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Prediction of energy loss along the non-prismatic reach of a compound channel using ANN

B. Naik, Kamel Miri & K.K. Khatua
Department of Civil Engineering, National Institute of Technology, Rourkela, India

ABSTRACT: Flooded Rivers usually generate transition reaches making the width of floodplain varies. Additional energy loss occurs during interaction between main channel and floodplain as well as due to non-uniformity of flow occurring during movement through non-prismatic reach. The calculation of energy loss in a non-prismatic compound channel is more complex as compared to a non-prismatic simple channel and prismatic compound channel. Hence an easily implementable technique the ANN can be used for predicting the energy loss at different sections of a converging compound channel for different geometry and flow conditions. At first experimental investigations have been performed to study the dependency of flow variables to predict the energy loss, then the ANN technique is applied. The model performed quite satisfactory results. The model can also be used for estimating energy loss on-line but the accuracy of the model depends upon the proper training and selection of data points.

1 INTRODUCTION

Distribution of energy in a compound channel is an important aspect in river hydraulics which needs to be addressed properly. It is seen that, the river generally exhibit a two stage geometry (deeper main channel and shallow floodplain called compound section) having either prismatic or non-prismatic geometry (geometry changes longitudinally). Due to flow interaction between the main channel and flood plain, the flow in a compound section consumes more energy than a channel with simple section carrying the same flow and having the same type of channel surface. Due to continuous settlement of people near the river bank and due to other natural causes, the channel with floodplain cross sections behaves as converging/diverging compound channel. An improper estimation of floods in these regions, will lead to an increase in the loss of life, and properties. The modelling of such flows is of primary importance when seeking to identify flooded areas and for flood risk management studies etc. There is always a strong interaction exist between the deep main channel and shallow floodplain even for a prismatic compound channel. In non-prismatic compound channels with converging/diverging floodplains, due to continuous change in floodplain geometry along the flow path, the resulting interactions and momentum exchanges is further increased (Bousmar et al. 2004; Proust et al. 2006; Rezaei 2011). This extra momentum exchange is very important parameter and should be taken into account in the overall flow modelling of a spatially varied river flow. The flow interaction between the main channel and a prismatic flood plain have been investigated intensively by many investigators such as Knight and Demetriou (1983), Shiono and Knight (1991), Khatua and patra (2008), Khatua et al. (2012) etc. They showed that there are three main sources of energy losses occurring in a compound channel flow assuming in uniform flow conditions those are bed friction, momentum flux due to both turbulent exchange and secondary current across the total cross section. But in a non-prismatic compound channel where the flow is highly non-uniform causing remarkable additional contraction loss of energy making prediction of all flow variables more complex. In the past, numerous studies on channel contractions have been presented by different investigators. Hager (1987) investigated local head losses in different zones along the contraction and their effects on the discharge characteristics. Molinas and Marcus (1998) proposed a discharge equation that considered the energy losses due to contractions. But their study were limited to short, abrupt channel contractions. Conventional approaches lack in providing high accuracy for the prediction of the energy losses in channels due to neglecting the factors causing non-uniformity of flow. That's why a new and accurate technique is highly demandable. The present research investigates some experimental findings of converging compound channels of different geometry and converging angles. The effect of geometry and converging angle on flow prediction of such channels are studied and finally an efficient approach is proposed to estimate the energy losses with the help of Artificial Neural Network (ANN) which is a promising computational tool. Some of the important past studies in this direction are Neuro-Fuzzy model to simulate Coolbrook-White equation by Walid and Shyam (1998), prediction of friction factor in smooth open channel flow using ANN by Bigil and Altum (2008) and Yuhong and Wenxin (2009), and prediction of discharge in straight compound open channel flow by Mrutyunjaya Khatua and S.S. Mahapatra (2011). New experiments have been conducted to analyse the behaviour of water surface profile and energy losses caused by floodplain contractions. An evaluation for the energy losses in different converging section of a compound channel reach for different hydraulic and geometric conditions are done and the dependency of energy loss for such channels are analysed. An attempt is also made to develop a mathematical model based on ANN to predict the energy losses due to contraction for several converging compound channels and the results are finally compared with the experimental data.

