

Prediction of shear stress distribution in compound channel with smooth converging floodplains

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Abstract: Climate change can have a profound impact on river flooding, leading to increased frequency and severity of floods. To mitigate these effects, it is crucial to focus on enhancing early warning systems and bolstering infrastructure resilience through improved forecasting. This proactive approach enables communities to better plan for and respond to flood events, thereby minimizing the adverse consequences of climate change on river floods. During river flooding, the channels often take on a compound nature, with varying geometries along the flow length. This complexity arises from construction and agricultural activities along the floodplains, resulting in converging, diverging, or skewed compound channels. Modelling the flow in these channels requires consideration of additional momentum transfer factors. In this study, machine learning techniques, including Gene Expression Programming (GEP), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), were employed. The focus was on a compound channel with converging floodplains, predicting the shear force carried by the floodplains in terms of non-dimensional flow and hydraulic parameters. The findings indicate that the proposed ANN model outperformed GEP, SVM, and other established approaches in accurately predicting floodplain shear force. This research underscores the efficacy of utilizing machine learning techniques in the examination of river hydraulics.

Keywords: Compound channel; Converging floodplains; Shear stress distribution; Non-dimensional parameters; Machine learning approaches.

INTRODUCTION

The dynamics of flow within a river are influenced by turbulence and the presence of three-dimensional objects. Consequently, selecting an appropriate modelling technique becomes a challenge when aiming to estimate various flow characteristics, including discharge, velocity, and shear stress. Mean velocities in both the main channel and floodplain fluctuate due to variations in hydraulic conditions. The determination of velocity profiles and fluid fields is contingent upon the presence of boundary shear stress. Beyond the bankfull stage, the flow within the primary channel exerts a propulsive or accelerating force on the flow across floodplains, inherently inducing a resistive or decelerating impact on the flow within the primary channel. The pioneering work on boundary shear distributions in open channels was conducted by Leighy (1932). Numerous scholars have conducted investigations on the resolution of boundary shear distributions in streams, using either direct or indirect methodologies. The analysis of shear forces at the bed helps elucidate the mechanism of bedload transfer, while the examination of shear forces at the walls offers a comprehensive perspective on variations in the channel pattern. Several researchers have conducted studies on the flow, velocity, and shear stress distribution on compound sections (Bhattacharya, 1995; Kar, 1977; Khatua et al., 2011a, b; Knight and Demetriou, 1983; Mohanty, 2013; Myers, 1987; Patra, 1999; Patra and Kar, 2000; Patra et al., 2004; Yang and Lim, 2005). Traditional channel division techniques are used for the assessment of discharge capacity in compound channels. It is postulated that the compound section is delineated by hypothetical interface planes located at the confluence of the main channel and the floodplain. The absence of shear stress in these regions suggests a lack of momentum transmission. The

momentum transfer phenomena were first examined by Sellin (1964) via laboratory research. Subsequently, several researchers discovered that the uneven distribution of boundary shear stress along the perimeter of straight compound channels could be attributed to momentum transfer. As a result, they developed an empirical equation for quantifying shear stress, as evidenced by the works of Knight and Demetriou (1983), Knight and Hamed (1984), Myers (1987), Stephenson and Kolovopoulos (1990), Patra et al. (2004), and Yang and Lim (2005). In their seminal work, Knight and Hamed (1984) proposed a theoretical framework to analyse the distribution of boundary shear stress in a compound channel with homogenous characteristics. Their model specifically focused on width ratio (α) values ranging up to 4. In their work, Khatua and Patra (2007) further investigated the subject matter by conducting more experimental observations. They subsequently formulated a model that encompasses channels with width ratios (α) ranging up to 5.25. In their study, Mohanty and Khatua (2014) proposed a novel model for a channel characterized by values of α ranging from 6.67 to 11.96. Extensive investigations were conducted in laboratory flumes to study both prismatic and meandering compound channel designs. Nevertheless, a comparison between the compound section data of prismatic compound channels and non-prismatic compound channels revealed significant discrepancies in the estimation of shear force carried by floodplains. These errors can be attributed to the omission of additional mass and momentum transfer, as elucidated by Bousmar and Zech (2002), Bousmar et al. (2004), Rezaei (2006), and Rezaei and Knight (2009). The additional momentum exchange associated with this phenomenon must be considered when doing flow modelling for non-prismatic compound channels. The study conducted by Proust et al. (2006) investigated the phenomenon of asymmetric geometry,

specifically focusing on its enhanced convergence rate. An augmented convergence angle of 22° leads to heightened levels of mass transfer and head loss. The flow behaviour of skewed, two-stage converging and diverging channels was investigated by Chlebek et al. (2010). The researchers noted an elevation in head losses resulting from the transfer of mass and momentum, as well as the homogeneity of velocity on shrinking floodplains. Additionally, they discovered an augmented velocity gradient on the expanding floodplains. The observed variations in flow distribution may be attributed to alterations in the flow force between the main channel and floodplains within different subsections. Rezaei and Knight (2011) conducted a study on compound channels with floodplains that are non-prismatic. The authors examined the depth-averaged velocity, local velocity distributions, and boundary shear stress distributions at different convergence angles. The analysis of depth-averaged velocities provides insights into the impact of contractions on velocity distributions. Notably, these contractions lead to an augmentation of velocity in close proximity to the walls of the main channel. This effect is particularly pronounced in the latter portion of the convergence reach. Additionally, for cases where the relative depth is high, the lateral flow entering the main channel also contributes to these velocity variations. The study conducted by Yonesi et al. (2013) examines the influence of roughness in floodplains on the occurrence of overbank flow in compound channels with non-prismatic floodplains. Raising the depth ratio or reducing the roughness ratio effectively reduces the velocity gradient between the main channel and the floodplain at the middle and end of the divergence stretch. The rate of change in velocity, as shown by the gradient, exhibited a rise in magnitude as the angle of divergence saw an increase. The magnitude of shear stress increases with the augmentation of surface roughness on the floodplain. The researchers Naik and Khatua (2016) proposed a novel equation that allows for the estimation of the distribution of boundary shear stress by using non-dimensional geometric and flow variables.

The use of soft computing approaches has seen a growing trend in the estimation of parameters inside compound channels, as shown by the studies conducted by Zahiri and Azamathulla (2014), Najafzadeh and Zahiri (2015), and Parsaie et al. (2015, 2017). GEP has a notable advantage over other soft computing approaches due to its ability to generate simpler equations without making assumptions about the pre-existing structure of the connection. However, the current body of literature on river engineering using the GEP technique is limited, with just a few studies available (Azamathulla et al., 2013; Guven and Gunal, 2008; Guven and Aytek, 2009; Pradhan and Khatua, 2017). Wang et al. (2010) examine three techniques for modelling and predicting water level and ice jam thickness. These techniques are based on data collected from field observations of river ice jams in the Quyu Reach of the Yellow River in China. To be more precise, we compare the simulation results produced by the conventional multi-variant regression approach with those obtained from the backpropagation neural network and the support vector machine approaches. Based on the findings from simulation and field observations, it has been determined that both the backpropagation neural network approach and the support vector machine method outperform the multi-variant regression method in terms of accuracy. In this study, Khuntia et al. (2018) used an ANN methodology to forecast the distribution of wall shear stress in straight compound channels. Mohanta et al. (2021) used several AI techniques, such as MARS, GMDH-NN, and GEP, to formulate model equations for compound channels characterized by meandering patterns and relative roughness. In comparison to the GEP and MARS models, the findings indicate that the proposed GMDH-NN model exhibited a high degree of accuracy in

