Development of Artificial Neural Network Model for Simulating the Flow Behavior in Open Channel Infested by Submerged Aquatic Weeds

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Most of surface water ways in Egypt suffer from the infestation of aquatic weeds especially submerged ones which cause lots of problems for the open channels and the water structures such as increasing water losses, obstructing the water flow, and reducing the efficiency of the water structures. Accurate simulation of the water flow behavior in such channels is very essential for water distribution decision makers. 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 present study aims towards introducing the use of ANN technique to model and predict the impact of the existence of submerged aquatic weeds on the hydraulic performance of open channels. Specifically the current paper investigates utilizing the ANN technique in developing a simulation and prediction model for the flow behavior in an open channel experiment that simulates the existence of submerged weeds as branched flexible elements. This experiment was considered as an example for implementing the same methodology and technique in a real open channel system. The results of current manuscript showed that ANN technique was 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.

Key Words: 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 the agricultural lands allover the world. Egypt is no exception from this fact where 33,000 km length of canals supplies irrigation water to the cultivated lands. However, the drained water is collected in Egypt through 16,000 km length of open drains. The main task and responsibility of the 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, ..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. For the sake of not making this introduction very long, only the most recent literature will be

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described in this section.

Regarding the characteristics of flow in open channels with rigid roughness, Nagy and Watanabe (1999) investigated, through experimental and numerical studies, the tractive shear stress in a movable bed of open channels covered with non-submerged rigid vegetation. In this study, the vegetation was simulated by vertical rigid cylinders of bamboo sticks with diameter of 0.3 cm and arranged in a staggered shape on the sandy bed. The total stress as well as the tractive shear stress was obtained from the experimental results. In addition, the threshold movement of particles was experimentally observed. Utilizing the experimental data, the authors developed a mathematical relation between the total shear stress and the tractive shear stress within the vegetation zone. Through these analyses, the effect of vegetation density on the critical shear stress values was profoundly assessed. On the other hand, the authors presented a numerical model based on the fluid dynamics equations for no-uniform two dimensional flows. The authors concluded that the developed model was a powerful tool to estimate the surface water levels, mean cross section velocity, and drag force due to existence of vegetation and tractive bed shear stress along the channel. Later Nagy and Watanabe (2000) investigated the incipient motion at the bottom of streams covered with rigid vegetation. Three patterns of uniform size bed material were experimentally studied. Two types of flume experiments were carried out for non-uniform and uniform flow conditions. Three densities of long non-submerged vegetation plants were alternatively simulated. Similar to the authors' study presented in 1999, the vegetation in the current study (2000) was simulated by vertical rigid cylinders of bamboo sticks with a diameter of 0.3 cm and arranged in a staggered shape on the sandy bed. Utilizing the various experiments' data, a new expression for the boundary shear stress ratio was developed using the linear regression analysis. The authors showed that the increase of vegetation density at the bottom of streams caused a decrease in the ratio of tractive stress to the total applied stress. In addition, the authors developed and presented a modified shield's diagram for incipient motion in streams with rigid vegetation. Finally, the authors presented analytical expression for the critical boundary stress considering the vegetation density.

Regarding the characteristics of flow in open channels with flexible roughness, El-Samman (1995) studied, experimentally, the effect of submerged weeds' distribution over the wetted perimeter and weeds density on the characteristics of trapezoidal vegetated channels. Throughout this extensive experimental work, the author has reached a general conclusion which was the significant impacts of the submerged weeds' distribution and densities' variations on the flow capacity, canal efficiency, channel maintenance, and head loss. In addition, the author of this study developed an empirical mathematical formula describing the relationship between the equivalent Manning's roughness and the product of the average velocity and hydraulic radius. Finally and utilizing all the collected data from the experimental works, the author presented the effect of submerged weeds (distribution and density) on the water flow reduction using empirical mathematical formulations. In 1999, El-Samman continued his line of research by conducting a study that involved many experimental works to investigate the effect of aquatic weeds cutting on the water surface profile, velocity distribution, and hydraulic efficiency of open channels. Throughout the extensive experimental and statistical analyses efforts, the author concluded that the presence of aquatic weeds increases the channel water surface slope and the hydraulic efficiency of the channel was reduced with the reduction of weeds' height by cutting. In addition, the author stated that the aquatic weeds were responsible for the non-uniformity of the flow. Finally, the author reached a general conclusion that the control of aquatic weeds by cutting to reduce their heights was not a useful method to improve the hydraulic efficiency of channels.

