# PREDICTION OF FLOW IN NON-PRISMATIC COMPOUND CHANNELS USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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## ABSTRACT

Discharge estimation in rivers is the most important parameter in flood management. Predicting discharge in the non-prismatic compound open channel by analytical approach leads to solving a system of complex nonlinear equations. In many complex mathematical problems that lead to solving complex problems, an artificial intelligence model could be used. In this study, the adaptive neuro-fuzzy inference system (ANFIS) is used for modeling and predicting of flow discharge in the non-prismatic compound open channel. Comparison of results showed that the divided channel method with vertical division lines with the coefficient of determination (0.73) and root mean square error (0.009) is accurate among the analytical approaches. The non-dimensional parameters like friction factor ratio, area ratio, hydraulic radius ratio, bed slope, width ratio, relative flow depth, angle of converging or diverging, relative longitudinal distance, flow aspect ratio have been taken as input parameters in for predicting discharge. The ANFIS model with a coefficient of determination (0.98) and root mean square error (0.005) for the testing stage has a suitable performance for predicting the discharge in the non-prismatic compound open channel.

***Keywords: Non-prismatic compound channels; Gamma Test, M test, relative flow depth; width ratio, relative flow depth; ANFIS***

## 1. INTRODUCTION

River plays a very important role for day-to-day activity of human civilization. Due to availability of water and fertile land near the river bank, most of the civilization flourished thereby. But during flood, the main river channel forgets its boundary and inundates the surrounding floodplains causing loss of life and economy of the country.

From the last five decades, many investigators carried out their research in straight prismatic compound channel to estimate the discharge in such channel (Sellin 1964, Wormleaton et al. 1982, Knight and Demetriou 1983, Shiono and Knight (1989), Devi et al. 2016). But very few investigation has been done in non-prismatic compound channel. James and Brown (1977) is the first to conduct experiment in skewed type compound channel with different skew angle. Later Chlebek (2009) studied the effect energy slope behaviour in skewed type non-prismatic compound channel. Shiono et al. (1999) conducted experiment in meandering compound channel. But very few number of research has been done for converging and diverging compound channel cases. Bousmar et al. (2002) is the first to carried out the experiment in converging compound channel for three different angle. Then Proust (2005) studied the effect of convergence in asymmetric compound channel with abrupt floodplain contraction with converging angle 22°. Improper estimation of calibrating coefficient may lead to erroneous results. Thus artificial intelligence has been used to developed model which can able to provide satisfactory results in determining the discharge in non-prismatic compound channel.

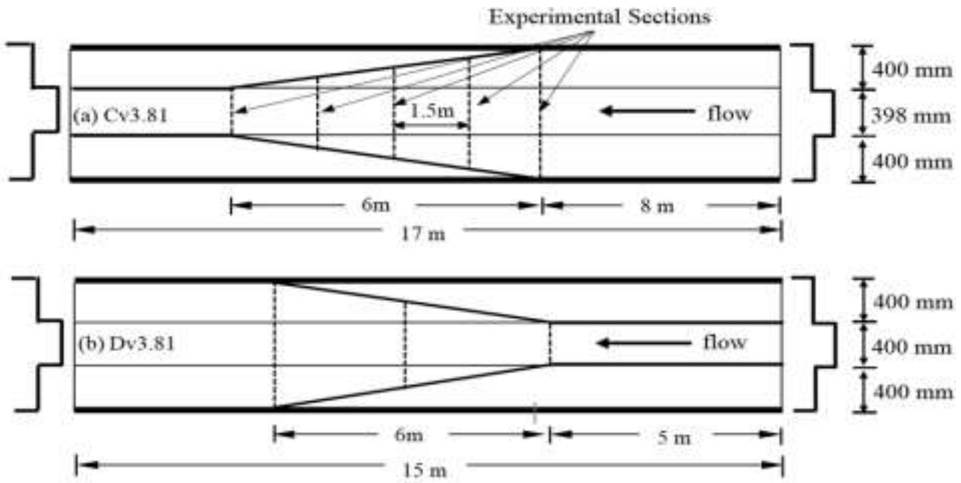



**Figure 1. Schematic diagram of non-prismatic compound channel, (a) Converging compound channel ($\theta$=3.81°), (Rezaei 2006) and (b) Diverging compound channel ($\theta$=3.81°), (Yonesi et al. 2013)**

## 2. METHODOLOGY

Initially, a review was conducted on the important parameters which are an influence on the behavior of flow in the compound open channel, and then the four famous analytical approaches that have been proposed to calculate the flow discharge are presented. To assess the performance of these analytical approaches, 196 data sets related to the flow discharge in the non-prismatic compound channels were derived from the researchers that were conducted by Bousmar (2002), Bousmar et al. (2006), Rezaei (2006), Yonesi et al. (2013) and Naik and Khatua (2016).

