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VELOCITY PREDICTION BY USING FUZZY LOGIC

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Abstract: An artificial neural network (ANN**)**, usually called neural network (NN) consists of mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. Modern neural networks are non linear statistical modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. The bend of channel varies according to its radius, degree of angle at its curvature and depth at different sections of channel due to which the velocity of the flow of water at the bend of channel vary at different sections. Hence it is necessary to study and predict the velocity for planning and management of water resources. In this regard, prediction of velocity at a bend of channel was studied using experimental setup of flume and thus various experiments were conducted, The observations were recorded and data regarding varied radius, depth ,theta were collected and from this velocity was measured. In this regard prediction of velocity was done using artificial neural network with components in channel bend i.e. angel of bend, radius of bend, flow depth and Karmans constant as input data except Karmans constant, while the velocity as a target output, The total no. of samples recorded are 315. It was observed that different methods were used such as MLP, recurrent networks etc for prediction of parameters of hydrology but the method of Fuzzy Logic was never applied while using ANN. Hence depending on the data representation and the application the model Fuzzy logic is used to train and learn the data sets. Hence after training for number of runs, learning and testing the results obtained were satisfactory. Supervised neural networks that use an MSE cost function can use formal statistical methods to determine the confidence of the trained model. The MSE on a validation set can be used as an estimate for variance. This value can then be used to calculate the confidence interval of the output of the network, assuming a normal distribution. The results of the study showed that predictions of velocity using artificial neural network are reasonable, suitable and of acceptable accuracy. Hence prediction of velocity at the curvature of channel by ANN may be useful for water quality planning and management.

Keywords: Karmans constant, an artificial neural network (ANN**),** flume, neural network (NN), Fuzzy Logic and water resources.

I. INTRODUCTION

Lacks of water resources and optimum management have been two recent challenges of water resources engineering. Population growth, decrease of useable water resources, improvements in lifestyle, growing rate of consumption, climate change and several other parameters have caused useable water to be a significant problem for future. Economic and efficient use of water resources and its management have an increasingly significant role. Prediction of velocity of water at the river channel is one of the methods which can be recently considered for management of water resources. The prediction can be used for water resources planning and management in case they are of acceptable accuracy. There are two steps for prediction of velocity like other water quality parameter. First precise study of experiments performed which gives various factors on which velocity is dependent. Even the data is recorded and obtained from this experiment which helps for the selection of model according to the obtained information. Second, developing data driven Models using information and collected data. In the latter technique, relationship between input and output data can be found using input data, but still physical understanding of phenomena is significant for having suitable input data for model. ANN is one of the data driven models which has recently been applied as a tool for modeling complicated processes. American Society of Civil Engineering (ASCE) research committee reported that ANN can be applied for various hydrological branches and they reached the conclusion that ANN is able to simulate many of complicated nonlinear processes. Hence further among various method of ANN which are used in different case studies of hydrology the method of Fuzzy logic has rarely used so it was decided to predict the velocity using Fuzzy Logic and get the acceptable results. After performing the experiment using setup of flume the velocity measurements were recorded at each 300 interval on bend and 50 cm on straight reaches. At each cross section observations were taken at three verticals. At each vertical, three observations were taken at mid-depth, surface and bottom. Further the recorded observation data was trained using Fuzzy logic for number of times with certain Number of runs and epochs. The results of the study showed that predictions of velocity using artificial neural network are reasonable, suitable and of acceptable accuracy. Hence prediction of velocity at the curvature of channel by ANN may be useful for water quality planning and management.

II. THEORY

The development of artificial neural network was inspired by the studies of the ability of the brain to learn from experience without predefined knowledge of underlined physical relationship. ANN is a broad term covering a large variety of network architectures. The most common of which is a multilayer perceptron. Given a set of input vectors and associated target output vectors, the objective of any ANN algorithm is to learn a rule that captures the underline functional relationship between the input vectors and the target vectors. Mathematically each target vector Z is an unknown function f of the input vector x.

$$Z = f(x) \text{ - - - - - - - } (5.1)$$

The test of any network is to learn a function f. The network includes a set of parameters, the values of which are varied to modify function f', which is computed by the network and should be as close as possible f. The weight parameters are determined by training the ANN on the training data set. Many types of neural networks have been proposed by changing the network topography, node characteristics and the learning procedure. Examples of these are hopfied network, Kohonon network and back propagation network. Fig.1 shows a general structure of MLP. Each layer in the network consists of nodes or neurons which are connected to nodes in the previous and following layers by connections. Input data are presented to the network through the input layer. Data are passed from the input layer to the hidden layer. Each node in the hidden layer receives the weighted outputs of the node in the preceding layer. These outputs are then summed and added a threshold value. The node input is then passed through and activation function to produce the node output. This node output is then used to compute the inputs for nodes in the following layer until the final output is calculated.

