow discharges

As clearly stated previously, this simulation group tackles the issue of the impact of different flow discharges on the water surface profile in the investigated flume. The amount of data utilized for the ANN models' training was described in section 7; the current section presents the results of the testing and prediction processes for these models regarding the twelve ANN models developed for the different distributaries' operation cases for the two weeds' densities. Due to the length limitation of the current manuscript, only few examples of the prediction processes' results will be presented in graph format. However, the maximum percentage relative error between the predicted results and the actual measurements for all twelve ANN models for Q = 45 l/s along the entire flume length is presented in Table 3. Note that this percentage relative error is computed based on Eq. (6) as follows:

$$PRE = (\text{Absolute Value } (ANN\_PR - AMV) / AMV) * 100 \quad (6)$$

Where:

PRE : Percentage relative error

ANN_PR : Prediction results using the developed ANN model

AMV : Actual measured value

Fig. 10 shows the percentage relative errors for the testing process of the D1 open case for 0.25 (stem/cm^2) weed density. It is clear from this Fig. that the developed ANN model was capable of predicting the water surface profile in the main channel with maximum percentage relative error equal to 1.6 % for Q = 45 l/s when the model was trained with different flow discharges as mentioned previously. On the other hand, Fig. 11 shows the same type of results for D1 operation case for 0.0625 (stem/cm^2) weed density. Results, presented in this figure, proved that the ANN model, developed for this case, was very successful in predicting the water surface profile along the main channel for Q = 45 l/s since the maximum relative error was less than 2 %.

Regarding the D3 & D6 open operation case, Figs. 12 and 13 show the percentage relative errors computed along the main channel between the predicted values and the actual measured values for Q = 45 l/s series for the two weeds' densities 0.25 and 0.0625 (stem/cm^2), respectively. The results, presented in

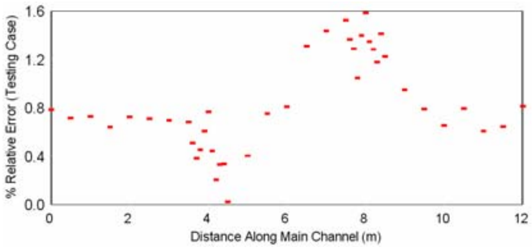

Fig. 10. Percentage relative error between the predicted ANN results and the actual measured data for D1 operation case for 0.25 (stem/cm^2) weed's density for Q = 45 l/s.

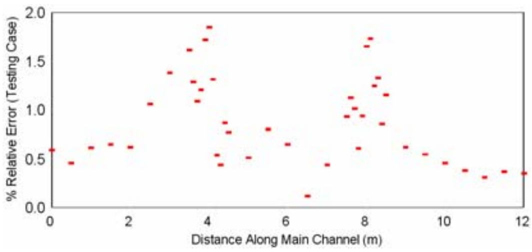

Fig. 11. Percentage relative error between the predicted ANN results and the actual measured data for D1 operation case for 0.0625 (stem/cm^2) weed's density for Q = 45 l/s.

Table 3. Maximum percentage relative errors between the predicted results and the actual measurements for Q = 45 (l/s) along the entire flume length for all ANN models developed within the different flow discharge group.

Sub-simulation case	Weeds density (stem/cm^2)	Maximum percentage relative error (%)
D1 Open	0.25	1.58
D1 Open	0.0625	1.84
D2 Open	0.25	2.16
D2 Open	0.0625	1.62
D3 Open	0.25	1.78
D3 Open	0.0625	2.23
D1 & D4 Open	0.25	1.83
D1 & D4 Open	0.0625	1.5
D2 & D5 Open	0.25	1.75
D2 & D5 Open	0.0625	2.55
D3 & D6 Open	0.25	1.96
D3 & D6 Open	0.0625	1.65

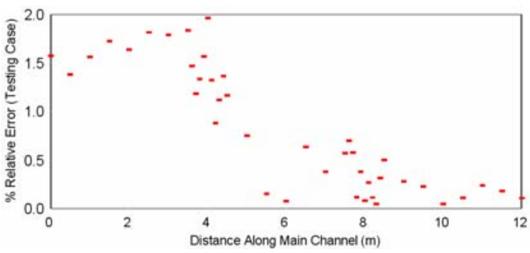

Fig. 12. Percentage relative error between the predicted ANN results and the actual measured data for D3 and D6 open operation case for 0.25 (stem/cm^2) weed's density for Q = 45 l/s.

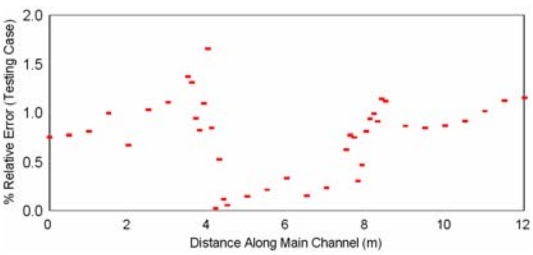

Fig. 13. Percentage relative error between the predicted ANN results and the actual measured data for D3 and D6 open operation case for 0.0625 (stem/cm^2) weed's density for Q = 45 l/s.

these two figures, prove that the developed ANN models were capable of simulating the actual behavior of the investigated open channel's water surface profile since the maximum relative errors were less than 2 % for the two weeds' densities cases.

