Neural network model for predicting flow characteristics in irregular open channels

Mostafa A. M. Abdeen
Dept.. of Eng. Mathematics and Physics, Faculty of Eng., Cairo University. Cairo, Egypt

Water surface profile determination in open channels is very essential for better irrigation and water management. Most of the open channels in Egypt have irregular cross section. Therefore, any computation to determine the water surface profile in these channels has to take into consideration the random irregularity of the cross section along the channel. Due to this irregularity, the flow is not uniform and it has to be considered as gradually varied flow. Artificial Neural Network (ANN) has been widely used in the past five years in civil engineering applications. The present study aims towards introducing the use of ANN technique to model and predict the hydraulic characteristics of the water surface profile in natural open channels. Synthetically generated data was used in the study to show the applicability of using ANN technique for modeling natural open channel behavior. The present study implemented ANN technique to predict flow depths and average flow velocities along the channel reach when the geometrical properties of the channel cross sections were measured or vice versa. The results of this study show that ANN technique is capable, with small computational effort and high accuracy, of predicting the different hydraulic characteristics of irregular open channels.

من الضروري تحديد مناسيب سطح المياه فى القنوات المكشوفة للتحكم في نظام الري والحفاظ على المياه و أدارتها بكفاءة . تتميز أغلب القنوات المكشوفة فى مصر بقطاع غير منتظم لذلك عند حساب منسوب سطح المياه لابد من الآخذ فى الاعتبار شكل القطاع غير المنتظم وتغيره على طول مسار القناة . ونتيجة طبيعية لهذه التغيرات في القطاع المائي فان معدل سريان المياه لا يمكن اعتباره منتظم ولابد أن يدرس على أنه متغير . تم استخدام الشبكات العصبية الاصطناعية في تطبيقات عديدة في محال الهندسة المدنية وقد أثبت نجاحه . البحث المقدم هنا يدرس استخدام هذه الشبكات في بناء نموذج رياضي لحساب مناسيب سطح المياه في القنوات المكشوفة ذات القطاع المتغير و التنبؤ عن طريق هذه الشبكات بالخواص الهيدروليكية لهذه القنوات باستخدام أقل عدد من البيانات المتاحة في الطبيعة . و قد نجحت هذه الدراسة في محاكاة خصائص القطاع المائي و كذلك السرعة المتوسطة في قناة مكشوفة ذات قطاع متغير الشكل ومعامل احتكاك محيطه المبتل . هذه القناة قد تم دراستها في بحث سابق و قد استخدمت نتائج تلك الدراسة لبيان تطبيق و فعالية الشبكات العصبية الاصطناعية في مجال هيدروليكا القنوات المكشوفة في هذا البحث التي أثبتت نجاحها التام في هذا المحال و ذلك قد تم توضيحه من خلال النتائج المقدمة .

Keywords: Neural networks, Open channel hydraulics, Irregular cross section channels

1. Introduction

Water surface computations in irregular open channels require collecting several data items and thereafter using numerical techniques to accurately perform these computations. Abdin and Abdeen [1] presented a comprehensive study that developed a straight forward methodology to compute the water surface profile in irregular channels based on certain data items for the irregular cross sections that had to be collected along the channel.

Artificial Neural Network (ANN) has proven its capability in modeling several water engineering problems. Kheireldin [2] presented a study to model the hydraulic characteristics of severe contractions in open channels using ANN technique. The results of his study showed the applicability of using the ANN approach in determining relationship between different parameters with multiple input/output problems. These results proved that the performance of the ANN in simulating the hydraulic behavior of severe contraction was a complete success. Tawfik et al. [3] showed the applicability of using the ANN technique for modeling rating curves with hysteresis sensitive criterion. Ramanitharan and Li [4] applied in their study the ANN with back-propagation algorithm for modeling ocean waves; significant wave height and period were taken into account for their study. Fourteen different networks were tested in the analyses to choose the best one based on the Root Mean Square Error (RMS) for the forecasting purpose. The study showed the applicability of modeling the ocean wave forecasting with different neural networks for wave height and period. Minns [5] investigated the general application of ANN in modeling rainfall runoff process. The ANN was applied to both real and theoretical catchments with both measured and synthetically generated data. 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 depths. Solomatine and Toorres [6] presented a study of using ANN in the optimization loop for the hydrodynamic modeling of reservoir operation in Venezuela. They stated that the ANN representation of the hydrodynamic/hydrologic model can easily allow the incorporation of the various modeling components into the optimization routines.