It is quit clear from the literature mentioned previously that the hydraulic efficiency of open channel with aquatic weeds infestation has been extensively investigated throughout experimental work. However, no modeling efforts were performed to simulate the behavior of water surface profile of open channels infested by submerged weeds for the various weeds densities and distributions. In addition, no efforts were performed to model the prediction of the water surface profile behavior when the distribution and densities of aquatic weeds change.

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. 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, several researchers have incorporated ANN technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. Abdin and Abdeen (2005) 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 Abdin and Abdeen (2005) study showed that ANN method with less computational efforts was very efficiently capable of simulating and predicting the stochastic behavior of the well draw down resulted from the continuous constant pumping in the middle of a confined aquifer with subsurface heterogeneous hydraulic conductivity. 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.

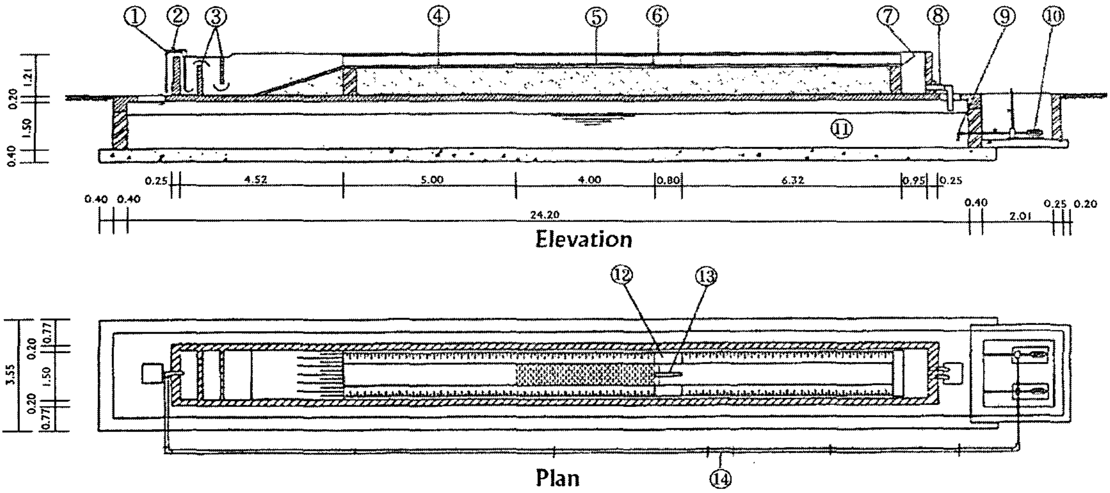
It is quit clear from the previously presented literature that ANN technique showed its applicability in simulating and predicting the behavior of different hydraulic problems. Therefore, the presented study is aimed towards utilizing the ANN technique in modeling the impact of submerged aquatic weeds on the water surface profile behavior in open channels.

2. Problem Description

The current paper investigates the problem of the existence of submerged aquatic weeds in open channels and their impacts on the flow behavior in these channels. Specifically, the current study presented in this manuscript utilizes the ANN technique in developing a simulation and prediction model for the flow behavior in open channels infested by submerged aquatic weeds. 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 Osman, 2003 in his Master Thesis. Detailed description about this experimental work is presented in the following section.