## 3. Sources of Data

For this research work, we collected the experimental data on converging and diverging compound channel along from the are published papers by Bousmar (2002), Bousmar et al. (2006), Rezaei (2006), Yonesi et al. (2013) and Naik and Khatua (2016).

Table 1. Details of hydraulic and surface parameters for all types of channel collected from experimental work and published data for diverging and converging compound channel

| Verified Test Channel | $Q$ in ($m^3$/s) | $n$ | β | $Re$ in (x $10^5$) | $Fr$ |
|---|---|---|---|---|---|
| 1 | 2 | 3 | 5 | 6 | 7 |
| Bousmar (2002)/Cv3.81 | 0.010-0.020 | 0.0107 | 0.213-0.537 | 0.338-1.326 | 0.26-0.60 |
| Bousmar (2002)/Cv11.3 | 0.010-0.020 | 0.0107 | 0.18-0.532 | 0.286-1.312 | 0.29-0.58 |
| Bousmar et al. (2006)/Dv3.81 | 0.012-0.020 | 0.0107 | 0.218-0.514 | 0.341-1.393 | 0.38-0.86 |
| Bousmar et al. (2006)/Dv5.71 | 0.012-0.020 | 0.0107 | 0.253-0.541 | 0.344-1.308 | 0.25-0.66 |
| Rezaei (2006)/Cv1.91 | 0.015-0.040 | 0.0084 | 0.178-0.522 | 0.420-1.451 | 0.56-0.81 |
| Rezaei (2006)/Cv3.81 | 0.014-0.025 | 0.0091 | 0.151-0.509 | 0.387-1.813 | 0.35-0.71 |
| Rezaei (2006)/Cv11.31 | 0.013-0.023 | 0.0091 | 0.198-0.505 | 0.428-1.924 | 0.38-0.76 |
| Yonesi et al (2013)/Dv3.81 | 0.037-0.0615 | 0.0139 | 0.142-0.363 | 1.435-1.934 | 0.24-0.34 |
| Yonesi et al (2013)/Dv5.71 | 0.037-0.0615 | 0.0139 | 0.142-0.352 | 1.356-1.854 | 0.27-0.36 |
| Yonesi et al (2013)/Dv11.3 | 0.037-0.0615 | 0.0139 | 0.143-0.359 | 1.281-1.742 | 0.29-0.38 |
| Naik and Khatua (2016)/Cv5 | 0.043-0.062 | 0.011 | 0.15-0.30 | 0.472-1.461 | 0.64-0.83 |
| Naik and Khatua (2016)/Cv9 | 0.042-0.059 | 0.011 | 0.15-0.30 | 0.408-1.613 | 0.56-0.76 |

| | | | | | |
|---|---|---|---|---|---|
| Naik and Khatua (2016)/Cv12.38 | 0.040-0.054 | 0.011 | 0.15-0.30 | 0.506-1.736 | 0.58-0.70 |

Observed discharge in $m^3$/s- $Q$, Manning's roughness coefficient-$n$, Relative depth-$\beta$, Reynolds number -$Re$, Froude number-$Fr$