It is proven from the literature that ANN technique is capable of modeling several hydraulic and water resources problems. The present study aims towards applying this technique to model and predict the water surface profile in irregular open channels.

2. Artificial neural network

The ability of the brain to perform several difficult operations and recognize complex patterns has formed the subject matter of cognitive psychology that has in turn strongly influenced the study of artificial intelligence (AI), Minns [5]. ANN came to reality with the aid of the high technology available represented in fast computers that can efficiently model sophisticated physical phenomena. In brief, ANN is a mathematical technique that simulates the behavior of the human's brain in understanding and learning from previous experience the physical nature of a given problem. Generally, ANN consists of layers of processing units (representing biological neurons) where each processing unit (neuron) in each layer is connected to all processing units in the adjacent layers At least three layers have to be implemented to simulate any proposed problem. The first layer is the input layer where all the inputs to the problem are represented. The third layer is the output layer where all the target outputs are stored. The second layer is a non-visible one and it is called hidden layer. The number of hidden layers varies according to the problem. Each of the mentioned layers consists of several neurons according to the task of this layer. The first layer (input layer) consists of several neurons each one of them represents one input for the studied problem. On the other hand, the output layer consists of several neurons representing the several output for the problem. While the hidden layers are structured based on the problem needs so that the whole network can understand and simulate the physical behavior of the problem. Probably, it is worth mentioning here that the ANN technique depends mainly on an elementary training stage to adjust its different modeling coefficients. Thereafter, the resulted ANN model can be applied for the prediction stage.

2.1. Neural network structure

Neural networks are models of biological neural structures. The starting point for most networks is a model neuron as shown in fig. 1. This neuron is connected to multiple input and produces a single output. Each input is modified by a weighing value (w). The neuron will combine these weighted inputs and, with reference to a threshold value and an activation function, will determine its output. This behavior follows closely the real neurons work of the human brain. In the network structure, the input layer is considered a distributor of the signals from the external world while hidden layers are considered to be feature detectors of such signals. On the other hand, the output layer is considered a collector of the features detected and the producer of the response.

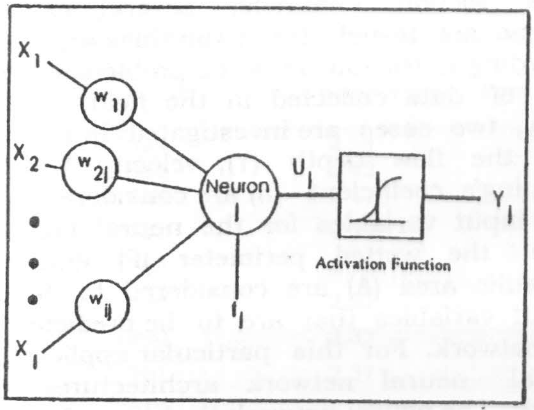

Fig. 1 Typical picture of a model neuron that exists in every neural network.

