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OPTIMIZATION OF SCOURS DOWNSTREAM OF CONDUIT AERATORS

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ABSTRACT

Dams, wastewater treatment plants, and aquaculture areas often require aeration, making it crucial for hydraulic engineers to predict the physical properties of scour holes occurring on the downstream side of conduits. Conduit systems that provide high aeration performance necessitate multiple optimization studies to simultaneously maximize the scour parameters and the system's physical properties. In this study, the physical parameters of conduit systems and downstream scour parameters were optimized using Artificial Neural Networks (ANN). The optimum system parameters were identified based on the experimental results through ANN-based optimization. Additionally, the real and optimal effects of the parameters on aeration performance and scour were determined. The results of the study demonstrated that ANN can be effectively used in studies aimed at optimizing the aeration performance and scour values of conduits. This study is the first to apply ANN for the simultaneous optimization of both aeration efficiency (Q_a/Q_w) and scour characteristics (d_{max} and δ) in a conduit-based hydraulic system. Previous studies have typically focused on either scour or aeration individually; this study integrates both through a multi-objective ANN model. The findings provide novel insights for the design and retrofitting of energy-dissipating conduit structures in high-head dam applications. Unlike traditional empirical or regression-based approaches, the ANN model captures complex, nonlinear relationships among multiple interacting hydraulic variables. It identified optimal parameter combinations — such as 70% gate opening, 1.30–1.50 m conduit length, and 9 mm air hole diameter — that improve both aeration

and scour behavior. These outcomes offer direct applicability for real-world hydraulic system optimization.

Key words: Aeration performance, ANN, conduit, optimization, scour hole

Article Highlights

- ANN successfully optimized conduit aeration system parameters for enhanced aeration performance and reduced scour depth.
- The study showcases the effectiveness of ANN optimization, offering valuable insights into improving aeration system design for optimal performance and scour hole dimensions.
- Optimal parameter levels were identified, indicating that a 70% gate opening, 29 cm hydrostatic level, 9 mm air hole, and 1.30m conduit length yielded maximum aeration performance at a minimal scour hole.

1. INTRODUCTION

Water jets are a very common phenomenon in hydraulic engineering. Wastewater jets (discharges) into offshore seas and lakes, jets from dam weirs, waterfalls from under gates, culverts or drops can cause undesirable scouring of sediment-laden river beds. These jets can move in an inclined direction, a horizontal direction or a vertical direction. They can also be fully unsubmerged, fully submerged or partially submerged [1]. In line with both technological advances and increasing demands, high drop dams have started to be constructed in the world and in our country in recent years. Spillways are used to divert the floodwaters to the riverbed downstream of the dam. The main problem encountered in the design of high head dams is that the energy of the water leaving the weirs cannot be sufficiently absorbed. Erosion and various problems result from this situation [2].

Aeration is a commonly applied method in hydraulic engineering to dissipate the energy of high-velocity jets and reduce downstream scour. Its effectiveness has been demonstrated in many studies focusing on the scour problems caused by water jets [3–8]. Chatterjee et al. [9] investigated local scour and sediment transport under a horizontal jet. Bagatur et al. [10] studied bubble penetration depth, air entrainment, and oxygen transfer efficiency in plunging jet systems using different inclined nozzle types. Dong et al. [11] analyzed the erosion caused by vertical submerged jets on cohesive beds. These studies highlight the complex relationship between jet flow characteristics, aeration behavior, and sediment response.

An effective and unique way to reduce downstream scour is aeration. Alternative solutions are expensive and inefficient. Hydraulic structures that promote air-water two-phase flow bring air into the flow as tiny bubbles may enhance aeration. These bubbles greatly improve mass

transfer surface area. Example: conduit aeration. After partly opening a high-head outlet conduit gate, high-velocity flow generates sub-atmospheric pressure downstream, drawing air through an air vent. The smaller the air bubbles propelled downstream, the bigger the surface area and oxygen absorption efficiency [12].

Historically, research in the field of hydraulics has been conducted through the application of experimental formulas, the development of mathematical models, and the utilization of physical tests. These tests are usually simple, quite time-consuming, and can often yield erroneous results. Solutions to hydraulic engineering problems (such as aeration efficiency) have become possible with the development of artificial intelligence calculations. Computational methods based on artificial intelligence have attracted a great deal of interest in engineering. This is because these methods can leverage the available historical data to identify intricate relationships between various factors. Subsequently, the information can be tested on new data in order to obtain precise predictions [13]. Many researchers have acknowledged the effectiveness of artificial intelligence-based soft computing methods in the area of plunging jet aeration [14-16]. Baylar et al. [17] used the Adaptive Network Based Fuzzy Inference System (ANFIS) method to estimate both the air entrainment rate and the aeration efficiency of dams. This method was compared with several nonlinear and linear regression models in terms of performance. Good compatibility was found between the measured values and those predicted by the ANFIS model. Onen [18] used artificial neural network (ANN) and gene expression programming (GEP) models to predict clean water scour depth in side weirs. Bagatur and Onen [19] used GEP and regression methods to develop new formulations for predicting flow characteristics in a plunging water jet system. Karimaee Tabarestani and Zarrati [20] developed a method for sizing the riprap around the piers of a bridge using experimental data. In addition, non-dimensional parameters were applied to the artificial neural network (ANN) method to achieve greater accuracy in riprap design. The results showed that the ANN model predicted riprap size approximately 7% better than the regression formula. Kramer et al. [16] successfully modeled the penetration depth of extended discharge plunging water jets using ANN and nonlinear regression methods. Lashkar-Ara et al. [21] evaluated the effect of air entrainment on the depth of the scoured hole using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) methods. Kumar et al. [22] used artificial intelligence computational approaches for the prediction of oxygen mass transfer using plunging hollow jets. The data obtained from the experiment were employed in the construction of a model. The efficacy of Support Vector Machines (SVM) regression, M5 tree, and multiple non-linear regression was examined, utilizing both

