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Numerical modeling of Converging Compound Channel Flow

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Abstract

This paper presents numerical analysis for prediction of depth-averaged velocity distribution of compound channels with converging flood plains. Firstly, a 3D Computational Fluid Dynamics (CFD) model is used to establish the basic database under various working conditions. Numerical simulation in two phases is performed using the ANSYS-Fluent software. $k-\omega$ turbulence model is executed to solve the basic governing equations. The results have been compared with high quality flume measurements obtained from different converging compound channels in order to investigate the numerical accuracy. Then ANN (Artificial Neural Network) are trained based on the Back Propagation Neural Network (BPNN) technique for depth-averaged velocity prediction in different converging sections and these test results are compared with each other and with actual data. The study has focused on the ability of the software to correctly predict the complex flow phenomena that occur in channel flows.

Keywords: compound channel, stage discharge, Prismatic, non-prismatic, ANN, ANSYS

1 INTRODUCTION

Distribution of depth-averaged velocity is important aspect in river hydraulics and engineering problems in order to give a basic understanding of the resistance relationship, to understand the mechanisms of sediment transport and to design sustainable channels etc. Due to continuous settlement of people near the riverbank and due to natural causes, the channel with floodplain cross-sections behaves as converging type non-prismatic compound channels. An improper estimation of floods in these regions, will lead to an increase in the loss of life and property. A number of authors [1-8] has investigated the depth-averaged velocity distribution and flow resistance in prismatic compound cross-sections. These models are not appropriate to predictions in compound channels with converging flood plain because of non-uniform flow occurs from section to section. Therefore, there is a need to evaluate the depth-averaged velocity in the main channel and floodplain at various locations of a converging compound channel. Converging channel flows, being highly complicated, are a matter of recent and continued research. For a

47 better understanding of the structure of turbulent flow in converging compound channels, it is
48 necessary to undertake detailed measurements. Because of the difficulty in obtaining sufficiently
49 accurate and comprehensive field measurements of velocity and shear stress in converging
50 compound channels under non-uniform flow conditions, considerable reliance must still be
51 placed on well focused laboratory investigations under steady flow conditions to provide the
52 information concerning the details of the flow structures and lateral momentum transfer.
53 Attention must be paid to the fact that physical models are very expensive, especially when a
54 large number of influencing parameters have to be studied. Sometimes, it is impossible to
55 construct a physical model for certain prototypes. Therefore, there is urgent need for economic
56 mathematical prediction models. In past a lot of experimental research has been done on
57 prismatic compound channel flows but relatively less usage has been made of numerical
58 techniques on non-prismatic compound sections. After the development of powerful computers
59 and sophisticated CFD (Computational Fluid Dynamics) techniques, much research is now being
60 conducted using these techniques in different research areas. This is not only due to economy
61 and less time required with CFD methodology but also due to the fact that through CFD one can
62 cover those aspects of flow behavior which are very difficult to observe through
63 experimentation. In recent years, numerical modeling of open channel flows has successfully
64 reproduced experimental results. Computational fluid dynamics (CFD) has been used to model
65 open channel flows ranging from main channels to flood plains. Simulations have been
66 performed by Krishnappan & Lau (1986), Kawahara & Tamai (1988) and Cokljat (1993). CFD
67 has also been used to model flow features in natural rivers by Sinha et al. (1998), Lane et al.
68 (1999), and Morvan (2001). Hodkinson (1996, 1998) was one of the first to present results using
69 a commercial CFD. In this case FLUENT was used to predict the 3D flow structure in a 90-
70 degree bend on the River Dean in Cheshire. Pan & Banerjee (1995), Hodges & Street (1999),
71 and Nakayama & Yokojima (2002) studied free surface fluctuations in open channel flow by
72 employing the LES method. Hsu et al. (2000) have reported the existence of the inner secondary
73 currents in the rectangular open-channels, which occur at the junction of the free surface and
74 sidewall. Knight et al. (2005) applied state-of-the-art CFD software to explore the physics within
75 open-channel flows. In their research work they applied three different turbulent models, namely
76 the $k-\epsilon$, Reynolds Stress model by Speziale, Sarkar and Gatski (SSG) by Speziale et al. (1991)
77 and Reynolds Stress ω or SMC- ω (implemented in ANSYS-CFX) models to trapezoidal channel.
78 Thomas and Williams (1995a) and Cater and Williams (2008) simulated an asymmetric
79 rectangular compound channel using LES for a relative depth of $\beta = 0.5$. They have predicted
80 mean stream wise velocity distribution, secondary currents, bed shear stress distribution,
81 turbulence intensities, TKE, and calculated lateral distribution of apparent shear stress. Gandhi et
82 al. (2010) determined the velocity profiles in two directions under different real flow field
83 conditions and also investigated the effects of bed slope, upstream bend and a convergence /
84 divergence of channel width. Kara et al. (2012) compared the depth-averaged stream wise
85 velocities obtained by LES with calculated by analytical solution of Shiono and Knight Method
86 (SKM), and concluded that the analytical approach to their problem requires calibration of the
87 lateral eddy viscosity coefficient, λ , and the secondary current parameter, Γ . Xie et al. (2013)
88 used LES to simulate asymmetric rectangular compound channel. In this study the distributions
89 of the mean velocity and secondary flows, boundary shear stress, turbulence intensities, TKE and
90 Reynolds stresses were in a good agreement with the experimental data. Filonovich (2015) used
91 ANSYS-CFX package to allow the simulation of uniform flows in straight asymmetric

92 trapezoidal and rectangular compound channels with several different RANS turbulence closure
93 models.

94

95 In the last decade machine-learning methods were the subject of many researches in engineering
96 problems and also in water resources engineering (Cheng et al., 2002; Lin et al., 2006;
97 Muzzammil, 2008; Wang et al., 2009; Wu et al. 2009; Ghosh et al., 2010; Safikhani et al.,
98 2011). Bilgil and Altun (2008) predicted friction factor in smooth open channel flow using ANN.
99 Sahu et al. (2011) proposed an artificial neural network model for accurate estimation of
100 discharge in compound channel flume and Moharana and Khatua (2014) studied the flow
101 resistance in meandering compound channels by using ANFIS. Abdeen (2008) adopted an ANN
102 technique to simulate the impacts of vegetation density, flow discharge and the operation of
103 distributaries on the water surface profile of open channels. Yuhong and Wenxin (2009) studied
104 the application of ANN for prediction of friction factor of open channel flows. The ANN
105 technique has also been successfully applied to compound open channel flow for the prediction
106 of the hydraulics characteristics, such as integrated discharge and stage-discharge relations
107 (Bhattacharya & Solomatine 2005; Jain 2008; Unal et al. 2010; Sahu et al.2011)

108

109 In the first part of this paper, 3D numerical simulations of flow field with two phases (water &
110 air) are carried out with the software ANSYS FLUENT to study the variation of velocity profiles
111 in different converging sections of a compound channel. In multiphase fluid flow, a phase is
112 described as a particular class of material that has a certain inertial response and interaction with
113 the fluid flow and the potential field in which it is immersed. Currently there are two approaches
114 for the numerical calculation of multiphase flows: The Euler-Lagrange approach and the Euler-
115 Euler approach. Even though air is considered as a secondary material we have taken it in
116 analysis to give it more real time analogy, by compromising over the computational time.

117 In order to solve turbulence equations, the $k-\omega$ model is used since more accurate near wall
118 treatment with automatic switch from wall function to a low Reynolds number formulation based
119 on grid spacing. Numerical results are verified using experimental data obtained in an
120 experimental analysis in the Hydraulics and Fluid Mechanics Laboratory of the Civil
121 Engineering Department of NIT, Rourkela. This study shows that the numerical model results
122 have good agreement with experimental ones. There are always some limitations in experimental
123 studies and obtaining experimental data in every point of a channel is not easy. Also after doing
124 an experimental test and obtaining the velocity in the desired point, measuring the velocity in
125 other points needs to do the experimental test again. Artificial intelligence is evaluated here as a
126 solution to this problem. By training an ANN based on experimental data of the points that are
127 available, the ANN assists investigators in calculating the velocity at other points of the channel
128 with good accuracy. This paper employs ANN for the prediction of depth average velocity of
129 converging compound channel, after using the computational fluid dynamics (CFD) technique to
130 establish the basic database under various working conditions. Quite a few model available for
131 prediction of depth average velocity usually under performs when the meagre datasets are used
132 for estimation. Generally, this happens while predicting the depth average velocity for a wide
133 range of hydraulic conditions and geometries of compound channel. To alleviate the above
134 problem, a robust prediction strategy based on an ANN has been proposed. It is demonstrated
135 that the ANN model is quite capable of predicting a depth average velocity with reasonable
136 accuracy for a wide range of hydraulic conditions.