Considering the small values for the maximum percentage relative errors, presented in table 3, It is quite clear that all ANN models developed for the current different flow discharges simulation case were very successful in predicting the water surface profile along the entire length of the investigated flume for Q = 45 l/s when these models were developed and trained by using other flow discharge values. These results show that ANN approach could model and simulate the behavior of the water surface profile in the investigated flume that is infested by different densities of submerged aquatic weeds and supplies water to different distributaries with different operation scheduling.

8.2 Water depth measurements locations

As mentioned previously, this simulation group utilizes the ANN technique for modeling the water surface profile along the last one-third of the investigated flume when data measurements were only carried out for the first two-thirds of this flume under the same circumstances of two weeds' densities and different distributaries' operation cases and for all flow discharges. The amount of data utilized for the ANN models' training was described in section 7, and therefore, the current section presents the results of the testing and prediction processes for these models regarding the twelve ANN models developed for the different distributaries' operation cases for the two weeds' densities. Due to the length limitation of the current manuscript, only few examples of the prediction processes' results will be presented in graphs' format. However, the maximum percentage relative errors between the predicted results and the actual measurements for all twelve ANN models for all investigated five flow discharges along the last one third of the flume length are presented in Table 4.

Fig. 14 shows the percentage relative errors for the testing process of the D2 & D5 open case for 0.25 (stem/cm^2) weed density for Q = 25 l/s. It is clear from this Fig. that the developed ANN model was capable of predicting the remaining water surface profile in the main channel with maximum percentage relative error equal to 1.4 % for Q = 25 l/s when the model was trained with different data measurements along the first two-thirds of the flume for all flow discharges.

On the other hand, Fig. 15 shows the same type of results for D2 & D5 operation case for 0.25 (stem/cm^2) weed density for Q = 45 l/s. Results, presented in this figure, proved that ANN model, devel-

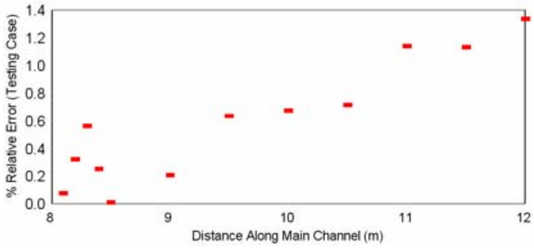

Fig. 14. Percentage relative error between the predicted ANN results and the actual measured data for D2 & D5 operation case for 0.25 (stem/cm^2) weed's density for Q = 25 l/s along the last one-third of the flume.

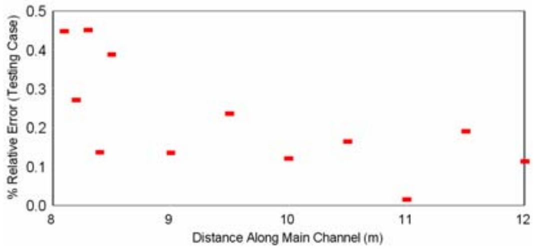

Fig. 15. Percentage relative error between the predicted ANN results and the actual measured data for D2 & D5 operation case for 0.25 (stem/cm^2) weed's density for Q = 45 l/s along the last one-third of the flume.

oped for this case, was very successful in predicting-the water surface profile along the remaining length of the main channel for Q = 45 l/s since the maximum relative error was less than 0.5 %.

Regarding the second weed's density (0.0625 stem/cm^2), figures 16 and 17 show the prediction results of the developed ANN models for D1 & D4 operation cases for Q = 30 l/s and D3 operation case for Q = 35 l/s, respectively. The results presented in these two figures show that ANN models were quite successful in predicting the remaining water surface profile along the investigated flume when the models were only trained by using part of the water depth measurement data since the maximum percentage relative error was less than 3 % in both cases. On the other hand, table 4 shows the maximum percentage relative errors for all the twelve ANN models developed within this simulation group for the two weeds' densities and for the different distributaries' operation cases.

Considering the small values for the maximum percentage relative errors, presented in Table 4, It is quite clear that all ANN models developed for the current water depth measurement locations simulation case were very successful in predicting the water surface profile along the last one-third of the investigated flume length for all flow discharges when these models were developed and trained by using the first two-thirds of the water depth data measurements. These results show that ANN approach could model and simulate the behavior of the water surface profile in the investigated flume that are infested by different

Table 4. Maximum percentage relative errors between the predicted results and the actual measurements for all flow discharges along the last one-third of the flume length for all ANN models developed within the water depth measurement locations group.