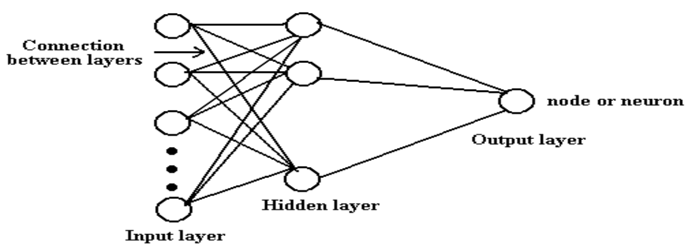


Fig.1 General Structure of MLP

Commercially available neural network software package Neuro 4 for excel with a feed forward back propagation neural network has been used for this study for forecasting longitudinal velocity component in channel bend flocculator. All ANNs are arranged in layers. There are three types of layers, each having a different role in the overall operation of the networks, the input layer, where the data pattern is presented, the hidden layers and the output layer. Each layer is made up of several nodes and the layers are interconnected by correlation weights. The way that nodes are connected, the number of hidden layers and the number of processing unit per layer, determine the way the computation proceeds. After arranging the inputs and the output (one), the part remaining is deciding the processing elements in the input and the output layer, number of hidden layers and the learning rule. Extensive trials have been performed to define number of processing elements and hidden layers. A substantial number of combinations of number of processing elements per layer and number of hidden layers are tested. Every created network architecture is trained and subsequently tested on the testing data whether or not to accept it. A time lagged recurrent network with single hidden layer has been accepted because it has given a best fit to the available data as compared to other architectures. TDNN is memory structure of ANN just like RAM or ROM. RAM or ROM requires external operations while TDNN does not require any external operations, known as real time memory structure of ANN.

Fuzzy logic is a form of multi valued logic derived from fuzzy set theory to deal with reasoning that is robust and approximate rather than brittle and exact. In contrast with "crisp logic", where binary sets have two-valued logic fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic and probabilistic logic are mathematically similar – both have truth values ranging between 0 and 1 – but conceptually distinct, due to different interpretations—see interpretations of probability theory. Fuzzy logic corresponds to "degrees of truth", while probabilistic logic corresponds to "probability, likelihood"; as these differ, fuzzy logic and probabilistic logic yield different models of the same real-world situations.

III. EXPERIMENTATION

3.1 Experimental setup of Flume

The experiments were conducted on a rectangular flume of galvanized iron sheet. The flume comprised of three meters straight inlet section followed by a curve of 1800 and the central radius (rc) 1.05 meters and the exit straight of 3 meters length. The total length of the flume was 9.29 meters. It was supported on concrete blocks about 150 mm above laboratory floor. The three-meter long straight reach on upstream of the bend section was found to be of sufficient length to ensure flow establishment. The flume was of size 30 cm wide and 40 cm deep. The longitudinal slope given to the channel was 1: 600. Gated control was provided at the down-stream end of the channel to regulate the depth of the flow in the channel. Flow entered the tank of size 60 × 60 × 60 cm in which baffles and screens were provided. The space between the baffles and screens was filled in with stones of 20 to 40 mm size to dissipate turbulence. The flume is shown in 2. The water supply was from rectangular overhead tank. The constant pressure head was maintained at the inlet of channel. The flow was recirculated.

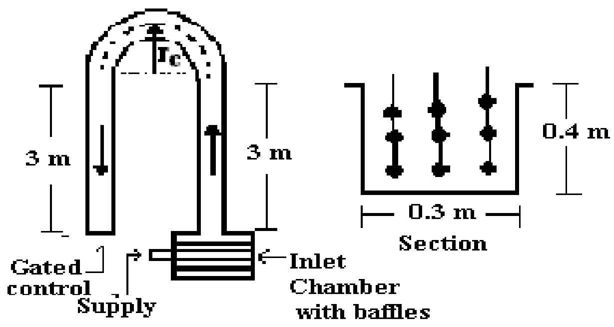


Fig. 2 Experimental Setup

IV. VELOCITY MEASUREMENTS

For measuring the longitudinal velocity Vθ at different points, a sensitive propeller current meter designed and fabricated by CWPRS, Pune was used. This velocity meter, consists of two parts.