2 ANALYSIS OF ENERGY LOSSES AND INFLUENCING PARAMETERS

The resistance to flow of a channel can be significantly increased by the presence of contractions of floodplain. Various methods exist for accounting the additional resistance which are generally for simple channels or meandering channels. It has been confirmed that ignoring contraction losses due to converging cross-section can introduce significant error in channel conveyance estimation.

Consider a prismatic compound channel which has total width = B and main channel width of b. Let the floodplain has been contracted from width B at section 1 to the width of b at section 5 as shown in Figure 1. Here the total converging part of the channel has been divided into 5 arbitrary sections where the corresponding average flow depths occurring are let Y_1, Y_2, Y_3, Y_4 and Y_5 respectively. The energy loss between two consecutive sections can be calculated from the equation of conservation of energy between those sections. For calculating the energy, let the datum may be taken as bottom of extreme downstream end of the converging part of the channel. i.e. here the channel bottom at section 5. The total energy with non-uniform flow can be considered as the sum of macroscopic kinetic energy, potential energy of the gravity force and of the internal energy Proust et al. (2010). The change in internal energy between two consecutive sections is very less as compared to the corresponding potential and kinetic energies.

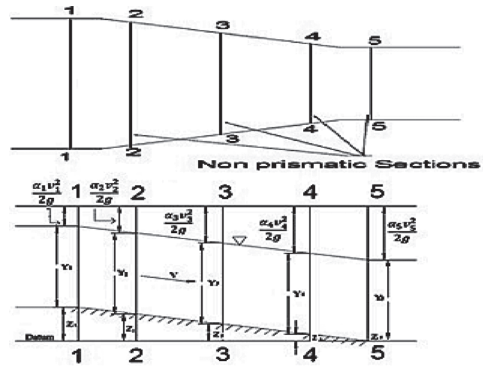

Figure 1. Sketch of energy profile for converging channels at NITRKL.

Therefore the contribution of internal energy here is not considered while applying the conservation of energy principle for any two sections i.e. section 1 and section 2.

$$E_1 = Z_1 + Y_1 + \frac{V_1^2 \alpha_1}{2g} \tag{1}$$

$$E_2 = Z_2 + Y_2 + \frac{V_2^2 \alpha_2}{2g} \tag{2}$$

where E = total energy head at any section, Z the bottom elevation of the respective section above the datum, Y the flow depth, V the mean velocity at that section and α_1 and α_2 are the velocity head correction factor at that consecutive sections. Considering h_1 the total energy loss between those two sections, we can write.

$$Z_1 + Y_1 + \frac{V_1^2 \alpha_1}{2g} = Z_2 + Y_2 + \frac{V_2^2 \alpha_2}{2g} + h_1 \tag{3}$$

It may be noted that the energy loss (h_l) may not be linearly varying between sections to sections. It mainly depends on the channel geometry, converging angle, and surface and flow conditions (Naik and Khatua, Rezai).

Knowing the energy loss between two sections, the energy slope between those sections can be calculated by

$$S_f = h_1/l = (E_1 - E_2)/l \tag{4}$$

where $h_1 = E_1 - E_2/l$, and l is distance between two consecutive sections. Calculation of this energy slope is helpful for correct estimation of flow or average velocity in any part of the non-prismatic sections. This is further helpful for drawing the energy gradient and the energy slope. The energy losses between sections to section of the present experimental converging compound channels and channels of Rezai (2006) for different converging floodplain angles and geometries are calculated using equation (4). Here the entry of the converging of the section is taken as reference for calculating the length of the reach. As the estimation of energy loss depends on prediction of total energy at any section which is a difficult task because of dependency on different hydraulic and geometric variability that exist in such compound channels. It is very difficult to establish the nonlinear relation of geometrical and hydraulic input parameters with energy loss. Apart from these loss factors, there are other two remarkable energy loss factors such as interaction between the main channel and floodplain and the second factor is due to contraction of floodplain. This complex phenomenon existing in a non-prismatic compound channel makes prediction of flow more complex. Looking to this an ANN techniques can be easily applied to predict the energy loss, the calculation of which has directly or indirectly have significant effect on predicting important variables such as stage-discharge relationship, shear stress distribution, energy slope prediction, flow distribution etc. Therefore an attempt is made here to predict the Energy Loss of a non-prismatic compound channel using Artificial Neural Network (ANN).

