Flow Discharge Determination in Straight Compound Channels Using ANNs

A. Zahiri and A. A. Dehghani

***Abstract*—**Although many researchers have studied the flow hydraulics in compound channels, there are still many complicated problems in determination of their flow rating curves. Many different methods have been presented for these channels but extending them for all types of compound channels with different geometrical and hydraulic conditions is certainly difficult. In this study, by aid of nearly 400 laboratory and field data sets of geometry and flow rating curves from 30 different straight compound sections and using artificial neural networks (ANNs), flow discharge in compound channels was estimated. 13 dimensionless input variables including relative depth, relative roughness, relative width, aspect ratio, bed slope, main channel side slopes, flood plains side slopes and berm inclination and one output variable (flow discharge), have been used in ANNs. Comparison of ANNs model and traditional method (divided channel method-DCM) shows high accuracy of ANNs model results. The results of Sensitivity analysis showed that the relative depth with 47.6 percent contribution, is the most effective input parameter for flow discharge prediction. Relative width and relative roughness have 19.3 and 12.2 percent of importance, respectively. On the other hand, shape parameter, main channel and flood plains side slopes with 2.1, 3.8 and 3.8 percent of contribution, have the least importance.

***Keywords*—**ANN model, compound channels, divided channel method (DCM), flow rating curve

I. Introduction

IN recent years, some research areas have received considerable attention and interest, among them, hydraulics of compound open channels and Artificial Neural Networks (ANN). Compound channels consisting of a deep main channel together with one or two wide floodplain(s), have many applications in hydraulic engineering practice. According to high gradient of flow velocity between main channel and floodplains, a strong lateral momentum exchange takes place across the interface. This momentum transfer between subsections significantly reduces the flow conveyance of compound channel [1]. Although several 1D, 2D and 3D mathematical models have recently been developed by various researchers for study of momentum transfer, both in laboratory flumes and natural rivers, unfortunately theoretical analysis of conveyance in these channels is not yet practical useful [2]. Due to high importance of proper calculation of flow discharge in compound channels, especially in flood events, there is a critical need to develop an appropriate method to give optimal solutions.

In this paper, an attempt is made to develop a mathematical model based on ANN to predict the flow discharge of straight compound channels. After designing of an optimal topology for ANN model and the training process, it was tested against the rest of data sets.

II. Discharge Computations in Compound Channels

According to the high difference of flow depths and Manning's roughness coefficients in main channel and floodplains and hence the large velocity difference between these subsections, a strong lateral momentum transfer induced across the interface. The traditional methods such as Divided Channel Method (DCM) ignore this strong shear stress at interfaces. In these methods, compound channels have analyzed by dividing the cross section into three subsections which are easier to analyze. In figure 1, a compound section with three vertical subdivided sections is shown. Total flow discharge is the sum of discharges calculated separately in each subsection using an appropriate conventional friction formula e.g. Manning [3]:

$$Q = \sum_{i=1}^{N} Q_i = \sum_{i=1}^{N} \frac{A_i R_i^{2/3} S_0^{1/2}}{n_i} \tag{1}$$

Where Q is flow discharge in compound channel, A is area, R is hydraulic radius, S0 is bed slope and n is manning roughness coefficient. In this equation, i refer to subsections e.g. main channel and floodplains and N is total number of subsections.

Comparison of the results of this method against with the experimental data showed that up to 40% error may be obtained [4].

Some modified methods have been presented for straight compound channels, among them: 2D analytical model [5], φ index method [4], the lateral division method [6], the coherence method [7], discharge ratios [8], weighted divided channel method [9], exchange discharge method [10], 2D analytical model [11] and modified weighted divided channel method [12]. Most of these methods are presented based on limited data in experimental flumes. Among these different

A. Zahiri is with Gorgan University of Agricultural Sciences and Natural Resources, Iran (e-mail: zahiri@gau.ac.ir).

A. A. Dehghani, is with Gorgan University of Agricultural Sciences and Natural Resources, Iran (e-mail: a.dehghani@gau.ac.ir)

methods, the 1D coherence method and 2D analytical model have promising applications in flumes and natural rivers [7]-[13]-[14], but extending them for all types of compound channels with different geometric and hydraulic conditions is certainly difficult.

