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ANFIS BASED APPROACH TO PREDICT SEDIMENT REMOVAL EFFICIENCY OF VORTEX SETTLING BASIN

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ABSTRACT

The intricate flow dynamics within a vortex settling basin (VSB) make it challenging to establish a generalized regression model for accurately estimating sediment removal efficiency. Therefore, this study proposes an alternative approach using the Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the sediment removal efficiency of VSB. The model is developed based on a comprehensive and reliable database sourced from literature, encompassing a wide range of hydraulic and geometrical variables from laboratory and field studies. The sediment removal efficiency of the VSB is modelled as a function of five key variables: water abstraction ratio, depth ratio, width ratio, diameter ratio, and particle Reynolds number. Training and testing data are extracted from laboratory and field datasets in various reputable references. Numerical tests reveal that ANFIS yields more accurate VSB removal efficiency predictions than previous empirical approaches. Sensitivity analysis further indicates that the particle Reynolds number exerts a more significant influence on sediment removal efficiency than the other independent parameters. This ANFIS-based approach offers an enhanced understanding and prediction capability for the complex processes occurring within a VSB.

Keywords: ANFIS, Vortex, Settling basin

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INTRODUCTION

The sedimentation of canals, especially in power canal systems, poses a risk of turbine damage and reduced power plant efficiency if sediment loads exceed the canal's transport capacity (Remini and Remini, 2003; Remini and Bensafia, 2016; Remini, 2019; Toumi and Remini, 2020). In hydroelectric facilities and irrigation canals, sediment extractors are often used to avert this. Various extractors, including tunnels, vortex tubes, rectangular settling basins, and vortex settling basins, aim to exclude sediment particles from the diverted water (Remini and Hallouche, 2005; Remini, 2011; Remini, 2017). Vortex-settling basins are the subject of the present investigation due to their potential advantages. The study evaluates the performance of vortex settling basins compared to other extractor types, considering factors such as sediment removal efficiency, dimensions, residence time, and cost-effectiveness. The investigation involves experimental work, data collection, and analysis to assess the effectiveness of vortex-settling basins in mitigating sediment-related issues in canals and hydropower plants. Additionally, reviewing existing literature and case studies contributes to a comprehensive understanding of sediment extraction methods in this context.

By introducing a tangential, higher-velocity flow into a cylindrical basin that features an orifice at its central bottom, Vortex-type sediment extractors have successfully addressed the limitations associated with traditional settling basins by utilizing vortex flow within a basin as a separation mechanism. Consequently, a combination of vortex conditions arises, with a free vortex forming near the orifice and a forced vortex developing in the outer region toward the periphery. The resulting secondary flow prompts fluid layers near the basin floor to move towards the central outlet orifice. This movement causes sediment particles in the flow to follow a helicoidal path towards the orifice, allowing for a longer settling length than the basin's dimensions. Consequently, relatively higher velocities can be sustained within the basin. The sediment that reaches the centre can be continuously flushed out through the orifice. The definition sketch of a vortex settling basin is shown in Figure 1 (Ansari and Athar, 2013; Ansari and Khan, 2014; Athar, 2000; Athar et al., 2002, 2005; Cecen and Bayazit, 1975; Curi et al., 1979; Mashauri., 1986; Ogihara and Sakaguchi, 1984; Paul et al., 1991).