1. Mechanical part of the instrument consists of a propeller type sensor with its diameter 15 mm, which is connected to the electronic unit by a shielded cable of 5 m length.
2. The electronic unit consists of signal processor, controller, counter and display unit. The electrical pulses from the propeller are fed to the signal processor, which converts them to compatible pulses. These pulses are then fed to the counter.
3. The controller consists of a triggering and timing circuit, which allows the output of a signal processor to be fed to the counter for duration selected by the user, from the front panel rotary switch.
4. The counting circuit consists of a counter connected to a four digit LCD (Liquid Crystal Display). The unit operates on four 1.5 volts cells (batteries).The specifications of the propeller current meter are as below.

Range - 5 cm/sec.
Resolution - 1 count
Display - 4 digit LCD display
Sampling period - In multiple of 10 sec upto 60 sec.
Supply - 1.5 V x 4 pen light cells, Size of propeller - 15 mm.

V. OBSERVATIONS RECORDED

The observations recorded were located on u/s entrance straight reach, and similarly on d/s of straight reach. Measurements were recorded at each 300 interval on bend and 50 cm on straight reaches. At each cross section observations were taken at three verticals. At each vertical, three observations were taken at mid-depth, surface and bottom. At the surface to allow for propeller blades to be fully immersed, observations were taken at 5 mm below the surface, near the bed, to ensure that propeller's blade don't touch the bed of the flume, observations were taken 5 mm above the bed. The depths were measured with the help of a pointer gauge. The pointer gauge was fixed on the projected sides of channel with a trolley. The propeller placed in the flowing water such that its axis is in the direction of the flow. The propeller rotates at a speed proportional to the speed of water. The number of revolutions of propeller was recorded at each point. The numbers of revolutions were measured three times to achieve accuracy in velocity measurements. These average numbers of rotations were converted to velocity with the help of calibration chart supplied by CWPRS, Pune. The experiments were performed for 5 runs, with different discharges. The total numbers of 314 observations were recorded, Table 1. Another set of experiment was performed where maximum number of observations was recorded on downstream reach of channel bend to know the decay effect. Uniform flow was practically maintained throughout the experiment for each run. This was verified by measuring depth at the beginning, after every hour and at the end of each run. The discharge was measured with the help of a calibrated bend meter fitted to a supply pipe.

VI. DATA COLLECTION

The input/output data required for ANN has been collected from the experiments carried out on 1800 channel bend flocculator in the laboratory. As stated in the experiment performed, the velocity component in the channel bend is a function of angle of bend, radius of bend, flow depth and Karmans constant, Dahigaonkar34 and hence selected as input data except Karman's constant, velocity as a target output. The total numbers of samples recorded were 314.

VII. DATA DIVISION

The development of any model requires the partitioning of the data in to statistically similar subsets in order to calibrate and test the model. The method used in this research work was based on trial and error method which produces a output based on statistical similarities such as mean and variance. The training and testing data were chosen so that they contain values from each cluster. Division of the calibration data into training and testing subsets ensures that overfitting does not occur. The parent data sets was divided into 75% training, 10% cross validation and 15% testing. The testing set was kept aside in the calibration process. Application of this approach resulted in 235, 31 and 48 data points in the training, cross validation and testing respectively.

7.1 FUZZY MODEL- TSK

No. of inputs- 03, No. of output-01, Hidden layer-00, Membership Function- BELL, Transfer Function – Linear Axon, Learning Rule – Momentum, Step size – 1.00,Momentum – 0.70,MSE – Minimum Threshold – 0.01

VIII. TRAINING AND TESTING OF MODEL

Learning or training involves modifying the weights until the network is capable of reproducing the target output within specified error margin for the respective input pattern. A neuron usually receives many simultaneous inputs. Each input has its own relative weight which gives the input impact that it needs on the processing elements summation function. These weights perform the same type of function as do the varying synaptic strengths of biological neurons. In both cases, some inputs are made more important than others so that they have a greater effect on the processing element as they combine to produce neural response. Weights are adaptive coefficient within the network that determines the intensity of the input signal as registered by the artificial neuron. The training adopted for the network is supervised learning. When a network is trained repeatedly in order to improve its performance on the training data, there is possibility that the network will finally memorise the training samples and not learn the underlying pattern. This is called overfitting. It is more likely to happen to networks with large number of processing units and will results in poor generalisability. The ability to generalize, that is to produce reasonable accurate outputs from unfamiliar inputs, is important when neural network is used for forecasting, Lekkas. For this reason network with fewer parameters are preferred in order to avoid overfitting. The network parameters (weights and biases) should be adjusted only on account of the training set but error should be monitored on the test data sets. The error on the test data wills normally

