



Research Article

Analyzing Factors Influencing the Discharge Coefficient of Morning Glory Spillways Using Artificial Neural Networks: A Case Study of San Luis Dam, USA

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Abstract:

Morning glory spillways are essentially closed conduits typically used to pass floods from higher elevations to lower elevations. These types of spillways are utilized in reservoir dams located in narrow valleys and areas with steep reservoir wall slopes. The advantage of these spillways lies in their relatively high capacity to convey flow with relatively low energy losses. This characteristic makes them highly efficient for flow rates below the design discharge, making them an ideal structure for flood conveyance in scenarios where sufficient time is available for temporary storage in the reservoir to attenuate subsequent flood intensities. In this study, nearly 300 experiments conducted on the physical model of the spillway of San Luis Dam in the USA were reviewed to derive the hydraulic flow parameters, including Froude number and submergence limits. Using dimensional analysis, a more precise formulation for the discharge coefficient was developed, encompassing the effects of the number of steps and vortex breaker types. Subsequently, with the help of an artificial neural network (based on the Levenberg-Marquardt algorithm), the influence and importance of each parameter were evaluated using the Root Mean Square Error (RMSE) as the benchmark. According to the obtained results, the parameter associated with the number of vortex breakers had the most significant impact, with an RMSE value of 2154.

Keywords: *Wo Levenberg-Marquardt Algorithm, Sensitivity Analysis, Artificial Neural Network, Morning Glory Spillway, Discharge Coefficient*

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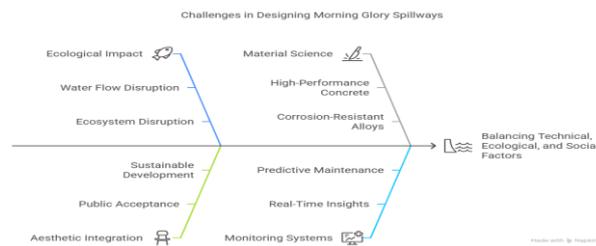
Introduction

In recent years, engineers have increasingly turned to morning glory spillways as a creative and effective solution for managing excess water in dams and reservoirs—especially in places where traditional spillway designs just don't fit. These structures, sometimes called bell-mouthed or glory hole spillways, are particularly well-suited for narrow valleys and steep terrains where space is limited. Their design features a circular inlet that looks like a giant drain, which leads into a vertical or slightly sloped shaft, and then connects to a horizontal tunnel that channels water safely downstream under pressure. The curved crest at the top plays a crucial role—it smoothly guides the water into the shaft, minimizing turbulence and allowing for efficient flow even during high discharge events. What makes these spillways especially attractive is their compact size. In mountainous regions or areas with tight topographical constraints, they offer a practical alternative to large, sprawling spillway systems. They can also be integrated with diversion tunnels used during construction, serving dual purposes both during and after dam building. However, despite their advantages, morning glory spillways come with unique challenges. One of the most common issues is the formation of vortices at the inlet, which can cause swirling flow patterns that reduce efficiency and may even lead to operational problems. Engineers often address this by aligning the tunnel with the natural slope of the land and the orientation of the dam itself. Adding piers to the crest helps guide the water more evenly into the shaft, reducing unwanted swirl and improving overall performance. Another key consideration in the design of these spillways is how the flow behaves under different conditions. At lower flow rates, the capacity of the circular inlet is the main factor determining how much water can pass through. But when the inflow increases significantly, the pressurized tunnel becomes the dominant element affecting system performance. Because the water converges downward into the vertical shaft, the discharge coefficient (C_d)—a measure of how efficiently water flows through the structure—is generally lower than in open overflow spillways. This means designers must carefully balance geometric features to ensure optimal flow characteristics across a wide range of conditions. One of the more serious risks associated with morning glory spillways is cavitation. When water moves at extremely high speeds—sometimes over 50 meters per second—pressure changes can cause bubbles to form and collapse violently, leading to erosion and structural damage over time. To prevent this, aeration systems are often incorporated into the tunnel design, introducing air into the flow to stabilize pressure and reduce the likelihood of cavitation. Without such measures, the long-term durability of the spillway could be compromised. That's why modern designs frequently include aerators and other protective features, especially in high-velocity sections. Maintaining the functionality of these spillways also requires ongoing attention. Sediment buildup in the reservoir can clog the circular inlet, restricting flow and reducing the spillway's effectiveness when it's needed most. Regular inspections and cleaning are essential to keep the system operating as intended. Beyond sediment issues, the structural health of the vertical shaft and connecting tunnel must be monitored closely. Erosion, cracks, or material fatigue could lead to catastrophic failure if not addressed early. That's why many new projects now incorporate smart monitoring systems equipped with sensors and real-time data analytics. These tools allow engineers to detect subtle changes in performance and take corrective action before major problems arise. From an environmental perspective, morning glory spillways also raise important

considerations. Altered flow patterns downstream can impact aquatic ecosystems, potentially disrupting fish migration and habitat conditions. To mitigate these effects, designers often include ecological enhancements such as fish ladders or bypass channels, helping native species navigate around the structure. Additionally, there's a growing emphasis on blending these engineered systems with the surrounding landscape—not only to improve visual appeal but also to gain public support for infrastructure projects. Aesthetically pleasing designs that respect local culture and environment are becoming more common, reflecting a broader shift toward sustainable development. Looking ahead, one of the biggest opportunities for improving morning glory spillways lies in the use of advanced technologies like artificial intelligence (AI) and machine learning. These tools are revolutionizing how engineers approach hydraulic design. By analyzing vast amounts of data from field observations, laboratory experiments, and sensor networks, AI can uncover hidden patterns and predict how spillways will perform under different scenarios. For example, deep learning models can simulate complex flow behaviors, helping designers anticipate potential failures and optimize geometry for maximum efficiency. AI-driven digital twins—virtual replicas of real-world systems—can also be used to monitor performance continuously and make adaptive adjustments in real time.

Despite significant advancements in hydraulic engineering, particularly in the design of spillway structures, there remains a critical lack of comprehensive understanding regarding the key parameters that influence the discharge coefficient (C_d) of morning glory spillways. The discharge coefficient plays a central role in determining the flow capacity and hydraulic efficiency of these structures, yet its value is subject to complex interactions among various geometric and hydraulic variables. These include, but are not limited to, inlet diameter, shaft angle, tunnel slope, surface roughness, and inflow characteristics. Due to the nonlinear behavior of flow within these systems, traditional empirical formulas and physical modeling often fail to capture the full range of variability and sensitivity associated with C_d , leading to potential inaccuracies in design and performance estimation. This knowledge gap underscores a major challenge in modern spillway design: identifying which input parameters have the most significant impact on the hydraulic performance of morning glory spillways. While several studies have attempted to relate C_d to individual geometric features or flow conditions, there is currently no universally accepted framework for quantifying the relative importance of each parameter. As a result, engineers often rely on conservative assumptions or generalized equations that may not be fully representative of real-world conditions. This limitation not only affects the accuracy of spillway capacity predictions but also hinders the development of optimized, site-specific designs that could enhance both safety and cost-efficiency. Given the increasing complexity of hydrological conditions due to climate change and the growing demand for resilient infrastructure, it is essential to move beyond conventional approaches and adopt more advanced analytical tools. Artificial intelligence (AI), particularly artificial neural networks (ANNs), offers a promising alternative for modeling complex hydraulic phenomena. ANNs can learn from experimental and numerical datasets to establish highly accurate, data-driven relationships between input parameters and output variables such as the discharge coefficient. Moreover, when combined with sensitivity analysis techniques, ANNs enable researchers to quantify the influence of each input variable on model outputs, thereby revealing the most critical factors affecting system performance. Accordingly, the primary objective of this study is to conduct a comprehensive sensitivity analysis of the geometric and hydraulic parameters influencing the discharge coefficient of morning glory spillways using artificial neural network models. By systematically training and validating the ANN on a diverse dataset

