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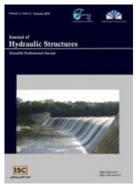

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A Prediction of Manning's n_r in Compound Channels with Converged and Diverged Floodplains using GMDH Model

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Abstract

In the study of natural waterways, the use of formulas such as Manning's equation is prevalent for analyzing flow structure characteristics. Typically, floodplains exhibit greater roughness compared to the main river channel, which results in higher flow velocities within the main channel. This difference in velocity can lead to increased sedimentation potential within the floodplains. Therefore, accurately determining Manning's roughness coefficient for compound channels, particularly during flood events, is of significant interest to researchers. This study aims to model the Manning roughness coefficient in compound channels with both converging and diverging floodplains using advanced soft computing techniques. These techniques include a multi-layer artificial neural network (MLPNN), Group Method of Data Handling (GMDH), and the Neuro-Fuzzy Group Method of Data Handling (NF-GMDH). For the analysis, a dataset from 196 laboratory experiments was used, which was divided into training and testing subsets. Input variables included parameters such as longitudinal slope (S_o), relative hydraulic radius (R_r), relative depth (D_r), relative dimension of flow aspects (δ^*), and the convergent or divergent angle (θ) of the floodplain. The relative Manning roughness coefficient (n_r) was the output variable of interest. The results of the study showed that all the models performed well, with the MLPNN model achieving the highest accuracy, characterized by $R^2 = 0.99$, $RMSE = 0.001$, $SI = 0.0015$, and $DDR = 0.0233$ during the testing phase. Further analysis of the soft computing models indicated that the most critical parameters influencing the results were S_o, R_r, D_r, δ^*, and θ. These findings highlight the effectiveness of soft computing techniques in accurately modeling the Manning roughness coefficient in complex channel conditions and provide valuable insights for future research and practical applications in the management of flood events and waterway analysis.

Keywords: Compound Channel, Non-Prismatic Floodplain, relative Manning's roughness, NF-GMDH.

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Notation

n_r	Relative Manning's Roughness Coefficient
GMDH	Group Method of Data Handling
NF-GMDH	Neuro-Fuzzy Group Method of Data Handling
MLPNN	Multilayer Perceptron Neural Networks
D_r	relative flow depth
R_r	relative hydraulic radius
δ^*	relative dimension of the flow aspects
θ	angle of divergence and convergence of the section
S_o	longitudinal slope
R^2	Coefficient of Determination
DDR	Developed Discrepancy Ratio
RMSE	Root mean square error

1. Introduction

1.1. Background and Significance of Compound Channel Analysis

One of the central topics in hydraulic engineering has consistently been the analysis of river flow characteristics. As rivers traverse various terrains, including flat plains and mountainous regions, their cross-sectional profiles undergo significant changes [1]. Typically, rivers experience unsteady flow conditions. Furthermore, floods contribute to irregular and non-uniform flow patterns. These challenges are compounded by the meandering nature of rivers, particularly in plains where numerous bends are present. In contemporary river hydraulic modeling, the compound channel approach is employed, considering both the floodplain and the main channel [2]. Notably, the floodplain generally exhibits a lower flow velocity compared to the main channel, resulting in sediment deposition that increases the roughness of the floodplain relative to the main channel [3]. The most common metric for describing river discharge is the water level flowing through the river. A key component of river flow studies is the accurate prediction of discharge. During flooding events, rivers may overflow their banks, causing damage to areas beyond the floodplain. Precise discharge capacity calculations are essential for the construction, management, and maintenance of open channels, as well as for flood prediction efforts [2]. Consequently, techniques for accurately determining the discharge capacity of channels are vital for effective flood control. Accurate discharge predictions for open channels necessitate reliable roughness coefficient estimates. The Manning, Chezy, and Darcy-Weisbach equations are traditionally used to estimate discharge in uniform flow conditions within simple, non-prismatic compound channels. These methods were originally developed for basic channels to ascertain the roughness coefficient of the bed material [4]. However, in non-prismatic channels, bed roughness, geometric configurations, and hydraulic properties significantly influence the roughness coefficients. Therefore, a model to predict roughness coefficients is derived by incorporating these variables [2].

In open channel flow, Manning's formula is the most widely used approach due to its simplicity and practicality. Manning's formula, however, must be used with appropriate caution when applied to non-uniform compound channels. To accurately represent the boundary's real or effective variation, as Yen [5] proposed for simple uniform flows, Manning's n is considered a roughness factor that quantifies the roughness in terms of a geometric measure. The calculation of the roughness coefficient in compound channels is complicated by various hydraulic factors. Numerous techniques exist for determining a channel's roughness coefficient, including using tables, photographs, and mathematical formulas. While traditional methods may provide satisfactory results for simple channels, they often fail for more complex sections, particularly non-prismatic compound channels. As a result, there is a growing preference for soft computing methods to calculate Manning's coefficient due to their ability to handle complex hydraulic conditions [6].

1.2. Advances in Soft Computing Techniques

Researchers are increasingly turning to soft computing methods to model and estimate hydraulic flow parameters, especially in compound open channels with non-prismatic floodplains, because of the limited accuracy of numerical models and conventional techniques [7–11]. The complexity of non-prismatic channels requires sophisticated models to predict flow characteristics accurately. In compound channels with prismatic floodplains, various advanced methods have been employed to predict flow discharge. These include artificial neural networks [2], which simulate the flow dynamics based on learning from data, and fuzzy adaptive neural network models [12,13], which incorporate fuzzy logic to handle uncertainties in the flow parameters. Additionally, multivariate adaptive regression splines (MARS) [14] provide a flexible modeling approach that captures nonlinear relationships in the data, and gene expression programming [15], a type of evolutionary algorithm, has been used to develop predictive models based on natural selection principles. The MARS model, in particular, has been effectively utilized to predict discharge in meandering open channels [16], demonstrating its capability to manage complex flow patterns.