Decrease during the initial iterations together with the error on the training set. However, when the network begins to overfit the data, the error on test set will begin to rise as presented in Fig.3.

Therefore, training procedure must be forced to stop before reaching a minimum and consequently produced a more general network. Training was governed by specifying number of epochs equal to 600, after several trials. Model is trained for three runs, which yielded the best results. Back propagation algorithm has been used as a training algorithm in feed forward multilayered neural network.Training was governed by minimizing the mean square root error between observed and predicted value of velocity. Fig.4 indicates the average MSE for 3 runs. The desired output and network output is shown in Fig.5. The average of final MSEs is found to be 0.009217, Table 1. Though the number of epoch during training was set to 1000 epochs, the maximum epoch required were 600 to achieve the above value of MSE, this was achieved for run no. 3 of training, Table 1. The performance level of network is indicated in Table 2 with an 'r' value = 0.80. This level of agreement is very acceptable for a prediction operation. Table 3 shows the velocity output after training the network. Fig.6 shows the relation between velocity at input and output level. The model is tested for its performance after its training has been completed.

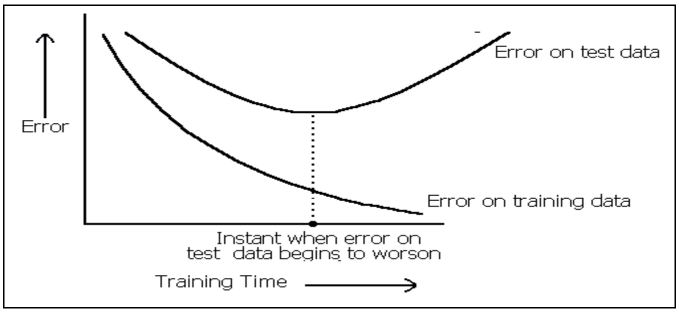


Fig. 3 Training of Network

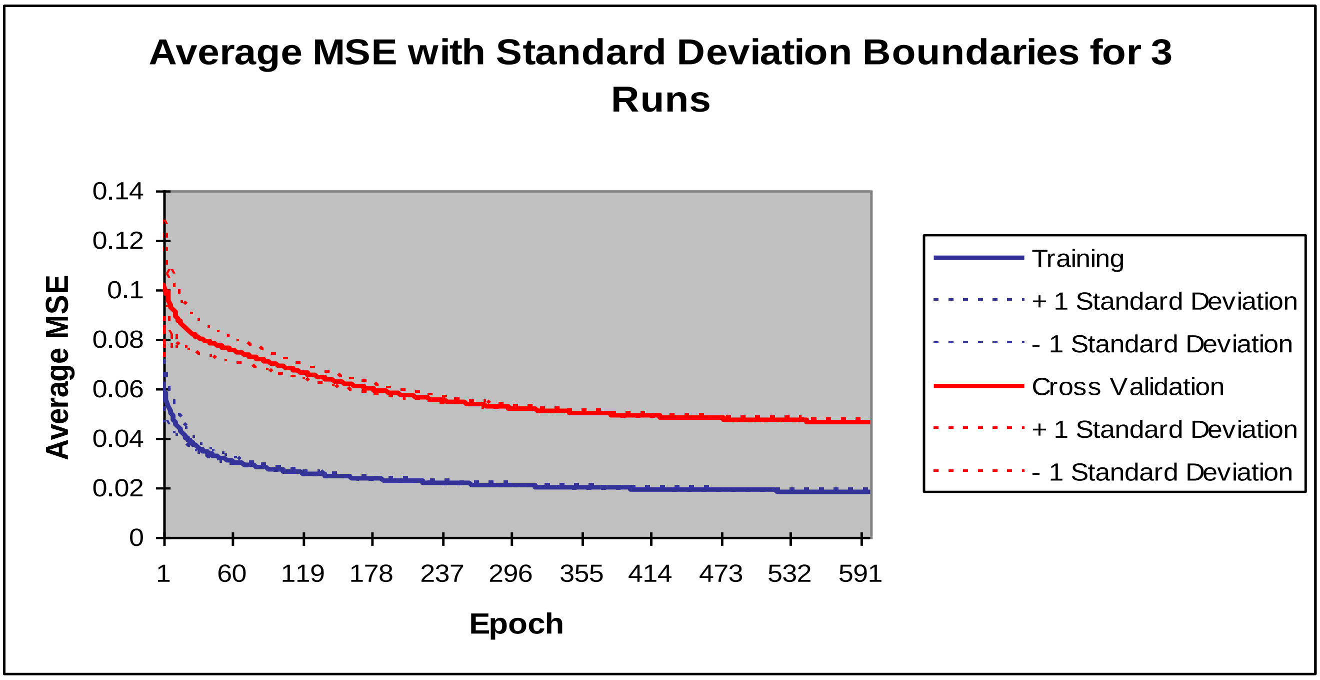
IX. SENSITIVITY

The term Sensitivity in the study process is mentioned on the Basis of the factors through which the velocity output has been determined. It specifies the dependency of velocity on the mentioned factors. After testing the data it was observed that the output of the velocity is affected due to the variation in the angle of bend i.e. theta at the