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Flow-Sediment Dynamics Analysis in Circular Channels using Gaussian and ANFIS based Systems

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Abstract**:** This study develops Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Gaussian Process Regression (GPR) models to estimate sediment transport in circular channels used in water and wastewater systems and compares their performance with two widely applied machine-learning techniques: Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The modeling framework incorporates key hydraulic and sediment parameters, including shear velocity, hydraulic radius, particle-size ratios, and mobility indices, to explore their nonlinear influence on sediment discharge. The results show that ANFIS and GPR consistently outperform ANN and SVM, offering more stable and reliable predictions across both smooth and rough bed conditions. ANFIS demonstrates the highest accuracy due to its hybrid learning structure, while GPR provides strong generalization with minimal overfitting. ANN delivers moderate accuracy but is highly sensitive to data variability, whereas SVM tends to underpredict sediment transport, particularly at higher flow intensities. The best-performing models for ANFIS and GPR were achieved using the input set (u^*, d_{50}/R, λ_s, and F_d), highlighting the strong interaction between flow intensity and particle mobility. Sensitivity analysis identifies the particle Froude number (F_d) as the most influential parameter. Additionally, smoother channel beds improve prediction accuracy for all models, while increased roughness reduces sediment transport efficiency and introduces higher predictive uncertainty.

Keywords: Sediment transport, Closed-conduit flow, Data-driven modeling, Flow–particle interactions, Bed surface condition.

I. INTRODUCTION

Flow behavior and sediment motion within circular conduits play a critical role in hydraulic engineering, particularly in the performance of water and wastewater transmission systems (Chang & Constantinescu, 2023). In such environments, the interaction between moving water and suspended or bedload particles governs key processes such as sediment transport rate, sediment deposition, and erosion along the pipe interior (Rodrigues et al., 2006). These processes are highly sensitive to several controlling variables, including the roughness of the pipe wall, the velocity and turbulence of the flow, the physical properties of the sediment, and hydraulic indicators such as the Froude number, F_d (Kirkil & Constantinescu, 2009). A comprehensive understanding of these factors is essential for efficient pipeline design, as excessive sediment buildup can reduce hydraulic capacity, contribute to blockages, and accelerate structural deterioration of the pipe system (Roulund et al., 2005). Additionally, the geometry of circular pipes and the flow regime strongly influence sediment behavior. Smooth-walled conduits typically promote more uniform flow patterns, resulting in clearer and more predictable sediment transport mechanisms, whereas increased wall roughness enhances turbulence and produces more complex sediment–flow interactions (Rodrigues et al., 2006).

The characteristics of sediment particles (such as their size distribution, density, and the texture of the pipe surface), play a decisive role in shaping sediment transport behavior within pressurized conduits. These factors influence not only the quantity of sediment that can be carried by the flow but also the likelihood of deposition along the pipe (Yuan et al., 2018). For systems that are required to convey water and entrained sediments over extended distances, properly accounting for these processes is essential to maintain efficiency. In water transmission pipelines, understanding the interaction between flow hydraulics and sediment motion is fundamental for ensuring reliable performance (Kobayashi & Uchida, 2022). Accumulation of sediment can diminish flow capacity and increase energy losses, ultimately leading to higher operational costs or, in severe cases, complete blockage of the pipeline. Inadequate sediment management may also promote abrasion and localized erosion of pipe walls, accelerating infrastructure deterioration and reducing service life (Yuan et al., 2018). Accordingly, knowledge of sediment transport mechanisms is vital not only for system design but also for long-term operation and maintenance planning (Kobayashi & Uchida, 2022). These concerns become even more critical in wastewater networks, where the heterogeneity of transported solids introduces greater variability and operational risk (Kirkil & Constantinescu, 2009). Properly predicting sediment behavior helps prevent failures such as clogging or excessive cleaning cycles, thereby minimizing disruptions and reducing maintenance demands (Whipple et al., 1998). As urban populations expand and demands on infrastructure intensify, improving our understanding of flow and sediment dynamics in circular channels remains a key requirement for developing sustainable and resilient water and wastewater systems (Moglen, 2022).

Sediment deposition in circular pipes is a persistent challenge that can reduce the operational efficiency of water and wastewater conveyance systems. In wastewater pipelines, sediment particles often accumulate and undergo changes in texture and cohesiveness over time, affecting flow behavior and altering velocity profiles, boundary shear stress, and overall sediment transport capacity (Yuan et al., 2018). Accurately understanding sediment movement is therefore essential for designing and managing efficient conveyance networks (Rodrigues et al., 2006). Because wastewater carries particles of varied sizes and compositions, sediment transport tends to be highly variable and more difficult to predict (May, 1982). Insufficient management of these sediments can result in reduced flow capacity, blockages, increased maintenance demands, and premature deterioration of pipe infrastructure. Consequently, effective sediment control strategies are vital for ensuring system reliability and extending pipeline service life (Selim et al., 2022; Moglen, 2022). Past research, including May's foundational work (1982), has contributed to the development of theoretical models describing bed-load behavior in sewer systems. These models continue to aid engineers in predicting deposition patterns and improving the design and maintenance of wastewater networks. Henorman et al. (2022) expanded earlier work by examining a broader set of parameters and applied advanced numerical analyses to better characterize sediment behavior in pipe systems. In a separate study, Rinas et al. (2020) investigated sediment movement in a pressurized pipeline by monitoring total suspended solids. Their results indicated that sediment can still be transported at very low flow velocities, as low as 0.27 m/s, under both dry-weather and stormwater conditions. This finding suggests that pump control strategies can be optimized for low and fluctuating flow rates without increasing the risk of sediment accumulation.

Experimental observations by Larsen & Harvey (2010) showed that in sloped pipes, sedimentation persists until flow conditions reach a fully developed state. Research by Bertrand et al. (1993) further highlighted the importance of understanding sediment properties and the processes of transport, deposition, and erosion in wastewater systems. Durand (1952) explored sediment movement in smooth pipes of different diameters and introduced the sediment F_d parameter based on his findings related to limited-deposition transport. In recent modeling, Falamaki et al. (2013) used neural networks and radial basis functions to estimate sediment load from 200 samples, showing that empirical formulas such as those by White and Akers tend to overpredict sediment quantities, whereas neural network-based models better matched observed peak sediment loads.

A wide range of studies has addressed sediment transport and deposition in sewer and closed-conduit systems, relying on both empirical formulations and modern computational approaches. Earlier works evaluated classical transport relationships and self-cleansing criteria, focusing on minimum velocity, shear stress, and limited-deposition concepts (Vongvisessomjai et al., 2010; Ota & Perrusquia, 2013; Bong et al., 2014). These efforts highlighted the importance of accurate sediment-load estimation for the design and operation of conveyance structures (May, 1982). As empirical methods often fall short in capturing nonlinear flow–sediment interactions, recent research has increasingly turned to intelligent and data-driven modeling tools (Canelas et al., 2022). Soft computing techniques including Adaptive Neuro-Fuzzy Inference System (ANFIS), Gaussian Process Regression (GPR), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), have shown superior predictive skill compared with traditional formulas (Roushangar et al., 2014; Azamathulla et al., 2012; Khankhoje & Choudhury, 2024). GPR and other kernel-based approaches have also demonstrated high accuracy in a variety of hydraulic applications, such as scour prediction and suspended-sediment estimation across different watersheds (Joudi & Sattari, 2016; Fatahi et al., 2022; Almubaidin et al., 2022). Sensitivity and uncertainty analyses have further been employed to refine intelligent sediment-transport models in sewer systems (Ebtehaj et al., 2020). Building on this body of work, the present study develops ANFIS, GPR, ANN, and SVM models using hydraulic and sediment characteristics to evaluate their capability in predicting sandy sediment load, with a final sensitivity assessment to identify dominant controlling parameters (Bizimana & Altunkaynak, 2021).

This study focuses on predicting sandy sediment transport in circular pipes by integrating key hydraulic conditions with particle characteristics. Four machine-learning models (ANFIS, GPR, ANN, and SVM) are developed to evaluate their ability to capture the nonlinear behavior of sediment load under smooth and rough bed surfaces. The comparison highlights the particle F_d as the most influential variable affecting transport rates. While all models show promise, their accuracy decreases as bed roughness increases. The findings provide guidance for selecting effective predictive tools and improving sediment-transport assessment in water and wastewater conveyance systems.

