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# USE OF GENE-EXPRESSION PROGRAMMING TO ESTIMATE MANNING'S ROUGHNESS COEFFICIENT FOR A LOW FLOW STREAM

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## ABSTRACT

Manning's roughness coefficient (n) has been widely used to estimate flood discharges and flow depths in natural channels. Therefore, although extensive guidelines are available, the selection of the appropriate n value is of great importance to hydraulic engineers and hydrologists. Generally, the largest source of error in post-flood estimates is caused by the estimation of n values, particularly when there has been minimal field verification of flow resistance. This emphasizes the need to improve methods for evaluating the roughness coefficients. Trinidad and Tobago currently does not have any set method or standardised procedure that they use to determine the n value. Therefore, the objective of this study was to develop a soft computing model in the calculation of the roughness coefficient values using low flow discharge measurements for a stream. This study presents Gene-Expression Programming (GEP), as an improved approach to compute Manning's Roughness Coefficient. The GEP model was found to be accurate, producing a coefficient of determination ($R^2$) of 0.94 and Root Mean Square Error (RSME) of 0.0024.

**Keywords:** Gene-Expression Programming; Manning's Roughness Coefficient; Open-Channel Flow

## INTRODUCTION

History has shown that Trinidad and Tobago is virtually free from the majority of natural disasters such as volcanoes, hurricanes and pestilence. The most common natural disaster encountered in Trinidad is flooding.

The Caroni River Basin upstream of the water treatment plant is the only major surface water source being studied extensively in Trinidad. The Water Resources Agency (2001) has generally found that the characteristics of the Caroni basin are applicable to the rest of Trinidad. Characteristics of rivers and streams flowing through urbanised areas are heavily polluted. Industries such as agriculture and manufacturing discharge their untreated waste directly into streams (Narinesingh 2014). Untreated sewage is also a major contributor of organic pollution which causes low dissolved oxygen levels and high bacteria counts in rivers.

These issues of pollution directly impact flow characteristic and channel geometry, and if not monitored properly, the natural parameters of the rivers could regularly change significantly. Fortunately, the Water and Sewerage Authority (WASA) has various programs including the “Adopt A River Initiative” which is geared at involving the community and corporate citizens in the improvement of watersheds in Trinidad and Tobago. However, more can be done to address the issues of pollution and the effects of climate change on the water resources for countries.

Understanding various parameters in open channel flow is important because they play a pivotal role in many unique water managements in Trinidad. These techniques include measuring discharge in irrigation channels, streams, storm water systems and wastewater processing for monitoring effluent discharge (Dwyer 2018).

It should be noted that the most recent major flood event reported in the country took place in October 2018 affecting an estimate of 150,000 people in 4,100 households, approximately 11 percent of the population (Forest 2018). The event was so destructive that it was officially classified as a national disaster and resulted in an estimated US $3.7 Million dollars in damages (Fontes de Meira and Phillips 2019). Additionally, approximately 75 percent of local farmers in the country had been severely affected through the loss of crops and livestock. It is on the heels of these devastating impacts that one begins to understand that accurate information about the characteristics of rivers is important for flood forecasting.

Moreover, discharge measurement in rivers is a challenging job for hydraulic engineers. The stage and the discharge of a river vary depending on the magnitude of rainfall intensity that the river basin or watershed receives. Additionally, Azamathulla et al. (2011) states that discharge at a section in a river is not a function of stage alone. The study further indicates that the discharge of a river is dependent on several factors such as channel geometry, bed roughness and longitudinal roughness, but quantification of all these factors is impractical.

Even though the data, guidelines, and equations are readily available in terms of estimating roughness coefficients, for the entire range of flow depth, only one n value is selected. Wohl (2000); Costa and Jarrett (2008), and Jiang and Li (2010) agreed that there is no exact method for determining n in natural rivers. Therefore, extensive field data is required to reduce the uncertainties in the estimation of n values (H. Md. Azamathulla 2012).

