27 th International Conference on Hydraulics, Water Resources, Environmental and Coastal Engineering (HYDRO 2022 INTERNATIONAL) at Punjab Engineering College Chandigarh, India during December 22 -24, 2022

Friction Factor Prediction of Heterogeneous Channel Using Artificial Neural Network (ANN)

Ajit, P.[1], Meher, M[2]., Dash, S.[3] and Sharma, A.[4]

[1]*Post Graduate Student, Department of Civil Engineering, NIT Rourkela - 769008, India;*
[2]*Post Graduate Student, Department of Civil Engineering, NIT Rourkela - 769008, India;*
[3]*Under Graduate student, Department of Civil Engineering, NIT Rourkela - 769008, India*
[4]*Assistant Professor, Department of Civil Engineering, NIT Rourkela - 769008, India*
Email: sharmaannitrkl.ac.in

Abstract

An exact forecast of the friction factor coefficient is crucial in hydraulic engineering, because it has a direct impact on the design of hydraulic structures, the computation of velocity distribution, and the precise estimation of energy losses. Friction factor of a channel is a kind of frictional force that prevents the river from moving forward as it flows downhill, and basically it depends on the smoothness or roughness of the channel. This study is an attempt to rank the input parameters that have a major impact on the friction factor. To do so, first data collection is done. Then artificial neural network (ANN) model is created in Python using those data, and then model's performance was tested using regression graphs. Prediction capabilities of various equations proposed by different authors were validated by plotting regression graphs and by comparing the values of coefficients of determination(R^2). At last, analysis is done by individual graphs, between input and output parameters. The result revealed that the friction factor decreases with increase in flow depth, friction slope, shear velocity, particle size, and flow discharge and discharge has shown a larger impact on the value of friction factor as analyzed from the graphs. The model provided in this study, when compared with other models produced better results when measured on the basis of the value of coefficient of determination.

Keywords: Flow resistance, Flow depth, Flume test, Coefficient of Determination, Artificial Neural Network

1. Introduction

Flow resistance is defined as a kind of force that stops a river from accelerating as it flows downhill. It is a theoretical equation that quantifies friction resistance, according to Darcy-Weisbach Grain resistance, form drag, wave resistance, and drag owing to flow unsteadiness all contribute to flow resistance in an open channel flow.

Various researches were conducted in distinct channels for formulating a comprehensive flow resistance equation. Kouwen and Moghadam (2000), estimated the value of friction factor for non-submerged, flexible vegetation. The proposed model was found out to be capable of estimating roughness coefficients for vegetative zones. Sharma and Kumar (2018), formulated the flow resistance in seepage-affected alluvial channel. An empirical equation is suggested which is the function of flow Reynold's number, friction Reynold's number, and seepage particle

Reynold's number and performs better for seepage-affected alluvial channel. Ahmad et al. (2018), in his study, determined the flow resistance coefficient for open channel vegetation. The results show that the arrangement of vegetation played an important role, where closely spaced ones were having higher values of velocities than those with higher spacings. Dolling and Varas (2002), in his study, presented the Monthly streamflow prediction using ANN. The Neural Network represented very close values of measured flows and hence was considered to be a good approach to calculate flow prediction. Kumar (2014), in his paper, Predicted the Flow velocity in vegetative channel using hybrid ANN. The results showed that flow depth and drag coefficient were found to be having major impact on mean velocity. The generalization capability of the model was found out to be very good considering there were so many parameters affecting the flow resistance.

It is very difficult to analyse the impact of so many input parameters on output using traditional physically based modelling systems. As a result, it became necessary to implement machine learning algorithms to plot out various curves showing the relations of different parameters with flow resistance. Data mining approaches were useful in modelling processes where the available knowledge was insufficient to put the essential data into a mathematical framework. Also, certain empirical equations will work only for a particular range or specific criteria but ANN is free of this functional structure and will work with any range used in the model's development.

The fundamental goal of this study is to create a flow prediction model for a heterogeneous channel. In this present work, the main objective is to rank the input parameters that have a major impact on the friction factor of the channel. Regression graphs are plotted to check the performance of the model with respect to other models proposed by different authors. As a final step, individual graphs between input parameters and output parameter are drawn and analysis is done.

2. Materials and Methods

To achieve the aforementioned goals, first the literature based on flow resistance on different channels and the use of ANN in the prediction of data has been studied. Then a total of 90 data were collected from Sharma and Kumar (2018) based on various median grain size, bed slope, main flow discharge, and downward seepage rate. Using the collected data, a neural network model is created. Re-modelling process is done after checking the performance of the model. Then the results were analysed and plots were created to predict the performance of the model. Finally, sensitivity analysis was done to rank parameters based on its impact towards output.