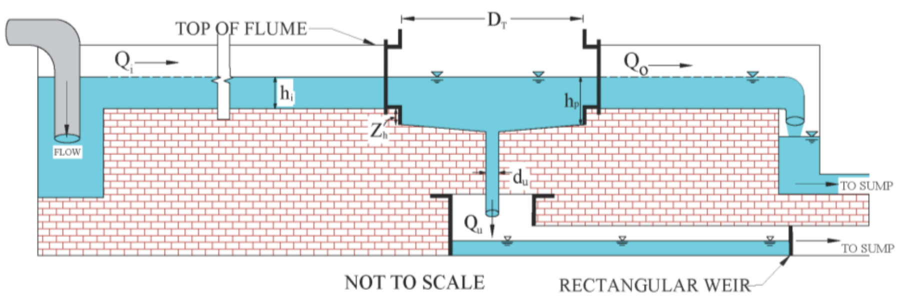

Figure 1: Definition sketch of vortex settling basin

Cecen and Akmandor, (1973) provided formulas for determining the basin diameter, sidewall height, and orifice diameter based on a given discharge, sediment size, and desired η_0. Several empirical equations for establishing the dimensions of the vortex basin and η_0, when sediment and flow-related factors are specified (Paul, 1988; Paul et al., 1991). Vortex chamber-type sediment extractors with different geometric configurations into three types and derived an expression for the parameter (Athar, 2000; Athar et al., 2002). Athar et al., (2005) analyzed the literature and laboratory experiment data, considering a wide range of water abstraction ratios, sediment particle Reynold's number, aspect ratio, and a new parameter represented as h_p/d_u. Ansari and Athar (2013) investigated the impact of the diameter and width ratio on the sediment removal efficiency of Vortex Settling Basins (VSB). Ansari and Khan (2014) investigated how the placements of the inlet and outlet channels affected the differences in the sediment removal efficiency of vortex settling chambers and created a new removal efficiency prediction model. Sharafati et al. (2021) introduced four hybrid AI models (ANFIS-PSO, ANFIS-GA, ANFIS-ACO, and ANFIS-DE) for predicting removal efficiency in sediment dischargers. The ANFIS-PSO model demonstrated the highest predictability, showing maximum correlation coefficient values of 0.915 and 0.916 for the training and testing, respectively, among the developed hybrid models. Kiringu and Basson, (2021) employed both numerical and physical modeling techniques to investigate the trapping of very fine sand particles (greater than 75 mm) utilizing Vortex Settling Basins (VSBs) in the context of small river diversion projects.

Despite the thorough analysis of extensive laboratory and field data gathered from the literature, the estimated removal efficiency values often need to be more consistent with their actual values. This discrepancy is attributed in part to the intricate nature of the phenomenon and, in part, to the limitations of the commonly employed analytical tool by many earlier investigators, namely, statistical regression. Adopting the Adaptive Neuro-Fuzzy Inference System (ANFIS) is an alternative approach to address the challenges associated with variability in physical modelling. ANFIS, known for its high flexibility in data mining, is utilized in the current study to predict the sediment removal efficiency of a vortex-settling basin.

This study aims to consolidate past observations regarding sediment removal efficiency in vortex-settling basins and assess the efficacy of ANFIS compared to statistical approaches for modelling sediment removal efficiency prediction in Vortex Settling Basins (VSB).

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The fuzzy logic approach expresses uncertainty through linguistic terms rather than numerical values. The fuzzy inference system consists of three main components: a rule base with fuzzy if-then rules, a database defining membership functions, and an inference system combining rules to produce results (Şen and Altunkaynak, 2004). The fuzzy logic modelling process involves determining membership functions, constructing fuzzy rules, and defining output characteristics, output membership functions, and system results (Firat and Güngör, 2008; Sazi Murat, 2006).

ANFIS combines the learning capabilities of artificial neural networks (ANNs) with the reasoning abilities of fuzzy logic. ANFIS can model complex and nonlinear relationships without requiring expert knowledge traditionally needed in standard fuzzy logic design. There are two types of fuzzy inference systems: Mamdani and Takagi-Sugeno (TS). Mamdani is preferred for capturing expert knowledge due to its intuitive rule base, but it involves a substantial computational burden and requires a defuzzification step. Takagi-Sugeno uses a weighted average for crisp output, avoiding the need for classical defuzzification and offering better processing time. However, TS requires effective parameter selection, and ANFIS was developed to optimize these parameters using a hybrid learning algorithm. The present study employs a first order Sugeno inference system within ANFIS (Jang, 1993).

To present the ANFIS architecture, two fuzzy if-then rules based on first order Sugeno model are considered.

Rule 1. If x_1 is A_1 and x_2 is B_1 then $f_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2. If x_1 is A_2 and x_2 is B_2 then $f_2 = p_2x_1 + q_2x_2 + r_2$

where x_1 and $x_2$are the crisp inputs to the i^{th} node, A_i and B_i are the linguistic labels such as low, medium, high etc., which are characterized by convenient membership functions, and A_i, q_i and r_i are the consequent parameters.

The ANFIS architecture having five layers to implement the above mentioned two rules is shown in Figure (2), in which a circle indicates a fixed node, where as a square indicates an adoptive node.

The functional details of these layers are as follows:

Layer 1 (Input Layer): This layer represents the input variables to the system. Each node in this layer generates membership grades of the crisp inputs which belong to each of the convenient fuzzy sets by using membership functions.

Each node's output O_i can be represented as:

$$O_i^1 = \mu_{(A_i)}(x_1) \; for \, i = 1,2$$

$$O_i^1 = \mu_{(B_i-2)}(x_2) \; for \, i = 3,4 \tag{1}$$

$$O_i^1 = \mu_{(A_i)}(x_1) = e^{-0.5\left(\frac{x-c_i^2}{a_i}\right)} \tag{2}$$

Where μ_{Ai} and μ_{Bi} are the membership functions for the A_i and B_i fuzzy sets respectively and a_i and c_i are the premise parameters and these parameters change the shape of the membership function from 1 to 0. Various membership functions, such as triangular, generalized bell function, Gaussian function, etc., can be applied to determine the membership grades. In the present study, the Gaussian membership function represented as Equation (2) is used.