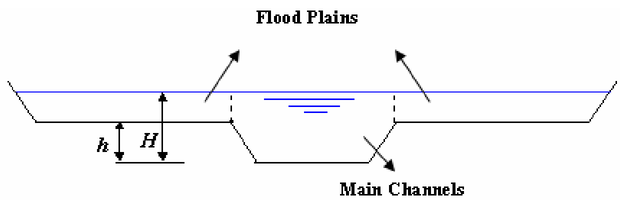

Fig. 1 Analyzing of compound channels in traditional vertical divided channel method

III. ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is a mathematical tool, which tries to represent low-level intelligence in natural organisms and it is a flexible structure, capable of making a non-linear mapping between input and output spaces [15]. In this paper multi layer perceptron network (MLP) and radial basis function (RBF) based on back propagation learning rule were used.

A. Multi Layer Perceptron (MLP) network

The MLP network sometimes called Back Propagation (BP) network shown in figure 2 is probably the most popular ANN in engineering problems in the case of non-linear mapping and is called "Universal Approximator". It consists of an input layer, a hidden layer and an output layer. The input nodes receive the data values and pass them on to the first hidden layer nodes. Each one of them collects the input from all input nodes after multiplying each input value by a weight, attaches a bias to this sum, and passes on the results through a nonlinear transformation like the sigmoid transfer function. This forms the input either for the second hidden layer or the output layer that operates identically to the hidden layer. The resulting transformed output from each output node is the network output. The network needs to train using a training algorithm such as back propagation, cascade correlation and conjugate gradient. Basically the objective of training patterns is to reduce the global error, defined below [15]:

$$SSE = \sum_{i=1}^{n_p} \sum_{j=1}^{n_o} (T_{pj} - O_{pj})^2 \qquad (2)$$

Where Tpj is the jth element of the target output related to the pth pattern, Opj is the computed output of jth neuron related to the pth pattern, n_p is the number of patterns and no is the number of neurons in the output layer.

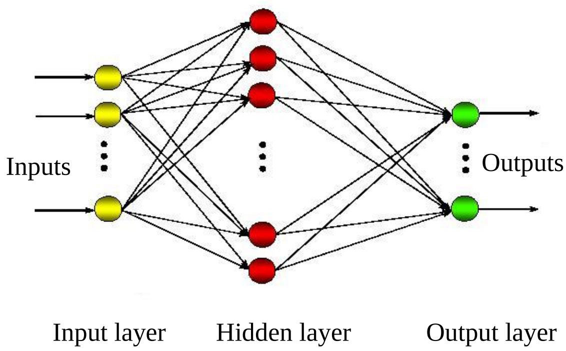

Fig. 2 Multi layer perceptron neural network

Although this model has extensive applications in water engineering subjects such as sediment concentration prediction in rivers [16], river flow modeling [17], rainfall-runoff modeling [18], nitrate concentration in rivers [19], hydrologic modeling [20], combined flow over and under the gates [21], simulation of stage-discharge relationships in rivers [22], computing of flow resistance in smooth open channels [23] and estimating of backwater through bridge constrictions [24]. Looking at literatures shows that a few studies available on using ANN in compound channels. Liu and James [2] by using ANN on experimental meandering compound channels showed that there is up to 15% discrepancy between predicted and measured flow discharge.
In this paper, the flow rating curve of straight laboratory and field compound channels have predicted using ANN. For ANN modeling, Qnet2000 software has used.

