

# An Artificial Intelligence-Driven Evaluation of Scour Depth Around Bridge Piers

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## ABSTRACT

Accurate estimation of scour depth around bridge piers remains a challenging task due to the complex interaction between flow hydraulics and sediment dynamics; however, it is vital to safeguard bridge stability and reduce economic and human losses. Empirical relations are insufficient to satisfactorily simulate this very complex phenomenon. This study proposes intelligent models for the estimation of scour depth around bridge piers using three different modelling approaches, namely Multilayer Perceptron Artificial Neural Networks (MLP-ANN), Radial Basis Function Networks (RBFN), and Multigene Genetic Programming (MGGP). In addition, dimensional analysis was used to reach dimensionless quantities, simplifying the complex relations and also improving the accuracy of the models. The ANN model achieved the highest accuracy, with an  $R^2$  value of 0.94, an RMSE of 0.032, and a WI of 0.97, indicating an excellent alignment with the observed data. The MGGP model yielded an  $R^2$  of 0.91, demonstrating balanced performance in multiple statistical metrics. In contrast, the Basis Radial Function (BRF) model, although robust, employed a more conservative estimation approach, with an  $R^2$  of 0.86, and exhibited limited sensitivity to extreme values. The results of the sensitivity analysis revealed that the bedload transport rate, dimensionless time, and depth-to-width ratio are critical parameters in scour depth calculations, which tangibly confirms the ability of ANNs and dimensional analysis to improve anti-scouring in designs and maintenance, and reduce the failure risk of structures. The findings highlight the effectiveness of machine learning in enhancing hydraulic prediction and improving the resilience of bridge design.

*Keywords-scour; artificial neural networks; artificial intelligence; bridge pier; dimensional analysis*

## I. INTRODUCTION

Scour around bridge piers occurs due to localized sediment erosion induced by high-velocity flow and vortex formation near the pier base, weakening the stability of the foundation and contributing to bridge failures. Traditional empirical models often overlook the complex site-specific factors that influence this process. Advanced data-driven models can capture the nonlinear relationships between flow dynamics, pier geometry, and sediment behavior, providing more accurate and reliable tools for bridge design and safety evaluation [1].

In the last few decades, the importance of finding accurate scour depth predictor models has increased, as traditional empirical formulas provide low accuracy in some cases, particularly in complex/nonlinear hydraulic conditions [2]. Artificial Intelligence (AI) methods, such as Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Random Forests (RF), have been used to flexibly estimate scour depth using various hydraulic parameters [3]. AI models can enhance engineering design practices, mitigate structural risk, and promote sustainability in bridge infrastructure [4]. ANNs have also been utilized to predict the

stable scour depth around bridge piers, extending the capabilities beyond the limitations of traditional theoretical and conventional empirical models. Multilayer neural network models have been used with experimental data, showing close agreement between neural network prediction and experimental data, with greater precision than conventional models [5]. Generative AI has also been applied in structural response assessment, necessitating more intricate evidence of validity due to concerns over transparency and consistency. Therefore, combining several AI models can promote accuracy in testing [6]. The Genetic Programming (GP) model has demonstrated superior accuracy compared to ANFIS (Adaptive Neuro-Fuzzy Inference System) and conventional empirical equations, achieving an average prediction error of only 6%. Its application to the Imbaba Bridge in Egypt confirmed its reliability by providing consistent and dependable scour depth predictions across various hydraulic conditions [7].