137

138 **2 EXPERIMENTAL WORKS**

139 Experiments have been conducted at the Hydraulics and Fluid mechanics Laboratory of Civil
140 Engineering Department of National Institute of Technology, Rourkela, India. Three sets of non-
141 prismatic compound channels with varying cross section were built inside a concrete flume with
142 Perspex sheet measuring 15m long \times 0.90m width \times 0.5m depth. The width ratio (α = flood plain
143 width (B)/main channel width (b)) of the channel was 1.8 and the aspect ratio (δ = main channel
144 width (b)/main channel depth (h)) was 5. Keeping the geometry constant, the converging angles
145 of the channels were varied as 12.38° , 9° and 5° respectively. Converging length of the channels
146 fabricated were found to be 0.84m, 1.26m and 2.28m respectively. Longitudinal bed slope of the
147 channel was measured to be 0.0011, satisfying subcritical flow conditions at all the sections of
148 the non-prismatic compound channels. Roughness of both floodplain and main channel were
149 kept smooth with the Manning's n 0.011 determined from the inbank experimental runs in the
150 channel. The flow conditions in all sections were turbulent. A re-circulating system of water
151 supply was established with pumping of water from the large underground sump located in the
152 laboratory to an overhead tank from where water flows under gravity to the experimental
153 channels. Adjustable vertical gates along with flow strengtheners were provided in the upstream
154 section sufficiently ahead of rectangular notch to reduce turbulence and velocity of approach in
155 the flow near the notch section. An adjustable tailgate at the downstream end of the flume helps
156 to maintain uniform flow over the test reach. Water from the channel was collected in a
157 volumetric tank of fixed area that helps to measure the discharge rate by the time rise method.
158 From the volumetric tank water runs back to the underground sump by the valve arrangement.
159 For present work the experimental data Rezaei (2006) have been used. Rezaei (2006) have also
160 used converging compound channels of angles 11.31° , 3.81° , 1.91° giving the same subcritical
161 flow and smooth surfaces. They have found the depth-averaged velocity and boundary shear
162 distribution of the same channels under different flow conditions. Figure 1(a) shows the plan
163 view of experimental setup. Figure 1(b) shows the plan view of different test reach with cross-
164 sectional dimensions of both NITR & Rezaei (2006) channels. Figure 1(c) shows the typical grid
165 showing the arrangement of velocity measurement points along horizontal and vertical direction
166 in the test section.

167
168 A movable bridge was provided across the flume for both span-wise and stream-wise movements
169 over the channel area so that each location on the plan of compound channel could be accessed
170 for taking measurements. Water surface depths were measured directly with a point gauge
171 located on an instrument carriage. The flow depth measurements were taken along the center of
172 the flume at an interval of 0.5 m both in upstream and downstream prismatic parts of flume and
173 at every 0.1 m in the converging part of the flume. A micro-Pitot tube of 4.77 mm external
174 diameter in conjunction with suitable inclined manometer and a 16-Mhz Micro ADV (Acoustic
175 Doppler Velocity-meter) was used to measure velocity at these points of the flow-grid. In some
176 points, micro-ADV cannot take the velocity reading (up to 50cm from the water surface). In such
177 points Pitot tube was used to take the velocity. The Pitot tube was physically rotated with respect
178 to the main stream direction until it gave maximum deflection of the manometer reading. A flow
179 direction finder having a minimum count of 0.1° was used to get the direction of maximum
180 velocity with respect to the longitudinal flow direction. The angle of limb of Pitot tube with
181 longitudinal direction of the channel was noted by the circular scale and pointer arrangement

182 attached to the flow direction meter. The overall discharge obtained from integrating the
183 longitudinal velocity plot and from volumetric tank collection was found to be within $\pm 3\%$ of the
184 observed values. Using the velocity data, the boundary shear at various points on the channel
185 beds and walls were evaluated from a semi log plot of velocity distribution.

186
187
188

3 NUMERICAL MODELING

189 A number of CFD packages (Fluent, CFX, Star-CD, and others) are now available and have been
190 used for research in water flows Van Hoffa et al. (2010). In recent past, a good number of
191 researchers have used these software packages for prediction of different aspects of 3D flow
192 fields e.g Sahu et al. (2011). They detected that flow features in compound channels are
193 dependent on topography of the channel, surface roughness etc. However, the flow behavior
194 changes are still an unresolved phenomenon and attempts are underway to address this problem.
195 These researchers attempted to predict the flow behavior using different numerical models as it is
196 difficult to capture all flow features experimentally but still a lot of work is to be done. This is
197 due to various problems which are encountered in numerical modelling such as grid generation,
198 choice of turbulence model, discretization scheme, specifying the boundary and initial conditions
199 etc.

200 In this work, an attempt has been made to improve the understanding of 3D flows in converging
201 compound channels. For this purpose, a 3D numerical code FLUENT has been tested for its
202 suitability for simulation of flood flows. Initially, the closure problem of governing equations
203 was considered as there is no universal closure model which is acceptable for all flow problems.
204 Each has its own advantages and disadvantages. Therefore, some consideration must be taken
205 when choosing a turbulence model including, physics encompassed in the flow, level of accuracy
206 and computation resources available one has to attempt different models and then to choose the
207 one producing best results. The models tested here were standard $k-\epsilon$, LES and $k-\omega$. The one
208 with best output (standard $k-\omega$ in this case) was then used for all simulation works. The $k-\omega$
209 model is chosen on the basis of the computational time and resource availability. Beside the fact
210 that $k-\epsilon$ more or less produce same results as that of the $k-\omega$ model but the other two-equation
211 model ' $k-\omega$ ' performs better near the wall region and $k-\epsilon$ performs better in the fully turbulent
212 region (Filonovich 2015). On the other hand, LES partially resolves the turbulence and give good
213 results when compared to experimental data (Kara et al. 2012). The overall idea of modelling
214 through sub grid model for small time and length scale (Kolmogorov scales i.e. ratio of small
215 eddies to large eddies lengthwise as well as time wise) and resolving the large scale through
216 governing equation needs an exceptionally high computation effort. To optimize such
217 computational resource and time requirement, $k-\omega$ model is chosen even though compromises
218 are made over the results which are acceptable than spending high in computational resources
219 and time. It was used for prediction of resultant velocity contours on free surface, pressure,
220 turbulence intensity and secondary flow velocities at different sections along the converging
221 length.

222 Generally FLUENT involves three stage. The first stage is the pre-processing, which involve
223 geometry creation, setting of grid and defining the physics of the problem. The second stage
224 involves the application of solver to generate a numerical solution. In the third stage post-
225 processing takes place, where the results are visualized and analyzed.

226 **3.1 Geometry**

227 The first step in CFD analysis is the explanation and creation of computational geometry of the
228 fluid flow region. A consistent frame of reference for coordinate axis was adopted for creation of
229 geometry. Here in coordinate system, x axis corresponded the lateral direction which indicates
230 the width of channel bed. Y axis aligned stream-wise direction of fluid flow and Z axis
231 represented the vertical component or aligned with depth of water in the channel. The origin was
232 placed at the upstream boundary and coincided with the base of the center line of the channel.
233 The water flowed along the positive direction of the y-axis. The simulation was done on a non-
234 prismatic compound channel with a converging flood plain. The setup of the compound channel
235 is shown in Figure 2.

236 For identify the domain six different surfaces are generated. Figure 3 shows the different
237 Geometrical entities used in a non-prismatic compound channel

- 238 • Inlet
- 239 • Outlet
- 240 • Free Surface
- 241 • Side Wall
- 242 • Channel Bottom
- 243 • Centre line

244

245 **3.2 Mesh generation**

246

247 The second and very important step in numerical analysis is setting up the discretized grid
248 associated with the geometry. Construction of the mesh involves discretizing or subdividing the
249 geometry into the cells or elements at which the variables will be computed numerically. By
250 using the Cartesian co-ordinate system, the fluid flow governing equations i.e. momentum
251 equation, continuity equation are solved based on the discretization of domain. The meshing
252 divides the continuum into a finite number of nodes. Generally, one of three different methods,
253 i.e. Finite Element, Finite Volume and Finite Difference, can discretize the equations. Fluent
254 uses Finite Element (FE) based Finite Volume Method (FVM). This alternative uses the control
255 volume analysis, which is vertex-centered, i.e. the solution correlation variables are saved at the
256 nodes (vertices) of the mesh. The concept of FVM is used to convert the partial differential
257 equation into system of algebraic equation, which can be solved through closure. Two prominent
258 discretization steps involved at this stage are discretization of the computational domain and
259 discretization of the equation. The discretization of the computational domain is done through
260 mesh generation, which can be identified later through control volume constructions. However, a
261 very dense mesh of nodes causes excess computational time and memory. For CFD analysis,
262 more nodes are required in some areas of interest, such as near wall and wake regions, in order to
263 capture the large variation of fluid properties. Thus, the structure of grid lines causes further
264 unnecessary use of computer storage due to further refinement of mesh. In this study, the flow
265 domain is discretized using an unstructured grid and body-fitted coordinates. Unstructured grid is
266 used so that intricacies can be covered under the grid which is left over in structured one. The
267 detailed meshing of the flow domain is shown in Figure 4.