2.1 Selection of Input Parameters

Various empirical formulas were suggested by different authors in order to predict the values of corresponding flow resistance. Charlton created an empirical formula for flow resistance in gravel river beds based on the field investigation, which turned out to be a function of flow depth and median particle diameter. The flow resistance in steep pool streams was studied by Lee and Ferguson. They discovered that form drag and skin friction are the main causes of flow resistance in steep streams. Kuelegan (1938) looked into turbulent flow resistance in circular pipes and discovered a link between flow resistance, flow depth, and median grain diameter. Grain resistance, form drag, wave resistance, and drag due to flow unsteadiness are all factors in open channel flow resistance, according to Rouse (1965). California and Limerinos, The Department of Water Resources looked at flow resistance in natural channels and discovered a link between it, flow depth, and median grain diameter.

Based on a field research, Charlton et al. (1978) developed an empirical formula for flow resistance in gravel river banks, which is a function of flow depth and median particle diameter. Thompson and Campbell (1979) studied the flow resistance of a large boulder-paved canal and came up with an empirical flow resistance expression. Based on flume and field tests, (Bray, 1979; Griffiths 1987) discovered that flow resistance is linearly proportional to flow depth and inversely proportional to median grain diameter.

After conducting many studies, an equation was established which showed that the friction factor is a function of a set of input factors and can be expressed as:

$\boldsymbol{\lambda = f\,(R, d_{50}, u^*, h, S_f, Q)}$

where R is hydraulic radius, d_{50} is the median size of sediment, u^* is shear velocity, h is flow depth, S_f is the friction slope, and Q is the flow discharge.

2.2 Artificial Neural Network (ANN)

ANN is a 'black-box model' described as a "computational mechanism capable of acquiring, representing, and computing a mapping from one multivariate space of information to another, given a collection of data defining that mapping." ANN are inspired by the human brain's ability to recognise patterns. Figure 1 shows a simple circuit of neurons or nodes coupled together in a neural network model. (Merghadi et al., 2020).