This paper aims to determine if the GEP model can be applied to accurately derive the Manning's Roughness Coefficient for selected Trinidadian rivers. Several statistical parameters would be used to gauge the applicability of the GEP model to estimate the Manning Roughness Coefficient.

## LITERATURE REVIEW

### Gene-Expression Programming (GEP)

Software-oriented computing techniques can be an efficient method for exploring difficult problems in water resources engineering and may help to acquire better empirical insights into complex multi parameter problems, in which it can reduce the range of plausible solutions or the possible solution field (C. Prakash Khedun 2013)**.** Several open-source and commercial software are available that can be used for modelling predictive roughness coefficient values. This study uses the Gene-Expression Programming model, found in the GeneXpro program.

Gene-Expression Programming (GEP) is an extension and combination of the more widely used Genetic Programming and Genetic Algorithms. GEP through multiple regression analysis is capable of examining the relationship between a single dependent variable and a set of independent variables, in addition to modelling these relationships (Maliki et al. 2011). GEP creates populations modules which introduces genetic variation and reproduces them according to fitness. When this process is repeated several times, eventually a generation achieves an output of better solutions to problems, therefore GEP is referred to as a learning or evolutionary algorithm**.**

Recent works in GP and GEP were conducted by Azamathulla et al. (2011) on the prediction of longitudinal dispersion coefficients in streams using GP, Azamathulla et al. (2010) on bridge pier scour and Ghani and Azamathulla (2014) on sediment transport, which they confirmed the suitability of applying GP and GEP for water resource engineering studies. More importantly, Azamathulla et al. (2011) developed mathematical models for the developed Manning's roughness coefficient based on the GEP techniques for the Colorado high gradient streams.

**Gene-Expression Programming to Estimate Manning's Roughness Coefficient**

In many reported experiments in literature, GEP did not perform better than existing methods such as the Support Vector Machine (SVM), Artificial Neural Networks (ANN), M5 Model Trees. One major reason as highlighted by (Mihai Oltean 2002) was that the success rate of GEP increases with the number of genes in the chromosome. However, after a certain value, the success rate decreases if the number of genes in the chromosome is increased. This happens due to forcing a complex chromosome to encode a less complex expression.

It is expected that rivers with larger depths and all around larger cross-sectional areas will have a lower n in comparison to shallow and or smaller channels. Factors such as sedimentation, blockage, weather and changes to rivers geometric shape might've occurred since the data was collected.

From the various studies and reports, it appears to be a lack of interest in Trinidad to use soft computing over the various empirical methods available. This may be because obtaining various flow measuring equipment and calculating n from the data gathered, is simpler than taking the additional time learn to computing the field data in a complex GEP program. Azamathulla et al. (2010) noted in his study on the use of GEP to predict bridge pier scour, that results were significantly better than results from conventional statistical methods. However, even though the n is expected to be more accurate using GEP, perhaps the difference in accuracy in this case is not significant enough to justify using GEP over the empirical methods.

**The Photographic Method of Roughness Coefficient Evaluation**

This method uses generated photos to show all the necessary kinematics and characteristics of the channel. From the photos taken parameters such as position at which flood line in the bed can be noticed, the peak flow in the canal which was measured by the specific hydrometric wing and the marks of high-water levels which can be used for determining the surface profile at peak flows (Elvis Žic 2009). For this method the n is estimated based on measured flows, shapes of water surfaces and characteristics which are observed on more than two transversal sections within the bed. This method has ± 15% accuracy under different flow conditions.

**Ven Te Chow Method for Roughness Coefficient Determination**

The determination of n in this method has been performed by using a table with predetermine *n* values (Chow 1959) developed a standardize reference table that quotes the minimal, normal and maximum rates of the n for every single type of open canal.

(Chow 1959) presented that the roughness coefficient varies in the cross section due to the variation in water levels, that is, the lower the water depth the higher the coefficient value, since the effects of the irregularities of the canal bottom are more evident.