In [8], machine learning models achieved 95.93% accuracy in predicting scour depth at bridge piers, surpassing the accuracy of traditional methods. Scour depth predictions using ANN and ANFIS models have been found to be accurate, with flow velocity and particle diameter being the most influential factors. Hybrid models with different algorithms provide more accurate scour depth predictions compared to single traditional equations [4, 9]. In [10], a hybrid Adaptive Neuro-Fuzzy Inference System- Differential Evolution algorithm/Singular Value Decomposition (ANFIS-DE/SVD) model was developed to predict scour around pier groups, utilizing SVD and DE for parameter tuning and Pareto analysis to enhance accuracy. Sensitivity analysis revealed that pier diameter and number were key factors. In addition, models such as Extreme Learning Machine (ELM) and Extreme Gradient Boosting (XGBoost) outperformed traditional empirical equations in predicting scour, being consistent with theoretical knowledge of scour [11]. In [12], ANN and ANFIS were compared to Dimensional Analysis-Based Empirical Equations (DAEE) equations for estimating scour depth around bridge piers. The Double Layer DL ANN-3 model (Nash-Sutcliffe Efficiency - NSE = 0.986) outperformed both, with pier dimensions identified as the key factor. In [13], RF and XGBoost-PSO achieved high accuracy ( $R \approx 0.995$ ) in scour depth prediction. In [14], the superior performance of ELM and GEP techniques in estimating scour depth was highlighted, despite some challenges. In [15], the ELM model predicted scour depth at pier shoulders with high accuracy (correlation coefficient  $R = 0.97$ , Root Mean Square Error RMSE = 0.162) and low uncertainty ( $\pm 0.026$ ), outperforming traditional equations and proving effective for engineering applications.

This study uses artificial intelligence to estimate the scour around bridge piers and evaluate advanced modelling techniques. Reviewing past data enables the development of a new AI-based model, offering improved reliability compared to conventional techniques. This study utilizes the influence of hydraulic factors to evaluate the performance of AI models compared to traditional equations, enhancing design decision-making and refining bridge design and maintenance strategies.

## II. THE ROLE OF AI IN ENGINEERING

Artificial intelligence, with machine learning as a key component, plays a crucial role in modern engineering by combining data analytics and statistical methods. This integration improves predictive accuracy and facilitates more informed decision-making in engineering projects [16]. Higher-level solutions to complex problems can be achieved by combining AI with engineering data interpretation and analysis. Dimensional Analysis (DA) can convert big data into actionable information, simplifying various operational processes and enhancing decision accuracy.

## III. ARTIFICIAL NEURAL NETWORK (ANN)

ANNs function like the human brain, utilizing interconnected neurons to process complex data. The Multi-Layer Perceptron (MLP) is the most commonly known type of ANN and has been widely used to improve predictive analysis of data in engineering models based on large datasets [17]. The MLP-ANN model was developed using the Neural Networks tool in the SPSS software. This model was trained by passing the input forward through the network (forward propagation) and getting outputs. The weights and biases were iteratively adjusted using the classic backpropagation algorithm, which calculates the error gradient and changes the parameters to minimize the difference between the estimated and observed values. Backpropagation is commonly used to train feedforward neural networks because of its efficiency. The learning rate was 0.01. The algorithm stopped the training process after 1000 epochs or continued if the model error was still greater than 0.001. These values were used as hyperparameters in the experiment to ensure stable and efficient convergence. Training continued until either the error function was minimized or the maximum number of iterations was reached. This algorithm proved extremely useful in capturing the complex and nonlinear relationships inherent in scour prediction with high precision.

## IV. RADIAL BASIS FUNCTION NETWORKS (RBFN):

RBFN is a neural network that combines supervised learning with unsupervised learning. The hidden layer of an RBFN uses the Gaussian function as the activation function. RBFN consists of the Input Layer, which pushes the input data directly through, the Hidden Layer, which uses an unsupervised learning-trained RBF to calculate the distances between the inputs and the function centers, and the Output Layer, which uses backpropagation to adjust weights to minimize errors. This study implemented an RBFN using the Neural Networks module of the SPSS software. The model was developed, taking the 10 input variables and normalizing them (both input and output) in the first hidden layer of 20 neurons with a Gaussian radial basis activation function. The spread (width) parameters of the radial basis functions were adaptively optimized, with minimum and maximum values of 0.137 and 0.45. Training was achieved using the linear least squares algorithm to estimate the weights of the output layer, and convergence was satisfied once the error criterion was 0.001 or the maximum training epochs had been reached. The input variables were normalized to the range [0, 1] to ensure that all features are equal in weight and improve stability.

