Artificial Neural Network Applications for Predicting Drag Coefficient in Flexible Vegetated Channels

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***Abstract*—Previously numerous equations were developed using conventional methods to estimate vegetal drag coefficient by treating submerged and emergent vegetation independently, there is need to derive a generalized relationship that can be applied irrespective of the vegetation submergence with respect to flow depth. In this regard, the present study uses artificial neural network (ANN) as an advanced tool for prediction of drag coefficient in flexible vegetated channels. The training and testing patterns of the proposed ANN model were based on experimental results from the field and laboratory studies that combined both the submerged and emergent grass. A functional relation based on flow parameters and vegetation properties was derived through the use of dimensional analysis. The ANN model developed herein showed significantly better results in several model performance criteria when applied for verification.**

***Index Terms*—Artificial Neural Network; Dimensional Analysis; Drag Coefficient; Flexible Vegetated Channels.**

I. Introduction

The flow resistance in open channel are usually derived from the viscous and drag force over the wetted perimeter [1]. This drag is categorized into three comprising – soil grain roughness, form roughness, and vegetative roughness. The vegetation drag is the most significant compared to others, as it has the utmost flow resistance that eventually decreases the average flow in vegetated channels [2, 3]. Thus, this will lead to rise in flow depth and residence time of sediments in the channel due to drag of vegetation [4]. Drag coefficient is an important parameter, this is because the drag enhanced the tendency for trapping, deposition, and stabilization of sediments, and its increases flow resistance and decreases the bed shear stress, which results in reduction of bed load transport capacity and erosion rate. Several procedures were proposed by researchers to model flow - vegetation interactions and sediment transport in open-channel [5-10]. Also, vegetation-induced drag force has been systematically studied by Kothyari, Tang, Wu and others [1, 11, 12]. However, with these investigations, it was deduced that there are discrepancies for the derivations of vegetation drag which necessitate for a general formula in evaluation of drag coefficient [13]. In addition, conventional regression has been used to develop mathematical equations in estimating hydraulic variables, such as drag coefficient, in vegetated channels. This approach of regression was found to either over or under-estimate the hydraulic variables. Thus, for a better and accurate predictions, soft computing techniques such as artificial neural network (ANN) are nowadays employed in water resources engineering to estimate hydraulic and hydrologic variables [14-16].

Therefore, the main objective of this paper is to develop ANN model that will compute the vegetal drag coefficient in natural grassed channels irrespective of the grass submergence in relation to flow depth. Thus, field and laboratory experiments were conducted to collect hydraulic data to establish the ANN model.

II. Functional Relationship

A functional relationship was formulated based on the criteria of Wu *et al.* [1], Tang *et al.* [11], Kothyari *et al.* [12] and Wilson *et al.* [17] that the drag coefficient C_D is depended on Reynolds number R_h, vegetation density, λ measured as per unit meter; submergence ratio S, and length of vegetation reach, L_v. Also, theoretically, C_D depends on the channel slope, S_o. Thus, C_D could be expressed as follows:

$$C_D = f(R_h, \lambda, L_v, S, S_o) \tag{1}$$

It follows that (1) can be expressed as (2) based on dimensional homogeneity:

$$C_D = f'(\mathrm{R}_h, \lambda L_v, S/S_o) \tag{2}$$

The value of R_h, can be determined based on the vegetation height, h_v [11] as expressed by (3):

$$R_h = \frac{V h_v}{\nu} \tag{3}$$

Also, the submergence ratio, S, can be expressed as follows [11]:

$$S = \frac{h}{h_v} \tag{4}$$

And the vegetation density, λ, based on the idea of Xia and Nehal (2013):

$$\lambda = \frac{A_v}{V_w} \quad (5)$$

where, h_v = vegetation height, h is the water depth, A_v = Area of vegetation, $A_v = B*L_v$, B = width of the channel and V_w = volume of water, $V_w = A_v*h$.

However, C_D is determined depending on whether the vegetation is emergent or submerged condition. For the case of emergent vegetation (6) is used, while for the case when the vegetation was submerged (7) was applied:

$$C_D = \frac{2.g.S_o}{U^2\lambda} \quad (6)$$

$$C_D = \left(\frac{H}{h_v}\right)\frac{2.g.S_o}{U^2\lambda} \quad (7)$$

where, U is the mean velocity of flow (m/s), g = gravity constant (m^2/s), H = depth of water above the vegetation.