2.1 Experimental work

The experimental work performed by Osman, 2003 for his Master 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 and has 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 Figure 1 as they were presented in the Master Thesis of Osman, 2003. On the other hand, the underground reservoir is shown in Figure 2. The inlet part of the flume and the basin are shown in Figure 3. The dimensions of the inlet part are 4.52 m long, 1.63 m wide, and 1.16 m height besides two vertical reinforced concrete walls to decrease any excessive energy by the jets diffusion vertically through a short distance. However the basin dimensions are 3.0 m long, 1.63 m wide, and 1.21 m height besides a ramp with 3 : 1 slope is allocated 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. Figure 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 Egyptian canals infested by weeds as stated by Osman, 2003 in his Thesis. The reader is referred to the



1 5 inch diameter pipe
2 Control valve
3 Turbulence elimination
4 Horizontal bed trapezoidal flume
5 Branched flexible roughness
6 Sluice gate
7 Tilted tail gate
8 Inch diameter drain pipe
9 5 inch diameter suction pipe
10 Group of motor and pump
11 Underground reservoir
12 Wing wall
13 Pier
14 Current flow meter

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

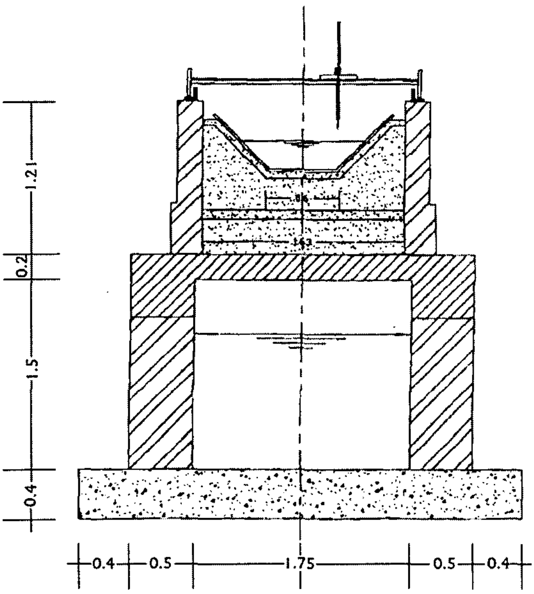


Fig. 2 Underground Reservoir for the experimental flume

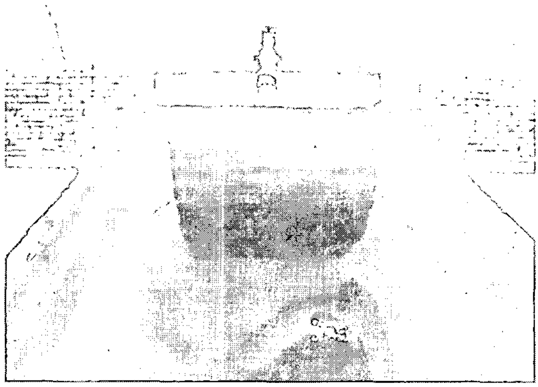


Fig. 3 The flume inlet and the basin

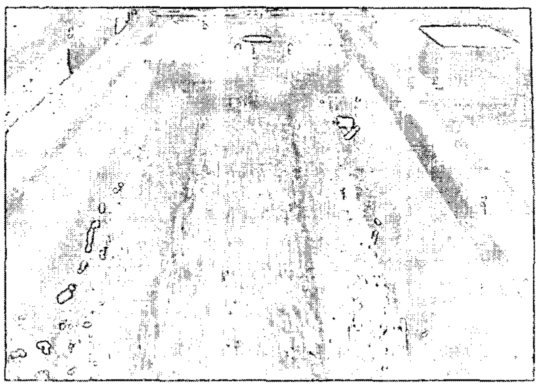


Fig. 4 The flume trapezoidal cross section covered by the plastic sheets

Osman's study presented in 2003 for complete details about all experiment's description, materials, and measuring tools.