V. MULTIGENE GENETIC PROGRAMMING (MGPP)

MGPP was used to develop formulas for complex issues, such as scour depth. GP was used to increase the predictability of the genetic algorithm using a relatively straightforward and simple model [18]. This study used GenexProTools 5.0. The configuration was guided by the scientific literature and had iterative tuning. Initially, the MGPP model was made up of 4 symbolic genes. The length of the chromosome was 5 with a population size of 100. The crossover, mutation, and reproduction rates were 85%, 10%, and 5%, respectively. Tournament selection was used to enhance convergence efficiency. All constants were optimized during the genetic evolution. Sediment properties and flow characteristics were used to make the scour depth the output target value. The Bootstrap method was used to capture the interaction of variables and to decrease the effect of outliers.

VI. DATA COLLECTION

The dataset used in this study involved findings from validated experiments carried out on the scour of bridge piers under different hydraulic and geometric conditions, as reported in the literature [18-33]. These studies generated diverse measurements of parameters governing the scour process and are considered reliable. Flow and sediment-related characteristics, pier geometry, and environmental parameters were collected as variables. These parameters were further organized and preprocessed to provide input variables for AI models, while the maximum scour depth ( $d_s$ ) was assigned as the output variable. The following equation describes the relationship between scour depth and these factors:

$$d_s = f \left( V, V_c, B, h, g, \nu, C_s, L, \rho_w, \rho_s, d_{50}, \tau_b, \alpha, T, S, \tau_c, SG, \theta, \tau_c, T \right) \quad (1)$$

VII. DIMENSIONAL ANALYSIS

Dimensional analysis simplifies complex relationships by defining dimensionless parameters, as described in Buckingham's  $\pi$ -theorem. This ensures physical consistency in the model and enables its application across a wide range of hydraulic scenarios. In addition, these dimensionless groups reduce the number of independent variables expressed in:

$$\frac{d_s}{B} = f \left( \frac{V B}{\nu}, \frac{V}{\sqrt{gh}}, C_s, \frac{L}{B}, \frac{\tau_b}{(\rho_s - \rho_w) g d_{50}}, K_\alpha \right) \quad (2)$$

The bedload transport rate is  $\theta = \frac{\tau_b}{(\rho_s - \rho_w) g d_{50}}$ , the flow angle of attack is given by  $K_\alpha = \left( \cos \alpha + \left( \frac{L}{B} \right) \sin \alpha \right)^{0.65}$ , non-dimensional time is given by  $T^* = (T_{flow} * V) / h$ ,  $d_{armor} = \tau_c * SG / [f_w * g * (SG - 1)]$ , and  $\tau_c = [(f_s - f_w) * g * d_{50} * \theta]$ . Here,  $B$  is the pier diameter/width (m),  $d_{50}$  is the median particle size (m),  $d_{armor}$  is the critical particle size (m),  $d_s$  is the maximum scour depth (m),  $g$  is the gravitational acceleration (m/s<sup>2</sup>),  $h$  is the flow depth (m),  $K$  is an empirical coefficient,  $L$  is the length of the pier (m),  $S$  is the spacing between piers (m),  $V$  is the flow velocity (m/s),  $V_c$  is the critical flow velocity (m/s),  $\alpha$  is the angle between the approaching water flow and the longitudinal axis of the pier ( $^\circ$ ),  $\theta$  is the Shields' parameter,  $\nu$  is the viscosity of water (m<sup>2</sup>/s),  $\rho_s$  is the density of sediment (kg/m<sup>3</sup>),  $\rho_w$  is the density of water (kg/m<sup>3</sup>),  $\tau_b$  is the bed shear stress (N/m<sup>2</sup>),  $\tau_c$  is the critical shear stress (N/m<sup>2</sup>),  $SG$  is the specific gravity, and  $T_{flow}$  is the flow time (s).

