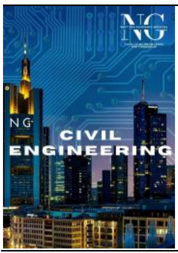

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Machine Learning Approaches for Estimating Roughness Coefficients in Two-Stage Sinuous Channels

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HIGHLIGHTS

- AI-based models (GPR, ANN, GEP, ELM) were developed to predict Manning's roughness coefficient in two-stage sinuous channels.
- Sensitivity analysis identified key hydraulic parameters influencing roughness adjustment.
- GEP model outperformed others and was successfully applied to real flood data from the Baitarani River.

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ABSTRACT

Estimating the flow rate of streams during floods is rarely successful due to a lack of dependable data from the field in natural areas. Predicting discharge depends greatly on the value of Manning's roughness coefficient. The study uses Artificial Neural Networks (ANN), Gene Expression Programming (GEP), Extreme Learning Machines (ELM) and Gaussian Process Regression (GPR) as AI techniques to determine Manning's roughness coefficient in two-stage sinuous channels. Relative width, depth ratio, sinuosity ratio, channel bed slope and sinuous belt width ratio are the input variables used for the model. They were taken into account to determine the roughness adjustment factor. Several experiments were run to test how different parameters affect roughness prediction. Results of the developed AI models were compared to those of established analytical methods using various statistical tricks. During the testing phase, the highest accuracy was achieved by GPR and ANN (R^2 = 0.82). After that, GEP reached R^2 = 0.79 and ELM R^2 = 0.65. Predictions of Manning's n using the GPR method are quite accurate. However, the GEP model's ability to generate a generalized model equation for Manning's n makes it particularly valuable. Based on the above, the GEP model's expression was applied to estimate Manning's n for measurements of a flood from the Baitarani River in India. It was confirmed that the proposed models can work in experimentally small-scale environments and real rivers.

1. INTRODUCTION

The design of hydraulic structures, velocity fluctuation over the channel cross-section, and the assessment of energy losses are all significantly impacted by the friction factor expressed in terms of Manning's roughness (n). The dynamic nature of river flow makes rivers inherently intricate and multidimensional. The momentum and turbulence

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transferred between the main river and the floodplain are affected during floods. Both geometric and hydraulic factors, such as the nature of the channel bed, influence roughness coefficients in sinuous channels. Numerous studies have subjected both direct and indirect methods for prediction of friction coefficient or Manning's n. A roughness model was proposed by Cowan (1956) to calculate the value of the modified Manning's irregularity coefficient contemplating the irregularity of channel surface, shape, obstructions, and sinuosity. Limerions (1970) made an effort to calculate Manning's n by taking into account the particle size or different-size boulders and the hydraulic mean radius. A mathematical equation was proposed by Jarrett (1984) for the deducing Manning's n considering the bed slope (longitudinal bed slopes greater than 0.002). Shiono et al. (1999) provided a method for estimating the flow rate in sinusoidal channels using Manning's equation, taking into account the effect of sinuosity and bed slope. Further, Khatua et. al. (2012) proposed an analytical formulation for calculating friction coefficients in meandering compound channels.

River engineering is often plagued with uncertainty when it comes to flood prediction and flow analysis. It is dangerous and cumbersome for filed experiments during high stage floods in broad rivers. In these cases, an alternate method for finding the flow features such as flow depth, and discharges, is to use machine learning algorithms (MLAs) or an AI-based method. Various problems in the fields of water resources, hydraulics, and hydrology have been effectively tackled with the help of MLAs like the Artificial Neural Network (ANN), Gaussian Process Regression (GPR), Genetic Algorithm (GA), Gene Expression Programming (GEP), Multivariate Adaptive Regression Splines (MARS), Model Trees (MT), Extreme Learning Machine (ELM), Group Method of Data Handling (GMDH), Support Vector Machines (SVM), and K-Nearest Neighbours (KNN) (Benabdesselam et al., 2022; Deo & Sahin, 2015; Gholami et al., 2020; Mehdizadeh et al., 2017; Milukow et al., 2018; Mohanta & Patra, 2021; Mohanta & Patra, 2019; Mohanta et al., 2018a; Mohanta et al., 2021; Najafzadeh et al., 2018; Pradhan & Khatua, 2018; Shankar Das et al., 2022; Sharghi et al., 2018; Shende & Chau, 2018; Varvani & Khaleghi, 2018). Pradhan et al. (2017) adopted GEP to model the Manning's friction factor and estimate the discharge of two-stage sinuous channels. Mohanta et al. (2018c) applied GMDH-NN method to make predictions about the Manning friction coefficient in meandering channels. Das et al. (2021) developed and verified an equation methodology for determining discharge in converging and diverging type non-prismatic two-stage channels, showing the acceptability of GEP approach than the traditional channel division method. Mohanta and Patra (2021) provided discharge estimated method for compound meandering channel by using GEP approach. In order to give kernel-based machine learning algorithms an effective, practical, and probabilistic foundation, Rasmussen et al. (1999; 2010) developed the Gaussian process regression (GPR). Bonakdari (2011) effectively modeled the flow pattern of a 900 mild bend using numerical model along with AI approaches i.e. ANN, and GA. Bhattacharya et al. (2007) utilised ANN and MT to simulate the flow of sediment in open channels. In order to examine the average velocity and discharge for small streams, Genc et al. (2014) used ANN and ANFIS.