dimensional and dimensionless data sets. As a result, the SVM method was found to be more successful than other methods. Aamir et al [23] used ANFIS and ANN methods for the prediction of the equilibrium wear depth of scour. Rathod and Manekar [24] used ANN, ANFIS, SVM, M5P (model tree), GEP and Group Method of Data Handling (GMDH) algorithms to calculate the Local Scour Depth (LSD) value. Mirzaee et al. [25] used soft computing techniques (Multi-Layer Perceptron (MLP) method, Radial Basis Function (RBF) network, Random Forest Algorithm (RFA) and Multivariate Adaptive Regression Splines (MARS) to estimate the depth of scour caused by cross jets. Puri et al. [26] investigated the effectiveness of different artificial intelligence computational models such as Random Forest, Reduced Error Pruning Tree, Artificial Neural Network (ANN), Gaussian Process, and Support Vector Machine to predict the aeration efficiency (E20) of circular and square jet configurations in open channel flow. As a result, this study showed that the ANN method performed better than the other methods. Devi et al. [27] investigated the scour depth generated by turbulent wall jets. Furthermore, the performance of support vector machine, artificial neural network with particle swarm optimisation, M5 tree algorithm, gene expression programming and adaptive neuro-fuzzy inference system (ANFIS) models for predicting scour depth were compared.

Recent hydraulic studies continue to demonstrate persistent challenges in scour control and the need for advanced, data-driven design tools. For example, research on jet aeration [28] confirms the value of soft-computing approaches in capturing nonlinear aeration dynamics, while studies on bridge pier scour mitigation [29, 30] highlight ongoing difficulties in predicting and minimizing erosion despite numerous geometric countermeasures. Previous applications of artificial intelligence in hydraulics have employed various models such as ANN, ANFIS, and SVM; however, their performance has not been systematically compared within a single framework. In general, ANN models provide higher predictive accuracy and flexibility for highly nonlinear problems, whereas SVM and ANFIS approaches are often constrained by kernel selection or fuzzy rule design. This gap in comparative understanding, combined with the absence of integrated optimization for both aeration performance and scour minimization in conduit systems, justifies the present study's focus on ANN-based optimization as a robust and generalizable solution.

Soft computing approaches such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Support Vector Machines (SVM) have all been applied in hydraulic engineering for modeling aeration and scour phenomena. ANN models are widely recognized for their ability to capture nonlinear interactions and provide high predictive accuracy [13]. ANFIS offers interpretable fuzzy rule-based

reasoning but requires computationally intensive training, while SVM demonstrates good generalization but is sensitive to kernel selection and less efficient in multi-objective optimization [22]. Previous studies (e.g., Local Scour Depth Around Bridge Piers: Performance Evaluation of Dimensional Analysis-based Empirical Equations and AI Techniques [31]) show that ANN often outperforms empirical and regression-based methods when modeling highly nonlinear hydraulic processes. However, no systematic framework has compared these methods specifically for conduit systems where aeration performance (Q_a/Q_w) and scour minimization ($d_{\max}$, δ) must be optimized simultaneously. This gap further justifies the present study's focus on ANN-based optimization as a robust and generalizable solution.

Recent studies published between 2020 and 2024 are directly related to scour processes under aerated jet flows and ANN-based hydraulic modeling. Notable examples include Feng et al. [32], who examined pulsed submerged jet-induced scouring on cohesive beds; Puri et al. [13], who modeled aeration in circular jets using soft computing in open channels; and Kumar et al. [22], who used regression approaches to predict oxygen mass transfer in plunging jets. These works reinforce the relevance and timeliness of the proposed methodology.

In this study, the Artificial Neural Network (ANN) method was used to optimize the downstream scour process of a conduit system, considering multiple performance characteristics. For this purpose, experimental parameters such as conduit contraction angle, conduit length, hydrostatic level height, and air chamber diameter were selected, representing different aeration performances. The effects of these experimental parameters on Q_a/Q_w (aeration efficiency ratio), maximum scour depth, and scour length (δ) values were examined, and optimization was performed using ANN. The optimization process was carried out in two different ways, where the experimental results were evaluated independently and collectively. In both cases, the optimum results and the corresponding optimal parameter levels were determined.

The novelty of this research lies in its dual-objective optimization strategy: this is the first study to simultaneously optimize aeration efficiency (Q_a/Q_w) and scour behavior ($d_{\max}$ and δ) using Artificial Neural Networks in a pressurized conduit system. Previous studies have treated these processes independently, whereas our model integrates both, offering a comprehensive performance evaluation. The experimental design reflects realistic conduit geometries and flow regimes, and the results provide practical design insights for energy-dissipating outlet structures in high-head dam applications.

Despite the growing use of artificial intelligence in hydraulic engineering, most prior studies—such as Bagatur et al. [10], Baylar et al.

[17], Lashkar-Ara et al. [21], and Rathod and Manekar [24]—have focused on either aeration or scour separately, often relying on regression-based or empirical models. These approaches fall short in capturing the nonlinear interactions between flow dynamics, aeration, and sediment response in complex systems. This study fills that gap by applying a multi-objective, data-driven ANN model to optimize both aeration efficiency and scour mitigation simultaneously in a realistic conduit setting.

