Point Form Velocity Prediction in Meandering Open Channel using Artificial Neural Network

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Abstract—Prediction of point form velocity is extremely essential for the hydraulic engineer. Flow parameters like boundary shear stress, roughness co-efficient, discharge etc. are directly depending upon velocity distribution. Hence accurate prediction of the velocity distribution is mandatory. In this study, point form velocity in the down stream of flow is predicted at different sections of the meandering channel. Back propagation learning rule in ANN network is considered for further analysis, as this network is well adept with pattern recognition and forecasting. In this further analysis, position of the point and depth of flow are taken as input and point form velocity is the output.

Keywords—Point form velocity; velocity distribution; meandering open channel

I. INTRODUCTION

Open channel flow has attracted the attention of environmental and hydraulic engineers due to its complex nature. Owing to a number of flow phenomena involved, many studies have been conducted to seek the detailed hydrodynamics characteristics of complex combined flows [16, 6, 8]. Over the past few decades, numerous researchers have attempted to construct the velocity profile to understand the flow structure in open channel flow through laboratory and field studies. The instruments like hot-film anemometer [23], laser doppler anemometer [19, 9], fibre-optic laser doppler velocimeter [13], particle-image velocimeter [14], acoustic doppler velocimeter (ADV) [10] and acoustic doppler velocity profiler [12] are used for experiments to identify the flow structures. These studies resulted in a substantial increase in the understanding of form and processing interrelationships in channel geomorphology including applications in the dynamic analysis of channels.

In recent years, considerable advancement of numerical approach to simulate hydraulic patterns in complex natural channels has taken place. Advances have included numerous techniques to describe 2D and 3D velocity profiles [18][4]. Therefore, it is required for the development of alternative methodologies to better understand the simulation of complex conditions in natural channels [11, 2]. The sophisticated techniques can enhance the development of the velocity profile models and turbulence simulation of nonlinear complex characteristics of flow conditions, especially turbulent flows. In this present work, an attempt has been made to predict the velocity profile in sinuous open channel. In this study, a back propagation (BP) algorithm of artificial neural network (ANN) is used for the prediction of discharge in a compound open channel flow. Important past studies in this direction are Neuro-fuzzy model to simulate Coolbrook-White equation [21], prediction of friction factor in smooth open channel flow using ANN [1, 22], and prediction of friction factor in pipe flow problems [5]. A simple but reliable prediction method for estimating discharge of flood channel is highly desirable for field engineers. Therefore, an easily implementable technique like ANN has been adopted in this work. The motive of the recent work is to predict the point form velocity across the channel in various sections. ANN is capable of predicting the velocity profile along flow direction with adequate accuracy.

II. VELOCITY PROFILE

The velocity profiles of fully developed turbulent open channel flow are of great interest to engineers, particularly in the estimation of erosion and sediment transport in alluvial channels. Recent research has represented that the velocity profile is the driver of physical habitat quality for aquatic species [2]. Due to the practical importance of the problem, many studies have been conducted to seek the velocity profiles in open channel flow experimentally using pilot tubes, hot film anemometer [3] or a laser-doppler anemometer [9, 13]. Various semi-empirical models have then been provided to simulate the velocity profile of fully developed turbulent channel flow [17, 7].

One of the most popular velocity distribution models is the log-law [20][15]. This law was derived by assuming that “shear stress is constant” when applied near bed. But it has also been applied in the outer flow region with modification of the von Karman constant. Prandtl (1932) had developed the general form of velocity distribution which considers shear stress as well as shear velocity to be constant throughout. This law is applied near bed region where viscous flow is predominant but skeptical about the outer layer where turbulence of flow exists and Reynolds stress associated with it makes the shear stress variable. But this can be applicable near the bed where the surface is smooth or the roughness negligible. Also this method can
be applied for full depth in center line of wide channel where secondary circulation effect is very less as described by Nezu et al. (1984). This law can be represented as:

\[
\frac{u}{U_*} = \frac{1}{k} \ln \frac{U_* y}{v} + C
\]

where \( k \) is the von Karman constant; \( C \) is a constant, \( p \) is mass density, \( v \) is the kinematic viscosity, \( U_* = \) shear velocity, \( u = \) flow point velocity.

### III. EXPERIMENTAL DETAILS

For the purpose of present research, one meandering experimental compound tilting flume was used. The tilting flume is made by hydraulic jack arrangement. Inside each flume, separate meandering channels are cast using 50 mm thick Perspex sheets. To facilitate fabrication, the whole channel length has been made in blocks of 1.20 m length each. The model thus fabricated has details as: the meandering channel section has the main channel dimension of 120 mm x 120 mm and flood plain width, \( B = 440 \) mm. The channel is cast inside a tilting flume of 450 mm width and 400 mm depth. The bed slope of the channel is kept at 0.0019.

The measuring device consists of a point gauge mounted on a traversing mechanism to measure flow depths with least count of 0.1 mm. Point velocities were measured at a number of locations across the channel section using a Pilot tube. The Pilot tube was physically rotated with respect to the main stream direction till it recorded the maximum deflection of the manometer reading. A flow direction finder having a least count of 0.1 was used to get the direction of maximum velocity with respect to the longitudinal flow direction. The angle of limb of Pilot tube with longitudinal maximum velocity with respect to the longitudinal flow having a least count of 0.1 mm. Point velocities were measured at a number of locations across the channel section using a Pilot tube.