predicting the values. In their study, Mohseni and Naseri (2022) used ANN and SVM as computational techniques to predict the water surface profile in compound channels with vegetated floodplains. Based on the obtained findings, it can be concluded that the SVM method exhibited superior performance compared to both the ANN and regression models. In their recent study, Naik et al. (2022) introduced a unique equation that utilizes GEP to forecast the water surface profile in converging compound channels by including geometric factors. In their work, Yonesi et al. (2022) investigated the modelling of discharge in compound open channels with non-prismatic floodplains (CCNPF) using soft computation models, namely MARS and GMDH. The results were afterward compared with those produced from MLPNN. The statistical error indices demonstrate that the suggested models exhibit satisfactory accuracy in estimating the flow discharge in the CCNPF. Cheng et al. (2022) conducted measurements of water temperature and environmental variables at many locations in the primary channel of the middle part of China's South-to-North Water Transfer Project. The heat balance status of this water transfer route has been analysed using the provided temperature data. A novel method has been devised using support vector machine (SVM) theory to determine the amount of heat lost or gained by flowing water in a channel during winter. This innovative technique uses the Gaussian radial basis as its kernel function. By using supervised machine learning, the analysis of observed water temperature data reveals that the air-water temperature differential and thermal conditions are the primary variables influencing the heat loss or heat absorption of a water body. In their research, Bijanvand et al. (2023) employed soft computing methodologies, including the MLPNN, GMDH, NF-GMDH, and SVM, to forecast water surface elevation in compound channels featuring converging and diverging floodplains. The SVM model demonstrated exceptional performance throughout the testing phase, as substantiated by the statistical metrics. Kaushik and Kumar (2023a) used machine learning methodologies to predict the water surface profile of a compound channel with converging floodplains in their research. The predictions were developed by considering a mix of geometric and flow factors. The findings suggest that the ANN model, when compared to GEP, SVM, and existing methods, demonstrated a notable level of precision in predicting the water surface profile. In their study, Kaushik and Kumar (2023b) used GEP as a methodology to develop an innovative equation that describes compound channels with converging floodplains. The equation is formulated using non-dimensional geometric and flow variables and was used to predict the boundary shear force transmitted by floodplains. The findings indicate that the estimated fraction of shear force borne by floodplains determined by GEP has a good degree of agreement with the actual data.

Previous research has shown that there has been little focus on investigating the impact of flow characteristics on the distribution of shear stress in non-prismatic compound channels, as well as the development of novel methods for predicting shear stress. Consequently, further investigations are being conducted at elevated flow rates on compound channels with converging floodplains that do not have a uniform cross-sectional shape. In this investigation, three non-linear machine learning techniques, namely GEP, SVM, and ANN, are employed to forecast the shear force carried by the floodplains (S_{fp}). These predictions are based on both the geometric and hydraulic characteristics of the compound channel with converging floodplains. This research aims to identify a robust methodology, namely among the proposed techniques for accurately determining the proportion of shear force distribution on the floodplain (S_{fp}) in compound channels including convergent floodplains. The calculation of

the distribution of shear force on the floodplain, as determined by different researchers using various methodologies, is estimated. The efficacy of the generated models is evaluated by analysing their performance and errors.

MATERIALS AND METHODS

Data source

The present study incorporates the works of Rezaei (2006), Naik and Khatua (2016), as well as the experimental data collected by the author. Table 1 presents data about the experimental channel dimensions of compound channels with different geometric features.

Experimental setup

The tests were conducted in the Hydraulics laboratory, which is situated under the Department of Civil Engineering at Delhi Technological University. The trials were carried out inside a masonry flume with dimensions of 12 m in length, 1.0 m in width, and 0.8 m in depth. In this study, a compound cross

section was created using brick masonry, with a main channel width of 0.5 m and a depth of 0.25 m (Figure 1). Figure 1 provides a comprehensive depiction of the geometric attributes associated with a two-stage channel. The construction of the converging portion of the channel included the use of brick masonry, which was employed to achieve a converging angle denoted as $\theta = 4^\circ$. The compound channel consists of a prismatic segment of 6 m in length, followed by a non-prismatic section spanning 3.6 m, with the remaining portion being the downstream section. The experiment included conducting the flume at six distinct flow rates. Flow properties, including the stage-discharge relationship, water surface profile, velocity distribution, and shear stress distribution, were measured for each discharge in both the prismatic section (PS) and different non-prismatic portions (NPS), as seen in Figure 2. The parts denoted as NPS1 and NPS5 represent the first and final segments of the converging component, respectively. On the other hand, NPS3 corresponds to the central region of the converging section. The NPS2 serves as an intermediary segment situated between NPS1 and NPS3. NPS4 may be regarded as the intermediary segment situated between NPS3 and NPS5.

Table 1. Experimental channel dimensions (Kaushik and Kumar 2023a).

Verified test channel	Type of channel	Angle of convergent (θ)	Longitudinal slope (S)	Cross-sectional geometry	Total channel width (B) (m)	Main channel width (b) (m)	Main channel depth (h) (m)	Converging length (L) (m)	Aspect ratio (δ)
Channel 1 Rezaei (2006)	Converging	11.31°	0.002	Rectangular	1.2	0.398	0.05	2	7.96
Channel 2 Rezaei (2006)	Converging	3.81°	0.002	Rectangular	1.2	0.398	0.05	6	7.96
Channel 3 Rezaei (2006)	Converging	1.91°	0.002	Rectangular	1.2	0.398	0.05	6	7.96
Channel 1 Naik and Khatua (2016)	Converging	5°	0.0011	Rectangular	0.9	0.5	0.1	2.28	5
Channel 2 Naik and Khatua (2016)	Converging	9°	0.0011	Rectangular	0.9	0.5	0.1	1.26	5
Channel 3 Naik and Khatua (2016)	Converging	12.38°	0.0011	Rectangular	0.9	0.5	0.1	0.84	5
Present Channel	Converging	4°	0.001	Rectangular	1.0	0.5	0.25	3.60	2

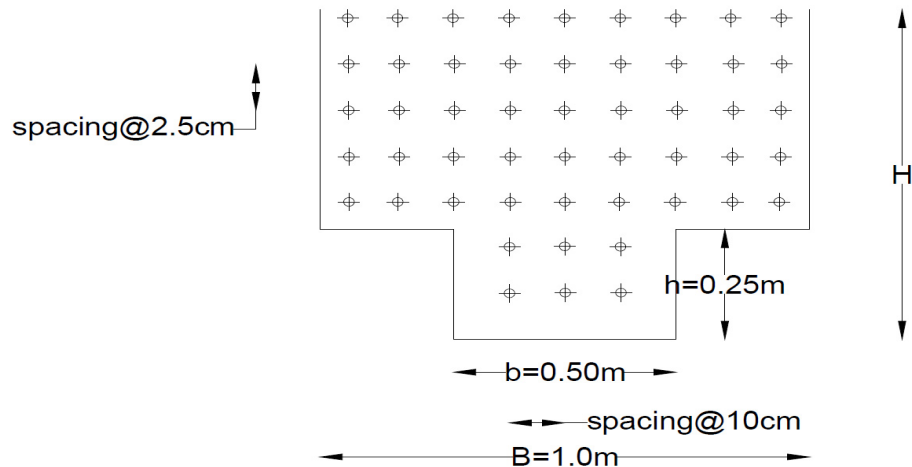


Fig. 1. Compound channel cross section.