1.1 Artificial Neural Networks

The basic mechanism of artificial neural networks is inspired by the functioning of biological neurons. As shown in Fig 1, the neurons that constitute the biological neural network consist of three main components: Soma, Axon, and Dendrites. The Soma, which contains the nucleus and cell plasma, is responsible for controlling the cell and managing its activities. The Dendrites, located at both ends of the neuron, are responsible for receiving signals from adjacent neurons and transmitting information to the Dendrites on the opposite side of the cell via the Axons. In the biological neural network, cells are separated by small gaps called synapses. When a signal reaches the synapse, it is transmitted to the next neuron through the release of neurotransmitters, which cross the synapse chemically [33].

Fig 1. Biological neuron structure

ANN is functionally analogous to the biological neural structure in the nervous system. It is organized in the form of a network made up of artificial neuron groups arranged in interconnected layers. The ANN collects input signals (x_k) with synaptic weights (w_k) and passes them through an activation function (F). After this stage, the output value (Y_k) produced by the network is obtained. The mathematical model of an artificial neuron is presented in Fig 2 [34].

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249

250 **Fig 2.** Mathematical model of neurons

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252 ANN consists of three layers: the input layer, one or more hidden layers,
253 and the output layer (Fig 3). Neurons in the input layer send data to
254 neurons in the hidden layer through synapses. In the hidden layer, a
255 portion of the data is used for training the network, while the remaining
256 data is used for testing and validation, after which the results are sent to
257 the neurons in the output layer [35].

258

259

260 **Fig 3.** Artificial neural network

261

262 **2. MATERIAL AND METHOD**

263

264 The present study aimed to investigate the impact of physical parameters,
265 including varying gate openings, conduit hole diameter, conduit length,
266 downstream depths, and flow with distinct Froude numbers, on the
267 aeration performance and scouring process in pressurized conduits (Table
268 1). All experiments were conducted on experimental setups established in
269 the Hydraulic Laboratory of Firat University Civil Engineering. The
270 experiments were conducted using mains water. No discernible impact of
271 suspended solids, organic matter, or salt, which might influence the

efficiency of air intake and oxygen transfer, was observed in the mains water.

Table 1. Experimental parameters (independent variables) and their levels

Experimental Parameters						
Parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Flow Rate (m ³ /s)	3.00	4.50	6.00	6.75	7.50	9.00
Submersion Depth (m)	0.20	0.30	0.40			
Conduit Length (m)	1.00	1.50	2			
Hole Diameter (m)	0.05	0.10	0.15			
Opening Percentage (%)	30	40	60			

The selected parameters — flow rate (Q_w), conduit length (L), gate opening ratio (K), submergence depth (ht), and air hole diameter ($\emptyset$) — were chosen based on their primary influence on both aeration and scour, as supported by hydraulic literature and engineering practice. These variables represent design-adjustable, first-order controls in conduit systems and are sufficient to capture dominant behaviors under the experimental conditions. Second-order effects such as jet trajectory or boundary roughness are either dependent on these primary parameters or minor under the observed flow regime. Experiments were conducted according to this plan, and the results, as shown in Table 2, were obtained.

Table 2. Summary of input and output parameters used in the study

Type	Symbol	Description	Unit
Input Parameter	Q_w	Flow rate	m ³ /s
Input Parameter	ht	Downstream hydrostatic level	m
Input Parameter	L	Conduit length	m
Input Parameter	$\emptyset$	Diameter of air intake hole	m
Input Parameter	K	Gate opening ratio	%
Output Parameter	Q_a/Q_w	Aeration efficiency ratio	
- (dimensionless)			
Output Parameter	d_{max}	Maximum scour depth	cm
Output Parameter	δ	Horizontal scour length	cm

The Fig 2 illustrates the components used in the experimental setups. In the course of the experiments, the system was operated in a reverse

cycle. A suction hose supplied the water in the 1.5 x 1.5 x 3.0 m tank to the pump (Fig 4). The pump was utilized to elevate the pressure and subsequently deliver it to the system in a pressurized state. The flow control valve and Kohne brand electromagnetic flow meter adjusted the water flow rate. The front side of the assembly was manufactured from tempered glass. In order to perform three-dimensional measurements (in the x, y, and z directions) of the scour parameters, a movable measuring stand was incorporated into the set-up, and an electronic limnimeter was placed on it. On the downstream side of the apparatus, a gate was installed that adjusts the hydrostatic level to the desired height and can move vertically.

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(a)

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(b)

320 **Fig 4.** Experimental setup, (a) (b) definition sketch

321 The diameter of the pipeline conveying the water to the conduits was
322 chosen to be 3 inches, the same size as the pump outlet diameter, to
323 eliminate local head losses. A galvanized metal pipe with a diameter of 8.09
324 cm and a circular cross-section of 100, 150 and 200 cm in length were used
325 as conduits to facilitate air intake into the system (Fig 5). To investigate

the effect of the downstream hydrostatic water level on scour, three different levels were defined, and the downstream pool was filled with water up to these levels. The first level was considered submerged (20 cm), the second level was submerged (30 cm), and the third level was deeply submerged (40 cm). In addition, three different hole diameters of 5, 10 and 15 mm were used to find the effect of the conduit air intake hole on scour.

Fig 5. Circular cross-section conduit

The opening ratios for the conduits were selected as 30, 40, and 60 percent (Fig 6).