In recent years, climate change has become a major factor in weather patterns, data and trends previously observed will need revisiting. In the case of Trinidad, it is predicted that climate change will affect the island by casing an increase in extreme rainfall and more extended drought periods (The Water Resources Agency 2001). Streambank vegetation creates turbulence, reduces the capacity of channels and retards flow. It is likely that streambank vegetation may be less abundant in cases of longer droughts, predicted by climatologist. However, in cases where vegetation is prevalent adjustments values are required as a correction to the n value. Of the flow-resisting factors analysed by Cowan (1956), channel vegetation has the largest adjustment values and thus probably the greatest potential effect on the total n selected for a reach (Coon 1998). Corrections for vegetation are primarily applicable to channels where vegetation is uniformly distributed across a channel section and for channels less than 100 ft wide. (Coon 1998) also found that narrower channels generally require larger adjustments for vegetation, and wide channels with no substantial channel-bottom vegetation would require little to no adjustments.

**Empirical Methods and Formulas for Roughness Coefficient Determination**

The Manning's formula is the standard equation for determination of natural stream flows, where *Q* is the discharge (in $m^3/s$), n is Manning's roughness coefficient, *A* is the area of the wetted channel cross-section (in $m^2$), $R = A/P$ is the hydraulic radius of the channel cross-section (in meters) and *S* is the friction slope (Ladson et al, 2003).

$$Q = \frac{1}{n} A R^{2/3} S^{1/2} \tag{1}$$

The variable for n has numerous empiric equations that exist in scientific and engineering literature. However, these equations are situational to certain applicable conditions (refer to Table 1 in the appendix). In this report a comparison of accuracy between these various n equations will be drawn, with the ultimate intention of comparing them with the soft computed model (GEP) on a graph labelled the predicted n vs observed n.

## METHODOLOGY

### Data Description

The data set used in this study was obtained from the Water and Sewerage Authority - Water Resource Agency (WASA-WRA), Trinidad and from personal field readings. The discharges were derived from measurements of the cross-sectional area of the stream and the mean velocity within each section was found and summed together to derive the mean velocity at that cross section of the river (WMO 1980). The WRA had recorded several readings over a span of 10 years, from 2010 to 2019, at several sections along the stream. Data from 20 sections for the stream were used. The readings chosen were separated as

70% data for calibration and next 30% data for validation/ testing purpose for all the models.

**Development of the GEP Model**

In this model, a training process is carried out using experimental data to train the GEP algorithm. In the training, the measured flow parameters are introduced to GEP as input parameters, while the n is introduced as a target parameter.

On account of the available data, a population size of 20 chromosomes was selected. After obtaining the population size, the next step would be to choose the fitness function. For this problem, the fitness, $f_i$, of the program, i, is measured by the equation below:

$$f_i = 1000 \frac{1}{1+E_i} \tag{2}$$

Where: $E_i = P_{ij} - O_j$

Where $P_{ij}$ is the value predicted by the individual chromosome i for fitness case j and $O_j$ is the observed value for fitness case j. For $P_{ij} = O_{ij}$ means that $E_{ij} = 0$ representing a perfect solution with no error. The advantage of this kind of fitness functions is that the system can find the optimal solution by itself and the run will continue until the maximum fitness is achieved (Ferreira, 2001).

Then the terminals and functions were chosen. The four basic arithmetic operators (+, -, x, /) and square root (√) and power (^) operators were used as functions while the terminals selected was Discharge (Q), slope (S), Cross-sectional Area (A) and Wetted Perimeter (P). Although many more mathematical operators could have been used, the goal was to achieve a relatively simple expression to represent the n.

The next step involved determining the number of genes, head and tail length for each gene in a chromosome. In this study, a single gene and two head lengths are initially used. Then, the number of genes and heads were increased one at a time during each run while monitoring the training and testing performances of each model. It was observed that more than two genes and a head length greater than eight did not significantly improve the training and testing performance of the GEP models. Thus, the head length, h = 7, and three genes per chromosome are considered for each GEP model. Since the maximum number of arguments per function is equal to two, giving $n_{max} = 2$, the tail length would be calculated by the following relation:

$$t = h(n-1)+1 \tag{3}$$

$$t = 7(2-1)+1 \tag{4}$$

Giving tail length, t = 8

It should also be noted that all genetic operators such as mutation, inversion, transposition (insertion sequence (IS), root insertion sequence (RIS) and gene transposition), recombination or crossover (1-point, 2-point and gene recombination), and specific genetic operators were used. Two one-point mutations with mutation rate of 0.044 were used. Lastly, the linking function used to join the sub-expression tress was the addition operator (+).