Layer 2 (Fuzzification Layer): Fuzzy membership functions are applied to the input variables to represent their degree of membership to linguistic terms. The nodes in this layer are fixed nodes. The AND/OR operator is applied to get one output representing the antecedent results for a fuzzy rule, i.e., firing strength. The outputs of the second layer, called firing strengths O_i^2, are the products of the corresponding degrees obtained from layer 1, termed w, i.e.

$$O_i^2 = w_i = \mu_{(A_i)}(x_1)\mu_{(B_i)}(x_2) \text{ i=1,2} \tag{3}$$

Layer 3 (Rule Layer): This layer computes the firing strength of each rule by combining the fuzzy membership values. The nodes of this layer are fixed nodes-labelled N. The main target is to compute the ratio of firing strength of each i^{th} rule to the sum of the firing strength of all rules. The firing strength in this layer is normalized as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{\sum_i w_i} \quad i{=}1{,}2 \tag{4}$$

Layer 4 (Normalization Layer): The firing strengths are normalized to ensure consistent scaling. The nodes of this layer are adoptive nodes and uses the above ratio as weighing factor. The contribution of the i^{th} rule towards the total output or the model output and/or the function defined is calculated by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x_1 + q_i x_2 + r_i) \quad i{=}1{,}2 \tag{5}$$

where $\overline{w}_i$ is the i^{th} node output from the previous layer and (p_i, q_i, r_i) is the set of parameters of this layer. These parameters are called as consequent parameters.

Layer 5 (Output Layer): The output of the system is computed by aggregating the contributions of all rules. This layer has one node for single output, which is a fixed node labelled as S. This node computes the overall output by summing all incoming signals and it is the last step of ANFIS. The overall output of the ANFIS is calculated as:

$$f(x_1, x_2) = \frac{w_1(x_1,x_2)f_1(x_1,x_2)+w_2(x_1,x_2)f_2(x_1,x_2)}{w_1(x_1,x_2)+w_2(x_1,x_2)} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{6}$$

$$O_i^5 = f(x_1, x_2) = \textstyle\sum_i \bar{w}_i f_i$$

$$O_i^5 = \bar{w}_1 f_1 + \bar{w}_2 f_2 = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

The task of the learning algorithm is to tune all the modifiable parameters, namely (a_i c_i) and (p_i, q_i, r_i) to make the ANFIS output match the training data. This learning algorithm is a hybrid algorithm consisting of the gradient descent and the least-squares estimate. Using this hybrid algorithm, the rule parameters are recursively updated until acceptable error is reached. Each iteration includes two sweeps, one forward and one backward. In the forward pass, the antecedent parameters are fixed, and the consequent parameters are obtained using the linear least-squares estimate. In the backward pass, the consequent parameters are fixed, and the output error is back propagated through the network, and the antecedent parameters are updated accordingly using the gradient descent method. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass.

The learning mechanism employed in the Adoptive Neuro-Fuzzy Inference System (ANFIS) employs a hybrid strategy that merges the gradient descent method with the least-squares estimate. This amalgamated algorithm plays a pivotal role in fine-tuning the adjustable parameters of the ANFIS model, explicitly targeting the antecedent parameters (a_i c_i) and the consequent parameters (p_i, q_i, r_i). The primary objective of this learning algorithm is to iteratively modify these parameters to ensure a harmonious alignment between the ANFIS output and the training data. This iterative process persists until a satisfactory level of error is attained.

Let's delve into the specifics of the hybrid-learning algorithm:

a) **Initialisation:** The parameters amenable to modification (a_i, c_i, p_i, q_i, r_i) undergo an initialisation process, either randomly or according to predefined criteria.
b) **Forward Pass:** In the forward pass, the antecedent parameters (a_i c_i) remain constant, while the consequent parameters (p_i, q_i, r_i) are determined using the linear least-squares estimate. The linear least-squares estimate minimises the sum of squared errors between the actual output and the output predicted by the current parameter set. This step is critical for refining the consequent parameters to better suit the training data.
c) **Backward Pass:** During the backward pass, the consequent parameters (p_i, q_i, r_i) are held steady, and the output error undergoes backpropagation through the network. The antecedent parameters (a_i c_i) are then updated using the gradient descent. This method involves adjusting the parameters opposite to the gradient of the error function concerning the parameters. This iterative refinement process enables the system to minimise the overall error by fine-tuning the antecedent parameters.
d) **Iteration:** A single iteration of the learning algorithm encompasses both the forward and backward passes. This iterative process is repeated for a predetermined number of iterations or until a convergence criterion is met.
e) **Convergence Check:** The learning algorithm updates the parameters until the error reaches a satisfactory level or until a predefined convergence criterion is fulfilled. This criterion might be based on the error change or the parameter alteration between successive iterations.
f) **Output Calculation:** Upon achieving convergence, the final set of consequent parameters obtained from the forward pass is utilised to compute the output of the ANFIS for new input data.

It is crucial to emphasise that this hybrid learning algorithm, elucidated by Jang, (1993), amalgamates the advantages of gradient descent and least-squares estimation methods. The gradient descent facilitates local adjustments for parameter fine-tuning, while the least-squares estimate contributes a global optimisation perspective, enhancing the adaptability and generalisation capabilities of ANFIS.