B. Data sets

Nearly 400 flume and field data sets of flow rating curves from 30 different straight compound sections was selected for training and testing ANN model. Most of these data are collected from experimental works carried out by HR-Wallingford in England in compound channel flumes with large-scale facility. Also, some of field data was collected from natural rivers (River Severn at Montford bridge, River Main and Rio Colorado). The cross section of a typical compound channel with berm inclination is shown in figure 3. The ranges of geometric and hydraulic characteristics of compound channels used in this paper for ANN model development are listed in table I.

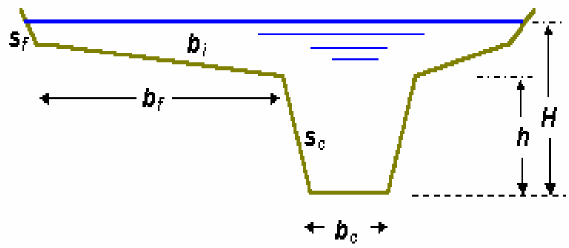

Fig. 3 Typical compound channel cross section with berm inclination

TABLE I
RANGE OF GEOMETRIC AND HYDRAULIC VARIABLES USED IN ANN MODEL

Symbol	Variable Definition	Variable Range
h	Bankfull height	0.031 - 6 (m)
b_c	Main channel width	0.152 – 21.4 (m)
b_f	Floodplain width	0 - 63 (m)
s_c	Main channel side slope	0 – 2
s_f	Floodplain side slope	0-7.1
b_i	Berm inclination	0 – 0.062
n_c	Manning's roughness coefficient of main channel	0.01 – 0.036
n_f	Manning's roughness coefficient of flood plains	0.01 – 0.05
S_0	Bed slope	0.000185 – 0.005
H	Flow depth	0.036 – 7.81 (m)
Q	Flow discharge	0.003 – 560 (m^3/s)

C. Input parameters

Flow hydraulics and momentum exchange in straight compound channels is significantly influenced by geometric and hydraulic variables. The important dimensionless geometric ratios are considered here as input variables for ANN model.

1- Depth parameter, *Dr*, defines the ratio of the flow depth on the floodplain to the flow depth within the main channel:

$$D_r = \frac{H - h}{H} \tag{3}$$

2- Width parameter, B_r, defines the ratio of the floodplain width to the main channel width:

$$B_r = \frac{b_f}{b_c} \tag{4}$$

3- Roughness parameter, n_r, is the ratio of Manning's roughness for the floodplain and that for the main channel:

$$n_r = \frac{n_f}{n_c} \tag{5}$$

4- Aspect ratio, S_r , is defined as the ratio of main channel width to bank height the:

$$S_r = \frac{b_c}{h} \tag{6}$$

5- Bed slope, S_0 .

6- Main channel side slope, s_c .

7- Flood plain side slope, s_f .

8- Berm inclination, b_i .

It must be noted that for the asymmetrical compound channels, the geometric characteristics of right and left floodplains may be different. Therefore, 13 input variables have been used in the ANN model.

D. Output parameter

The only one output parameter of ANN model is the dimensionless flow discharge ratio expressed as the ratio of the total observed discharge to the bankfull flow discharge.

E. Design of ANN topology

Commonly, ANN models have three layers, input, output and hidden layers. Although for common engineering practices, one hidden layer is sufficient for model training and testing, but it is showed that for very complicated phenomena, it is may be necessary to construct two or more hidden layers.

In this paper, a MLP neural network with 13 variables in input layer and one variable in output layer were used for ANN training. Due to limitation of RAM memory and executive time required for training, the number of nodes in input and hidden layers should be kept as small as possible. Selection of optimum number of nodes in hidden layer is an iterative procedure. For doing this, we begin with small numbers of nodes and sequentially, with increasing them, correlation coefficient (r) and root mean square error (RMSE) of predicted outputs are checked until predictions proved to be insensitive with respect to increase of nodes in hidden layer. In this case, r and RMSE should reach to the optimum values. Using this procedure, the smallest system design is selected as optimal ANN model. Following training of ANN model, testing process should be done. In this paper, 70% (280 data series) and 30% (115 data series) of data were used for training and testing, respectively.