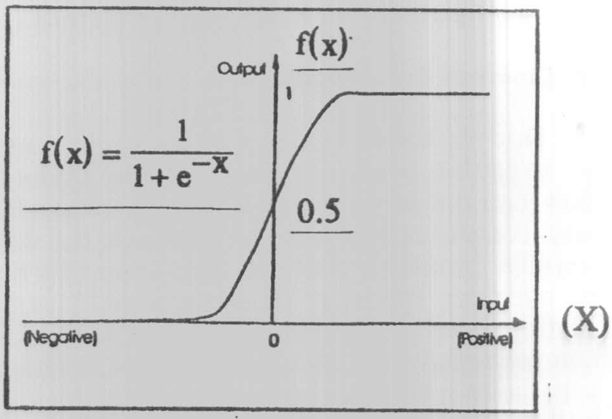

Fig. 2. The Sigmoid activation function used in the designed networks.

2.2. Neural network operation

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 eqs. [2]:

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

and

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

For every neuron, *j*, in a layer, each of the *i* inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th}. This activation function can take several forms but the most commonly used one is the Sigmoid function which has an input to output mapping as shown in fig. 2. The resulting output, Y_j, is an input to the next layer or it is a response of the neural network if it is the last layer. There is some other activation functions that are commonly used by the researcher in this field such as step, linear, hyperbolic, and Gaussian functions. In applying the neural network technique in this research neutralist software [7] was used.

2.3. Neural network training

The next step in neural network procedure 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 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 eqs. [2]:

$$w_{ij} = w_{ij}^{©} + LR * e_j * X_i, \tag{3}$$

and,

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

Where, w_{ij} is the corrected weight, w'_{ij} is the previous weight value, LR is the learning rate,

e_j is the error term, X_i is the i^{th} input value, Y_j is the output, and d_j is the desired output.

3. Problem description

Due to the irregularity of the cross section in irregular channels, most of the time the flow can not be considered uniform. Therefore, any computations aim to evaluate the water surface profile in natural open channels have to consider the flow to be gradually varied. Abdin and Abdeen [1] presented a comprehensive numerical computational scheme to estimate the water surface profile in natural open channels. They developed straightforward methodology to evaluate the geometrical properties of the irregular cross sections along the channel and thereafter applied the gradually varied flow differential equation to determine the water surface profile using synthetically generated data. In the present paper, the ANN technique is applied to these synthetic data for the purpose of predicting the water surface profile and the average flow velocities along the channel when the geometrical properties are measured or vice versa. The mathematical and hydraulic input parameters for the example solved by Abdin and Abdeen [1] in their numerical study are listed in table 1. The reader is referred to their paper for the complete set of the input data of this example including the normally distributed Manning's roughness coefficient (n) and the six irregular cross sections data. Their results of the simulation along the channel reach are presented in table 2.

4. Neural network design

To develop a neural network in order to simulate the hydraulic characteristics of the gradually varied steady state flow in irregular cross section channels, several network designs are tested. Input variables are tested according to the nature of the problem and the type of data collected in the field. In this study, two cases are investigated. In the first case the flow depth (Y), velocity (V), and Manning's coefficient (n) are considered to be the input variables for the neural network while the wetted perimeter (P) and the hydraulic area (A) are considered to be the output variables that are to be predicted by the network. For this particular application, several neural network architectures are tested. The neural network that gives the best results is chosen to be the selected network that simulates this study case. Fig. 3 shows the schematic diagram for a generic neural network. In our study case, the chosen network consists of 4 layers including the input and output ones. The input layer consists of 3 neurons, each of the two hidden layers consists of 5 neurons, and the output layer consists of 2 neurons. The Sigmoid function as shown in fig. 2 is used as the activating function for all of the neurons in the chosen design. This particular function typically has a narrow region about zero wherein the output will be roughly proportional to the input, but outside this region the Sigmoid function will limit to full inhibition or full excitation [7]. The Sigmoid function can be expressed mathematically as follow [2]:

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

From eq. 5, it is clear that the function value (f(x)) lies between 0 and 1. The training parameters of the chosen network for this study case are presented in table 3.