The study demonstrated AI approaches namely GEP, ANN, GPR and ELM for predicting roughness coefficient by considering six observational non-dimensional constraints as input variables such as relative width $(\alpha = B/b)$, depth ratio $(\beta = (H-h)/H)$, sinuosity ratio (s_r), slope of channel bed (S_o) and sinuous belt width ratio $(\omega = B_{MW}/B)$ for forecasting the Manning's friction n.

2. METHODOLOGIES FOR PREDICTING MANNING'S COEFFICIENT

Estimating flood conveyance relies profoundly on how well friction roughness can be predicted. Friction roughness such as Manning's n represents the resistance of flow and the roughness of the bed. Several authors have assessed the effect of geometric and hydraulic features on expecting Manning's n, and in this citation, the Single Channel Method (SCM) is used to obtain the flow rate in two-stage channels based on a reformed value of the roughness coefficient. Traditional flow formulae, namely Manning's equation is designated for estimating flow rate in compound channel as

$$Q = \frac{1}{n} R^{\frac{2}{3}} S_0^{\frac{1}{2}} A \qquad (1)$$

where S_0 is indicated the rate of flow for compound channels, n the Manning's friction roughness, S_0 the bed slope of the compound channel, A the total cross-sectional area of the compound channel, R the mean hydraulic radius of the compound channel.

From the familiarity of literature, the roughness coefficient, Manning's n and Darcy-Weisbach's f is formulated by different investigators. Cowan (1956) determined the value of n by simplifying the effects of some factors as:

$$n = (n_b + n_1 + n_2 + n_3 + n_4)m \qquad (2)$$

where, n_b is the default significance for a smooth, conventional channel with identical flow, n_1 the adjusting factor taking surface unevenness into account, the adjustment factor influencing the channel cross-section's parameters of geometry, n_3 the adjustment factor by taking into account channel impediments, n_4 the adapting assessment for vegetation's flow situations., and m is the channel's sinuosity correction factor. Further, the SCS method was modified considering various sinuosity ranges of the sinuous channel (Fasken, 1963).

$$n'/n = (f'/f)^{(1/2)} = 1.0, \text{ For } s < 1.2 \quad (3a)$$

$$n'/n = (f'/f)^{(1/2)} = 1.15 \text{ For } 1.2 \le s < 1.5 \quad (3b)$$

$$n'/n = (f'/f)^{(1/2)} = 1.3 \text{ For } s \ge 1.5 \quad (3c)$$

where, n and f represents the base value of Manning's and Darcy-Weisbach's factor respectively, n' and f' are the adjusted Manning's and Darcy-Weisbach's value, s the sinuosity of the sinuous channel. It is a simple and most widely used methodology for selecting roughness coefficient values. Extensive open channel tests were conducted by Toebes and Sooky (1967) to confirm the impact of bed inequality, gradient, and depth of flow for calculating flow rate in two stage sinuous channels as a function of sinuosity and is given by

$$f' / f = 1 + 6.89R \text{ For } s = 1.1 \quad (4)$$

where, R indicates the mean hydraulic radius, s refers to the sinuosity. To describe Manning's friction coefficient for natural channels with high ascent bed slope, Jarrett (1984) proposed a method without the sinuous effects as

$$n = 0.32 S^{0.38} / R^{0.16} \quad (5)$$

where S is the slope of channel bed, R is the hydraulic mean radius in meter. James (1992) modified the SCS technique to propose Linearized Soil Conservative Service (LSCS).James' (1992) generalised roughness coefficient value, which takes into account some sinuosity range, is as follows:

$$\frac{n'}{n} = 0.43s + 0.5, \text{ For } s < 1.7 \quad (6a)$$

$$\frac{n'}{n} = 1.3, \text{ For } s > 1.7 \quad (6b)$$

where, n = base value of Manning's n, n' = adjusted value of n, s = sinuosity of curved channel. Sinuosity (s) is represented in terms of Darcy-Weisbach's factor (f) in Eq. 7, which can be used to estimate the discharge through bed roughness factor developed by Shino-Knight (1999) by taking into account the sinuosity and slope of the meandering channels.

$$s = 10\left(\frac{f}{8}\right)^{\frac{1}{2}} \quad (7)$$

Taking into account the channel geometry and sinuosity, the coefficient of roughness can be predicted with an equation developed by Jena (2007) as

$$n = \frac{b^{1/6} s}{94.32 \delta S_o^{0.25}} \quad (8)$$

where δ is the ratio of the channel width to the depth of flow in channels, b is the width of the channel, S_o is the channel bed slope. Khatua et al. (2011) investigated some intensive smooth and rigid sinuous channels to formulate n considering the hydraulic mean radius (R), sinuosity (s), viscosity of water (υ), longitudinal channel bed slope (S_o), acceleration due to gravity (g), and aspect ratio (δ), which is described as

$$n = \frac{s \upsilon^{0.72} S_o m^{0.29}}{7k \delta g^{0.86} R^{1.2}} \quad (9)$$

In Eq. 9, k is a constant of value 0.001. Dash and Khatua (2016) established an equation for Manning's n which is dependent on aspect Ratio (δ), Froude number (Fr), Reynolds number (Re), sinuosity (S), and bed slope (S_o). The relationship between them can be written as in Eq. 13.

$$n = 0.013(1 - 0.015\delta - 0.116 + 0.3021 ln(s) + 0.15 Re 0.0924 \\ - 0.3 ln(Fr) - 9.852 S_0 (1\text{-}374 S_0) \quad (10)$$

Pradhan and Khatua (2017) proposed the adjusted value of n which has the influence on relative depth (β), Froude's number (Fr), width ratio (α), Reynold's number (Re), longitudinal bed slope (S_o), sinuosity (s) and length scale factor (m), which is shown in Eq. 11.