1.3. Gap in Research and Study Objective

Despite these advancements, there is a noticeable gap in research regarding the estimation of Manning's roughness coefficient in non-prismatic compound channels with converging and diverging floodplains using soft computing methods. The unique hydraulic characteristics of these channels, including variations in cross-sectional geometry and flow patterns, pose significant challenges for traditional modeling approaches. Therefore, this study focuses on developing advanced soft computing models, specifically Group Method of Data Handling (GMDH), Neuro-Fuzzy GMDH (NF-GMDH), and Multi-Layer Perceptron Neural Networks (MLPNN), to estimate the relative Manning's roughness coefficient (nr) in such channels. These models are designed to capture the complex interactions between hydraulic and geometric parameters, providing more accurate and reliable estimates of roughness coefficients. The GMDH algorithm is a self-organizing method that constructs models by iteratively selecting the best combination of input variables, making it well-suited for handling complex datasets. The NF-GMDH model combines the strengths of fuzzy logic and GMDH, enabling it to manage uncertainty and imprecision in the data while constructing accurate predictive models. MLPNN, a type of artificial neural network, consists of multiple layers of interconnected neurons that learn to represent the underlying patterns in the data through training. By leveraging these advanced soft computing techniques, the study aims to address the limitations of traditional methods and provide a robust framework for predicting Manning's roughness coefficient in non-prismatic compound channels. The development and validation of these models involve comprehensive data collection and analysis, ensuring that the models are capable of generalizing across different hydraulic conditions and channel configurations. This research not only contributes to the field of hydraulic engineering by enhancing the accuracy of flow predictions but also supports flood management and channel design by providing reliable tools for estimating channel roughness under complex flow conditions.

1.4. Contribution to the Field

This study introduces the application of advanced soft computing models, including GMDH, NF-GMDH, and MLPNN, for predicting Manning's roughness coefficient in complex compound channels with converging and diverging floodplains. While previous research has primarily focused on simpler or prismatic channels, this work addresses the challenges presented by non-prismatic geometries. By leveraging these advanced models, the accuracy and reliability of roughness coefficient predictions in such channels can be significantly enhanced. This research contributes to the field by providing a novel methodological framework that can be utilized for improved flood management and channel design, thus advancing the current understanding and capabilities in hydraulic engineering.

2. Materials and Methods

The dataset employed for estimating the nr using soft computing models comprises 196 experimental data sets that focus on converging and diverging compound channels. These data sets have been gathered from several published papers, specifically those authored by Bousmar [17], Bousmar et al. [18], Rezaei [19], Yonesi et al. [20], and Naik and Khatua [21]. This collection of data, which is summarized in Table (1), was compiled by Das et al. The discussion in this section covers several key aspects: it outlines the significant parameters, details both the input and output variables, and provides a comprehensive overview of the soft computing models that have been utilized. Furthermore, it delves into the modeling strategies that were employed as well as the criteria used for evaluation. An illustrative view of the non-prismatic compound channel with various converging geometries is provided in Figure (1).

a) b)

Figure 1. A view of the compound channel with non-prismatic floodplains a) θ =11.3º and b) θ = 3.8º [22]

The Manning roughness coefficient in this study is determined through the analysis of five critical input parameters:

1. **Longitudinal slope (S_o)**: This represents the gradient of the channel along its length.
2. **Relative Hydraulic radius (R_r)**: This is the ratio of the hydraulic radius to a reference value.
3. **Relative flow depth (D_r)**: This denotes the ratio of the flow depth to a reference depth.
4. **Relative dimension of the flow aspects (δ*)**: This parameter reflects the proportion of certain flow characteristics relative to a reference dimension.
5. **Convergence or divergence angle (θ)**: This measures the angle of the floodplain, with a positive sign indicating a convergence angle and a negative sign indicating a divergence angle.

By analyzing these parameters, the research aims to accurately determine the Manning roughness coefficient, which is crucial for understanding and modeling flow behavior in compound channels.

Through the careful analysis of these parameters, this research endeavors to precisely determine the Manning roughness coefficient. This coefficient is essential for comprehending and accurately modeling the flow behavior in compound channels. The research focuses on the relative Manning roughness coefficient of the flow, denoted as n_r, which was selected as the primary output variable. This coefficient n_r is defined as the ratio of the Manning roughness coefficient in the main channel (n_{mc}) to the Manning roughness coefficient in the floodplain (n_{fp}). Mathematically, this relationship is expressed as $n_r = \frac{n_{mc}}{n_{fp}}$. The aforementioned parameters can be encapsulated within a functional relationship, which is articulated in Eq. (1).

$$n_r = f\left(S_0, R_r, D_r, \delta^*, \theta\right) \tag{1}$$

Table 1 provides a comprehensive summary of the statistical analysis conducted on the various parameters that were employed to determine the relative Manning roughness coefficient within compound channels. These channels are characterized by floodplains that either converge or diverge. The analysis meticulously examines each parameter's influence and how they collectively contribute to the accurate calculation of the roughness coefficient, offering a detailed insight into the hydraulic behavior of such complex channel systems.

Table 1- Range of collected data set and Statistical analysis of parameters involved in determining n_r

Source	*Range*	S_0*10^{-3}	R_r	D_r	δ^*	θ	n_r
	max		4.590	0.522	6.540		0.830
	min		0.869	0.114	0.905		0.070
Rezaei [15]	st div	2.003	1.219	0.143	1.940	-3.81	0.278
	avg		2.505	0.305	4.313		0.591
	median		2.610	0.348	5.150		0.719
	max		4.400	0.538	6.360		0.837
	min		0.591	0.101	0.808		0.059
Bousmar [13]	st div	0.9	1.185	0.161	1.831	-11.3 -3.81	0.295
	avg		2.248	0.345	3.980		0.605
	median		2.392	0.416	4.585		0.747
	max		4.200	0.539	6.290		0.832
	min		0.561	0.102	0.819		0.052
Bousmar et al [14]	st div	0.9	1.187	0.152	1.926	5.71 3.81	0.289
	avg		2.361	0.321	4.166		0.592
	median		2.663	0.347	4.931		0.722
	max		35.090	0.364	1.900		0.806
	min		1.910	0.103	0.229		0.143
Yonesi et al [16]	st div	0.88	10.046	0.096	0.622	11.31 3.81	0.236
	avg		10.192	0.224	1.373		0.482
	median		6.600	0.252	1.656		0.552
	max		7.260	0.325	4.450		0.716
	min		0.850	0.059	0.293		0.047
Naik & Khatua [17]	st div	1.1	1.849	0.094	1.489	-13.38 -5	0.248
	avg		3.604	0.199	3.138		0.519
	median		3.595	0.227	3.795		0.634

2.1. Soft Computing Techniques

2.1.1. Group Method of Data Handling (GMDH)

The GMDH (Group Method of Data Handling) model, originally developed by Ivakhnenko [23] in the 1960s, has since been widely applied and refined in various fields, including hydraulic engineering. This model's ability to construct self-organizing networks makes it particularly suitable for handling complex datasets. The GMDH model is a sophisticated type of neural network that includes an input layer consisting of various variables and parameters, several intermediate layers, and an output layer. This model improves the precision of forecasting physical phenomena by incorporating optimization methods and approximation techniques into its framework. The connections between a system's input and output parameters in this neural network can be described through Volterra function series, which are similar to the discretized polynomial proposed by Kolmogorov-Gabor, as illustrated in the subsequent equation.

