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Prediction of Discharge in Straight Compound Channels using Conventional and Soft Computing Tools

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ABSTRACT
Proper assessment of discharge capacity of a river is needed for design, operation and maintenance of channels. Estimation of stream flows in the compound open channel by numerical approach is very complex as it involves inputs from a good number of parameters. During high floods and where gauging stations are not located, it becomes very challenging to predict the discharge at these locations and the situation. Measurement of discharge at this stage becomes risky and the quantum of flow estimated are based on extrapolation of Gauge – discharge curves that are mostly inaccurate. Actual discharge is always different from the calculated values. Tools such as soft computing techniques are used to resolve the real world problems. Also the actual data collected from river need to be mapped with the experimental results. This mapping can reveal the suitability of the techniques used in prediction as well for justification of the experimental setup done with good financial investments. Three different data sets are used to compare the best suited soft computing technique for discharge predictions.

Keywords: Single Channel Method, Divided Channel Method, CES, FUZZY, ANFIS.

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I. INTRODUCTION

Estimation of stream flow in the natural rivers is fundamental to the River hydraulics. Complexities of the flow estimation become more pronounced, when the flow goes over bank and the channel becomes compound. A compound channel can be characterized as a main channel flanked by adjoining floodplains. Estimation of discharge is always needed for design of any hydraulic structure and the safe disposal of flood water. In general Manning`s, Chezzy`s or Darcy-Weisbach equations are used in case of simple channels to estimate the discharge. When the flow overtops the banks and spreads to its adjoining floodplains, the flow behavior becomes more complex due to difference in shear between the sections leading to momentum transfer. Such channel conditions are simulated, replicated or modeled in controlled laboratory conditions by taking different flow characteristics and parameters into consideration. Researchers have suggested different methods for discharge computation in compound channels. These methods can be the traditional approaches; the Single Channel Method (SCM) or Divided Channel Methods (DCM) [1, 2, 3, 4 & 5] or it can be the numerical tools. In SCM, the whole compound channel is considered as single cross section and the discharge is computed either by using Manning's or Chezy's equation. In DCM, various interface plains originating from the junction between the main channel and the floodplains is considered. The slower moving floodplain flow is separated from the faster flowing main channel flow by using that interface. Discharge for each sub section is calculated separately and added to gate the section discharge of the whole channel.

The other approaches among the DCM, the work of Prinos-Townsend [6] suggesting the 'area method' as more reliable alternative or the Ackers approach suggesting a correction to the DCM and naming as (COHM) is well referred [7]. Patra and Kar [8] proposed variable interface plane of separation of main channel flow from the floodplain that changes its location following the flow depth. Khatua and Patra [5] emphasized on interface length to quantify momentum transfer that is reported to have given good results. Approaches for river discharge predictions can be categorized as empirical, statistical, analytical or using soft computing tools. However, a method is chosen depending on a number of factors including the purpose of prediction, availability of data, channel type and other hydrological characteristics. Many methods are presented based on the statistical analysis of flow data which are not found to be suitable for practical approaches for all locations. Regression analysis is most often used as handy tools for the observed data. It can be used to forecast the behavior of the targeted stream [9].

Deka and Chandramouli [10] tested a neural network model and compared the discharge results with a conventional curve fitting approach. Bhunia and Dwivedi [11] established the rating curve using soft computing techniques to transform the observed stages into the corresponding discharges. Grid partitioning method was used to develop the model and compared against the conventional regression analysis which used subtractive clustering.

Beaman [12] undertook numerical modeling for the in-bank and over-bank flows using Shiono Knight Method (SKM) through large eddy simulation technique and applied a numerical model named as Conveyance Estimation System (CES). This model was employed by the Environment Agency (EA) of England for estimation of river conveyance across Europe with success. Chang et al. [13] used a counter propagation fuzzy-neural network (CFNN) for predicting real time stream flow of Da-Cha river of Taiwan. One hour ahead flood forecasting was made possible using CFNN and compared their results with auto regressive moving average with exogenous variable model (ARMAX).

Jayabardhena et al. [14] summarized the outcome of discharge prediction from hydrological modeling using daily time lagged rainfall and discharge data from four rivers by applying fuzzy logic approach. The results claimed robustness of the model by comparing against the observed data only. As per Dastorani et al. [15] data acquisition systems always bear short breaks which lead to gaps in flow data series. They have utilized ANN [Simon] and Adaptive Neural Fuzzy Inference System (ANFIS) to reconstruct the missing data. The main preference was towards new data driven techniques over traditional methods on missing flow data reconstruction. Keisin et al. [16] filled the gaps in missing data with synthetic data in the training set using auto regressive moving average model. The generated data was used to train the ANFIS model and predictions were compared with the ANFIS performance when only a limited number of observed flows were employed in the training data set collected from Dim Stream, Turkey. However, no other method or techniques were used for comparison. Folorunsho et al. [17] discussed about various types of methods used for stream flow prediction. They studied the data of river Kaduna, Nigeria and suggested that the related parameters are non-linear, stochastic and uncertain in nature. For that they suggested ANFIS as a robust technique. Flow prediction was done simply using the Graphical User Interface for ANFIS available in MATLAB software package. The predicted values were collected from command line and compared against observed values. A model was developed, but the reliability of the same was difficult to realize. Moharana et. al [18] used ANFIS for prediction of discharge in smooth and rough surface and compared the result with a traditional method using roughness coefficient from Linearised Soil Conservation Service Method. They utilized the GUI of MATLAB software package where there is little scope for further moderation in the model.

