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Calculation of Friction velocity in Straight Rectangular Channel in Unsteady flow condition Using Artificial Neural Network

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Abstract

Generally, the flow in natural rivers is unsteady. Accurate assessment of various flow properties like friction velocity and bed shear stress in an open channel flow under unsteady condition is of crucial importance to hydraulic engineers since it helps in estimation of erosion, sediment transport etc. Bed shear stress can be properly predicted by accurate calculation of the friction velocity which is generally influenced by the geometry, roughness, and hydraulic parameters of the channel. In the past, very few studies have been carried out to calculate the bed shear stress in unsteady open channel flows. This study proposes an artificial neural network (ANN) model for the prediction of bed shear stress in straight rectangular channels in unsteady flow condition for both rising and falling limb of hydrograph. The most influential parameters such as depth of flow, discharge, rising and falling time of hydrograph, bed slope of the channel, and roughness condition are considered as input parameters. Vast amount of experimental data from previous researches comprising of input parameters have been used for both training and validation of the model. The models utilised here are back-propagation neural network (BPNN) models, which can perform well for broad ranges of independent parameters. A statistical error analysis employing large data sets is used to confirm the efficacy of the models. The result shows that the ANN network is giving R^2 value of 0.9186 for rising limb and 0.9334 for falling limb of hydrograph.

Keywords: Unsteady flow, Bed shear stress, Friction velocity, artificial neural network, Hydrograph

1. Introduction

Natural rivers and waterways frequently have unsteady flows especially during the time of flood propagation. Field research has demonstrated the significant effect of bed shear stress on bed load movement, suspended load distribution during the passage of a flood. The accurate estimation of bed shear stress can be done by properly predicting of the friction velocity. However under steady flow conditions, determining the friction velocity is a difficult task and it is unquestionably much more challenging in unsteady flow conditions. It is due to the fact that in unsteady flow condition numerous variables are involved in the function relationship and the fact that differential equations cannot be integrated in closed forms unless in extremely simple circumstances. Because of theoretical and practical issues much fewer methods have been developed to calculate the friction velocity in unsteady flow in comparison to steady flow conditions

The investigation of the non-uniform flow over a small incline positioned in an open channel was done by Tsujimoto et al (1990).The study of gradually accelerated flows in a smooth channel by using a hot-film anemometer was done by Cardoso et al. (1991). In gravel-bed channels, frictional resistance was explored by Tu and Graf (1993). In a smooth channel, the turbulence characteristics for accelerating and decelerating flows were discovered by Nezu et al. (1994). Study on the velocity profiles, turbulence intensity, and Reynolds stress for accelerating and decelerating flows in a rough channel were conducted by Kironoto and Graf (1995). Experimental studies on bed shear stress for non-uniform unsteady flow in open channels were conducted by Song (1994) and Graf and Song (1995). Velocity and Reynolds stress profiles for non-uniform flow were investigated by Song and Graf (1994) and Song and Graf (1996). Study on the velocity and turbulence profiles for non-uniform and unsteady flows was done by Song and Chiew (2001). Additionally, they arrived to theoretical Reynolds stress expressions by assuming a power law of velocity distribution. The investigation on the unsteady flow both theoretically and experimentally over fixed and mobile bed was conducted by Zaosong Qu (2002). An expression for Reynolds Shear Stress and bed shear stress in non-uniform open channel flow with steam wise sloping bed by considering universal velocity distribution law (logarithmic law), Reynolds and continuity equation in two-dimensional open channel were developed by S Dey et. al. (2005). A comparison of the values of friction velocity using unsteady flow formulation with the steady flow formulation and also estimated the error using steady state formulation were done by K.P.P. Pathirana et al (2008).