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ijk} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k + \cdots \quad (2)$$

where x_0, x_1, x_2, …, x_m is input vectors, and a_0, a_1, a_2, …, a_m is the vector of weight coefficients. In the GMDH structure, every neuron requires at least two inputs. The relationship between the variables influencing both input and output in each neuron is represented by a stimulus function, which can be linear or non-linear. The fundamental structure of the GMDH model is represented by the following formula involving quadratic polynomials with two input variables [24].

$$y = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_2^2 + w_5 x_1 x_2 \quad (3)$$

Where in $w_0, w_1, \cdots, w_5$ coefficients are polynomials. To construct the GMDH network, begin by considering binary combinations of the input parameters. Next, calculate the weight coefficients and corresponding error values for each neuron using the least squares method. An error criterion is then applied at each layer to select the optimal neurons based on classification features.

$$E = \frac{1}{n}\sum_{i=1}^{n}\left(y_{obs_i} - y_{prd_i}\right)^2 \quad (4)$$

y_{obs_i} and y_{prd_i} include observed and calculated values obtained from the numerical model, respectively. E and n denote the number of observational data points and the calculation error in each neuron (partial descriptor), respectively. The structure of the developed GMDH model can be observed in Figure 2.

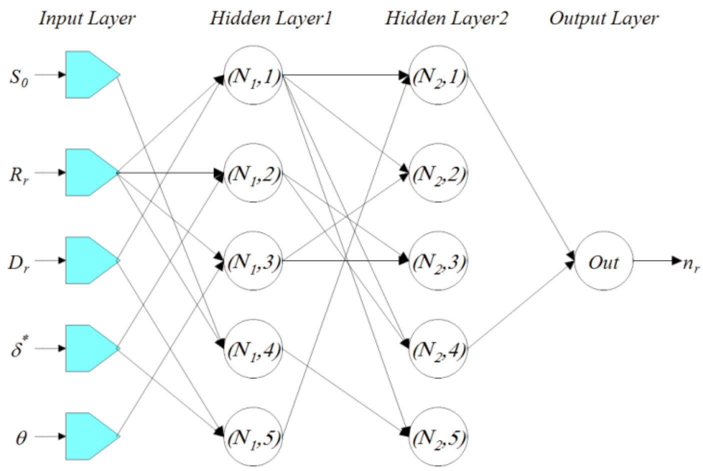

Figure 2. illustrates the structure of the GMDH network designed for estimating the relative Manning roughness coefficient in compound channels featuring converging and diverging floodplains.

2.1.2. Development of the NF-GMDH model

2.1.2.1. Neuro-Fuzzy Group method of data handling (NF-GMDH)

The Neuro-Fuzzy Group Method of Data Handling (NF-GMDH) model is an advanced soft computing technique that synergistically combines the principles of fuzzy logic with the self-organizing capabilities of the GMDH algorithm. This approach is particularly advantageous in modeling complex systems where uncertainties and imprecisions are inherent, such as hydraulic systems with non-prismatic compound channels.

The foundation of the NF-GMDH model lies in its use of simplified fuzzy reasoning rules. These rules allow the model to handle vagueness and ambiguity in the data, providing a robust framework for prediction. A typical fuzzy rule in the NF-GMDH model can be formulated as follows:

If *x* is *A* and *y* is *B*, then *z* is *C* [12].

In this context:

x and *y* represent input variables,

A and *B* are fuzzy sets associated with the inputs,

z is the output variable.

The NF-GMDH model employs Gaussian membership functions to define the fuzzy sets. The Gaussian function is chosen for its smooth and continuous nature, which is suitable for modeling hydraulic phenomena. The membership function for the *k*-th fuzzy rule of the *x*-th input value is expressed as [25]:

$$\mu_k(x) = \exp\left(-\frac{(x - c_k)^2}{2\sigma_k^2}\right) \tag{5}$$

where:

μ_k denotes the membership degree of x in the *k*-th fuzzy rule,

c_k represents the center of the Gaussian function,

σ_k is the standard deviation, determining the width of the Gaussian function.

Each neuron in the NF-GMDH model processes two input variables and generates an output, which subsequently serves as an input for the neurons in the following layer. The output of each neuron is defined as:

$$y = \sum_{k=1}^{m} w_k \mu_k(x) \tag{6}$$

where:

w_k is the weight associated with the *k*-th fuzzy rule,

μ_k is the membership degree of the input.

The model constructs its network by iteratively selecting the best combination of input variables, optimizing the connections between the inputs and outputs through fuzzy rules.

The NF-GMDH model is structured in multiple layers, with each layer comprising several neurons. The hierarchical design enables the model to capture complex interactions and dependencies among the variables. Each neuron's output in the current layer is determined by the outputs from the neurons in the preceding layer, allowing for a deep learning process that enhances the model's accuracy and generalization capabilities [26].

Training the NF-GMDH model involves determining the parameters that minimize the prediction error. Each neuron in the model includes six unknown coefficients: four Gaussian parameters (centers and widths) and two weighting coefficients. These parameters are optimized using sophisticated algorithms to ensure the model accurately reflects the underlying data patterns.