The GeneXpro Tools software containing the Gene-Expression Programming model was run for a number of generations and was stopped when there was no improvement in the fitness function value and coefficient of determination (Refer to Figure 1).

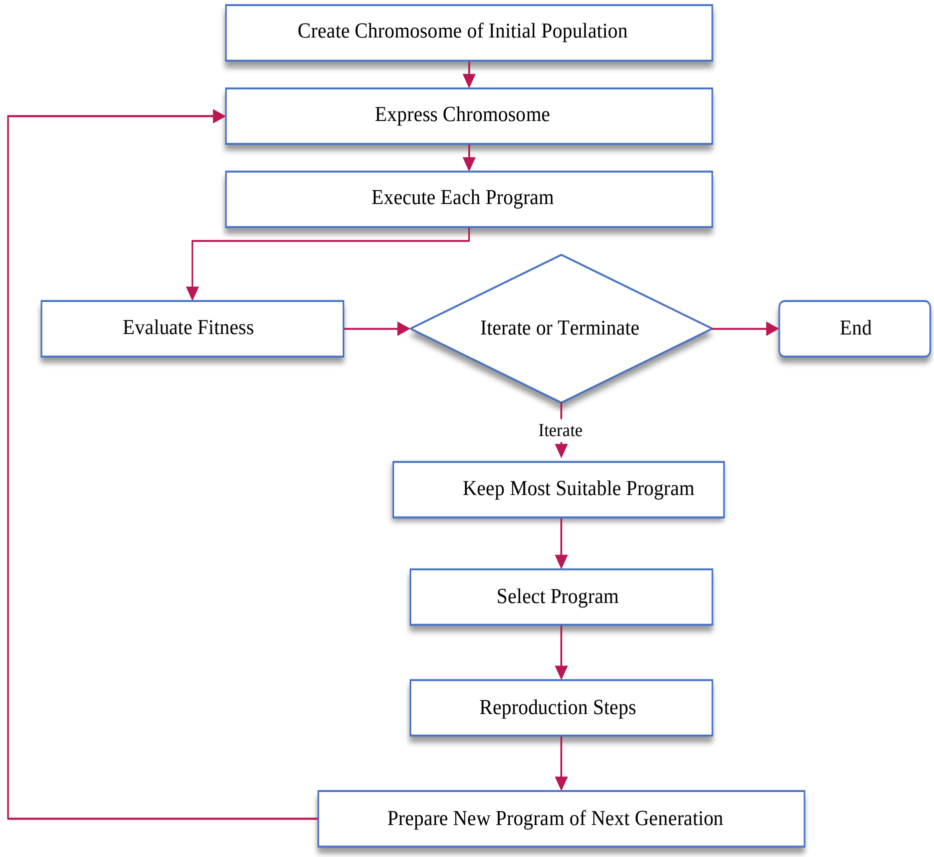


**Figure 1: Summary of the Gene-Expression Programming algorithm**

**Table 1: Summarised GEP model parameters for Manning's Roughness Coefficient**

| Parameters | Values |
|---|---|
| Population size | 20 |
| Set of function | +, -, *, /, √, ^ |
| Set of terminals | Q,A,P,S |
| Random numerical constant (RNC) | 05 |
| RNC type | Floating point |
| Range of RNC | [-10, 10] |
| Length of head | 08 |
| Number of genes | 03 |
| Linking function | + |
| Fitness function | RMSE |
| Rate of mutation | 0.044 |
| Rate of inversion | 0.1 |
| Rate of IS transposition | 0.1 |
| Rate of RIS transposition | 0.1 |
| Rate of Gene transposition | 0.1 |
| Rate of One-point recombination | 0.1 |
| Rate of Two-point recombination | 0.3 |
| Rate of Gene recombination | 0.3 |
| Rate of Dc-specific mutation | 0.044 |
| Rate of Dc-specific inversion | 0.1 |
| Rate of Dc-specific IS transposition | 0.1 |
| Rate of Random constant mutation | 0.01 |