The review of literature indicates that limited work are reported in using soft computing techniques for discharge prediction for compound channels with smooth and rough floodplains.

For this present work the soft computing techniques used are CES, FUZZY and ANFIS [19] for prediction of discharge, to compare with available numerical models. The prediction are carried out using observed river data along with laboratory experimental channel data having smooth and rough surface. The aim of the present work is to propose a discharge prediction model that can be suitable for all types of compound channels.

II. EXPERIMENTAL SET UP

The current research uses straight compound channel with symmetrical floodplain fabricated with perspex sheet inside a tilting flume at the Fluid Mechanics and Hydraulics Engineering Laboratory of the Civil Engineering Department, at National Institute of Technology, Rourkela. The main channel is trapezoidal cross section with smooth floodplain in one run and vegetated floodplains in other runs. In the floodplains different roughness materials are used to provide the effect of vegetation. For roughening a synthetic mat is used in the floodplains surfaces having spikes of data sets synthetic mat used in the floodplains were having spikes 12mm long 1.5mm width with 72 spikes were there per square inch. In another observation wire mesh is used for roughening the surfaces in the floodplains. In the third case wire mesh in main channel with crushed stone at floodplains are used while in the fourth case smooth main channel with crushed stone in floodplains are used. Wire mesh used was having mesh opening size of 3mm x 3mm with wire diameter of 0.4mm. Crushed stones used for roughening have equivalent sand roughness of 3.39 mm.

Water is supplied to the channel from an underground sump with a re-circulating system through one overhead tank (Fig.1) having channel section shown in Fig.2. From the overhead tank water flows down to the stilling basin located at the upstream of the experimental channel, followed by a series of baffle walls to avoid turbulence in the flow Fig.3(a)..(h). At the downstream end, there is a rectangular notch. A masonry volumetric tank located at the downstream and is used for calibration of flow rate. Velocity measurements are recorded at different depth of flows in the main channel and in the floodplains using pitot tube along with a slanting manometer attached to the flume. For ease of collecting readings, a traverse moving bridge is used over the flume.

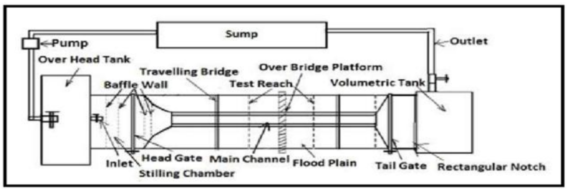


Fig. 1: Schematic drawing of whole experimental set up with tilting flume

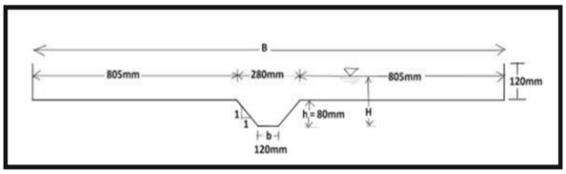


Fig. 2 Straight Compound Channel Section

Fig. 3 (a..h)Schematic drawing of whole experimental system with tilting flume

III. DATA COLLECTION

Besides the data collected from the present experimental set up data sets from Flood facility at HR Wallingford UK and the reported data from other investigators are taken for analysis [1, 3, 20, and 21]. From the researchers report data for smooth and rough channels with different hydraulic parameters were taken into account for the present study.

Data sets observed from three sets of experimental channels (smooth channel = data set 1, rough channel = data set 2 and smooth + rough= data set 3) are grouped and named as they are used in the analysis.

While establishing stage versus discharge relationship from above mentioned data sets as a single input group parameter, different neural networks for predictions such as the RBF, Elman, Cascade and BPN are used. It is assessed that Cascade performed best followed by BPN in case of daily data sets and Cascade followed by RBF for monthly or cumulated data sets as reported earlier [22, 23 and 24].

Again in this study different hydraulic parameters are taken as input data viz. bed slope (S_0), roughness in floodplains (n_{fp}), hydraulic radius (R_T), width ratio (α) and depth ratio (ß). With these multiple inputs, attempt was made to predict flow rate of the streams. In past, different numerical methods like Single channel method (SCM), Horizontal Division Methods (HDM), Vertical Division Methods (VDM), Interacting Divided Channel Method (IDCM), Modified Divided Channel Method (MDCM) were used for prediction of discharge [5]. In case of HDMs and VDMs, interface planes are not considered for HDM I and VDM I whereas it is taken into accounts in case of HDM II and VDM II for computation of discharge. These methods are not found to be adequate for all the types of channel geometry and roughness. Moreover, the applications of these methods are cumbersome and time consuming. The Conveyance and Afflux Estimation System (CES/AES) software tools are tried for estimation of discharge with a limited success [24].

IV. METHODOLOGY

Brief discussions about methodology of different soft computing techniques used in this study are presented. As noted earlier Cascade Neural Network was included in the analysis for comparison with other methods.