It is quite challenging to create any friction velocity model utilising mathematical, analytical, and numerical approaches when analysing the connections among dependent and independent components. Additionally, these models start to become noticeably laborious and cumbersome; as a result, an easy-to-implement method like artificial neural networks (ANNs) might be welcomed for forecasting friction velocity in unsteady open channel flow. Artificial neural networks are quick, which eliminates the need for complicated computations while also reducing the effort required for testing. In this article, straight rectangular channel data sets with a wide range of geometry, hydraulic, and roughness characteristics are used to create models. This paper uses an ANN due to its simplicity and dependability as a predictor of friction velocity in both the rising and falling limb of the hydrograph because variations in influencing parameters of a straight rectangular channel make it difficult to estimate friction velocity using a mathematical or analytical model. 150 experimental data sets, including both rising and falling limb, are employed in this investigation. First bed shear stress data and influencing parameters like depth of flow, discharge velocity of flow in both rising and falling limb, slope and bed material data are collected from previous researches and then the prediction of this flow variable was performed using an artificial neural network's back propagation (BP) technique.

2. Materials and Methods

2.1 Source of data

Several experimental hydrograph data sets were employed in this investigation. The hydrographs that this study took into account are as follows S-15-936, S 30-931 of Graf and Song (1995), NS1 (1) of Tu and Graf (1993), TM-01, TM-02, TM-03, TM-04, and TM-05 of Zhaosong Qu (2002).Table 1 provides the details of channel setup and flow details in the channel. Table 2 provides the details of discharge, velocity, bed material, rising and falling time of hydrograph and bed slope at which the experiments are conducted.

Table-1 Channel and flow details for mentioned hydrograph

	Width of Flume(m)	Length of Flume(m)	Type of flow	Type of flume
Tu and Graf (1993)	0.6	16.8	Sub Critical	Rectangular
Graf and Song (1995)	0.6	16.8	Sub Critical	Rectangular
Zhaosong Qu (2002)	0.6	16.8	Sub Critical	Rectangular

Table2. Details of experimental data used in the analysis

Hydrograph name	Discharge (l/s)	Depth of Flow (cm)	Velocity (cm/s)	Shear Velocity (cm/s)	Bed Slope (%)	t_r(s)	t_f (s)	D_{50} (cm)
TM-01	50.4-135.1	12.3-20.5	68.6-109.6	4.8-7.3	-0.3	150	150	0.58
TM-02	53.2-141	12.4-20.7	71.3-113.5	4.8-7.3	-0.3	100	200	0.58
TM-03	47.2-162.7	10.9-21.2	72.2-128.7	4.9-7.8	-0.3	50	50	0.58
TM-04	47.2-156.8	11.1-20.5	71.2-129	5.1-7.1	-0.3	30	30	0.58

TM-05	52.4-167.5	11.9-22	73.6-127	5.1-8.2	-0.3	300	300	0.58
S-15-936	50.6-92.3	14-18.3	60.2-84.9	4.17-6.02	0. 3	25	25	1.23
S 30-931	58.5-89.1	11-13.7	88.3-108.2	6.52-8.06	-0.15	50	52	1.35
NS1 (1)	22.8-119.3	9-21.2	40.8-94.9	3.29-8.5	0.2	51	59	1.23

2.2 Selection of Influencing Parameters

As input parameters for the modelling of shear velocity ($u*$) in both rising limb and falling limb of hydrograph, this study included the significant factors, including longitudinal bed slope (S_0), velocity (u), depth of flow (d), discharge (Q), bed material (D_{50}), and rising time (t_r) and falling times (t_f). To ascertain how the independent characteristics depended on shear velocity, this study investigated fresh experimental data sets that were collected from the rectangular channel from the previous research papers.

2.3 Artificial Neural Network

Artificial neural network (ANN) is a crucial and constantly developing computing technique. An ANN is made up of the association of simple handling elements, like as neurons or nodes, which are organised in layers. It is a back-propagation (BP) neural network model made up of *I* input neurons, *m* hidden neurons, and *n* output neurons in a three-layered feed forward architecture. The input layer feeds the network with data. The output layer receives prepared data from the network, while the hidden layer processes all the data it receives from the input layer. External receptors receive the output data. In this network layers are connected to the resulting layers through these connections, which are referred to as weights and weighted values.The connectivity weights are improved to restrict predefined cost functions in this network.