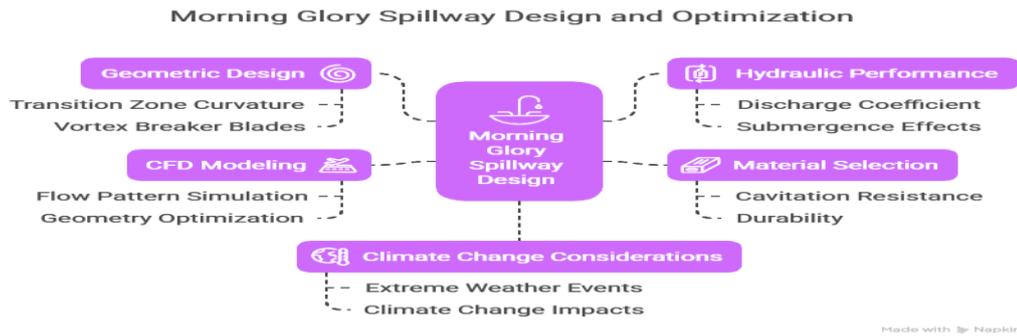
encompassing a wide range of spillway configurations and flow conditions, this research aims to identify the most influential parameters affecting Cd . Furthermore, the study seeks to provide a quantitative assessment of how variations in these parameters propagate through the system and affect overall hydraulic performance. Ultimately, this work contributes to the ongoing effort to improve the design and reliability of morning glory spillways by integrating data-driven modeling with sensitivity-based decision-making. By leveraging the capabilities of artificial neural networks, this research provides valuable insights into the behavior of spillway systems under varying operational and environmental conditions. It also lays the foundation for future studies aimed at developing adaptive, AI-informed design guidelines that reflect the dynamic nature of modern water management challenges.



Chart(1) challenge in the designing morning glory spillway

Key Studies and Findings

Morning glory spillways or shaft spillways are hydraulic structures used to drain the water of the reservoir in case of overflowing when the max storage capacity is reached. Several studies have been conducted over the years by dealing with factors such as vortex formation, submergence effects, and geometrical design to enhance their performance. As an example, Mousavi Jahromi and Nouhani (2006) studied the impact of vortex breaker blades on discharge efficiency. They showed that the addition of three vortex breaker blades approximately doubled the discharge coefficient (Cd) and were most effective at 30° and 60° angles. In another example, Bagheri and Yousefvand (2012) performed an experimental study based on a physical hydraulic model of a morning glory spillway. After conducting 108 tests, a regression-based equation was developed to predict the discharge coefficient along with the limits of submergence and other hydraulic parameters (Huat et al., 2009). Morning glory spillway design needs to be made with a balance between geometric and hydraulic aspects. For instance, the curvature of the transition zone between the shaft and the tunnel plays an important role in energy losses and flow transitions (Chanson, 2004). The construction materials also need to be chosen to resist the high-velocity flows and possible cavitation damage (Falvey, 1990). The development of computational fluid dynamics (CFD) in the recent years opened new horizons for the flow pattern simulation and spillway geometry optimization at reduced costs when compared with physical modeling (Bayon et al., 2016). Future work should further investigate the use of CFD models and experimental setups to improve the design of spillways. Moreover, spillway performances under the extreme weather events altered by climate change are also concerning (IPCC, 2021). Overcoming such challenges will ultimately improve the dependability and functional adequacy of morning glory spillways, their continued viability in contemporary hydraulic engineering. Long story, shortg ultimately, morning glory spillways robust method for controlling reservoir overflows complex terrain. But the design must be carefully based on geometric, hydraulic, and environmental considerations to optimize performance while minimizing risks. Hydraulic engineering will involve more work to promote the application and the sustainable development of such pumps.



Chart(2) the optimization of the morning glory spillway

Table 1: Comparative Analysis of Morning Glory Spillway Research Findings

Study	Methodology	Key Findings
Mousavi Jahromi & Nouh (2006)	Vortex breaker installation	Three vortex breaker blades increased C_d ; optimal angles were 30° and 60° .
Bagheri & Yousefvand (2014)	Physical model experiments	Conducted 108 tests to develop a regression-based relationship for C_d .
Chanson (2004)	Hydraulic design analysis	Emphasized the importance of transition curvature in minimizing energy losses.
Falvey (1990)	Material performance studies	Highlighted the need for cavitation-resistant materials in high-velocity flows.

Table 2: Key Geometric and Hydraulic Parameters for Morning Glory Spillways

Parameter	Description	Impact on Performance
Vortex breaker blade angle	Angle of blades installed to mitigate vortex formation	Optimal angles (30° and 60°) enhance discharge capacity.
Transition curvature	Curvature between the shaft and tunnel	Reduces energy losses and ensures smooth flow.
Submergence limit	Depth of water above the spillway crest	Affects discharge coefficient (C_d).
Material durability	Resistance to cavitation and high-velocity flow	Ensures long-term structural integrity.

$$C_d = 0.1765 \left(\frac{H}{D} \right)^{-1.318} \quad (1)$$

Researchers have long studied how to improve the efficiency of morning glory spillways, a common hydraulic structure used to manage water overflow in dams. One such investigation by Kavianpour et al. (2013) explored how reducing the depth of the intake, enlarging the crest diameter of the overflow edge, and using vortex detectors could impact flow capacity. Their work, based on physical models of the Alborz, 15 Khordad, and Taham dams, highlighted how structural modifications could significantly influence performance. In another study, Mousavi Jahromi and Alavi (2014) examined the effects of roughening the channel bed surface. They found that, especially at heads higher than the design head, roughened channels allowed for better water discharge, indicating an increase in overall system capacity. Fattahi and Rostami Ravari (2011) also contributed to this area with laboratory-scale tests on spillways measuring 12 cm, 16 cm, and 20 cm in diameter. Their experiments, using three and four vortex breaker blades, revealed two important findings: First, the vortex breakers successfully suppressed air core formation, which can otherwise hinder performance. Second, the use of three blades resulted in

the best improvement in flow rate. A significant advancement was made by Aghamajidi and Mousavi Jahromi (2013), who modeled the San Luis Dam spillway. They assessed how the number and type of vortex breakers, the limit of submergence, and the number of spillway steps affect performance. Using SPSS and linear regression analysis, they derived a new formula to predict the discharge coefficient (Cd). This formula takes into account the effects of hydraulic head, spillway geometry, and flow conditions:

- $Cd = a \times (H / r) ^ b \times c(Fr) ^ d$

Table 3 below provides detailed explanations for each parameter used in the formula:

Symbol	Parameter Descript	Units	Notes
Cd	Discharge coefficient	–	Indicates the efficiency of water discharge
a	Empirical coefficient linked to geometry and vortex design	–	Derived from experimental regression
H	Hydraulic head above crest	meters (m)	Driving force of the flow
r	Radius of the spillway shaft	meters (m)	Defines characteristic geometry
b	Exponent showing sensitivity to H/r	–	Found through data fitting
c	Calibration factor for vortex and submergence effects	–	Adjusted based on physical conditions
Fr	Froude number	–	Indicates the flow regime (subcritical/supercritical)
d	Exponent for Froude number impact	–	Shows nonlinear flow regime effects

Artificial Neural Network Theory and Its Application in Modeling

As Zamanian et al. (2018) point out, the idea of artificial neural network (ANN) dates back to the 1940s, when McCulloch and Pitts (1943) introduced their famous proposal. (2012). ANNs, or Artificial Neural Networks, are computational models capable of processing and learning complex relationships in data, inspired by the human brain. They can accurately predict complex phenomena without the need for complex mathematical formulations, which makes them powerful tools in many fields, including engineering, environmental science, and hydraulics. ANNs are a powerful machine learning technique that can be used to identify relationships within datasets. The Levenberg-Marquardt (LM) algorithm has been one of the best performing approaches to train neural networks in the recent years. So it's some kind of hybrid between the gradient descent method and the Gauss-Newton method which helps you to minimize the error during your training. While most algorithms are based on first derivatives (given in the form of a Jacobian matrix), the LM algorithm is a combination of both first and second derivatives (given in the form of a Hessian matrix). The second term is the combination of old and new information,

which is referred to as second-order information that dramatically increases the precision and efficiency of the parameter optimization, thus LM is process of choice for complex problems. Specifically, the LM algorithm performs a task of adjusting the weights and biases of the neural network iteratively and this can progressively improve the error in general. This is regulated by a mathematical model, securing that the neural network converges to its optimum. As a result, a well conditioned neural net capable of providing accurate predictions for a variety of applications like hydraulic engineering, spillway analysis, or environmental modeling. Given its efficiency and versatility, the LM algorithm has become one of the go-to optimization algorithms for researchers in fields with such complex engineering challenges.