$$n = \frac{1}{250}\left(\frac{R^{0.84} S_o^{0.25} m^{0.08} s}{g^{0.25} \alpha \beta \nu^{0.5}}\right) \quad (11)$$

3. ASSESSMENT OF ROUGHNESS CORRECTION FACTOR THROUGH VARIOUS AI MODELS

The study's main goal was to investigate how effectively artificial intelligence approaches could forecast the roughness coefficient (Manning's n). For the training and testing data stages, a total of 179 numbers of data are employed in the modelling process. Experiments were performed in sinuous compound channels at the hydraulics engineering laboratory in the Department of civil engineering at the National Institute of Technology Rourkela (NITR), India. Previous research studies by the authors (Mohanta & Patra, 2019; Mohanta et al., 2020; Mohanta et al., 2021; Mohanta et al., 2022) adequately described the experimental setting of these meandering compound channels. The present work referred to other experimental studies which are also used as dataset of present research work for calculating the roughness coefficient (1984; Greenhill et al., 1993; James & Wark, 1992; 1977; 2007; 1989; Knight & Sellin, 1987; 2013; 2000; Toebes & Sooky, 1967; Willetts & Hardwick, 1993) which can be found from previos research articles of the author (Mohanta, 2019; Mohanta et al., 2018b).

Researchers have utilised various data segregations between testing and training data, which generally varies with challenges The division of training and testing data is done without following any specific rules. About 75% of the data in this study are intended for training, while the remaining 25% are utilized to test the proposed model.

Here, it is presumed that, the Manning's n or roughness correction factor (n'/n) of the meandering compound channel is dependent on some dimensionless parameters like α , β , ω , s and S_o . The required dimensionless equation can be written as

$$n'/n = f\left(\alpha,\ \beta,\ \omega,\ s_r,\ S_o\right) \tag{12}$$

where n' is the developed value of Manning's coefficient and n is the roughness coefficient's base value (See Table 1).

3.1 Assessment of n'/n Using Gene-expression programming (GEP)

Gene-expression programming (GEP), a variation of genetic programming (GP) (Koza 1992),which develops logical and mathematical symbols or expressions, decision trees, polynomial constructions, and so on. With the aid of GeneXproTools 5.0, it is used to generate an equation for the Manning's correction factor (n'/n) in meandering compound channels. Details of GEP approach, we can found from previous research publication of the author (Mallick et al., 2020; Mohanta, 2019; Mohanta & Patra, 2021).

In Eq. (12), Manning's correction factor is described as a function of both geometrical and hydraulic parameters. As the connecting function between three genes in the current multigenic programming, an addition operation was carried out. After 278404 generations, the fitness function value and coefficient of determination of the training and testing data did not significantly change, suggesting that the generations may have ceased. The root mean square error (RMSE) is employed as a fitness function. Table 1 lists the parameters that were utilised to construct the GEP model and have an impact on its performance. All of these factors are found by trial and error in order to build the best model of the GEP, which is represented as an algebraic equation between the input and output variables.

Table 1. Parameters and Functions of the GEP Model's Operations.

Details of GEP Parameter/Function	Operations Setting
Function Set	+, −, ×, ÷ and e^x
Linking Function	Addition
Data Type	Floating-Point
Fitness Function	*RMSE*
Number of Genes	3
Number of Chromosomes	45
Gene Size	23
Head Size	8
Program Size	43
Constants per Gene	15
Literals	10
Inversion, Insertion sequence (IS) and Root insertion sequence (RIS) transposition rate	0.00546
One-point, Two-point recombination and Gene transposition rate	0.00277
Mutation	0.00138
Gene recombination rate	0.00755
Number of Generations	278404

The simplified analytical form of the proposed GEP model is expressed as

$$n'/n = \left(-1.17/(\alpha\beta(\beta-\omega)+exp(s_r)-8.12)\right)+exp\left((0.31-\omega)(43.2S_o)\right) \\ -\left(S_o(\omega+14.62)(18.01+\alpha)\right) \tag{13}$$

Under these assumptions of 5.66 ≤ α ≤ 16.08, 0.08 ≤ β ≤ 0.83, 0.000675 ≤ S_o ≤ 0.0061, 1.04 ≤ s ≤ 4.11 and 0.39≤ ω ≤1, the statement (13) holds true. As illustrated in Fig. 1, the GEP model for estimating is represented by an expression tree (ET) representing the Eq. (13). In Fig. 1, d0 stands for α , d1 for β, d2 for ω , d3 for s_r , d4 for S_o , and C1, C2 represent the numerical constants employed in the model's first gene. The constants for the model's second gene are denoted by C3, C4, C5, C6, and C7. The constants C8, C9, and C10 are also utilised in the model's third gene.

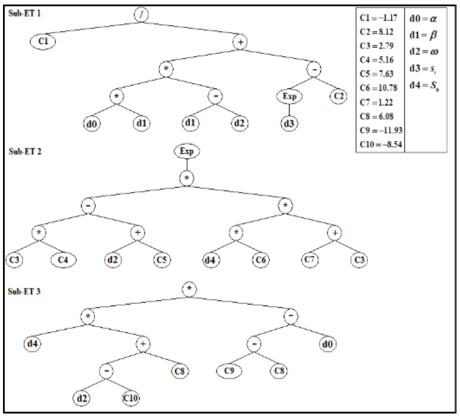

Figure 1. Expression Tree (ET) for GEP Formulation.