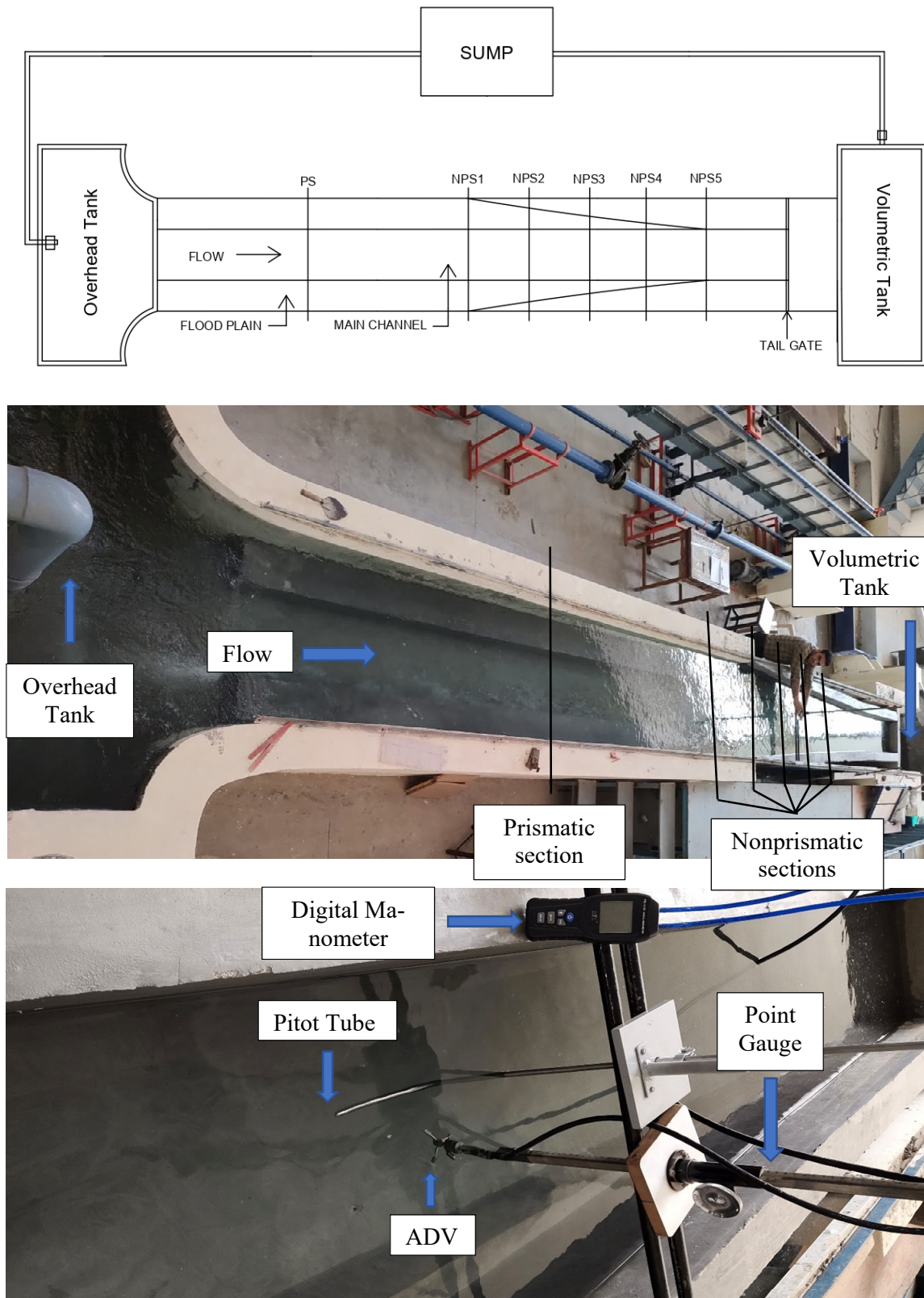


Fig. 2. Experimental setup.

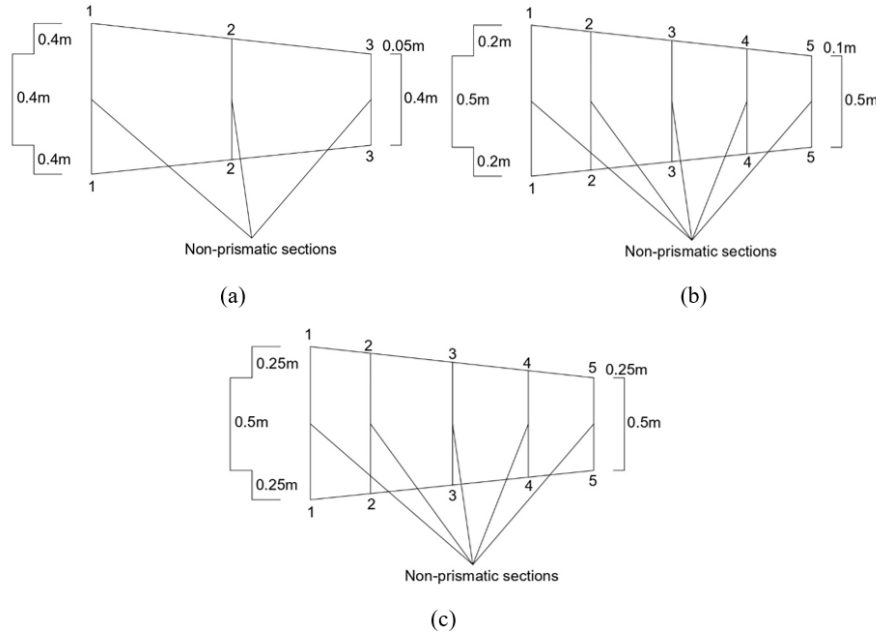


Fig. 3. Nonprismatic sections of (a) Rezaei (2006) (b) Naik and Khatua (2016) (c) Present channel.

The subcritical flow regime was seen under various circumstances in the two-stage channel, which had a longitudinal bed slope of 0.001. The estimation of Manning's n value was conducted based on data obtained from both in-bank and over-bank flows in the floodplains and main channel. The water supply in the experimental channel is sourced from an underground sump and transferred to an above tank by the system. The water originating from the channel is collected inside a volumetric tank that is equipped with a v-notch. The v-notch was appropriately adjusted in order to accurately quantify the discharge emanating from the experimental channel. Subsequently, it facilitates the return of the fluid to the sump situated underneath. Figure 2 depicts the experimental configuration and the assortment of apparatus used in the investigation. Figure 3 illustrates the plan view of the non-prismatic cross-sections of Rezaei (2006), Naik and Khatua (2016), and the present channel. A tailgate was constructed at the downstream end of the flume to regulate the water surface profile and enforce a predetermined flow depth inside that section of the flume. A precision point gauge with a precision of 0.1 mm was used to measure the profile of the water surface at distances of 1.0 m and 0.3 m in the prismatic and non-prismatic sections, respectively. The researchers used an ADV to measure the mean velocity of the cross-section and the three-dimensional velocity distributions around the wetted perimeter. The measurements were taken at vertical intervals of 2.5 cm and horizontal intervals of 10 cm, as seen in the grid format presented in Figure 1. The data obtained via the use of the ADV were processed and refined using the Horizon ADV program. The measurement of lateral distributions of boundary shear stress was conducted using a Preston tube with an outer diameter of 5 mm at the identical portions where the velocity distributions were examined. The pressure differential was measured using a digital manometer. Subsequently, the calibration equations proposed by Patel (1965) were used to compute the shear stress values.

Theoretical background

Compound open channels have been the subject of investigation by several researchers, who have conducted simulations to

analyse the boundary shear stress. In their seminal work, Knight and Demetriou (1983) introduced Equation (1) to describe compound channels, with values of α ranging up to 4. Knight and Hamed (1984) proposed Equation (2) as a means to include the presence of channels with non-uniform roughness in the analysis. Khatua and Patra (2007) introduced Equation (3) to represent the α within the range of 0 to 5.25. In their study, Khatua et al. (2012) derived Equation (4) to calculate the value of α , with a maximum limit of 6.67. In their study, Mohanty and Khatua (2014) introduced a new equation, denoted as Equation (5), which is applicable for values of α that are less than or equal to 12. In their study, Devi et al. (2016) developed a mathematical model, represented by Equation (6), to analyse a range of α between 3 and 12, relative flow depths between 0.10 and 0.50, and aspect ratios of the main channel between 3 and 10. Equation (7) was formulated by Naik and Khatua (2016) to describe the behaviour of converging compound channels with a width ratio of $\alpha = 1.8$ and an aspect ratio of $\delta = 5$. In their study, Kaushik and Kumar (2023b) proposed a new Equation (8) using the GEP approach to analyse compound channels with different floodplain angles.

$$S_{fp} = 48(\alpha - 0.8)^{0.289}(2\beta)^m \quad (1)$$

$$S_{fp} = 48(\alpha - 0.8)^{0.289}(2\beta)^m \{1 + 1.02\sqrt{\beta \log \gamma}\} \quad (2)$$

$$\text{where } m = \frac{1}{[0.75e^{0.38\alpha}]}$$

$$S_{fp} = 1.23(\beta)^{0.1833}(38\ln\alpha + 3.6262)\{1 + 1.02\sqrt{\beta \log \gamma}\} \quad (3)$$

$$S_{fp} = 4.1045 \left(\frac{100\beta(\alpha-1)}{1+\beta(\alpha-1)} \right)^{0.6917} \quad (4)$$

$$S_{fp} = 3.3254 \left(\frac{100\{\beta\alpha\delta - \beta(\delta+2s)\}}{\beta\alpha\delta + (1-\beta)(\delta+s)} \right)^{0.7467} \{1 + 1.02\sqrt{\beta \log \gamma}\} \quad (5)$$

$$S_{fp} = 3.576 \left\{ \frac{100\beta \left(\alpha - 1 - \frac{2.5s}{\delta} + \frac{0.5s}{\delta^2} \right)}{\left(1 + \frac{s}{\delta} \right) + \beta \left(\alpha - 1 - \frac{2s}{\delta} \right)} \right\} \quad (6)$$

$$S_{fp} = 18.505 + 62.140(\beta)^{0.631} - 24.42(X_t) + 1.38(\theta) \quad (7)$$

$$S_{fp} = \left[\left(\frac{(\alpha + \beta) \times (X_r + 7.77)}{4} \right) - \left(\frac{\alpha - 3.95}{2} + \frac{\alpha + 0.196}{2} \right) \right]^2 + \left[\frac{14.56X_r^2 - 38.14X_r}{\alpha^2} \right] + \tan[\text{Max}((\beta + 2.62), (\theta - 7.23)) + 1.50]^2 + 10.25 \quad (8)$$

However, while comparing the aforementioned equations with compound open channels that have narrowing parts, significant discrepancies are seen. Hence, the current work has examined the variation in the floodplain shear force (S_{fp}) with respect to various non-dimensional geometric and flow factors in a non-prismatic compound channel. Both the primary channel and the floodplain subsections of these compound channels have a consistent level of roughness. Manning's n values of 0.013 are assigned to all of the aforementioned smooth surfaces. In a complex channel characterized by limited floodplains, the distribution of boundary shear varies across different sections. The boundary shear force in a non-prismatic channel is believed to be influenced by various dimensionless factors, including the width ratio (α), relative depth ratio (β), aspect ratio (δ), converging angle (θ), relative distance (X_r), longitudinal slope (S_o), energy slope (S_e), discharge ratio (Q_r), Froude number (F_r), and Reynolds number (R_e). A diverse range of parameters is carefully chosen to ensure that the final model equations may be effectively applied across many channels. In order to streamline the equation for a straight compound channel, it is proposed to consider the converging angle (θ) as negligible and thereafter simplify the equation for the straight compound channel.