METHODOLOGY

The methodology of the present study is presented herein.

Collection of Laboratory and field data

Comprehensive experimental data about various types of vortex-settling basins were acquired through laboratory experiments conducted by researchers viz. (Ansari, 2008; Ansari and Athar, 2013; Ansari & Khan, 2014; Athar, 2000; Athar et al., 2002; Curi et al., 1979; Esen, 1989; Mashauri., 1986; Paul et al., 1991). Additionally, field data sourced from the investigations of (Mashauri., 1986; Paul, 1988; Paul et al., 1991) were incorporated. The non-dimensional parameters employed in the present study have been systematically organized in Table 1.

Table 1: Range of dimensionless parameters used in present study

S.No.	Source	Q_u/Q_i Min.- Max (%)	Z_h/h_p Min.- Max	$\omega_o d_{50}/\nu$ Min.- Max
1	(Curi et al., 1979)	3.60–10.60	0.337 – 0.727	65.30
2	(Mashauri., 1986) M-I	5.60–18.20	0.848	1.25 – 120.8
3	(Mashauri., 1986) M-II	3.90–6.60	0.793	4.26 – 20.63
4	(Mashauri., 1986) M-III	3.30–14.0	0.832	0.21 – 8.45
5	(Paul, 1988)	2.20 – 22.0	0.538	0.43 – 0.51
6	(Esen, 1989)	4.70 – 6.90	0.30- 0.75	10.1-126.6
7	(Paul et al., 1991)	12.0 – 22.0	0.172-0.571	4979.8
8	(Athar, 2000; Athar et al., 2002)	8-17	0.192-0.649	0.15-127.29
9	(Ansari, 2008; Ansari & Athar, 2013)	0.0 - 20.0	0.558 - 0.684	0.175 - 100.77
10	(Ansari & Khan, 2014)	0.0 - 20.0	0.56-0.67	18.35-100.41

S.No.	Source	D_T/d_u Min.- Max	D_T/B Min.- Max	h_p/d_u Min.- Max	η_o Min.- Max (%)
1	(Curi et al., 1979)	17.72-70.87	5.0	2.76-2.90	48.0 – 89.0
2	(Mashauri., 1986) M-I	25.0-33.33	1.28	-	45.0 – 80.0
3	(Mashauri., 1986) M-II	25.0-50.0	1.28	-	87.0 – 90.0
4	(Mashauri., 1986) M-III	17.98-59.88	1.28	-	40.0 – 90.0
5	(Paul, 1988)	24.10-97.09	3.01-5.02	-	23.0 – 41.0
6	(Esen, 1989)	37.03	5.0	2.77	84.0 – 90.0
7	(Paul et al., 1991)	21.23-28.33	5.0	5.0-8.46	72.0 – 90.0
8	(Athar, 2000; Athar et al., 2002)	10.0	5.0	1.45-1.61	20.0–90.0
9	(Ansari, 2008; Ansari & Athar, 2013)	9.91 - 38.76	4.87 - 25.17	1.5-2.8	21 – 89
10	(Ansari & Khan, 2014)	9.91	4.87	1.18-1.41	21 – 95

Dimensional analysis for sediment removal efficiency of vortex settling basin

The removal efficiency of vortex settling basin (η_0) can be expressed as a function of the discharge in inlet channel (Q_i), discharge through underflow outlet (Q_o), difference in elevation between bed of vortex chamber and overflow outlet channel (Z_h), the head at the periphery of the basin (h_p), diameter of vortex chamber (D_T), width of inlet canal (B), diameter of underflow outlet (d_u), median size of sediment particles (d_{50}), the fall velocity of the sediment particle (ω_0), the kinematic viscosity of water (ν) and acceleration due to gravity (g) (Ansari and Athar, 2013).

$$\eta_0 = f\,(Q_i, Q_u, Z_h, h_p, D_T, B, d_u, d_{50}, \omega_0, \nu, g) \tag{8}$$

The Buckingham theorem makes it simple to organize the variables of Equation (1) into the subsequent non-dimensional form (Ansari and Athar, 2013).

$$\eta_o = f\left(\frac{Q_u}{Q_i}, \frac{Z_h}{h_p}, \frac{D_T}{B}, \frac{D_T}{d_u}, \left(\frac{\omega_o d_{50}}{\nu}\right)\right) \tag{9}$$

Here $Q_R = \frac{Q_u}{Q_i}$ represents the discharge ratio, $Z_R = \frac{Z_h}{h_p}$ is the depth ratio, $B_R = \frac{D_T}{B}$ is the width ratio, $D_R = \frac{D_T}{d_u}$ is the diameter ratio and $R_e = \left(\frac{\omega_o d_{50}}{\nu}\right)$ is the particle Reynolds number. Such a functional relationship can be used to develop an ANFIS model for the removal efficiency of the vortex settling basin.