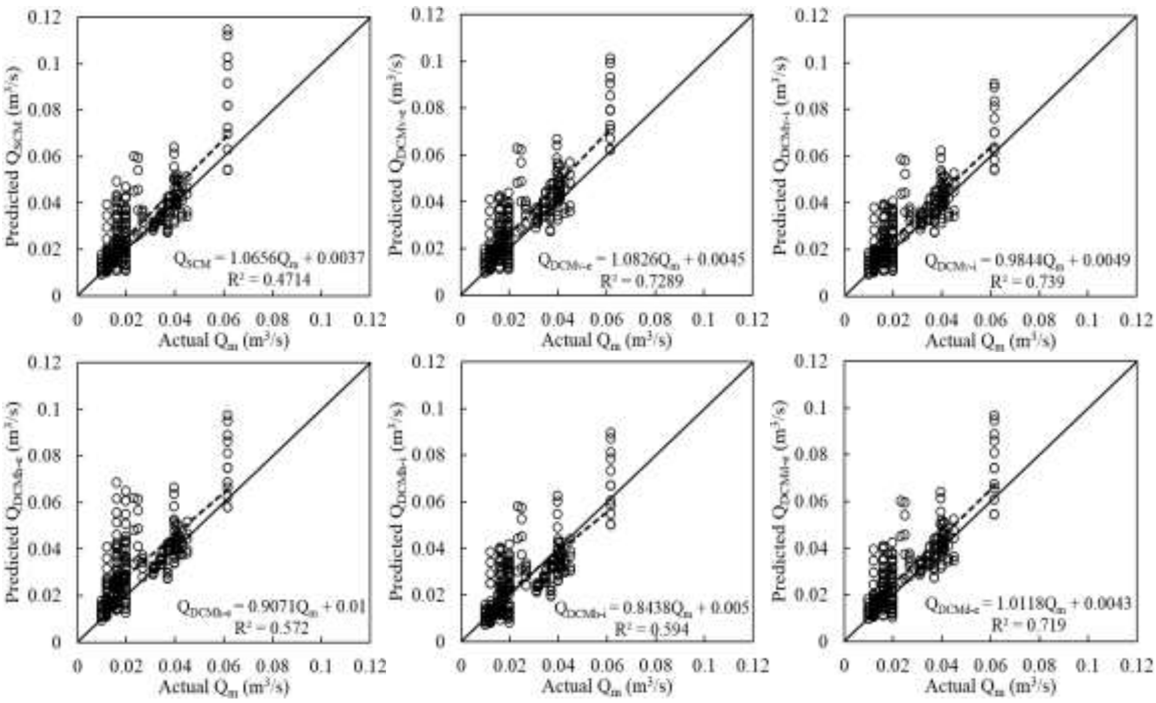
## 4. Influence flow Parameters

From extensive literature survey on compound channels, it is seen that the investigators such as Knight and Demetriou (1983), Yang (2005), Dash and Khatua (2016), Parsaei et al. (2016) have suggested that flow in compound channel depends on width ratio, relative flow depth, Area ratio, hydraulic radius ratio, friction factor ratio and bed slope. Das et al. (2016) proved the dependency of energy loss on diverging or converging angles and relative longitudinal distance for non-prismatic geometry. Hence, the authors, in the present study, for the development of ANFIS model considered the nine non-dimensional input parameters which influence the flow quantity at different section of non-prismatic reach. The details about the non-dimensional parameter are described below:

Total 9 flow variables were chosen as input parameters and flow as an output parameter. The dependency flow ($Q$) on these aforementioned parameters can be written in a functional relationship as $Q = f\left(f_r, A_r, R_r, \beta, S_0, \delta^*, \alpha, \theta, X_r\right)$

Table 3. Statistical characteristics of the data under consideration

| Statistical characteristics | $F_r$ | $A_r$ | $R_r$ | $\beta$ | $S_0$ | $\delta^*$ | $\alpha$ | $X_r$ | $\theta$ | $Q$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Maximum | 0.84 | 22.59 | 35.09 | 0.54 | 0.002003 | 6.54 | 3.02 | 1.00 | 11.31 | 0.0615 |
| Minimum | 0.31 | 0.93 | 1.70 | 0.11 | 0.000880 | 1.41 | 1.33 | 0.00 | -13.4 | 0.0100 |
| Std. Dev. | 0.09 | 3.73 | 3.15 | 0.12 | 0.000423 | 1.27 | 0.55 | 0.32 | 7.01 | 0.0136 |
| Mean | 0.70 | 4.37 | 3.51 | 0.34 | 0.001226 | 4.40 | 2.10 | 0.42 | -2.17 | 0.0244 |
| Median | 0.71 | 3.00 | 2.80 | 0.33 | 0.000990 | 4.19 | 2.00 | 0.33 | -1.91 | 0.0199 |