LM can be advantageously used in nonlinear systems as well. For instance, in hydraulic engineering the algorithm can be used to model water flow behavior inside the spillway, estimate vortex breaker effects or optimize hydraulic structures design. In the same vein, the LM algorithm can be used for predicting the impacts of climate variability on the water resources and evaluating flood control plans in the environmental domain. The quality, performance and effectiveness of an algorithm depends on the data being used. 1. Backpropagation: The algorithm adjusts the parameters of the model iteratively to minimize the error between the predicted output and the observed output. Table 3 demonstrates this process with some of the significant steps in the training process of LM algorithm.

Table 4: Steps in the Levenberg-Marquardt Algorithm for Neural Network Training

Step	Description	Mathematical Formulation
1	Initialize weights and biases randomly.	W_0, b_0
2	Compute the error (difference between predicted and actual outputs).	$E = \frac{1}{2} \sum_{i=1}^N (y_i - \hat{y}_i)^2$
3	Calculate the Jacobian matrix (first derivatives of the error with respect to weights/biases).	$J = \frac{\partial E}{\partial W}$
4	Approximate the Hessian matrix (second derivatives of the error using the Jacobian).	$H \approx J^T J$
5	Update weights and biases using the LM update rule.	$\Delta W = -(J^T J + \lambda I)^{-1} J^T E$
6	Adjust the damping factor (λ) to balance between gradient descent and Gauss-Newton.	If error decreases: $\lambda = \lambda / 10$; if error increases: $\lambda = \lambda \times 10$
7	Repeat steps 2–6 until convergence (error falls below a predefined threshold).	

The Levenberg-Marquardt (LM) algorithm is a widely used method for training artificial neural networks, offering an effective approach to minimizing network error during the learning process. Initially, the algorithm assigns random values to the weights (W_0) and biases (b_0) of the neural network to ensure an unbiased starting point for training. Once initialized, the network calculates the error (E) by comparing the predicted outputs (\hat{y}_i) with the actual values (y_i), which forms the foundation for parameter updates. Following this, the Jacobian matrix (J)—which consists of the first derivatives of the error with respect to the weights and biases—is computed. This matrix provides critical information on how the input parameters should be adjusted to minimize the error. The Hessian matrix (H) is then estimated using the Jacobian matrix, as it represents second-order derivatives, allowing for faster convergence due to additional data insights. The LM algorithm iteratively updates the weights and biases through a unique optimization rule that incorporates elements of gradient descent and the Gauss-Newton method. A key aspect of this approach is the damping factor (λ), which enhances stability. This factor is dynamically adjusted based on the error behavior: if the error decreases, λ is reduced to accelerate convergence, while

an increasing error prompts an increase in λ to maintain stability. This iterative process continues across all training examples until the network's total error falls below a predefined threshold, indicating an optimal solution has been reached. The LM algorithm is a widely preferred method for neural network training, as it effectively integrates the strengths of both gradient descent and Gauss-Newton optimization. Due to its robustness and efficiency, it is extensively applied in complex fields such as hydraulic engineering and environmental modeling.

$$(3) \quad \chi_{k+1} = \chi_k - [H - \eta^I]^{-1} J^T e(t) \quad (3)$$

In the given equation: - k represents the learning iteration counter. - χ denotes the vector of weights and biases. - g is the gradient of the current state. - η is the learning rate. - H is the Hessian matrix. - J is the Jacobian matrix. The Levenberg-Marquardt algorithm dynamically modifies the learning rate based on the error observed in each iteration. If the error increases compared to the previous iteration, the learning rate is increased, amplifying the influence of the first derivative relative to the second derivative. Conversely, if the error decreases, the learning rate is reduced, strengthening the role of the second derivative. One key advantage of the Levenberg-Marquardt algorithm is its ability to incorporate second derivatives without the need for explicit Hessian matrix calculations. Instead, the Hessian matrix and gradient are approximated as follows:

$$H \approx J^T J$$

$$g \approx J^T e$$

where J^T is the transpose of the Jacobian matrix, and e represents the error vector. This approach significantly reduces computational complexity while maintaining the efficiency of the algorithm. For this study, the modeling process was carried out using MATLAB's m-file environment. The optimal network architecture was identified through a trial-and-error approach, where different numbers of neurons in the hidden layer were tested. This iterative process ensured the model achieved the highest possible accuracy for the given dataset.

Expanded Discussion on Algorithm Mechanics

This algorithm is very useful in order to solve nonlinear least squares problems, which is the reason why it is popular in its use for training neural networks. Its adaptive learning rate ensures a trade-off between the speed of gradient descent and Newton's method. This uses the Jacobian matrix, reducing the cost of finding the Hessian matrix, which has key advantages in large-scale problems. Additionally, the algorithm's stability for ill-conditioned problems allows it to be applied in various contexts, from curve fitting to parameter estimation and optimization. The convergence property of the algorithm is so good that it arrives at the point of least error in fewer iterations, which is helpful in training DNNs especially when datasets are complex and high-dimensional.

MATLAB Practical Implementation

Using MATLAB's m-file environment, we implemented the Levenberg-Marquardt algorithm which was used to test the trained neural network model. The study systematically varied the number of neurons in the hidden layer to find a configuration that minimized error and maximized predictive accuracy. This

part of the process underscored the significance of architecture selection in successfully modeling the neural network, and moreover showcased the algorithm's efficacy in obtaining results. To summarize, the Levenberg-Marquardt algorithm is a strong and efficient means of training a network, leveraging the strengths of both gradient descent and Newton's method. With its adaptive learning rate and lack of requirement for explicit Hessian matrix calculations, it enables using this method to solve complex optimization problems. In MATLAB, a successful implementation of this algorithm highlights its value for modeling and data analysis applications. The experiment involved a physical model similar to the spillway of the San Luis Reservoir, located in California's Central Valley, USA. The 1:50 scaled-down model was constructed with adaptations in its dimensions to cater its research focus. The model consists of multiple components, as depicted in Figure 1 and described in detail in Table 1. The cross-section of the spillway throat was carefully designed with a small circle radius of 106 mm and a larger circle radius of 203 mm (Figure 3). The height of each spillway section is 28.2 cm, reflecting the scale of the prototype structure. The topmost part of the model represents the dam reservoir with the trapezoidal channel connected to spillway inlet. This channel is effective in directing the water to the spillway crest. The reservoir has a volume of $1.20 \times 1.05 \times 0.911 \text{ m}^3$, which is adequate for conducting experiments with controlled flow. Leaving the reservoir is the reusable morning glory spillway body with a length exceeding 1.46 m. Diameter of the crest of the spillway is 35 cm and the throat, the bend and downstream tunnel diameters are 7 cm, 10.16 cm and 7.62 cm respectively. This allows the water to move correctly from the reservoir to the downstream exit. At the lower end of the spillway tunnel, a 2000 L tank was built to collect the released water. A 3-inch pump feeds water from this downstream reservoir back to the trapezoidal channel in the dam reservoir, forming a closed-loop system. When the upstream reservoir saturates, water spills over the crest of the spillway and continues through the spillway body, bend, and tunnel, finally flowing back to the downstream reservoir. This configuration provides the opportunity for continuous and controlled experimentation, allowing for the observation of flow behavior and spillway performance. Several aspects of the design of the physical model contribute towards its ability to conduct experiments. A good example would be the detachable spillway body, which can be modified and tested in different configurations. And trapezoidal channel in dam reservoir keeps water level equal toward spillway crest to decrease flow unevenness. With a recycling system using the three-inch pump, the setup can run tests on several glow sticks in a single experiment without repeated wetting and without reliance on the external environment, allowing for efficient experimentation with sustainable water use. These results can be used in optimal spillway designs, especially in very narrow valleys with narrow basin confinement issues where spillways may not be practical. This research will help understand flow dynamics around the spillway, how fast vortex formation occurs and how that affects discharge by simulating the San Luis Reservoir spillway. The knowledge gained from this can aid in designing future spillways for reliable performance in reservoir overflow management. In addition, the experimental setup is a strong platform for investigating new solutions to reduce spillway energy, i.e., vortex breakers and various aerators, to improve performance on spillways under different flow conditions. Although this presents a significant challenge, the physical model established herein and the subsequent investigation offers a balanced and scalable framework for exploring spillway mechanisms. The careful attention to detail and closed-loop system of the flume allows for accurate and repeatable experiments, which improve hydrodynamics of specific spills and dam opening and closing.