VIII. DESCRIPTIVE STATISTICS

Descriptive statistics in Table I reveal significant hydraulic and geometric variability in the data. The positive skewness in the Froude number ( $Fr$ ),  $T^*$ , and  $S/B$  indicates that medium to low-energy flow conditions dominate scour development. The narrow 95% confidence intervals for all variables enhance the reliability of the data. The presence of negative values results from the normalization process applied to the dataset, which centers variables around zero to enhance model training while maintaining the integrity of the original physical parameters. Figure 1 analyzes the data spread and identifies central values and deviations related to scour around bridge piers. Whiskers indicate extreme cases, particularly in geometric variables such as pier length-to-width ratio and pier spacing, highlighting the influence of design on scour enhancement under specific flow conditions. Figure 2 illustrates the strength and direction of relationships between the main variables. A strong negative correlation between relative scour depth and Reynolds number ( $Re$ ) and depth-to-width ratio suggests that scour depth decreases as  $Re$  increases. Conversely, a strong positive correlation between  $d_s/B$  and normalized flow time suggests that longer flow durations are associated with increased scour. Additionally, positive correlations exist between pier spacing and scour risk, indicating that relative velocity interacts with other factors.

TABLE I. DESCRIPTIVE STATISTICS OF VARIABLES

Statistic	Re	Fr	C <sub>s</sub>	L/B	θ	α	T*	S/B	V/V <sub>c</sub>	h/B	d <sub>s</sub> /B
Number of observations	581	581	581	581	581	581	581	581	581	581	581
Minimum	-0.9	-0.5	-1.2	-1.5	-1.1	-2.1	-0.4	-0.2	-2.3	-1.2	-1.3
Maximum	1.8	3.9	2.5	5.0	4.2	2.6	4.0	8.3	4.8	3.1	3.1
Frequency of minimum	1.0	1.0	85.0	9.0	1.0	9.0	404	551	1.0	134	6.0
Freq. of maximum	134	3.0	12.0	1.0	3.0	1.0	11.0	3.0	6.0	8.0	1.0
1 <sup>st</sup> Quartile	-0.8	-0.4	-1.0	-0.8	-0.7	-1.3	-0.4	-0.2	-1.0	-1.0	-0.8
Median	-0.4	-0.4	-0.2	-0.8	-0.2	-0.2	-0.4	-0.2	-0.1	-0.5	-0.1
3 <sup>rd</sup> Quartile	0.1	-0.2	0.9	1.1	0.3	1.1	-0.2	-0.2	0.9	1.2	0.6
Skewness (Pearson)	1.1	2.8	0.6	0.4	1.6	-0.1	3.5	6.1	1.8	0.6	0.7
Lower bound on mean (95%)	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Upper bound on mean (95%)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Mean absolute deviation	0.8	0.6	0.8	1.0	0.7	0.9	0.5	0.4	0.7	0.9	0.8

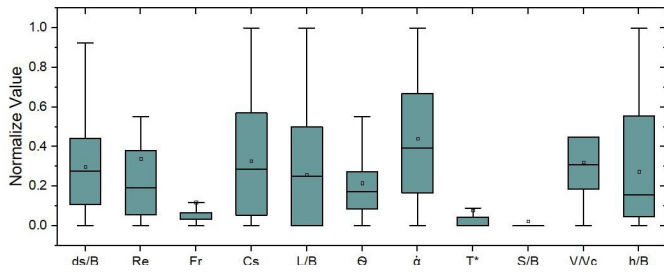


Fig. 1. Boxplot of the distribution of standardized values for the main variables.

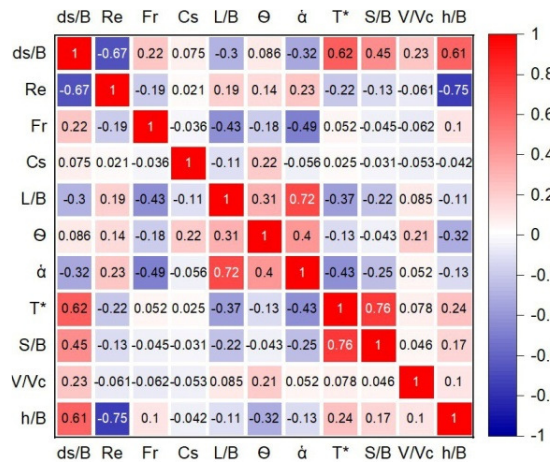


Fig. 2. Correlation heatmap for the main variables of the study.