The optimization process involves:

- Initialization: Setting initial values for the Gaussian centers, widths, and weights.
- Forward Pass: Calculating the output of each neuron based on the current parameters.
- Error Calculation: Measuring the difference between the predicted and observed values using metrics such as RMSE.
- Backward Pass: Adjusting the parameters to reduce the error, typically using gradient descent or other optimization techniques.
- The final output of the NF-GMDH model is obtained by averaging the outputs of the last layer's neurons, ensuring a stable and reliable prediction.
- The NF-GMDH model's integration of fuzzy logic with the GMDH algorithm provides several benefits:
- Handling Uncertainty: Fuzzy logic effectively manages the uncertainties and imprecisions in hydraulic data, leading to more accurate predictions.
- Self-Organization: The GMDH component allows the model to self-organize, selecting the most relevant input variables and structuring the model dynamically.
- High Accuracy: The combined approach results in high prediction accuracy, as evidenced by the performance metrics obtained during model validation.

In summary, the NF-GMDH model offers a powerful and flexible tool for estimating the Manning roughness coefficient in complex hydraulic conditions. By leveraging the strengths of both fuzzy logic and the GMDH algorithm, this model provides accurate and reliable predictions, which are crucial for effective hydraulic engineering and management.

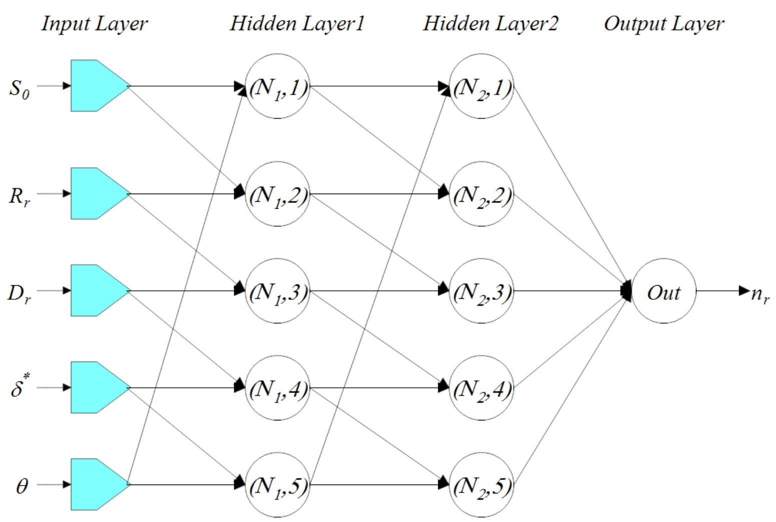

Figure 3. The structure of the NF-GMDH network developed to estimate the relative Manning roughness coefficient in the compound channels with converging and diverging floodplains.

2.1.3. Multiple-Layer Perceptron Neural Network (MLPNN)

The Multi-Layer Perceptron Neural Network (MLPNN) is a widely used type of artificial neural network, first introduced by Rumelhart et al. [27]. This model has been extensively applied in various fields, including hydraulic engineering, due to its ability to model complex, non-linear relationships in data. The MLPNN model consists of multiple layers of neurons, typically including an input layer, one or more hidden layers, and an output layer. Each neuron is connected to others through weighted connections, and the model learns by adjusting these weights during training through a process called backpropagation. Previous researchers have successfully utilized MLPNN to predict various hydraulic parameters, demonstrating its effectiveness in handling complex datasets. Most studies in water engineering leverage multi-layer perceptron networks with error back-propagation algorithms [28]. The optimal network structure is determined through careful consideration of configuration and activation functions. During training, initial weights are set either randomly or based on prior experimental findings. Typically, MLP networks use sigmoidal activation functions and are trained using techniques like Levenberg-Marquardt for enhanced performance and efficiency [29]. Structuring an effective network for a problem involves three main stages: stabilization of structure, training iterations, and performance validation. Figure 4 illustrates the developed neural network model architecture in this study.

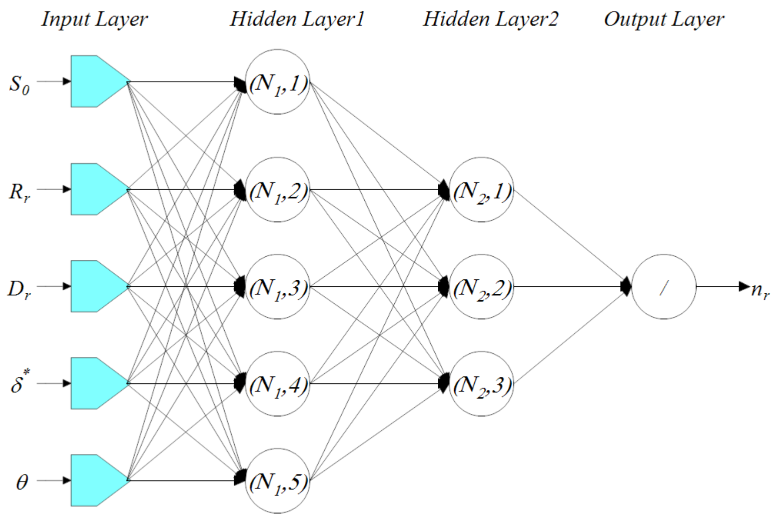

Figure 4. illustrates a schematic representation of the multilayer neural network architecture designed for estimating the relative Manning roughness coefficient in compound channels featuring converging and diverging floodplains.

2.2. Modeling Strategies and Evaluation Criteria

2.2.1. Modeling Strategies

In Eq. (1), soft computing models are employed to utilize five input parameters for predicting the relative Manning roughness coefficient in compound channels with non-prismatic floodplains. This necessitates selecting an optimal combination of one to five parameters for input variable configuration. Various methods can streamline this selection process. One approach involves applying the Gamma test, as previously employed by Das et al., to identify promising input combinations. Another method assesses model structure to prioritize influential parameters, enhancing the weighting assigned to them during the formulation of mathematical models. To evaluate model accuracy in this study, R^2 and *RMSE* metrics were employed. Data consisting of 196 samples were divided into training (80%) and testing (20%) sets. The training set facilitated model calibration, while the testing set validated its performance. Random assignment was used due to the non-time series nature of the data collection process.