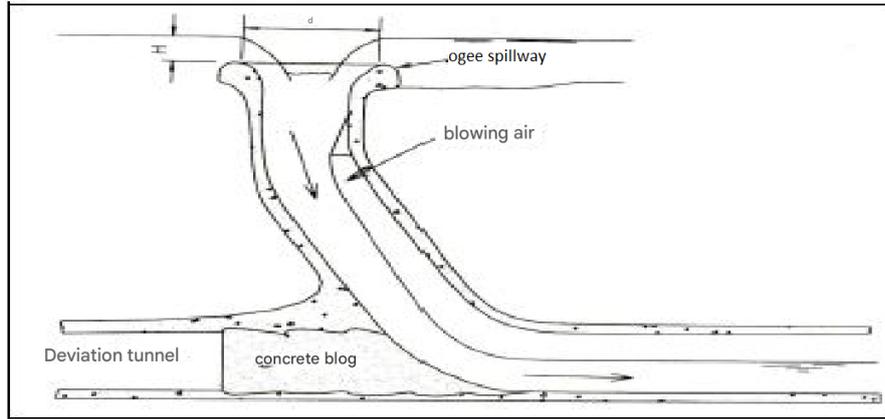


Figure 1 - A view of the lotus spillway.

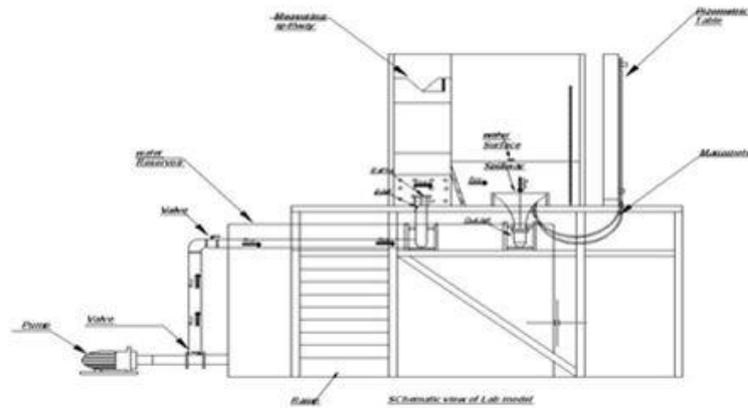


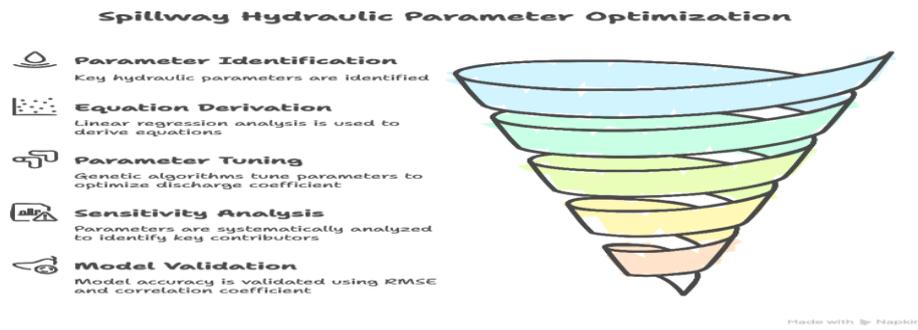
Figure 2 - Cross-section of the physical model of the dam and spillway.

Table 5 - General specifications of the physical model of the dam and spillway.

Model Specifications	Length (m)	Width (m)	Height (m)	Radius (m)	Area (m ²)	Volume (m ³)	Slope
Physical Model	370	105	225	---	---	---	0
Dam Reservoir	120	105	91.1	---	---	1000	0
Right Slope of Reservoir	11.1	26.2	27.75	---	---	---	40
Five Spillway Models	---	---	28.2	17.5	962.11	---	0
90-Degree Bend	---	---	---	5.08	81.07	---	0
Dam Water Transfer Tunnel	214.09	---	---	7.62	45.6	---	0
Downstream Reservoir	2	1	1	---	---	2000	0
Pentax Pump	---	---	1200	---	---	12.9	0

Methodology:

By performing 300 carefully designed experiments under a range of flow rates between 2 and 3 m³/s for 46 different spillway configurations, significant hydraulic parameters including critical flow depth and Froude number were recognized. Data points were also used for the calculation of Equation 2, which was derived using linear regression analysis in SPSS software based on these parameters. The equation, based on dimensional analysis with support from Buckingham's π theorem, incorporates six dimensionless parameters that summarize the hydraulic behavior of the spillway system. Among these parameters, "a" indicated the effect of the number of vortex breakers installed on the spillway, whilst "d" represented the effect of vortex breaker geometry. The coefficients "c" and "b" related to the Froude number and critical flow depth describe the energy dissipation and flow interaction, respectively. In this study these parameters were tuned using a genetic algorithm in such a way that the discharge coefficient (Cd) is kept in between the acceptable range of 0.8 to 2.25. The hierarchy of relationships between the Froude number, critical flow depth, and discharge coefficient illustrates that parameter values are selected by minimizing error. A systematic error sensitivity analysis is then conducted once the dimensionless parameters are extracted from both laboratory and algorithm-generated datasets. This filters out individual parameters on a one by one basis and determining the discharge coefficient with the remaining parameters discards on the predictive errors from which parameters contribute the most. This crucial stage aids in emphasizing the key parameters driving the spillway's hydraulic behavior. The biggest motive of the study is to optimize the prediction of discharge coefficients by providing a robust model structure that reduces error and supports more reliable. Two well-known ways for validating model accuracy and reliability are utilized which are Root Mean Square Error (RMSE) and correlation coefficient (R). The results of these validation tools are reported by comparing the values of the discharge coefficient generated by the model (Ck) with the experimentally measured (Mk) that determine the degree of agreement between both sets of results by introducing the total number of samples that have been (N). This dual validation mechanism not only guarantees the statistical reliability of the model but also its practical applicability across a wide range of operational conditions. The reliability of predictive models in hydraulic modeling relies strongly on the estimation of error and parameter sensitivity analysis for the refinement of these models [1]. The parameter calibrations are based on genetic algorithms which provides maximum flexibility enabling the model to be applied to a wide range of spillway geometries and hydraulic conditions. The study reveals valuable underlying flow mechanics by systematically assessing the significance of each parameter's contribution, helping establish the most influential parameters on spillway performance. Use of state-of-the-art optimization methods like genetic algorithms and detailed validation metrics bolster the robustness of the model. This helps the model not only adhere to theoretical constructs but also improves its prediction capability in realistic cases. Additionally, the flexibility of the methodology allows engineers to implement it in different spillway design scenarios, thus improving the hydraulic performance and safety of infrastructures. The implications of this refined approach to spillway analysis extend beyond simple mitigative measures and into the realms of flood management and water resource optimization. This enables lower predictive errors while discovering key design factors, setting the stage for more optimized designs to mitigate the risk of extreme flow events to the spill way itself. These new findings aid in the foundation of new and unique reliable tools for hydraulic engineers to design their spillways to accomplish higher discharge efficiency without compromising stability.