Table 1
Mathematical and hydraulic parameters (after Abdin and Abdeen [1])

Parameter	Value	Units
Units system	'SI'	-
Number of input stations	6	-
Computational tolerance	0.00001	-
ΔX	60	m
Water depth (initial value)	2.16	m
Water discharge	14.16	m^3/s
X-beginning	1524	m
X-end	3353	m

Table 2
Original data for the reach under study (results of simulation after Abdin and Abdeen)

Distance(m)	Flow depth Y (m)	Flow velocity V (m/s)	Manning coef. n	Perimeter P(m)	Area A (m2)
1524	2.44	0 70	0.035	13.58	20.21
1585	2.42	0 71	0.025	13.56	19 99
1646	2 41	0 71	0.035	13.57	19.89
1707	2.39	0.72	0.025	13.55	19.65
1768	2 38	0.73	0.025	13.55	19.54
1829	2.37	0.73	0.017	13.55	19.44
1890	2.37	0.73	0.015	13.58	19.41
1951	2.37	0.73	0.027	13.61	19.40
2012	2.36	0.73	0.033	13.60	19.26
2073	2.34	0.75	0.025	13.57	19.01
2134	2.33	0.75	0.020	13.57	18.88
2195	2.33	0.75	0.020	13.58	18.82
2256	2.32	0.76	0.028	13.59	18.75
2316	2.31	0.77	0.012	13.58	18.56
2377	2.31	0.76	0.035	13.60	18.56
2438	2.29	0.84	0.019	13.10	16.91
2499	2.28	0.91	0.012	12.66	15.50
2560	2.28	1.00	0.026	12.22	14.15
2621	2.24	1.15	0.029	11.59	12.35
2682	2.28	1.19	0.016	10.56	11.97
2743	2.37	1.26	0.014	8.90	11.26
2804	2.29	1.35	0.031	8.99	10.51
2865	2.08	1.65	0.019	8.67	8.61
2926	1.84	2.19	0.027	7.71	6.46
2987	1.78	2.15	0.024	7.83	6.61
3048	1.85	1.84	0.036	8.62	7 70
3109	1.63	2.13	0.023	8.20	6.64
3170	1.73	1.81	0.028	9.02	7.84
3231	1.80	1.59	0.019	9.68	8.90
3292	1.99	1.26	0.014	10.63	11 21
3353	2.19	1.02	0.018	11.45	13.86

Table 3
List of network parameters

Network Parameter	Value
Learning rate	1.0
Momentum	0.9
Training tolerance	0.1
Testing tolerance	0.3
Input noise	0.0
Function gain	1.0
Scaling margin	0.1
Calculation method	Fixed point

These parameters can be described with their tasks as follows:

Learning Rate; determines the magnitude of the correction term applied to adjust each neuron's weights when training.

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

Training Tolerance; defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process.

Testing Tolerance; it is similar to Training Tolerance, but it is applied to the neural network outputs and the target values only for the test data.

Input Noise; provides a slight random variation to each input value for every training epoch.

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

Scaling Margin; adds additional headroom, as a percentage of range, to the rescaling computations used by neuralyst in preparing data for the neural network or interpreting data from the neural network.

The second case investigated in this manuscript considers the wetted perimeter, flow area, and Manning's roughness coefficient are the input variables for the neural network while the flow depth and velocity are considered to be the output variables that are to be predicted by the network after its learning. Again For this application, several neural network architectures are tested. The neural network that gives the best results is chosen to be the selected network that simulates this study case. It consists of 4 layers including the input and output ones. The input layer consists of 3 neurons, the first hidden layer which represents the second layer in the network architecture consists of 4 neurons, the second hidden layer which represents the third layer in the network consists of 3 neurons, and the output layer consists of 2 neurons. Once again the Sigmoid function is chosen to be the activation function for this case also since it is proven to give the best prediction for the outputs. The training parameters of the chosen network for this study are similar to the ones selected for the first case network.