As shown in Figure 1, the sluice gate is fixed at the downstream end of 4 m bed segment from the flume that is covered by the plastic roughness elements. During the experimental work of Osman, 2003, the author ran his experiments for the smooth case first with various flow discharges and gate openings. Thereafter he ran the experiment with same flow discharges and gate openings pattern to produce a gate upstream heading up for the water surface profile that is higher than the smooth case. The ANN models developed in the current study investigates the prediction pattern for this particular case when the upstream gate water depths in a vegetated channel are higher than the smooth channel water depths for the same flow and gate openings patterns.

2.2 Data categories utilized for the ANN

Throughout the experiments, various data inputs were used as a sensitivity analysis for the water surface behavior in the vegetated channel. Five discharges (37, 34, 31, 28, and 25 l/s) and five sluice gate openings (17, 15, 13, 11, and 9 cm) were used in the study presented by Osman, 2003 and they will also be utilized in the development of the ANN model within the current presented study. In addition, two weeds densities (D1 and D2) were also used in the experimental program representing the number of flexible roughness elements distributed per unit area. These two densities, D1=0.25 and D2=0.0625 No. of stem/cm^2, are also used for the development of the ANN models through the current study. Throughout the experimental works, the water surface profile depths were measured along the flume length for the various parameters (flow discharges, sluice gate openings, and two weeds densities) mentioned previously. These water depths' realizations are the main outputs for the developed ANN models within the current presented study.

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 Figure 5. This neuron is connected to multiple inputs and produces a single output. Each input is modified by

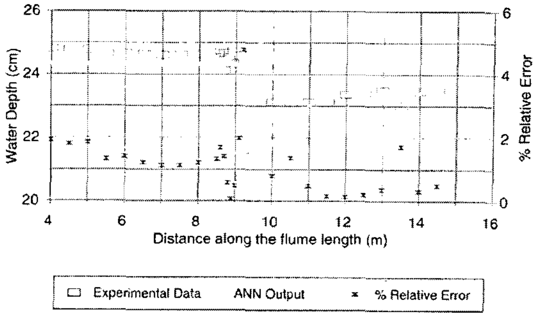


Fig. 5 Typical picture of a model neuron that exists in every neural network

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 jth neuron in any layer is described by two sets of equations as follows:

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

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

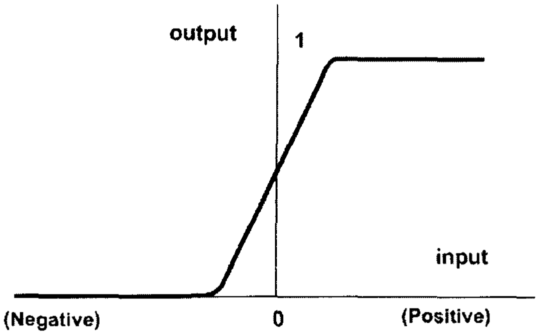


Fig. 6 The sigmoid activation function used in most of the designed networks

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 6. 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 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.

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 :

$$w_{ij}=w'_{ij}+LR(e_jX_i) \tag{3}$$

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 ith 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 open channels infested by aquatic weeds using ANN technique, the experimental work of Osman, 2003 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 sluice gate openings, several simulation cases are considered in this study. These simulation cases can be divided into two 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 plastic weeds. While the second group simulates and models the impact of sluice gate openings on the water surface profile in the experimental flume. For both investigated groups, two weeds densities, as mentioned earlier, are considered within the current presented study.

7. Neural Network Design

To develop a neural network in order to simulate the impact of the aquatic weeds existence in open channels on the water surface profile 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

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)	Weeds' density	Sluice Gate openings (cm)	Water Depth along the flume (cm)
Second Group	Different Sluice Gate Openings	Flow Discharge (l/s)	Distance along the flume (m)	Weeds' density	Sluice Gate openings (cm)	Water Depth along the flume (cm)

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 weeds densities have been utilized for the development of the different ANN models in the current research. In addition, two ANN models have been designed for interpolation and extrapolation data sets.