III. Developing the Artificial Neural Network

ANN is a powerful mathematical modelling tool that has the ability to process complex input-output relationships, similar to the human brain [17]. This means ANNs are based on the concepts of biological nervous system [18]. They are mostly applied to predict or forecasting the value of an output (depended variable) based on known values of independent variables in an input layer, particularly where the relationships between these variables are not simple linear. Levenberg - Marquardt (LM) back propagation algorithm was used in training the network. This is because LM is an effective training algorithm for training smaller networks [19]. The algorithm uses Newton method that approximate the network error using second order relationship. To execute the process, program algorithm of the LM was developed using Matlab version 2015a, where the values of C_D, was set as the target, while R_h, $\lambda.L_v$ and S/S_o were set as the input as expressed by (2). The ANN model for predicting the value of C_D, the optimum number of hidden neuron was selected to be 11 for best performance. 70% of the experimental data set was randomly selected for training the ANN model network. The remaining 30% of the data set were used for model validation and testing.

The performances of the regression equation and ANN were evaluated using the statistical parameters like coefficient of determination (R^2) and mean square error (*MSE*).

IV. Experimental Procedure

A. Field Data Acquisition

Figure 1 shows the study area which is located at Universiti Sains Malaysia (USM) Engineering Campus, Nibong Tebal, Penang, Malaysia. In USM three basic types of swale can be distinguished as Type A, Type B and Type C swales with single, double and triple subsurface modules respectively [20]. However, hydraulic and hydrologic data were obtained in grassed swale Type B in this study. All hydraulic data were obtained using an installed automatic flow meter (American Sigma InSight 4.200), this flow meter recorded the flow level (depth), velocity and discharge at every 15 minutes interval. The swale has a bed slope of 1 in 500. The average grass height in the swale varied from 25 to 40 mm. Axonopus Compressus commonly known as Cow grass was used within the channel bed of the swale Type B, where the grass may be submerged or unsubmerged depending on the flow depth and the grass height. This grass was chosen been commonly available in Malaysia which is currently adopted in the ecological swale of USM for the management of runoff. The technical details of swale components have been discussed by Ghani et al. [20]. Also, using the techniques of surveying the average cross-sectional area of the grassed swale was determined as presented in Figure 2.

Figure 1: Flow through the Grassed Swale Type B

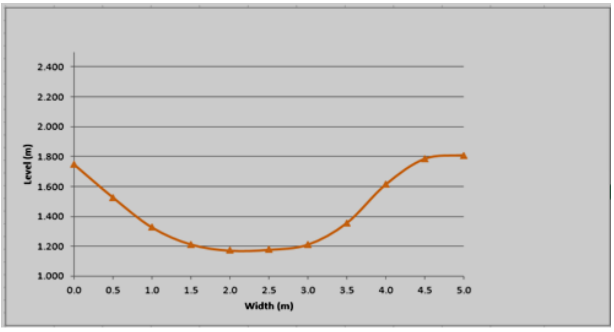

Figure 2: Cross Section of Swale Type B

B. Laboratory Experiments

Experiments were conducted in a concrete channel of working dimension 12 m x 1.5 m x 1 m, at the physical modelling laboratory of River Engineering and Urban Drainage Research Center (REDAC), Universiti Sains Malaysia. The overall length of the channel is 16 m and comprises inlet sump, test flume and the outlet sump. Figure 3 shows test channel with *Cow grass* planted over a length of 10 m, under a bed slope of 1 in 1000. A grass height of 50 mm was maintained throughout the experiments. Three (3) different flow depths of y = 0.15 m, y = 0.20 m and y = 0.40 m, were used to create flow over the grass under submerged condition. Flow velocity was measured using Acoustic Doppler Velocimeter (ADV). Velocity distributions were determined at five (5) different vertical points, measured along 7 – cross sections, starting from the inlet 3.0 m, 4.5 m, 5.5 m, 6.0 m, 6.5 m, 8.5 m and up to 11.5 m, respectively. At each vertical point, 8 different depths were measured in fractions of the flow depths, that is, 0.2y, 0.25y, 0.3y, 0.4y, 0.5y, 0.6y, 0.7y and 0.8y, respectively. Hence, average vertical velocities were calculated and used for developing the ANN model.

Figure 3. Laboratory test channel

V. Results and Discussion

Figure 4 and 5 show the respective readings obtained in grassed swale Type B for the flow depth, and velocity variations due to different rainfall events in September 2009. The readings were taken continuously at 15 minutes intervals using the automatic flow meter.