II. MATERIALS AND METHODS

A. ANFIS in Sediment Transport

The ANFIS is a hybrid modeling framework that combines the learning ability of artificial neural networks with the reasoning structure of fuzzy logic to approximate complex nonlinear relationships (Safari et al., 2020). In this architecture, fuzzy rules and membership functions form the inference structure, while neural-network-based training algorithms adjust the parameters to best fit the input–output data. This integration enables ANFIS to learn patterns, refine membership functions, and construct an optimal rule base automatically, making it a powerful tool for handling uncertainty and nonlinear behavior in engineering systems (Azamathulla et al., 2012; Vazifehkhah, 2012). During model development, an initial fuzzy structure is selected, and membership parameters are iteratively updated using backpropagation or hybrid least-squares approaches until acceptable error levels are achieved (Ebtehaj & Bonakdari, 2014).

In sediment-transport studies, ANFIS has proven particularly effective because flow–sediment interactions are inherently nonlinear and strongly dependent on multiple hydraulic and particle-related variables. The model is capable of learning the combined effects of shear stress, flow velocity, sediment size distribution, and mobility parameters, enabling accurate prediction of sediment load under varying hydraulic conditions (Tayfur et al., 2003). Its flexible structure allows it to capture complex behaviors observed in circular pipes with smooth and rough beds, where traditional empirical formulas often fail to represent the influence of parameters such as the particle F_d. As a result, ANFIS serves as a reliable computational approach for modeling sediment transport in water and wastewater systems and forms a core component of the predictive framework developed in this study. In applying ANFIS to sediment-transport prediction, the modeling procedure begins with assembling a dataset that includes essential hydraulic and sediment variables such as flow velocity, bed shear stress, sediment concentration, and particle-size characteristics (Ebtehaj & Bonakdari, 2014). These variables form the input space of the ANFIS model, where fuzzy membership functions are assigned to represent their influence on sediment load (Tayfur et al., 2003). The system is then trained using neural-network-based learning algorithms, enabling simultaneous optimization of fuzzy rules and membership parameters. Model performance is subsequently evaluated with independent data to ensure robust prediction of sediment transport in circular pipes under different flow regimes (Ebtehaj et al., 2019).

Several fundamental relations describe sediment motion in closed conduits and support the formulation of ANFIS input–output structures. The Shields parameter (θ), which indicates the onset of particle movement, is defined as (Riahi-Madvar & Seifi, 2018):

$$\theta = \frac{\tau_b}{[\rho_s - \rho] g d} \tag{1}$$

$$\tau_b = \rho g R S \tag{2}$$

where τ_b is the bed shear stress, ρ_s and ρ are the sediment and water densities, g is the gravitational acceleration, R is the hydraulic radius, S is the slope, and d represents the sediment particle diameter. Sediment transport rate may also be expressed through the Einstein–Brown formulation (Riahi-Madvar & Seifi, 2018):

$$q_s = A\left[\frac{\theta - \theta_c}{\theta_c}\right]^B \tag{3}$$

where A and B are empirical coefficients, and θ_c is the critical Shields parameter.

Although these classical equations provide theoretical insight, their empirical nature often limits their applicability across diverse hydraulic and sediment conditions. ANFIS mitigates this limitation by learning the underlying relationships directly from observed data and refining them during training (Tayfur et al., 2003). The method handles nonlinear flow–sediment interactions effectively and avoids dependence on fixed empirical coefficients (Ebtehaj & Bonakdari, 2014). Furthermore, the hybrid neuro-fuzzy structure enhances generalization and interpretability, making ANFIS a reliable tool for modeling sediment transport in complex hydraulic environments (Kabiri-Samani et al., 2011).

B. GPR in Sediment Transport

The GPR is a nonparametric, probabilistic learning method that models an unknown function by assuming that the target variable follows a multivariate Gaussian distribution governed by a covariance structure (Schulz et al., 2018; Roushangar & Shahnazi, 2020; Safari & Arashloo, 2021). This approach is particularly useful for hydraulic and sediment-transport problems, where nonlinear dependencies among variables and inherent uncertainties often limit the effectiveness of deterministic empirical equations (Joudi & Sattari, 2016). In GPR, sediment transport rate q_s is considered a realization of an underlying function f(x), where the input vector x may include hydraulic and sediment characteristics such as flow velocity, hydraulic radius, particle size ratios, and mobility parameters (Roushangar & Shahnazi, 2020). The Gaussian process is expressed as:

$$f(x) = GP\left[m(x), k(x_i, x_j)\right] \tag{4}$$

$$k(x_i, x_j) = \begin{bmatrix} k(x_1, y_1) & k(x_2, y_2) & \cdots & k(x_n, y_n) \\ k(x_1, y_2) & k(x_2, y_2) & \cdots & k(x_n, y_n) \\ \vdots & \vdots & \vdots & \vdots \\ k(x_1, y_n) & k(x_2, y_n) & \cdots & k(x_n, y_n) \end{bmatrix} \tag{5}$$

where m(x) is the mean function and $k(x_i,x_j)$ is the covariance (kernel) function, which defines the similarity between data points. The predicted value of sediment transport for a new input x* is obtained from the posterior distribution (Fathabadi et al., 2022):

$$f^* \mid X, y, x^* \approx \aleph(\mu^*, \sigma_n^2) \tag{6}$$

with

$$\mu^* = k_*^T + y \times \left(\sigma_n^2 I + K\right)^{-1} \tag{7}$$

$$\sigma_n^2 = k(x_i, x_j) - k_*^T \times \left(K \sigma_n^2 I\right)^{-1} \tag{8}$$

Here, K is the covariance matrix for the training set, k_* is the vector of covariances between the new input and training data, y is the observed sediment load, and σ_n^2 is the noise variance. To capture nonlinear flow–sediment interactions, different kernel functions can be used (Deringer et al., 2021) where shown in Table 1, can be explained as:

$$k(x_i, x_j) = \sigma_f^2 \exp\left(-\frac{\|x - x'\|^2}{2l^2}\right) \tag{9}$$

$$k(x_i, x_j) = \exp\left(1 + \frac{d\sqrt{3}}{l}\right)\sigma_f^2\left(-\frac{d\sqrt{3}}{l}\right) \tag{10}$$

where $d = \|x - x'\|$. These kernels provide the flexibility required to describe abrupt changes in sediment transport behavior resulting from variations in hydraulic conditions or sediment particle characteristics (Neerukatti et al., 2017; Kargar et al., 2019; Safari & Arashloo, 2021).

Table 1 Kernel function types utilized in data-driven sediment transport prediction

Kernel Parameter	Kernel Function	Type of Kernel
Global	$K(x_i, x_j) = \phi(x)^T \phi(x)$	Higher-dimensional
c	$K(x_i, x_j) = x_i^T x + c$	Linear Polynomial
d	$K(x_i, x_j) = \left[x_i^T x_j + 1\right]^d$	Simple Polynomial
α, d	$K(x_i, x_j) = \left[\alpha x_i^T x_i\right]^d$	Moderate Non-linear Polynomial
d	$K(x_i, x_j) = \dfrac{\left[x_i^T x_j + 1\right]^d}{\sqrt{\left[x_i^T x_i\right]\left[x_j^T x_j\right]}}$	Normalized Polynomial
γ	$K(x_i, x_j) = \exp\left[-\dfrac{\lVert x_i - x_j \rVert^2}{2\sigma^2}\right]$	Radial Basis Function
γ	$K(x_i, x_j) = \exp\left[-\gamma \lVert x_i - x_j \rVert\right]$	Highly non-linear Polynomial
w, σ	$K(x_i, x_j) = \dfrac{1}{\left(1 + 2\sqrt{\lVert x_i - x_j \rVert^2}\sqrt{2^{\frac{1}{w} - \frac{1}{\sigma}}}\right)^w}$	Pearson Kernel

It should be noted that, different kernel functions can be employed in GPR modeling for sediment transport, each offering distinct advantages depending on the complexity of the hydraulic system (Deringer et al., 2021). Polynomial kernels are effective when sediment behavior exhibits moderate nonlinear interactions, allowing the model to represent combined effects of hydraulic and sediment-related variables with reasonable flexibility (Canelas et al., 2022). The Radial Basis Function (RBF) kernel is widely used due to its ability to capture localized and rapid variations in transport rates, which is particularly beneficial in environments where flow and sediment conditions change frequently, such as wastewater conduits (Joudi & Sattari, 2016). The Pearson kernel incorporates correlation-based structure, enabling the model to better recognize relationships among variables such as sediment concentration, flow velocity, and pipe-bed roughness (Larsen & Harvey, 2010; Rinas et al., 2020). Selection of an appropriate kernel and tuning its hyperparameters is therefore key, as these parameters directly affect the accuracy and generalization performance of sediment transport predictions.