Regarding the different flow discharges group, the interpolation ANN model considers the neural network training for $Q=25,28,34$, and 37 (l/s) and the prediction and testing processes for the developed model are for $Q=31$ (l/s). For the training and testing processes, the sluice gate opening is kept constant at $a=9.0$ (cm). The extrapolation ANN model, for this group of simulations, considers the network training for $Q=25,28,31$, and 34 (l/s) and the prediction and testing process for the developed model are for $Q=37$ (l/s); and the sluice gate opening is kept constant at 9.0 (cm).

Regarding the different sluice gate openings simulation group, the interpolation ANN model considers the network training for 9, 11, 15, and 17 (cm) and the prediction and testing process for the developed model are for $a=13$ (cm) ; and the flow discharge is kept constant at 34 (l/s). While the extrapolation ANN model considers the network training for 9, 11, 13, and 15 (cm) and the prediction and testing process for the developed model are for $a=17$ (cm) ; and the flow discharge is kept constant at 31 (l/s). These two sub-simulation cases are developed to prove the concept of using ANN models for investigating the water surface profile in open channels infested

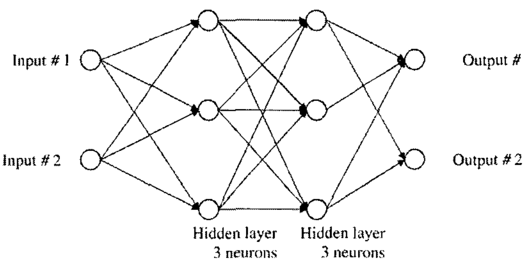


Fig. 7 General schematic diagram of a simple generic neural network

by aquatic weeds that considers all data possibilities. It is probably worth mentioning here that two ANN models are developed for each interpolation and extrapolation case for the two simulation groups utilizing the two weeds' densities mentioned previously.

On the other hand, if the ANN models were to be applied to a field application, not laboratory experiment, the type of input data 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 open channels infested by aquatic weeds based on minimizing the Root Mean Square Error (RMS-Error). Figure 7 shows a schematic diagram for a generic neural network.

Due to the extreme difficulty of the investigated

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

Simulation case	Sub-simulation case	Weeds Density	No. of layers	No. of neurons in the different layers					
				Input	1^{st} hidden	2^{nd} hidden	3^{rd} hidden	4^{th} hidden	Output
Different Flow Discharges	Interpolation	0.25	5	4	4	4	4	-	1
		0.0625	6	4	6	6	6	6	1
	Extrapolation	0.25	5	4	4	4	4	-	1
		0.0625	5	4	4	4	4	-	1
Different Sluice Gate Openings	Interpolation	0.25	5	4	9	9	8	-	1
		0.0625	5	4	10	10	10	-	1
	Extrapolation	0.25	5	4	6	6	6	-	1
		0.0625	5	4	6	6	6	-	1

problem in the current presented study, one specific neural network is designed and developed for each sub-simulation case (Interpolation and Extrapolation) among the two simulation cases for the two main 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 very important to mention here that some of the developed models incorporated the sigmoid activation function presented in Figure 3, while other models utilized the Hyperbolic activation function. This choice for this 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, Shin (1994). The Sigmoid function can be expressed mathematically as follows:

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

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 is can be discriminating, Shin (1994).

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 training process. LR=1 for all developed ANN models.

Momentum (**M**): determines the "life time" of a correction term as the training process takes place. M=0.9 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=0.01 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 (1994), 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. 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 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 flume that is infested by aquatic weeds. The amount of data utilized for the ANN model 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 interpolation and extrapolation models as well as the two weeds densities.