**Data Analysis**

The observed Manning Roughness Coefficient ($n_{obs}$) was determined by transposing the equation 1 to make $n_{obs}$ the subject of the formula resulting in Equation 4. The remaining parameters were filled with the data received from the WRA at each cross section.

The performance of GEP in training and testing sets was validated in terms of the common statistical measures coefficient of determination ($R^2$) and root mean square error (RMSE) (Refer to equations below). A graph of observed n ($n_{obs}$) versus predicted n ($n_{model}$) was also used to visually illustrate the difference between the GEP model and the conventional n.

***Pearson's Correlation Coefficient (R)***

$$R = \frac{\sum_{k=1}^{n} Q_k h_k - \sum_{k=1}^{n} Q_k \sum_{k=1}^{n} h_k}{\sqrt{\left[\sum_{k=1}^{n} Q_k^2 - \left(\sum_{k=1}^{n} Q_k\right)^2\right]\left[\sum_{k=1}^{n} h_k^2 - \left(\sum_{k=1}^{n} h_k\right)^2\right]}} \tag{5}$$

Where:

*Q* – Discharge

*h* – Stage

*n* – Number of data points

***Root Mean Square Error (RMSE)***

$$RMSE = \sqrt{\sum_{k=1}^{n} \frac{\left(Q_{obs\,k} - Q_{model\,k}\right)^2}{n}} \tag{6}$$

Where:

$Q_{obs,\,k}$ – Actual (Observed) Discharge

$Q_{model,\,k}$ – Predicted Discharge from model

*n* – Number of data points

## RESULTS AND DISCUSSION

The parameters that mainly contribute to the determination of n for both GEP and regression models in this study were the wetted perimeter (P), area (A), bed slope (S), discharge (Q) and relative smoothness ($d_{84,50}$). However due to the relative smoothness data being unavailable, this research was unable to use relative roughness as a parameter in the GEP, the regression models and the various equation used to calculate roughness coefficient.

Unavailable field data meant that the required parameters for the various empirical equations were unable to be obtained, making the Manning's formula the only empirical equation in the study being used to produce observed values of *n*. The remaining parameters (A, P, S, Q) were used as the independent variables to generate an accurate model for the n. Jarrett (1984) generated an equation to estimate n using hydraulic radius and relative smoothness for his data. The results substantially underestimated n values as the slope steepness increased. Previous studies demonstrated that flow resistance has a great affiliation with hydraulic radius and slope in high gradient streams (Jarret 2012). High gradient streams are classified as streams with Slopes (S>0.002m/m), which majority of the streams are. Most of the higher gradient channel are located in the north and east of Trinidad due to the topography of the northern range.

**Roughness Coefficient Prediction Formulae**

The Gene Expression model consisted of one dependent variable (*n*) and four independent variables (S, P, Q, A) ensuring n is modelled in terms of these variables. Based on the results of the GEP model the expression tree in Figure 2 was produced. This was simplified to generate the equation below, which was used to determine the n for the stream:

$$n_{\text{model}} = \left( \frac{\frac{S/AP}{Q}}{AP - 3.108} \right) + \frac{\frac{A}{-5.808} - S^{P}}{2.874\left[(-8.008 - P) + Q\right]} + \frac{\frac{P}{P^{1/2} + A}}{-5.228^{2} - A/Q} \qquad (7)$$