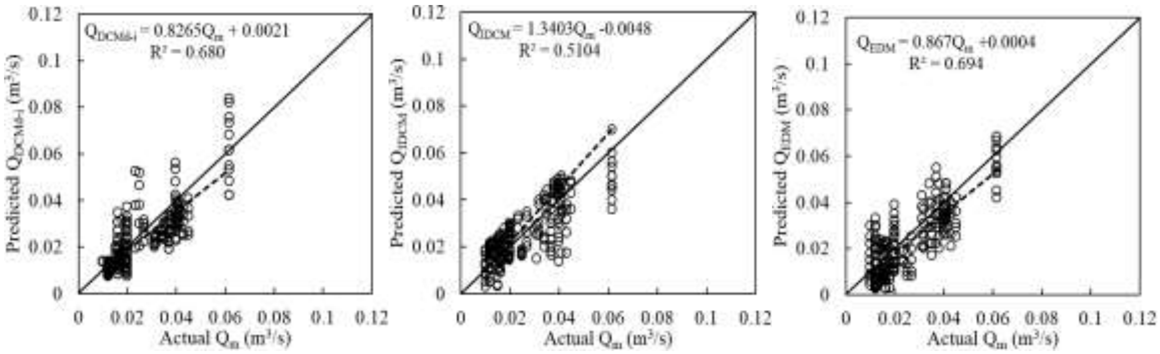


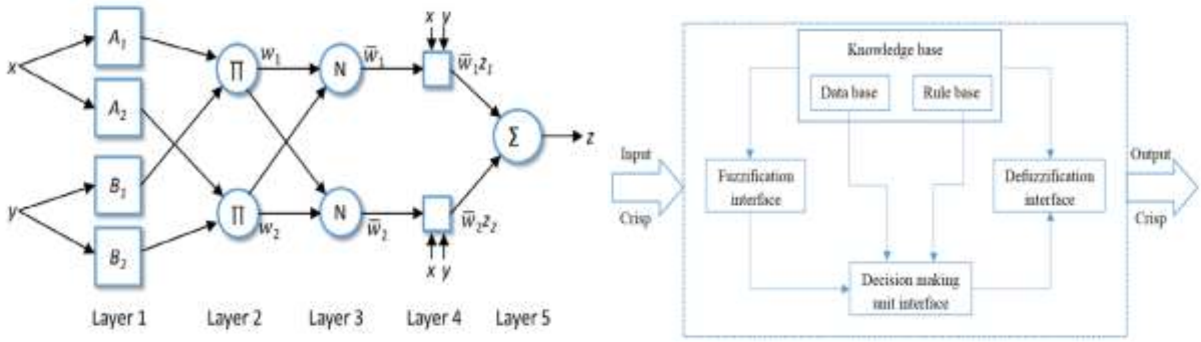

**Figure 3. Correlation between the result of analytical approaches versus the measured discharge**

Table 3. Error indices result of the analytical approaches

| Methods | $R^2$ | MAE | MAPE | RMSE | E |
|---|---|---|---|---|---|
| SCM | 0.47 | 0.0073 | 43.57 | 0.017 | -3.293 |
| $DCM_{v-e}$ | 0.73 | 0.0079 | 36.93 | 0.011 | -2.990 |
| $DCM_{v-i}$ | 0.74 | 0.0064 | 30.67 | 0.009 | -1.651 |
| $DCM_{h-e}$ | 0.57 | 0.0088 | 41.01 | 0.013 | -4.517 |
| $DCM_{h-i}$ | 0.59 | 0.0073 | 32.50 | 0.010 | -2.032 |
| $DCM_{d-e}$ | 0.72 | 0.0066 | 31.18 | 0.010 | -2.018 |
| $DCM_{d-i}$ | 0.68 | 0.0064 | 26.20 | 0.008 | -0.732 |
| IDCM | 0.51 | 0.0091 | 35.37 | 0.039 | -8.213 |
| EDM | 0.69 | 0.0072 | 32.81 | 0.008 | -0.814 |

## 5. Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) is an AI method, is a sequence of ANN and fuzzy system that uses the learning effectiveness of the ANN to evolve the fuzzy IF-THEN rules with proper membership functions derived from the training pair, whichever in turns lead to inference. Such networks shun the obligation of manual optimization of fuzzy network parameters and the tuning of the network parameters can be obtained by means of ANN. The merger of both ANN and FIS thus improves system performance without intervene of operators. ANFIS antiquated used in many water resources problems viz. modeling of hydrological time series, reservoir operations, rainfall-runoff prediction and other related fields.