IX. MODEL PERFORMANCE EVALUATION INDICATORS

Figure 3 demonstrates the accuracy of three machine learning models (ANN, BRF, and MGGP) based on the relative scour depth ( $d_s/B$ ) collected data. The ANN model demonstrated its ability to identify fundamental trends, as it accurately fits the observed distribution. In contrast, BRF demonstrated a more confined and less dispersed distribution, potentially suggesting that the model predictions are more conservative. In contrast, the MGGP also demonstrated an increased distribution, capturing all the data variability, but may be more exposed to higher estimated variance. Relative scour depth values  $d_s/B$  were compared for all three forecasting models (ANN, BRF, and MGGP), as shown in Figure 4. The set distribution and point clustering are very close to the optimal prediction line, indicating that the forecasting models provide highly accurate predictions. BRF offers a more conservative approach to handling extreme data with a narrower distribution than ANN. ANN provides a more accurate prediction compared to BRF and MGGP. Figure 5 and Table IV demonstrate the predictive capacities of the ANN, MGGP, and BRF models in estimating the relative scour depth around the bridge piers, including the correlation coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Standard Deviation (STD). The ANN model demonstrates the closest agreement with observed data, indicating strong correlation and low prediction error. The MGGP model also shows reasonable predictive capacity, while the BRF model exhibits comparatively lower consistency in capturing observed variations.

TABLE II. ANN PARAMETER ESTIMATES

Predictor	Predicted				
	Hidden Layer 1			Output Layer	
	H(1:1)	H(1:2)	H(1:3)	$d_s/B$	
Input Layer	(Bias)	.827	-.049	-1.119	
	$R_e$	-.428	-.292	.186	
	$F_r$	2.055	-.401	.060	
	$C_s$	.119	-.151	.063	
	$L/B$	.053	-.112	-.109	
	$\theta$	.240	.062	-1.366	
	$\alpha$	.100	-.135	.292	
	$T^*$	.830	.179	.180	
	$S/B$	.239	-.154	-.184	
	$V/V_c$	-.232	.390	-.171	
	$h/B$	.095	.442	.095	
Hidden Layer 1	(Bias)				-.923
	H(1:1)				.880
	H(1:2)				.619
	H(1:3)				-.563

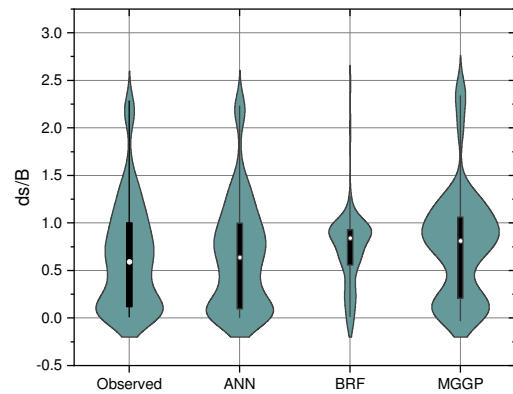


Fig. 3. Violin plot comparing the performance of different predictive models used in the study against the observed data.

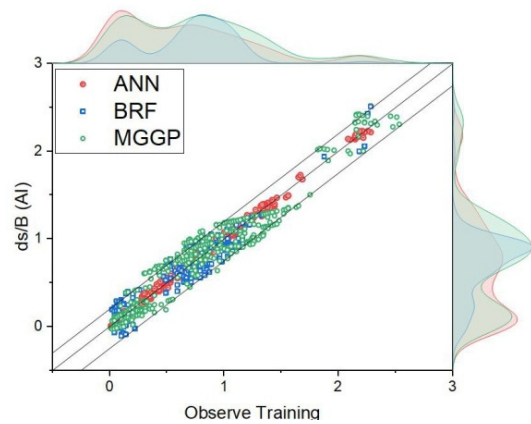


Fig. 4. Scatter plot with  $\pm 10\%$  error and density plot illustrate the performance of the predictive models.