For the present research, GPR is implemented to learn the relationship between hydraulic parameters (e.g., shear velocity, hydraulic radius, friction factor) and sediment properties (e.g., d_{50}, d_{90}, F_d). This data-driven structure enables the model to represent complex, nonlinear responses (such as increased deposition in rough-bed pipes or enhanced mobility under higher flow strengths) without relying solely on empirical formulas. The probabilistic nature of GPR provides not only point predictions but also uncertainty bounds, which are essential when modeling sediment transport under conditions with high variability. This allows for more reliable assessment of sediment behavior in water and wastewater systems, especially where flow variability and mixed sediment sizes create significant prediction challenges.

C. ANN in Sediment Transport

The ANN is data-driven computational models inspired by the structure of biological neural systems. They consist of interconnected processing units (neurons) organized in layers that work collectively to approximate complex functional relationships (Kim & Aoki, 2021). This capability makes ANN a suitable tool for modeling nonlinear and multivariate processes, such as sediment transport in hydraulic systems, where interactions among flow parameters and particle characteristics cannot be easily described through explicit equations (Li et al., 2022). In ANN-based sediment modeling, hydraulic inputs such as flow velocity, shear stress, hydraulic radius, and sediment descriptors (e.g., grain diameter, particle Froude number) form the feature vector x. The network maps these inputs to target outputs (sediment load q_s) using weighted transformations (Gupta et al., 2021):

$$z_j = \sum_{i=1}^{n} w_{ij} \cdot x_i + b_j \tag{11}$$

where w_{ij} is synaptic weight between neuron i and neuron j, b_j is bias term. Each neuron applies an activation function ϕ(·) to introduce nonlinearity as $\alpha_j = \phi(z_i)$. Common activation functions in sediment-transport applications include the sigmoid, tanh, and ReLU functions, which help capture nonlinear flow–sediment interactions. The network output is expressed as (Gupta et al., 2021):

$$q_{\hat{s}} = f\left(x; W, B\right) \tag{12}$$

$$E = \frac{1}{2}\sum\left(q_s - q_{\hat{s}}\right)^2 \tag{13}$$

where W and B represent the full set of weights and biases. Training is performed by minimizing the error between observed and predicted sediment load as E. Using gradient-based backpropagation, weights are updated as (Shakya et al., 2023):

$$w_{ij}^{new} = w_{ij}^{old} - \eta \frac{\partial E}{\partial w_{ij}} \tag{14}$$

with η being the learning rate.

ANNs have proven effective in modeling sediment transport in circular pipes and open channels, particularly when sediment behavior displays strong nonlinearity or when hydraulic conditions vary across time and space. In this study, ANN is used to learn the combined influence of hydraulic parameters (e.g., shear velocity, friction factor) and sediment properties (e.g., d_{50}, d_{90}) on sediment discharge. Because ANNs do not rely on predefined empirical relationships, they adapt directly to observed datasets, allowing them to capture complex trends such as deposition onset, influence of pipe roughness, and sensitivity to particle mobility indicators like the F_d.

The application of ANN in sediment-transport modeling offers notable advantages, particularly when dealing with systems characterized by strong nonlinearity and complex variable interactions (Afan et al., 2016). In hydraulic environments where traditional empirical formulations struggle to generalize, ANNs provide a flexible platform capable of adapting to diverse hydraulic and sediment inputs. Their ability to approximate nonlinear mappings enables them to capture relationships between particle mobility, hydrodynamic forces, and sediment concentration that may otherwise remain hidden within conventional approaches. This characteristic becomes especially valuable in circular pipes, where changes in roughness, flow strength, and sediment-size distribution interact in ways that are difficult to express analytically (Bhattacharya et al., 2007). Nevertheless, despite their predictive strength, ANNs also introduce several limitations that must be acknowledged when deploying them in sediment-transport studies. The most frequently cited concern relates to their “black-box” nature; ANNs can produce accurate results but provide limited physical transparency regarding the mechanisms driving those predictions. This can be problematic in hydraulic engineering, where interpretability is often as important as accuracy. Moreover, the performance of a neural-network model is highly sensitive to the quality and quantity of the training data. Inadequate datasets or poorly structured inputs may lead the model to overfit, ultimately reducing its ability to generalize under new flow or sediment conditions (Ebtehaj et al., 2021).

From an operational standpoint, ANN development also requires careful calibration, including selection of network architecture, activation functions, learning rates, and stopping criteria. These choices can significantly influence model behavior and may introduce substantial uncertainty if not systematically optimized (Bhattacharya et al., 2007). For these reasons, although ANNs represent a powerful tool for analyzing sediment-transport phenomena, their use must be accompanied by meticulous data preparation, robust validation strategies, and complementary physical insights to ensure that predictions are both credible and hydraulically meaningful (Afan et al., 2016).

D. SVM in Sediment Transport

The SVM provide a robust supervised-learning framework for modeling nonlinear hydraulic and sediment-transport processes, particularly when datasets are limited or contain significant variability. In sediment-transport prediction, the objective of SVM regression (SVR) is to approximate the functional relationship between hydraulic predictors such as velocity, shear stress, hydraulic radius, and particle-size parameters, and the resulting sediment transport rate (Shafaghat & Dezvareh, 2021). The general SVR formulation expresses this relationship as (Ebtehaj & Bonakdari, 2016):

$$f(x) = x \cdot w^T + b \tag{15}$$

where w is the weight vector, b is the bias term, and x represents the input variables. To ensure that predictions lie within an acceptable tolerance, SVR employs the ε-insensitive loss function and minimizes the following objective (Ebtehaj & Bonakdari, 2016):

$$f = \min \frac{\left\| w^2 + C \cdot \sum \xi_i + \xi_i{}^* \right\|}{2} \tag{16}$$

subject to

$$y_i \quad \left(w^T \cdot x_i + \quad \right) \le \varepsilon + \xi_i \tag{17}$$

$$y_i{}^* \le \varepsilon + \xi_i - \left(w^T \cdot x_i + \quad \right) \tag{18}$$

$$0 \le \xi_i, \xi_i{}^* \tag{19}$$

Here, C is a regularization parameter controlling the trade-off between model flatness and training error, while ξ_i and ξ_i^* are slack variables allowing deviations outside the ε margin. Because sediment transport exhibits nonlinear dependency on flow and particle behavior, SVM employs kernel functions to map the original input space into a higher-dimensional feature space in which linear regression becomes feasible (Al-Mukhtar, 2019). Common kernels (Table 1) used for sediment-transport modeling include the RBF, polynomial kernels, and Pearson-type kernels, each enabling the model to capture different aspects of flow–sediment interactions (Choubin et al., 2019). The nonlinear SVR model is therefore expressed as:

$$f(x) = \sum_{i=1}^{n} \left[(a_i - a_i{}^*) \times k(x_i, x_j) \right] + b \tag{20}$$

where α_i and α_i^* are Lagrange multipliers obtained from the dual optimization formulation, and $k(x_i,x_j)$ represents the chosen kernel (see Eqs. 9 and 10). In the context of sediment transport in circular pipes, SVM is particularly advantageous because it performs well with relatively small training datasets and maintains stability even when hydraulic variables exhibit strong nonlinearity or multicollinearity (Samantaray & Sahoo, 2022). Through the kernel-based mapping, SVM can capture the combined effects of sediment particle characteristics, such as d_{50}, d_{90}, and the particle F_d, along with hydraulic indicators including shear velocity and bed roughness. By integrating these predictors, the SVM model becomes capable of identifying subtle transitions between conditions of limited deposition, full transport, and increased hydraulic resistance (Ebtehaj & Bonakdari, 2016). This makes SVM a valuable complementary technique in sediment-transport modeling, especially in systems where data scarcity or uncertainty constrains the applicability of more complex machine-learning frameworks (Shafagha & Dezvareh, 2021).