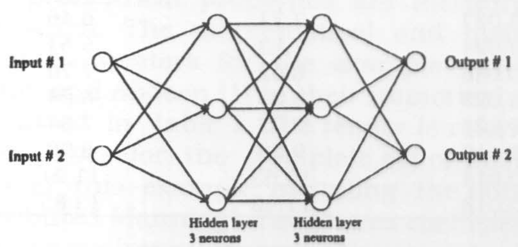

Fig. 3 General schematic diagram of a generic neural network

5. Results and discussion

In the first case investigated in this manuscript, the output of the designed neural network is the wetted perimeter. The hydraulic area of the irregular cross sections along the channel while the flow depth and velocity are considered to be the input variables or the measured data if it was field experiment. The results of the chosen network compared with the original date are presented in figs. 4 and 5 for the wetted perimeter and hydraulic area, respectively. Up to this point the neural network has been trained and these figures show how well trained the proposed neural network has become. In addition, some data were reserved for testing the prediction power of the proposed network. Table 4 shows results of the Artificial Neural Network in comparison with the original ones for the first case. It is clearly shown how powerful the designed network in predicting both the wetted perimeter and the hydraulic area when the flow depth and velocity are known.

For the second case studied in this paper. the output of the designed neural network are the flow depth and velocity of the irregular cross sections along the natural open channel reach while the wetted perimeter and the hydraulic area are considered to be the input variables. The results of the chosen network compared with the original data are presented in figs. 6 and 7 for the depth and velocity, respectively. These two figures show how well trained the neural network has become in simulating the water surface profile. Similar to the process adapted in the first case studied in this manuscript, some data were reserved for testing the prediction power of the proposed network. Table 5 shows results of the ANN in comparison with the original ones for the second case. It is clearly shown how powerful the designed network in predicting both the flow depth and velocity in irregular cross section open channel.

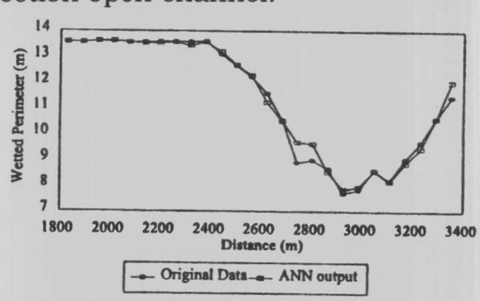

Fig. 4. Neural network output vs. the corresponding original data for the wetted perimeter in the first study case along the channel reach.

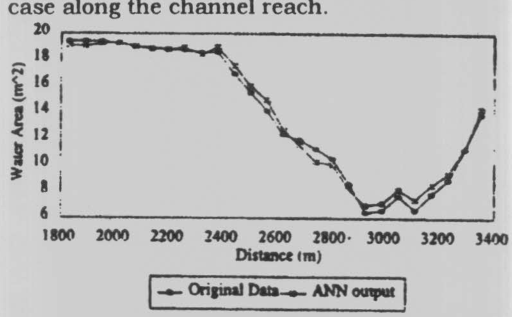

Fig. 5. Neural network output vs. the corresponding original data for the water area in the first study case along the channel reach.

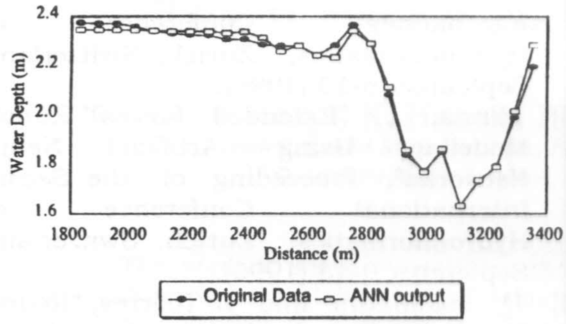

Fig. 6. Neural network output vs. the corresponding original data for the water area in the first study case along the channel reach.