The input parameters described in section C, were used for training process. The correlation coefficients (r) of ANN model were 0.99 and 0.97 in training and testing, respectively. The RMSE was 0.0183. Run time of this model was nearly 8 minutes. The percent contributions of each input parameter on the output results are presented in table II.

TABLE II
PERCENT CONTRIBUTIONS OF INPUT PARAMETERS OF ANN MODEL

Input Variable	Contribution Percent
Depth ratio	47.6
Width ratio	19.3
Roughness ratio	12.2
Aspect ratio	2.1
Bed slope	4.0
Main channel side slope	3.8
Floodplain side slope	3.8
Berm inclination	7.2

As it can be seen, depth ratio has a significant effect on the output variable. On the other hand, the total importance percent of four side slopes parameters are less than 8. The aspect ratio has insignificant effect, too. Figure 4 shows the graphical comparison of ANN model results against the measured data. The DCM results are presented, too. As it can be seen, the DCM over predicts the relative discharges up to 300%. The ANN model, in both training and testing process, has satisfactory predictions.

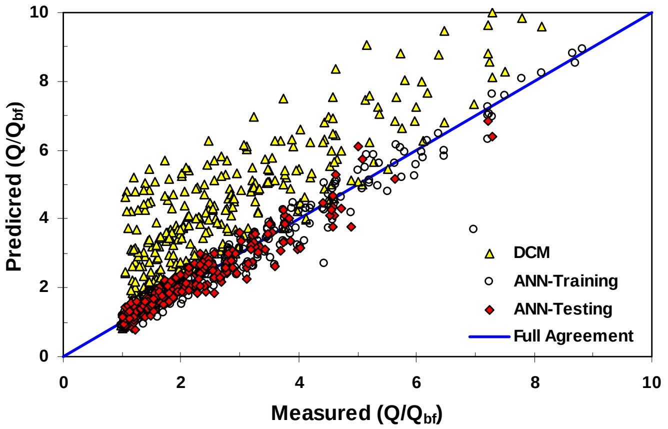

Fig. 4 Comparison of ANN model and DCM results with measured data

IV. CONCLUSION

In this paper, a MLP artificial neural networks has been developed for flow discharge prediction in straight compound channels. A wide range of geometric and hydraulic characteristics of laboratory and field data points of compound channels have been used for training and testing the ANN model. A system of ANN model with 8 input and one output parameters with one hidden layer with 24 nodes was selected as an optimal case. In this optimal model, the correlation coefficients for training and testing processes are 0.99 and 0.97, respectively. On the other hand, the correlation coefficient for traditional method (DCM) is only 0.52. Comparison of ANN model results with measured flow discharges of compound channels shows considerable improvement in comparison to the traditional method (DCM) currently used in numerical river models.

REFERENCES

[1] L. A. Martin, and W. R. C. Myers, "Measurement of overbank flow in a compound river channel," *Proc. of Instn. Civil. Engineering*, England, Part 2, pp. 645-657, 1991.

[2] W. Liu, and C. S. James, "Estimating of discharge capacity in meandering compound channels using artificial neural networks," *Canadian Journal of Civil Engineering*, Vol.27, No.2, pp. 297-308, 2000.

[3] V. T. Chow, *Open channel hydraulics*, McGraw-Hill, London, 1959.

[4] P. R. Wormleaton, and D. J. Merrett, "An improved method of calculation for steady uniform flow in prismatic main channel/flood plain sections," *Journal of Hydraulic Research, IAHR*, Vol.28, pp. 157-174, 1990.

[5] K. Shiono, and D. W. Knight, "Mathematical models of flow in two or multi stage straight channels," *Int. Conf. on River Flood Hydraulics*, England, pp. 229-238, 1990.

[6] J. B. Wark, P. G. Samuels, and D. A. Ervine, "A practical method of estimating velocity and discharge in compound channels," *Int. Conf. River Flood Hydraulics*, England, pp. 163-172, 1990.