2.1 *Selection of hydraulic parameters*

Flow hydraulics and momentum exchange in converging compound channels are significantly influenced by both geometrical and hydraulic variables. The computation of flow variables in a converging compound channel is more complex than that for simple compound channel. The geometrical and flow factors responsible for the estimation of energy losses at different reaches of a converging compound channel are

i. Relative flow depth (β) = $(H-h)/H$. where H = height of water at a particular section and, h = height of water in main channel
ii. Converging angle denoted (θ)
iii. Width ratio (α) i.e. ratio of width of floodplain (B) to width of main channel (b)
iv. Aspect ratio (σ) of main channel i.e. ratio of width of main channel to depth of main channel
v. Relative distance (Zr) from a reference or origin i.e. The distance of the arbitrary reach or section in longitudinal direction of the channel/total length of the non-prismatic channel. Total five flow variables were chosen as input parameters and energy loss as output parameter.

3 EXPERIMENTAL PROCEDURE AND RESULTS

Experiments had been conducted at the Hydraulics and Fluid mechanics Laboratory of Civil Engineering Department of National Institute of Technology, Rourkela, India. Two sets of non-prismatic compound channels with varying cross sections were built inside a concrete flume measuring 15 m long × 0.90 m width × 0.55 m depth and flume with perpex sheet of same dimensions. The width ratio of the channel was $\alpha = 1.8$ and the aspect ratio was $\sigma = 5$. Keeping the geometry constant, the converging angles of the channels were varied as 12.38° and 5° respectively. Converging length of the channels fabricated were found to be 0.84 m and 2.28 m respectively. Water was supplied through a series of Centrifugal pumps (each 15 hp capacity) discharging into a large RCC overhead tank. In the downstream end there was a measuring tank followed by a sump which feed the water to the overhead tank through pumping. This arrangement completes the recirculation system of water for the experimental channels. The plan view of experimental channels is shown in Figure 2a. Typical grid showing the arrangement of velocity measurement points along horizontal and vertical direction at the test section is shown in Figure 2b. At the downstream end another adjustable tail gate was provided to control the flow depth and maintain a uniform flow in the channel. A movable bridge was provided across the flume for both span wise and stream wise movements over the channel area so that each location on the plan of

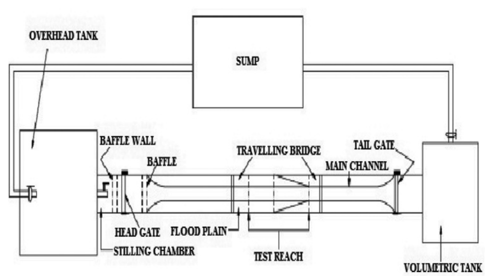

Figure 2a. Plan view of experimental setup.

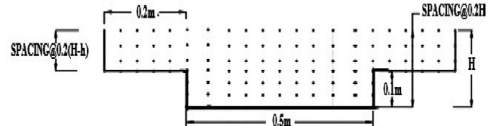

Figure 2b. Typical grid showing the arrangement of velocity measurement points at the test section.