8.1.1 Interpolation sub-simulation case

Two weeds densities have been considered for this sub-simulation case. Figure 8 shows the testing and prediction results for the developed ANN model, where its layers structure is presented in Table 2, for weeds density equals 0.25 for the interpolation case. Specifically, this figure shows comparison between the water surface profile from experimental data, reserved for testing the developed ANN model, and the water surface profile computed using the developed ANN model. In addition, the percentage relative errors between the experimental and ANN computed water depths data are presented in this Figure. These results show that the ANN model is successful in predicting the experimental data with maximum per-

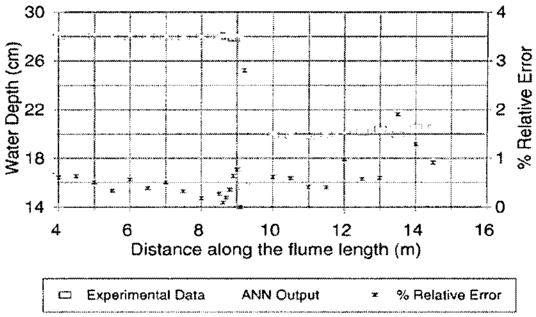


Fig. 8 Testing and prediction results for the interpolation case — different flow discharges group — weeds density=0.25 No. of stem/cm^2

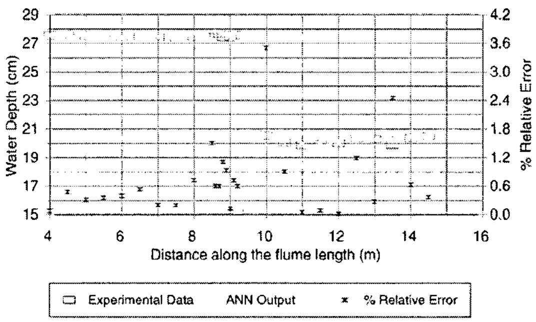


Fig. 9 Testing and prediction results for the interpolation case — different flow discharges group — weeds density=0.0625 No. of stem/cm^2

centage relative error equals to 3%. This high accuracy in the performance of the developed ANN model shows how powerful the ANN technique in simulating the water surface profile in flumes infested by aquatic weeds for this specific density (0.25). On the other hand, Figure 9 shows the same series of results for weeds density equals 0.0625. It can be easily shown from the comparison between the experimental data and the ANN model's results as well as the percentage relative errors, presented in this Figure, that the developed ANN model is quit successful in simulating the water surface profile in the investigated flume with aquatic weeds infestation.

8.1.2 Extrapolation sub-simulation case

Full description about this simulation case was presented in section 7 of the current manuscript as well as the data categories utilized for each of the training and testing processes. In addition, the architecture of the ANN, designed for this case, is presented previously in Table 2. Similar to what was mentioned for the interpolation case; two weeds densities have been considered for this extrapolation case. Figure 10 shows the comparison between the developed ANN model results and corresponding experimental data as well as the percentage relative errors between them for weeds density equals 0.25. The results presented in this figure shows that the maximum percentage relative error was less than 4% which indicates directly the high accuracy of the developed ANN model in simulating the water surface profile in the investigated flume. Regarding the weeds density 0.0625, Figure 11 shows the comparison results mentioned previously associated with the percentage relative errors. Again, for this case of weeds density, the maximum relative error between the developed ANN model and experimental data was less than 3% which also indicates that the developed ANN model was very successful in simulating the physical behavior of the water surface profile in the studied flume that was infested by aquatic weeds.

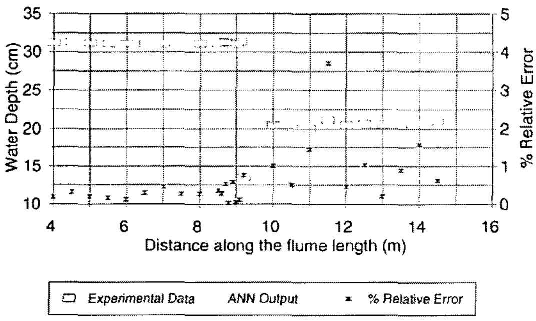


Fig. 10 Testing and prediction results for the extrapolation case — different flow discharges group — weeds density=0.25 No. of stem/cm^2