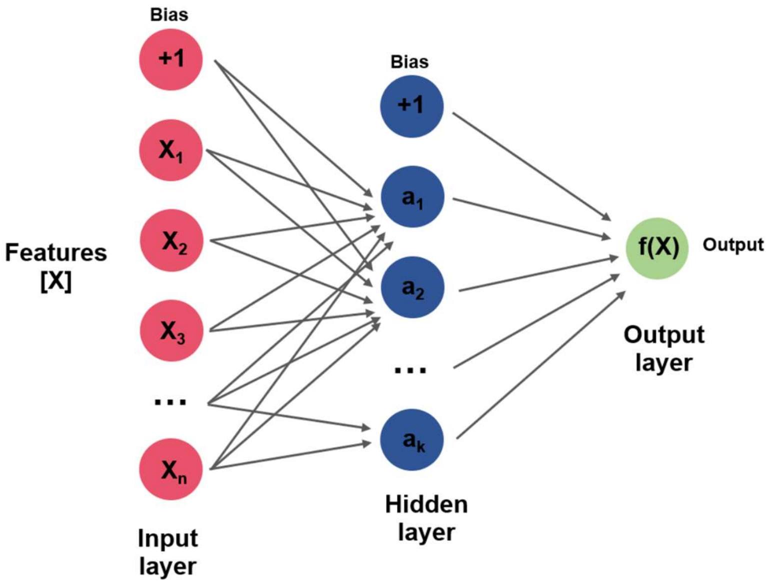


Figure 1: Simple multi-layer perceptron artificial neural network

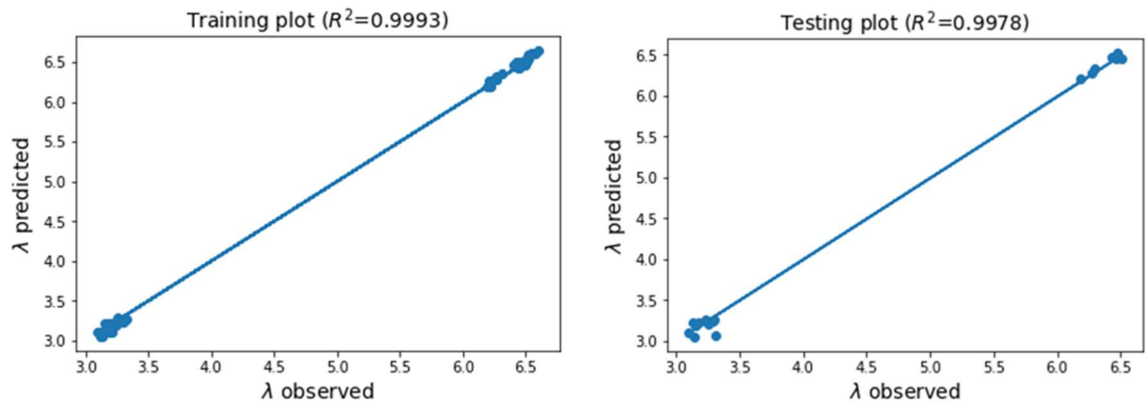
A total of 90 data were included in the modelling. In neural networks, the sample size of the data collection is critical. For model creation and validation, neural networks often demand greater sample sizes than traditional statistical approaches. In general, the higher the sample size, the more likely a neural network will be able to accurately represent the underlying complicated patterns without overfitting or underfitting. For the purpose of developing the ANN model, 80 percent of observations (regardless of source) were assigned to training sets, while 20 percent were given to testing sets.

3. Results and Discussions

Machine learning was used throughout the modelling and analysis process. Python is the programming language used to create the model. This project involves creation of ANN model using the data points provided. Firstly, we collected the data and stored it in a data frame, and then using the data frame we plotted different regression plots. After plotting the regression plot, we checked the performance of the model by comparing the coefficient of determination with its maximum value.

According to the neural network theory, more is the R^2 value, more accurate the model is. For data prediction, there are two typical training algorithms: Levenberg–Marquardt optimization and BFGS quasi-Newton method, as well as multiple regression analysis. It's worth mentioning that ANN predictions made with Python produced better outcomes than those made with other training techniques.

For neural modelling, 80% of data were used for training and remaining 20% for testing.



(a) (b)

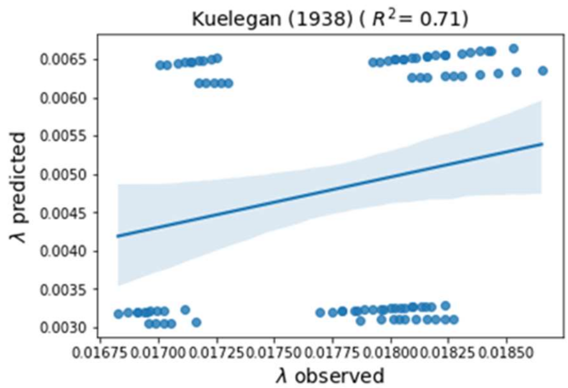
Figure 2: Regression plot of (a) Training dataset; (b) Testing dataset.

Figure 2 depicts the results of neural modelling. Figure 2(a) and Figure 2(b) shows that the linear coefficient of correlation between observed data and values predicted by neural nets is quite strong, with values of 0.9993 and 0.9978 in training and testing respectively. This shows the performance of the model is good.

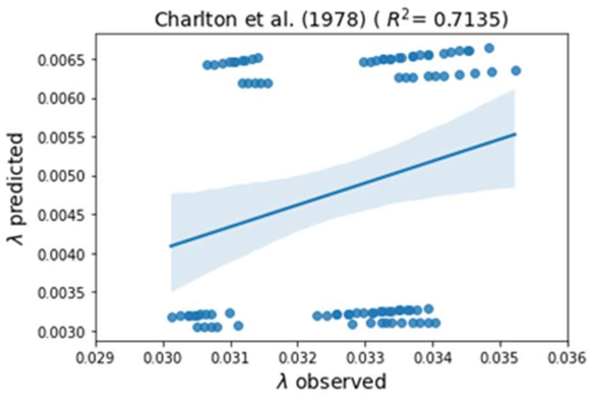
Table 1: Equations provided by different authors used for validation.

AUTHOR	EQUATION
Kuelegan (1938)	$\frac{1}{\sqrt{\lambda}} = 2.303\log(\frac{R}{d_{50}}) + 2.21$
Limerinos and California (1970)	$\frac{1}{\sqrt{\lambda}} = 2.303\log(\frac{R}{d_{50}}) + 0.35$
Charlton et al. (1978)	$\frac{1}{\sqrt{\lambda}} = 2.303\log(\frac{(h+d_{50})}{d_{50}}) + 0.03$
Bray (1979)	$\frac{1}{\sqrt{\lambda}} = 1.36(\frac{h}{d_{50}})^{0.281}$