2.2.2. Evaluation Criteria

In this research, a variety of statistical measures were utilized to evaluate and contrast the performance of the developed models. Among these measures were the Coefficient of Determination (R^2), Root Mean Square Error (*RMSE*), and Scattering Index (*SI*). To visually compare the performance of the models, Taylor diagrams were employed. Furthermore, a new metric, the Developed Discrepancy Ratio (*DDR*) index, was introduced to provide a more comprehensive evaluation of the models' tendencies towards over-prediction or under-prediction across different input data sets. The *DDR* index calculates the ratio of predicted values to observed values minus one; positive values indicate over-prediction, while negative values denote under-prediction. Detailed formulas for computing each of these indices are provided in Eq. (7) through (10).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{8}$$

$$SI = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}}{\bar{x}} \tag{9}$$

$$DDR = \left(\frac{x_i}{y_i}\right) - 1 \tag{10}$$

In these equations, n represents the number of data points, x_i denotes the predicted results from numerical simulations, y is the outcome derived from laboratory experiments, and $\bar{x}$ is the mean value of the results obtained from laboratory measurements, calculated using Eq. (11).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{11}$$

This approach ensures a robust and nuanced assessment of the models' predictive capabilities, allowing for precise identification of their strengths and weaknesses in various scenarios.

3. Results and Discussion

In this section, we thoroughly present and analyze the findings derived from the development and application of soft computing models, specifically the Group Method of Data Handling (GMDH), Neuro-Fuzzy GMDH (NF-GMDH), and Multi-Layer Perceptron Neural Network (MLPNN). These models are utilized to estimate the relative Manning roughness coefficient (n_r) in compound channels characterized by converging floodplains. Each model is discussed in detail to provide a comprehensive understanding of their performance and the methodology employed.

3.1. GMDH Model Estimation Results

This subsection elaborates on the outcomes obtained through the implementation of the GMDH model for estimating the relative Manning roughness coefficient in compound channels with non-prismatic floodplains. As outlined in the materials and methods section, the GMDH model operates using neurons governed by quadratic polynomial equations. Each neuron within the model incorporates two specific parameters. The governing equation of each neuron comprises six coefficients, which are meticulously calibrated during the training phase. The primary objective of this calibration is to minimize the error between the predicted and actual values of the relative Manning roughness coefficient. The GMDH model's strategy for development is selective, ensuring that not all neurons from the initial layer contribute to the subsequent layers. Instead, only those neurons that exhibit superior accuracy in estimating the relative Manning roughness coefficient are chosen for inclusion in the next layer. This selective approach enhances the model's overall accuracy and efficiency. Figure 3 illustrates the architecture of the GMDH model tailored for estimating the relative Manning roughness coefficient in compound channels with non-prismatic floodplains. The statistical performance metrics of the developed GMDH model during the training phase are notably high, with a coefficient of determination ($R^2_{\mathrm{GMDH\ train}}$) of 0.992 and a root mean square error (RMSE) of 0.0088. During the testing phase, these metrics slightly improve, with $R^2_{\mathrm{GMDH\ test}}$ reaching 0.993 and RMSE decreasing to 0.0068. Furthermore, the scattering index (*SI*), which is a measure of the dispersion of the data points around the regression line, is calculated to be 0.028 for the training phase and 0.004 for the testing phase. These results indicate a high level of accuracy and reliability in the model's estimations. Figure 5 provides a comparative visualization of the GMDH model's performance across the training and testing phases.

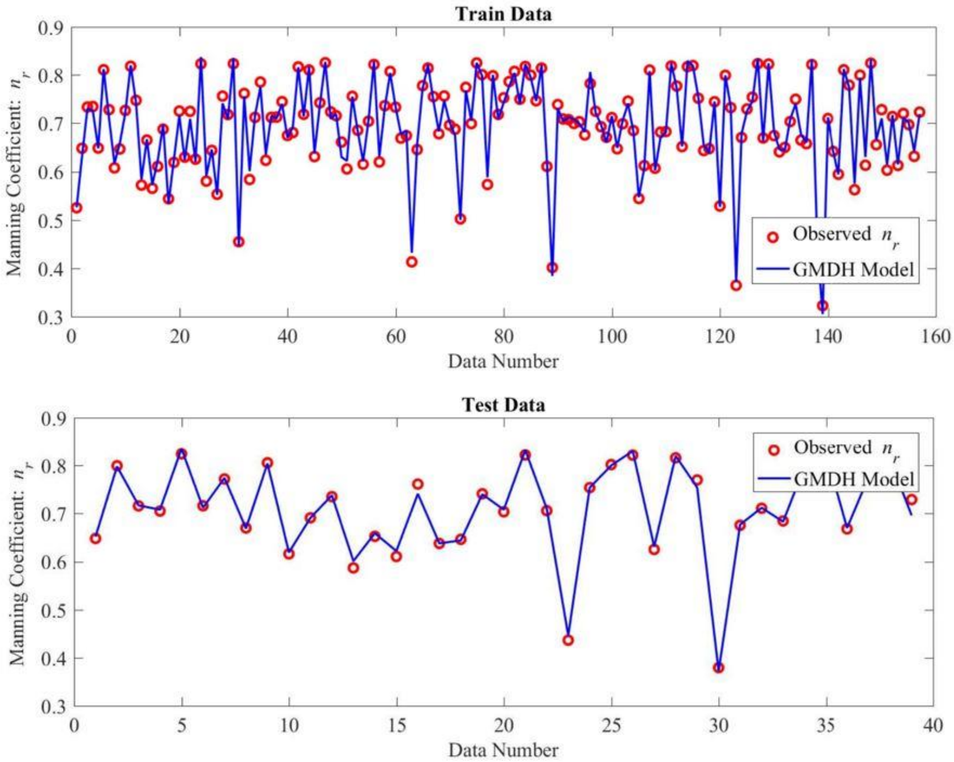

Figure 5. Comparison between training and testing phases for GMDH model performance

3.2. NF-GMDH Model Estimation Results

In this subsection, we delve into the results yielded by the NF-GMDH model, which integrates the principles of neuro-fuzzy systems with the GMDH approach. As depicted in Figure 4, the NF-GMDH model features a complex structure comprising two hidden layers. Each hidden layer consists of five neurons, contributing to the model's ability to capture intricate patterns within the data. The output layer, on the other hand, consists of a single neuron that aggregates the outputs from the neurons in the preceding hidden layer by computing their average. The performance metrics for the NF-GMDH model during the training phase indicate a coefficient of determination ($R^2_{\text{NF-GMDH train}}$) of 0.87 and an RMSE of 0.0335. During the testing phase, these metrics are $R^2_{\text{NF-GMDH test}}$ of 0.78 and an RMSE of 0.0425. Additionally, the SI for the NF-GMDH model's performance in the training phase is calculated to be 0.048, while in the testing phase, it is 0.06. These performance indicators suggest that while the NF-GMDH model is robust, it does exhibit some variability in its predictive accuracy between the training and testing phases. Figure 6 illustrates the NF-GMDH model's performance during its development phases, providing a visual comparison of its predictive capabilities in both training and testing scenarios.