channel curvature and it does not much get affected through variation of radius and depth of channel. Fig 7 shows the sensitivity results and table 4 represents the dependencies value. As comparing the graphical representation in fig no.8, 9 & 10 it was observed that the straight line is obtained when the graph between theta and velocity was drawn.

X. VALIDITY OF ANN MODEL

Validation involves evaluating the network performance on a set of test data that were not used for training. Before a developed neural network model can be used to predict longitudinal velocity channel bend flocculator there is a need to establish the validity of the prediction it generates. The evaluation of the network on the test problems has been under taken after training has been completed. Fig.5 represents the desired output and the actual output by network. The performance of the network is evaluated on the basis of MSE and value of r. Table 2 presents its performance for 48 records. Table 3 indicates the actual output after testing. The network output is compared quantitatively by using regression statistics, Table 3. Fig. 6 represents comparison of observed values and model values which is acceptable. Hence model can be used to forecast future values.

XI. RESULTS

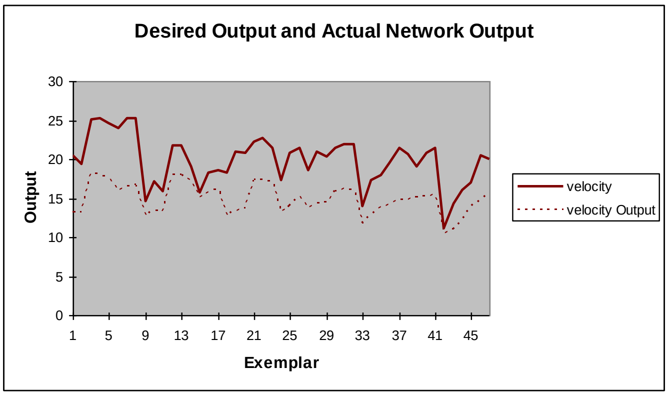


Graph 1: Average MSE with standard deviation boundaries for 3 Runs

All Runs	Training Minimum	Training Standard Deviation	Cross Validation Minimum	Cross Validation Standard Deviation
Average of	0.01822201	0.000495651	0.046253938	0.000921771
Average of Final	0.01822201	0.000495651	0.046253938	0.000921771
Best Networks	Training	Cross Validation		
Run #	3	3		
Epoch #	600	600		
Minimum MSE	0.01779481	0.045388073		

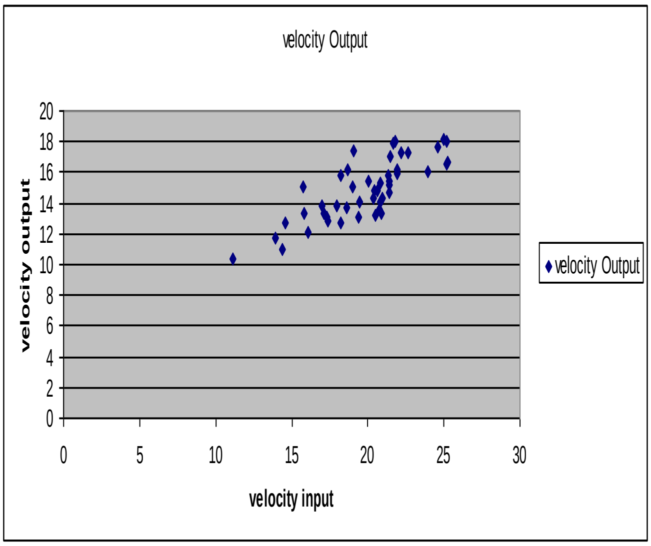
Performance	Velocity
MSE	28.93404549
NMSE	2.958879264
MAE	5.010692578
Min Abs Error	0.702906723
Max Abs Error	8.624480667
r	0.802117274