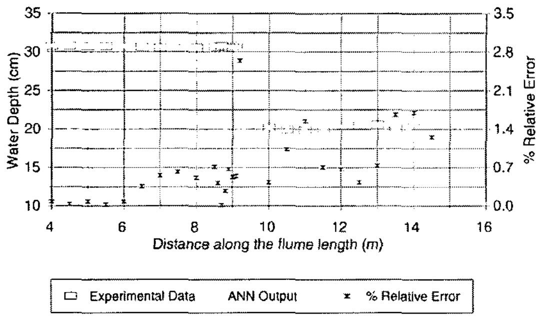


Fig. 11 Testing and prediction results for the extrapolation case — different flow discharges group — weeds density=0.0625 No. of stem/cm^2

8.2 Different sluice gate openings

As clearly stated previously, this simulation group tackles the issue of the impact of different sluice gate openings on the water surface profile in the flume that is infested by aquatic weeds. The amount of data utilized for the ANN model training and testing was described in details in section 7, and therefore, the current section presents the results of the testing and prediction processes for these models regarding the interpolation and extrapolation models as well as the two weeds densities.

8.2.1 Interpolation sub-simulation case

Two weeds densities have been considered for this simulation case. Figure 12 shows the results of the comparison between the developed ANN model and the corresponding experimental data as well as the percentage relative errors between them for weeds density equals 0.25. The maximum relative error presented in this figure was less than 10% which indicates accurate trust in the developed ANN model in simulating the water surface behavior in the investigated problem. Despite the fact that this error was more than what was com-

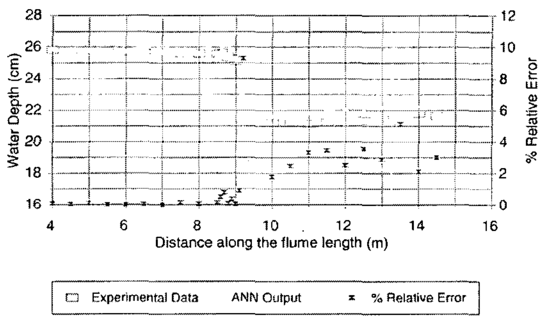


Fig. 12 Testing and prediction results for the interpolation case — different sluice gate openings, group — weeds density=0.25 No. of stem/cm^2

puted for the flow discharges group of simulations, but it is still considered small errors considering the impact of extensive aquatic weeds existence on changing the water depths along the investigated flume. On the other hand, Figure 13 shows the comparison results between the developed ANN model and experimental data as well as their associated percentage relative errors for weeds density equals 0.0625. The results presented in this figure shows that the maximum percentage relative error was less than 5% which directly indicates that the developed ANN model for this case with 0.0625 weeds density was very successful in simulating the water depths changes within the investigated flume. It is probably worth mentioning here that the case of extensive weeds density (0.25 weeds density) results in less accurate prediction for the developed ANN compared with the small weeds density case (0.0625 weeds density). This finding can be directly reasoned to the impact of more weeds on changing the water depths along the flume.

8.2.2 Extrapolation sub-simulation case

Full description about this simulation case was presented in section 7 of the current manuscript as well as the data categories utilized for each of the training and testing processes. In addition, the architecture of the ANN, designed for this case, is presented previously in Table 2. Similar to what was mentioned for the interpolation case; two weeds densities have been considered for this extrapolation case. Figure 14 shows the comparison between the developed ANN model results and the corresponding experimental data as well as the percentage relative errors between them for weeds density equals 0.25. The results presented in this figure shows that the maximum percentage relative error was less than 3.5% which indicates directly the high accuracy of the developed ANN model in simulating the water surface profile in the investigated flume. Regarding the weeds density 0.0625, Figure 15 shows the comparison results between the developed ANN model and the corresponding experimental data associated with the percentage relative errors. For this case of weeds density, the maximum percentage relative error between the developed ANN model and experimental data was less than 5% which also indicates