compound converging channel could be accessed for taking measurements. Point velocities were measured along verticals spread across the main channel and flood plain so as to cover the width of entire cross section. Measurements were also taken from mid-point of main channel to the left edge of floodplain at a number of horizontal layers in each vertical point. The lateral spacing of grid points over which measurements were taken was kept 5 cm inside the main channel and the flood plain. Velocity measurements were taken by Pitot static tube (outside diameter 4.77 mm) and two piezometers fitted inside a transparent fibre block fixed to a wooden board and hung vertically at the edge of flume the ends of which were open to atmosphere at one end and connected to total pressure hole and static hole of Pitot tube by long transparent PVC tubes at other ends. The angle of limb of Pitot tube with longitudinal direction of the channel was noted by circular scale and pointer arrangement attached to the flow direction meter. Pitot tube was physically rotated with respect to the main stream direction till it records the maximum deflection of the manometer reading. A flow direction finder was used to get the direction of maximum velocity with respect to the longitudinal flow direction. Steady uniform discharge was maintained in every runs of the experiments and several runs were conducted for overbank flow with relative depth varying between 0.15–0.51. Table 1 shows the hydraulic parameters of different channels used in this paper. For the present analysis, we have also used the data of Rezai (2006). Rezai (2006) conducted experiment on different converging angles. As said before, total converging part of the channels has been divided into 5 arbitrary sections. Now we have evaluated the energy losses in the flow due to convergence of floodplain at different sections of the converging portions.

From the experimental results on converging compound channels, it is seen that the energy loss between two sections at the begging is higher than that in later sections. These value gradually decreases and reaches minimum just before the mid of converging section. After reaching minimum, there is a gradual increase trend is observed. This may be due to that at the entry section there is a huge loss of energy because of sudden contraction from prismatic part to non-prismatic part. After that the flow gets a transition reducing the loss and it is believed that the transition is complete before mid-section. In the lower width ratio converging experimental channels energy loss is higher at initial overbank flow depths then the loss decreases and reaches minimum at the end of non-prismatic section. This is because the present lower width floodplain converging compound channels have a shorter reach as compared to other higher

Table 1. Hydraulic parameters for the experimental channel data set collected from literature experiments.

Verified test channel	Types of channel	Angle of convergent (Θ)	Longitudinal slope (S)	Cross sectional geometry	Total channel width (B)	Main channel width (b)	Main channel depth (h)	Width ratio B/b	Ranges of energy loss in two consecutive sections
					Meter	Meter	Meter		Joule
Rezai (2006)	Convergent (CV2)	11.31°	0.002	Rectangular	1.2	0.398	0.05	3	0.0004–0015
Rezai (2006)	Convergent (CV6)	3.81°	0.002	Rectangular	1.2	0.398	0.05	3	0.004–0.0028
Rezai (2006)	Convergent (CV6)	1.91°	0.002	Rectangular	1.2	0.398	0.05	3	0.0011–0.0137
N.I.T. Rkl	Convergent	5°	0.0011	Rectangular	0.9	0.5	0.1	1.8	0.0000015–0.0044
N.I.T. Rkl	Convergent	12.38°	0.0017	Rectangular	0.9	0.5	0.1	1.8	0.000032–0.0016

width ratio channels. The results show that the energy loss is non-linearly depending on those non-dimensional parameters. Therefore an attempt has been taken to model the prediction of energy loss by applying an efficient ANN tool which are described below.