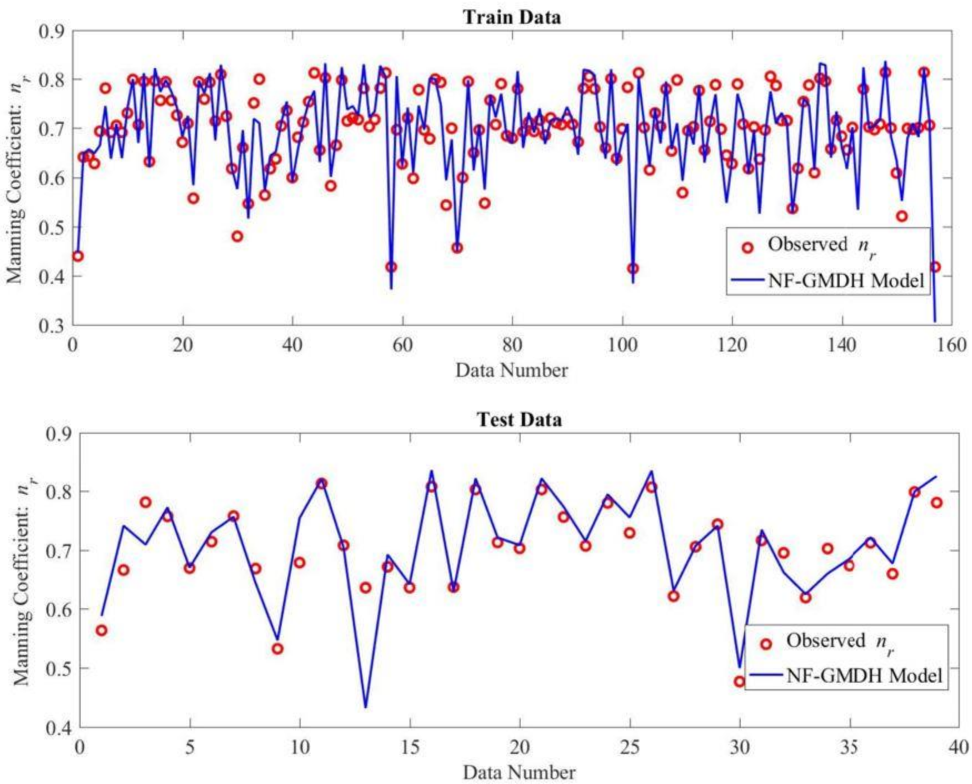

Figure 6. Comparison between training and testing phases for NF-GMDH model performance

3.3. MLPNN Model Estimation Results

The MLPNN model represents a prevalent soft computing approach in Hydraulic Engineering. As outlined in the materials and methods section, its development follows a systematic trial-and-error methodology. The architecture of the MLPNN comprises two hidden layers: the first layer is composed of five neurons, and the second layer consists of three neurons. The schematic of the constructed MLPNN model is illustrated in Figure 2. The statistical indicators of the developed MLPNN model in the training phase are $R^2_{\text{MLPNN train}} = 0.999$ and $RMSE_{\text{MLPNN train}} = 0.001$, and in the test phase are $R^2_{\text{MLPNN test}} = 0.999$ and $RMSE_{\text{MLPNN test}} = 0.001$. The scattering index (*SI*) of this model's performance in the training and testing phases is equal to $SI_{\text{MLPNN train}} = 0.0012$ and $SI_{\text{MLPNN test}} = 0.0015$. The performance of the developed MLPNN model in different phases of development (training and testing) is presented in Figure (7).

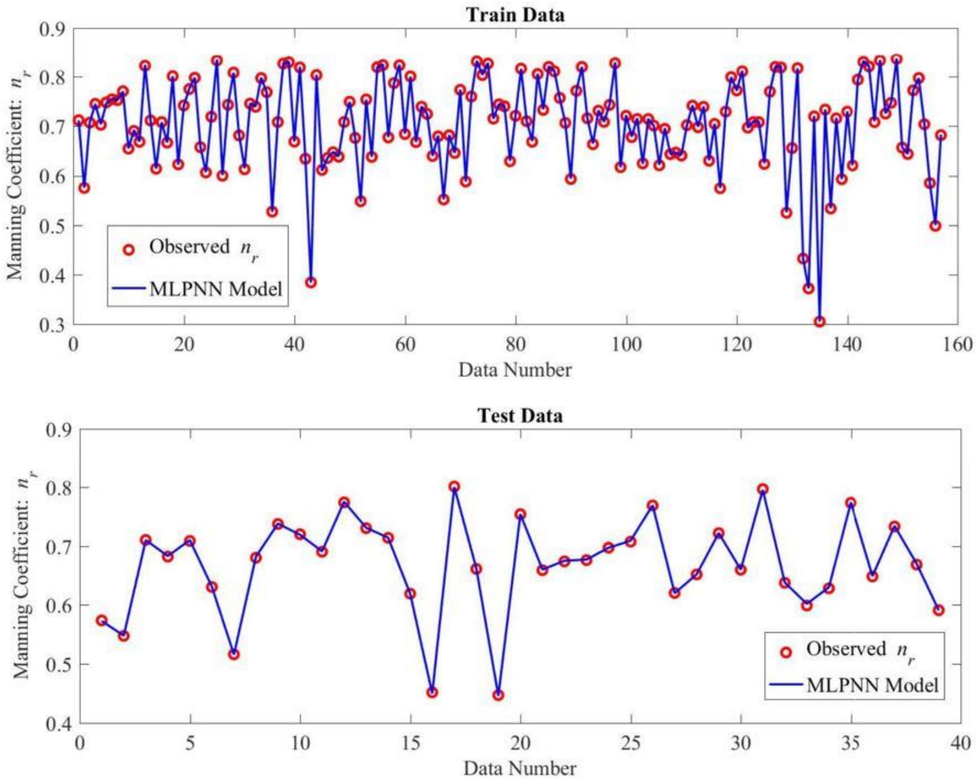

Figure 7- Comparison between training and testing phases for MLPNN model performance

Table 2 presents the statistical indices used to evaluate errors in the model for estimating the relative Manning roughness coefficient.