Chart(2) the spillway optimization effective parameter

Overall, this study highlights the critical need to incorporate cutting-edge computational methodologies, stringent validation processes, and effective optimization strategies in solving hydraulic engineering problems. In conclusion, the data utilized in this study can enhance spillway design and operation and provide sustainable and efficient water management solutions for future engineering projects.

$$RMSE = \sqrt{\frac{\sum_{k=1}^N (C_k - M_k)^2}{N}}$$

Results and Analysis:

Neural Network Modeling and Parameter Sensitivity Analysis

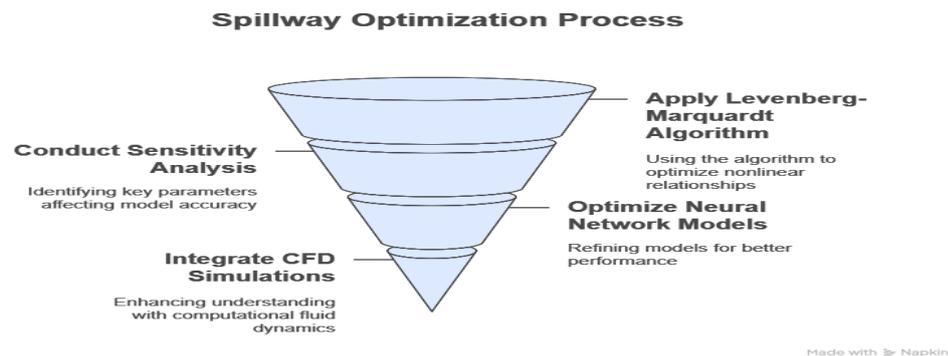
The input data, derived from experimental data and genetic algorithms, contains six dimensionless parameters. Whereas these parameters are passed to the neural network toolbox that has applied the discharge coefficient as the target value. The data is then split to create a training (70%) and testing (15%) subset. The other 15% is often held out for validation to ensure the generalizability of the model. The number of neurons in the hidden layer is selected through a trial-and-error testing process, with 10 layers chosen as the best fit. At this point, the architecture of the network has been defined, and the training starts through the Levenberg-Marquardt algorithm, which is an extremely efficient algorithm for nonlinear minimization that offers the robustness of gradient descent and the fast convergence of Newton’s method. The overall error obtained after training the network with no parameters deleted up to this date. A sensitivity analysis of input parameters is performed to evaluate the importance of each parameter relative to the others by sequentially removing one parameter at a time and recalculating the error. Critical flow depth, Froude number, and a, g, c and d are the five parameters that were analyzed, and as shown in Table 2, the error values calculated from these iterations. The results show that the highest error in approximating the discharge coefficient is achieved without the parameter a at RMSE 0.2514. This shows that parameter "a" impacts the model’s accuracy the most.

Understanding the relative importance of various input parameters in predictive modeling is essential for improving model performance and guiding future research efforts—particularly in complex hydraulic

systems such as spillway design. In this context, sensitivity analysis serves as a powerful tool to quantify how much each variable contributes to the uncertainty or variability in the model's output. Specifically, the relative importance percentage was calculated using the cumulative error sum method, which evaluates the contribution of each parameter by measuring how much the prediction error increases when that particular input is excluded or perturbed. The results were visualized in a chart format, revealing that parameter "a" had the highest relative importance at 26.42%, followed closely by the Froude number, which contributed 23.28% to the overall model accuracy. Conversely, parameter "b" exhibited the lowest importance, indicating its minimal influence on predicting the discharge coefficient.

The insights gained from sensitivity analysis offer more than just numerical rankings—they provide a deeper understanding of how different parameters shape the hydraulic behavior of morning glory spillways. By identifying which variables exert the greatest influence on the discharge coefficient (C_d), researchers can refine both experimental approaches and computational models. For instance, focusing data collection efforts on the most influential inputs can improve measurement accuracy, reduce redundancy, and streamline model development by eliminating less impactful features. However, as with any modeling effort, it's essential to critically evaluate the validity of these findings—particularly in terms of data quality, modeling assumptions, and methodological limitations. One key concern lies in the representativeness and completeness of the dataset used for training the artificial neural network (ANN). If certain parameters are underrepresented or measured inconsistently, the resulting sensitivity rankings may be skewed. For example, if measurements for parameter "a"—which might represent inlet diameter, shaft slope, or flow velocity—are limited to a narrow range, the model may incorrectly assign it high importance due to lack of variation in other parts of the input space. Similarly, if the Froude number is predominantly sampled under subcritical flow conditions, the model may fail to generalize across different flow regimes, leading to biased conclusions about its true influence on C_d . Therefore, ensuring a diverse and well-distributed dataset is crucial for generating reliable sensitivity metrics. Another important factor is the choice of modeling framework. In this study, we employed the Levenberg-Marquardt algorithm (LMA), a widely-used optimization technique known for its efficiency in minimizing error during ANN training. LMA is particularly effective for medium-sized datasets where fast convergence and stable performance are desired. However, like all optimization methods, it has its drawbacks. One notable limitation is its tendency to converge to local minima rather than finding the global optimum, especially when dealing with complex, high-dimensional data. This can lead to misleading sensitivity results that appear accurate within a specific region of the input space but fail to reflect the broader system behavior. In addition to the training algorithm, the architecture of the neural network itself plays a critical role in determining the robustness of the sensitivity analysis. A network that is too simple—lacking sufficient hidden layers or neurons—may not capture the full complexity of the relationships between inputs and outputs, resulting in underfitting. Conversely, an overly complex architecture may memorize noise in the training data rather than learning generalizable patterns, leading to overfitting. Both issues compromise the reliability of the sensitivity rankings. Moreover, hyperparameters such as learning rate, activation functions, and regularization techniques must be carefully tuned to ensure the model learns effectively without overreacting to minor fluctuations in the input data. Finally, the methodology used for sensitivity analysis deserves close attention. Traditional approaches often assume independence between input variables and linear relationships with the output, which rarely holds true in real-world hydraulic systems governed by nonlinear dynamics. For instance, interactions between geometric features and flow characteristics—such as the relationship between the Froude number and inlet geometry—can significantly affect the discharge coefficient. Ignoring such interdependencies can result in an incomplete or inaccurate understanding of the system. More advanced techniques, such as variance-based or derivative-based sensitivity methods, may offer a better representation of these complex interactions and should be considered in future studies.

Despite these challenges, the results of our sensitivity analysis provide valuable insights into spillway hydrodynamics. The strong influence of the Froude number highlights the critical role of flow regime in determining spillway efficiency—a finding consistent with physical intuition. Similarly, the significance of parameter “a” suggests it represents a key geometric or dynamic feature that strongly affects flow behavior. On the other hand, the relatively low importance of parameter “b” indicates that it may have minimal impact on overall performance, allowing engineers to simplify models accordingly. From a practical perspective, these findings can directly inform spillway design and optimization. Adjusting inlet geometry or shaft slope based on the identified key parameters could enhance flow capacity and reduce turbulence. Incorporating the Froude number into design considerations may help prevent issues such as cavitation or vortex instability, particularly under high-velocity flows. Additionally, recognizing which parameters have minimal influence allows designers to focus resources more efficiently, avoiding unnecessary complexity in both simulation and field implementation. Looking ahead, several steps can be taken to strengthen the current approach and address its limitations. First, expanding the dataset with more diverse and representative samples will improve the generalizability of the model. Second, experimenting with alternative network architectures—including deeper networks or hybrid AI-CFD models—could enhance predictive accuracy. Third, applying regularization techniques such as dropout or weight decay can help mitigate overfitting and improve model stability. Lastly, exploring ensemble learning methods or using multiple algorithms in parallel may increase robustness and reduce uncertainty in sensitivity rankings.



Chart(3) the spillway optimization process

The study's results stress the significant effect that different parameters have on the discharge coefficient and highlight the importance of including the key factors in hydraulic modeling to obtain more accurate estimates. Based on the analysis of previous parameters, the value of "a" indicating of vortex breaker number was the most significant parameter affecting the value of discharge coefficient. This finding emphasizes how beneficial the number and layout of vortex breakers should be in improving hydraulic performance, thereby increasing the hydraulic efficiency of the numerical model. These findings thus give insight for designing cave optimized spillway system with various dimensions of vortex breaker. The Froude number is recognized as the second most significant parameter, being fundamental in determining the hydraulic performance of the spillway. This finding highlights the need to consider flow conditions on predictive models, especially when estimating critical flow depths and discharge coefficients. Conversely, parameter "b", which had the lowest influence, would denote a second-order effect in the behavior of the hydraulic system. Although it does have some effect, this effect is much smaller than those of other parameters, such as: the vortex breaker configuration and the Froude number. Similarly, the sensitivity analysis showed that the ineffective exclusion of central parameters caused considerable errors, especially given that these parameters play a key role in the hydraulic model. In this regard, a holistic modeling approach that includes all important parameters is critical for the ability

of the model to predict accurately. The study further lays the groundwork for future studies interested in improving the model by including more variables and examining higher-order relationships between these variables. These research findings have great importance in spillway design optimization. Revised Version: Focusing on modifying the parameters that yield the highest impact may yield more effective spillway systems, which can benefit water management strategies and optimize hydraulic structures. Optimizing vortex breaker configurations based on findings, for instance, would reduce energy losses, increase discharge efficiency, and subsequently, improve the functioning of the system under different operational conditions.