TABLE III. STATISTICAL PERFORMANCE INDICATORS.

Model	R	RMSE	MAE	STD
ANN	0.99	0.032	0.025	0.57
MGGP	0.95	0.054	0.041	0.63
BRF	0.91	0.067	0.059	0.50

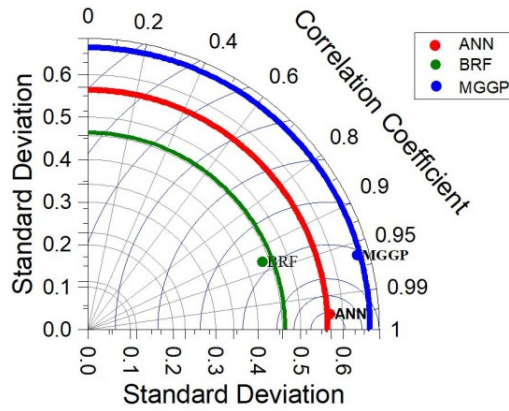


Fig. 5. Taylor plot illustrating the performance of the predictive models.

Various statistical measures were used to evaluate model performance: NSE (measures prediction accuracy), WI (assesses prediction accuracy with a perfect match at 1), RMSE, MSE, STD, CC (strength of the relationship between actual and predicted values),  $R^2$ , BIAS (average difference between actual and predicted values), ME (average error between predictions and actual values), EVS (variance explained by the model), and Theil's U-statistic (compares forecast accuracy with a naive model) [34]. Figure 6 presents a comprehensive comparison of model performance based on statistical indicators, visually displaying the strength of each model in simulating the relative scour depth. The ANN model stands out for its superior performance in most accuracy metrics, with  $R^2=0.98$ ,  $CC=0.99$ ,  $NSE=0.97$ , and  $WI=0.96$ , reflecting its high efficiency in explaining the data variance and replicating the actual behavior of the phenomenon. In contrast, the MGGP model demonstrates balanced performance, with notable improvements in WI and EVS, but exhibits greater variance in error metrics, such as RMSE and Theil's U, indicating flexibility in handling data but less stability compared to the ANN. The BRF model, although it performs well in specific metrics, such as LM and SD, clearly lags in accuracy and determination metrics, highlighting its more conservative nature, which can limit its ability to capture the full data variance. These results confirm that ANN outperforms a broad range of performance metrics, making it the most suitable model for scour evaluation around bridge piers.

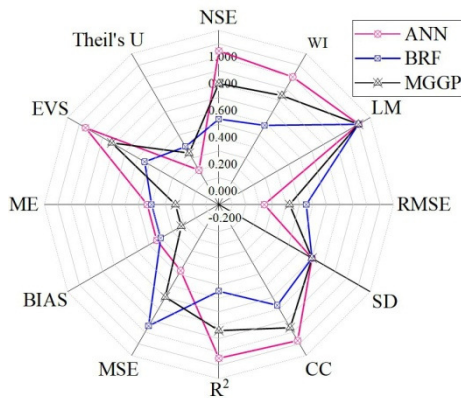


Fig. 6. Radar chart comparing the performance of the three models based on an integrated set of statistical indicators.

X. INDEPENDENT VARIABLE IMPORTANCE

Figure 7 presents the variable importance analysis in predictive models for scour depth around bridge piers, indicating that the most significant factors are  $\theta$ ,  $h/B$ , and the Froude number. These factors indicate the joint effect of water depth and flow dynamics on local vortex strength. Exposure time is also significant in scour processes. However, some variables, such as  $C_s$  and  $L/B$ , play a secondary role when interacting with other hydraulic factors.