3.2 Assessment of n'/n Using Gaussian Process Regression (GPR)

Applications for model approximation, multivariate regression, and experiment design use the Gaussian Process Regression (GPR), which is based on a Bayesian learning algorithm (Girard et al., 2003; Quinonero-Candela & Rasmussen, 2005). Gaussian distributions of random variables which is known as the Gaussian Process has the benefit of a unified integration of a number of ML activities, including model preparation and hyper-parameter estimation.The outcomes from regretion process result with better interpreatability since they are less affected by bias. The GPR has utilised the following relation to determine the output (y) for the input (x).

$$y_i = f(x_i) + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2) \tag{14}$$

where ε is the Gaussian noise. The error ε is normally and identically distributed with zero mean and variance σ^2 and $f(x_i)$ is drawn by a Gaussian process, x specified by kernel function. R is the real space, and f is the unknown function. A linear combination of basis functions with the following description provides a discrete approximation of the function

$$\hat{f}(x, m) = \sum_{j=1}^{M} m_j \varnothing_j(x) \tag{15}$$

in which $\{\varnothing_j(x)\}_{j=1}^{M}$ is a set of either linear or nonlinear basis functions; $m = [m_1, \ldots m_M]^T$ stands for anonymous weight vector, estimated by means training dataset which include M predictor observations, $x = \{x_i\}_{j=1}^{N}$ (i.e., each row of the n-column matrix X is an observation of x). Assuming the error term in the model, the Eq. 15 is stated as

$$y = \sum_{j=1}^{M} m_j \varnothing_j(x) + \varepsilon \tag{16}$$

where the ε is the bias function known as Gaussian noise, $y = [y_1, \ldots y_N]^T$ the actual prediction standards. Gaussian priors for transformed function values is the creating component of GPR (Rasmussen & Williams, 2006). Any finite subclass of the Gaussian priors follows a joint Gaussian distribution, as described by its second-order statistics.

An appropriate covariance function and its parameters are selected in training process of GPR model. GPR model is trained by maximizing the marginal likelihood also termed as Bayesian inference at a particular value of Gaussian noise (Pal and Deswal, 2010). For modelling n'/n, the Pearson VII function is used as Kernel function which is determined through $\left[1 + \left(2\sqrt{\|x_i - x_j\|^2}\sqrt{2^{(1/m)} - 1}/\sigma\right)^2\right]^{-m}$. Here, γ, σ and m are the kernel-precise constraints. The factor σ indicates the Pearson width, whereas m is the tailing factor of the ultimate when the Pearson VII function is used for curve-appropriate resolves. The optimal values of the amount of Gaussian noise are needed for the GPR, in addition to the selection of a kernel and kernel-specific parameters. In present study, Gaussian noise is taken as 0.20, m and σ is taken as 0.5 and 0.4 respectively.

3.3 Assessment of n'/n Using Extreme Learning Machine (ELM)

Single-layer feed-forward neural networks (SLFNs) with hidden neurons and random input weights are used by the ELM to achieve output convergence (Huang et al., 2006). Training takes relatively little time, as the hidden layer bias is learned from separate data points. Traditional neural network models cannot be used to achieve this goal (Acharya et al., 2014; Deo & Sahin, 2015). The feed-forward network's parameters, the hidden layer biases and input weights are used by the ELM model to forecast outputs. The output weight is linked to neuron layer's hidden unit to the output layer. The hidden layer output matrices are subjected to generalised inverse operation. For N random separate input illustrations $(x_k, y_k) \in Z^M \times Z^M$ with N hidden nodes and having an activation function $g(\bullet)$, the SLFNs are described as

$$\sum_{i=1}^{N} w_i g(x_k; c_i, a_i) = y_k, \qquad k = 1, 2, 3, \ldots, M \tag{17}$$

where $c_i \in Z$ is the random bias of the i^{th} unknown node and $a_i \in Z$ the initial weight vector which connects the i^{th} hidden node and the input node, w_i the weight vector which connects the i^{th} hidden node to the output node. $g\left(x_k ; c_i, a_i\right)$ the output of the i^{th} hidden node concerning the input sample x_k. Further, Eq. (17) can be modified as:

$$Gw = Y \tag{18}$$

where
$$G=\begin{bmatrix} g\left(x_1;c_1,a_1\right) & \ldots & g\left(x_1;c_M,a_M\right) \\ g\left(x_N;c_1,a_1\right) & \ldots & g\left(x_N;c_M,a_m\right) \end{bmatrix}_{M\times N} \tag{19}$$

$$w=\left(w_1^T w_2^T,\ldots\ldots w_N^T\right)_{n\times N}^T \tag{20}$$

$$Y=\left(y_1^T y_2^T,\ldots\ldots y_N^T\right)_{n\times N}^T \tag{21}$$

where Y represents the output weights and is a result of deriving least square solution from the linear system mentioned above. There is arbitrary selection of input weights and hidden layer biases whereas the outputs are computed analytically.

For predicting Manning's friction coefficient through ELM outline, network of three-layers are used to construct the model design as shown in Fig. 2. The five input neurons are taken as the interpreter variables i.e. $x=[\alpha,\omega,s_r,S_o,\beta]$. The output layer in the ELM architecture has one neuron demonstrating the predicted n'/n. A highest of 20 neurons is trailed randomly in the hidden layers. Finally, an optimal of 10 nodes is selected for ELM architecture. The ELM model developed with the help of sigmoid bias function (RBF) as the activation function. Finally, a 5-10-1 neural network framework of ELM is obtained.