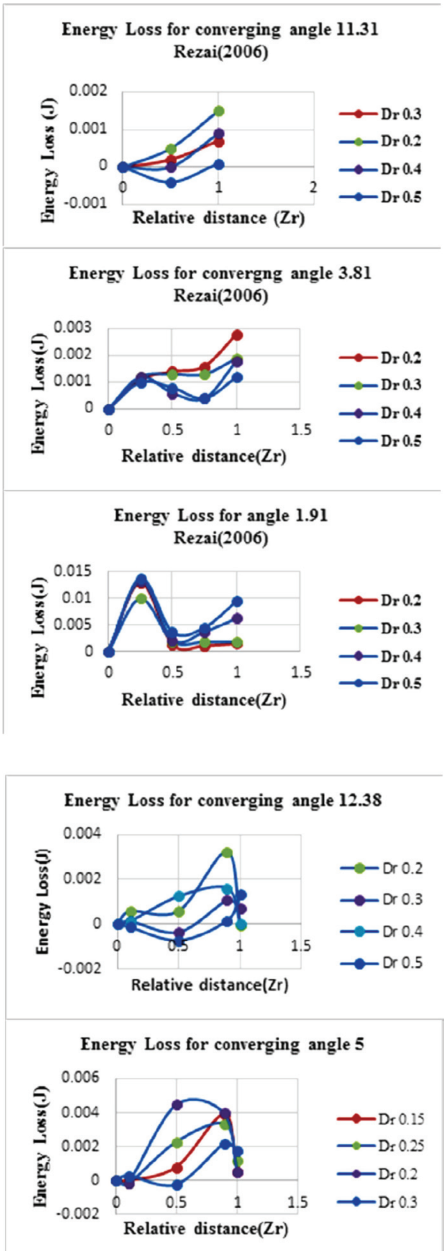

Figure 3. Energy losses vs relative distance for different converging angles.

4 ARTIFICIAL NEURAL NETWORK

ANN is a new and rapidly growing computational technique. In recent years it has been broadly used in hydraulic engineering and water resources. It is a highly self-organised, self-adapted and self-trainable approximator with high associative memory and nonlinear mapping. ANNs can be seen to be a simplified model of human nervous system; it can simulate complex and nonlinear problems by employing a different number of nonlinear processing elements i.e. the nodes or neurons. Nodes are connected by links or weights. ANNs may consist of multiple layers of nodes interconnected with other nodes in the same or different layers. Various layers are referred to as the input layer, the hidden layer and the output layer. Input layer receives information from the external source and passes this information to the network for processing. Hidden layer receives information from the input layer and does all the information processing, and output layer receives processed information from the network and sends the results out to an external receptor. The input signals are modified by interconnection weight, known as weight factor W_{ij} which represents the interconnection of *ith* node of the first layer to the *jth* node of the second layer. The sum of modified signals (total activation) is then modified by a sigmoidal transfer function *(f)*. Similarly output signals of hidden layer are modified by interconnection weight *(*W_{ij}*)* of *kth* node of output layer to the *jth* node of the hidden layer. The sum of the modified signal is then modified by a pure linear transfer function *(f)* and output is collected at output layer.

Let $Ip = (I_{p1}, I_{p2}, \dots, I_{pl})$, $p = 1,2, \dots, N$ be the *pth* pattern among N input patterns. W_{ji} and W_{kj} are connection weights between *ith* input neuron to *jth* hidden neuron and *jth* hidden neuron to *kth* output neuron respectively.

Output from a neuron in the input layer is

$$Opi = Ipi, i = 1,2, \dots 1 \tag{5}$$

Output from a neuron in the hidden layer is

$$\begin{aligned} Opj &= f(NET\ pj) \\ &= f\left(\sum_{i=0}^{l} Wji\ Opi\right),\ j = 1,2.\, m \end{aligned} \tag{6}$$

Output from a neuron in the hidden layer is

$$\begin{aligned} Opk &= f(NET\ pk) \\ &= f\left(\sum_{i=0}^{l} Wkj\ Opj\right),\ k = 1,2.\, n \end{aligned} \tag{7}$$

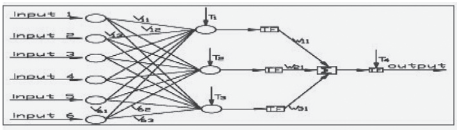

Figure 4. The architecture of back propagation neural network model.

4.1 *Sigmoidal function*

A bounded, monotonic, non-decreasing, S Shaped function provides a graded non-linear response. It includes the logistic sigmoid function

$$F(x) = \frac{1}{1 + e^{-x}} \tag{8}$$

where x = input parameters taken.

The architecture of back propagation neural network model. That is the *l-m-n* (*l* input neurons, *m* hidden neurons, and *n* output neurons) is shown in the Figure 4.