[7] P. Ackers, "Stage-Discharge functions for two-stage channels," *Water and Environmental Management*, Vol. 7, pp. 52-61, 1993

[8] W. R. C. Myers, and J. F. Lyness, "Discharge ratios in smooth and rough compound channels," *Journal of Hydraulics Engineering, ASCE*, Vol.123, No.3, pp. 182-188, 1997.

[9] M. F. Lambert, and W. R. C. Myers, "Estimating the discharge capacity in straight compound channels," *Engrs Wat., Marit. and Energy*, Vol.130, pp. 84-94, 1998.

[10] D. Bousmar, and Y. Zech, "Momentum transfer for practical flow computation in compound channels," *Journal of Hydraulic Engineering, ASCE*, Vol 125, No. 7, pp. 696-706, 1999.

[11] D. A. Ervine, K. Babaeyan-Koopaei, and R. H. J. Sellin, "Two-Dimensional solution for straight and meandering overbank flows,", *Journal of Hydraulic Engineering, ASCE*, Vol.126, No.9, pp. 653-669, 2000.

[12] S. Atabay, "Stage-discharge, resistance and sediment transport relationships for flow in straight compound channels," Ph.D. dissertation, Dept. Civ. Eng., The University of Birmingham, UK, 2001.

[13] D. W. Knight, K. Shiono, and J. Pirt, "Prediction of depth mean velocity and discharge in natural rivers with overbank flow," *Int. Conf. on Hydraulics and Environmental Modeling of Coastal, Estuarine and River Waters*, England, pp. 419-428, 1989.

[14] B. Abril, and D. W. Knight, "Stage-Discharge prediction for rivers in flood applying a depth-averaged model," *Journal of Hydraulic Research, IAHR*, Vol. 122, No. 6, pp 616-629, 2004.

[15] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, 1986. "Learning internal representation by error propagation," Parallel distributed processing. Volume 1, D. E. Rumelhart and J. L. McClellend, EDs, MIT Press, Cambridge, 1986.

[16] H. M. Nagy, K. Watanabe, and M. Hirano, "Prediction of sediment load concentration in rivers using artificial neural network model," *Journal of Hydraulic Engineering, ASCE*, Vol. 128, No.6, pp. 588-595, 2002.

[17] O. Kisi, "River flow modeling using artificial neural networks," *Journal of Hydrologic Engineering, ASCE*, Vol.9, No.1, pp. 60-63, 2004.

[18] B. C. W. Dowson, and R. Wilby, "An artificial neural networks approach to rainfall-runoff modeling," *Journal of Hydrologic Science*, Vol.43, No.1, pp. 47-66, 1998.

[19] J. P. Suen, and W. Eheart, "Evaluation of neural networks for modeling nitrate concentration in rivers," *Journal of Water Resource Planning and Management, ASCE*, Vol.129, No.6, pp. 505-510, 2003.

[20] R. S. Govindaraju, and A. R. Rao, "*Artificial neural networks in hydrology*," Kluwer Academic, Dordrecht, The Netherlands, 2000.

[21] A. M. Negm, A. M. Al-Brahim, and A. A. Al-Hamid, 2002. "Combined-free flow over weirs and below gates," *Journal of Hydraulic Research, IAHR*, Vol.40, No.3, pp. 359-365, 2002.

[22] B. Bhattacharya, and D. P. Solomatine, "Applied of artificial neural network in stage-discharge relationships," *4th Int. Conf. on Hydroinformatics*, USA, 2000.

[23] A. Bilgil, and H. Altun, "Investigation of flow resistance in smooth open channels using artificial neural networks," Flow Measurement and Instrumentation, Vol. 19, No. 6, pp. 404-408, 2008.

[24] G. Seckin, S. Mevlut, M. Cobaner and T. Haktanir, "Application of ANN techniques for estimating backwater through bridge constrictions in Mississippi River basin," *Advances in Engineering Software*, Vol.40, pp. 1039-1046, 2009.