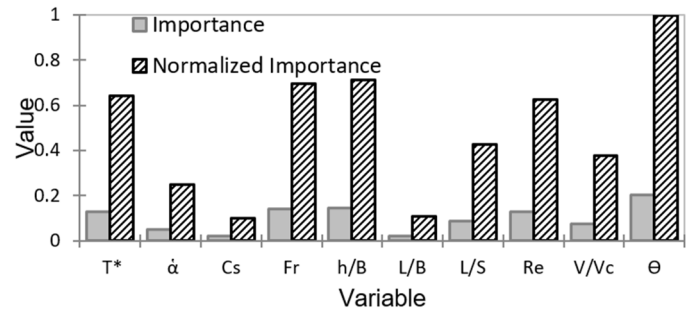


Fig. 7. Analysis of the importance of variables used in predictive models for scour depth around bridge piers.

XI. SENSITIVITY ANALYSIS

The sensitivity analysis between two key variables affecting the relative scour depth ( $d_s/B$ ) and the pier depth-to-width ratio ( $h/B$ ) reveals that the interaction between these variables is crucial in determining the scour level (Figure 8). As  $h/B$  increases in conjunction with  $\theta$ , the scour depth sharply rises, indicating that a higher water level relative to the pier size, combined with sediment transport rate  $\theta$ , intensifies vortex effects around the pier base, accelerating erosion rates. Conversely, lower values of both  $h/B$  and  $\theta$  are associated with reduced scour depth, reflecting relative stability in the hydraulic system under these conditions. This highlights the sensitive and complex nature of scour around piers, where the interaction between variables is more influential than the effect of any single variable.

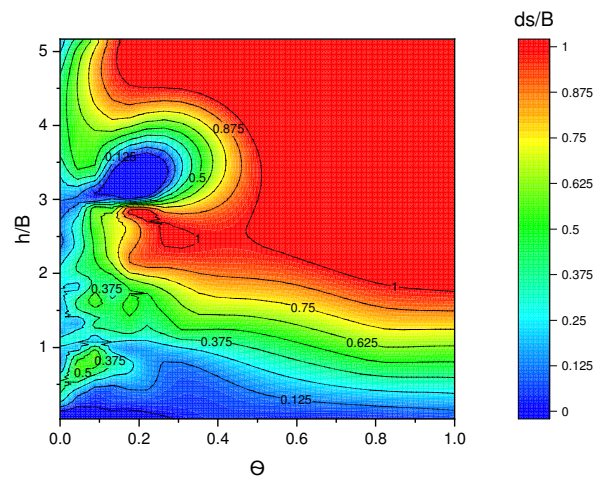


Fig. 8. Sensitivity analysis contour plot for the variables affecting the relative scour depth.

## XII. CONCLUSION

This study aimed to improve the prediction of scour depth around bridge piers by applying advanced AI models, namely ANN, RBFN, and MGGP, in conjunction with key hydraulic and structural parameters. In contrast to previous studies, this one employed a more comprehensive dataset and incorporated a wider set of input variables derived through dimensional analysis. This enabled the models to capture more complex hydraulic behaviors and enhance predictive accuracy. The results demonstrated a strong consistency with established hydraulic principles, enhancing both the scientific relevance and practical applicability of the developed models. Key findings are summarized as follows:

- The ANN model showed superior predictive accuracy and alignment with actual data.
- Sensitivity analysis showed that increasing  $\theta$  and  $h/B$  together led to a significant increase in  $d_s/B$ , demonstrating the cumulative effect of these variables.
- The MGGP model showed balanced performance in indices such as WI and EVS, with a good  $R^2$  compared to BRF.
- The BRF model was conservative and had limited efficiency in representing extreme data, limiting its representation of critical cases.
- Scatter plots, Taylor diagrams, and radar charts were used to assess model performance, revealing variability in model efficiency across accuracy and dispersion indices.
- Strong relationships were found between  $d_s/B$  and Reynolds number ( $Re$ ), Froude number ( $Fr$ ), and pier spacing ( $S/B$ ), confirming the interactive impact of hydraulic and engineering factors.

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