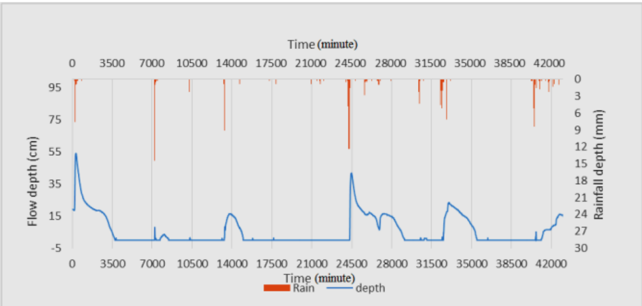

Figure 4: Variation of Flow Depth with Rainfall Events for September 2009

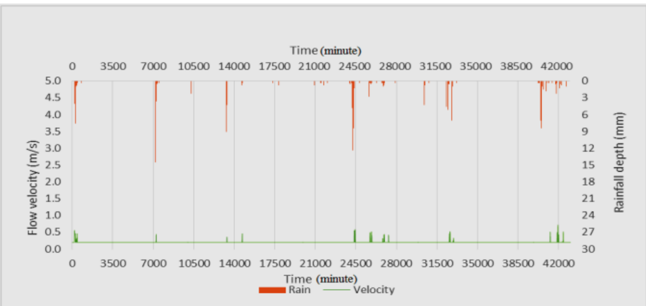

Figure 5: Variation of Flow Velocity with Rainfall Events for September 2009

Using the above data in Figures 4 to 5, Figures 6 and 7, were produced to indicate the relationship between the C_D with R_h and S. From this figure, it shows that the drag C_D, has a fair correlation coefficient because it combines both submerged and unsubmerged vegetation. However, the correlation coefficient for C_D versus S was quite high, indicating strong relationship.

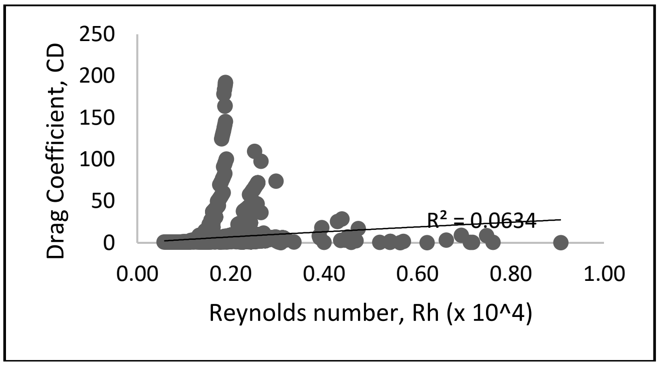

Figure 6: Variation of Drag Coefficient with Reynolds Number for Grassed Swale

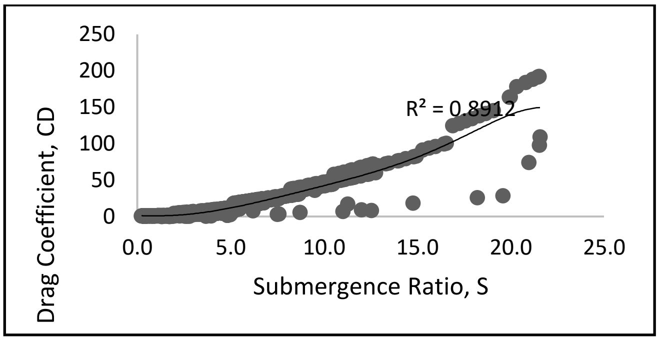

Figure 7: Variation of Drag Coefficient with Submergence Ratio for Grassed Swale

While Table 1 shows the hydraulic flow parameters obtained for the laboratory experiments. Using this table, Figure 8 was plotted to illustrate the respective variations of C_D with Reynolds number, R_h. From this figure, it shows that the drag C_D with R_h as the correlation coefficient R^2 is more than 80%. These results obtained under laboratory conditions are approximately similar to the earlier results presented for the grassed swale selected for field study that combines both the submerged and unsubmerged vegetation. However, the laboratory experiment was mainly focused only on submerged vegetation.