The equation that is necessary to be dimensionless may be expressed as:

$$S_{fp} = F(\alpha, \beta, \delta, \theta, X_r, S_o, S_e, Q_r, F_r, R_e) \quad (9)$$

SVM model

The SVR method is a frequently deployed machine learning approach utilized for regression analysis. The approach being discussed works on similar principles to SVMs used for classification but with the aim of predicting a continuous output variable based on input factors. The core principle that underlies SVR is to ascertain a function that can proficiently establish a mapping between input variables and output variables, with low error, while simultaneously adhering to a pre-established margin. The achievement of this aim necessitates the transformation of the input variables into a higher-dimensional space using a kernel function. Drucker et al. (1997) subsequently calculate the regression line that maximizes the margin while ensuring that the error remains within a preset tolerance threshold. SVR demonstrates a significant advantage in its ability to efficiently handle non-linear relationships between input and output variables. The achievement of this goal is helped by using kernel functions, such as polynomial, radial basis function, and sigmoid functions, among others. The aforementioned functions facilitate the representation of complex interdependencies among variables (Smola and Schölkopf, 2004). The use of SVR has shown to be beneficial in several fields, such as finance (Sharma et al., 2012), transportation (Yeh et al. 2010), and medical imaging (Borges et al., 2016). The careful selection and fine-tuning of the kernel function and its related parameters are crucial in achieving optimum performance. A commonly used technique for converting a linear classifier into a non-linear classifier is the application of a non-linear function to transfer the input space x onto a feature space F . A different methodology entails using a non-linear function to facilitate the process of mapping. The separating function in space F can be expressed as:

$$f(x) = w^T \varphi(x) + b \quad (10)$$

The statistical approach represented by the algebraic function $f(x, w)$ may be described inside the subspace as follows:

$$w = \sum_{i=1}^n \alpha_i x_i \quad (11)$$

$$f(x, w) = \sum_{j=1}^n \alpha_j x_j \varphi_j(x) + b \quad (12)$$

$$f(x) = \sum_{i=1}^n \alpha_i x_i^T x + b \quad (13)$$

In the feature space, F , this expression takes the form:

$$f(x) = \sum_{i=1}^n \alpha_i \varphi(x_i)^T \varphi(x) + b \quad 0 \leq \alpha_i \leq C \quad (14)$$

$$k(x, x') = \varphi(x)^T \varphi(x') \quad (15)$$

$$f(x) = \sum_{i=1}^n \alpha_i k(x, x_i) + b \quad (16)$$

On the other hand, there is a wide array of additional kernel functions available that may be used in different contexts to improve overall performance.

Linear kernel: $k(x_i, x_j) = x_i^T x_j$

Polynomial kernel: $k(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$

RBF kernel: $k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0$

Sigmoid kernel: $k(x_i, x_j) = \tanh(\gamma x_i^T x_j + r), \gamma > 0$

The SVM model utilizes the parameters C , γ , r , and d . The effectiveness of the model relies on the quality of the chosen settings for its parameters, as well as the kernel parameters. The careful choice of values for the parameters C , γ , and r is of utmost importance in effectively controlling the complexity of the regression model. Nevertheless, the task of identifying the most suitable parameters is further hampered by the sophisticated complexity involved in their selection. Kernel functions are used to decrease the dimensionality of the input space and assist the process of categorization. The method of refining the SVM model involves exposing it to data sets, which is similar to the refinement process seen in other neural network models. The assessment of the proportion of shear stress borne by floodplains in a compound channel with converging floodplains was conducted using a dependable and high-caliber experimental dataset. Before constructing the SVM model, the dataset is divided into training and testing subsets using a 70:30 ratio in MATLAB R (2019). The model is then created using a cubic kernel function, which was determined to be the most optimal choice among the other kernel functions available.

ANN model

The ANN is a prominent computational approach that is now seeing significant breakthroughs in its progress. An artificial neural network is a computational model composed of linked units known as neurons or nodes, arranged in a hierarchical structure to facilitate manipulation and analysis. The ANN is structured according to the backpropagation neural network (BPNN) model and consists of three layers in a feedforward configuration. The three layers consist of a set of input neurons, denoted as I , a set of hidden neurons, denoted as m , and a set of output neurons, denoted as n . The input layer functions as the first stage for data to enter the neural network. The hidden layer, also known as the intermediate layer, receives input data from the previous layer, known as the input layer, which is largely responsible for processing the data. The second layer, referred to as the output layer, receives the processed data from the network.

The data obtained from the output is sent to external receptors. ANNs consist of interconnected layers that are sequentially linked to one another. The aforementioned relationships are often referred to as weights and weighted values, respectively. The augmentation of connectivity weights is a strategy for regulating the behaviour of specified cost functions inside an ANN (Kaushik and Kumar, 2023a).

The current study used an ANN methodology to predict the shear force borne by floodplains in a compound channel with converging floodplains. A feedforward neural network is implemented in MATLAB R (2019) using the backpropagation training algorithm with the objective of prediction. Before applying the network to any issue, the network must undergo a training phase. During this phase, the adjustment of weights and biases for each output neuron is performed in line with the training approach, with the objective of restricting the intended output of each output neuron. The training of ANNs encompasses three key components: inter-neuron weights, which dictate the significance of input sources; a sigmoid transfer function, which regulates the output level of neurons; and a collection of learning laws, which govern the adjustment of weights during the training process. During the training phase, it is common practice to use a non-linear function, often in the form of a sigmoid function (Kaushik and Kumar, 2023a):

$$F(a) = \frac{1}{1 + e^{-a}} \quad (17)$$

The result is sent to the succeeding layer of nodes for further processing. The BPNN techniques consist of four distinct steps. The aforementioned processes may be delineated as follows:

Sum the weighted input:

$$Nod_z = \sum_{i=1}^n (W_{xz}k_x) + \epsilon_z \quad (18)$$

Transform the weighted input:

$$Out_z = \frac{1}{1 + e^{-Nod_z}} \quad (19)$$

Sum the hidden node output:

$$Nod_y = \sum_{j=1}^m (W_{zy}Out_y) + \epsilon_y \quad (20)$$

Transform the weighted sum:

$$Out_y = \frac{1}{1 + e^{-Nod_y}} \quad (21)$$

The architecture of the neural network was designed with ten neurons in the input layer, ten neurons in the hidden layers, and one neuron in the output layer. Figure 4 depicts the fluctuation of neural network parameters, including the gradient, mean, and validation tests. During the training phase, the gradient and mean exhibit fluctuations at certain phases, ultimately decreasing, while the validation checks rise as the number of generations increases. This is an outcome of the optimization process, particularly gradient descent, which occurs during the training of ANNs. The repeated modifications to the weights, led by the gradient, strive to discover a collection of weights that minimizes the loss function and generates precise predictions on the training data. Figure 5 illustrates an error detected during the training, testing, and validation phases. The training error first had a rapid decline, then moved to a more consistent deceleration. After 30 generations, the network achieved convergence and demonstrated the lowest possible error value. The reduction in error seen during the training of an ANN is a direct result of the optimization process, which is led by the techniques of gradient descent and backpropagation. The parameters of the model are fine-tuned to discover the most effective setup that minimizes the error on the training data, with the ultimate objective of obtaining strong generalization performance.