Development of ANFIS model

The ANFIS input, illustrated in Figure 2, undergoes conversion into fuzzy membership functions. These functions are combined, and an average process is applied to obtain output membership functions, leading to the final desired output.

The construction of the ANFIS model, depicted in Figure 3, involves inputs *(Q_R, Z_R, B_R, D_R, R_e)* and output η_0. Genfis2 is employed to create a first-order Sugeno fuzzy system, utilizing seven membership functions for η_0 estimation. A fuzzy logic toolbox in MATLAB is utilized to establish the causal relationship for sediment removal efficiency. The training process involves 80% of randomly selected data for training and 20% for testing/validation. ANFIS, combined with a fuzzy subtractive clustering algorithm, forms the initial rule base. The number of clusters is determined experimentally, with a cluster radius of 0.557 and seven clusters. The ANFIS model employs a hybrid learning rule for training based on input/output data pairs, completing training at epoch 300. Details of the membership functions are presented in Figure 3**Erreur ! Source du renvoi introuvable.**, showcasing the influence of each input parameter on the output after training. Table 2 summarizes the results of the ANFIS model.

The performance evaluation of the ANFIS model includes the coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). The training stops when an acceptable error level is achieved, or the number of iterations exceeds a predetermined maximum.

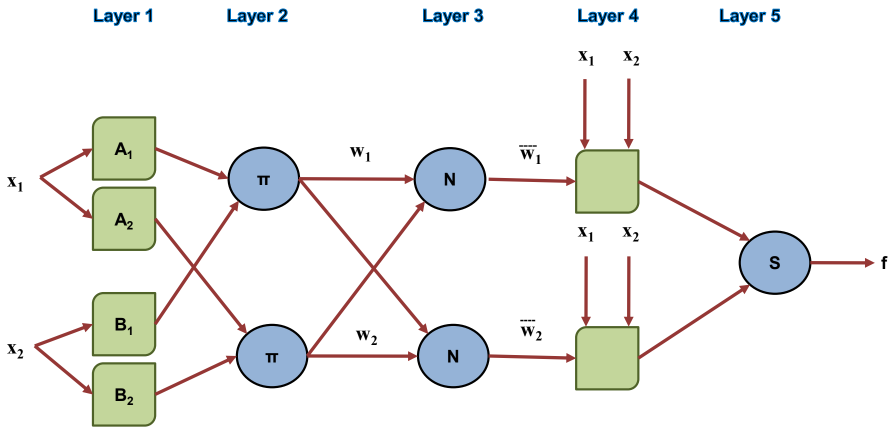

Figure 2: Basic architecture of ANFIS

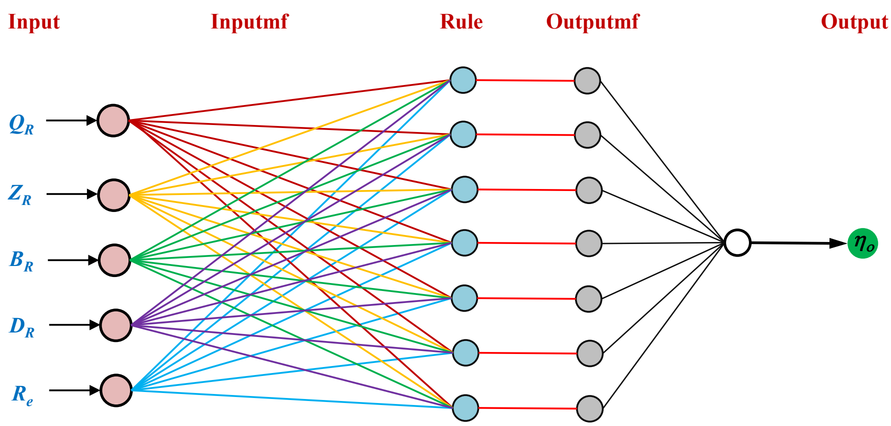

Figure 3: The ANFIS for sediment removal efficiency

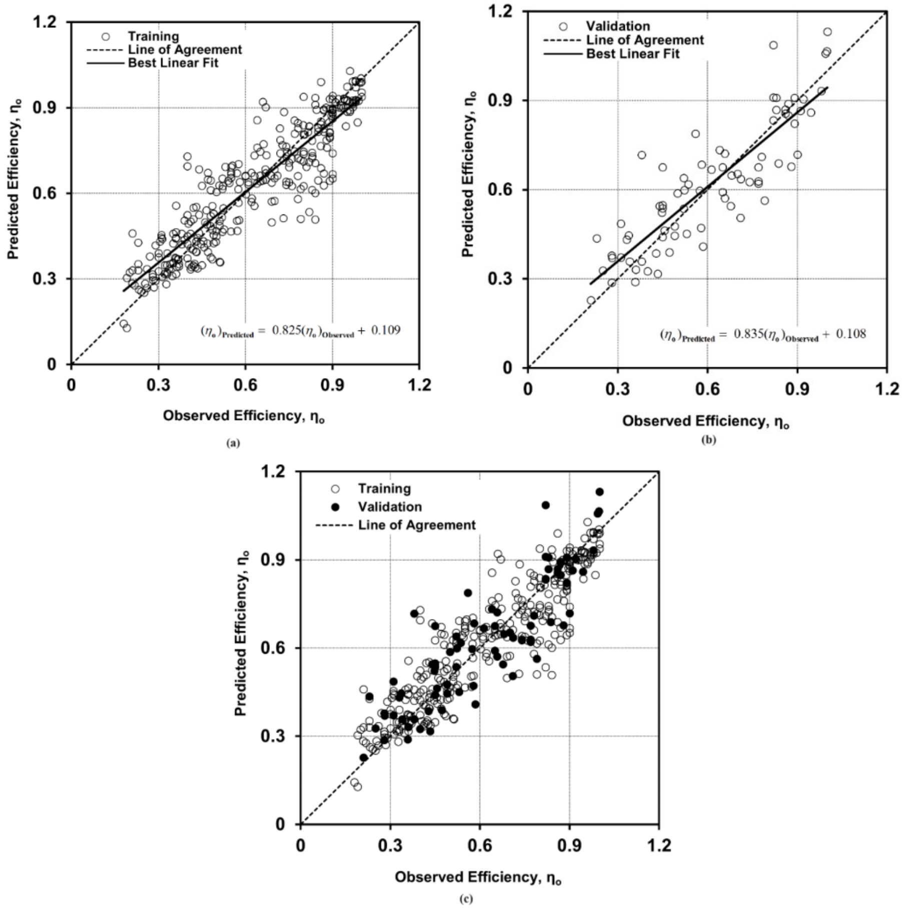

Figure 4: Comparison between observed and computed values of efficiency

Table 2: Detail of ANFIS model parameters

S. No.	Parameters	Number
1	Number of inputs	5
2	Number of membership functions for each input	7