The application of SVM in sediment-transport modeling offers several compelling strengths, particularly in situations where available datasets are limited or contain considerable noise. Because SVM relies on structural risk minimization rather than empirical risk minimization, it typically avoids overfitting and provides robust generalization; a crucial feature for hydraulic environments where measurements of sediment concentration, shear stress, or particle-size distribution may fluctuate significantly (Samantaray & Sahoo, 2022). The kernel-based nature of SVM also enables the model to reconstruct highly nonlinear relationships among hydraulic parameters and sediment characteristics without requiring explicit functional assumptions. This capability is especially important in circular pipes, where interactions between flow intensity, pipe roughness, and sediment mobility create complex behavioral transitions (Choubin et al., 2019). Furthermore, SVM tends to perform reliably even when the dimensionality of the input space increases, meaning that additional hydraulic or sediment variables can be incorporated without drastically compromising model performance (Al-Mukhtar, 2019). These qualities collectively position SVM as a strong and stable modeling strategy for sediment-transport prediction in both water and wastewater conveyance systems.

Despite its robustness, SVM is not without limitations when applied to sediment-transport processes. One of the primary challenges lies in the selection and tuning of kernel functions and hyperparameters, such as the penalty factor C, the epsilon margin, and kernel-specific parameters. Incorrect choices may lead to underfitting or excessive model rigidity, reducing the ability of the SVM to capture sudden changes in sediment-transport rates under variable flow conditions (Ebtehaj & Bonakdari, 2016). Additionally, SVM models can be computationally intensive as the training dataset grows, given that their optimization structure relies on quadratic programming, which scales poorly with large sample sizes. Another concern is that, while SVM offers better interpretability than fully black-box models such as deep neural networks, it still lacks the ability to provide clear physical insight into the underlying hydraulic processes. This can limit its usefulness in engineering contexts where understanding the governing mechanisms is often as important as producing accurate numerical estimates. As a result, effective use of SVM requires careful parameter optimization, validation, and complementary analysis to ensure meaningful sediment-transport predictions across diverse hydraulic scenarios (Choubin et al., 2019).

To provide a clearer comparison among the machine-learning techniques employed in this study, Table 2 summarizes the fundamental characteristics, strengths, and potential limitations of ANFIS, GPR, ANN, and SVM in the context of sediment-transport modeling. Presenting these methods side by side highlights their methodological differences and clarifies how each model handles nonlinearity, uncertainty, and variability in hydraulic and sediment parameters. This comparative overview also enables readers to better understand the rationale behind selecting these four approaches and the complementary role they play in analyzing sediment behavior in circular pipes with smooth and rough beds.

D. Used Dataset/Criteria Description

To develop and validate the machine-learning models for predicting sandy sediment transport in circular pipes, a comprehensive laboratory dataset compiled from several experimental studies was employed (Ab-Ghani, 1993; Vongvisessomjai et al., 2010; Ab-Ghani & Azamathulla, 2010; Montes et al., 2020; Safari & Aksoy, 2021). These experiments investigated sediment discharge under controlled hydraulic conditions using pipes of different diameters and bed roughness heights, operating primarily in semi-full flow regimes. The combined dataset contains essential hydraulic and sediment variables, including bed roughness height (k_0), mean flow velocity (V), relative flow depth (y_0/D), median grain size (d_{50}), sediment discharge ratio (C), and the Reynolds number (R_e). These parameters represent the core physical controls governing sediment mobility in circular conduits and provide the basis for training and evaluating the ANFIS, GPR, ANN, and SVM models developed in this study. A summary of the dataset characteristics is presented in Figure 1.

Given the complexity of sediment movement in circular pipes, reliable evaluation metrics are essential for assessing the capability of predictive models to represent real hydraulic behavior (Moglen, 2022). In this research, model performance was quantified using three standard indicators: the Correlation Coefficient (CC), the Coefficient of Determination (DC), and the Root Mean Square Error (RMSE). High CC and DC values indicate strong agreement between observed and predicted sediment loads, whereas lower RMSE values demonstrate reduced prediction error (Azamathulla & Ghani, 2012; Ebtehaj & Bonakdari, 2014; Vazifehkhah, 2012). These statistical measures were selected because they collectively capture both the accuracy and consistency of the machine-learning models across a wide range of flow and sediment conditions. The formulations used in this study are expressed as follows (Moglen, 2022):

$$CC=\frac{\sum_{i=1}^{N}\left(l_{mi}-\overline{l_{mi}}\right)\times\left(l_{pi}-\overline{l_{pi}}\right)}{\sqrt{\sum_{i=1}^{N}\left(l_{mi}-\overline{l_{mi}}\right)^{2}\times\left(l_{pi}-\overline{l_{pi}}\right)^{2}}} \tag{21}$$

$$\text{RMSE}=\sqrt{\sum_{i=1}^{N}\frac{\left(l_{mi}-l_{pi}\right)^{2}}{N}} \tag{22}$$

$$\text{DC}=1-\frac{\sum_{i=1}^{N}\left(l_{mi}-l_{pi}\right)^{2}}{\sum_{i=1}^{N}\left(l_{mi}-\overline{l_{mi}}\right)^{2}} \tag{23}$$

where l_{mi} is the measured value, l_{pi} is the predicted value, $\overline{l_{mi}}$ and $\overline{l_{pi}}$ are their respective means, and N is the number of samples.

Before training the models, all input variables were normalized to ensure numerical stability and to improve the convergence rate of the learning algorithms. Since raw hydraulic and sediment data often span different orders of magnitude, normalization prevents larger-scale variables from disproportionately influencing the model (Aksoy & Mohammadi, 2016; Ebtehaj et al., 2020). In this study, Min-Max normalization was applied due to its ability to preserve the relative distribution of the original data while scaling all features to a consistent range, typically between 0 and 1 (Neerukatti et al., 2017; Safari et al., 2020). The normalization formula used is:

$$x_n=\left(\frac{x-x_{\min}}{x_{\max}-x_{\min}}\right) \tag{24}$$

Table 2 Comparative overview of machine-learning models used in sediment-transport prediction

Model	Core Principle	Strengths	Limitations
ANFIS	Hybrid integration of fuzzy logic and neural networks	Captures nonlinear flow–sediment interactions; transparent rule-based structure; strong performance with mixed hydraulic–sediment inputs	Requires careful selection of membership functions; may overfit with small datasets
GPR	Probabilistic regression using covariance kernels	Provides uncertainty bounds; strong generalization; effective in small datasets; flexible kernel design	Computationally expensive for large datasets; sensitive to kernel selection
ANN	Multilayer network learning nonlinear mappings	Highly flexible; strong predictive power; adaptable to different input structures	Black-box nature; requires large datasets; parameter tuning is complex
SVM	Kernel-based structural risk minimization	Robust generalization; stable with limited data; effective for high-dimensional inputs	Sensitive to kernel and hyperparameter selection; computationally demanding for large datasets