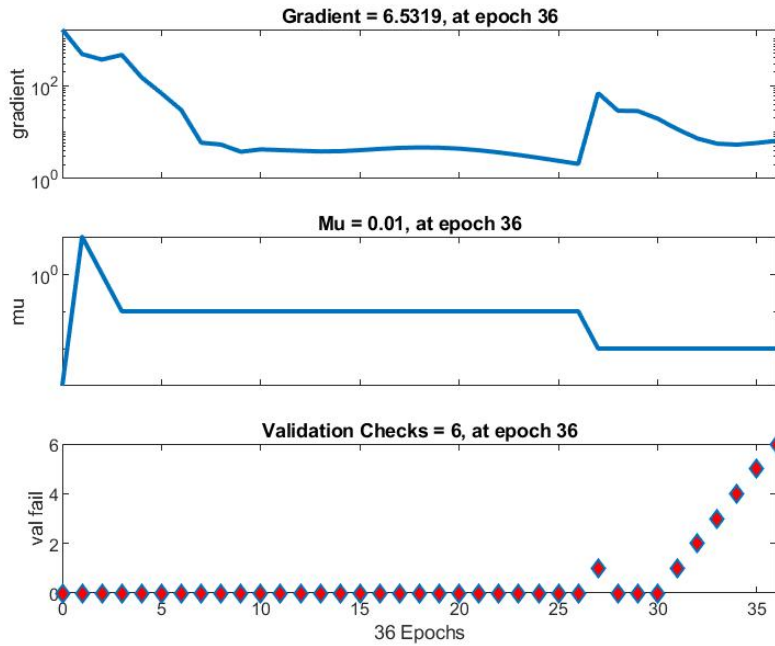


Fig. 4. ANN training parameters.

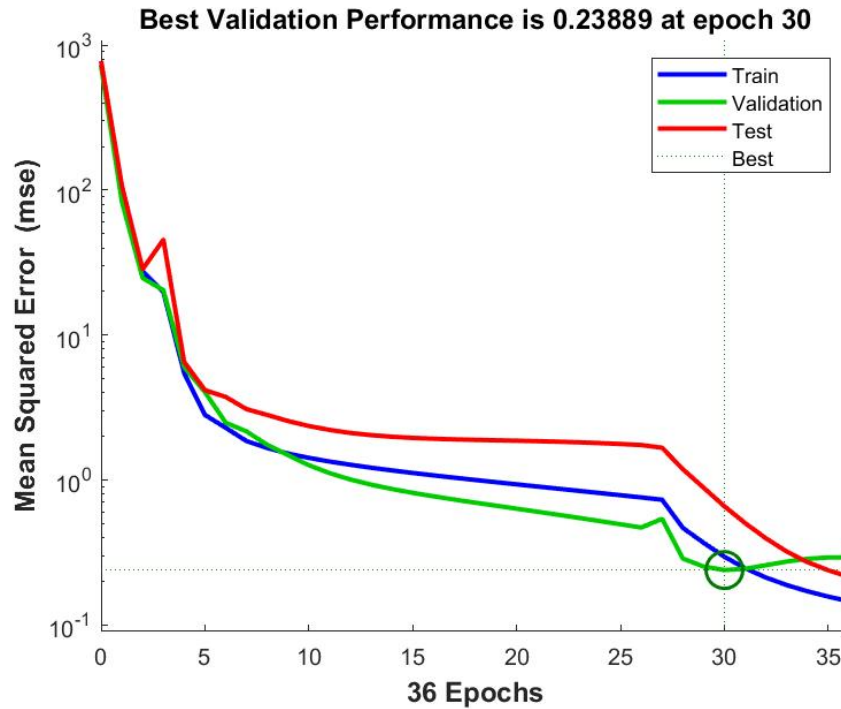


Fig. 5. BPNN convergence curve.

GEP model

The use of GEP, a computational approach, enables the evolution of computer programs capable of solving complex problems. The first idea was introduced by Dr. Cândida Ferreira in 1992, as a component of her PhD dissertation at the University of Coimbra, situated in Portugal. The technique of the GEP is based on the basic principles of genetics and the process of natural selection. The operating mechanism of this system is the iterative development of a collection of computer programs through a sequence of mutation and selection procedures. The GEP technique encompasses the representation of individual programs as symbol sequences, which may be subjected to a range of genetic operations, such as combining and mutation. The selection of programs with higher performance on a specific task in each succeeding generation leads to an improvement in their overall fitness. The ability of GEP to effectively handle many goals simultaneously makes it an important tool in the field of optimization. The GEP has been widely used across several fields, including but not limited to data analysis, categorization, and modelling. According to Ferreira (2001), empirical data indicates that GEP has enhanced efficacy when compared to other evolutionary computation methods such as genetic programming and evolutionary strategies, particularly within certain problem areas. Furthermore, researchers have extended the GEP technique to support complex data structures such as trees and graphs. This has been achieved by the incorporation of modified genetic operators, as described by Otero et al. (2016).

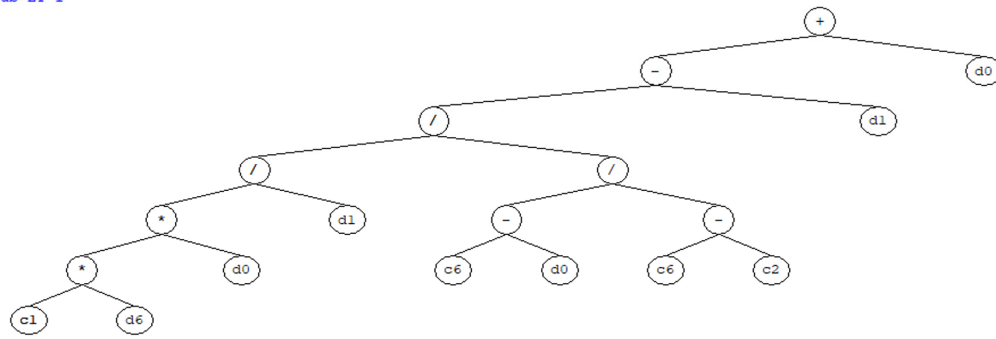
The current study utilizes a modelling methodology in which the goal value is denoted as $\%S_{fp}$, while the ten independent components are regarded as input variables, as described in Equation (9). The construction of the model's structure included the use of the four basic arithmetic operators (+, −, ×, /) in combination with GeneXproTools 5.0 (2014). In general, the modelling procedure used high-calibre datasets that were randomly allocated during two discrete phases. Several models were created for the

Table 2. Selection standards and attributes for the GEP model.

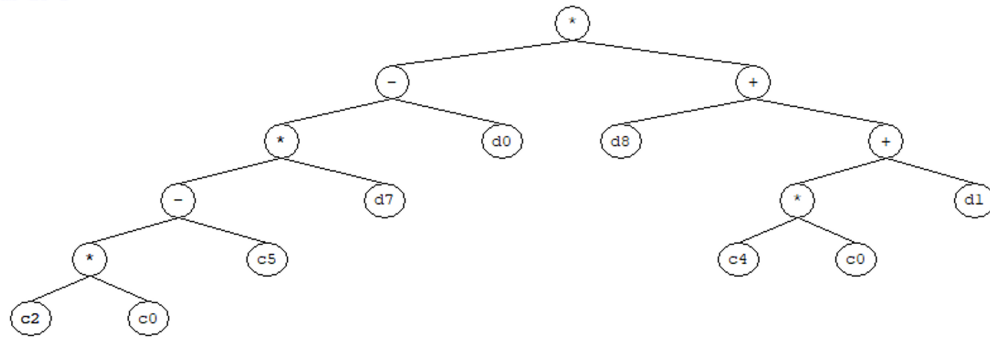
Description of parameter	Parameter setting
Function set	+, −, ×, /
Number of chromosomes	30
Head size	12
Number of genes	6
Gene size	38
Linking function	Addition
Fitness function	RMSE
Program size	114
Literals	36
Number of generations	476664
Constants per gene	10
Data type	Floating-point
Mutation	0.00138
Inversion	0.00546
Gene recombination rate	0.00277

present investigation, using different ratios of training and testing datasets, program dimensions, and generations. The characteristics of the best model are shown in Table 2. The current investigation used the root-mean-squared error (RMSE) as the fitness function, which was designated as E_i . The fitness (f_i) was determined by using an equation developed from an expression tree, which took into consideration the cumulative total of mistakes with respect to the target value. The technique of addition was used as the method for joining the genetic components. Figure 6 illustrates the expression tree (ET) representing the percent shear force of the compound channel predicted from the GEP model. In the present representation, the input parameters are denoted as d_0 to d_9 , whilst the constant values for gene one are assigned as $G1c1$, $G1c2$, and $G1c6$. The expression tree may be used to derive a mathematical formula that establishes a correlation between the input and output variables.