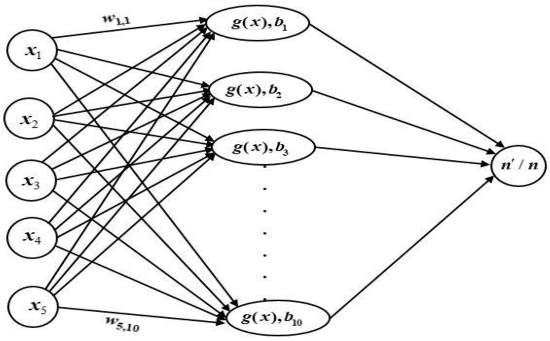

Figure 2. Evolved Structure of ELM for Forecasting Roughness Correction Factor (n'/n).

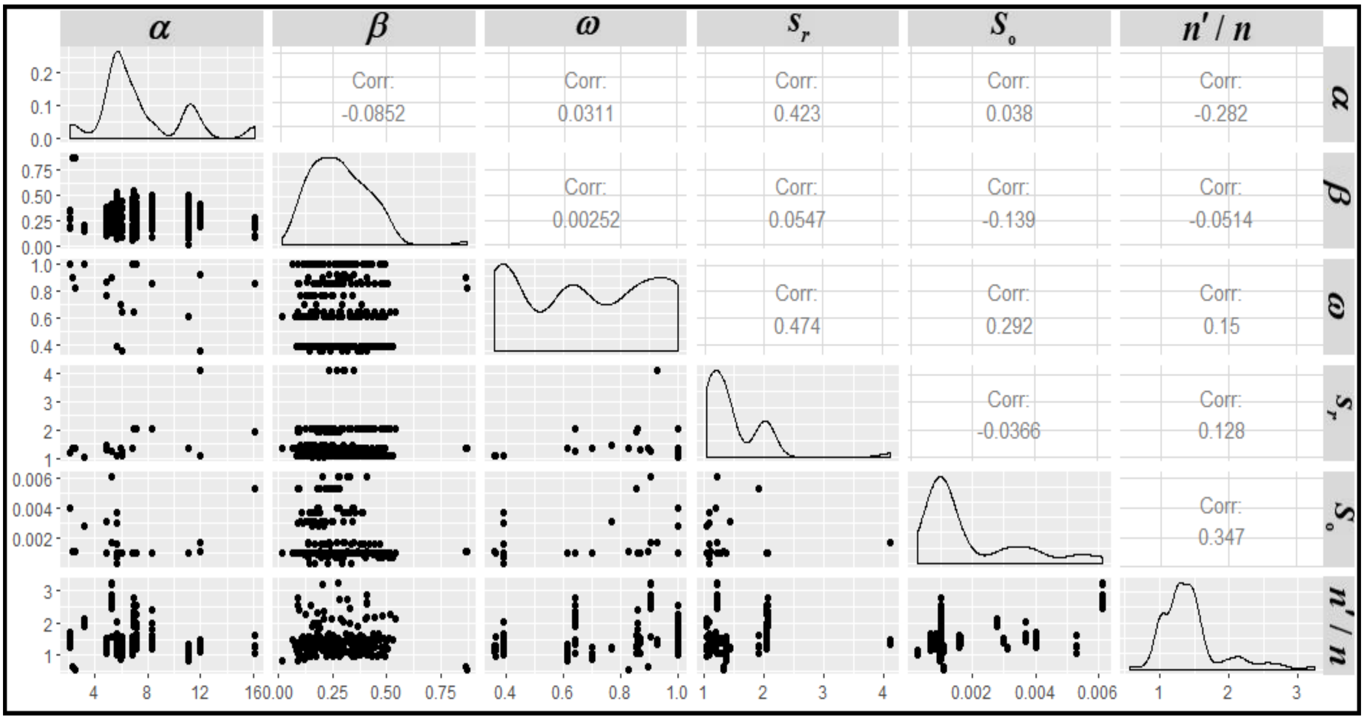

Figure 3. Scatter Plot Matrix of Individual Parameters and n'/n for ANN modelling.

3.5 Assessment of n'/n Using Artificial Neural Network (ANN)

A vast number of computational units, or neurons, are linked together in an Artificial Neural Network (ANN). Parallel distributed processing describes the capabilities of a neural network, which can be massively parallel. To approximate a random function, ANN is put to use. In this study, we used multilayer Feed-forward (MLFF) neural networks for forecasting roughness correction factor (n'/n). The five numbers of input neurons such as α,β,ω,s_r and S_0 are considered to predict n'/n. Matrix of scatter plot of independent parameters and output n'/n is shown in Fig. 3. Four layers, specifically input layer, two hidden layers, and output layer are systematized in these networks. Under some weights, neurons of each layer are connected to neurons of the adjacent layer. Using the best training method, the correction of the connective weights between neurons are involved in the network training process. The architecture of ANN model involved for predicting n'/n is shown in Fig. 4.

Since there is no established method for calculating the number of neurons in the hidden layer, the process is exceedingly complicated. These neurons are a utility of total number of input components and the maximum quantity of linearly separated input space regions. Thus, the number of hidden layer neurons can be obtained through trial-and-error method. The procedure is repeated until the network reaches a minimal error value determined by both the ANN model and data from experiments.

3.6 Backpropagation Error Method

This technique uses the back-propagation algorithm to calculate errors. The actual output values are compared with the neural network's assigned input and outputs obtained. The computed errors are propagated backward and corrections are made by changing connection weights. The process occurs in continuation till the time a sufficient degree of convergence is attained. Weight update formulas, are employed for weight optimization. These equations represent output neurons as a function:

$$\Delta W_{jk} = -\eta \frac{dP_k}{dnet_k} \Delta P_k P_j \quad (22)$$

$$\Delta W_{ij} = -\eta \frac{dP_i}{dnet_j} \sum_k^K \frac{dP_k}{dnet_k} W_{jk} \Delta P_k P_j \quad (23)$$

where P_i is the prediction of the i^{th} neuron in the input layer, P_j the prediction of the j^{th} neuron in the hidden layer, P_k is the prediction of the k^{th} neuron in the output layer and ΔW the change in the weight strength.