**(a)** **(b)**

**Figure 4. (a) A schematic diagram of ANFIS structure and (b) A schematic diagram of fuzzy based inference system**

## 5.1 Architecture and basic learning rules

ANFIS is a rule-based fuzzy logic model that its rules perform in the course of the training operation of the model. As shown in Fig. 4a, five layers are used to build up this inference structure. In this connectionist structure, the input (layer 0) and output (layer 5) nodes portray the inputs and the output, respectively. In the hidden layers, there are several fixed and flexible nodes functioning as membership functions (MFs) and rules. To explain the procedures of an ANFIS, we consider two input variables x, y and one output variable z. In ANFIS model the relationship between input and output is stated by the use of if-then fuzzy rules. Then, the model involves two fuzzy rules based on Takagi and Sugeno's type (Sahu et al. 2011) that can be expressed as follows:

Rule 1: If x is $A_1$ and y is $B_1$ then $z_1 = p_1 x + q_1 y + r_1$
Rule 2: If x is $A_2$ and y is $B_2$ then $z_2 = p_2 x + q_2 y + r_2$
where $A_1$, $B_1$, and $A_2$, $B_2$ are the linguistic level, $p_1$, $q_1$, $r_1$ and $p_2$, $q_2$, $r_2$ are the consequent parameters. If $z_1$ and $z_2$ are constants instead of linear equations, we have zero order TSK fuzzy-model. A typical ANFIS structure, which can be seen in Fig. 4a includes 5 layers.

Table 5. Determining the best combination for flow ($Q$) in non-prismatic compound channel

| Exp. No. | Combination of Input parameters | Gamma | Std. error | V-ratio | Mask |
|---|---|---|---|---|---|
| 1 | All inputs | -0.009 | 0.006 | -0.036 | 111111111 |
| 2 | All inputs-$f_r$ | -0.006 | 0.005 | -0.027 | 011111111 |
| 3 | All inputs-$\alpha$ | -0.003 | 0.004 | -0.014 | 111111011 |
| 4 | All inputs-$X_r$ | -0.006 | 0.006 | -0.027 | 111111101 |
| **5** | **All inputs-$\theta$** | **-0.001** | **0.007** | **-0.007** | **111111110** |
| 6 | All inputs- $X_r$,$\theta$ | 0.004 | 0.004 | 0.017 | 111111100 |
| 7 | All inputs- $X_r$,$\alpha$ | -0.008 | 0.007 | -0.034 | 111111001 |
| 8 | All inputs- $\theta$, $\delta^*$ | 0.061 | 0.023 | 0.247 | 111110110 |
| 9 | All inputs- $\theta$, $X_r$ | 0.004 | 0.004 | 0.017 | 111111100 |
| 10 | All inputs- $\alpha$ , $X_r$, $\theta$ | 0.008 | 0.003 | 0.034 | 111111000 |
| 11 | All inputs-$A_r$,$R_r$ | -0.011 | 0.006 | -0.045 | 100111111 |
| 12 | All inputs- $A_r$,$R_r$ $\theta$ | 0.003 | 0.007 | 0.014 | 100111110 |
| 13 | $F_r$, $A_r$,$R_r$,$\beta$,$S_0$ | 0.017 | 0.017 | 0.070 | 111110000 |
| 14 | $\alpha$ , $\beta$, $\theta$ , $X_r$, $S_0$, | 0.07 | 0.030 | 0.280 | 000110111 |
| 15 | $\alpha$ , $\beta$, $\delta^*$ , $X_r$, $S_0$ | 0.005 | 0.003 | 0.023 | 000111110 |
| 16 | $F_r$, $A_r$,$R_r$, $S_0$ | 0.054 | 0.020 | 0.216 | 111010000 |
| **17** | **$F_r$, $R_r$,$\beta$, $S_0$** | **0.0002** | **0.010** | **0.001** | **101110000** |
| 18 | $\alpha$ , $\beta$, $S_0$ | 0.097 | 0.053 | 0.388 | 000110100 |
| 19 | $F_r$, $R_r$,$S_0$ | 0.038 | 0.012 | 0.155 | 101010000 |
| 20 | $F_r$, $\beta$,$S_0$ | 0.028 | 0.011 | 0.114 | 100110000 |

## 5.2 ANFIS model Development

In order to develop an ANFIS model, the input and output data were mapped to the domain [0.05,0.95] employing the Eq. (18) because the best range recommended for normalization is between 0.05 and 0.95 (Hsu et al. 1955). This would increase the accuracy and speed of ANFIS performance.

$$a_{norm} = 0.05 + 0.95\frac{(a - a_{\min})}{(a_{\max} - a_{\min})}$$

where $a_{norm}$ and $a$ are the normalized and original inputs; $a_{min}$, and $a_{max}$ denote minimum and maximum of the input ranges, respectively.