3	Type of membership functions for each input	Gaussian
4	Fuzzy rules	7
5	Type of membership functions for each output	Linear
6	Number of membership functions for output	7
7	Nodes	92
8	Linear parameters	42
9	Nonlinear parameters	70
10	Total parameters	112
11	Training data pairs	311
12	Checking data pairs	77
13	Cluster radius	0.557

RESULTS AND DISCUSSIONS

The assessment of model performance is conducted through error estimation parameters, namely *R^2, MAPE*, and *RMSE*. Table 4 provides these metrics for both the regression and ANFIS models. A visual representation of the comparison between the calculated sediment removal efficiency, derived from the ANFIS model, and observed values is illustrated in **Erreur ! Source du renvoi introuvable.** for both the training and testing datasets. This comparative analysis offers insights into the accuracy and reliability of the ANFIS model in predicting sediment removal efficiency.

Table 3: Available relationships for sediment removal efficiency of vortex settling basin

S.No.	Investigator	Available Relationships
1	(Paul et al., 1991)	$\eta_0 = 98 + 0.92 \rightleftarrows log(V_s/W)$
2	(Paul et al., 1991)	$\eta_0 = 97.8(V_s/V_{to})^{0.0045}(Q_u/Q_i)^{0.01}$
3	(Athar et al., 2002)	$\eta_0 = 2.24(Q_u/Q_i)^{0.25}(Z_h/h_p)^{0.35}(\omega_0 d_{50}/\nu)^{0.15}(Q_w^2/gR_T^3h_p^2)^{0.11}$ and $\eta_0 = 1.35(Q_u/Q_i)^{0.25}(Z_h/h_p)^{0.35}(\omega_0 d_{50}/\nu)^{0.15}(Q_w^2/gR_T^3h_p^2)^{0.11}$
4	(Athar et al., 2005)	$\eta_0 = 0.4(Q_u/Q_i)^{0.27}(D_T/d_u)^{0.1}(\omega_0 d_{50}/\nu)^{0.12}(h_p/d_u)^{0..35}$
5	(Ansari and Athar, 2013)	$\eta_o = 0.44 \left(\frac{Q_u}{Q_i}\right)^{0.19}\left(\frac{Z_h}{h_p}\right)^{0.15}\left(\frac{\omega_o d_{50}}{\upsilon}\right)^{0.11}\left(\frac{D_T}{d_u}\right)^{0.11}\left(\frac{D_T}{B}\right)^{0.10}$
6	(Ansari and Khan, 2014)	$\eta_0 = 0.559(D_T/B)^{-0.212}(D_T/d_u)^{-0.025}(h_p/d_u)^{0.227}(Q_u/Q_i)^{0.116}(\boldsymbol{\omega_0 d_{50}/\nu})^{\mathbf{0.107}}(\boldsymbol{Z_h/h_p})^{\mathbf{-0.257}}$