268

269 **3.3 Solver setting**

270

271 3.3.1 Setup

272 After the meshing part is completed, various inputs are given in the Setup section. **VOF** (volume
273 of fluid) model is the only model available for open channel flow simulation in ANSYS-
274 FLUENT, which is based on the idea of volume fraction (Hirt and Nichols 1981). In this method,
275 a transport equation is solved for the volume fraction at each time step whereupon the shape of
276 the free surface is reconstructed explicitly using the distribution of the volume fraction function.
277 The “reconstruction” of the free surface can be explained more clearly through the concept of
278 water volume fraction. Free surface is defined as the cell, which takes the value of the water
279 volume fraction as non-zero while a zero value indicates that no fluid is present in the cell. The
280 value of 0.5 for the water volume fraction is indicative of the fact that free surface position is
281 detected. This method can define sharp interfaces and is robust. VOF is capable of calculating
282 time dependent solutions. Flow in an open channel is generally bound by channel from all
283 directions except for the upward free surface. To achieve a free surface zero friction interface, a
284 command called “surface_symmetry” is given in named selection. Velocity inlet for inlet and
285 pressure outlet for outlet is defined and the roughness coefficient is added to the walls for “no
286 slip” condition. Transient flow was chosen because the flow parameters were varied in time in
287 the experiment. Gravity is check marked and the value for Z-axis is given as -9.81 because
288 gravity acts downward opposite to the z-direction vector. As mentioned earlier, the turbulence
289 model was chosen as k- ω model. PISO was selected for solving the pressure equation, as it is
290 generally a pressure-based segregated algorithm recommended for transient flow conditions (Issa
291 1986). Also, PISO scheme may aid in accelerating convergence for many unsteady flows.
292 Finally, solver is patched and run to apply all the settings as well as conditions mentioned above.
293 It’s just finalizing and complying the settings. The equation solved in the CFD are usually
294 iterative and starting from initial approximation, they iterate to a final result. However, these
295 iterations are terminated at some step to minimize the numerical effort. This termination are done
296 on the basis of normalized residual target which is by default is set to 10^{-4} , which leads to loose
297 convergence target. For problems like compound channel in order to obtain more accuracy
298 residual target should be placed a value near around 10^{-6} . Time step size was set to 0.001s and
299 number of iteration given was 1000 for better accuracy and convergence of the iteration. Time
300 step size, Δt , is then set in the Iterate panel, Δt must be small enough to resolve time-dependent
301 features; making sure that the convergence is reached within the number of max iterations per
302 time step. The order of magnitude of an appropriate time step size can be estimated as ratio of
303 typical cell size to the characteristic flow velocity. Time step size estimate can also be chosen so
304 that the unsteady characteristics of the flow can be resolved (e.g. flow within a known period of
305 fluctuations). To iterate without advancing in time, use zero time steps.

306

307 3.3.2 Governing Equations

308 ANSYS Fluent uses the finite volume method to solve the governing equations for a fluid. It
309 provides the capability to use different physical models such as incompressible or compressible,
310 inviscid or viscous, laminar or turbulent etc. The most practical and still the most popular
311 method of dealing with turbulence is that based on the RANS method. With this method, all
312 scales of turbulence are modelled. Several models were studied to compare the effect of
313 turbulent modeling in the converging compound channel, including the following: (1) k-Epsilon,
314 (2) k- ω and (3) Large Eddy Simulation (LES) model. Here k- ω model is used for turbulence
315 modeling. The k- ω model solves the k-transport equation and a transport equation for ω . The k-
316 transport equation and the transport equation for ω can be written (Wilcox 1988)

317

318
$$\frac{\partial k}{\partial t} + U_i \frac{\partial k}{\partial x_i} = \frac{\partial}{\partial x_i} \left(\frac{v_t}{\sigma_k} \frac{\partial k}{\partial x_i} \right) + P - \beta' k \omega \quad (1)$$

319
320
$$\frac{\partial \omega}{\partial t} + U_i \frac{\partial \omega}{\partial x_i} = \frac{\partial}{\partial x_i} \left(\frac{v_t}{\sigma_\omega} \frac{\partial \omega}{\partial x_i} \right) + \alpha \frac{\omega}{k} P - \beta \omega^2 \quad (2)$$

321
322 and the eddy viscosity is given by

323
324
$$v_t = k / \omega \quad (3)$$

325
326 P is the turbulence kinetic energy production rate. Menter [49] as suggested the turbulence
327 equation:

328
329
$$P = \min (P, 10\beta' k \omega) \quad (4)$$

330 It represents the rate at which the energy is fed from the mean flow to each stress component.
331 The estimation of the production term can be done directly from the stress and the mean flow
332 strain rate components and thus needs no modelling other than this all other terms need
333 modelling.

334 The k- ω model involves five empirical constants β' , β , α , σ_k and σ_ω . They have their universal
335 constant values, which have been derived on the basis of high quality data. Their values vary
336 from one turbulence model to another. For any particular turbulence model, the values of these
337 constants remain same for all simulation purposes. For standard k- ω , their values are presented in
338 Table 2.

339
340

3.3.3 Boundary conditions

341 Four different types of boundary condition were considered in this study. These are (i) inlet, (ii)
342 outlet, (iii) water surface, and (iv) walls of the geometry

343 (i) Inlet

344 The velocity distribution at the upstream cross-section was taken as inlet boundary condition. At
345 the inlet, turbulence properties i.e. k (turbulence kinetic energy) and (ω turbulence dissipation
346 rate) must be specified. These were calculated as [28]

347
348
$$k = IU^2 \quad (5)$$

349
350
$$\omega = \frac{k^{1/2}}{l} \quad (6)$$

351
352 Where I is the turbulence intensity and U is the mean value of stream-wise velocity. l is the
353 turbulence length scale

354 (ii) Outlet

355 At the outlet, the pressure condition was given as the boundary condition and pressure was fixed
356 at zero. Importance of the outflow boundary at an appropriate location can be explained through
357 the influence of the downstream condition. Thus it makes extremely imperative to put the
358 downstream end far enough to prevail the fully developed state.

359 (iii) Channel and Floodplain Boundaries

360 A no-slip boundary condition was considered at the walls. This means that the velocity
361 components should be zero at the walls. The no-slip condition is the default, and it indicates that

362 the fluid sticks to the wall and moves with the same velocity as the wall, if it is moving. The wall
363 is the most common boundary condition in bounded fluid flow problem. Setting the velocity near
364 wall as zero under no-slip condition is appropriate condition for the solid boundary. The wall
365 boundary condition in the turbulent flow is implemented and initiated by evaluating the
366 dimensionless distance ' z^+ ' from the wall to the nearest boundary node. This dimensionless
367 distance is the function of the near wall node to the solid boundary, friction velocity and the
368 kinematic viscosity. The near wall treatment will depend on the position of the nearest to the
369 boundary node. If $z^+ \leq 11.06$ the nearest to boundary node will lie in the viscous sub-laminar
370 layer where profile is linear and very fine meshing is required. This will tend to intensify the
371 computation effort, which is being dedicated for near wall treatment. In another case where
372 $z^+ > 11.06$ the nearest boundary node will lie in the buffer layer which is the transition region
373 from viscous sublayer and the log law region. The main shortcoming of the wall function
374 approach is their dependability on the nearest node distance from the wall, which cannot be
375 overcome through refining since it does not guarantees high accuracy. Nevertheless, the problem
376 of discrepancy in the wall function approach can be subsidized through Scalable wall function
377 where limiting the z^+ value to not fall below 11.06 (the intersection of linear profile and log-law)
378 is concentrated. Therefore, all mesh points are made lie outside the viscous sublayer and all fine
379 mesh discrepancies are circumvented.

380 Thus, standard wall-function, which uses log-law of the wall to compute the wall shear stress is,
381 used [50]. Fluid flows over rough surfaces are encountered in diverse situations. If the modeling
382 is a turbulent wall-bounded flow in which the wall roughness effects are considered significant,
383 it can include the wall roughness effects through the law-of-the-wall modified for roughness.

384 (iv) Free Surface

385 The water surface was defined as a plane of symmetry, which means that the normal velocity and
386 normal gradients of all variables are zero at this plane. Free surface in the present study is
387 modeled through VOF for estimating the domain for air and water (multiphase problem).

388

389 **3.4 Results**

390 A variety of flow characteristics can be considered in the post-processing software of CFD
391 packages. This work has been concerned with the velocity distribution and the results are
392 compared with experimental measurements. In general the user should make an attempt to
393 validate the CFD results with known data so that there can be some confidence in the solution. In
394 the case of open channel flow, the validation is most likely to take the form of a comparison
395 against physical measurements and a qualitative understanding of what features should be
396 present in the flow. As part of the analysis, the user may also wish to perform a sensitivity study
397 and vary any parameters (such as roughness here) which have a degree of uncertainty, and
398 determine what influence they have on the solution.

399

400 **4. PREDICTION USING ANN**

401

402 ANN is a new and rapidly growing computational technique and an alternative procedure to
403 tackle complex problems. In recent years it has been broadly used in hydraulic engineering and

404 water resources [36, 37]. It is a highly self-organized, self-adapted and self-trainable
 405 approximator with high associative memory and nonlinear mapping. ANNs may consist of
 406 multiple layers of nodes interconnected with other nodes in the same or different layers. Various
 407 layers are referred to as the input layer, the hidden layer and the output layer. The inputs and the
 408 inter-connected weights are processed by a weight summation function to produce a sum that is
 409 passed to a transfer function. The output of the transfer function is the output of the node. In this
 410 paper, multi-layer perception network is used. Input layer receives information from the external
 411 source and passes this information to the network for processing. Hidden layer receives
 412 information from the input layer and does all the information processing, and output layer
 413 receives processed information from the network and sends the results out to an external
 414 receptor. The input signals are modified by interconnection weight, known as weight factor W_{ij}
 415 which represents the interconnection of i^{th} node of the first layer to the j^{th} node of the second
 416 layer. The sum of modified signals (total activation) is then modified by a sigmoidal transfer
 417 function (f). Similarly output signals of hidden layer are modified by interconnection weight
 418 (W_{ij}) of k^{th} node of output layer to the j^{th} node of the hidden layer. The sum modified k signal is
 419 then modified by a pure linear transfer function (f) and output is collected at output layer.