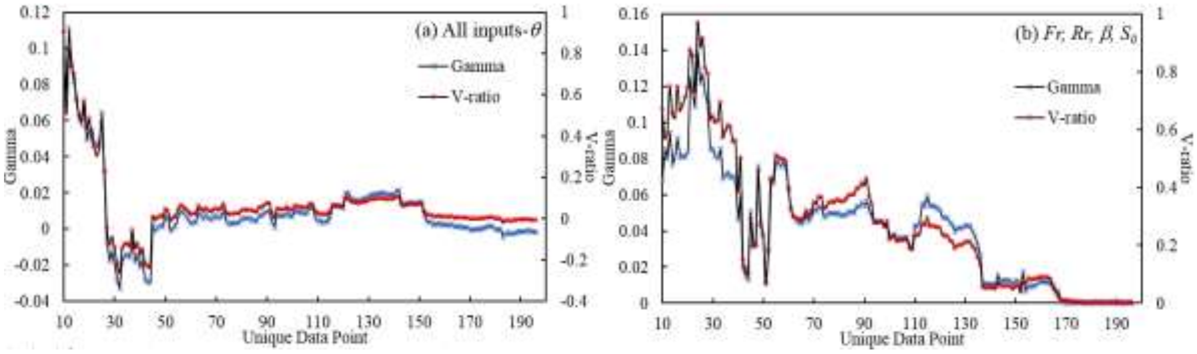



**Figure 5. M-test curve: the variation of gamma statistic and V-ratio with unique data points to determining the proper length for training data for mask a) [111111110] and b) [101110000]**

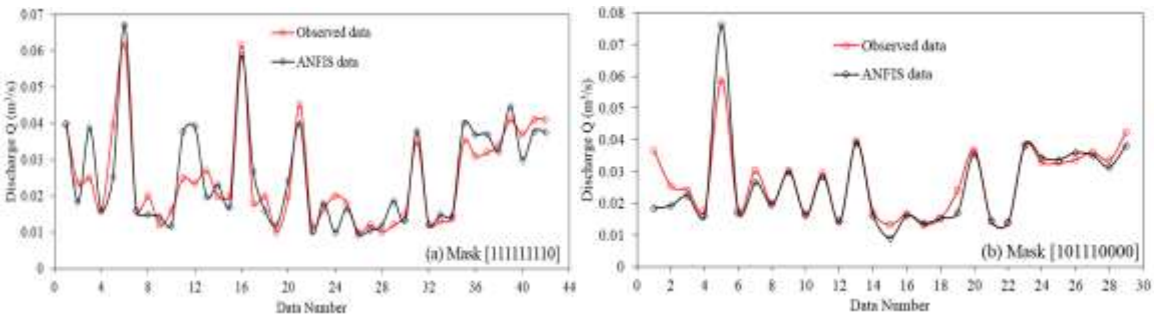



**Figure 6 Predicted and observed for calibration and testing step of ANFIS model (Square symbol indicate the extreme high values resulted from the model)**

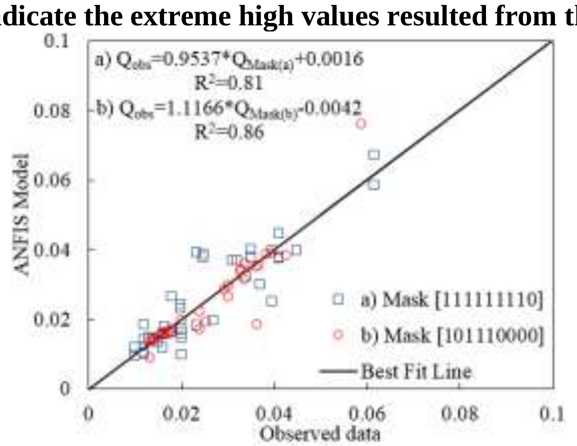



**Figure 8 Comparison of ANFIS model predicted value and observed value of discharge**

Table 6 Details of the best ANFIS model performance

| Subtractive clustering | | Grid partitioning (gaussmf-linear) | |
|---|---|---|---|
| 8 input Parameters | $F_r$, $A_r$, $R_r$, $\beta$,$S_0$,$\delta$*,$\alpha$, $X_r$ | 4 input Parameters | $F_r$, $R_r$, $\beta$,$S_0$ |
| Rules | 18 | No. of MF | 4444 |
| Range of influence | 0.52 | MF | gaussmf |