In order to forecast the friction velocity in unsteady open channel flows in both rising limb and falling limb of a hydrograph in a straight rectangular channel, an ANN technique is applied in this study. For prediction, a back propagation training approach is used to prepare a feed forward kind of network. Figure 1 depicts the entire ANN process inside the network, and Figure 2 depicts the simulation process inside the neural network with processing parts. The network is initially trained before being applied to any problem and each output neuron's goal output is constrained by conforming the weights and biases during the training method. Three elements make up training in ANNs: (1) weights between neurons that describe the relative importance of the input sources; (2) a sigmoid transfer function that regulates the stage of a neuron's output; and (3) an arrangement of learning laws that shows how the weights are changed during training. The nonlinear function used in training is generally a sigmoid function (Govindaraju 2000a).

$$F(a) = \frac{1}{1+e^{-a}} \ldots\ldots\ldots\ldots\ldots (1)$$

Where a is the total of bias and the weighted input value. The subsequent layer of nodes receives the outcome. Feed forward back-propagation neural network (BPNN) approaches consist of the following four steps:

1. Summation of the weighted input

$$Nod_z = \sum_{i=1}^{n} (W_{xz} k_x) + \epsilon_z \ldots\ldots\ldots\ldots\ldots (2)$$

Where Nod_z represents the sum for the z^{th} hidden node; n represents the total number of input nodes; W_{xz} represents the connection weight between the x^{th} input and the z^{th} hidden node; k_z represents the normalised input at the x^{th} input node; and z represents the bias value at the z^{th} hidden node.

2. Transformation of the weighted input

$$Out_z = \frac{1}{1+e^{-Nod_z}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where Out_z represents output from the zth hidden node

3. Summation the hidden node output

$$Nod_y = \sum_{j=1}^{m} \left(W_{zy} k_y\right) + \epsilon_y \ldots\ldots\ldots\ldots\ldots (4)$$

Where Nod_y represents sum of y^{th} output node; m represents total number of hidden nodes; W_{zy} represents connection weights between the z^{th} hidden node and the y^{th} output node; and $\in_y$ represents the bias value at the y^{th} output node; and the last is

4. Transformation of the weighted sum

$$Out_y = \frac{1}{1+e^{-Nod_y}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where Out_y represents output at the yth output node.

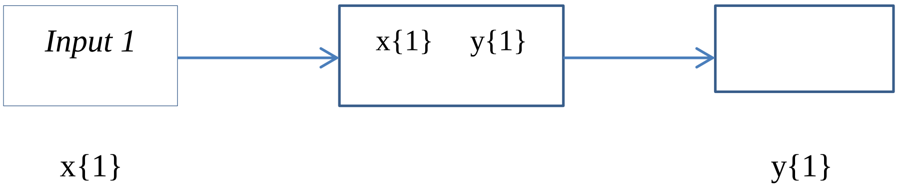

Figure 1 Total simulation process of ANN model

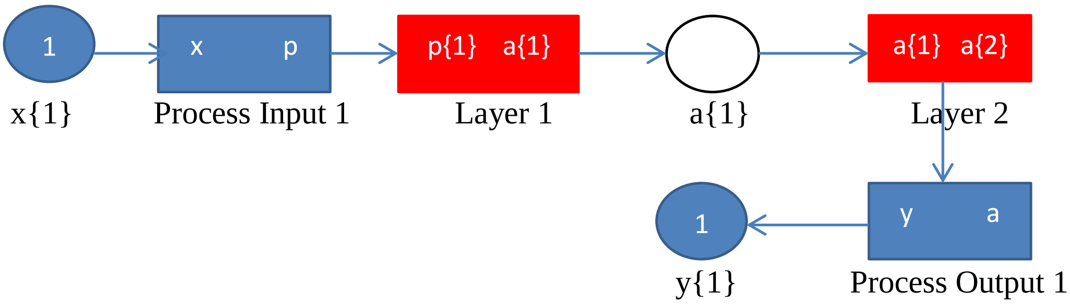

Figure 2 Simulation process with processing elements inside neural network

2.4 Neural Network mapping for calculation of friction velocity

The relationship between the influencing parameters and the friction velocity in a straight, rectangular channel under an unsteady flow situation in both the rising and falling limbs of the hydrograph is