4.1 Conveyance estimation system (CES)

Hydraulic engineers of United Kingdom have developed a software tool for estimation of flood water levels of streams [25]. Different part of the software tool incorporates roughness advisor, conveyance generator, uncertainty estimator, backwater module, afflux estimator etc. Roughness advisor takes care of roughness values. Basing on roughness and stream section, conveyance generator uses the Lateral Distribution Method (LDM) to find the depth average velocity from which the stream discharge is computed.

4.2 Fuzzy Inference System

Fuzzy Inference System (FIS) is a logical system based on if-then fuzzy rules. The rules map the input variables to a single output variable using if-then statements and fuzzy decision making procedure. Mamdani and Sugeno function [13, 16, 26, 27 and 28] method is most commonly used in different fields like automatic control, data classification decision analysis, expert systems and others. The tool was used to fuzzily data sets with the inference system and defuzzified to get the predicted values. In fuzzy inference system the rules are:

If x_1 is A_1 **and** x_2 is A_2.....X_n is A_n,

then $y = f[x_1, x_2, ...x_n]$
where A_i are the fuzzy sets, x_i the inputs and y the output. In this system, if section of the rule is a real function of the input values and is linear statement such as $a_1x_1+a_2x_2+.....+a_nx_n$, the output of each rule is aggregated to produce the final crisp output. The model was developed by using MATLAB commercial software (R2014a).

4.3 Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-fuzzy system (ANFIS) is a hybrid technique where the fusion of neural networks and fuzzy logic find their strengths [28, 29]. Since it integrates both neural networks and fuzzy logic principles, it can capture benefits of both in a single framework. Hence ANFIS is referred as a universal estimator; which corresponds to a set of fuzzy if-then rules that have capability of approximation to nonlinear functions. Using a given input and output data set, the fuzzy inference system is constructed whose membership function parameters are tuned using a hybrid method consisting of back propagation for the parameters associated with input membership functions and least squares estimation for the parameters associated with the output membership functions. It rallies round in reducing the training error throughout the learning process. Subtractive fuzzy clustering is used to establish the rule-based relationship between the input and output variables. It's a technique for automatically generating fuzzy inference systems by detecting clusters in input-output training data.

V. MODEL DEVELOPMENT

For the current study, a MATLAB code is developed using R2014a. The number of inputs to FIS is five where as there is a single output, that is, the discharge. The ANFIS model consists of Sugeno type Fuzzy system and three Gaussian type membership functions that are taken for each input [26]. The output membership function is linear with four numbers of rules. The optimum structure of the model is determined through trial and error procedure. The function goes steadily after a few iterations due to faster hybrid learning rule indicating successful mapping of model parameters. Training errors are found to be decreasing with increase in epochs. Predicted flows are compared with the observed values. Different numbers of data points are used to test the efficiency of the developed mode for all the five data sets.

5.1 Model Performance

The performances of all the models developed in this study are evaluated using different standard statistical performance measures [30]. Here five performance indices are employed; Average absolute Relative Error (AARE), Normalized Mean Biased Error (NMBE), Pearson's Correlation coefficient (R), Nash-Sutcliff efficiency (E) and Normalized Root Mean Square Error (NRMSE). These parameters are calculated using the following expressions:

$$\text{AARE}(\%)=\frac{1}{N}\sum_{i=1}^{N}\left(ABS\left(\frac{(P_i-O_i)}{P_i}\right)*100\right) \quad (1)$$

$$\text{NMBE}(\%)=\frac{\frac{1}{N}\sum_{i=1}^{N}(P_i-O_i)}{\frac{1}{N}\sum_{i=1}^{N}O_i} \quad (2)$$

$$R=\frac{\sum_{i=1}^{N}(O_i-\overline{O_i})(P_i-\overline{P})}{\sqrt{\sum_{i=1}^{N}(O_i-\overline{O})^2(P_i-\overline{P})^2}} \quad (3)$$

$$E=\frac{S_0-S}{S_0}, \quad (4)$$

and

$$\text{NRMSE}=\frac{\left[\left(1/_N\right)\sum_{i=1}^{N}(P_i-O_i)^2\right]^{1/2}}{\left(1/_N\right)\sum_{i=1}^{N}O_i} \quad (5)$$

where $So=\sum_{i=1}^{N}(O_i-\overline{O})^2$ and $S=\sum_{i=1}^{N}(O_i-P_i)^2$, P_i is the estimated discharge, O_i the observed value and N the total number of readings. AARE compares the relative error in prediction in respect to the actual value. It is regarded as the predictive capability of a model is the smaller AARE value, is its better performance. NMBE provides mean biasness in the prediction. Positive value indicates over prediction and negative value implies under prediction. Commonly used correlation coefficient signifies the strength of linear relationship between observed and predicted values. Value of R may not perform better giving higher or lower value as per the biasedness of the model. Nash–Sutcliffe efficiency can range from −∞ to +1. An efficiency of 1 (E = 1) corresponds to a perfect match of modeled discharge to the observed data. An efficiency of 0 (E = 0) indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero (E < 0) occurs when the observed mean is a better predictor than the model essentially. The NRMSE statistics indicates a model's ability to predict a value away from the mean. It should be close to zero which depicts least error in prediction.