420
 421 Let $I_p = (I_{p1}, I_{p2}, \dots, I_{pl})$, $p=1, 2, \dots, N$ be the p^{th} pattern among N input patterns. W_{ji} and W_{kj} are
 422 connection weights between i^{th} input neuron to j^{th} hidden neuron and j^{th} hidden neuron to k^{th}
 423 output neuron respectively.

424 Output from a neuron in the input layer is

$$425 \quad O_{pi} = I_{pi}, i=1, 2 \dots l \quad (7)$$

426
 427 Output from a neuron in the hidden layer is

$$428 \quad O_{pj} = f(\text{NET}_{pj}) = f(\sum_{i=0}^l W_{ji} O_{pi}), j = 1, 2, m \quad (8)$$

429
 430 Output from a neuron in the hidden layer is

$$431 \quad O_{pk} = f(\text{NET}_{pk}) = f(\sum_{i=0}^l W_{kj} O_{pj}), k=1, 2, n \quad (9)$$

432
 433

436 **4.1 Sigmoidal Function**

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

$$439 \quad F(x) = \frac{1}{1+e^{-x}} \quad (10)$$

440 Where x = input parameters taken

441
 442 The architecture of back propagation neural network model, that is the l-m-n (l input neurons, m
 443 hidden neurons, and n output neurons) is shown in the fig.5

444 **4.2 Learning or training in back propagation neural network**

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

452 Mean Squared Error, E_p for pattern is defined as

$$453 \quad E_p = \sum_{i=1}^n \frac{1}{2} (D_{pi} - O_{pi})^2 \quad (11)$$

454 Where D_{pi} is the target output, O_{pi} is the computed output for the i^{th} pattern.

455 Weight changes at any time t , is given by

$$456 \quad \Delta W(t) = -nE_p(t) + \alpha \times \Delta W(t - 1) \quad (12)$$

457 n = learning rate i.e. $0 < n < 1$

458 α = momentum coefficient i.e. $0 < \alpha < 1$

459 **4.3 Source of data**

460 The data are collected from research work done in Hydraulic and Fluid Mechanics Laboratory,
461 NIT Rourkela, [44] data, available at the laboratory of University of Birmingham, Wallingford
462 and also generated data by using ANSYS-15 .The descriptions of geometrical parameters of
463 above data are mentioned in Table.3.

464

465 **4.4 Selection of hydraulic parameters**

466 Flow hydraulics and momentum exchange in converging compound channels are significantly
467 influenced by both geometrical and hydraulic variables, the computation become more complex
468 when the floodplain width contracted and become zero. The flow factors responsible for the
469 estimation of depth-averaged velocities are

470 (i) Converging angle denoted as θ

471 (ii) Width ratio (α) i.e .ratio of width of floodplain to width of main channel

472 (iii) Aspect ratio (σ) i.e. ratio of width of main channel (B) to depth of main channel (h)

473 (iv) Depth ratio (β) = $(H-h)/H$, where H =height of water at a particular section and, h = height of
474 water in main channel

475 (v) Relative distance (X_r) i.e of point velocity in the length wise direction of the channel)/total
476 length of the non-prismatic channel. Total five flow variables were chosen as input parameters
477 and depth-averaged velocity as output parameter.

478

479 **5. RESULTS**

480

481 **5.1 Results of ANSYS and CES**

482

483 **5.1.1 Verification**

484 The values of depth-averaged velocity distributions of different cross-sections of the non-
485 prismatic compound channel are achieved from the numerical models like CES (Conveyance
486 Estimating System) and ANSYS then the results from the experimental data of both NITR and
487 [44] channels were compared in Figures 6-11. As illustrated in Figures 6-10, the numerical
488 model was in good agreement with experimental results but the results of the CES model have
489 some differences with experimental results. The Conveyance and Afflux Estimation System
490 (CES/AES) is a software tool for the improved estimation of flood and drainage water levels in
491 rivers, watercourses and drainage channels. The software development followed
492 recommendations by practitioners and academics in the UK Network on Conveyance in River
493 Flood Plain Systems, following the Autumn 2000 floods, that operating authorities should make
494 better use of recent improved knowledge on conveyance and related flood (or drainage) level
495 estimation. This led to a Targeted Program of Research aimed at improving conveyance
496 estimation and integration with other research on afflux at bridges and structures at high flows.
497 The CES/AES software tool aims to improve and assist with the estimation of:

- 498 • hydraulic roughness
- 499 • water levels (and corresponding channel and structure conveyance)
- 500 • flow (given slope)
- 501 • section-average and spatial velocities
- 502 • backwater profiles upstream of a known flow-head control e.g. weir (steady)
- 503 • afflux upstream of bridges and culverts
- 504 • uncertainty in accuracy of input data and output

505 Conveyance Estimation System (CES) is developed by joint Agency/DEFRA research program
506 on flood defence, with contributions from the Scottish Executive and the Northern Ireland Rivers
507 Agency, HR Wallingford. CES is based Reynolds-averaged Navier-Stokes (RANS) approach as
508 the solution basis for estimation of conveyance. RANS equation of CES has been solved
509 analytically by Shiono & Knight method. In this solution the converging fluid plain effect has
510 not been considered which is reflected by the results of depth-averaged velocity and giving much
511 error However, Fluent K- ω model take care of converging effect as well as interaction effect of
512 geometry of converging compound channel.

513

514 **5.2 Results of ANN**

515 5.2.1 Testing of Back propagation neural network

516 Determination of depth-averaged velocity distribution of compound channel with converging
517 flood plain is an important task for river engineer. Due to nonlinear relationship between the
518 dependent and independent variables any model tools to provide the accurate depth-averaged
519 velocity distribution. Numerical approach has also consumed more memory and time. So in the
520 present work the ANN has been tested. The total experimental data set is divided into training set
521 and testing set. For depth-averaged velocity calculations 32321 data are used among which 70%
522 are training data and 30% are taken as testing data. The number of layers and neurons in the
523 hidden layer are fixed through exhaustive experimentation when mean square error is minimised
524 for training data set. It is observed that minimum error is obtained for 5-7-1 architecture. So the
525 back propagation neural network (BPNN) used in this work has three layered feed forward
526 architecture. The model was run on MATLAB commercial software dealing with trial and error
527 procedure.

528

529 A regression curve is plotted between actual and predicted depth-averaged velocity of testing
530 data which are shown in figure (12) .It can be observed that data are well fitted because a high

531 degree of coefficient of determination R^2 of 0.91. Figure 13 shows the error histogram plot of the
532 model.

533

534 **6. ERROR ANALYSIS**

535

536 To check the strength of the model, with the result from CES error analyses have been done.
537 Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), Mean Squared
538 Error (MSE), the Root Mean Squared Error (RMSE) for all the converging compound channels
539 for different geometry and flow conditions have been estimated. Efficiency criterion like R^2 ,
540 Nash-Sutcliffe efficiency (E) have also been estimated to provide more information on the
541 systematic and dynamic errors present in the model simulation. The definitions of error terms are
542 described below. The detailed results of the error analysis have been presented in table 4 .The
543 expression used to estimate errors in different forms are

544 **1. Mean Absolute Error (MAE)**

545 The Mean Absolute Error has been evaluated as,

546

$$547 \quad MAE = \frac{1}{n} \sum_i^n \left| \frac{P_i - O_i}{O_i} \right| \quad (13)$$

548

549 Where P_i =predicted values, O_i =observed values

550

551 **2. Mean Absolute Percentage Error (MAPE)**

552 Mean Absolute Percentage Error also known as Mean absolute Percentage Deviation. It was
553 usually expressed as a percentage, and was defined by the formula

554

$$555 \quad MAPE = \frac{1}{n} \sum_i^n \left| \frac{O_i - P_i}{O_i} \right| \quad (14)$$

556 **3. Mean Squared Error (MSE)**

557 Mean Squared Error measures the average of the squares of the errors. It is computed as

$$558 \quad MSE = \frac{1}{n} \sum_i^n (P_i - O_i)^2 \quad (15)$$

559 **4. Root Mean Squared Error (RMSE)**

560 Root Mean Squared Error or Root Mean Squared Deviation is also a measure of the differences
561 between values predicted by model or an estimator and the actually observed values. These
562 individual differences are called as residuals when the calculations are performed over the data
563 sample that is used for estimation, and are known as estimation errors when computed out
564 of the sample. The RMSE is defined as

565

$$566 \quad RMSE = \sqrt{MSE} \quad (16)$$

567 **5. Coefficient of correlation R^2**

568 The coefficient of correlation R^2 can be expressed as the squared ratio between the covariance
569 and the multiplied standard deviations of the observed and predicted values. The range of R^2 lies
570 between 0 and 1.0 which describes how much of the observed dispersion is explained by the
571 prediction. A value of zero means no correlation at all whereas a value of 1 means that the
572 dispersion of the prediction is equal to that of the observation.