Here, the input layer, two hidden layers, and the output layer of the ANN model, respectively, use 5, 4, 1, and 1 neurons. First hidden layer is consisting of four neurons and second layer consists of single neuron in ANN architecture. Data are split into two groups for the procedure, with 75% of the data being used to train the network and 25% being used for testing. For, present case of study logistic activation function is used for ANN modelling. Weights connecting to neurons of two adjacent layers are shown in Fig 4.

4. RESULTS AND DISCUSSION

4.1 Model Performance Assessment

For an accurate assessment of the roughness correction factor as Manning's n'/n for sinuous compound channels, different AI models were developed using GEP, GPR, ELM, and ANN algorithms, each of which deals with a different set of independent non-dimensional parameters. The goodness of fit can be used to evaluate how well various models work. The effectiveness of the established models are assessed through their typical statistical inaccuracy measures such as the coefficient of determination (R^2), mean percentage error (*ME*), root-mean-square-error (*RMSE*), mean absolute error (*MAE*), mean absolute percentage error (*MAPE*), scatter index (*SI*) and coefficient of efficiency (*E*) (Mohanta, 2019; Mohanta & Patra, 2019; Mohanta et al., 2020; Mohanta et al., 2018a; Mohanta et al., 2022).

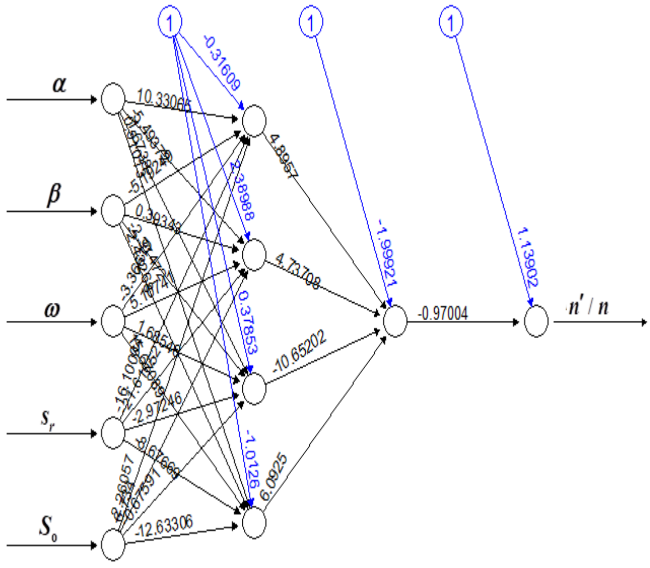

Figure 4. Evolved Structure of ANN for Predicting Manning's Correction Factor.

Earlier composite equations of manning's coefficient did not account for the influence of sinuous floodplain levees, such as the sinuosity ratio and the sinuous belt width ratio of the sinuous compound channels. To determine the efficacy of the current models in comparison to other existing composite roughness models, the authors applied the equations developed by various researchers [i.e., Eqns. 1 through 11] to all widely published experimental channel data along with the present experimental data to evaluate Manning's *n*.

Figure 5 shows the relationships between the predicted and actual values for a number of ML models. The data make it clear that the composite values are located extremely close to the line of perfect fit, suggesting that the constructed GPR, GEP, ELM, and ANN models have strong predictive skills. GPR is the most precise of the four methods. In comparison to GPR, GEP is preferable since it yields practically useful analytical non-parametric equations. The four developed AI models were evaluated for performance using R^2, *ME*, *E*, *MAE*, *RMSE*, *MAPE*, *SI* and *AIC* on both the training and testing datasets as shown in Table 2. When compared to ANN, GEP, and ELM, the

GPR model for predicting n'/n value performs admirably.