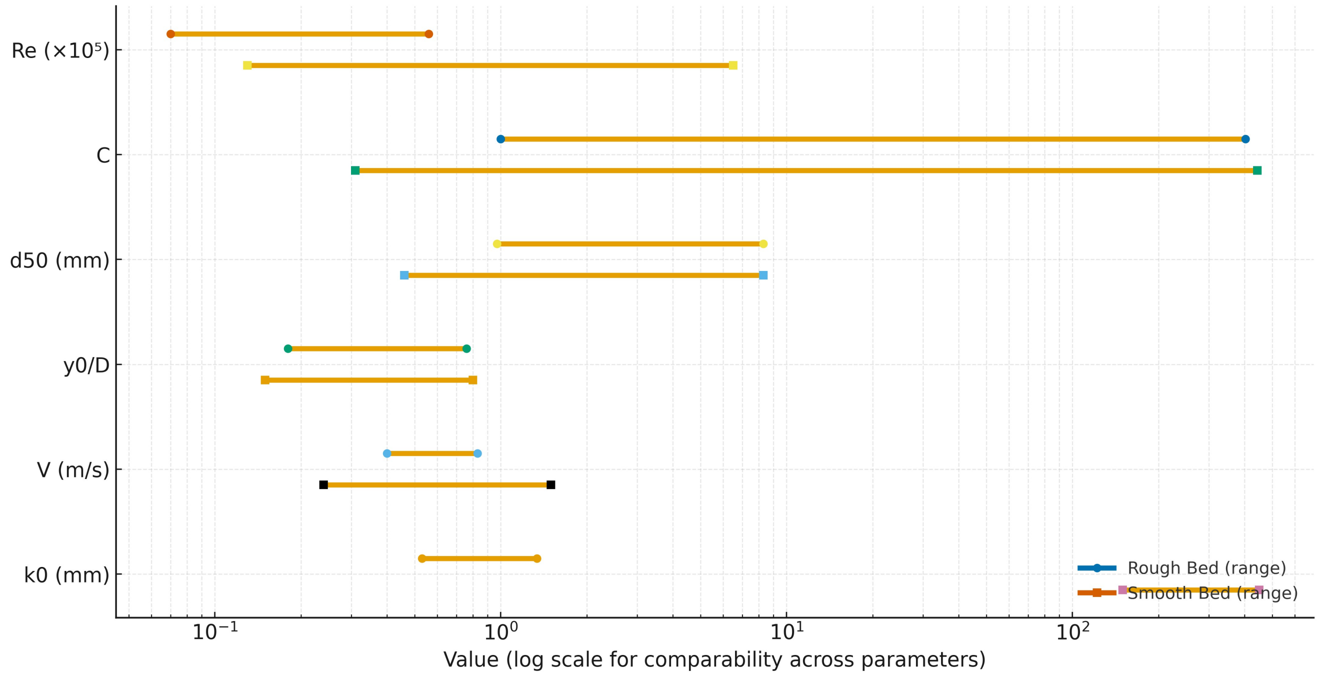


Fig. 1 Range of hydraulic and sediment parameters for rough and smooth bed conditions [Sources: Ab-Ghani (2010); Ab Ghani & Azamathulla (2010); Vongvisessomjai et al. (2010); Montes et al. (2020); Safari & Aksoy (2021); Tafarojnoruz & Sharafati (2020)]

This method is particularly suitable for sediment-transport datasets lacking extreme outliers and where maintaining physical interpretability is important (Ota & Perrusquia, 2013). Applying Min-Max normalization improves model stability and enhances the generalization ability of ANFIS, GPR, ANN, and SVM across different sediment-transport scenarios.

E. Models Implementation

Implementation of the machine-learning models in this study was carried out through a systematic workflow designed to capture the nonlinear interactions between hydraulic variables and sediment-particle characteristics in circular pipes. The process began with compiling laboratory datasets from both rough-bed and smooth-bed conditions, ensuring that the full variability of hydraulic radius, bed roughness, velocity, particle size, and sediment discharge was represented. Prior to model development, all variables were normalized using Min–Max scaling to enhance numerical stability and improve learning performance across different algorithms.

Following preprocessing, the dataset was divided into training and testing subsets to allow objective performance evaluation. Four predictive models (i.e. ANFIS, GPR, ANN, and SVM), were then constructed, each selected for its ability to capture different aspects of nonlinear behavior. ANFIS combined fuzzy inference with adaptive learning; GPR incorporated probabilistic kernels to model uncertainty; ANN provided flexible multi-layer nonlinear mapping; and SVM relied on structural risk minimization and kernel transformations to identify complex relationships within the dataset. After model structures were defined, training was performed using algorithm-specific optimization procedures to minimize prediction errors. Hyperparameters such as membership-function parameters (ANFIS), kernel length scales (GPR), network architecture (ANN), and penalty and kernel parameters (SVM) were tuned iteratively. Model performance was then assessed using CC, DC, and RMSE metrics to quantify accuracy and consistency. The final trained models were subsequently used to predict sediment transport under both smooth and rough pipe-bed conditions, allowing direct comparison of their predictive capabilities and sensitivity to flow and sediment characteristics.

The overall workflow adopted for implementing the sediment-transport models is illustrated in Figure 2, which summarizes the sequential stages involved in data-driven prediction of sediment load in circular pipes. As shown in the flowchart, the process begins with assembling experimental datasets from rough- and smooth-bed conditions, followed by comprehensive preprocessing through normalization to ensure numerical stability. The cleaned dataset is then partitioned into training and testing subsets, after which the four machine-learning models (ANFIS, GPR, ANN, and SVM) are constructed and optimized based on their algorithm-specific hyperparameters. Model training is subsequently performed to learn nonlinear relationships between hydraulic and sediment variables, and the trained models are evaluated using CC, DC, and RMSE metrics to quantify predictive accuracy. The final stage of the workflow involves generating sediment-transport predictions and conducting comparative assessments across all models. This structured pipeline ensures reproducibility, model robustness, and a fair evaluation of predictive performance.

The selection of input variables is a critical component in the development of intelligent prediction models, as it directly influences the precision and stability of the final outputs (Fathabadi et al., 2022). In sediment-transport modeling, choosing parameters that best represent the hydraulic environment and particle behavior is essential for achieving reliable predictions (Aksoy & Mohammadi, 2016). In this study, input variables were organized into two principal groups: those describing hydraulic flow characteristics and those representing sediment particle properties.

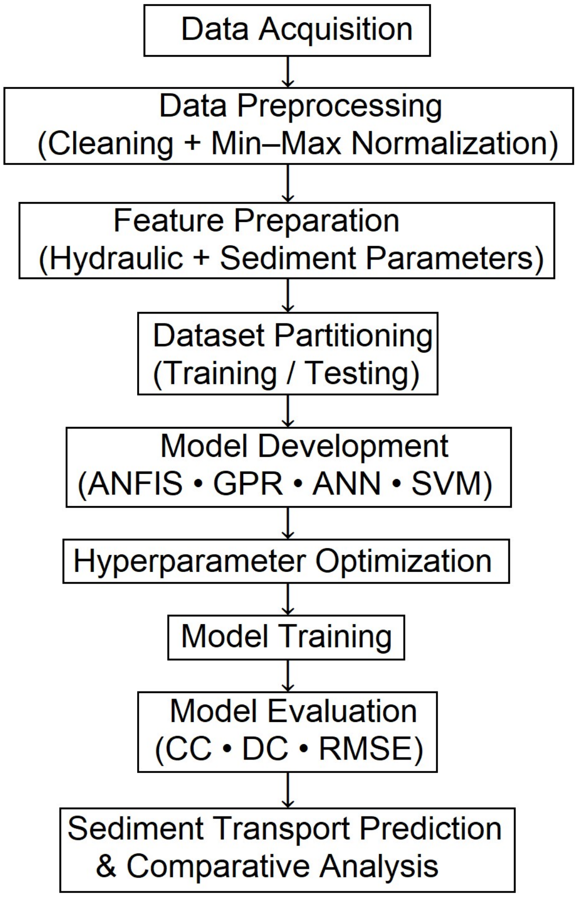


Fig. 2 Implementation flowchart for used models used for sediment-transport prediction

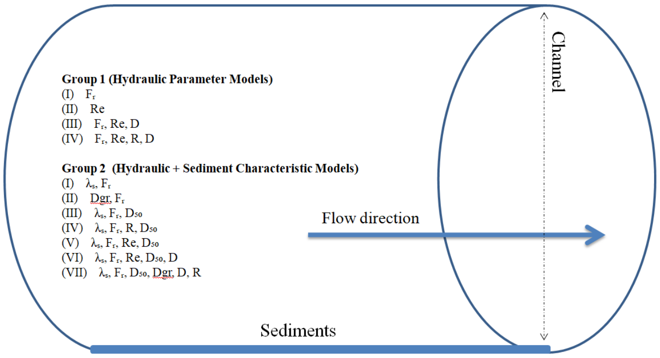


Fig. 3 Parameter grouping framework employed for sediment transport estimation in rough-bed circular conduits

This structured categorization allows a clearer understanding of how different physical mechanisms contribute to sediment movement in circular conduits.