| | | | |
|---|---|---|---|
| Squash factor | 1.2 | And method | prod |
| Accept ratio | 0.5 | Or method | max |
| Reject ratio | 0.15 | Defuzz method | wtaver |
| Type | Sugeno | Agg method | max |
| $R^2$ (Training) | 0.99 | $R^2$ (Training) | 0.96 |
| $R^2$ (Testing) | 0.82 | $R^2$ (Testing) | 0.86 |
| MAPE (Training) | 1.3% | MAPE (Training) | 8.62% |
| MAPE (Testing) | 16.1% | MAPE (Testing) | 9.42% |
| RMSE (Training) | 0.0001 | RMSE (Training) | 0.0026 |
| RMSE (Testing) | 0.0055 | RMSE (Testing) | 0.0051 |
| MAE (Testing) | 0.003 | MAE (Testing) | 0.0027 |
| E (Testing) | 0.99 | E (Testing) | 0.78 |

## 6. Results and Discussions

The analytical approaches and the ANFIS model were assessed by the data collected summarized in the Table 1 and 2. The accuracy of the analytical approaches and the ANFIS model were assessed by calculating the statistical error indices such as the coefficient of determination ($R^2$), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Nash-Sutcliff coefficient (E). The definitions of different errors are presented in (Das et al. 2016, Naik and Khatua 2016). It is noticeable that these indices shown in Table 4 and 6, provide a value for the average error and not give any information about error distribution, so in addition to calculating the indices error, the performance of them are shown in Figs. 6-8 between the observed values and calculated or predicted values.

## 7. Conclusions

In this study, some famous analytical approaches for calculating the discharge in the compound open channel were assessed. To this purpose 196, experimental data on non-prismatic compound channel which were published in the credible journal were collected. The result of the error indices calculation of the result of the analytical approaches showed that performance of the DCMv–i by the Coefficient of determination of about 0.73 has acceptable performance for calculating the discharge in the non-prismatic compound open channel. To achieve greater accuracy in the discharge calculation, the adaptive neuro-fuzzy inference system (ANFIS) was prepared based on the same data collected. Gamma test and M test has been performed to select the most significant non-dimensional input parameters combinations for modelling discharge. The following results has been achieved in the present investigation:

- Two model in ANFIS has been tested where for FIS generation, subtractive clustering for 8 input parameters and Grid partition for 4 input parameters has been performed. Calculating the error indices for the ANFIS results showed that the performance of the ANFIS model using 4 non-dimensional input parameters provide coefficient of determination of 0.98 and 0.86 for training and testing stages respectively is so suitable for modeling the discharge of non-prismatic compound open channel.

- Comparison of the performance of the ANFIS model with analytical approaches showed that the ANFIS model is more accurate as it is evident from the error indices.

**References**

Sellin, R. H. J. (1964). A laboratory investigation into the interaction between the flow in the channel of a river and that over its floodplain. La Houille Blanche, (7), 793-802.

Wormleaton, Peter R., John Allen, and Panos Hadjipanos. "Discharge assessment in compound channel flow." Journal of the Hydraulics Division 108, no. 9 (1982): 975-994.

Knight, D. W., & Demetriou, J. D. (1983). Floodplain and main channel flow interaction. Journal of Hydraulic Engineering, 109(8), 1073-1092.

Knight, D. W., Shiono, K., & Pirt, J. (1989, September). Prediction of depth mean velocity and discharge in natural rivers with overbank flow. In Proceedings of the International Conference on Hydraulic and Environmental Modelling of Coastal, Estuarine and River Waters (pp. 419-428). Gower Publishing

James, M. & Brown, B.J. 1977. Geometric parameters that influence floodplain flow, Report WES-RR-H-77-1, USACE, Vicksburg, USA.

Chlebek, J. (2009). “Modelling of simple prismatic channels with varying roughness using the SKM and a study of flows in smooth non-prismatic channels with skewed floodplains.” Doctoral dissertation, University of Birmingham.

Shiono, K., Al-Romaih, J. S., & Knight, D. W. (1999). “Stage-discharge assessment in compound meandering channels.” Journal of Hydraulic Engineering, 125(1), 66-77.

Bousmar, D. (2002). Flow modelling in compound channels (Doctoral dissertation, Birmingham University).

Yonesi, H. A., Omid, M. H., & Ayyoubzadeh, S. A. (2013). The hydraulics of flow in non-prismatic compound channels. J Civil Eng Urban, 3(6), 342-356.