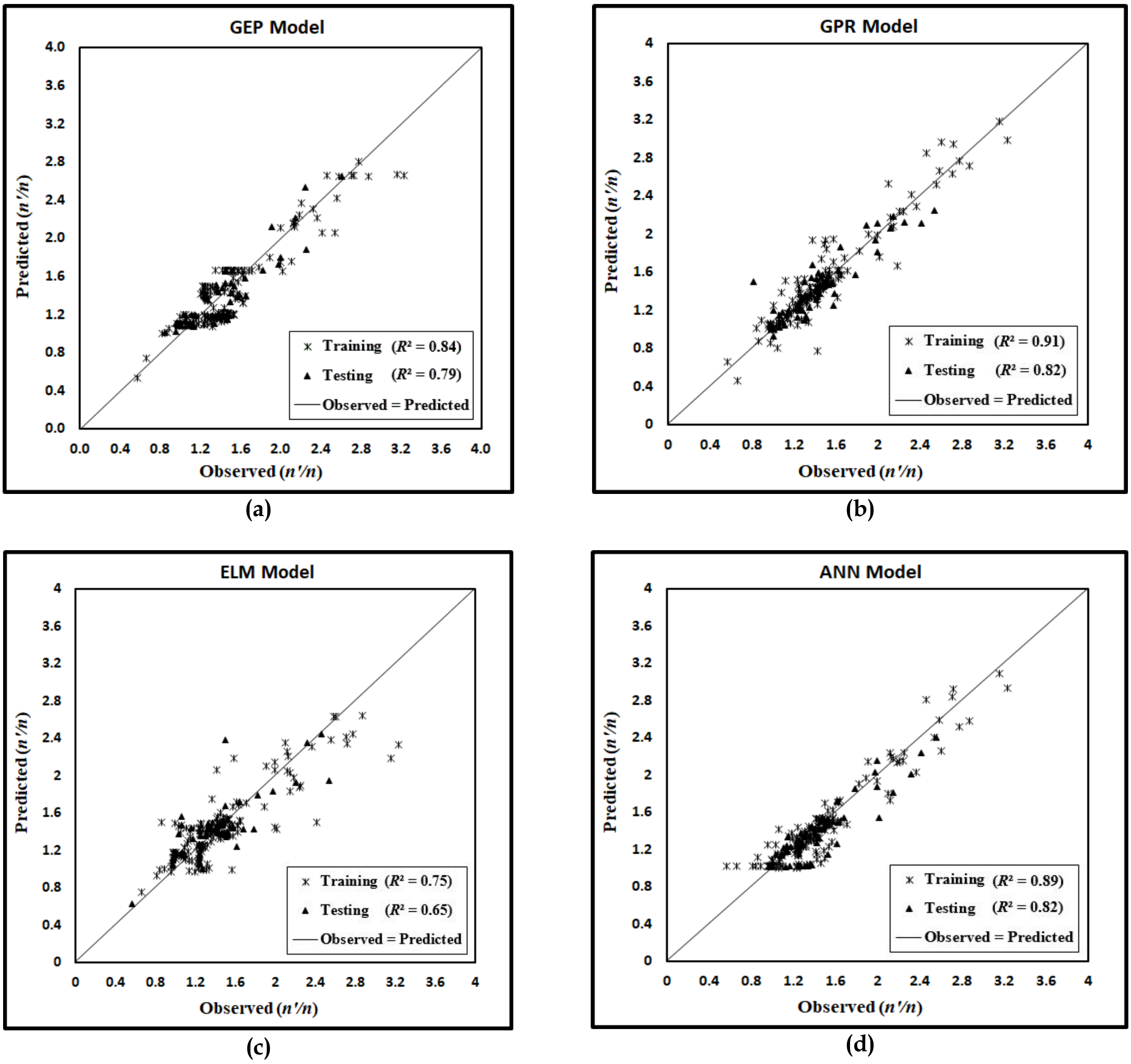

Figure 5. The correlation coefficient and the perfect fit line of 1:1 concerning the observed and predicted n'/n values for several AI approaches considering (a) GEP, (b) GPR, (c) ELM, and (d) ANN.

Table 2. Error Analysis through statistical measures of predicted n'/n by various AI models.

Index	GEP		GPR		ELM		ANN	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
R^2	0.84	0.79	0.91	0.82	0.75	0.65	0.89	0.82
ME (%)	-0.03	-0.79	1.81	0.71	1.99	3.37	0.000381	-3.17
MAE	0.15	0.14	0.085	0.113	0.156	0.162	0.108	0.122
RMSE	0.18	0.17	0.15	0.16	0.23	0.22	0.15	0.16
MAPE (%)	10.7	10.26	6.11	8.24	10.89	12.22	8.07	8.26
E	0.84	0.78	0.896	0.815	0.744	0.644	0.892	0.798
SI	0.12	0.12	0.096	0.10	0.15	0.155	0.098	0.104

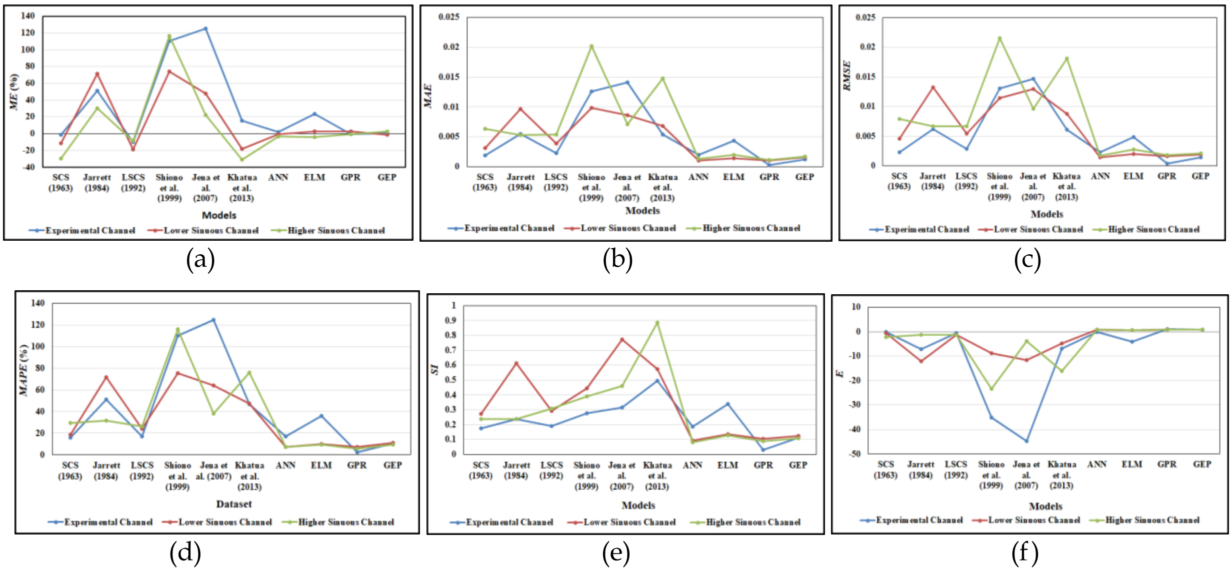

Figure 6. Investigation of different Manning's *n* prediction approaches for various sinuous channels through statistical index analysis considering (a) ME; (b) MAE; (c) *RMSE*; (d) *MAPE*; (e) *SI*; and (f) *E*.