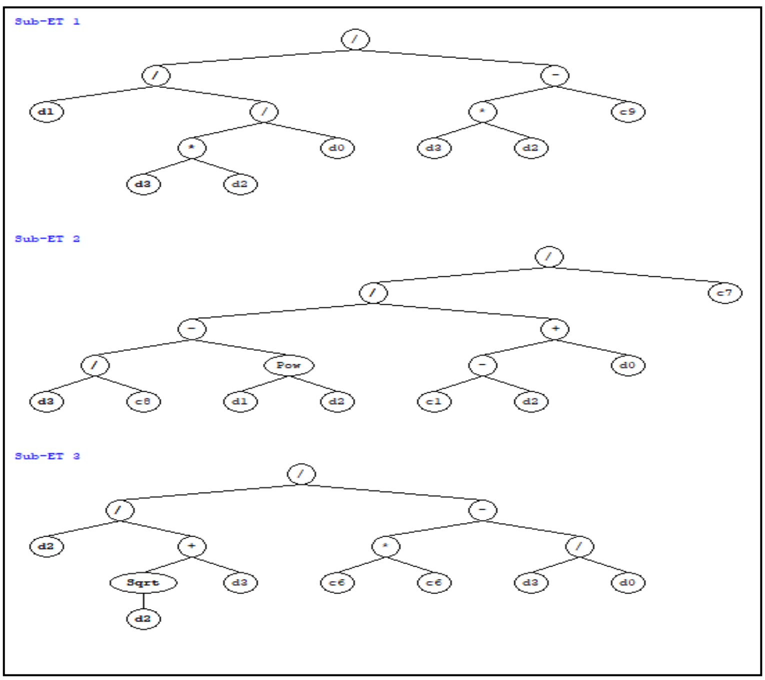


**Figure 2: Gene-Expression Trees used to formulate the Roughness Coefficient (n) formula**

## Comparative Analysis

Training and testing sets were evaluated in terms of the Coefficient of Determination ($R^2$) and Root Mean Square Error (RMSE). $R^2$ assessed how strong the linear relationship is between two variables were and the RMSE measured the error of a model in predicting quantitative data. The training and testing data results were similar which proved the validity of the output of the model. An $R^2$ higher than 0.6 is seen as worthwhile prediction model, $R^2$ for the GEP model was 0.94, suggesting that 94% of the variance in *n* can be predicted by the independent variables Q, P, A and S. These results prove that the proposed model can accurately predict the n without the relative smoothness.

Although the range of values were small, the GEP model produced very low errors with respect to the RSME evaluation. The lower the value of RMSE indicates a better fit which means the observed data points are much closer to the model's predicted values. The GEP's RSME was 0.0024.

Furthermore, a graph of observed roughness coefficient ($n_{obs}$) versus predicted roughness coefficient ($n_{model}$) was plotted (Figure 3). This graph gives a visual representation of the coefficient of determination ($R^2$) of 0.94, which represent an excellent relationship between the observed roughness coefficient and the modelled roughness coefficient.

Overall, the results of the prediction of the GEP model illustrated a very high correlation with minute errors, making it a model capable of predicting the n for streams with low flows.