Fig 6. Circular cross-section conduit gates opening ratios

An air inlet hole was opened just downstream of the gate in order to facilitate the introduction of atmospheric air into the water. The air inlet holes consists of a hole measuring 5, 10 and 15mm diameters and 200 mm in height. The velocity of the air entering the system was quantified using a Testo 435 anemometer. A series of experiments were conducted using different flows. Although free surface flow was observed at low flow, pressurized flow was observed at higher flow. The Froude number under the gate was calculated for each flow rate.

In order to determine the Froude number, the velocity and flow heights in the region known as the vena contracta, situated just below the gate, were calculated and taken into consideration. Although dimensional analysis (e.g., via the Buckingham π theorem) is commonly used in theoretical modeling, it is not a strict requirement in ANN-based models. The neural network learns complex nonlinear mappings directly from raw physical data. Our model, trained on over 100 parameter combinations, achieved over 95% prediction accuracy without prior non-dimensionalization. This confirms that the selected parameters inherently capture key dynamic behaviors — including Froude effects and aeration-scour interactions — even in dimensional form. Nevertheless, future research may explore dimensionless formulations (e.g., Froude, Weber, Reynolds numbers) for added interpretability and transferability. In this region, the high turbulence and two-phase flow conditions on the downstream side of the gate hinder accurate measurement of the velocity and flow heights.

2.1. ANN model development

In order to model the complex nonlinear relationships between the conduit parameters and the target scour/aeration outcomes, a feedforward backpropagation artificial neural network (ANN) was developed using MATLAB R2023a (Neural Network Toolbox). The network consisted of three hidden layers with 25, 15, and 8 neurons, respectively. The following configuration was used for training:

- **Network Type:** Feedforward backpropagation
- **Training Algorithm:** Levenberg-Marquardt (`trainlm`)
- **Activation Functions:**
 - Hidden layers: *tansig* (hyperbolic tangent sigmoid)
 - Output layer: *purelin* (linear)
- **Initial Learning Rate:** 0.01 (automatically adjusted during training)
- **Epoch Limit:** 1000 with early stopping based on validation loss
- **Data Division:** 70% training, 15% validation, 15% testing (random seed control applied)
- **Validation Criterion:** Minimum mean squared error (MSE) on the validation subset

The *tansig* activation function was chosen due to its nonlinear mapping capacity and its demonstrated performance in previous hydraulic engineering studies ([17], [21]). The model was trained and validated on a dataset of 110 experimental combinations, achieving over 95% prediction accuracy across all outputs (Q_a/Q_w , d_{max} , δ).

In comparison to alternative optimization techniques such as Genetic Algorithms (GA) and Response Surface Methodology (RSM), ANN was selected for its ability to learn complex, nonlinear relationships directly from experimental data. While GA is robust in exploring global optima, it often requires a large number of evaluations and is computationally expensive, especially when used in combination with physical experiments. RSM, on the other hand, assumes polynomial relationships and may not capture the full interaction complexity in turbulent, two-phase conduit flows. The ANN model, once trained, allows for rapid prediction and optimization over multiple parameters simultaneously, making it well-suited for the multi-objective nature of this study.

3. RESULTS AND DISCUSSION

In this study, the optimizations of Q_a/Q_w , maximum scour depth, and δ values were performed based on flow rate, submergence, conduit length, chamber diameter, and opening percentage values. In the first stage, the levels of the independent variables, as provided in Table 1, were determined in accordance with the objectives of the study. After this stage, an experimental design plan was developed to obtain the necessary data for optimization using ANN (Table 3).

Table 3. Experimental design plan and experimental results

Experimental Parameters						Experimental Results		
Exp No	Q_w	ht (m)	L (m)	$\emptyset$ (m)	K (%)	Q_a/Q_w	d_{max} (cm)	δ (cm)
1	3.00	0.30	1.00	0.05	40.0 0	0.32	6.36	27.2 7
2	7.50	0.20	1.00	0.15	30.0 0	1.93	13.89	41.0 3
3	3.00	0.20	2.00	0.05	60.0 0	0.16	7.99	29.2 2
4	3.00	0.30	1.00	0.15	40.0 0	0.42	6.67	25.8 1
5	6.75	0.20	1.00	0.15	60.0 0	0.57	14.71	45.4 6
6	3.00	0.30	2.00	0.05	40.0 0	0.39	6.79	25.3 6
7	7.50	0.40	1.50	0.10	60.0 0	0.64	6.36	29.6 7
8	7.50	0.40	1.50	0.10	40.0 0	1.37	6.36	29.5 3

9	7.50	0.20	2.00	0.10	30.0 0	1.68	14.43	39.4 0
10	3.00	0.40	1.50	0.15	60.0 0	0.23	3.75	18.9 5
11	6.75	0.40	1.50	0.15	40.0 0	1.64	7.02	28.8 3
12	6.75	0.20	1.00	0.10	30.0 0	1.18	14.53	42.6 9
13	9.00	0.40	1.00	0.05	60.0 0	0.73	5.22	28.7 7
14	6.75	0.40	1.50	0.05	30.0 0	1.71	6.80	27.8 4
15	7.50	0.30	2.00	0.15	60.0 0	0.91	12.41	36.5 9
16	6.00	0.30	2.00	0.15	30.0 0	1.94	14.08	29.1 5
17	6.00	0.30	1.50	0.10	60.0 0	0.45	12.62	35.2 8
18	7.50	0.40	1.50	0.05	30.0 0	2.01	6.32	27.6 2
19	3.00	0.30	1.50	0.10	30.0 0	0.46	6.58	24.1 5
20	3.00	0.40	1.00	0.15	60.0 0	0.21	3.76	19.1 1
21	3.00	0.40	2.00	0.15	60.0 0	0.25	4.01	17.7 7
22	6.00	0.20	2.00	0.05	40.0 0	0.98	15.56	38.6 4
23	7.50	0.40	1.00	0.15	40.0 0	1.68	6.55	28.8 4
24	7.50	0.30	2.00	0.05	60.0 0	0.70	11.83	38.6 6
25	3.00	0.30	1.00	0.05	30.0 0	0.44	6.46	24.9 2
26	6.00	0.20	2.00	0.10	40.0 0	0.91	15.89	37.7 6
27	6.00	0.40	2.00	0.15	60.0 0	0.70	7.81	23.6 2
28	6.00	0.30	1.00	0.05	60.0 0	0.42	12.39	36.4 2
29	6.75	0.40	1.00	0.10	30.0 0	1.39	6.95	27.4 3
30	6.75	0.30	1.50	0.15	40.0 0	1.56	12.47	39.1 2
31	4.50	0.30	2.00	0.15	40.0 0	0.86	11.38	27.1 3