VI. RESULTS AND DISCUSSIONS

Three types of model data sets as described before are considered for the analysis. Experimental data sets collected from Perspex sheet finished sections are considered as smooth. Roughening materials like a synthetic typical mat, wire mesh and crushed rough stones of nearly uniform size are changed in sequence on the floodplains for varying the roughness in the channel. In the third set up smooth and rough data sets are taken together for developing a combined model.

Above mentioned three data sets are used to predict discharge through three soft computing models namely Cascade Neural network (CNN), Fuzzy and ANFIS. Calculation of discharge has also been carried out using popular approaches such as the SCM and DCM (HDM, VDM, MDCM and IDCM) following the work of Khatua and Padhi [31and 32]. CES method has also been applied to get discharge values [33].

The results, in terms of various performance statistics from all models described above are presented next. Based on various statistical criteria, different models perform in their own way. Therefore a ranking index method as proposed by Abu-Farsakh and Titi [34] is carried out to evaluate the overall performance of the prediction models taking into account the five performance criteria. Combining all the five ranking criteria, a ranking index (RI) is obtained and all the models are given an overall rank. Lower is the index value; better is the rank of the model.

6.1 Performance evaluation of data set I

In the Data Set I, there are 140 data points out of which 30% data points are used for testing. Table 1 presents the statistical performance evaluation measures from different methods with smooth data. The AARE for smooth data is found to be the minimum for CES followed by ANFIS. NMBE for ANFIS shows positive value of 0.136 indicating slight over prediction. Higher value of *R* indicates better linear relationship. In case of ANFIS and CES, values of *R* are found to be 0.934 and 0.895 respectively. A value of *E* close to 1.0 indicates good model performance. Better values of *E* are obtained for CES followed by ANFIS. NRMSE value of 0.297 is the minimum in case of ANFIS.

Table 1: Performance evaluation measures from various methods for Data Set I

METHODS	AARE	NMBE	R	E	NRMSE
CASCADE	260.176	-0.705	-0.714	-0.736	0.842
FUZZY	57.744	1.677	0.113	-0.955	2.028
ANFIS	22.876	0.137	0.934	0.526	0.298
SCM	27.572	-0.077	0.850	0.349	0.372
HDM	26.131	-0.084	0.846	0.459	0.388
HDM II	46.288	-0.185	0.849	0.251	0.422
VDM I	19.204	-0.015	0.833	0.356	0.456
VDMII	23.099	-0.069	0.821	0.456	0.364
MDCM	42.424	-0.182	0.819	-0.123	0.427
IDCM	212.087	-0.654	0.832	-0.629	0.867
CES	18.116	-0.068	0.895	0.836	0.506

6.2 Ranking of Data Set I

Ranking for Data Set I is shown in Table 2. According to AARE criteria, CES is ranked 1 followed by ANFIS, VDM and HDM in order.

Table 2: Ranking for Smooth Data Set I

Models	Ranking					Ranking Index
	AARE	NMBE	R	E	NRMSE	
CASCADE	11	10	11	10	9	51
FUZZY	9	11	10	11	11	52
ANFIS	2	6	1	2	1	12
SCM	6	4	3	6	3	22
HDM	5	5	5	3	4	22
HDM II	8	8	4	7	5	32
VDM I	3	1	6	5	7	22
VDMII	4	3	8	4	2	21
MDCM	7	7	9	8	6	37
IDCM	10	9	7	9	10	45
CES	1	2	2	1	8	14

CASCADE gives the least efficient at rank 11. In case of 2nd ranking criteria using NMBE, VDM ranks I followed by CES and then SCM, while FUZZY ranks the least preceded by CASCADE and IDCM.

For 3rd ranking criterion, that is, using *R*, ANFIS takes up the first position followed by CES then SCM. CASCADE and Fuzzy are at the lower ends. Rank for other methods are in the range from 4 to 9 showing medium performance.

The next ranking criteria is using *E* for which CES topped the list followed by ANFIS, HDM, VDM and SCM in order of the sequence. FUZZY and CASCADE are at the lowest position.

For the last criteria that is using NRMSE; ANFIS is ranked at the first position where as Fuzzy is at the bottom of the list preceded by IDCM. VDM is at second position followed by SCM, HDM and MDCM in sequence. As given in Table 2, in the overall ranking system, ANFIS is ranked 1 with RI value 12 and followed by CES with value of 14. Next rankings obtained for HDM, SCM and VDM having same value of 22 where as MDCM ranking index value is 37. FUZZY, CES and IDCM got poor values as per index value.

6.3 Performance Evaluation for Data Set II

For rough data (Table 3), the statistical performance of AARE is found to be the lowest for CES with a value 14.99. Next is the ANFIS with 20.93. Cascade and Fuzzy have shown performance at middle label with values of 45 and 46 respectively. IDCM is having a value AARE of 76.748 but the rest of the methods i.e. SCM, HDM, VDM, MDCM have values of more than 90.

In the next ranking criteria using NMBE only, ANFIS gives better prediction followed by MDCM. VDM II, IDCM and CES gave under prediction with negative values. Cascade, Fuzzy and HDM have values indicating little over prediction where as VDM I and SCM have shown completely over prediction with values 8.78 and 16.95 respectively. For the third criteria that is using *R*, SCM scored the highest followed by ANFIS and

CES. Next, HDM, VDM, MDCM and IDCM are in the ranges from 0.43 to 0.41, whereas Cascade and Fuzzy are in the range of about 0.3. For the criteria *E*, only ANFIS is found to be close to 1 but others gave very high value except CES which is 0.344. NRMSE is the lowest for ANFIS followed by MDCM, VDM II, IDCM and CES respectively. Rest methods show very high magnitude of flow.