$$u^*{}_r = f(Q_r, V_r, h_r, t_r, S_0, D_{50}) \ldots\ldots\ldots (5)$$

$$u_f{}^* = f(Q_f, V_f, h_f, t_f, S_0, D_{50}) \ldots\ldots\ldots\ldots (6)$$

Where S_0 = longitudinal bed slope; $u*_r$ & $u*_f$ = friction velocity in rising and falling limb of hydrograph respectively; V_r & V_f = velocity in rising and falling limb of hydrograph respectively; h_r & h_f = depth of flow in rising and falling limb of hydrograph; t_r & t_f = rising and falling time of hydrograph, D_{50} = Size of the bed material.

A back-propagation neural network is used in this study. On a MATLAB platform, the ANN operated. Six neurons serve as the input layers in the neural network structure, twelve serve as the hidden levels, and one serve as the output layer. Figure 3 shows the architect of neural network in MATLAB. The various neural network settings for this system are shown in Table 2.

The minimum value of the error which is contained in it has been noticed among all the errors with respect to epochs/generations. After 116 generations for falling limb and 45 generations for rising limb, the network converged with a mean square error (MSE) of 0.3826 and 0.44894 respectively. (Figure 4, Figure 5)

Table 3 Details of training parameters used in the analysis

Parameter	Rising limb	Falling Limb
Epoch	1000	1000
Performance	0.162	0.247
Gradient	3.91×10^{-5}	3.53×10^{-5}
Mu	1.00×10^{-7}	1.00×10^{-7}