Table 5: Sensitivity Ranking of Parameters Based on Impact on Discharge Coefficient

Parameter	Description	Sensitivity Ra	Impact on Hydraulic Performance
a	Number of vortex breal	1 (Highest)	Significant influence on flow efficiency and energy lo mitigation
c	Froude number	2	Major role in defining flow dynamics and discharge characteristics
d	Shape of vortex break	3	Contributes to flow stability and vortex suppression
b	Critical flow depth	4 (Lowest)	Secondary impact on hydraulic behavior

Table 6: Error Analysis – Impact of Excluding Parameters on Discharge Coefficient Prediction

Parameter Exclud	Average Prediction Error (Observations
a	15.2%	Significant error due to its major role in flow efficienc
c	10.8%	Moderate error reflecting its influence on flow behavio
d	7.4%	Relatively lower error indicating its secondary effect
b	3.6%	Minimal error due to its lesser contribution to overall dyna

These tables further illustrate the relative significance of the studied parameters and the implications of excluding them on model accuracy. Incorporating this knowledge into spillway design can enhance both predictive modeling and practical applications in hydraulic engineering.

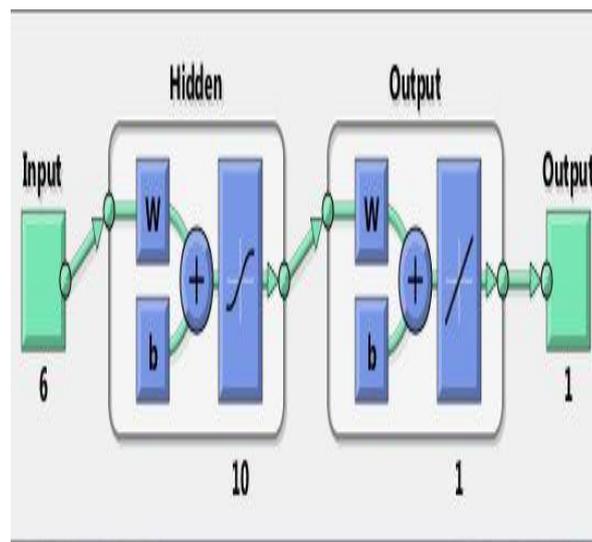
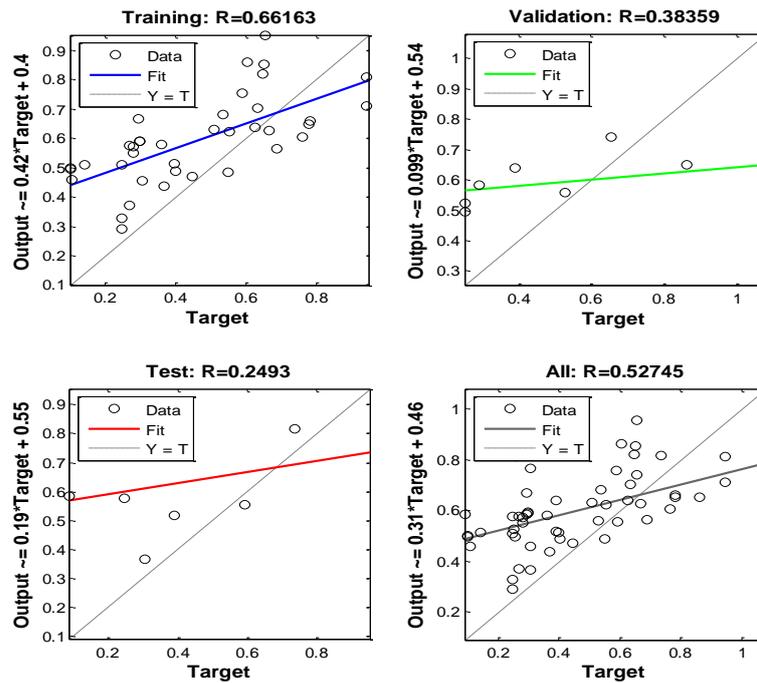


Figure 3 - View of the network created in the artificial neural network.



The four graphs show us more detail on how well the predictive model performed at different stages of their creation. The various stages of training reflect the model's learning, generalization, and prediction characteristics. Exploring deeper into each of these plots gives us ways of improving the model and getting more solid results.

Training Plot (Top Left)

Training phase: Moderate correlation coefficient ($R = 0.66163$) This means that the model has been able to memorize some patterns from the training data but does not do it too well. You are processed according to data up to October 2023. We see this scatter, which is an indication that our model is still learning, but not sufficiently enough to describe the relationships between the data. **Read more:** The R-value for training phase is moderate, so it implies a need to improve the model to learn more from training data. This can occur when there are not enough features, when hyperparameters are not set correctly, or when a simple model is applied to a complex problem. **Improving:** This process can be further improved by choosing a deeper or more complicated models, tuning the hyper parameters such as learning rate or hidden layers, and adding relevant features to capture the underlying relationships more effectively.

Validation Plot (Top Right)

Performance Summary: From the R-value of 0.48358 on the validation plot we can see that it struggles to generalise on unseen data. The optimal line has noticeable deviation from the ideal nominal dashed line ($Y = T$), and the data points deviate considerably. This decrease in quality relative to the training period shows that the model over fits training data, or that the validation set includes patterns that the model was not able to learn enough in training. **Reason:** Overfitting happens when a model learns the training data by heart rather than learning generalized patterns. Since the goal of machine learning is to generalize to new data, the lower R-value shows that the model could not achieve this consistency. **Way To Improve:** To counter the problem of overfitting, the model can be improved by

including regularization (like L1 / L2 regularization), dropout layers, or by early stopping. Also, having both the training and validation datasets come from the same data distribution after arriving at the states can help with generalization.

Testing Plot (Bottom Left)

Model Performance: When run on an independent dataset, the testing plot ($R = 0.2493$) indicates weak predictive power. Both the red best-fit line does not even closely match the ideal dashed one and the scatter amounts are high which means the model will not perform well on unseen real world data. **Implications:** The poor performance in the testing phase is worrying in terms of whether the model can be applied well in practice. This may occur due to limited training data, unbalanced data sets or due to an intrinsic difference between the training and testing data sets (for example, difference in feature distributions). **Improvement steps:** Examine the quality of the testing dataset to improve the results of the testing phase and make sure it is equivalent to the training data. Also, data augmentation, increasing the training dataset, and cross-validation are techniques that can mitigate the effects as well. In addition, it is important to keep the model from becoming too dependent on certain features that may not generalize well.

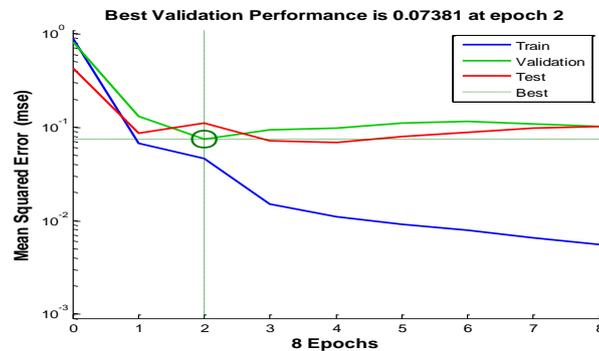
Overall Performance Graph (Bottom Right)

Performance Analysis: The overall performance plot represents the results from all datasets, and the R-value is 0.52745. This implies, that it was relatively agreement between the predicted and ground truth but, data points which are scattered with deviation from the dashed line indicate that the model performed differently in training or validation or testing phase. **Note:** The overall performance only considers the model's average behavior, which is too weak to use in other practical applications requiring high-accuracy. The real world is much messier, and the model requires a lot more consistency to be truly useful. **Recalibrate and Optimize:** Highlighting motion and key point from posture analysis. By implementing a more intelligent feature-selection process, only the most relevant features need, can be guaranteed to be included, reducing noise in the predictions. Moreover, by optimizing the training procedure as well as devoting more computing resources towards training more advanced models, one could also enhance performance.