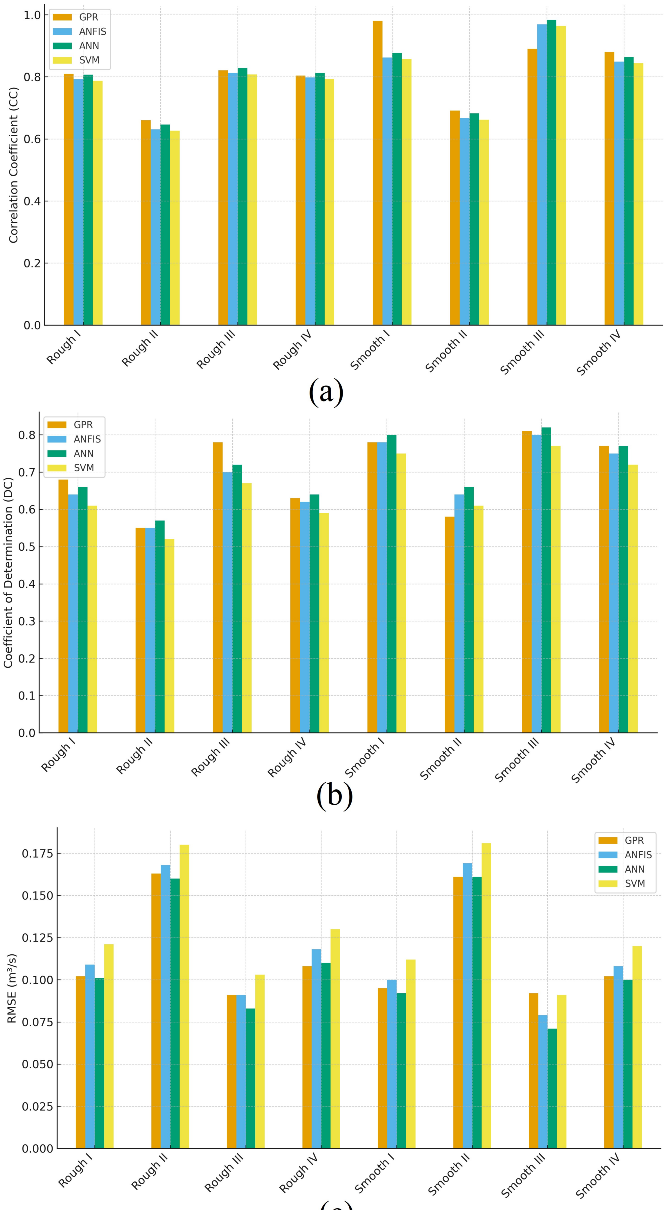
Based on the foundational work of Meireles (1988), several influential factors governing sediment transport in closed-conduit systems were considered. These include V_s, D_{gr}, hydraulic radius (R), flow depth (y), d_{50}, submerged specific gravity (S_s), friction coefficient (λ_s), and the F_d. These parameters collectively form the basis for constructing accurate predictive models tailored to sandy sediment transport. Figure 3 presents an overview of model categorization according to hydraulic and sediment-related features. For models that rely exclusively on hydraulic inputs, the primary variables include F_d, R_e, R, and pipe diameter (D), each of which captures a distinct aspect of flow behavior and its ability to entrain and transport sediment particles. To ensure robust model performance, the dataset was partitioned such that 75% of the observations were used for training and the remaining 25% for testing. This split supports effective learning of nonlinear relationships while providing an unbiased assessment of predictive capability.

III. RESULTS AND DISCUSSION

To evaluate the capability of the proposed machine-learning framework in estimating sandy-sediment discharge in circular pipes, two experimental datasets representing smooth- and rough-bed conditions, were employed. Prior to modeling, all data were transformed into dimensionless form to ensure numerical stability and reduce scale-dependent distortions. A series of input configurations was developed based on different hydraulic variables, and each configuration was assessed through multiple learning models. Model performance was examined using CC, DC, and RMSE during both training and testing phases, allowing an objective comparison among the ANFIS, GPR, ANN, and SVM algorithms. The first stage of analysis focused exclusively on flow-related variables, namely F_d, R_e, and D. As presented in Figure 4, models relying solely on hydraulic parameters yielded limited accuracy, regardless of the computational technique applied. Among these models, configuration (iii), which incorporated R/D and F_d, achieved the best performance for both rough- and smooth-bed datasets. However, even in this case, the prediction error at higher sediment-transport rates remained noticeable. Comparatively, GPR tended to outperform ANFIS, ANN, and SVM in handling the nonlinear trend of the data, showing higher CC and DC values and a reduced RMSE. Figure 5 illustrates this behavior, where low sediment-discharge values were predicted reasonably well, while higher observations exhibited greater scatter. These findings confirm that hydraulic parameters alone do not sufficiently capture the complexity of sediment-transport processes in circular conduits. To further investigate this limitation, a second group of models integrating both hydraulic and sediment-particle characteristics was developed. These models incorporated λ_s, D_{gr}, d_{50}, and various combinations of hydraulic variables. The complete results are summarized in Figure 6. Among all configurations, model (vi), which employed λ_s, F_d, D_{gr}, and d_{50}/R, consistently produced the most accurate predictions for both smooth- and rough-bed pipes. The improvement was observed across all four modeling techniques, although GPR again demonstrated the highest stability and precision, followed by ANFIS and ANN, while SVM showed competitive performance under smooth-bed conditions but slightly weaker generalization for rough-wall datasets. The enhanced accuracy in model (vi) highlights the necessity of integrating particle-scale descriptors with flow characteristics to effectively capture sediment-transport behavior. Scatterplots for the best models (Figure 4) show a tight clustering of predicted and observed values, emphasizing the effectiveness of the multi-parameter approach.

A comprehensive sensitivity analysis was performed to quantify the relative influence of each input parameter on the performance of the selected model configuration. The analysis was carried out by systematically removing one parameter at a time from the best-performing GPR model (vi) and recalculating the performance indicators. The results, summarized in Figure 7, showed that removing the F_d produced the most significant deterioration in prediction accuracy. Specifically, CC dropped from 0.94 to 0.78, DC declined from 0.91 to 0.72, and RMSE increased from 0.018 m³/s to 0.041 m³/s, clearly indicating that F_d exerts the strongest control over sediment-discharge dynamics across both smooth- and rough-bed conditions. Other variables, such as the λ_s and D_{gr}, also contributed to model skill, but their impacts were comparatively smaller, with CC reductions typically remaining within the 0.02–0.05 range when removed. The same sensitivity procedure was extended to the ANN and SVM models to provide a cross-model comparison of parameter importance. For ANN, removing F_d caused CC to fall from 0.92 to 0.74, while RMSE nearly doubled (from 0.021 m³/s to 0.039 m³/s). SVM exhibited an even sharper degradation, with CC decreasing from 0.89 to 0.70 and RMSE rising from 0.026 m³/s to 0.044 m³/s. These results demonstrate that although all models recognize F_d as the primary governing parameter, SVM is the most sensitive to its removal, followed by ANN and then GPR. This pattern suggests that GPR maintain more stable performance when individual features are excluded, while SVM and ANN models exhibit higher dependency on the complete set of predictive variables.