573
574

575 6. Nash-Sutcliffe efficiency E

576 The efficiency E proposed by Nash and Sutcliffe [51] is defined as:

$$577 E = 1 - \frac{\sum_i^n (O_i - P_i)^2}{\sum_i^n (O_i - \bar{O})^2} \quad (17)$$

578 Where \bar{O} represents the mean of calculated values. The range of E lies between 1.0 (perfect fit)
579 and $-\infty$.

580

581 7. CONCLUSIONS

582

583 In this study numerical analysis for prediction of depth-averaged velocity for compound channel
584 with converging flood plain using ANN were presented. In the first part of the paper, a 3D model
585 of turbulence stream pattern in compound channel with converging flood plains were simulated
586 using a numerical model. Using experimental and numerical analysis, variation of velocity
587 components for compound channel with converging flood plains were studied. The other part of
588 this paper dealt with the prediction of the depth-averaged velocity field using ANN. In the
589 prediction part, at first, BPNN neural networks were created. Then coordinates of different points
590 were applied as input values and corresponding velocity as target outputs to create ANNs. Some
591 experimental data were used to train the ANNs and some experimental data were used to test the
592 trained ANNs based on BPNN techniques. Finally, the results of ANN and CES methods were
593 compared in sections. The main conclusions of this study are as follows:

594

595 1. ANSYS shows a good conformity with the experimental results for predicting the depth-
596 averaged velocity.

597

598 2. Results of numerical model showed that the CES was not in good agreement with
599 experimental results for predicting the depth-averaged velocity. Since the one dimensional model
600 of CES is incompetent when it comes to more realistic results.

601

602 3. Results of ANNs that had been trained using BPNN indicated that the velocity field was
603 predicted with good approximation in both training and testing methods and it was concluded
604 that the proposed procedures are useful for velocity prediction in non-prismatic compound
605 channel with converging flood plain.

606

607 4. Different error analyses are performed to test the strength of the present ANN model. It is
608 found that MAE as 0.033, MAPE as 3.29 which less than 10%, MSE as 0.0004, RMSE as 0.02, E

609 as 0.0.95, R^2 as 0.99 where as CES gave MAE as 0.2, MAPE as 20, MSE as 0.008, RMSE as
610 0.08, E as 0.75, R^2 as 0.7.

611
612 5. The main advantage of ANN is the prediction of the approximate velocity at points where
613 experimental data are not available. In addition, the presented procedure can be used in
614 predicting some other properties of flow besides velocity, such as shear stresses, depth of water
615 or variations of channel bed. In addition, the presented procedure can be applied to prediction
616 and analysis of the properties of other types of channels and other structures across the flow.

617
618 Turbulence studies can also be carried out on the same guidelines indicating the turbulent
619 shearing through Reynolds stresses, secondary flow structures, and the turbulent kinetic energy,
620 which can significantly indicate the momentum exchange process and mass transfer due to
621 differential velocity due to two different stages. Overall studies consider only depth averaged
622 streamwise velocity prediction only, since the applicability of numerical modelling is
623 corroborated on the converging compound channel. Since the validation and error analysis shows
624 an undisputable results, which suggestively indicate the application of the numerical method for
625 further studies such as turbulence studies.

626 627 **8. ACKNOWLEDGEMENTS**

628
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632 633 634 635 **9. REFERENCES**

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- 757

Table1.Hydraulic parameters for the experimental channel data

Sl. No	Item Description	Converging Compound Channel
1	Geometry of main channel	Rectangular
2	Geometry of flood plain	Converging
3	Main channel width (b)	0.5m
4	Bank full depth of main channel	0.1m
5	Top width of compound channel (B1)	before convergence 0.9m
6	Top width of compound channel (B2)	after convergence 0.5m
7	Converging length of the channels	0.84m, 1.26, 2.26m
8	Slope of the channel	0.0011
9	Angle of convergence of flood plain (θ)	12.38,9, 5
10	Position of experimental section 1	start of the converging part
11	Position of experimental section 2	Middle of converging part
12	Position of experimental section	end of converging part.

Table 2. Values of the constants in the k- ω model (Wilcox 1988)

β'	β	α	σ_k	σ_ω
0.09	0.075	5/9	2	2

Table 3.Input and output data used for the present analysis

Sl.No	Converging angles	Flood plain type	Converging Length
1	1.91	Convergent	6m
2	3.81	Convergent	6m
3	11.31	Convergent	2m
4	5	Convergent	2.26m
5	9	Convergent	1.28m
6	12.38	Convergent	0.84m
8	2.5	Convergent	4.58
9	3	Convergent	3.82
10	4	Convergent	2.86
11	7	Convergent	1.64
12	10	Convergent	1.15
13	14	Convergent	0.8
14	15	Convergent	0.77

15	17	Convergent	0.68
16	20	Convergent	0.58

Table 4 Different Error Analysis

	ANN	CES
MSE	0.0004	0.008
RMSE	0.02	0.08
MAE	0.033	0.2
MAPE	3.29	20
E	0.95	0.70
R ²	0.99	0.75

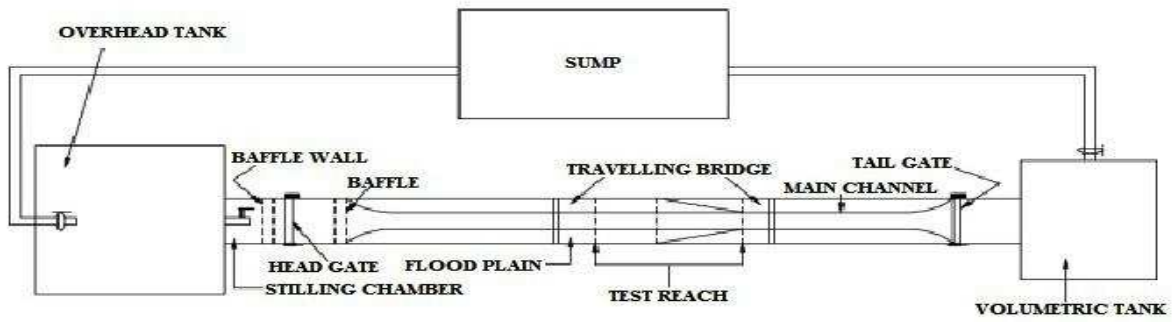


Figure 1(a). Plan view of Experimental Setup

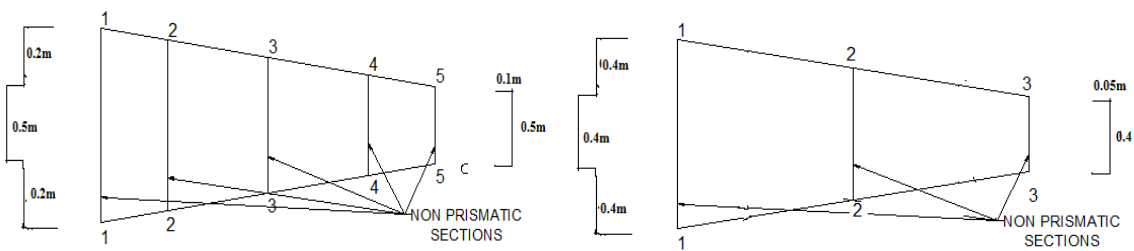


Figure 1(b). Plan view of different test reaches with cross-sectional dimensions of non-prismatic compound channel from both NITR & Rezaei (2006) channels

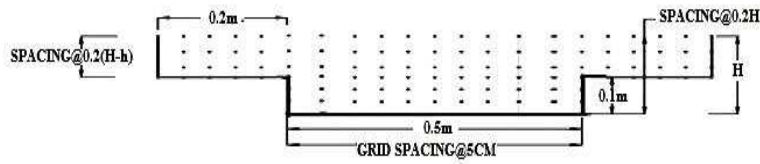
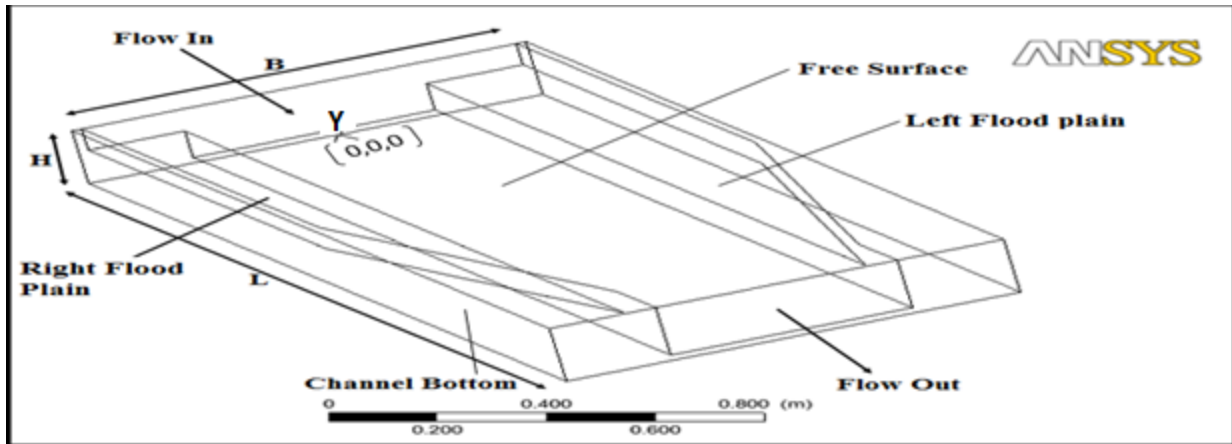
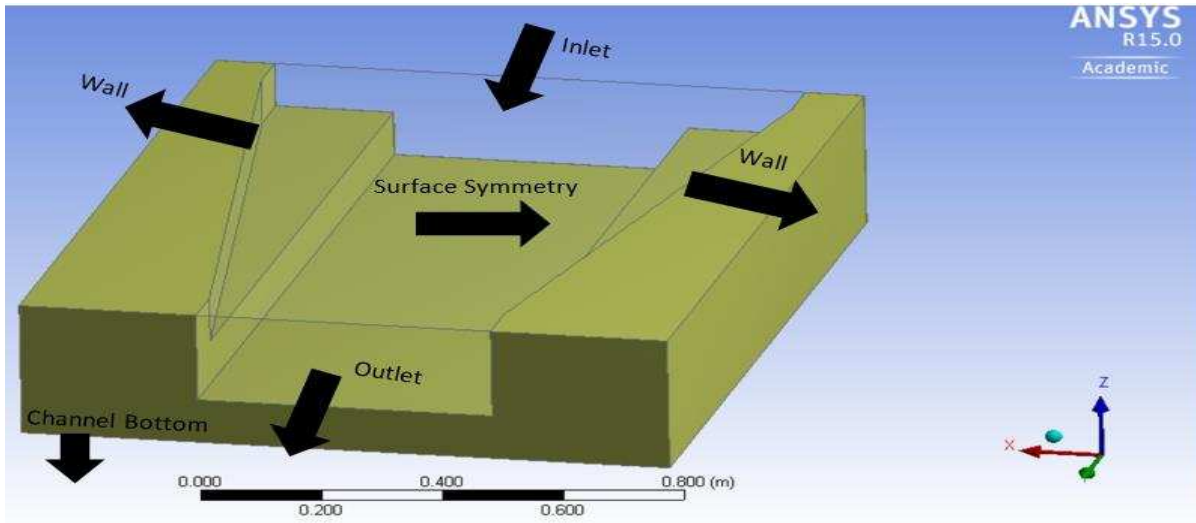