### TABLE I. DETAILS OF EXPERIMENTAL PARAMETERS

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Meandering Channel</th>
<th>Item Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>Geometry of main channel section</td>
<td>Trapezoidal</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>Main channel width (b)</td>
<td>120 mm</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>Bank full depth of main channel</td>
<td>120 mm</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>Top width of compound channel</td>
<td>280 mm</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>Slope of the channel</td>
<td>0.0019</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>Sinuosity</td>
<td>1.44</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>Flume size</td>
<td>0.45 m x 0.4 m x 12 m</td>
</tr>
</tbody>
</table>

### IV. BACK PROPAGATION NEURAL NETWORK (BPNN)

#### A. BPNN Architecture

Figure 1 shows the l-m-n (l input neurons, m hidden neurons, and n output neurons) architecture of a back propagation neural network model. Input layer receives information from the external sources and passes this information to the network for processing. Hidden layer receives information from the input layer, and does all the information processing and output layer receives processed information from the network and sends the results out to an external receptor. The input signals are modified by interconnection weight, known as weight factor \( W_{ij} \) which represents the interconnection of \( ij^\text{th} \) node of the first layer to \( j^\text{th} \) node of the second layer. The sum of modified signals (total activation) is then modified by a sigmoid transfer function \( (f) \). Similarly, output signals of hidden layer are modified by interconnection weight \( W_{kj} \) of \( k^\text{th} \) node of output layer to \( kj^\text{th} \) node of hidden layer. The sum of the modified signal is then modified by sigmoid transfer \( (f) \) function and the output is collected at the output layer.

Let \( I_p = (I_{p1}, I_{p2}, I_{p3},...I_{pn}), p=1,2,3,N \), be the \( p^\text{th} \) pattern among \( N \) input patterns where \( W_{pj} \) and \( W_{kp} \) are the connection weights between \( i^\text{th} \) input neuron to \( j^\text{th} \) hidden neuron, and \( j^\text{th} \) hidden neuron to \( k^\text{th} \) output neuron respectively. Output from a neuron is

\[
O_{pi} = I_{pi}, i=1,2,3..l.
\]

Output from a neuron in the hidden layer is

\[
O_{pj} = f(NET_{pj}) = f\left(\sum_{i=0}^{l} W_{pi} O_{pi}\right), j=1,2,...,m
\]

Output from a neuron in the output layer is

\[
O_{pk} = f(NET_{pk}) = f\left(\sum_{j=0}^{m} W_{kj} O_{pj}\right), k=1,2,...,m
\]

![Figure 1. Architecture of ANN for discharge estimation in straight compound channel](image)

#### B. Sigmoid Function

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

\[
f(x) = \frac{1}{1 + e^{-x}}
\]
where \( x \) = input parameters taken as described above

C. Learning or Training in BPNN

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

Mean square error, \( E_p \) for pattern \( p \) is defined as

\[
E_p = \frac{1}{2} \sum_{i=1}^{n} (D_{pi} - O_{pi})^2
\]

(6)

computed output for the \( i \)th pattern. Weight change at any time \( t \), is given by

\[
\Delta W(t) = -\eta E_p(t) + \alpha \times \Delta W(t-1)
\]

(7)

where \( \eta \) = learning rate i.e. \( 0 < \eta < 1 \)

\( \alpha \) = momentum coefficient i.e. \( 0 < \alpha < 1 \)

V. RESULTS AND CONCLUSION

For this analysis 75 data sets were used for input and 25 sets used for output and the training carried out with BPNN network. It was observed that after 1, 30,000 epochs the solution converges. The learning parameter is set to 0.07 and momentum parameters to 0.07. The convergence limit is set to 0.001 for this analysis. Further as mentioned 75 data sets are used for testing. After this the prediction contours are plotted for both actual and predicted velocities for validation of accuracy, as shown in Figure 2.

The regression analysis is carried out by calculating the residuals from the experimental data and predicted data for training data set as shown in Figure 3. The coefficient of regression of training is 0.94 and similarly the regression coefficient for testing data is 0.92. From the regression plots, it can be said that the data is well trained and tested.

VI. DISCUSSION

In this study, an artificial neural network model is proposed for accurate estimation of point form velocity in meandering channel having sinuosity 1.44. The contour plots and regression analysis in Figure 2 and Figure 3 show the adaptability of BPNN network. The basic reason for high degree of prediction accuracy lies in the fact that BPNN has a strong capability of non-linear mapping of inputs and outputs. The non-linear relation of position, depth of the

![Figure 2. Contours showing velocity distribution across the cross-section of meandering channel for: (a) BPNN actual data (b) BPNN predicted data.](image)

![Figure 3. Regression points of predicted point velocity to experimental point velocity: (a) training data (b) testing data.](image)
point where point form is measured, angle in radians from the apex as input parameters with point form velocity as output is accurately predicted with this network as discussed.

REFERENCES