Table 3: Performance evaluation measures from various methods with Rough Data Set II

Methods	AARE	NMBE	R	E	NRMSE
CASCADE	46.675	2.912	0.388	-249.314	3.517
FUZZY	45.745	2.724	0.314	-221.005	3.312
ANFIS	20.932	0.013	0.465	0.968	0.007
SCM	94.354	16.951	0.467	-6223.102	17.539
HDM	91.759	2.909	0.420	-2821.838	3.019
HDM II	91.841	2.304	0.419	-2874.432	2.437
VDM I	91.932	8.782	0.437	-2885.380	9.102
VDMII	90.882	0.563	0.427	-2207.063	0.582
MDCM	91.764	-0.451	0.420	-2815.685	0.487
IDCM	76.749	-0.642	0.431	-244.780	0.667
CES	14.993	-0.901	0.464	0.345	0.936

6.4 Ranking for Data set II

Table 4 shows the overall ranking of all the methods for Rough data set. Here again ANFIS gets the lowest value in the ranking index (RI=7). Individually it tops the list for NMBE, E and NRMSE criteria but it's second for R and AARE. CES scores 16 keeping it at second position showing better prediction for AARE and E but R, NRMSE and NMBE values are high.

Table 4: Ranking for Rough Data Set II

Methods	Ranking					Rank Index
	AARE	NMBE	R	E	NRMSE	
CASCADE	4	9	10	5	9	37
FUZZY	3	7	11	3	8	32
ANFIS	2	1	2	1	1	7
SCM	11	11	1	11	11	45
HDM	7	8	10	8	7	40
HDM II	9	6	9	9	6	39
VDM I	10	10	4	10	10	44
VDMII	6	3	6	6	3	24
MDCM	8	2	7	7	2	26
IDCM	5	4	5	4	4	22
CES	1	5	3	2	5	16

IDCM is next in the series with rank index 22. Individually it scores 4th position for NMBE, E and NRMSE where as 5th for NMBE and AARE. VDM II and MDCM both exhibited almost equal performance for all the five criteria and scored 4th and 5th position as per ranking index value. Fuzzy ranks 6th position with better performance for AARE and E only. Next Cascade and HDM II both reveals equal performance and secured 7th and 8th position with final ranking index 37 and 39. HDM ranked 9 with poor performance for R. VDM I and SCM both were at bottom two with rank 10 and 11 respectively.

6.5 Performance Evaluation of Data Set III

Next in combined mode for Data set III the statistical performance evaluation for all the 11 methods is presented in Table 5. The trend is similar to Data set I and Data set II. CES topped the list with lowest AARE value i.e. 18.0 followed by ANFIS and SCM respectively. MDCM and VDM II were at 4th and 5th position followed by HDM I and IDCM. Cascade and Fuzzy are at the bottom of the list with highest AARE values. In case of NMBE criteria, methods namely CASCADE, IDCM, FUZZY, HDM II and MDCM gave under prediction where as VDM and SCM have shown over prediction. But ANFIS have the value 0.162. For the third criteria R, CES, VDM II and IDCM scored positions first, second and third respectively. ANFIS was at 4th position. Cascade and Fuzzy were at bottom two. The E values for ANFIS is the highest that is 0.954. Next is CES that is 0.92 followed by HDM II and MDCM. CASCADE and SCM under predicted with poor performance. Next for NRMSE, the value of ANFIS was the lowest that is 0.255. The value for CES was 0.336 and for MDCM it was 0.353. HDM was in the range from 0.4 to 0.5. The values for IDCM, VDM II and Fuzzy were in the range from 0.7 to 0.8. However, VDM I, Cascade and SCM exhibited higher values beyond 1.0 indicating that the models are not well generalized.

Table 5: Statistical Performance evaluation measures from various methods for Smooth and Rough Data set

Methods	AARE	NMBE	R	E	NRMSE
CASCADE	129.257	-0.582	0.895	-0.0167	1.195
FUZZY	132.734	-0.503	0.868	0.441	0.885
ANFIS	26.874	-0.162	0.973	0.954	0.255
SCM	38.411	0.384	0.929	-0.171	1.301
HDMI	57.675	0.153	0.967	0.831	0.487
HDM II	78.287	-0.028	0.922	0.913	0.512
VDM I	88.603	0.508	0.949	0.189	1.067
VDM II	52.312	0.336	0.978	0.491	0.845
MDCM	47.545	-0.022	0.969	0.911	0.353
IDCM	67.205	-0.514	0.975	0.61	0.740
CES	18.001	0.168	0.992	0.920	0.336

6.6 Ranking of Data Set III

Table 6 presents the ranking index made for all the models for Data set III. Following the trend in Set I and II, ANFIS turns out to be the highest ranking method with RI=11 along with CES having the lowest