Table 2- The results of error evaluation by statistical indices

Model	Phase	Error Index			
		R^2	RMSE	SI	DDR%
GMDH	Train	0.992	0.0088	0.028	-0.003
	Test	0.993	0.0068	0.004	0.157
NF-GMDH	Train	0.87	0.0335	0.048	-0.005
	Test	0.78	0.0425	0.06	0.194
MLPNN	Train	0.999	0.001	0.0012	0.0324
	Test	0.999	0.001	0.0015	0.0233

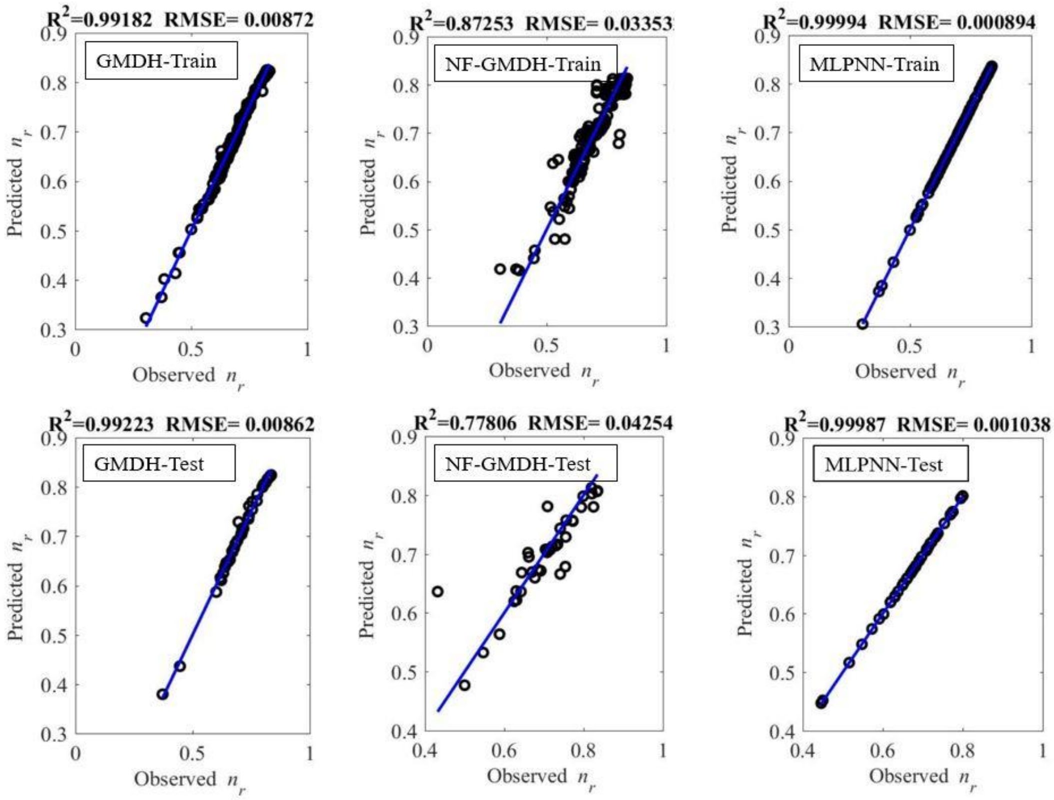

Figure 8- Comparison between predicted and observed values for n_r

Statistical analysis of the models developed in this study to estimate the Manning roughness coefficient reveals that the MLPNN model exhibited superior performance during the training phase, displaying significantly lower data scattering indices compared to alternative methods like GMDH and NF-GMDH. Figure 9 illustrates the DDR index comparison across the models during the testing phase.

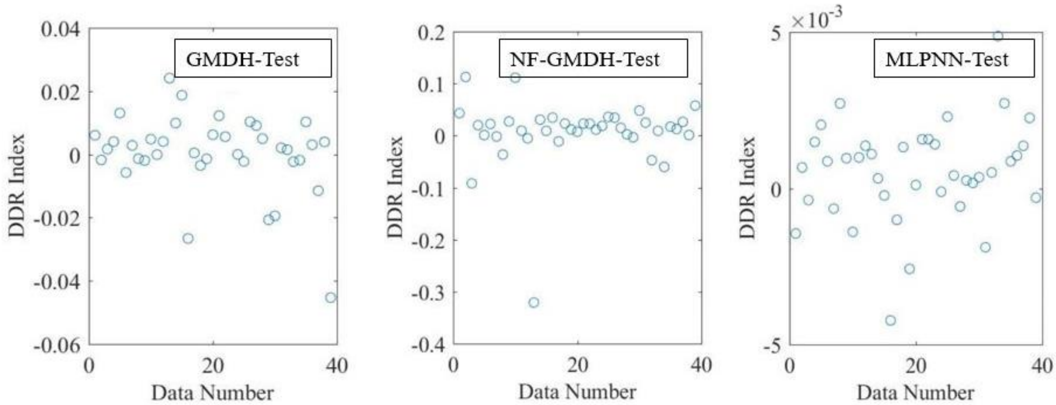

Figure 9. DDR index for models in testing phases

To effectively assess and differentiate model performance during both training and testing phases, Taylor diagrams are presented in Figures 10 and 11, respectively. Analysis of the training phase diagram demonstrates that the MLPNN model exhibits superior performance with the highest correlation coefficient and the lowest standard deviation among the compared models. Similarly, during the test phase, the GMDH and NF-GMDH models demonstrate comparable performance levels.