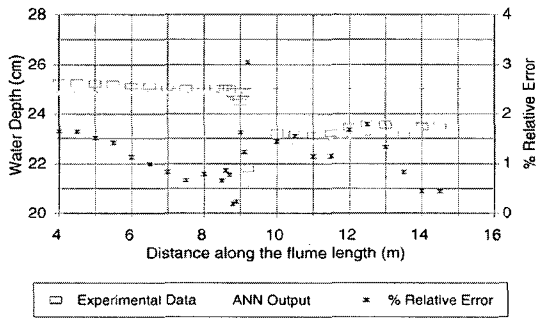


Fig. 14 Testing and prediction results for the extrapolation case — different sluice gate openings group — weeds density=0.25 No. of stem/cm^2

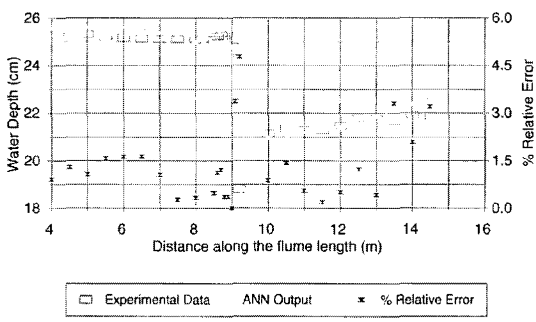


Fig. 13 Testing and prediction results for the interpolation case — different sluice gate openings group — weeds density=0.0625 No. of stem/cm^2

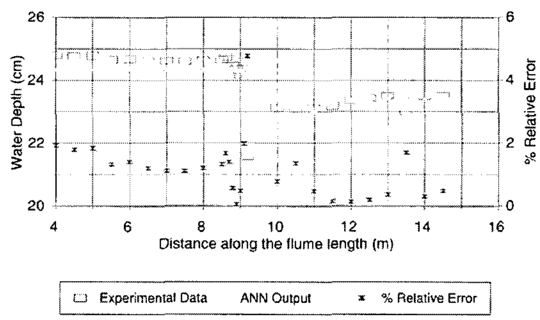


Fig. 15 Testing and prediction results for the extrapolation case — different sluice gate openings group — weeds density=0.0625 No. of stem/cm^2

that the developed ANN model was very successful in simulating the physical behavior of the water surface profile in the studied flume that was infested by aquatic weeds.

9. Summary

The majority of the Egyptian surface water canals suffer from the infestation of submerged aquatic weeds. The existence of these weeds causes lots of 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 existence.

Lots of experimental work was performed to investigate and measure the impacts of these weeds existence 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 modeling approach has proven its capabilities in providing very useful information and simulating various physical phenomena. Specifically, the Artificial Neural Networks (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 impacts of submerged aquatic weeds existence on the water surface profile in an experimental flume. Since the implementation of the ANN technique in studying the hydraulics' behavior of open channels, infested by submerged aquatic weeds, 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 are infested by aquatic weeds. Specifically, the experimental case data utilized in the current study considers several flow discharges that are similar to the ones for smooth case (channel without aquatic weeds infestation). This particular flow case results in a heading up for the water surface profile upstream the sluice gate within the experimental flume more than the smooth channel case.

10. Conclusion

Several simulation cases were considered in the current study. Specifically, different flow discharges and sluice gate openings are considered as the two main simulation groups. In addition, two weeds densities were utilized for these two simulation groups. Different ANN models were developed in the current study for the various investigated simulation cases. Part of the experimental data was utilized for the training process of the developed ANN models ; however, the rest of the data was used for testing the prediction power of the developed models.

The results of the various developed ANN models showed that 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. 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 the 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 the distribution and design irrigation engineers for their future water distribution plans along the different irrigation channels.

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