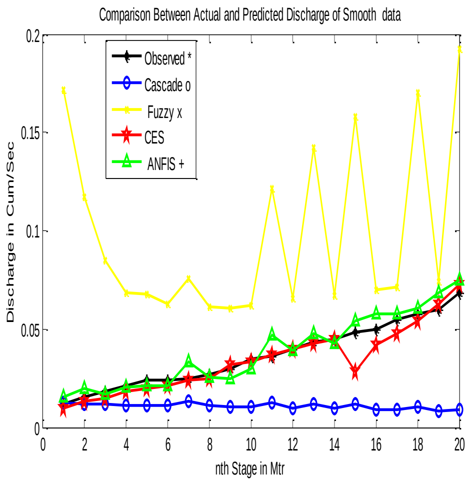
Table 6: Ranking of all methods for Data Set III

Methods	Ranking					Rank Index
	AARE	NMBE	R	E	NRMSE	
CASCADE	10	11	10	10	10	51
FUZZY	11	8	11	8	8	46
ANFIS	2	3	4	1	1	11
SCM	3	7	8	11	11	40
HDM I	6	4	6	5	4	25
HDM II	8	2	9	3	5	27
VDM I	9	9	7	9	9	43
VDM II	5	6	2	7	7	27
MDCM	4	1	5	4	3	17
IDCM	7	10	3	6	6	32
CES	1	5	1	2	2	11

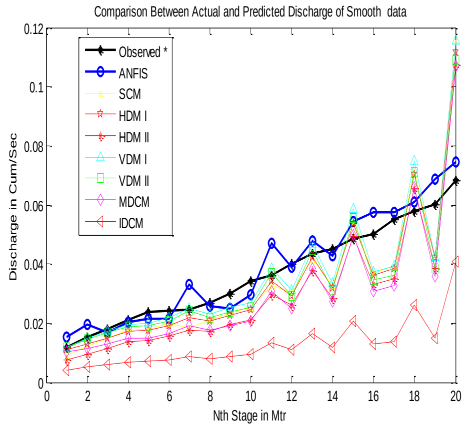
value. MDCM trailed with value of 17 followed by other models like HDM, VDM II, and IDCM etc with poor ranking by CASCADE, FUZZY and VDM I.

6.7 Discharge Prediction

The discharge prediction plots are presented in Fig. 5(a) and (b). Here the Data set I has been used to predict discharge for smooth channel. For data set I, 20 data points were chosen for testing and it is found that ANFIS performs well. Fig. 5(a) presents the prediction of discharge by Cascade, ANFIS, Fuzzy and CES against the actual value observed in cubic meter per second. At most of the points ANFIS was close to observed values, while other approaches such as Fuzzy, Cascade and CES gave erroneous result. Fig. 5 (b) depicts the same comparison for the traditional methods against the observed value as well as ANFIS. In Fig. 6 prediction of discharge against stage is plotted for rough surface of channel that is Data set II. Here also ANFIS model performs the best. For all stages it was close to observed values along with CES. Cascade and Fuzzy gave over prediction as depicted in Fig. 6(a).



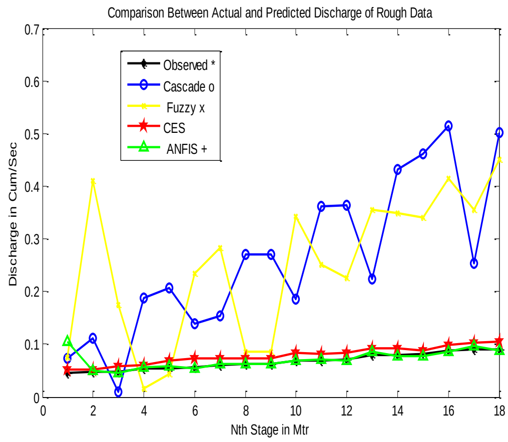
(a)



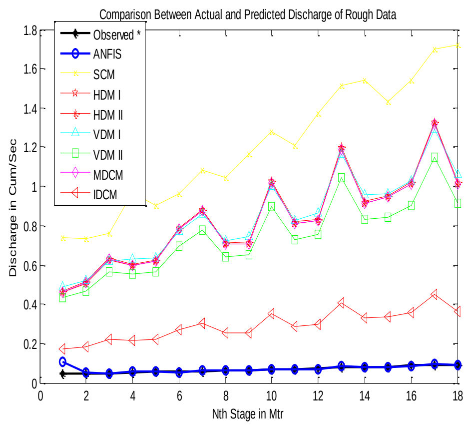
(b)

Fig 5 (a) and (b): Prediction of Discharge for Smooth Data Set

In Fig. 6(b) it can be observed that ANFIS was close to observed discharge values, while other traditional methods gave over prediction.



(a)



(b)

Fig 6 (a),(b): Prediction of Discharge for Data Set II

Fig. 7 shows the discharge for combined data that is both smooth and rough. Out of all the models some over predicted and some under predicted. Though initially CES results are found close to observed data but over prediction is high at higher stage values thus efficiency of CES was not good. The average error of FUZZY was too high and exhibits over predictions.