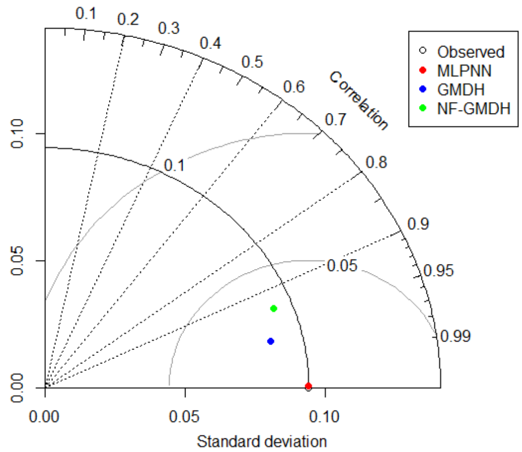

Figure 10. Taylor diagram of performance of developed models in the training phase

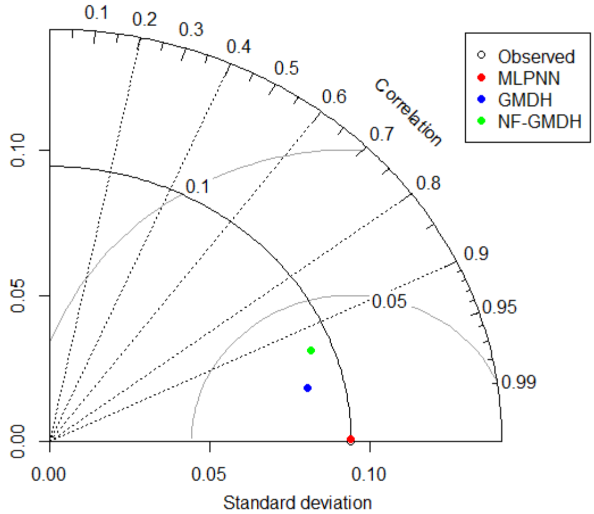

Figure 11. Taylor diagram of performance of developed models in the testing phase

3.4. Comparing with Previous Studies

To thoroughly evaluate the performance of non-prismatic compound channels in comparison to meandering compound channels, we conducted a comprehensive review of previous studies focusing on Manning's roughness coefficient in compound channels. The aim was to understand how different methodologies have been utilized to estimate Manning's coefficient and how our approach compares in terms of accuracy and reliability.

Mohanta et al. [30] conducted an in-depth study using advanced machine learning techniques to investigate Manning's coefficient in meandering compound channels. They applied several sophisticated methods including the Group Method of Data Handling Neural Network (GMDH-NN), MARS, and SVR. The results from their research showcased the exceptional predictive capabilities of these techniques. Specifically, the GMDH-NN method achieved an R^2 of 0.959 during the training phase and an *RMSE* of 0.0012. During the testing phase, the GMDH-NN maintained high performance with R^2 of 0.939 and an *RMSE* of 0.0013. These findings highlighted that the GMDH-NN method was superior to MARS and SVR in terms of accurately predicting Manning's n. Further advancing this research, Pradhan and Khatua [31] explored the application of GEP to estimate Manning's n in meandering compound channels. Their study indicated significant improvements over conventional methods, achieving an impressive R^2 of 0.999 and an *RMSE* of 1.625. This demonstrated the potential of GEP as a highly effective tool for such estimations. In our study, we conducted a comparative analysis of the statistical indices (R^2 and *RMSE*) from the models developed by Mohanta et al. [30] and Pradhan and Khatua [31], alongside our own models. The results showed that the soft computing models we introduced offered notably higher accuracy. Our models, designed using advanced computational techniques, consistently outperformed the previously mentioned methods in terms of precision and reliability. This comparison underscores the advancements made in the field of hydraulic engineering through the application of cutting-edge machine learning and computational techniques. By leveraging these advanced methodologies, we can achieve more accurate predictions of Manning's roughness coefficient, which is crucial for the design and analysis of efficient water conveyance systems. The continual improvement in predictive models not only enhances our understanding of flow dynamics in compound channels but also contributes to the development of more efficient and reliable engineering solutions.

4. Conclusions

This research has focused on the development and application of advanced soft computing techniques to estimate the relative Manning's roughness coefficient (n_r) in compound channels with converging and diverging floodplains. The study employed a dataset of 196 experimental observations and explored three distinct models: GMDH, NF-GMDH, and MLPNN. The comprehensive analysis and comparison of these models provided significant insights into their effectiveness and accuracy in predicting nr under complex hydraulic conditions. Key Findings:

1. Superior Performance of MLPNN: The MLPNN model demonstrated the highest accuracy among the three models, with an R^2 of 0.999 and the lowest *RMSE* of 0.001 during both the training and testing phases. The Scattering Index (*SI*) further validated the robustness of MLPNN, making it a highly reliable tool for hydraulic modeling in compound channels.
2. Effectiveness of GMDH and NF-GMDH: Both GMDH and NF-GMDH models also exhibited strong predictive capabilities, with R^2 values of 0.993 and 0.78, and *RMSE* values of 0.0068 and 0.0425 respectively, during the testing phase. These models, particularly GMDH, showed excellent performance in capturing the complexities associated with non-prismatic floodplain geometries.
3. Critical Parameters: The study identified longitudinal slope (S_o), relative hydraulic radius (R_r), relative flow depth (D_r), relative dimension of flow aspects (δ^*), and the convergent or divergent angle (θ) as crucial parameters influencing the Manning roughness coefficient. The models effectively integrated these parameters to provide accurate estimations of n_r.
4. Comparative Analysis: The developed models were compared with previous studies focusing on meandering compound channels. The MLPNN model, in particular, outperformed traditional methods and other advanced techniques such as GMDH-NN, MARS, and SVR in terms of accuracy and reliability. This highlights the potential of

soft computing models in handling complex flow conditions more effectively than conventional approaches.

5. Enhanced Predictive Models: The successful application of MLPNN, GMDH, and NF-GMDH models underscores the potential of soft computing techniques in enhancing predictive models for hydraulic engineering. These models provide more accurate and reliable estimates of roughness coefficients, which are essential for effective flood management, channel design, and waterway analysis.
6. Practical Applications: The findings of this study can be directly applied to real-world scenarios involving floodplain management and the design of water conveyance systems. Engineers and researchers can utilize these models to improve the accuracy of flow predictions, thereby optimizing the design and maintenance of hydraulic structures.
7. Future Research Directions: This research opens avenues for further studies on the application of soft computing models in different hydraulic contexts. Future research could explore the integration of additional parameters, the application of these models to other types of channels, and the development of hybrid models that combine the strengths of various soft computing techniques.

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