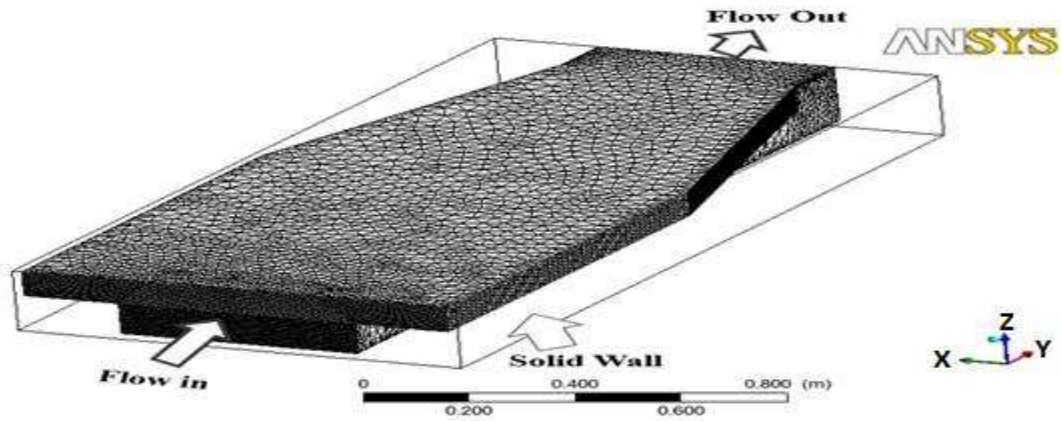
Figure 1(c). Typical grid showing the arrangement of velocity measurement points at the test sections (1-1,2-2,3-3,4-4 &5-5)



2. Geometry Setup of a Compound Channel with converging flood plains



3. Different Geometrical entities used in a compound channel with converging flood plain



4. A schematic view of the Grid used in the Numerical Model

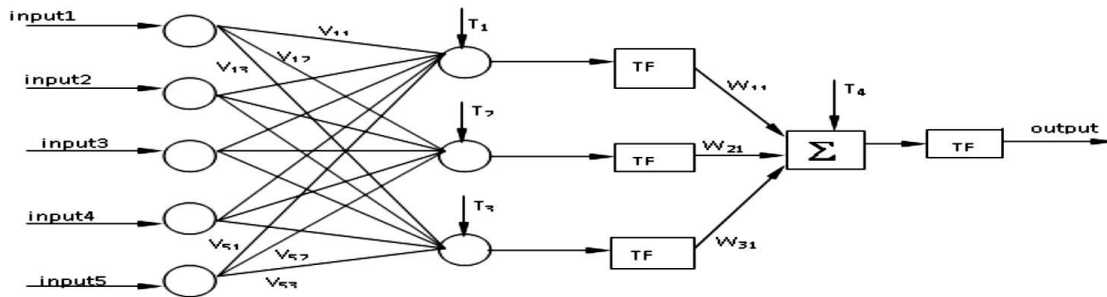
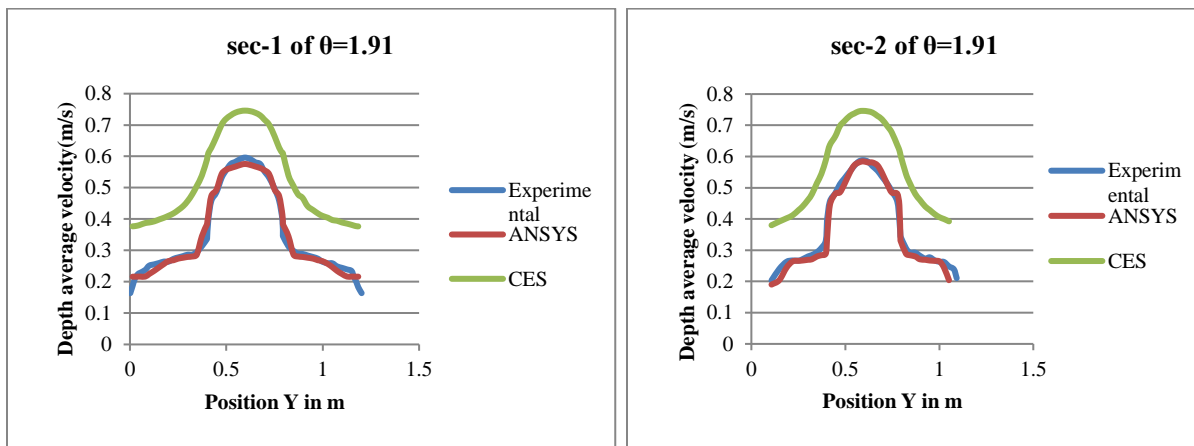