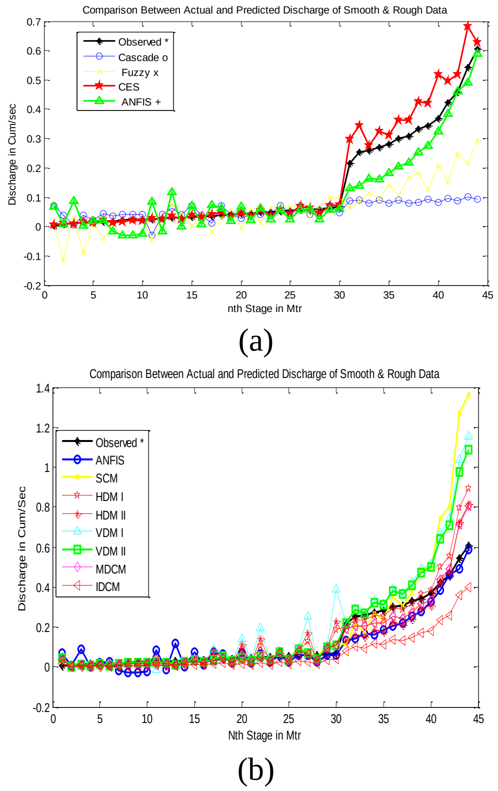


Fig 7(a),(b): Prediction of Discharge for Smooth and Rough Data Set

When the overall performance is considered, the ANFIS model performs the best for both low magnitude flow as well as for high magnitude flows followed by CES as depicted in Fig. 7(a) and (b).

Table 7: Final Ranking of all Models

Models	Ranking of All Models			Final Index
	Data Set I	Data Set II	Data Set III	
CASCADE	51	37	51	139
FUZZY	52	32	46	130
ANFIS	12	7	11	30
SCM	22	45	40	117
HDM	22	40	25	87
HDM II	32	39	27	98
VDM I	22	44	43	109
VDM II	21	24	27	72
MDCM	37	26	17	80
IDCM	45	22	32	99
CES	14	16	11	41

The final ranking in Table 7 shows the least score for ANFIS and thus it can be taken as the most suitable model for prediction of discharge for smooth and rough type of channels. CES gets the 2nd best performance followed by VDM II, MDCM, HDM, IDCM, VDM I, SCM. Fuzzy and CASCADE did not perform well having the highest ranking index of 130 and 139 respectively. Among the numerical methods VDM II performed the best followed by MDCM, HDM and IDCM. This work signifies the best output from the analysis of particular data sets used.

VII. CONCLUSIONS

This paper presents a study for comparison of the available numerical methods with few soft computing tools for prediction of discharge using stage data for straight compound channels. The prediction is carried out for three sets of data sets viz. (i) smooth experimental channel data, (ii) experimental channel with roughened surfaces with 3 types of materials in the floodplains in sequence and (iii) combining the data of (i) and (ii) as the third set. In the current study three types of datasets are employed to develop the soft computing tools viz Cascade Neural network, Fuzzy and Adaptive Neuro Fuzzy Inference system along with the CES. The popular numerical methods such as SCM and DCM (VDM, HDM, IDCM and MDCM) are also used for comparison. Five different types of statistical performance evaluation measures are employed to evaluate the performance of all the models. Results obtained from the work signify that the ANFIS model is a robust tool for prediction of discharge.

This result may be data specific. More data for other channel geometries can be used along with the present data for a more decisive conclusion. To realize the reliability of the developed model equations need to be derived for further analysis. After this study attempt will be made to collect river data sets and to incorporate as another model and combination of datasets from all the above four models will be taken as a fifth model.

REFERRENCES

[1] D.W. Knight and J.D. Demetriou, Flood plain and main channel flow interaction, Journal of Hydraulic Engineering, ASCE, 1983, 109(8), pp. 1073-1092.

[2] D.W. Knight, School of Civil Engineering ,The University of Birmingham- Conveyance in 1D River Models ", A report for HR Wallingford & The Environment Agency, 2001.

[3] W.R.C. Myers, Velocity and discharge in compound channels, Journal of Hydraulic Engineering, ASCE, Vol.113(6), 1987, pp. 753-766.

[4] K.C. Patra, and K.K. Khatua, Energy loss and Discharge Estimation in Two Stage Meandering and Straight Compound

Channel, EWRI of ASCE and IIT Kanpur 2006.

[5] K. K. Khatua, K. C. Patra and P. K. Mohanty, Stage Discharge Prediction for Straight and Smooth Compound Channels with Wide Floodplains, J. Hydraul. Eng., ASCE, vol. 138, no.1, pp.93-99, 2012.

[6] P. Prinos and R.D. Townsend, Comparison of Methods for predicting Discharge in Compound open channels, Adv. Water Resouces Vol. 7(4), 1984, pp.180-187.

[7] P. Ackers, Hydraulic Design of Two-Stage Channels, Proceedings of the Institution of Civil Engineers,Water, Maritime and Energy, Vol. 4, 1992,pp. 247-57.

[8] K C Patra, Flow Interaction of Meandering river with Flood Plains, PhD Thesis , IIT KGP, 1999.

[9] I. Kiline, H.K. Cigizoglu and A. Zuran, A Comparison of Three Methods for The Prediction of Future Stream Flow Data, Technical and Documental Research of 14th Regional Directorate, State Hydraulics Works, Istanbul, Turkey, 2000.

[10] P. Deka and V. Chandramouli, A Fuzzy neural Network Model for Deriving the River Stage Dischrge Relationship, Hydrol. Sci. J, Vol.48, 2003, pp.197-209.