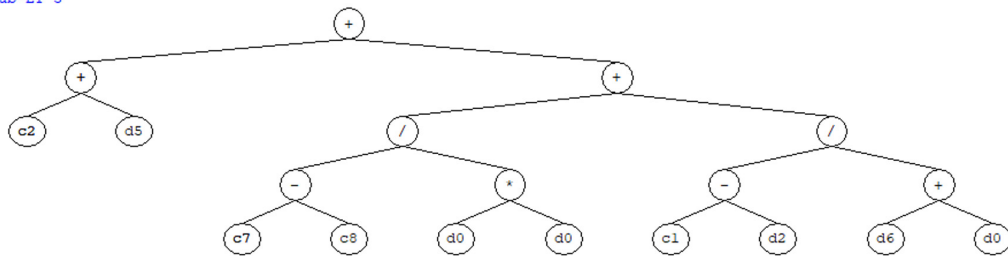
Sub-ET 1



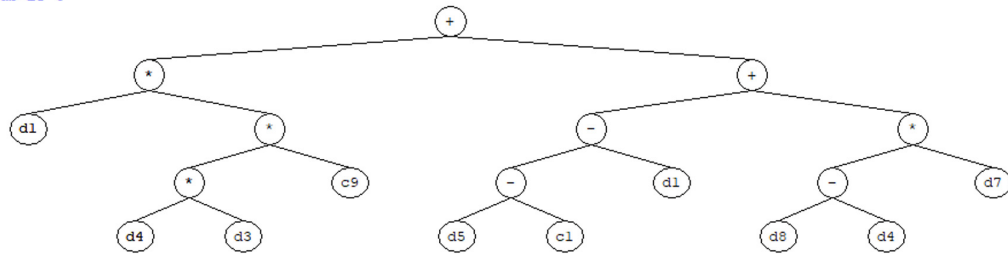
Sub-ET 2



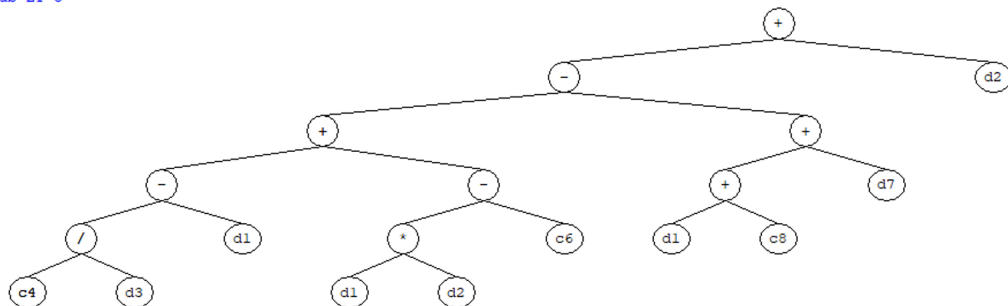
Sub-ET 3



Sub-ET 4



Sub-ET 5



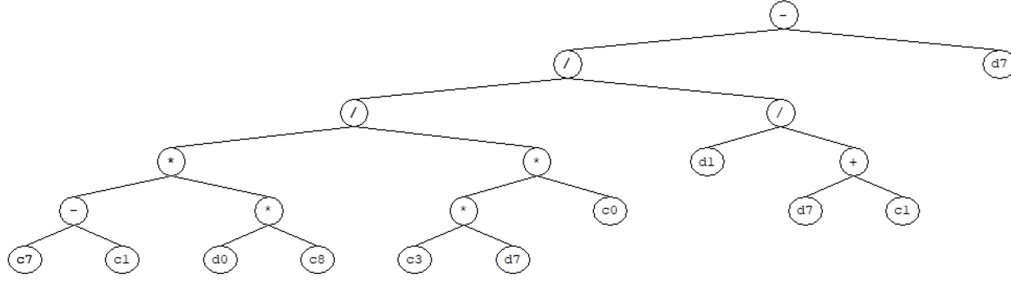


Fig. 6. GEP formulated expression tree.

Statistical measures

Various error analysis approaches were used to evaluate the accuracy of the machine learning models. The aforementioned metrics included the coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), scatter index (SI), coefficient of efficiency (E), and Akaike Information Criterion (AIC). The relevant equations were used to compute these measures (Kaushik and Kumar 2023a).

$$R^2 = \frac{\sum_{i=1}^N (a_i - \bar{a})^2 (p_i - \bar{p})^2}{\sum_{i=1}^N (a_i - \bar{a})^2 \sum_{i=1}^N (p_i - \bar{p})^2} \quad (23)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (p_i - a_i)^2 \quad (24)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - a_i)^2} \quad (25)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |p_i - a_i| \quad (26)$$

$$MAPE(\%) = \frac{1}{N} \sum_{i=1}^N \left(\frac{|p_i - a_i|}{a_i} \times 100 \right) \quad (27)$$

$$SI = \sqrt{\frac{\sum_{i=1}^N [(p_i - \bar{p}) - (a_i - \bar{a})]^2}{\sum_{i=1}^N a_i^2}} \quad (28)$$

$$E = 1 - \frac{\sum_{i=1}^N (p_i - a_i)^2}{\sum_{i=1}^N (a_i - \bar{a})^2} \quad (29)$$

$$AIC = N \log \left(\frac{1}{N} \sum_{i=1}^N (p_i - a_i)^2 \right) + 2k \quad (30)$$

RESULTS AND DISCUSSION

The connection between bed shear stress and longitudinal distance for various relative depths (range from 0.10 to 0.60) in a compound channel with converging floodplains ($\theta = 4^\circ$) is shown in Figure 7. The bed shear stress shows a linear augmentation in relation to the longitudinal distance till reaching the prismatic section. Nevertheless, it is observed that there is a sudden increase in shear stress along the longitudinal distance in the initial half of the channel's converging region. Additionally, in the latter half of this section, there is an abrupt rise in bed shear caused by the convergence of the channel's geometry, resulting in accelerated flow within the channel. The bed shear stress in both the main channel and floodplains exhibits an increase in magnitude as the longitudinal distance progresses. This increase is mostly attributed to the rise in relative depth, with greater relative depths seeing a more pronounced effect. The primary driver behind this phenomenon is the transfer of momentum from the main channel to the floodplains. The boundary shear stress distributions throughout the wetted perimeter of the

compound channel are depicted in Figure 8. The figure includes both prismatic and non-prismatic cross-sections and the relative flow depth β is set at 0.60. The distribution of boundary shear stress exhibits symmetry and expands progressively from section 1 to section 5. The largest value of boundary shear stress is seen near the centre of the main channel, and this value rises as the flow transitions from a prismatic portion to a non-prismatic segment. This increase in boundary shear stress may be attributed to the boundary resistance resulting from the converging shape of the channel. The magnitude of the boundary shear stress diminishes as it approaches the floodplain interface across all sections. At lower relative depths, in close proximity to the interface between the main channel and the floodplain, the boundary shear stress experiences a rapid fall, followed by a gradual decrease until reaching a minimum at both ends of the floodplain. At elevated relative flow depth, in the vicinity of the interface between the main channel and the floodplain, there is a rapid decline in shear stress. This is followed by a gradual increase towards the centre of both floodplains and subsequently a decrease towards the boundaries of the channel. This pattern arises due to the transfer of momentum from the floodplains to the main channel in the compound channel configuration.