Proust, S. (2005). “Ecoulements non-uniformes en lits composés: effets de variations de largeur du lit majeur.” Doctoral dissertation, INSA de Lyon.

Rezaei, B. (2006). Overbank flow in compound channels with prismatic and non-prismatic floodplains (Doctoral dissertation, University of Birmingham).

Proust, S., Bousmar, D., Rivière, N., Paquier, A., & Zech, Y. (2010). Energy losses in compound open channels. Advances in water Resources, 33(1), 1-16.

Bousmar, D., Wilkin, N., Jacquemart, J. H., & Zech, Y. (2004). “Overbank flow in symmetrically narrowing floodplains.” Journal of hydraulic engineering, 130(4), 305-312.

Bousmar, D., Proust, S., & Zech, Y. (2006, January). Experiments on the flow in an enlarging compound channel. In R. M. L. Ferreira, E. C. T. L. Alves, J. G. A. B. Leal, & A. H. Cardoso (Eds.), River Flow 2006: Proceedings of the International Conference on Fluvial Hydraulics, Lisbon, Portugal, 6–8 September 2006 (pp. 323-332).

Lotter, G. K. (1933). Considerations on hydraulic design of channels with different roughness of walls. Transactions, All-Union Scientific Research Institute of Hydraulic Engineering, Leningrad, 9, 238-241.

Al-Khatib, I. A., Dweik, A. A., & Gogus, M. (2012). Evaluation of separate channel methods for discharge computation in asymmetric compound channels. Flow Measurement and Instrumentation, 24, 19-25.

Devi, K., Khatua, K. K., & Khuntia, J. R. (2017). Discharge assessment in an asymmetric compound channel by zero shear interface method. ISH Journal of Hydraulic Engineering, 23(2), 126-134.

Bousmar, D., & Zech, Y. (1999). Momentum transfer for practical flow computation in compound channels. Journal of hydraulic engineering, 125(7), 696-706.

Parsaie, A., Yonesi, H., & Najafian, S. (2017). Prediction of flow discharge in compound open channels using adaptive neuro-fuzzy inference system method. Flow Measurement and Instrumentation, 54, 288-297.

Atabay, S., & Knight, D. W. (2006). 1-D modelling of conveyance, boundary shear and sediment transport in overbank flow. Journal of Hydraulic Research, 44(6), 739-754.

Huthoff, F., Roos, P. C., Augustijn, D. C., & Hulscher, S. J. (2008). Interacting divided channel method for compound channel flow. Journal of hydraulic engineering, 134(8), 1158-1165.

Naik, B., & Khatua, K. K. (2016). Boundary shear stress distribution for a converging compound channel. ISH Journal of Hydraulic Engineering, 22(2), 212-219.

Yang, K., Cao, S., & Liu, X. (2005). Study on resistance coefficient in compound channels. Acta Mechanica Sinica, 21(4), 353-361.

Das BS, Khatua KK, Devi K. Prediction of energy loss in compound channels having enlarging floodplains. InRiver Flow 2016 2016 Jun 24 (pp. 65-71). CRC Press.

Dash, S. S., & Khatua, K. K. (2016). Sinuosity dependency on stage discharge in meandering channels. Journal of Irrigation and Drainage Engineering, 142(9), 04016030.

Jang, R. J. (1991a). Fuzzy modeling using generalized neural networks and Kalmman filter algorithm. In Proceedings of the ninth national conference on artificial intelligence (pp. 762–767).

Jang, R. J. (1991b). Rule Extraction using generalized neural networks. In Proceedings of the forth IFSA World Congress (pp. 82–86).

Jang, R. J. (1993). ANFIS: Adaptive-network-based fuzzy inference system. IEEE Transaction on Systems of Max and Cybernetics, 23(03), 665–685.

Jang, R. J. (1994). Structure determination in fuzzy modeling: A fuzzy CART approach. In Proceedings of IEEE International conference on fuzzy systems, Orlando, Florida.

Sahu, M., Khatua, K. K., & Mahapatra, S. S. (2011). A neural network approach for prediction of discharge in straight compound open channel flow. Flow Measurement and Instrumentation, 22(5), 438-446.

Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence. London: Prentice- Hall International.

Chopra, S., Mitra, R. and Kumar, V. (2006) Analysis of Fuzzy PI and PD Type Controllers Using Subtractive Clustering. International Journal of Computational Cognition, 4, 30-34.