Table no.2

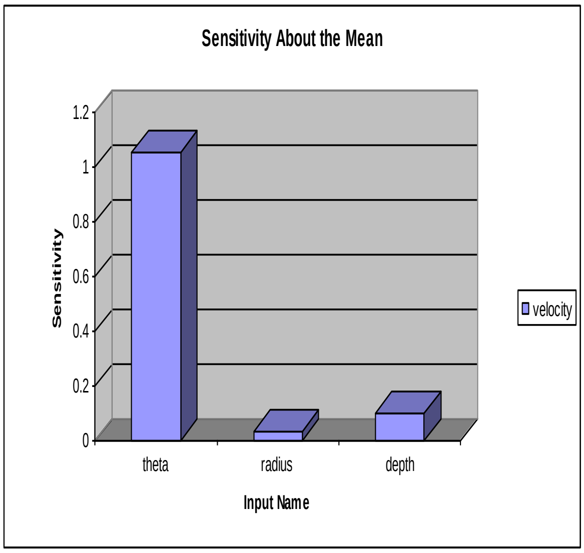


Graph 2: Desired output & actual network output

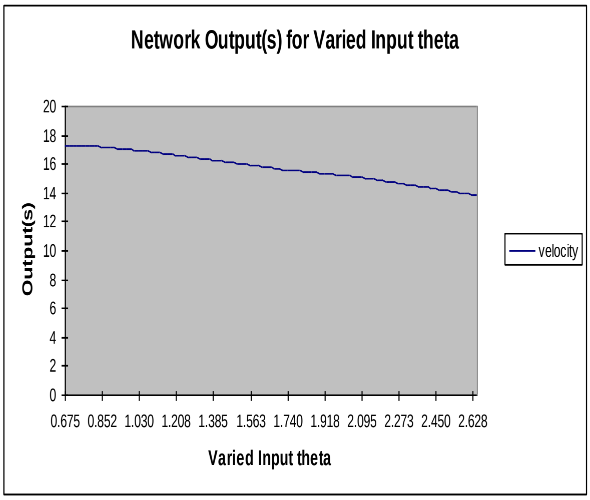
Theta	Radius	Depth	Velocity	Velocity output
0.17	120	2.55	20.5	13.2415876
0.17	120	5.1	19.42	13.1248369
0.17	105	0.5	25.02	18.2098446
0.17	105	2.55	25.19	17.9997673
0.17	105	5.1	24.62	17.5972443
0.17	90	0.5	23.92	16.0506649
0.17	90	2.55	25.19	16.5655193
0.17	90	5.1	25.26	16.6892204
0.5	120	0.5	14.58	12.7104397
0.5	120	2.75	17.11	13.2898407
0.5	120	5.5	15.8	13.3425846
0.5	105	0.5	21.82	17.9833794
0.5	105	2.75	21.69	17.9144955
0.5	105	5.5	19.09	17.3797436
0.5	90	0.5	15.74	15.0021639
0.5	90	2.7	18.23	15.7614889
0.5	90	5.4	18.65	16.1381454
1.04	120	0.5	18.23	12.6623173
1.04	120	2.6	20.92	13.3157511
1.04	120	5.2	20.76	13.6260052
1.04	105	0.5	22.2	17.3297997
1.04	105	2.5	22.65	17.3344765
1.04	105	5	21.46	17.0686531
1.04	90	0.5	17.3	13.1477823
1.04	90	2.5	20.85	14.0435781
1.04	90	5	21.4	15.1731453
1.57	120	0.5	18.618	13.7559977
1.57	120	2.65	20.985	14.2832937
1.57	120	5.3	20.377	14.3688135
1.57	105	0.5	21.369	15.8176727
1.57	105	2.65	21.914	16.2212334
1.57	105	5.3	21.945	15.9630423
1.57	90	0.5	13.902	11.7567358
1.57	90	2.6	17.37	12.7880926
1.57	90	5.2	17.977	13.866498
2	120	0.5	19.48	14.0884647
2	120	2.45	21.43	14.6845751
2	120	4.9	20.66	14.8376513
2	105	0.5	19	15.0421028
2	105	2.15	20.82	15.308013
2	105	4.3	21.4	15.373908
2	90	0.5	11.12	10.4170933
2	90	2.25	14.35	11.0196676
2	90	4.5	16.08	12.0789795