Table 1
Summary of laboratory flow parameters

Total Flow depth (m)	Fraction depth	Average Velocity, V (m/s)	Flow Area A (m^2)	Water depth, h (m)	Volume of water, V_w (m^3)	Submergence ratio, S	Vegetation density λ (m^{-2})	R_h (x 10^4)	Drag Coefficient C_D
y = 0.15	0.2y	1.42	0.05	0.03	0.45	0.60	33.33	7.11	0.000
	0.25y	1.11	0.06	0.04	0.56	0.75	26.67	5.54	0.001
	0.3y	0.57	0.07	0.05	0.68	0.90	22.22	2.86	0.005
	0.4y	0.50	0.09	0.06	0.90	1.20	16.67	2.50	0.011
	0.5y	1.15	0.11	0.08	1.13	1.50	13.33	5.75	0.003
	0.6y	0.99	0.14	0.09	1.35	1.80	11.11	4.96	0.007
	0.7y	1.07	0.16	0.11	1.58	2.10	9.52	5.35	0.008
	0.8y	0.67	0.18	0.12	1.80	2.40	8.33	3.36	0.026
y = 0.20	0.2y	0.37	0.06	0.04	0.60	0.80	25.00	1.87	0.009
	0.25y	0.48	0.08	0.05	0.75	1.00	20.00	2.38	0.009
	0.3y	0.32	0.09	0.06	0.90	1.20	16.67	1.58	0.029
	0.4y	0.63	0.12	0.08	1.20	1.60	12.50	3.17	0.013
	0.5y	0.26	0.15	0.10	1.50	2.00	10.00	1.30	0.118
	0.6y	0.17	0.18	0.12	1.80	2.40	8.33	0.85	0.402
	0.7y	0.16	0.21	0.14	2.10	2.80	7.14	0.81	0.590
	0.8y	0.31	0.24	0.16	2.40	3.20	6.25	1.56	0.210
y = 0.40	0.2y	0.45	0.12	0.08	1.20	1.60	12.50	2.24	0.025
	0.25y	0.44	0.15	0.10	1.50	2.00	10.00	2.18	0.042
	0.3y	0.32	0.18	0.12	1.80	2.40	8.33	1.60	0.112
	0.4y	0.34	0.24	0.16	2.40	3.20	6.25	1.68	0.182
	0.5y	0.09	0.30	0.20	3.00	4.00	5.00	0.45	3.955
	0.6y	0.10	0.36	0.24	3.60	4.80	4.17	0.52	4.299
	0.7y	0.14	0.42	0.28	4.20	5.60	3.57	0.69	3.300
	0.8y	0.12	0.48	0.32	4.80	6.40	3.13	0.59	5.787

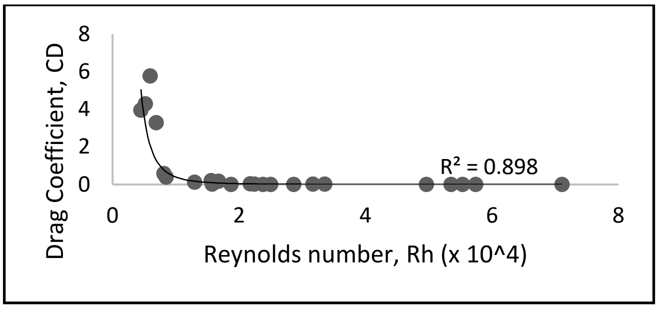

Figure 8: Variation of Drag Coefficient with Reynolds Number for Laboratory Experiment

VI. ANN Modelling of Vegetative Roughness

Table 2 illustrates the summary of statistical analysis for the prediction of the ANN model with R2 value close to unity. It follows that ANN model performed very good in predicting the drag coefficient of both submerged and emergent vegetation respectively using published data of Cantalice et al. [21], to serve as verification of the developed ANN model.

Table 2
Summary of statistical analysis on for Drag Coefficient Prediction by ANN

Process	MSE	R^2
Training	0.2751	0.9997
Testing	0.2042	0.9998
Verification	0.3141	0.9887 (submerged)
[21]	0.4050	0.9684 (Emergent)

MSE Mean Square Error; R^2 Coefficient of Determination

VII. Conclusion

The results obtained from this study show that the drag coefficient depends on the Reynolds number, vegetation density and submergence ratio. The drag coefficient, C_D, generally decreases with increase in vegetation density and Reynolds number, whereas it increases with increase in the grass submergence. The ANN model developed shows excellent performances when applied for verification, irrespective of the grass submergence with the flow depth.

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