[11] R. Mehta, P. K.Bhunia, K. Garvit and V. K. Dwivedi, Rating Curve Calibration using Grid Partitioning Technique, Indian Water Week 2012, pp.10-14.

[12] F. Beaman, Large Eddy Simulation of open channel flow for Conveyance Estimation, Doct. Thesis, University of Nottingham, 2010.

[13] Fi-John Chang, and Yen-Chang Chang, A counter propagation fuzzy-neural network modeling approach to real time stream flow prediction, Journal of Hydrology, Vol.245, No.1, 2001,pp.153-164.

[14] A.W. Jayawardena, E.D.P. Perera, B. Zhu, J.D. Amarasekara and V. Vereivalu, A comparative study of fuzzy logic systems approach for river discharge prediction, Journal of Hydrology, Vol. 514, 2014, pp.85-101.

[15] M. T. Dastorani, A. Moghadamnia, J. Piri and Miguel Rico- Ramirez, Application of ANN and ANFIS Models for Reconstructing Missing Flow Data, Environ Monit Assess, Vol. 166, 2010,pp. 421-434.

[16] M. Erol Keskin, Dilek Taylan and O. Terzi, Adaptive Neural-based Fuzzy Inference System (ANFIS) approach for modeling Hydrological Time Series, Hydrological Sciences Journal, Vol. 51, no.4, 2010, pp.588-988.

[17] J.O. Folorunsho, E.O. Iguisi, M. B. Muazu and S. Garba, Application of Adaptive Neuro Fuzzy Inference System (ANFIS) in River Kaduna Discharge Forecasting, Research Journal of Applied Sciences, Engineering and Technology, 4(21), 2012, pp.4275-4283.

[18] S. Moharana and K.K. Khatua, Prediction of Discharge in a Meandering Channel using ANFIS, River Flow –Murillo (Ed.) pp.1049-1055, 2012.

[19] Simon O. Haykin, Neural Networks- A Comprehensive Foundation, 2nd Ed., Pearson Education, 2006.

[20] S.A. Atabay and D.W.Knight, , The Influence of Floodplain width on the Stage Dischage Relationship for compound Channels, River Flow, Proceeding of Int. Conference on Fluvial Hydrolics, Louvail-La-NEUVE , Belgium, Vol.1, 2002, pp.197-204.

[21] B. Rezaei, Overbank flow in compound channels with prismatic and non-prismatic floodplains, Diss. University of Birmingham, 2006.

[22] A. Adhikari, K.C. Patra and K. K. Khatua, Applications of Neural Networks in Stage Discharge Studies, Proceedings of International Symposium on Hydro-2012, December, at IIT Bombay.

[23] A. Adhikari, K.C. Patra and K. K. Khatua, Stage Discharge Prediction using RBF and Elman Neural Networks", Advances in Engineering and Technology Series, Vol. 2,, (IEEE ICARET) 2013, pp. 1-6.

[24] Alok Adhikari, K. C. Patra and S. K. Das, Prediction of Discharge with Elman and Cascade Neural Networks, Reacearch Journal of Recent Sciences, Vol.2, 2013,pp. 279-284 (ISSN 2277-2502).

[25] Practical Channel Hydraulics- Roughness, conveyance and Afflux, web resource available at www.river-conveyance.net

[26] L.A. Zadeh, "Fuzzy Sets", Information Control, Vol. 8, No.3, 1965,pp.338-353.

[27] E.H. Mamdani and S. Assilian, An experiment in linguistic synthesis with a fuzzy logic controller, International Journal of Man-Machine Studies, Vol. 7, No. 1, pp. 1-13, 1975.

[28] J. Shing, and Roger Jang, ANFIS: Adaptive-Network-Based FUZZY Inference System, IEE Transaction on Systems, MAN, and Cybernetics, Vol. 23, No. 3, 1993, pp. 665-685.

[29] S. H. Chen, Y. H. Chang, L.C. Lin, and F.J. Chang, The Strategy of Building a Flood Forecast Model by Neuro Fuzzy Network,

Hydrological Processes, Vol.26, 2006, pp.1525-1540.
[30] D. C. S. Bisht, and Ashok, Jangid Discharge Modeling using Adaptive Neuro-Fuzzy Inference System, Int. Journal of Advanced Science and Technology , Vol.31, June 2011.
[31] Sanga Srinivasulu and Ashu. Jain, A comparative analysis of training methods for artificial neural networks rainfall-runoff models, Applied Soft Computing, Vol. 6, 2006,pp.295-306.
[32] P. K. Mohanty and K.K. Khatua, Estimation of Discharge and Its Distribution in Compound Channels, Journal of Hydrodynamics, Vol.26, No.1, 2014, pp144-154.
[33] E. Padhi and K.C. Patra, Stage Discharge Prediction in a Prismatic Compound Channel, Journal of Civil Engineering Research, Vol. 5. No.3, 2014, pp. 227-232.
[34] E. Padhi and K.C. Patra, Discharge prediction Approaches in Straight Compound Channels, Acta Geophysica, Vol 63, 2016, in press.
[35] M. Y. Abu-Farsakh and H.H. Titi, Assessment of direct cone penetration test methods for predicting the ultimate capacity of friction driven piles, Journal of Geotechnical and Geo environmental Engineering , 130, vol.9, (2004); pp.935-944.

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