4.2 Assessment of Proposed AI Models with Various Mathematical Approaches

The outcomes of roughness coefficient predicted by the models developed are compared to the analytical models of other researchers previously stated (Eq. 1 through 11). There are so many datasets used in the present study, performing an error analysis on each series of data. Therefore, the data series are divided into three groups: experimental datasets, lower sinuosity channel data $(1.0 < s < 2.0)$, and higher sinuosity channel data $(s \geq 2.0)$.

Error measures in terms of *ME*, *MAE*, *RMSE*, *MAPE*, *E*, and *SI* for Manning's roughness constant of several methods and the created model for distinct dataset are shown in Fig. 6. Figure 6 suggests that the GPR performs better than the other AI as well as analytical models.

Table 3. Testing of various models of discharge prediction of the River Baitarani

Models	Stage (*a*) = 41.2 m			Stage (*b*) = 40 m		
	Anticipated Discharge	Error (%)	MASE	Anticipated Discharge	Error (%)	MASE
GEP (AI Model)	13158.4	7.86	0.08	6985.8	-11.07	0.11
SCS (1963)	6058.3	-50.34	0.5	4500.4	-42.71	0.43
Jarrett (1984)	6489.3	-46.81	0.47	4820.6	-38.63	0.39
LSCS (1992)	4271.5	-64.99	0.65	3235.3	-58.81	0.59
Shiono et al. (1999)	4863.3	-60.14	0.6	3614.2	-53.99	0.54
Jena et al. (2007)	258.9	-97.88	0.98	194.9	-97.52	0.98
Khatua et al. (2013)	7062.4	-42.11	0.42	4562.2	-41.92	0.42

Table 4. Error analysis between different model equations for estimating discharge of River Baitarani.

Approaches	GEP	SCS (1963)	Jarrett (1984)	LSCS (1992)	Shiono et al. (1999)	Jena et al. (2007)	Khatua et al. (2013)
MAE	913.8	4748.1	9800.6	4372.6	6274.1	5788.8	4215.2
RMSE	914.9	4948.4	10031.6	4572.7	6488.6	5992.2	4315.0
MAPE (%)	9.46	46.52	97.70	42.72	61.90	57.06	42.02
E	0.82	-4.19	-20.32	-3.43	-7.92	-6.61	-2.94
SI	0.089	0.136	0.209	0.130	0.161	0.151	0.090

4.3 Application of GEP Model to River Data

For the constructed GEP model to be useful in modelling real-world events, it must meet certain requirements. Sometimes the most well-liked options are not the ones that turn out to be the best in hydraulic experiments. Therefore, the method needs to be tested with real-world data to ensure efficacy. The proposed model is applied to the Baitarani River to calculate the discharge along a stretch of sinuous compound channel for two different flood years (1985 and 1975) with flow depths of 7.5m and 8.63m. River Baitarani may be found in Anandapur, Odisha, India, with coordinates (longitude) $86^{\circ}8'$ E, (latitude) $20^{\circ}10'$ N, details can be found from the previous research article of the author(Mohanta, 2019; Mohanta & Patra, 2019; Mohanta et al., 2018b).

Model performance was evaluated by comparing the discharge calculated by the developed GEP technique to results from a number of analytical models for the River Baitarani, including the SCS (Fasken, 1963), Jarrett (1984), LSCS (James & Wark, 1992), Shiono-Knight (1999), Jena (2007) and Khatua-Patra (2011). Discharge data from GEP and other analytical models are shown in Table 3, confirming the GEP model's viability. The percentage of error (*E*) and Mean Absolute Scaled Error (*MASE*) for the Baitarani River data are presented in Table 3.

Table 4 displays the results of the authors' examination of the *RMSE, MAE*, *MAPE, E*, and *SI* for a number of different discharge methods. The GEP model is found to have the smallest average percentage inaccuracy. In terms of accuracy, the GEP model is shown to have the best results, with comparable values of 913.8 m^3/s, 914.9 m^3/s, 9.46%, 0.82 and 0.089 for *MAE, RMSE*, *MAPE, E*, and *SI*, respectively. The outcomes provide strong confirmation for the viability of the GEP approach in any relevant setting.

5. CONCLUSION

The fundamental purpose of this study is to show that the GPR and GEP model is sufficient for forecasting Manning's *n* further conveyance in two-stage sinuous channels. The relative merits of GPR, GEP, ELM, and ANN are evaluated with respect to machine learning fitness. Predictions of Manning's *n* using the GPR method are quite accurate. However, the GEP model's ability to generate a generalized model equation for Manning's *n* makes it particularly valuable. The proposed GEP model works for a variety of channel sizes and hydraulic conditions. Traditional approaches for calculating Manning's *n* have certain advantages but also have some limitations when used to the calculation of transport in sinuous compound channels. The developed model provides better outcomes for many datasets when compared to existing approaches considering case of error exploration, such as R^2, *MAE*, *RMSE, MAPE*, and *SI*. The created GEP model is well-suited for field research as shown by its low mean error and standard deviation, as well as by comparisons to other methodologies. Further expanding its usefulness, the GEP approach is also used to river data. The models built for this research show promise for use in a variety of contexts, including the assessment of Manning's *n*, the release of natural resources, and both small- and large-scale models.

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