32	6.00	0.30	1.00	0.15	40.0 0	1.17	13.00	34.2 9
33	3.00	0.20	1.00	0.15	40.0 0	0.37	7.85	29.5 9
34	9.00	0.30	1.50	0.10	40.0 0	1.59	9.45	37.6 5
35	3.00	0.40	2.00	0.10	30.0 0	0.52	3.96	16.6 9
36	3.00	0.30	2.00	0.05	60.0 0	0.18	6.79	25.4 9
37	6.00	0.20	1.00	0.10	60.0 0	0.35	14.88	40.8 0
38	4.50	0.20	1.00	0.15	40.0 0	0.63	12.55	33.4 5
39	6.00	0.40	1.00	0.10	30.0 0	1.19	7.23	23.8 5
40	4.50	0.40	1.50	0.15	40.0 0	0.85	5.99	21.3 1
41	9.00	0.20	2.00	0.05	40.0 0	1.62	11.65	41.4 4
42	9.00	0.20	1.00	0.10	40.0 0	1.23	11.14	43.5 3
43	3.00	0.20	2.00	0.10	60.0 0	0.15	8.16	28.5 5
44	7.50	0.20	1.00	0.05	60.0 0	0.51	13.04	47.6 7
45	4.50	0.30	1.50	0.05	40.0 0	0.62	10.14	30.5 7
46	6.00	0.20	2.00	0.15	30.0 0	1.73	16.57	33.4 3
47	6.00	0.40	2.00	0.15	40.0 0	1.50	7.81	23.5 0
48	9.00	0.20	1.00	0.15	60.0 0	0.81	11.44	42.3 7
49	6.00	0.20	2.00	0.05	60.0 0	0.46	15.56	38.8 4
50	9.00	0.20	2.00	0.15	30.0 0	2.86	12.40	35.8 4
51	4.50	0.30	2.00	0.10	60.0 0	0.29	11.07	28.1 5
52	6.75	0.40	1.00	0.15	40.0 0	1.43	7.04	29.0 7
53	6.75	0.30	2.00	0.05	40.0 0	1.28	12.72	38.7 8
54	6.00	0.40	1.50	0.15	60.0 0	0.66	7.30	25.1 8

55	6.75	0.40	1.00	0.10	40.0 0	1.02	6.85	30.0 2
56	6.75	0.30	1.50	0.15	60.0 0	0.73	12.47	39.3 2
57	3.00	0.40	2.00	0.10	40.0 0	0.38	3.90	18.2 6
58	3.00	0.40	1.00	0.05	30.0 0	0.46	3.64	18.3 7
59	9.00	0.20	2.00	0.10	40.0 0	1.50	11.89	40.4 9
60	3.00	0.40	2.00	0.05	40.0 0	0.41	3.82	18.6 9
61	3.00	0.20	1.50	0.10	40.0 0	0.30	7.63	30.2 9
62	6.00	0.40	2.00	0.10	40.0 0	1.07	7.60	24.2 6
63	7.50	0.30	2.00	0.10	40.0 0	1.39	12.08	37.5 9
64	6.75	0.30	1.50	0.10	40.0 0	1.11	12.14	40.3 9
65	9.00	0.40	1.00	0.15	30.0 0	2.76	5.56	24.7 7
66	4.50	0.40	2.00	0.05	60.0 0	0.33	6.11	21.2 3
67	6.00	0.30	1.00	0.10	40.0 0	0.84	12.65	35.4 1
68	9.00	0.20	1.00	0.15	30.0 0	2.34	11.62	38.5 4
69	3.00	0.40	1.50	0.05	60.0 0	0.18	3.57	20.0 2
70	7.50	0.30	1.00	0.10	60.0 0	0.53	11.31	40.6 2
71	6.75	0.20	2.00	0.15	40.0 0	1.48	15.70	42.0 8
72	4.50	0.40	2.00	0.10	30.0 0	0.88	6.33	18.8 7
73	3.00	0.40	2.00	0.15	40.0 0	0.53	4.01	17.6 8
74	6.00	0.20	1.50	0.10	60.0 0	0.40	14.85	40.4 5
75	6.00	0.30	1.50	0.05	30.0 0	1.41	12.55	32.8 4
76	3.00	0.30	2.00	0.10	40.0 0	0.36	6.93	24.7 8
77	9.00	0.30	1.00	0.15	40.0 0	1.94	9.72	36.7 7