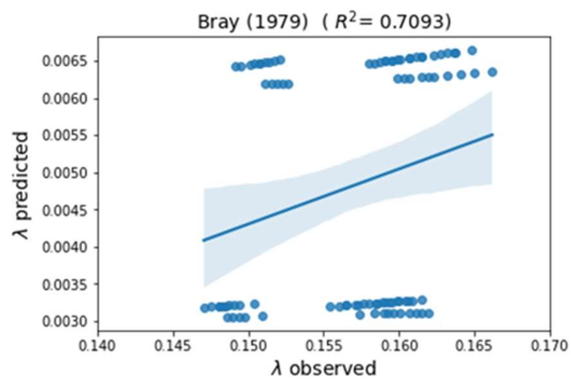
Validation Plots:



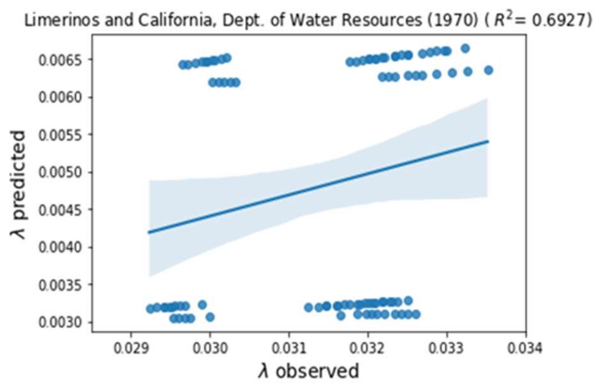
(a)



(b)



(c)



(d)

Figure 3: Performance analysis of (a) Kuelegan equation; (b) Charlton equation; (c) Bray equation; (d) Limerinos and Calfornia equation.

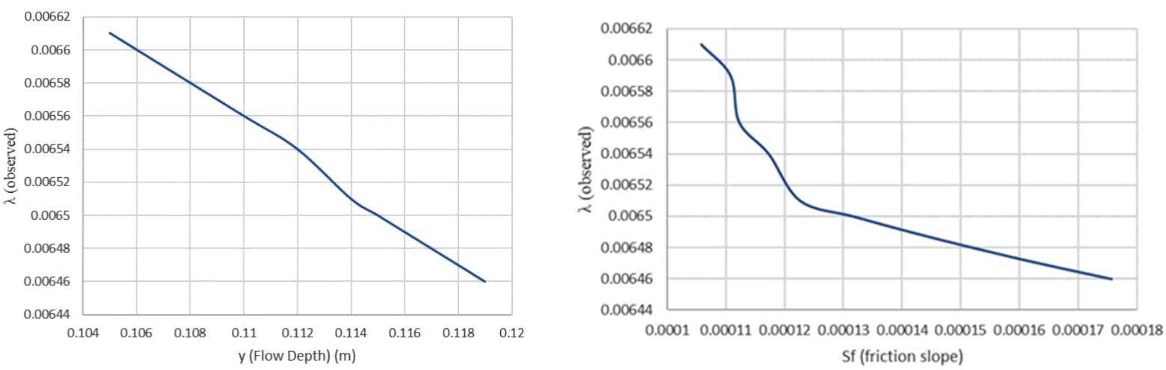
In this study, the formulas given in Table 1 were also put into test to see how well they are predicted. Figure 3 shows a performance study of these formulas. As the R^2 value is greater than 0.5, it can be concluded that the function given is accurate in all cases. With R^2 about 0.7135, Charlton et al.'s (1978) method predicts better than other formulas, as illustrated in Figure 3(b).

The connection weight between neurons in a neural network are the links between the network's input and output. By sensitivity analysis, connection weights of each parameter are calculated and is shown in Table 2. The ranking of each parameter is done according to their weights.

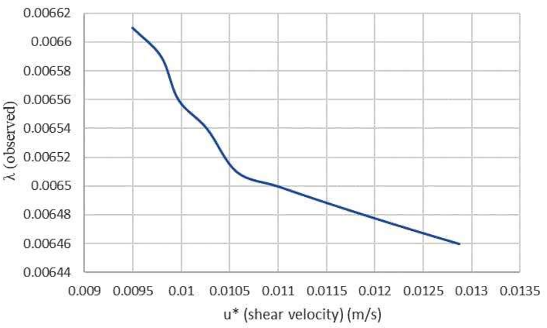
Table 2: Input significance and ranking of variables.