Table 4: Performance parameters of existing and ANFIS model

Source	Data set	Performance parameters					
		R^2	APE	MAPE	AAD	RMSE	STDV
(Paul et al., 1991)	Training	0.390	-93.0804	93.09521	61.85399	0.438161	92.25061
Model I	Testing	0.415	-83.4572	83.45724	57.31896	0.422229	77.42678
(Paul et al., 1991)	Training	0.395	-77.8913	78.58665	49.7755	0.381599	84.85917
Model II	Testing	0.420	-77.0255	77.46916	52.20955	0.381994	77.40152
(Athar et al., 2002)	Training	0.255	17.5660	41.40200	42.98800	0.334000	28.39500
	Testing	0.153	18.6220	40.18300	42.13500	0.323000	27.97300
(Athar et al., 2005)	Training	0.686	-2.81844	25.92357	22.94885	0.172541	25.81265
	Testing	0.641	-2.12772	26.52212	23.08555	0.181221	28.23479
(Ansari & Athar,	Training	0.423	2.59899	32.88808	31.08978	0.225918	24.90411
2013)	Testing	0.369	4.417783	32.13546	30.41322	0.234456	28.83672
(Ansari & Khan,	Training	0.753	-8.96823	25.02786	20.2135	0.149747	25.58304
2014)	Testing	0.737	-7.88695	24.36534	20.01028	0.152936	24.9883
ANFIS Model	Training	0.915	-3.27051	13.39407	11.00353	0.095064	15.41759
	Testing	0.884	-4.44876	15.83605	13.36804	0.105335	15.78243

Comparison of ANFIS model with existing relationships for η_o

A comparative analysis was conducted to assess the predictive accuracy of the ANFIS model regarding the sediment removal efficiency of Vortex Settling Basins (VSB). The ANFIS model was compared with existing relationships found in the literature, utilizing the same dataset, and the results are detailed in Table 4. The selected models for comparison were those formulated by (Ansari and Athar, 2013; Ansari and Khan, 2014; Athar et al., 2002, 2005; Paul et al., 1991), as indicated in Table 3.

It is evident from **Erreur ! Source du renvoi introuvable.** and Table 4 that the ANFIS model outperforms the available relations in predicting sediment removal efficiency. Table 4 explicitly highlights that the R^2 value attains its maximum at 0.915, while the MAPE, ADE, and RMSE values are notably low at 13.394, 11.004, and 0.0951, respectively, for the ANFIS model. These results signify a satisfactory estimation of VSB sediment removal efficiency, indicating the efficacy of the ANFIS approach in addressing nonlinearity within the data. The comparison suggests that applying fuzzy if-then rules in ANFIS is more suitable for processing efficiency data than the crisp value processing employed in existing relations. The present ANFIS model should be utilized within the range of data outlined in Table 1.

Sensitivity analysis

Sensitivity tests were conducted to assess the relative significance of each independent parameter (input) on the efficiency of removal (output) in the context of the Vortex Settling Basin (VSB). In the sensitivity analysis, each input parameter was systematically eliminated from the model, and its impact on predicting the removal efficiency of the VSB was evaluated based on criteria such as R^2, *MAPE*, and *RMSE*.

The comparison of different ANFIS models, where each model had one independent parameter removed, is outlined in Table 5. The results from Table 5 indicate that the Reynolds number, R_e, emerges as the most significant parameter for predicting the removal efficiency of the vortex settling basin. The variables, in descending order of sensitivity for the ANFIS model, are: R_e, D_R, Q_R, Z_R, and B_R. These findings align with the established understanding of the hierarchical importance of various parameters in influencing the removal efficiency of a vortex settling basin.

Table 5: Sensitivity analysis for ANFIS model

Input variables	Data set	Performance parameters					
		R^2	APE	MAPE	AAD	RMSE	STDV
All (Eq.9)	Training	0.914526	-3.27051	13.39406	11.00353	0.095063	15.41758
	Testing	0.883868	-4.44876	15.83605	13.36804	0.105334	15.78243
NO $\boldsymbol{Q_R}$	Training	0.866239	-5.49981	17.35569	14.23432	0.117417	19.64364
	Testing	0.839035	-6.00590	18.94599	16.28553	0.130895	19.69554
NO $\boldsymbol{Z_R}$	Training	0.8677	-5.07330	17.13828	14.04259	0.116816	20.08586
	Testing	0.823569	-4.43862	19.30155	16.3027	0.128441	19.35565
NO $\boldsymbol{B_R}$	Training	0.874829	-4.70265	16.39800	13.72777	0.113841	17.33267
	Testing	0.837571	-4.27344	16.99944	14.99758	0.122535	16.75058
NO $\boldsymbol{D_R}$	Training	0.863044	-4.91318	17.06345	14.35562	0.118705	20.41694
	Testing	0.812217	-5.21910	18.63489	16.22231	0.128462	17.19098

NO $\boldsymbol{R_e}$	Training	0.805484	-7.36045	22.48465	17.89191	0.139265	21.97371
	Testing	0.772839	-11.2471	24.22015	18.73921	0.14112	23.98218

CONCLUSION

This study explores the applicability of the Adaptive Neuro Fuzzy Inference System (ANFIS) as an alternative to conventional empirical prediction equations for estimating the sediment removal efficiency of vortex settling basins. The analysis involves an extensive dataset, incorporating both laboratory and field data, to predict sediment removal efficiency based on parameters such as Q_i, Q_u, Z_h, h_p, D_T, B, d_u, d_{50}, ω_0.