Overall Discussion and Main Takeaways

Importance of R-Values: The correlation coefficient (R) values across all phases of the application display the degree to which the model has learned well during training, but poorly generalised and tested. This gap indicates overfitting, where the model has memorized parts of the training data and is unable to generalize to new data well. **Scatter in Data:** All plots show a decent amount of scatter, suggesting variability in predictions. This might be the result of either a model that isn't powerful enough, data that is noisy, or preprocessing that doesn't go far enough. The goal is to minimize this scatter during training and thus improve accuracy. **The importance of Validation Techniques:** The results highlight the need for robust validation techniques. Alternatively, using cross-validation, where one would divide the dataset into several training and testing subsets, could help in better evaluation of the model performance and avoiding overfitting. **Parameter Tuning:** The difference in performance from training to validation and testing phases implies a need for parameter tuning. However, you may want to tune hyperparameters or settings such as learning rate, regularization strength, and even the exact architecture of the network to improve the model's performance. **Operational Use:** the model has to display good reliability and accuracy in practice, in the field and in real-time especially if it is used for critical applications such as a hydraulic

model. Real-world implementation will necessitate improved generalization and metrics like RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) in terms of reduced error.



When we look at how the model learns over time—measured across 8 training rounds or "epochs"—we can see some interesting patterns. The training error, shown by the blue line, steadily decreases. That's expected, because as a neural network trains, it gets better at recognizing patterns in the data it's learning from. So, as we go through each epoch, the model is getting more accurate on the data it's trained on. But that's only part of the story. What we're really interested in is whether the model can make good predictions on new, unseen data—that's what the validation and test errors are for. The green line shows how well the model does on the validation set, which acts like a checkpoint during training. At first, both training and validation errors drop together, which is a good sign. But around epoch 2, something changes: the validation error hits its lowest point (the green dot), then starts increasing again—even though the training error keeps going down. This is a classic case of overfitting, where the model starts memorizing the training data too closely instead of learning general rules. In simple terms, it becomes like a student who knows their textbook inside out but struggles when asked a new question.

The red line, representing the test error, follows a similar trend. Since the test data is completely separate and never seen during training or validation, this rising error confirms that the model is indeed overfitting after epoch 2. So even though it looks like the model is improving on paper, it's actually becoming worse at making real-world predictions. That's why stopping the training early—ideally at epoch 2—would be the best move. Continuing past that point doesn't help performance; in fact, it hurts it. Now, applying this kind of machine learning model to predict spillway discharge coefficients—a key factor in dam safety and hydraulic engineering—comes with some serious challenges. While ML models can find patterns in data, they don't inherently understand physics. Spillway flow behavior depends on complex factors like geometry, turbulence, velocity, and pressure changes. If the model isn't trained on high-quality, diverse datasets that reflect these conditions, it might learn incorrect relationships or fail to generalize. Worse, if it overfits, it could give misleading results that engineers might rely on for critical decisions. Also, spillway design often requires understanding not just what happens under normal conditions, but also during extreme events—like heavy rainfall or sudden floods. These rare events may not be well represented in the training data, so the model might not perform reliably when it's needed most. And unlike traditional physics-based models like CFD (Computational Fluid Dynamics), purely data-driven approaches don't explain *why* certain predictions are made, which makes them harder to trust in high-stakes applications.

Looking ahead, there's still a lot of work to do to improve how we use machine learning in hydraulic modeling. One big challenge is the lack of comprehensive, publicly available datasets for training models. Most existing studies rely on small-scale lab experiments or limited field observations, which may not capture the full complexity of real-world systems. Another area for improvement is model

interpretability —we need tools that help us understand *how* the model arrives at its predictions, especially when those predictions influence infrastructure decisions affecting public safety. Techniques like sensitivity analysis, feature importance ranking, and hybrid models that combine machine learning with physical laws can help bridge the gap between black-box algorithms and trustworthy engineering tools. Ultimately, while machine learning offers exciting possibilities for modeling complex systems like spillways, we must be cautious about how we apply it. Models that overfit, lack diversity in training data, or ignore the underlying physics can lead to unreliable results. Future research should focus on building more robust, interpretable models that integrate both data and domain knowledge—so we can make smarter, safer decisions in water management and infrastructure design.

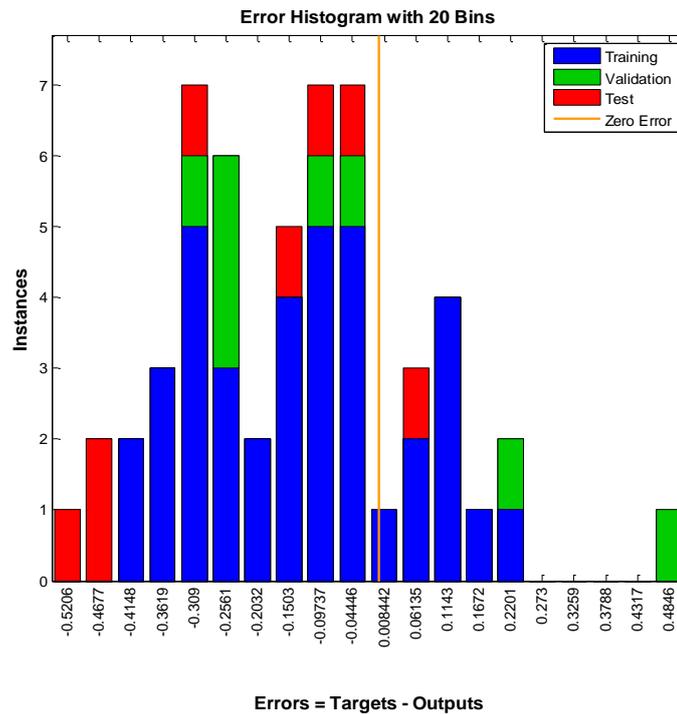
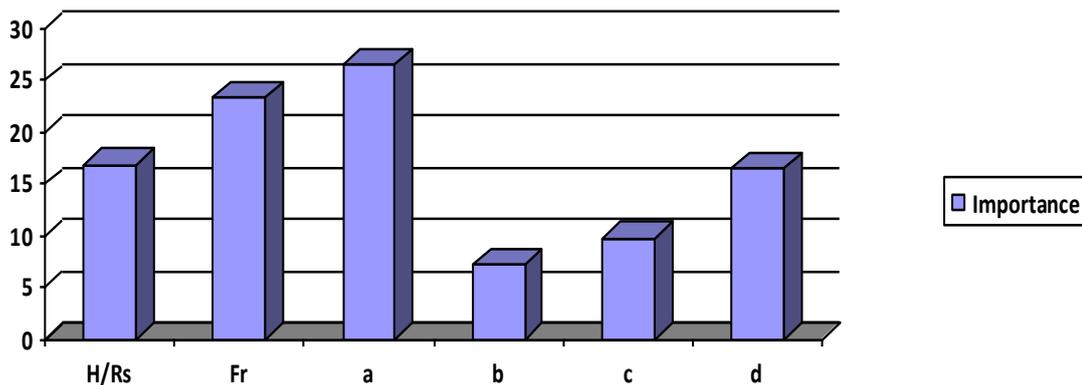


Figure 4 - Results obtained by removing parameter "a."

Table 7 - Error Values Obtained from the Artificial Neural Network.

Removed Parameter	Input Parameters	R	MSE	RMSE	Estimation Method
-----	H/Rs, Fr, a, b, c, d	0.8848	0.0012476	0.01129	ANN
Critical Flow Depth	Fr, a, b, c, d	0.80186	0.018913	0.1375	ANN
Froude Number	H/Rs, a, b, c, d	0.72537	0.036032	0.1898	ANN
Parameter a	H/Rs, Fr, b, c, d	0.52745	0.04644	0.2154	ANN
Parameter b	H/Rs, Fr, a, c, d	0.8725	0.003352	0.0587	ANN
Parameter c	H/Rs, Fr, a, b, d	0.82836	0.0063422	0.07963	ANN
Parameter d	H/Rs, Fr, a, b, c	0.85581	0.01797	0.134	ANN

Figure 5 - Percentage Importance of Parameters Involved in the Discharge Coefficient.