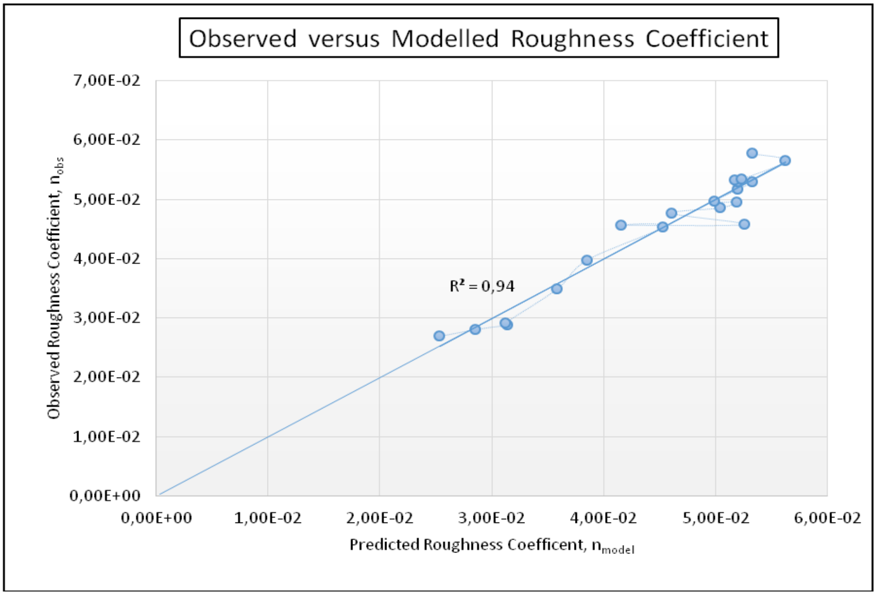


**Figure 3: Graph of Observed Roughness Coefficient versus Modelled Roughness**

## CONCLUSION

A successful investigation of predicting the n for low flows has been achieved. The studies which showed various methods of obtaining a roughness coefficient value had one factor in common, that is, all the models relied on field data to reduce the uncertainties in the estimation of n values. The GEP model had high correlations ($R^2 = 0.94$) and small errors (RMSE = 0.0024). This justifies that the GEP model can be used to accurately predict the n for low flow streams in Trinidad and Tobago. The overall paper provided insight on what methods exist in Trinidad in terms of the collection and calculation of data for roughness coefficients.

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### Conflict of interest

The authors declare no conflict of interest

### Data availability Statement

Upon request

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## APPENDIX

**Table 1: Comparison of the empirical equations for determining Manning's Roughness Coefficient (Adapted and Modified from Fischenich , 1997)**

| Researcher | Year | Equation | Applicable Conditions |
|---|---|---|---|
| Strickler | 1923 | $n=0.047\ .\ d^{\frac{1}{6}}$ | Low gradient stream; sediment of gravel size or smaller; bed material is the primary source of resistance; high within-bank flow |
| Henderson | 1966 | $n=0.034\ .\ d^{\frac{1}{6}}$ | Low gradient stream; sediment of gravel size or smaller; bed material is the primary source of resistance |
| Raudkivi | 1976 | $n=0.042\ .\ d^{\frac{1}{6}}$ | - |
| Raudkivi | 1976 | $n=0.013\ .\ {d_{65}}^{\frac{1}{6}}$ | - |
| Garde and Raju | 1978 | $n=0.039\ .\ {d_{50}}^{\frac{1}{6}}$ | - |
| Subramanya | 1982 | $n=0.047\ .\ {d_{50}}^{\frac{1}{6}}$ | - |
| Petryk and Bosmajian | 1975 | $n=n_0\sqrt{1+\left(\frac{c\sum A_i}{2gAL}\right)\left(\frac{1}{n_0}\right)^2 R^{\frac{4}{3}}}$ | For a densely vegetated floodplain. |
| Limerinos | 1970 | $n=\frac{0.8204\ .\ R^{\frac{1}{6}}}{11.6+2.\log(\frac{R}{d_{84}})}$ | Coarse bed material, straight channel alignment with little increase in width in the downstream direction; minimal vegetation on the banks and in the channel, relatively wide stream of simple trapezoidal shape |
| Burkham and Dawdy | 1976 | $n=C\ .\ \varepsilon^{\frac{1}{6}}$ | - |
| General Los Angeles method | | $n=\frac{(A_1 n_1+A_2n_2+A_3n_3+\ldots+A_N n_N)}{A}$ | - |
| Colbatch method | | $n=\frac{(A_1 n_1^{1.5}+A_2n_2^{1.5}+A_3n_3^{1.5}+\ldots+A_N n_N^{1.5})^{\frac{2}{3}}}{A^{\frac{2}{3}}}$ | - |
| Pavlovski, Muhlhofer, Einstein and Banks | | $n=\frac{(O_1 n_1^2+O_2n_2^2+O_3n_3^2+\ldots+A_N n_N^2)^{\frac{1}{2}}}{O^{\frac{1}{2}}}$ | - |