Comparing the results, the ANFIS technique demonstrates generally superior performance compared to traditional empirical equations, characterized by lower errors and higher correlation coefficients. The accuracy of sediment removal efficiency equations proposed by various researchers were evaluated using a diverse dataset, revealing that none of the existing predictors achieve satisfactory performance for vortex settling basin sediment removal efficiency. In contrast, the recommended ANFIS model provides computed sediment removal efficiency values that closely align with measured values. Qualitatively, the ANFIS model exhibits the lowest MAPE = 13.394, RMSE = 0.0951, APE = -3.4356, and the highest R^2 = 0.915 compared to existing relations.

Sensitivity analysis indicates that Reynolds number (R_e) is the most significant parameter, with the variables ranked in decreasing order of sensitivity for the ANFIS model being R_e, D_R, Q_R, Z_R, and B_R. However, given the limitations and uncertainties in the data, an ANFIS model incorporating all input variables is deemed desirable for a more comprehensive analysis.

Declaration of competing interest

The authors declare that they have no know competing interests or personal relationships that could have appeared to influence the work reported in this paper.

Notations

B	=	Bed width of the inlet channel
c	=	Concentration in parts per million
d	=	Diameter of the inlet pipe
D_T	=	Diameter of the vortex-settling basin
$D_T/B = B_R$	=	Width ratio
d_{50}	=	Median size of the sediment particles
d_u	=	Diameter of the under flow outlet orifice
g	=	Gravitational acceleration
h_i	=	Depth of flow at entrance of the vortex settling basin
h_p	=	Depth of flow at the periphery of the vortex settling basin

h_u = Depth of flow at the centre of the underflow outlet
ppm = Parts per million
Q_i = Discharge in inlet channel
Q_u = Discharge through underflow outlet
$Q_u/Q_i = Q_R$ = Water abstraction ratio
S_T = Bottom slope of the vortex settling basin
z = Depth in the basin measured from the bottom of basin
Z_h = Difference between the bed levels of vortex settling basin and overflow outlet channels
$Z_h/h_p = Z_R$ = Depth ratio
η_o = Efficiency of sediment removal
ν = Kinematic viscosity
ω_o = Fall velocity of the sediment particle
$\frac{\omega_o d_{50}}{\nu} = R_e$ = Particle Reynolds number

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APPENDIX

IMPLEMENTING THE CURRENT ANFIS-BASED PREDICTION MODEL FOR SEDIMENT REMOVAL EFFICIENCY OF VORTEX SETTLING BASIN

The utilization of the current model is characterized by its inherent simplicity and ease of application. Upon training, the neural networks can be serialized into a file format for preservation. Subsequently, within the MATLAB environment, the procedure involves invoking a designated function to derive the corresponding output for a specified input.

$output\ =\ evalfis(fis, input);$

This function conducts a simulation of the Fuzzy Inference System as *fis* based on the input and target data as *input* and *target*, respectively, producing corresponding output data as *output*. In a system featuring N input variables and L output variables, *input* represents an M × N matrix, where each row corresponds to a distinct input value. Likewise, *target* denotes a vector, where each row contains the corresponding target values.

Example 1

(i) *The values of input parameters,* $\left(\frac{Q_u}{Q_i}, \frac{Z_h}{h_p}, \frac{D_T}{B}, \frac{D_T}{d_u}, \left(\frac{\omega_o d_{50}}{\nu}\right)\right)$ *and the target,* (η_0) *are:*

(ii) $$input = \begin{pmatrix} 0.074 & 0.411 & 5.000 & 35.433 & 65.296 \\ 0.059 & 0.727 & 5.000 & 35.433 & 65.296 \\ 0.186 & 0.249 & 5.000 & 35.433 & 65.296 \\ 0.143 & 0.269 & 5.000 & 17.717 & 65.296 \\ 0.106 & 0.428 & 5.000 & 17.717 & 65.296 \end{pmatrix} \quad target = \begin{pmatrix} 0.960 \\ 0.890 \\ 0.970 \\ 0.930 \\ 0.890 \end{pmatrix}$$

(iii) *The predicted values of removal efficiency of vortex settling basin* (η_0) *can be calculated utilizing the subsequent functions:*

(iv) $fismat = anfis\big([input, target], genfis(input, target)\big);$

(v) $output\ =\ evalfis(fismat, input);$

(vi) *The results of output are as follows:*

(vii) $$output = \begin{pmatrix} 0.880 \\ 0.757 \\ 0.972 \\ 0.912 \\ 0.912 \end{pmatrix}$$