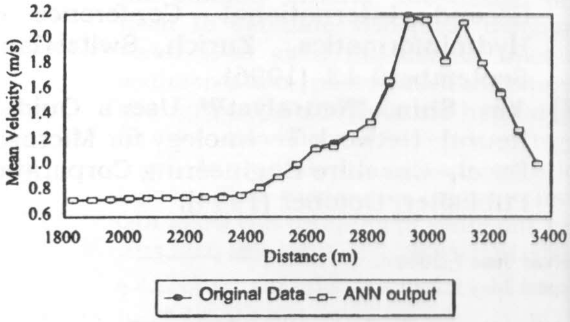

Fig. 7. Neural network output vs. the corresponding original data for the mean water velocity in the second study case along the channel reach.

6. Conclusions

The results of the neural network technique have shown that this approach is capable of identifying the relationship between different parameters with multiple input/output criterions. The artificial neural network presented in this study performs very well in simulating the water surface profile in irregular open channels. Two cases were investigated in this study and they were chosen to represent the actual field procedures for determining the water surface profile in irregular open channels. In addition, the prediction power and accuracy of the developed models (networks) for the two cases were examined and proved to be successful in identifying the different water surface profiles very accurately. Therefore, the designed networks presented in this study can be implemented in the evaluation of the water surface profile characteristics when few field data are measured.

Table 4
Comparison between results of the ANN and the corresponding ones for the first study case

Perimeter original data (m)	Perimeter evaluated output (m)	% Error in perimeter evaluation	Flow area original data (m2)	Flow area evaluated output (m2)	% Error in flow area evaluation
13.55	13.62	0,536	19,54	19.26	1.46
13.55	13.63	0,639	19,65	19.30	1.78
13.57	13.68	0,848	19,89	19.54	1.75
13.56	13.66	0,734	19.99	19.44	2.73
13.58	13.71	0,944	20.21	19.67	2.72

Table 5
Comparison between results of the ANN and the corresponding ones for the second study case

Depth-original data (m)	Depth evaluated output (m)	% Error in depth evaluation	Velocity-original data (m)	Velocity evaluated output (m)	% Error in velocity evaluation
2.38	2.35	1.4	0.73	0.73	1.3
2.39	2.35	1.7	0.72	0.73	1.5
2.41	2.35	2.4	0.71	0.73	2.9
2.42	2.35	2.7	0.71	0.73	2.3
2.44	2.35	3.4	0.70	0.73	3.8

References

[1] A. E. Abdin and M. A. M. Abdeen, "Numerical Computations of Water Surface Profile in Natural Open Channels" Proceeding the 3rd International Conference in Civil & Architecture Engineering held at the Military Technical College, Cairo - Egypt, March 3-4 (1999).

[2] K. A. Kheireldin, "Neural Network application for Modeling Hydraulic Characteristics of Severe Contraction", Proceeding of the Third International Conference, Hydroinformatics, Copenhagen – Denmark, August 24-26 (1998).

[3] M. Tawfik, A. Ibrahim, and H. Fahmy, "Hysteresis Sensitive Neural Network for Modeling Rating Curves", ASCE, Journal of Computing in Civil Engineering, Vol. 11 (3) (1997).

[4] K. Ramanitharan and C. Li, "Forecasting Ocean Waves Using Neural Networks", Proceeding of the Second International Conference on Hydroinformatics, Zurich, Switzerland, September 9-13 (1996).

[5] Minns, , "Extended Rainfall-Runoff Modeling Using Artificial Neural Networks", Proceeding of the Second International Conference on Hydroinformatics, Zurich, Switzerland, September 9-13 (1996).

[6] D. Solomatine and L. Toorres, "Neural Network Approximation of a Hydrodynamic Model in Optimizing Reservoir Operation", Proceeding of the Second International Conference on Hydroinformatics, Zurich, Switzerland, September9-13 (1996).

[7] Yin Shin, "Neuralyst™ User's Guide", Neural Network Technology for Microsoft Excel, Cheshire Engineering Corporation Publisher, October (1994).

Received: June 7, 2000
Accepted: May 5, 2001