4.2 *Learning or training in back propagation neural network*

Batch mode type of supervised learning has been used in the present case in which interconnection weights are adjusted using delta rule algorithm after sending the entire training sample to the network. During training the predicted output is compared with the desired output and the mean square error is calculated. If the mean square error is more, then a prescribed limiting value, it is back propagated from output to input and weights are further modified till the error or number of iteration is within a prescribed limit.

Mean Squared Error, *Ep* for pattern *p* is defined as

$$EP = \sum_{i=1}^{n} \frac{1}{2}(Dpi - Opi)^2 \tag{9}$$

where *Dpi* is the target output, *Opi* is the computed output for the *ith* pattern.

Weight changes at any time *t*, is given by

$$\Delta W(t) = -nEp(t) + \alpha \times \Delta W(t-1) \tag{10}$$

n = learning rate i.e. $0 < n < 1$
α = momentum coefficient i.e. $0 < \alpha < 1$

5 RESULTS AND DISCUSSIONS

5.1 *Testing of back propagation neural network*

From the entire experimental data sets, 70% of them were used for training for the ANN model and remaining 30% used for testing of the ANN model for both the Energy and Energy loss calculation. Train and test sets were selected randomly to find a optimum structure of ANN model.

For Energy Calculations 679 data were used among which 476 were training data and 203 were taken as testing data. Similarly for Energy loss modelling, 532 data set were used among which 373 data were taken as training data and the remaining 159 were taken as testing data. The number of layers and neurons in the hidden layer were fixed through exhaustive experimentation when mean square error was minimised for training data set. It was observed that minimum error obtained for 5-7-1 architecture. So the Back Propagation Neural Network (BPNN) used in this work has three layered feed forward architecture. The model was run on MATLAB commercial software dealing with trial and error procedure.

A regression curve is plotted between actual and predicted Energy and Energy Loss which are shown in Figures 5 and 6. It can be observed that data for both cases are well fitted because a high degree of coefficient of determination R^2 of 0.993 is obtained for the Energy Calculations and R^2 of 0.977 is obtained for the Energy Loss Analysis between the sections.

The residual analysis are carried out by calculating the residuals from the actual energy loss and

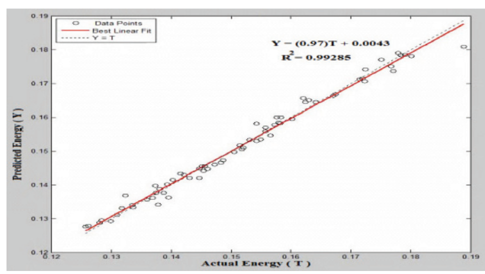

Figure 5. Correlation plot of actual energy and predicted energy.

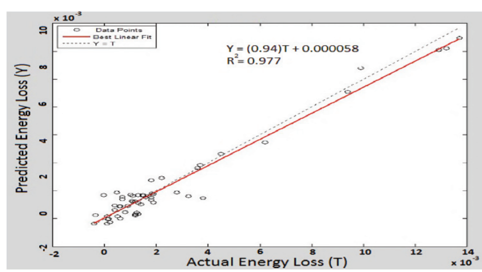

Figure 6. Correlation plot of actual energy loss and predicted energy loss.

predicted energy loss data. The residual testing and training data are plotted against the sample number as shown in Figures 7 and 8, which shows that the residuals are distributed evenly along the centreline of the plot. From this it can be said that the data are well trained.

The actual energy data and predicted energy data sets against the sample numbers are shown in Figure 9. Similarly the actual energy loss and predicted energy loss data against the sample number is shown in Figure 10. As the predicted data pattern follows actual data with little or no exception, it means the models predict the pattern of the data distribution with adequate accuracy.