PARAMETER	INITIAL WEIGHTS	FINAL WEIGHTS
Flow Depth (y)	0.322 **(2)**	0.656 **(5)**
Friction Slope (S_f)	0.489 **(5)**	0.581 **(4)**
Shear Velocity (u_*)	0.619 **(6)**	0.237 **(2)**
Size of the particle (d_{50})	0.315 **(1)**	0.738 **(6)**
Hydraulic Radius (R)	0.479 **(4)**	0.269 **(3)**
Discharge (Q)	0.373 **(3)**	0.225 **(1)**

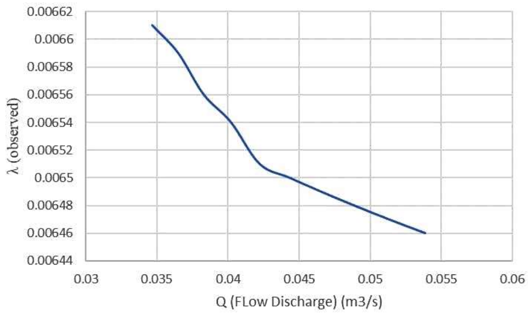
In this study, contribution plots for each of the predictor variables were created, as shown in Figure 4.



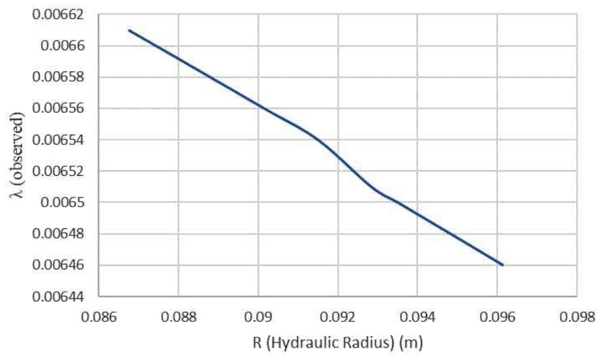
(a) (b)



(c)



(d)



(e)

Figure 4: Relationship between Friction Factor and (a) Flow Depth; (b) Friction Slope; (c) Shear Velocity; (d) Flow Discharge; (e) Hydraulic Radius.

Graphs clearly show that friction factor reduces almost linearly with respect to flow depth and hydraulic radius whereas non-linearly with respect to friction slope, shear velocity and flow discharge.

4. Conclusions

The current work develops a neural network model of flow resistance in a heterogeneous channel that includes all important characteristics based on a vast database of friction factors. In this way, all types of characteristics might have a qualitative effect on the prediction of friction factor in a heterogeneous channel. Given the large number of variables that influence flow resistance, the model's generalization capacity is excellent. Inaccuracies in establishing the governing parameters have an impact on prediction accuracy in engineering applications.

The following conclusions are derived from this study:

(i) Sensitivity analysis shown that discharge has the maximum impact on friction factor, followed by shear velocity, hydraulic radius, friction slope, flow depth and least by size of the particle.

(ii) Regression graphs shown that the performance of the model and the prediction capability of the equations proposed by different authors were quite accurate.
(iii) The friction factor decreases as flow depth, friction slope, shear velocity, particle size, and flow discharge increases.

References

Aliza Ahmad, N., Ali, Z., Mohd Arish, N., Mat Daud, A. and Amirah Alias, N., (2018). Determination of Flow Resistance Coefficient for Vegetation in Open Channel: Laboratory study. *IOP Conference Series: Earth and Environmental Science*, 140, p.012019.

Bray, D.I. (1979). "Estimating average velocity in gravel-bed rivers." *J. Hydraulics Div*., 105(9), 1103–1122.

Charlton, F.G., Brown, P.M., and Benson, R.W. (1978). *The hydraulic geometry of some gravel rivers in Britain Rep*. IT 180, 48Hydraul, Res. Stat. Wallingford, England.

Dolling, O. and Varas, E., (2002). Artificial Neural Networks for streamflow prediction. *Journal of Hydraulic Research*, 40(5), pp.547-554.

Keulegan, G. H. (1938). *Laws of turbulent flow in open channels* (vol. 21, pp. 707–741). US: National Bureau of Standards.

Kouwen, N. and Fathi-Moghadam, M., (2000). Friction Factors for Coniferous Trees along Rivers. *Journal of Hydraulic Engineering*, 126(10), pp.732-740.

Kumar, B., (2013). Flow prediction in vegetative channel using hybrid artificial neural network approach. *Journal of Hydroinformatics*, 16(4), pp.839-849.

Limerinos, J.T., and California. Dept. of Water Resources. (1970). *Determination of the Manning coefficient from measured bed roughness in natural channels*.

Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., ThaiPham, B., Bui, D. T., ... & Abderrahmane, B. (2020). Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews*, *207*, 103225.

Sharma, A. and Kumar, B., (2018). Flow resistance in seepage-affected alluvial channel. *ISH Journal of Hydraulic Engineering*, 26(2), pp.127-137.