78	4.50	0.20	1.50	0.05	60.0 0	0.26	11.94	35.2 2
79	9.00	0.20	1.50	0.05	30.0 0	2.07	11.05	40.3 8
80	6.00	0.40	2.00	0.10	30.0 0	1.45	7.72	22.1 8
81	4.50	0.20	2.00	0.10	30.0 0	0.74	13.23	29.3 6
82	4.50	0.30	1.50	0.05	30.0 0	0.85	10.29	27.9 4
83	6.75	0.20	1.00	0.15	30.0 0	1.65	14.93	41.3 5
84	4.50	0.20	2.00	0.15	40.0 0	0.77	13.39	31.1 1
85	7.50	0.20	1.00	0.15	40.0 0	1.42	13.68	44.8 9
86	7.50	0.40	1.50	0.15	40.0 0	1.92	6.53	28.6 0
87	6.75	0.30	2.00	0.10	40.0 0	1.19	12.98	37.8 9
88	4.50	0.40	1.00	0.05	60.0 0	0.27	5.72	22.8 3
89	6.00	0.40	1.50	0.15	40.0 0	1.41	7.30	25.0 5
90	3.00	0.30	1.50	0.15	30.0 0	0.65	6.76	23.3 9
91	7.50	0.30	1.00	0.15	40.0 0	1.60	11.62	39.1 5
92	7.50	0.20	2.00	0.10	60.0 0	0.58	14.21	43.3 1
93	6.75	0.40	2.00	0.15	40.0 0	1.74	7.51	27.0 4
94	9.00	0.20	1.00	0.05	30.0 0	1.80	11.07	40.7 2
95	7.50	0.40	2.00	0.05	40.0 0	1.57	6.66	28.3 5
96	3.00	0.20	1.00	0.15	60.0 0	0.17	7.85	29.7 4
97	6.00	0.20	1.00	0.10	30.0 0	1.01	15.11	37.1 1
98	4.50	0.30	1.50	0.10	40.0 0	0.58	10.35	29.8 6
99	9.00	0.40	1.00	0.15	40.0 0	2.04	5.48	27.1 0
100	3.00	0.40	1.50	0.15	30.0 0	0.68	3.81	17.2 3

101	9.00	0.40	2.00	0.15	30.0 0	3.37	5.93	23.0 3
102	6.75	0.20	1.00	0.05	60.0 0	0.44	14.02	48.0 4
103	3.00	0.20	1.00	0.10	60.0 0	0.12	7.64	30.7 0
104	3.00	0.40	1.00	0.05	60.0 0	0.16	3.58	20.1 9
105	3.00	0.40	2.00	0.15	30.0 0	0.73	4.07	16.1 6
106	9.00	0.40	1.50	0.15	30.0 0	3.17	5.55	24.5 6
107	9.00	0.30	1.00	0.15	30.0 0	2.63	9.87	33.6 1
108	6.75	0.20	2.00	0.15	30.0 0	2.01	15.94	38.4 6
109	7.50	0.40	2.00	0.15	30.0 0	2.77	7.09	24.5 2
110	9.00	0.40	1.50	0.05	30.0 0	2.44	5.29	25.9 5

During the optimization process, the ANN model developed in Matlab 2023a was used. Based on preliminary trials, the best prediction value was obtained from the three-hidden-layer ANN model, shown in Fig 7, with 25, 15, and 8 neurons in each layer. In the created ANN training set model, 70% of the experimental data was used for training, 15% for validation, and 15% for testing.

The selection of the three-hidden-layer ANN architecture (25–15–8 neurons) was based on an extensive model comparison process. During preliminary testing, various architectures ranging from 1 to 4 hidden layers and 5 to 30 neurons per layer were evaluated. The selection criteria included mean squared error (MSE), R^2 values on validation and test sets, and monitoring of overfitting using validation loss curves. The chosen architecture consistently produced the highest generalization performance, with R^2 values exceeding 0.95 across all target variables and no overfitting symptoms. This approach aligns with previous studies that used deep ANN structures to model nonlinear hydraulic interactions ([17], [21], [24]).

The dataset was divided into 70% training, 15% validation, and 15% testing subsets. This split ratio is widely accepted in ANN-based hydraulic studies and is known to provide a balance between training depth and generalization performance ([16], [21], [24]). We also tested other splits (e.g., 60–20–20 and 80–10–10) during model development and found that the 70–15–15 configuration yielded the best predictive performance in terms of minimizing validation loss and preventing overfitting. Given the

moderate dataset size ($n = 110$), this division also ensured sufficient data diversity in each subset.

Fig 7. Structure of the ANN model created for training

During the optimization phase, the ANN coding was performed such that Q_a/Q_w and $\square$ values were maximized, while the maximum scour depth was minimized. The predicted values obtained from ANN training and the actual values are provided in Table 4. Additionally, in Figures 8-10, the predicted values, actual values, and regression analysis results for all experiments are presented graphically. As can be seen from the values in the tables and graphs, the values obtained from the training show more than 95% similarity with the actual values.

Table 4. Predicted and actual values obtained after training

Experiment Name	Desired Outcome	Predicted Value	Actual Value	Index No
Q_a/Q_w	Maksimum	3.34	3.37	101
d_{max}	Minimum	3.63	3.64	58
$\square$	Maksimum	48.15	48.04	102

Fig 8. Predicted and actual values for Q_a/Q_w after training, with regression analysis results

Fig 9. Predicted and actual values for d_{max} after training, with regression analysis results

Fig 10. Predicted and actual values for d after training, with regression analysis results

After the completion of training in the ANN, optimization procedures were initiated. At this stage, the experimental results were evaluated independently and collectively, and optimization was performed in two different ways. The optimum results obtained from the independent evaluation of the experimental results are presented in Table 5 and Figures 11-13.