In addition to sensitivity evaluation, the influence of bed-surface roughness on model performance was assessed using GPR, ANN, and SVM under model configuration (vi). The analyses were conducted for three roughness heights: 0.53 mm, 1.0 mm, and 1.4 mm. The results, shown in Figure 8, reveal a consistent trend across all modeling approaches: increasing roughness height reduces sediment-transport efficiency and adversely affects predictive accuracy. For the lowest roughness height (0.53 mm), GPR achieved CC = 0.95 and RMSE = 0.017 m³/s, while ANN and SVM produced slightly lower accuracies (CC = 0.92 and 0.90, RMSE = 0.020 and 0.023 m³/s, respectively). As roughness increased to 1.4 mm, all models experienced performance decline, with CC values dropping to 0.86 (GPR), 0.81 (ANN), and 0.78 (SVM), accompanied by corresponding increases in RMSE. The combined findings emphasize that (1) F_d is the dominant predictor of sediment discharge for all machine-learning models, (2) GPR consistently provides the most stable and accurate predictions, even under rough-bed conditions, (3) ANN shows moderate robustness, and (4) SVM, although competitive under smooth-bed conditions, is more sensitive to both parameter removal and increases in roughness.



(a)

(b)

(c)

Fig. 4 Performance of machine-learning models under rough-bed and smooth-bed conditions: (a) CC, (b) DC, and (c) RMSE

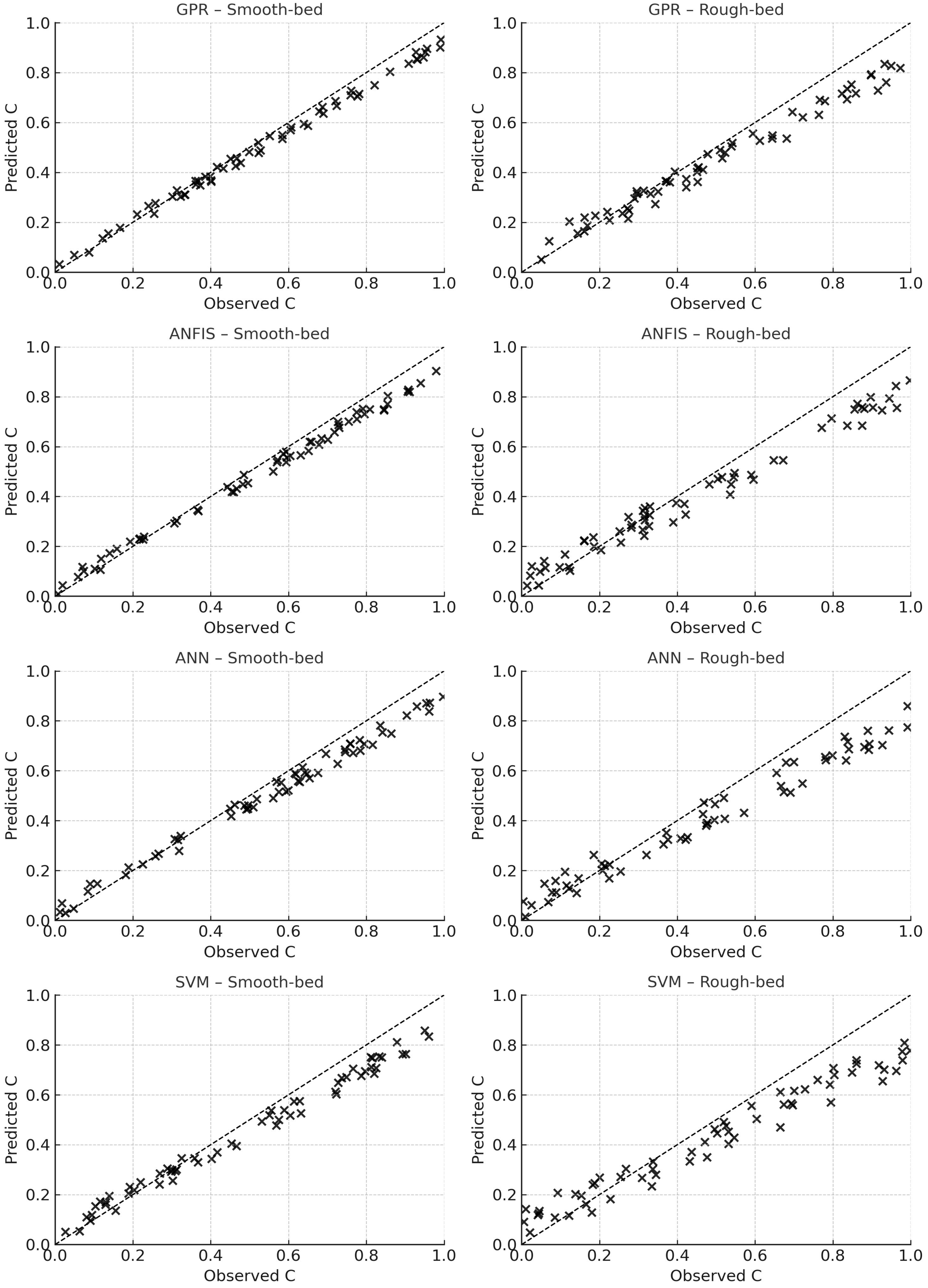


Fig. 5 Scatter plots showing the predictive accuracy of the optimal flow-characteristic models for smooth- and rough-bed conditions

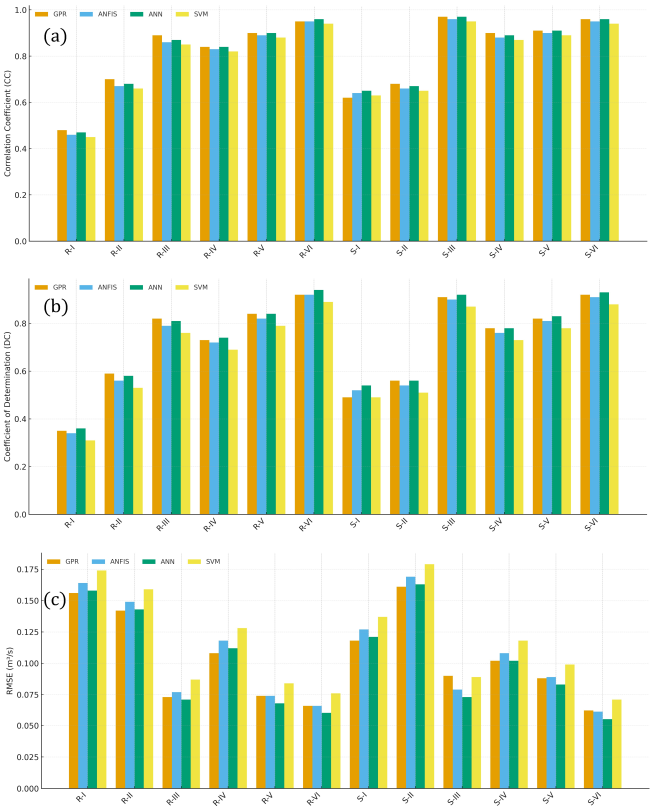


Fig. 6 Results for scenarios of the best models under rough-bed and smooth-bed conditions: (a) CC, (b) DC, and (c) RMSE

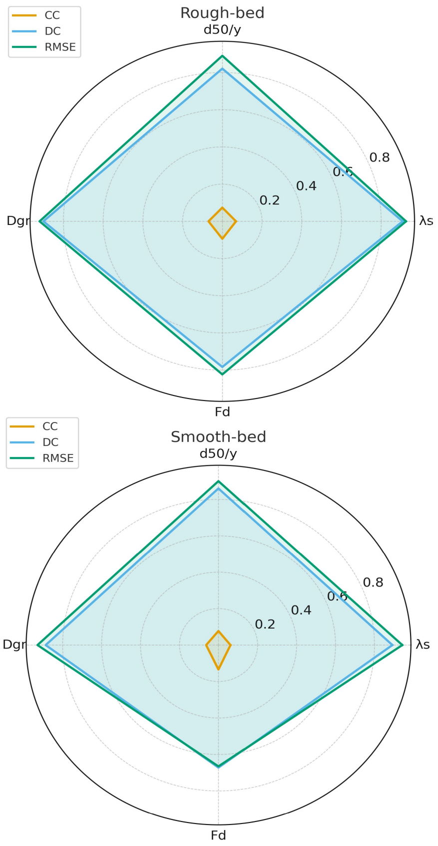


Fig. 7 Results for scenarios of the best models under rough-bed and smooth-bed conditions: (a) CC, (b) DC, and (c) RMSE