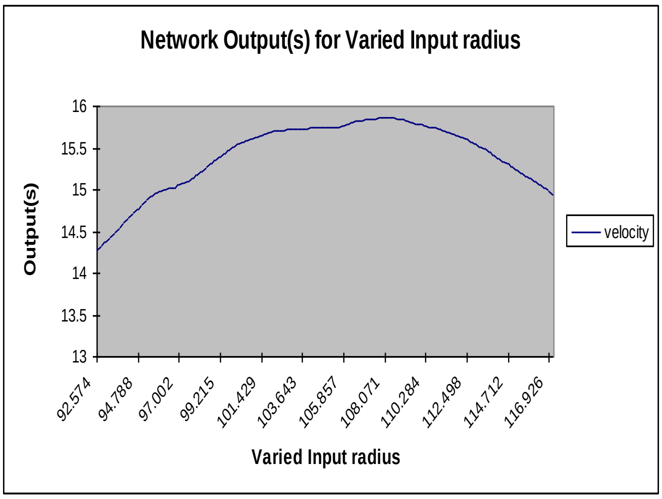
Graph 3: Velocity output



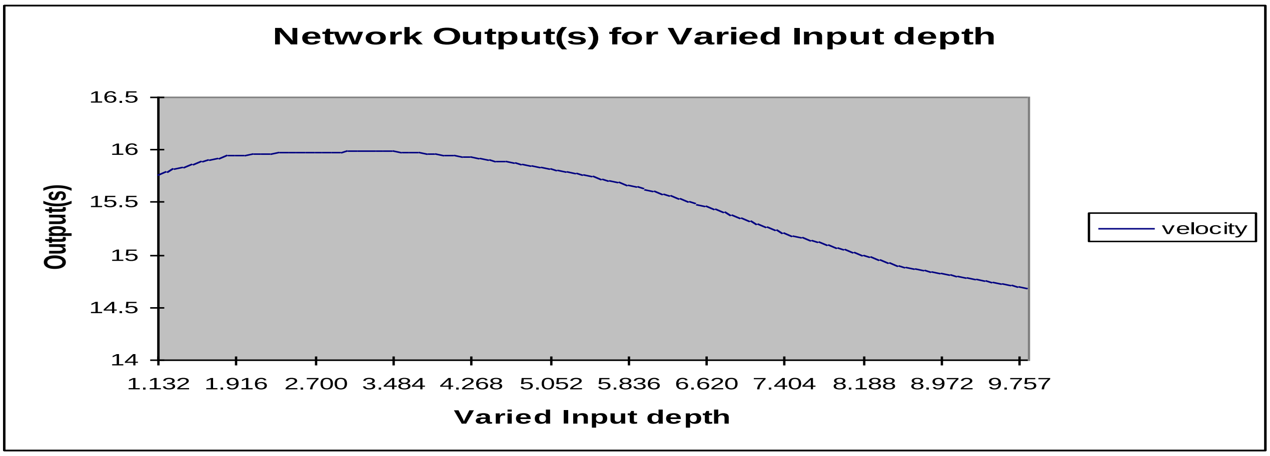
Graph 4: Sensitivity about the mean



Graph 5: Network outputs for varied input theta



Graph 6: Network outputs for varied input radius



Graph 7: Network outputs for varied input depth

XII. CONCLUSIONS

In this study, Fuzzy Logic Artificial neural network model were applied for the prediction of velocity at the curvature of the channel. The results obtained from model of neural network showed their acceptable precision in prediction of velocity in the study. From the results of the studies it can be stated that using Artificial Neural Network for predicting the velocity of flow the parameter theta can be considered as an effective option. The results of study also stated that fuzzy logic is one of the effective models in ANN. Also the results of study can be utilized in optimized management and planning of water resources of the study area.

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