Figure 9 displays scatter plots that compare the anticipated and actual values of $\%S_{fp}$ for each of the several machine learning algorithms. The proximity of the values to the line representing excellent agreement serves as compelling evidence for the predictive accuracy of the developed GEP, ANN, and SVM models. When comparing the three models, it can be seen that the predictions made by the ANN exhibit a higher degree of proximity to the best-fitting line in comparison to the GEP and SVM models. The ANN model demonstrates a more concentrated distribution of values along the fitted line. Hence, it can be concluded that the ANN model exhibits the highest level of agreement with the experimental data, as shown by the significant R^2 values. Figure 10 presents a comparison of the created models used to forecast the proportion of shear force carried by floodplains, using different approaches. The built models have shown remarkable proximity to the best-fitted line in comparison to earlier methodologies, indicating a robust potential for generalization. There is an absence of observable indications of the overtraining phenomena in their behaviour. Several of the suggested methodologies exhibit a clear bias toward estimating shear stress in floodplains. These models incorporate all the relevant parameters, such as discharge ratio, energy slope, Froude number, and Reynolds number, which were previously overlooked in earlier approaches. The evaluation of the GEP, ANN, and SVM models' performance was conducted using various statistical metrics, including the R^2 , MSE, RMSE, MAE, MAPE, SI, E, and AIC. These metrics are presented in Table 3. The table reveals that the ANN model demonstrates superior performance in comparison to other models constructed

using SVM, GEP, and previously developed methodologies. This is evident from the highest R^2 value of 0.998, lowest MSE value of 0.375, lowest RMSE value of 0.613, lowest MAE value of 0.338, and lowest MAPE value of 0.391 associated with the ANN model. The SI serves as a standardized measure for the quantification of inaccuracy. A lower SI value is indicative of a higher level of model performance. The ANN model has a significantly reduced SI value of 0.023 in both the training and testing stages, indicating a minimum level of error. The efficiency measure, represented as E, is assigned a value of 1 when there is a complete correspondence between the model and the observed data. The interval of E extends from negative

infinity to 1. The ANN model has an E value of 0.998 for both the training and testing datasets. The AIC is a widely used criterion in statistical model selection. It is used to choose the best suitable model by evaluating the statistical likelihood function. The model that has the lowest AIC value is regarded as the most optimum model. The ANN model has the lowest AIC score of -148.470 when compared to the other models proposed. The statistical study of several indices indicates that ANN exhibits superior performance compared to other machine learning techniques and established methodologies in forecasting the proportion of shear force borne by floodplains in compound channels with narrowing floodplains.

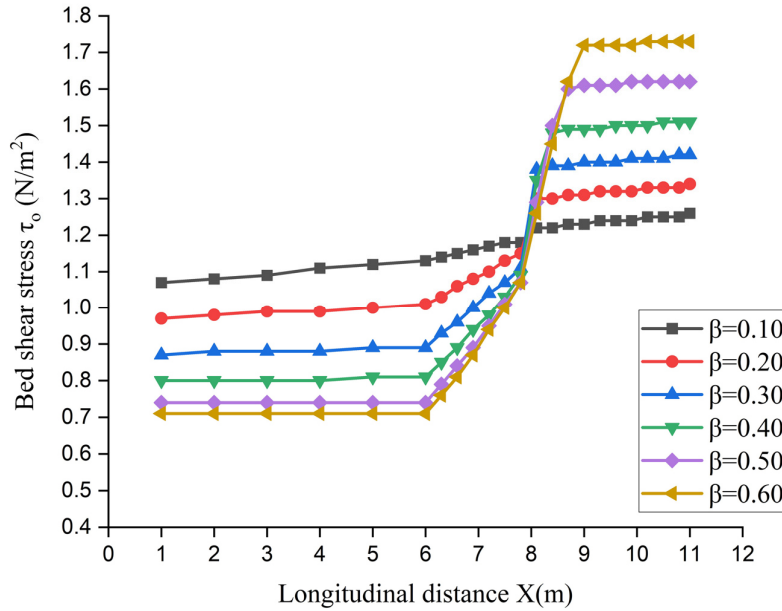


Fig. 7. Variation of bed shear stress along the longitudinal distance of the channel.

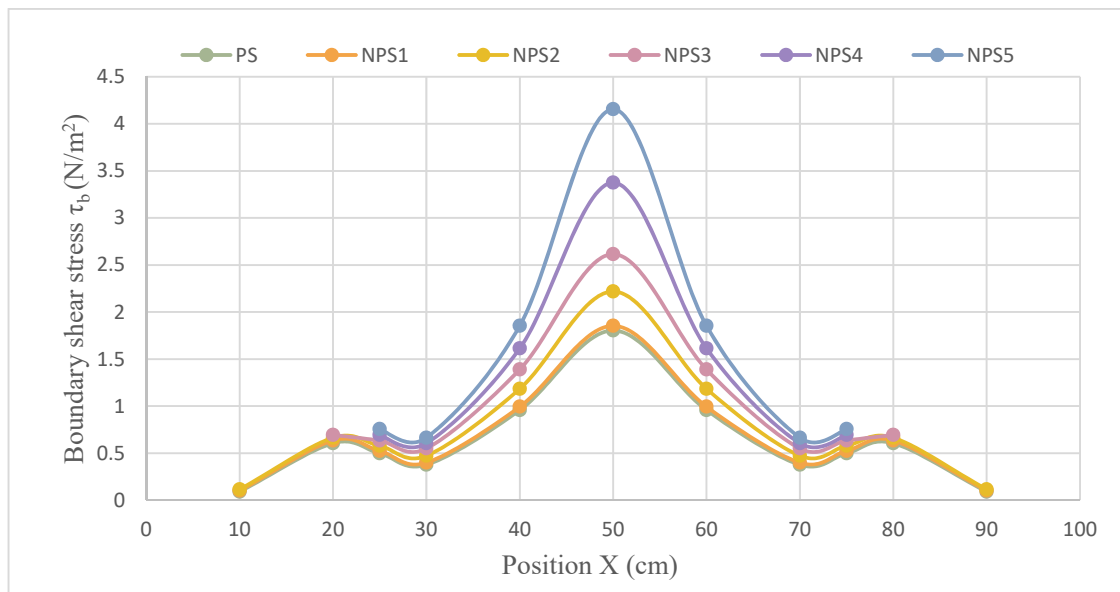


Fig. 8. Variation of boundary shear stress along the wetted perimeter.

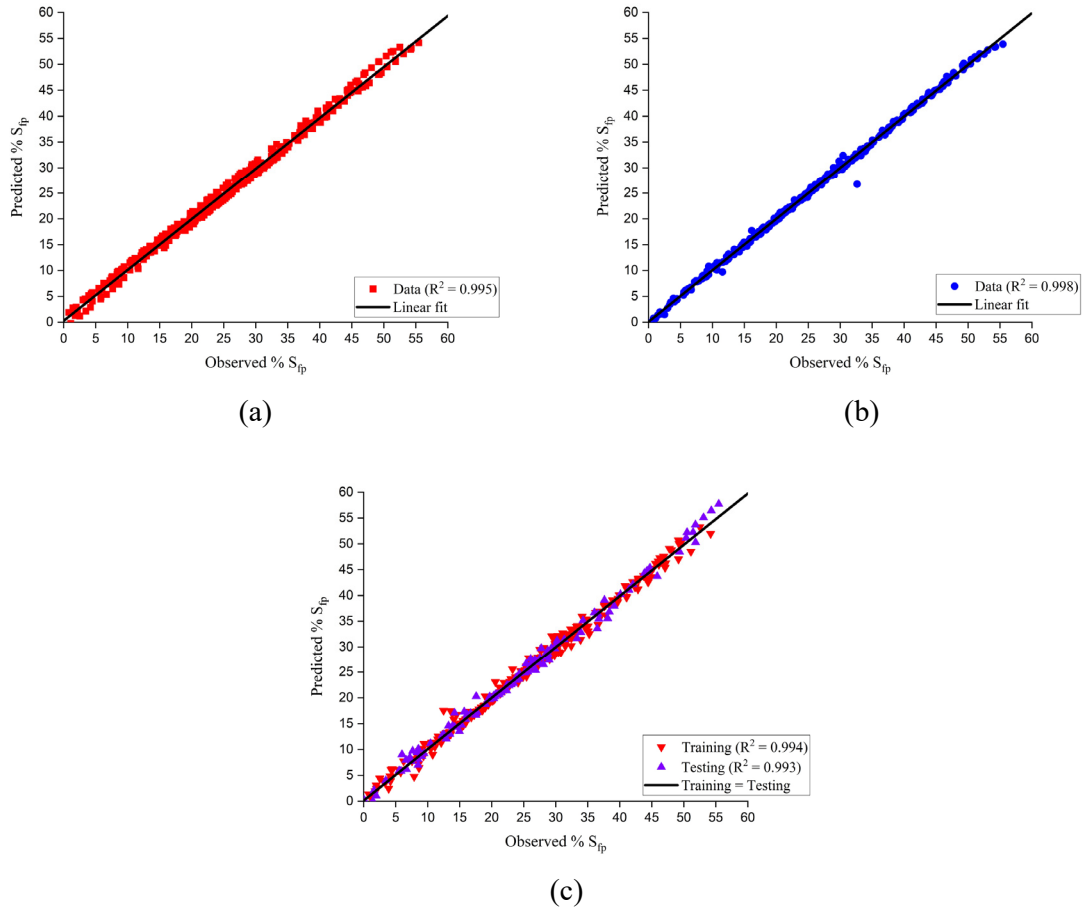


Fig. 9. Scatter plots of observed and predicted % S_{fp} for various ML models (a) SVM (b) ANN (c) GEP.