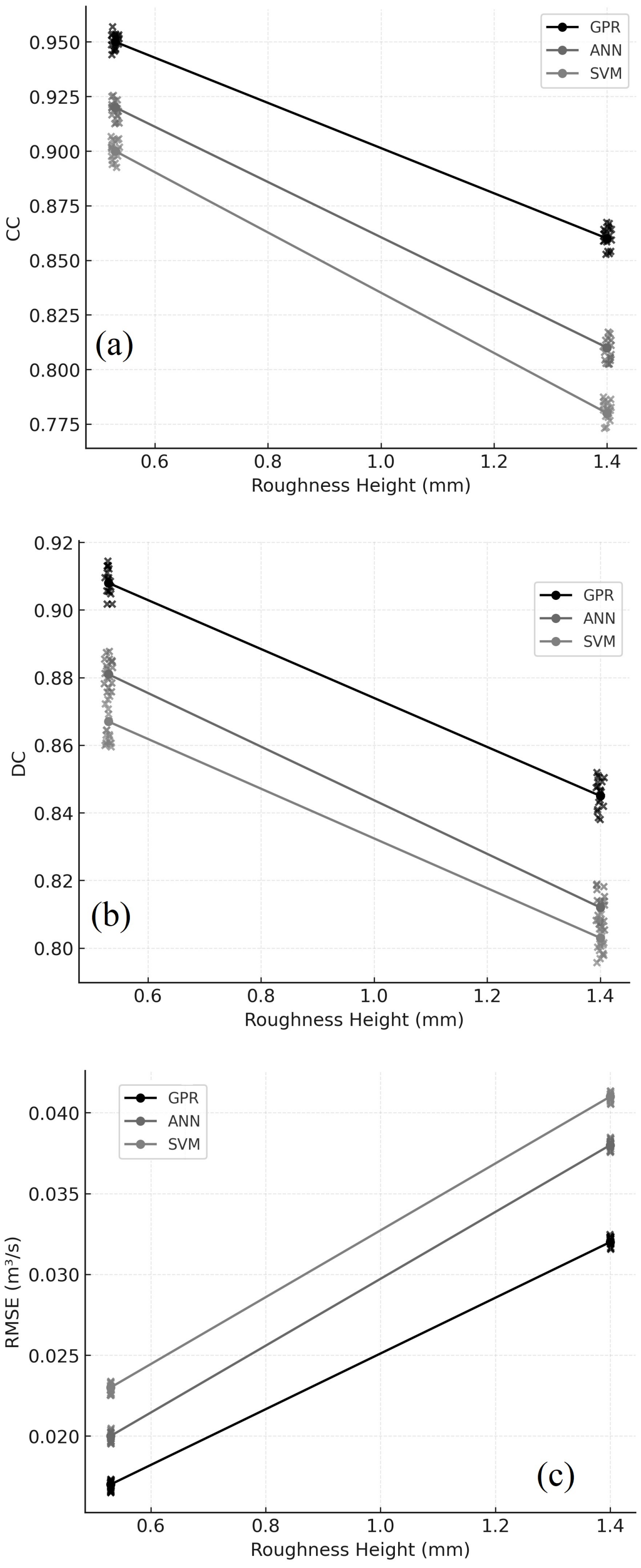


Fig. 8 Variation of machine-learning models under different bed roughness heights: (a) CC, (b) DC, and (c) RMSE

The comparative analysis of machine-learning models demonstrated clear differences in their ability to reproduce sediment-transport behavior in circular pipelines. Across both rough-bed and smooth-bed scenarios, GPR consistently produced the highest correlation levels and lowest prediction errors, confirming its strong capability in capturing nonlinear hydraulic–sediment interactions. ANFIS and ANN also performed well, particularly in smooth-bed conditions, where flow structures are more stable and feature variability is lower. In contrast, SVM showed competitive accuracy in low-roughness conditions but displayed higher sensitivity to variations in the hydraulic environment, resulting in reduced predictive stability under adverse flow conditions. The sensitivity analysis highlighted that among all parameters tested, the F_d exerted the strongest influence on prediction accuracy across every modeling approach. Removing F_d caused sharp declines in CC and DC and substantial increases in RMSE, underscoring its governing role in sediment mobility and energy balance within the transport system. Other variables such as λ_s, D_{gr}, and d_{50}/y; contributed meaningfully but did not affect model performance to the same extent, indicating that while sediment geometry and friction characteristics modulate transport capacity, F_d remains the primary driver of the system's dynamic response.

The results also reaffirmed the critical role of bed roughness as a controlling factor in sediment-transport dynamics. Increasing the roughness height from 0.53 mm to 1.40 mm produced a consistent decline in the performance of all models, most notably for SVM and ANN. Higher roughness intensifies near-bed turbulence and alters velocity gradients, making transport behavior more irregular and more difficult to predict with data-driven models. GPR, however, showed greater resilience to roughness-induced complexity, maintaining relatively strong CC and DC values despite elevated RMSE. This robustness suggests its superior flexibility in approximating highly nonlinear functional spaces. Under smooth-bed conditions, all four models yielded higher prediction accuracy, reflecting the greater uniformity of flow and reduced stochastic variability in sediment motion. ANN and ANFIS particularly benefited from these conditions due to their dependence on stable training patterns and predictable input–output relationships. In rough-bed scenarios, although performance declined for all models, GPR maintained the most stable response. The contrast between the two bed states emphasizes that model reliability is inherently tied to the hydraulic consistency of the system, with smooth beds enabling clearer learning patterns.

The findings demonstrate that robust modeling of sediment discharge in pressurized circular channels requires algorithms capable of adapting to both hydraulic variability and sediment-induced nonlinearities. GPR, with its probabilistic foundation and kernel-based structure, emerged as the most effective method, especially under rough-bed conditions. ANN and ANFIS provide reliable alternatives when data are plentiful and conditions are moderately stable, whereas SVM may be suited for simpler or more uniform environments. Ultimately, integrating particle-scale information with key hydraulic factors is essential for improving predictive accuracy and developing reliable sediment-management strategies in water and wastewater conveyance systems.

IV. CONCLUSION

This study provided a comprehensive evaluation of sediment-transport prediction in circular pipelines by comparing the performance of four advanced machine-learning models (i.e. GPR, ANFIS, ANN, and SVM), under both smooth and rough bed conditions. The results clearly demonstrated that incorporating both hydraulic parameters and sediment particle characteristics significantly enhances predictive capability compared to using flow variables alone. Among all tested inputs, the F_d was identified as the most influential factor, with its removal producing the steepest decline in model accuracy across every learning algorithm. This confirms its essential role in governing sediment mobility and energy exchange within pipe-flow systems. Across all scenarios, GPR consistently provided the most accurate and stable predictions, achieving the highest CC and DC values and the lowest RMSE, even when roughness height increased. ANN and ANFIS also performed well, particularly in smooth-bed conditions where flow uniformity enhanced their ability to capture input–output relationships. SVM, while competitive under minimal roughness, was more sensitive to parameter variability and turbulence effects, leading to reduced performance under rough-bed conditions. The analysis further revealed that increasing bed roughness from 0.53 mm to 1.40 mm caused a clear degradation in predictive accuracy for all models, confirming the destabilizing effect of turbulence and irregular shear stresses on sediment-transport processes. Nevertheless, GPR maintained stronger resilience to roughness-induced complexity than the other models, indicating its suitability for systems with high variability. Totally, the study demonstrates that accurate prediction of sediment discharge in circular pipes requires modeling tools that can accommodate nonlinear interactions and respond effectively to hydraulic irregularities. GPR stands out as the most robust method, while ANN and ANFIS serve as reliable alternatives under smoother flow conditions. The insights gained here can support improved design, operation, and management of water and wastewater transport systems, reducing sediment-related failures and enhancing long-term infrastructure performance.

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AUTHORS' CONTRIBUTIONS

Alireza Naseri conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Ramin Vafaei Poursorkhabi assisted in the development of the methodology and performed validation checks, provided supervision, conceptual guidance, and critical revision of the manuscript. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors have not disclosed any competing interests.

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