Fig.5. The architecture of back propagation neural network model



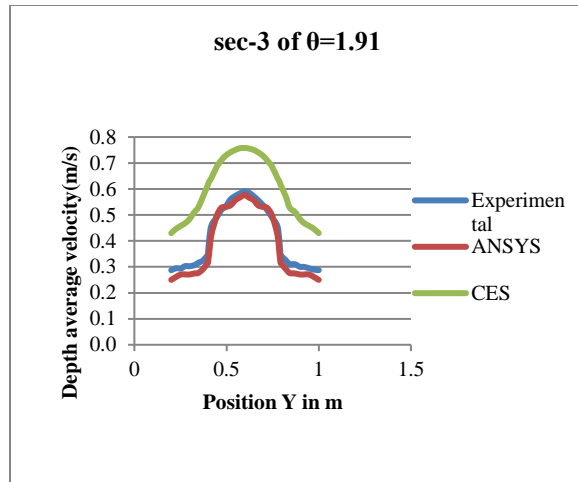


Figure 6 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta=1.91^0$

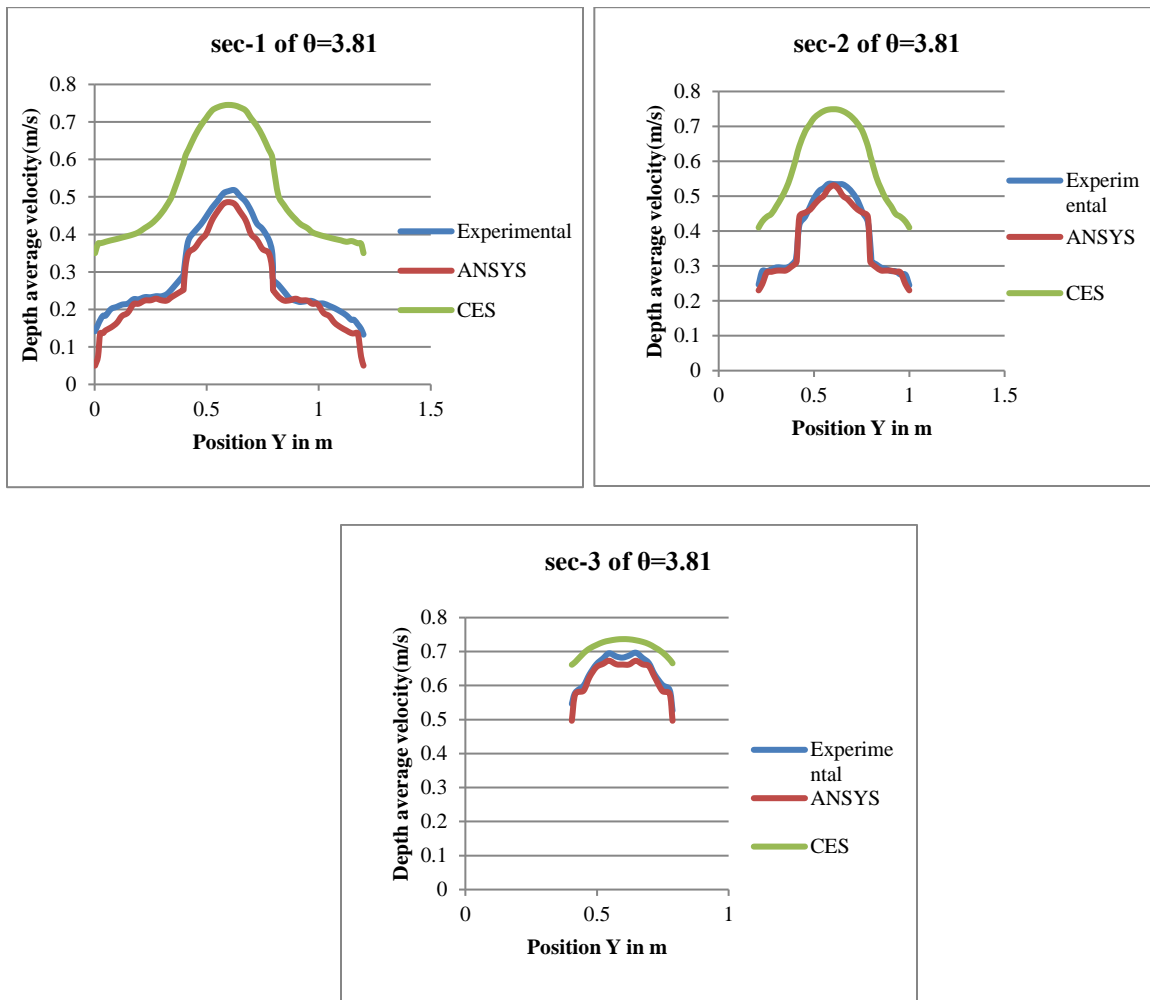


Figure 7 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta=3.81^0$

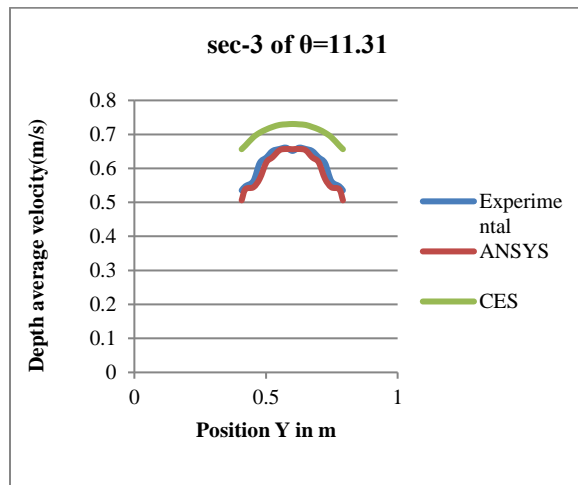
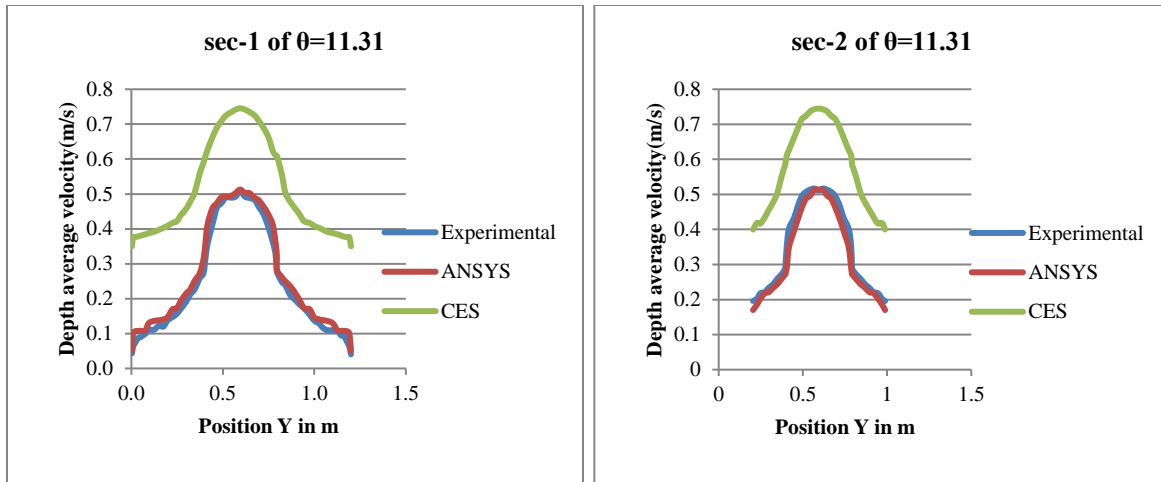
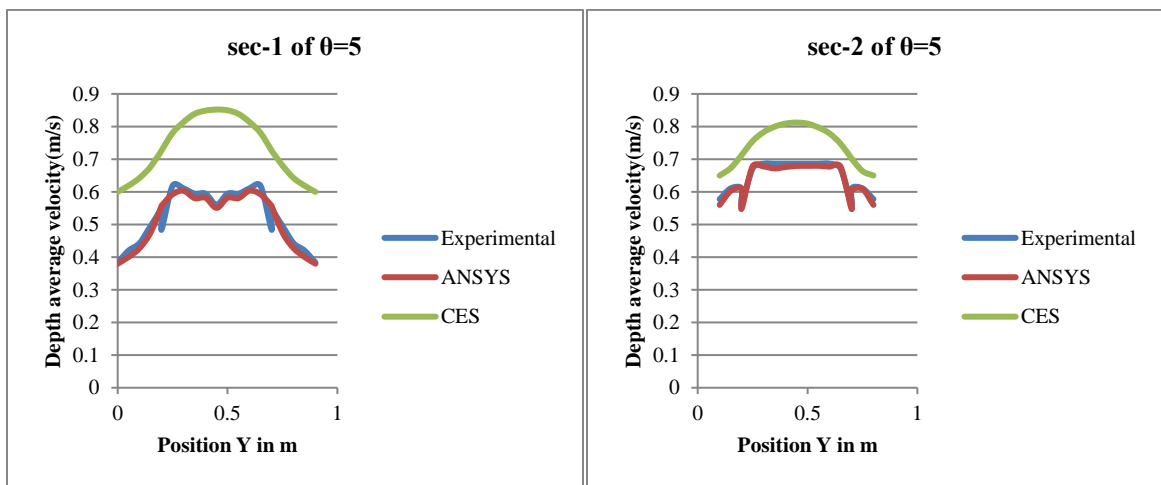