In hydraulic systems, aeration plays a critical role in modifying flow characteristics, particularly under high-velocity and pressurized conditions such as those observed in conduit flows. When air is introduced into a high-speed water jet (as in our experimental setup through strategically placed air holes), it transforms the flow into a two-phase mixture. This modification leads to several significant hydraulic effects that directly influence the scour process:

- Energy Dissipation: The entrained air increases turbulence and flow resistance. This leads to more energy being dissipated within the flow rather than being transferred to the bed material downstream. This energy reduction limits the erosive force acting on the sediment layer.
- Buoyancy Effects and Jet Diffusion: The entrained air decreases the overall density of the jet and increases its diffusivity. This causes the jet to spread over a larger area upon impact with the bed, thereby reducing the localized shear stress that causes scour.
- Reduction of Jet Momentum at Impact: Air bubbles introduce fluctuations and instabilities in the jet core, causing it to lose momentum before it reaches the bed. This is crucial for mitigating the depth of the scour hole, particularly in cohesive and loose sediment beds.
- Pressure Redistribution: Aeration helps prevent sub-atmospheric pressure zones forming beneath high-velocity jets, which otherwise can cause intense suction effects and cavitation. In our experimental setup, air vents just downstream of the gate neutralized this effect by stabilizing pressure gradients.
- Upstream Flow Stability and Reattachment: Aeration also dampens the formation of large-scale vortices by promoting earlier reattachment of the flow and smoothing the velocity gradients at the flow-bed interface, which stabilizes the bed against detachment.

These hydraulic principles were integrated into our experimental design and quantified using ANN-based modeling. As presented in Section 3 and illustrated in Figures 9-10 and tables, our ANN optimization clearly demonstrated that increased aeration (i.e., higher Q_a/Q_w ratios) consistently correlates with a reduction in maximum scour depth. For example, under optimal conditions ($Q_w = 11.17$ l/s, $h_t = 0.29$ m, $\varnothing = 9$ mm, gate opening = 70%), the system achieved an aeration ratio of $Q_a/Q_w = 2.43$ while limiting scour depth to $d_{max} = 7.93$ cm — significantly lower than non-optimized cases.

These findings are consistent with recent studies such as Feng et al. [28], Puri et al. [13], and Kumar et al. [22], which demonstrated the effectiveness of AI-based or data-driven techniques in modeling jet-induced aeration and scouring in various hydraulic configurations.

To further evaluate the robustness of the ANN model, a preliminary sensitivity analysis was conducted using the input perturbation method. Each input parameter was varied across its observed range while holding other variables constant to assess its influence on the output variables (Q_a/Q_w , d_{max} , and δ). The results showed that flow rate (Q_w) and gate opening ratio (K) had the greatest effect on Q_a/Q_w . Meanwhile, submergence depth (h_t) and conduit length (L) were most influential on d_{max} and δ . The air hole diameter ($\varnothing$) had a moderate impact across all outputs. These findings confirm that the model correctly reflects the dominant physical relationships within the system.

Table 5. Optimum parameter levels and results for each experiment

Exp. Name	Optimum Levels of Independent Variables					Optimum Results
	Flow Rate Q _w	Submer gence ht (m)	Conduit Length L (m)	Hole Diameter r Ø (m)	Opening Percentage K (%)	
Q _a /Q _w	15.00	0.36	1.75	0.14	20.00	3.58
d _{max} (cm)	3.50	0.40	0.50	0.09	50	1.54
□ (cm)	15	0.12	2.00	0.05	70.00	51.24

Fig 11. Optimum value and iteration graph for Q_a/Q_w

Fig 12. Optimum value and iteration graph for $d_{\max}$

Fig 13. Optimum value and iteration graph for $\square$

In a system considered as a whole, Q_a/Q_w , $d_{\max}$, and $\square$ values cannot be regarded as independent of each other. In an efficient system, the goal is to achieve minimum scour at the maximum distance with maximum aeration efficiency simultaneously. To this end, in the second phase of the optimization, the optimum parameter levels were determined where all three values are at their best. The values corresponding to these optimum parameter levels are provided in Table 6, and they are also graphically shown in Figures 14-16.

Table 6. Optimum parameter levels of the system and corresponding results

Exp. Name	Optimum Levels of Independent Variables					Optimization Results
	Flow Rate Q_w	Submergence ht (m)	Conduit Length L (m)	Hole Diameter r $\varnothing$ (m)	Opening Percentage K (%)	
Q_a/Q_w	11.1	0.29	1.42	0.09	70.00	2.43
d_{max} (cm)	7					7.93
$\square$ (cm)						37.71

Although alternative optimization methods such as Genetic Algorithms (GA) and Response Surface Methodology (RSM) are also commonly applied in hydraulic studies, they were not employed in this work due to their respective limitations. GA requires large computational effort, particularly for physical data, while RSM tends to simplify complex nonlinear interactions. The ANN model used in this study provided superior flexibility and accuracy in capturing multi-variable interactions, which justifies its use in this multi-objective optimization framework.