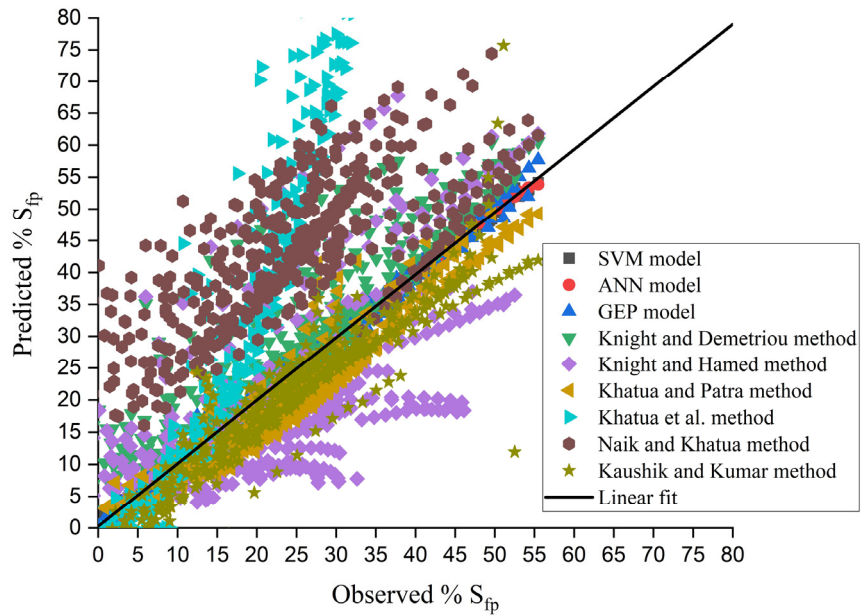


Fig. 10. Comparison of predicted value of % S_{fp} for different models.

Table 3. Statistical analysis of predicted %S_{fp} by different approaches.

Parameters	ANN model	GEP model	SVM model	Knight and Demetriou method	Knight and Hamed method	Khatua and Patra method	Khatua et al. method	Naik and Khatua method	Kaushik and Kumar method
R ²	0.998	0.993	0.995	0.767	0.416	0.895	0.847	0.568	0.961
MSE	0.375	1.234	0.869	71.704	144.986	29.911	4519.4	459.406	13.855
RMSE	0.613	1.111	0.932	8.468	12.041	5.469	67.226	21.434	3.722
MAE	0.338	0.807	0.827	5.884	9.705	4.631	45.777	19.416	2.990
MAPE	0.391	2.855	8.269	71.933	83.331	22.923	240.870	211.354	12.120
SI	0.023	0.041	0.034	0.313	0.442	0.199	2.472	0.790	0.285
E	0.998	0.993	0.995	0.618	0.228	0.841	−23.054	−1.445	0.961
AIC	−148.470	56.146	−4.158	754.796	875.886	604.429	1467.412	1074.230	105.920

CONCLUSIONS

This work presents an evaluation of the shear stress exerted on floodplains in a compound channel with converging floodplains. The assessment is conducted using machine learning techniques, including ANN, GEP, and SVM. The suggested models have been built using 396 meticulously gathered laboratory datasets from both current and previous work. These datasets pertain to non-prismatic compound channels characterized by varying converging angles and relative depths. The suggested model has apparent sensitivity to several factors, including width ratio, relative flow depth, aspect ratio, converging angle, relative distance, longitudinal bed slope, energy slope, discharge ratio, Froude number, and Reynolds number. The bed shear stress exhibits an increasing trend as one moves along the length of the channel and with respect to the relative flow depth. Nevertheless, a rapid increase in shear stress was seen in the converging portion, particularly in the latter half of the channel, due to the interaction and transfer of momentum between the main channel and floodplains. The largest wall shear stress was observed in the central region of the primary channel, with a rise in magnitude as the flow progresses downstream within the channel. At the junction between the main channel and the floodplain, the shear stress values experience a drop as a result of the momentum shift phenomenon. This decrease is seen to be at its lowest near the extremities of the channel for lower relative depths, while it rises towards the centre of the floodplain for greater relative depths. The connection between the percent shear force and the non-dimensional geometric and hydraulic variables of a converging compound channel is nonlinear for all relative flow depths. In contrast to past methodologies, the three proposed models provide superior outcomes in relation to statistical parameters. The results indicated that, in line with the established evaluation criteria, all three models ANN, GEP, and SVM exhibited a reasonable ability to estimate the shear force carried by floodplains of a compound channel with converging floodplains. The ANN model had superior performance in comparison to other models and earlier methodologies, as shown by its greatest R² value and lowest values for MSE, RMSE, MAE, MAPE, SI, and AIC.

In order to mitigate the negative impacts of flooding, it is crucial to have a comprehensive understanding of the flow dynamics in both prismatic and non-prismatic sections of rivers. This understanding should include the incorporation of extra momentum transfer in flow models. Such knowledge is essential for the effective construction of flood control and diversion structures. The models proposed in this paper possess practical implications for non-prismatic rivers, such as the River Main in Northern

Ireland, the Brahmaputra River in India, and other analogous river systems. The models used to predict the shear stress have some limitations, including high computational expenses, lack of interpretability, susceptibility to overfitting, and their black box character. Additionally, these models have specific drawbacks such as demanding data requirements, high processing intensity, sensitivity to parameters, restricted scalability, and being primarily designed for binary classification tasks. The computational cost of machine learning models is a crucial factor that affects their practicality, effectiveness, and capacity to handle larger datasets. Various elements contribute to the computational expense of machine learning models, including the complexity of the model, the size of the dataset, the complexity of the algorithm, the use of hardware acceleration, the tuning of hyperparameters, the application of feature engineering, the implementation of regularisation techniques, the number of model training iterations, and the need for real-time inference. Performance parameters are essential measures used to assess the efficacy and proficiency of machine learning models. These parameters provide valuable information about the performance of a model on a specific job and help in the selection and refinement of models. Several essential performance metrics are often used to evaluate machine learning models, including accuracy, precision, sensitivity, specificity, mean squared error, R-squared, and the confusion matrix. The results of this research will be valuable for informing the design of such structures, leading to a reduction in both economic and human losses.

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NOMENCLATURE

The following symbols are used in this paper:

B = total width of compound channel [m]
b = width of the main channel [m]
h = height of the main channel [m]
H = flow depth [m]

α = width ratio (B/b)
 β = relative flow depth [(H - h)/H]
 δ^* = flow aspect ratio (b/H)
 δ = main channel aspect ratio (b/h)
 θ = converging angle [degree]
 X_r = relative distance (x/L)
 L = converging length [m]
 x = distance between two consecutive sections [m]
 S_o = longitudinal bed slope [radian]
 S_e = energy slope [radian]
 Q_r = discharge ratio (Q/Q_b)
 Q = discharge at any depth [m^3/sec]
 Q_b = bankfull discharge [m^3/sec]
 F_r = Froude number
 R_e = Reynolds number
 S_{fp} = shear force carried by floodplains [percent]
 a = actual values
 p = predicted values
 $\bar{a}$ = mean of actual values
 $\bar{p}$ = mean of predicted values
 N = number of datasets
 k = number of variables
 a = sum of weighted input value plus bias
 Nod_z = sum for the zth hidden node
 n = total number of input nodes
 W_{xz} = connection weight between the xth input and the zth hidden node
 k_z = normalized input at the xth input node
 ϵ_z = bias value at the zth hidden node
 Out_z = output from the zth hidden node
 Nod_y = sum of yth output node
 m = total number of hidden nodes
 W_{zy} = connection weights between the zth hidden node and the yth output node
 ϵ_y = bias value at the yth output node
 Out_y = output at the yth output node

ABBREVIATIONS

ANN = Artificial neural networks
 GEP = Gene expression programming
 SVM = Support vector machines
 AI = Artificial intelligence
 MARS = Multivariate adaptive regression splines
 GMDH-NN = Group method of data handling neural network
 CCNPF = Compound open channels with nonprismatic floodplains
 MLPNN = Multilayer perceptron neural networks
 NF-GMDH = Neuro-fuzzy group method of data handling
 PS = Prismatic section
 NPS = Nonprismatic sections
 ADV = Acoustic Doppler velocimeter
 SVR = Support vector regression
 RBF = Radial basis function
 BPNN = Back-propagation neural network
 ET = Expression tree

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