Figure 8 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta=11.31^\circ$



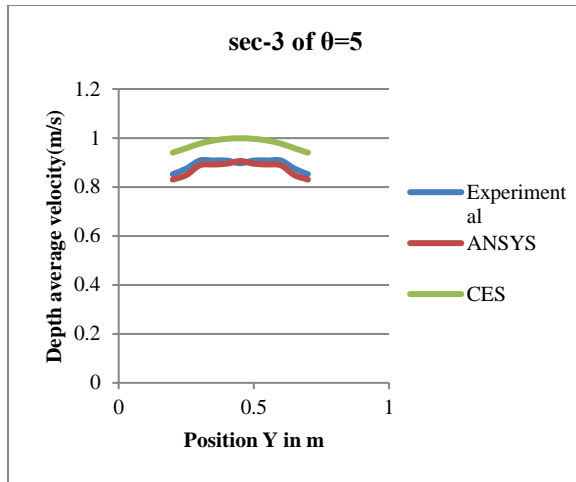


Figure 9 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta =5^0$

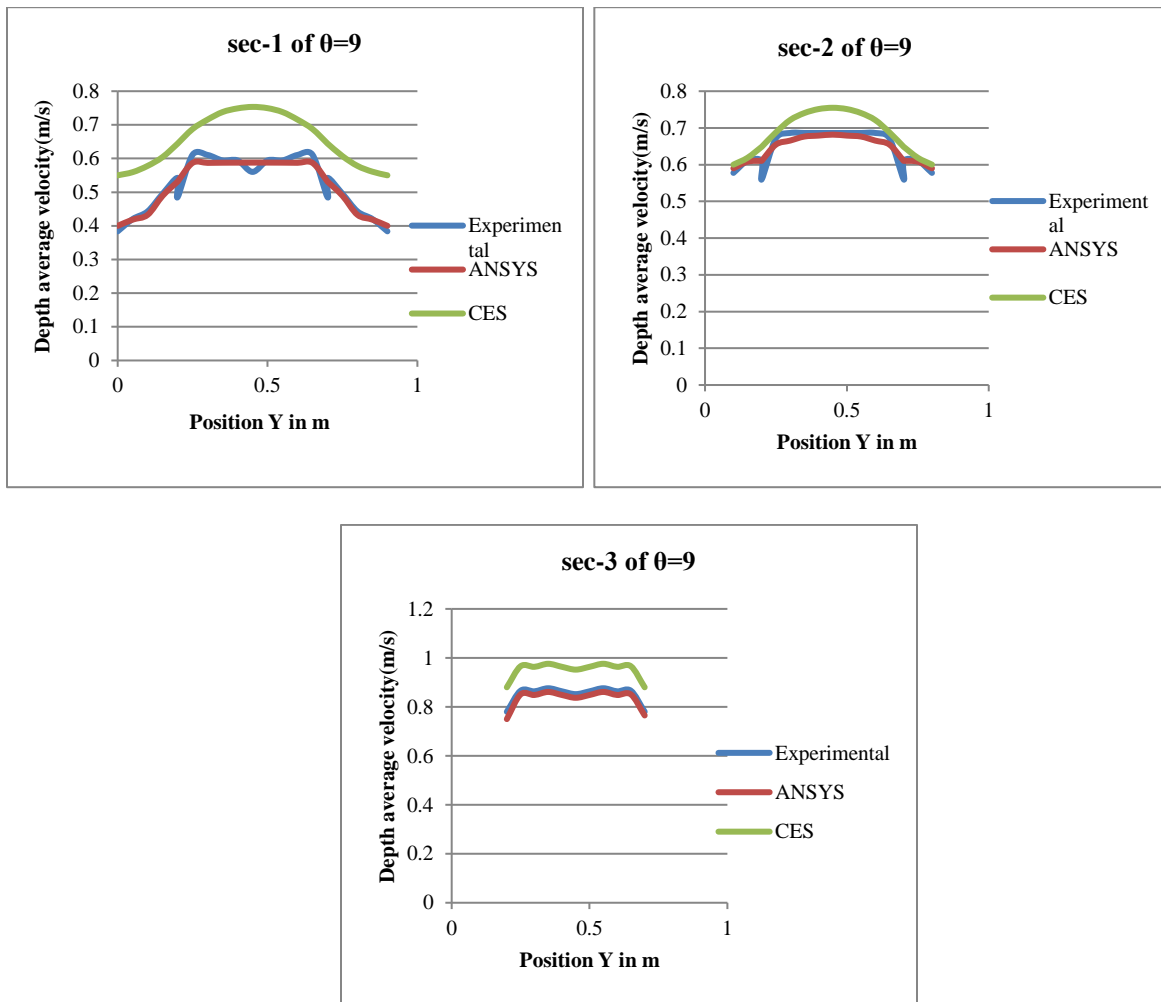


Figure 10 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta =9^0$

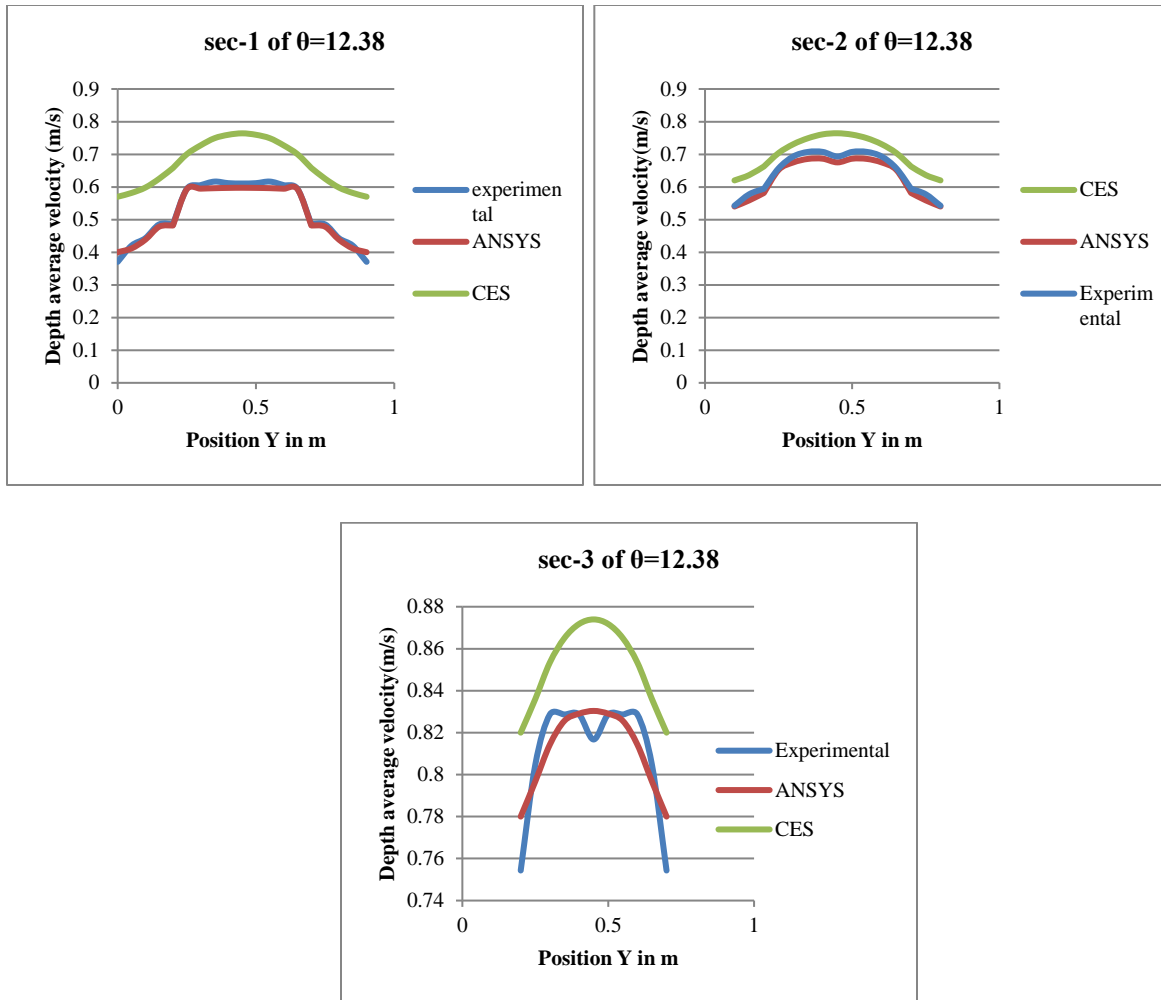


Figure 11 (a) , (b) , (c) Depth-averaged velocity of Sec 1, Sec 2 , Sec 3 of $\theta = 12.38^\circ$

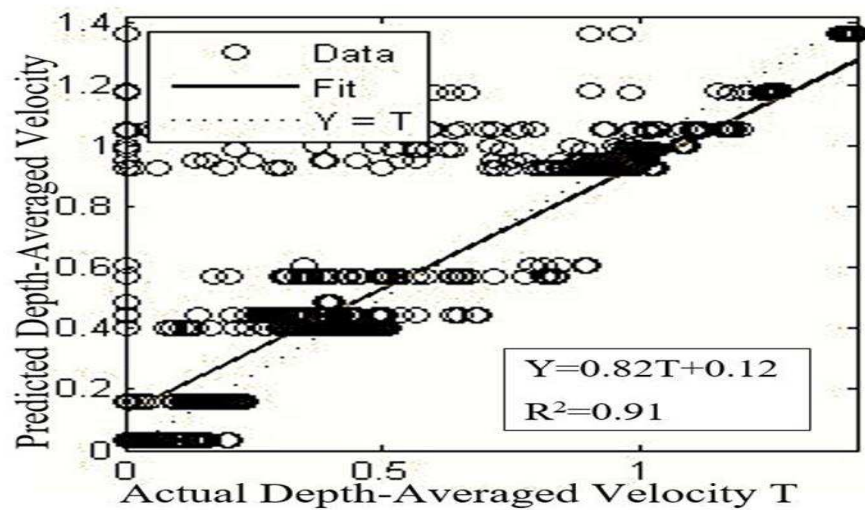


Fig 13 Correlation plot of actual depth-averaged velocity and predicted depth-averaged velocity

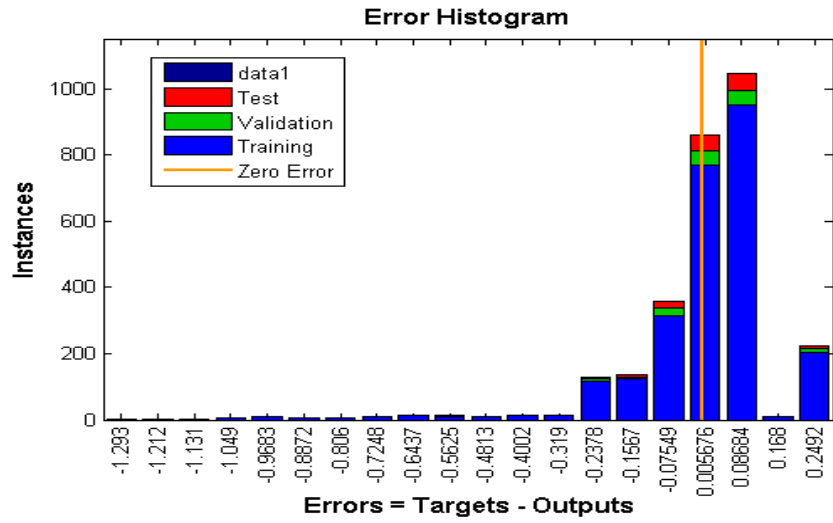


Fig 14 Error Histogram