Fig 14. Optimum value and iteration graph for Q_a/Q_w

Fig 15. Optimum value and iteration graph for $d_{\max}$

Fig 16. Optimum value and iteration graph for $\square$

4. CONCLUSIONS

Erosion at the downstream of hydraulic structures is prevented by aerating downstream water jets, a technique commonly used in water engineering. However, no study has been conducted on the use of systems with high aeration performance, such as conduits, for the erosion problem. Previous studies have highlighted several advantages of conduits, including their aeration performance and high energy efficiencies [36]. The studies in the literature have addressed the relationship between the physical design

parameters of conduits and aeration performance from a single perspective. No study has been conducted to optimize the effects of the downstream water jet of conduits on the erosion hole. This study aims to achieve the best erosion process performance of a conduit system using artificial neural networks (ANN). Multiple performance characteristics have been optimized simultaneously. For this purpose, design variables such as chamber diameter, conduit contraction ratio, conduit length, hydrostatic level, and aeration performance have been optimized. The following results were obtained from the experiments and analyses:

The predicted values obtained from the training of the created ANN model were found to be in agreement with the actual values (Table 3), demonstrating the reliability of the ANN model. When compared with the results provided in Table 3, it was found that values for Q_a/Q_w and λ reached maximum values, while d_{max} was minimized at parameter levels of 58, 101, and 102.

As a result of the optimization performed to determine the maximum values for Q_a/Q_w and λ and the minimum value for d_{max} , the values presented in Table 5 were obtained. Accordingly, the aeration performance was found to be $Q_a/Q_w = 3.58$, the maximum scour depth d_{max} (cm) = 1.54, and the scour length λ (cm) = 51.24 cm.

The optimum parameter levels obtained from the optimization performed to determine system dimensions that maximize aeration performance and scour length while minimizing scour depth are given in Table 6. In this case, the system with $Q_w = 11.17$ lt/s, hydrostatic level 29 cm, conduit length $L = 1.42$ m, cover opening ratio 70%, and air intake chamber diameter 9 mm was found to have aeration performance $Q_a/Q_w = 2.43$, maximum scour depth d_{max} (cm) = 7.93, and scour length λ (cm) = 37.71 cm.

The results obtained in this study provide valuable insights for optimizing the design variables of channel aeration systems to achieve the best aeration performance and erosion parameters. Furthermore, it has been shown that the artificial neural network method is highly effective in optimizing such multivariable aeration systems. The greatest advantage of this method is its applicability in complex and nonlinear systems. Additionally, the ability of the ANN model to self-train with experimental data in the training set and perform well even beyond the values in the data set during the optimization phase was observed. As seen from the optimum parameter levels provided in Table 6, the flow rate and cover opening ratio were found to be outside the initial parameter levels. Future studies may also integrate a dimensional similarity framework (e.g., using Froude or Reynolds numbers) to complement ANN-based optimization and improve generalizability across different hydraulic systems. Additionally, future research may incorporate global sensitivity analysis techniques (e.g., Sobol

or variance-based methods) to deepen the understanding of input-output interactions and improve model interpretability. In future studies, in addition to the ANN model, it is suggested to develop a mathematical model of the experimental data and compare the performance of these models.

These findings offer clear design guidance for real-world applications. For instance, the identified optimal values — such as a 70% gate opening, conduit lengths between 1.30–1.50 m, and air vent diameters around 9 mm — can be directly applied in the design of high-head dam outlet works, tunnel spillways, and aerated conduits. Moreover, the study provides a framework for retrofitting existing systems suffering from downstream erosion: simple modifications like adjusting gate openings or introducing aeration holes can significantly reduce scour without major reconstruction. By enhancing energy dissipation through passive aeration, the need for costly structural energy dissipators (e.g., stilling basins) can also be minimized. Finally, the ANN model demonstrated here can be adapted to real projects where field data are available, enabling engineers to integrate AI-driven optimization into the early stages of hydraulic infrastructure design.

Study Limitations and Future Work

While the present study provides valuable insights into the aeration–scour interaction using ANN modeling, it also has certain limitations. First, the experiments were conducted under controlled laboratory conditions using clear water, which may not capture complexities such as heterogeneous sediment composition, unsteady inflow conditions, or natural turbulence variability seen in real systems. Second, the trained ANN model was developed for a specific range of conduit geometries and flow conditions. Thus, extrapolation to field-scale systems or significantly different designs should be done cautiously. Third, although the ANN model successfully identified optimal design configurations, it lacks an explicit physics-based interpretability, as no dimensional similarity parameters were incorporated.

Future research may address these limitations through the following directions:

- Expanding the experimental database to include various sediment types, inlet conditions, and conduit shapes.
- Integrating physics-informed neural networks or hybrid models that combine dimensional analysis (e.g., Froude, Reynolds, Weber numbers) with machine learning inputs.

- Benchmarking the ANN model performance against other soft computing tools such as SVM, ANFIS, or gene expression programming.
- Applying the optimized framework to real hydraulic structures and validating predictions with field data.
- Incorporating multi-objective optimization strategies that account not only for hydraulic performance but also for environmental or economic considerations, such as minimizing energy loss or maintenance cost.
- In the present study, aeration performance (Q_a/Q_w) and scour control (d_{max} and δ) were treated with equal priority during the optimization process, given their combined importance for hydraulic safety and environmental efficiency in high-head conduit systems.
- Future work may benefit from incorporating multi-criteria decision-making (MCDM) frameworks — such as Analytic Hierarchy Process (AHP), TOPSIS, or Pareto-based methods — to guide optimization when designers or stakeholders need to explicitly prioritize between competing objectives like structural safety, oxygen transfer, and sediment control.
- In future studies, in addition to the ANN model, empirical or semi-empirical regression-based models may be developed for use in preliminary design; analytical formulations based on idealized assumptions can also be explored to improve interpretability.

Data Availability

All data generated or analyzed during this study are included in this published article.

Statements & Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [EA], [AA] and [MCT]. The first draft of the manuscript was written by [MCT], [RA], [MT]

and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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