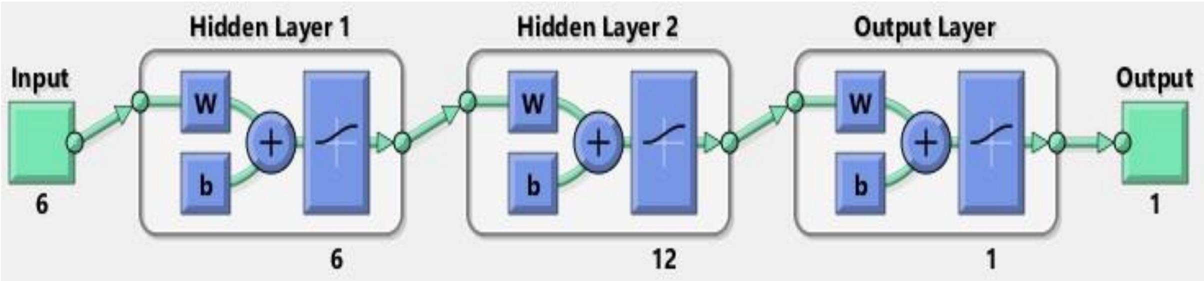

Figure 3 Elements of neural network in MATLAB

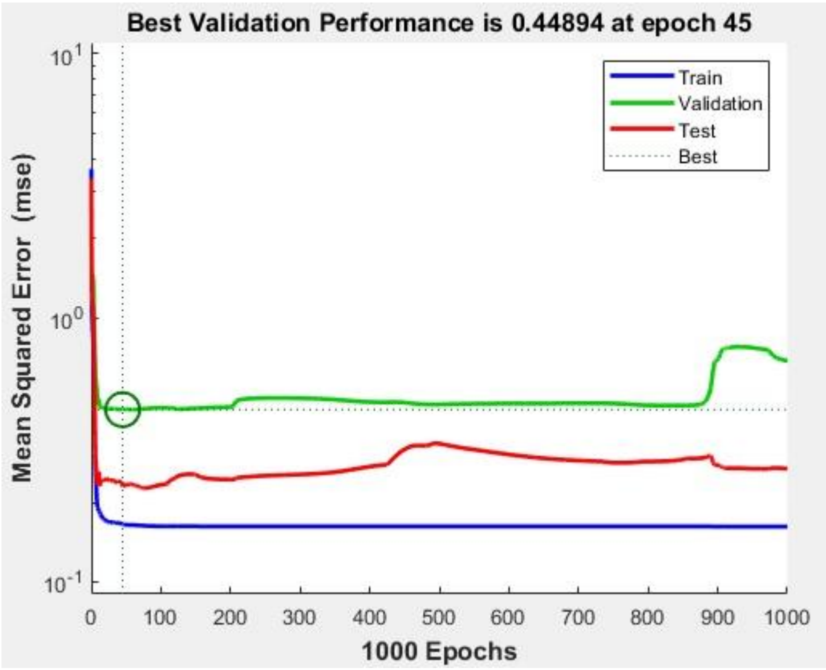

Figure 4 Convergence curve for training of BPNN recognizer under optimized feature parameters for rising limb of hydrograph

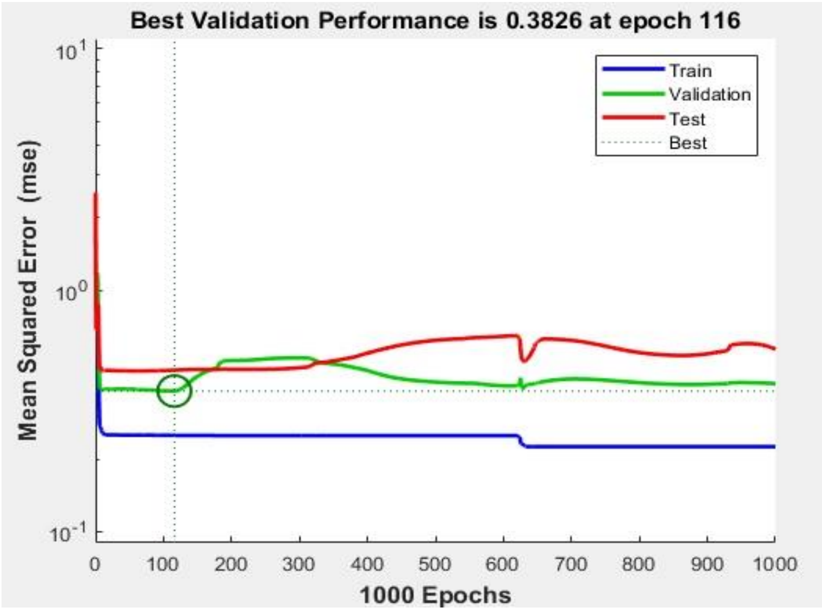

Figure 5 Convergence curve for training of BPNN recognizer under optimized feature parameters for falling limb of hydrograph

3. Results and Discussions

In this work, training and testing sets are created from each of the experimental data sets. Out of the 300 series of data set which are used for the model 150 data are used for rising limb and 150 data for falling limb of hydrograph. Now among these 150 data series 30 series of data sets are utilised for testing and validation, and 120 series of data sets are used as training data for both the cases .The ANN is used to determine the friction velocity in straight rectangular channels. Back-propagation neural network models were developed and put to the test for this use. After the data samples have undergone the required pre-processing, they were given to the network model when the neurons have a transfer function within the restricted ranges. Figure 7 and Figure 8 compares the actual *u** with the predicted *u** for rising limb and falling limb of hydrograph respectively; the coefficient of determination (R^2) is 0.9186 and 0.9334 for rising and falling limb of hydrograph respectively.