Sub-simulation case	Weeds density (stem/cm^2)	Maximum percentage relative error (%)
D1 Open	0.25	1.66
D1 Open	0.0625	2.82
D2 Open	0.25	1.34
D2 Open	0.0625	2.19
D3 Open	0.25	1.49
D3 Open	0.0625	2.59
D1 & D4 Open	0.25	3.88
D1 & D4 Open	0.0625	2.47
D2 & D5 Open	0.25	1.93
D2 & D5 Open	0.0625	2.67
D3 & D6 Open	0.25	2.71
D3 & D6 Open	0.0625	2.37

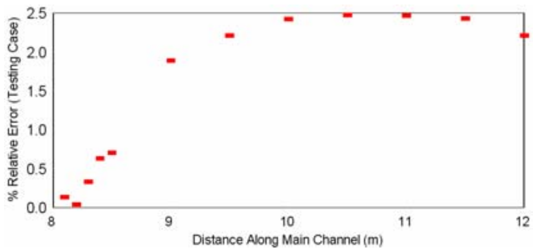

Fig. 16. Percentage relative error between the predicted ANN results and the actual measured data for D1 & D4 operation case for 0.0625 (stem/cm^2) weed's density for Q = 30 l/s along the last one-third of the flume.

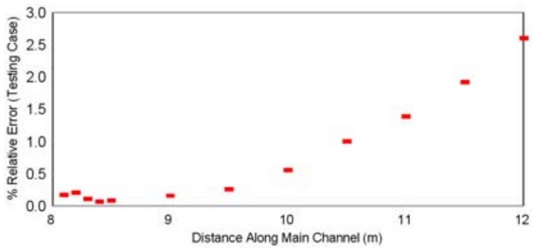

Fig. 17. Percentage relative error between the predicted ANN results and the actual measured data for D3 operation case for 0.0625 (stem/cm^2) weed's density for Q = 35 l/s along the last one-third of the flume.

densities of submerged aquatic weeds and supply water to different distributaries.

9. Summary and conclusion

The majority of the Egyptian surface water canals suffer from the infestation of submerged aquatic weeds. The existence of these weeds causes numerous problems for the hydraulic performance of these channels. Specifically, the water surface profile and subsequently the water distribution system within the Egyptian irrigation network are very much affected by these aquatic weeds.

A great deal of experimental work was performed to investigate and measure the impacts of these weeds on the hydraulic performance of the various open channels in Egypt. On the other hand, the mathematical modeling efforts for simulating these impacts are still very limited. However, the artificial neural networks (ANN) modeling approach has proven its capabilities in providing very useful information and simulating various physical phenomena. In addition, ANN has been recorded as a very powerful modeling technique and simulation process in predicting the behavior of different engineering systems.

The current study was aimed towards utilizing the ANN technique in investigating the impact of submerged aquatic weeds on the water surface profile in an experimental flume that supplies water to different distributaries. Since the implementation of the ANN technique in studying the hydraulic behavior of the infested open channels does not exist in the literature, the current study was directed towards proving the concept of utilizing this ANN in an experimental flume that is designed to simulate the Egyptian channels that have similar hydraulic functions. Specifically, the experimental case data utilized in the current study considers several flow discharges that pass through the investigated flume that is infested by two types of densities for submerged weeds and supplies water to several distributaries with different operational scheduling.

Several ANN models were developed in the current study to predict the water surface profile pattern for this particular case when the upstream water depths in the main vegetated channel are higher than the smooth channel water depths for the same flow rates. Two main simulation groups were considered in the current manuscript for investigating the different flow discharges and for investigating the lack of water depth measurement data. Each group was simulated by twelve ANN models to accommodate for the two weeds' densities and for the six distributaries' operation cases.

The results of the various developed ANN models showed that the ANN technique was very accurate and successful in simulating the water surface profile in the investigated flume with the existence of submerged aquatic weeds with two different densities and for all the different distributaries' operation cases. This conclusion is considered very encouraging for the scientific community to utilize the ANN approach in predicting the impacts of submerged aquatic weeds on the hydraulic performance of the Egyptian open channels within the irrigation and drainage networks. In addition, the implementation of the ANN concepts and models is foreseen to provide irrigation engineers with very useful information regarding the direct impacts of the aquatic weeds infestation on the hydraulic performance of open channels with almost no cost. This information is considered very essential to distribution and design irrigation engineers for their future water distribution plans along the different irrigation channels.

10. Guidelines for applying the ANN to a field scale channel

As mentioned previously, if the ANN models were to be applied to a field application, not laboratory experiment, the type of input data that needs to be collected would be the same as listed in Table 1. Similarly, the 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. However, in some real field earth open channels, the natural cross section does not remain constant along the channel distance as in laboratory experiments. Therefore, the cross section dimensions should be considered as input variables along the channel's distances besides what were mentioned in Table 1.

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