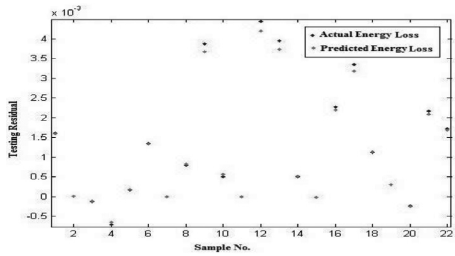

Figure 7. Residual distribution of testing data of energy loss.

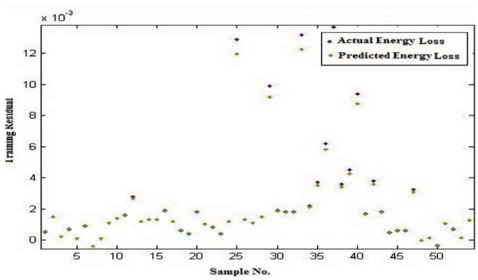

Figure 8. Residual distribution of training data of energy loss.

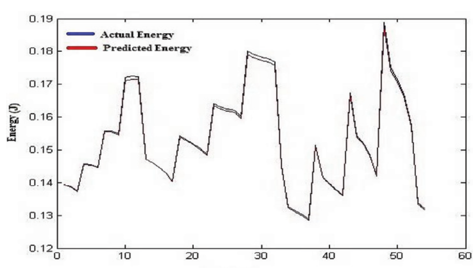

Figure 9. Comparison of actual and predicted energy training data.

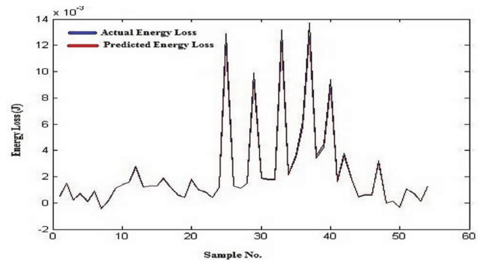

Figure 10. Comparison of actual and predicted energy loss (training data).

Table 2. Statistical results of empirical equation in predicting energy and energy loss.

Error calculations	Energy	Energy loss
MSE	0.00000045	0.00000006
RMSE	0.0006673	0.000238211
MAE	0.0004949	0.000107582
MAPE	0.3	4.49

6 CONCLUSIONS

1. From the experimental results on converging compound channels, it is seen that the energy loss between two sections at the begging is higher than that in later sections. These value gradually decreases and reaches minimum just before the mid of converging section. After reaching minimum, there is a gradual increase trend is observed. This may be due to that at the entry section there is a huge loss of energy because of sudden contraction from prismatic part to non-prismatic part. After that the flow gets a transition reducing the loss and it is believed that the transition is complete before mid-section.
2. In the lower width ratio converging experimental channels, energy loss is higher at initial over-bank flow depths then the loss decreases and reaches minimum at the end of non-prismatic section. This is because the present lower width floodplain converging compound channels have a shorter reach as compared to other higher width ratio channels.
3. Selection of energy loss of converging compound channels are found to depends upon a numbers of non-dimensional hydraulic and geometric parameters out of which aspect ratio, depth ratio, width ratio, relative distance, converging angle and relative depth are the most influencing parameters.
4. An ANN model is proposed for accurate estimation of energy loss of converging compound

channels. The trend and pattern of experimental data matches with predicted energy loss. The basic reason of high degree of prediction accuracy lies in the fact of capability of nonlinear mapping of inputs and outputs in a Neural Network system. The nonlinear relation of geometrical and hydraulic input parameters with energy loss is difficult to establish with traditional energy loss prediction methodology. In addition, the conventional techniques cannot be taken into account the real life factors operating in the system it can be inferred that this model is more adaptive to the prediction of energy loss under different conditions.

5. ANN model holds the energy loss prediction with minimal error i.e. MSE as 0.00000006 RMSE as 0.000238211 MAE as 0.000107582 and MAPE 4.49 which less than 10%. Similarly for energy MSE as 0.00000045 RMSE as 0.0006673 MAE as 0.0004949 and MAPE 0.3. So the present ANN model is more convincing model.

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