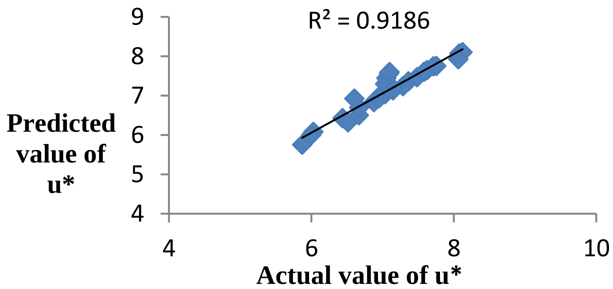

Figure 6 Actual u* vs. Predicted u* for Rising Limb of Hydrograph

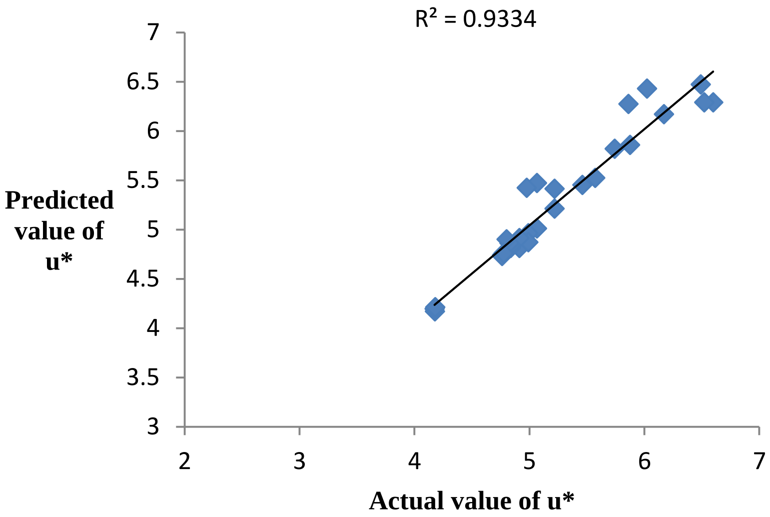

Figure 7. Actual u* vs. Predicted u* for Falling Limb of Hydrograph

Error Analysis

Four error analyses—the mean absolute percentage error (*MAPE*), mean absolute error (*MAE*), mean percentage error (*MPE*), and root mean square error (*RMSE*)—are taken into consideration in order to better understand the relationships between the results. Using Eqs. (13)– (16), the *MAPE*, *MAE*, *MPE*, and *RMSE* are calculated for both rising and falling limb of hydrograph.

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{(u*)_{measured}-(u*)_{predicted}}{(u*)_{measured}}\right| \text{ .... } (6)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(u*)_{measured} - (u*)_{predicted}\right| \text{ .... } (7)$$

$$MPE = \frac{100}{N}\sum_{i=1}^{N}\left(\frac{(u*)_{measured}-(u*)_{predicted}}{(u*)_{measured}}\right) \text{ .... } (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left((u*)_{measured}-(u*)_{predicted}\right)^2}{N}} \text{ .... } (9)$$

Using experimental data and data from the ANN model, several statistical studies are carried out to evaluate the effectiveness of the ANN model. The statistical error results from the ANN model using the BPNN technique is shown in Table 3.

Table 4 Statistical error analysis result from ANN model using BPNN technique

Parameters	Rising limb of Hydrograph	Falling limb of hydrograph
MAPE	1.55	1.87
MAE	0.108	0.1059
MPE	-0.81427	-1.0875
RMSE	0.181	0.177

If a model's MAPE, MAE, MPE, and RMSE values are close to zero, it can be argued that it is a good model. Hence from the above table we may conclude that ANN model using BPNN algorithm is a good model for forecasting the friction velocity for both rising and falling limbs.

4. Conclusions

In this study, a back-propagation neural network model is put out to forecast the friction velocity in a rectangular, straight channel. The ability of the ANN's nonlinear input-output mapping is the primary cause of the high level of prediction accuracy**.**

The statistical error data for the ANN model with BPNN method performance are as follows: rising limb *MAPE* =1.55, *MAE* = 0.247, *MPE* = -0.81427, *RMSE* = 0.181 and R^2=0.9186 for falling limb *MAPE* = 1.87, *MAE* = 0.1059, *MPE* = -0.10875, *RMSE* = 0.177 and R^2 = 0.9334. Data sets from the literature are used to get this conclusion. Wide ranges of discharge bed material D_{50}, velocity rising time of hydrograph and falling time of hydrograph times are used in this investigation. Due to the ANN's ability to map the nonlinear relationship between dependent and independent variables in complicated flow phenomena, the ANN model employed here is able to accurately forecast bed shear stress for both the rising limb and falling limb of a hydrograph in unsteady of open channel flow. The statistical error analysis also shows it to be true. Therefore In order to calculate friction velocity in a straight, rectangular channel under an unsteady flow state, field engineers can utilise this method.

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