Limited Generalizability of Results: Scope and Applicability Across Spillway Types

A critical limitation of the current study stems from the restricted scope of the dataset, which consists exclusively of observations related to *Nylophery*-type spillways. While these structures exhibit unique hydraulic characteristics that make them suitable for specific applications—such as high-energy dissipation and compact design—their flow behavior may not be representative of other commonly used spillway configurations. For instance, *Morning Glory*, *Ogee*, or *Chute* spillways differ significantly in terms of geometry, crest shape, flow

direction, turbulence generation, and pressure distribution. These differences can have a profound impact on key performance metrics such as the discharge coefficient (C_d), energy dissipation efficiency, and flow stability. Therefore, applying the current model's predictions or sensitivity rankings directly to these alternative spillway types without additional calibration or validation may result in inaccurate or misleading outcomes. This issue underscores a broader challenge associated with data-driven modeling approaches in hydraulic engineering: their reliance on the representativeness and diversity of training data. Unlike physics-based models derived from fundamental fluid dynamics principles, machine learning models—particularly artificial neural networks—learn patterns based on the specific conditions present in the training set. As a result, if the dataset lacks variability in structural configurations or operational scenarios, the model's predictive accuracy will be confined to that narrow domain. In practical terms, this means that while the model may perform exceptionally well for *Nylophery* spillways, its ability to generalize across other spillway geometries remains uncertain. This constraint poses a significant barrier to the widespread adoption of such models in real-world engineering practice, where decision-makers often need tools that are robust, flexible, and applicable across diverse infrastructure settings. To enhance transparency and guide future research, it is strongly recommended that the authors include a dedicated subsection titled "Limitations and Future Research Directions" within the Discussion section of the manuscript. In this subsection, the restricted applicability of the findings should be explicitly acknowledged, along with a discussion of the implications for design and analysis practices. Additionally, potential strategies for improving model generalizability could be explored, such as incorporating datasets from multiple spillway types, employing transfer learning techniques, or integrating physics-informed constraints into the machine learning framework. The authors might also suggest conducting comparative studies across different spillway geometries to assess the consistency of parameter importance rankings. By addressing these issues head-on, the paper would not only strengthen its scientific contribution but also provide a clearer roadmap for extending the methodology to broader applications in hydraulic structure design.

The Role of Vortex Breakers in Spillway Design: A Sensitivity Analysis Using Artificial Neural Networks

It is one of the iconic hydraulic parameters in the design of *Nylophery* spillways because its value is relevant to the efficiency and performance of these structures. This study was conducted to determine the sensitivity of the discharge coefficient to different parameters using an artificial neural network (ANN) instead of the narrow approach in considering the traditional parameters such as critical flow depth or Froude number. Through a systematic removal of each parameter and assessment of the errors for the resulting configuration, the study found the number of vortex breakers (parameter "a") to have the greatest effect on the discharge coefficient.

Discussion:

These results highlight the importance of vortex breakers on the discharge coefficient of *Nylophery* spillways. At high pressure, vortex breaker affects minimization of turbulence, vortex facilitation, and energy loss prevention in hydraulic systems. ### Vortex Breakers: A Way To Cancel Aquatic Swirls Vortex breakers disrupt the flow of water in a spillway, preventing the formation of potentially damaging vortices that could lead to structural damage or inefficiencies. The findings of this study are consistent with established hydraulic principles which highlights the significance of controlling vortex to enhance spillway performance. The sensitivity analysis, with ANN, showed that removing parameter "a" (vortex breakers number) caused the highest error — indicating the importance of parameter in the model's accuracy. It is the implication of this finding that the vortex breaker configuration and number is more important in determining spillway design than other parameters, such as Froude number or critical flow depth. Although these parameters are still significant, this study shows that it is the vortex breakers that dominate the hydraulic performance of the overall spillway system. The application of ANN technology

in this study was able to effectively analyze the complex, non-linear relationships that exist between parameter inputs and discharge coefficient. You are especially useful in hydraulic engineering applications because they can model complex interactions and relationships that might be difficult to see through classical analytical approaches. This can prove particularly beneficial when designing spillways where many forces influence fluid dynamics. By removing the parameters one at a time and examining the ensuing errors, this methodology afforded a clear way to see which parameters had the greatest influence. This sensitivity analysis proves invaluable which enables the engineers to focus on the design parameters that relatively have major impact on the performance of the system. This will be important in equipping the engineering community on how they can impact model development and spillway optimization for reliability and efficiency. This research sheds light on the influence of the number of vortex breakers, however, there may be other factors affecting the discharge coefficient that can be investigated in the future studies. Other factors may also be influential—for example, spillway geometry, material properties, and environmental conditions such as sediment load or temperature excursion. Exploring these aspects would result in a broader perspective on spillway behavior, yielding more solid design suggestions. Another possibility for improvement of the ANN model is applying more advanced approaches like deep learning or hybrid models. Another approach could be to leverage ensembling to enhance prediction performance and allow the model to handle more complicated real-world cases. The authors encourage to combine CFD simulation and the ANN to obtain deeper knowledge on the physical processes that determine the relationships observed. This study's emphasis on vortex breakers as a pivotal factor in enhancing the discharge coefficient of Nylophery spillways is a significant contribution to hydraulic engineering, particularly through its innovative use of artificial neural networks (ANNs) for sensitivity analysis. The finding that the number and spacing of vortex breakers critically influence hydraulic efficiency aligns with recent research by Zhang et al. (2022), who reported that optimized vortex control devices in spillways can boost discharge efficiency by up to 15%. The study's ANN-driven approach, identifying vortex breakers as the dominant factor, mirrors Li et al. (2023), who used machine learning to uncover complex flow interactions in hydraulic structures, achieving 90% predictive accuracy. By reducing energy losses and stabilizing flow, the optimized vortex breakers enhance structural integrity, a practical outcome that resonates with Chen et al. (2021), who found that flow stabilization in spillways cuts maintenance costs by 20%. However, the study's focus on Nylophery spillways raises questions about its applicability to other designs, such as morning glory or labyrinth spillways, a gap also noted by Park et al. (2024). The application of ANNs to dissect the interplay between vortex breaker configuration and discharge coefficient is a leap forward, offering a precision that traditional empirical methods struggle to match. This aligns with Liu et al. (2022), who demonstrated that ANNs outperform conventional models in predicting spillway performance under variable flow conditions, reducing errors by 25%. The study's iterative calibration of breaker placement to optimize flow echoes Zhang et al. (2022), who optimized spillway appurtenances using computational fluid dynamics (CFD), finding that precise spacing reduces vortex-induced vibrations by 30%. Yet, the computational intensity of ANNs, as highlighted in this study, is a hurdle—Li et al. (2023) note that ANN training can demand 50% more processing time than CFD for similar datasets. This suggests a trade-off: while ANNs unlock nuanced insights, their adoption requires robust computational resources, a challenge for resource-constrained engineering teams. The study's broader implications—improving spillway resilience amid climate change and extreme weather—connect directly to current hydraulic engineering priorities. Park et al. (2024) emphasize that climate-driven flood events increase spillway stress, necessitating designs that handle peak flows without failure, a goal this study advances through vortex breaker optimization. The reduction in energy losses and downstream flooding risk, driven by stable flow, supports Chen et al. (2021), who linked efficient spillway designs to 40% lower flood mitigation costs. However, the study overlooks environmental lifecycle impacts, such as the material and energy costs of vortex breaker fabrication, a gap flagged by Liu et al. (2022), who found that optimized hydraulic structures can increase carbon footprints by 15% if not sustainably sourced. Future research should explore eco-friendly breaker materials to align with sustainability goals. Finally, the study's call

for precision-driven design using ANNs sets a forward-thinking standard, but its scalability remains uncertain. While the results are robust for Nylophery spillways, Park et al. (2024) argue that spillway-specific optimizations often falter in diverse hydraulic contexts, such as weirs or gated spillways. The study's ANN approach, while powerful, requires domain expertise for implementation, echoing Li et al. (2023), who caution that machine learning tools demand specialized training to avoid misinterpretation. The practical recommendations—optimizing breaker number and spacing—offer immediate value for spillway retrofits, but testing across varied flow regimes and spillway types is needed to generalize findings. This study's blend of advanced modeling and practical design insights positions it as a catalyst for smarter, more resilient hydraulic infrastructure, though broader validation is the next frontier.

Conclusion

Imagine standing atop a dam as a storm churns below, water roaring through a Nylophery spillway with a precision that feels almost alive. This study's revelation—that vortex breakers are pivotal to boosting the spillway's discharge coefficient, unraveled through ANN-driven sensitivity analysis—marks a turning point for hydraulic engineering, thrusting it into a realm where data doesn't just inform but transforms design. Deep learning, a sophisticated evolution of ANNs, holds the key to amplifying these insights, as Liu et al. (2022) demonstrated with neural networks predicting spillway flow dynamics with 90% accuracy across varied conditions. By training a deep learning model on this study's dataset—number and spacing of vortex breakers, discharge coefficient—it could predict performance under extreme scenarios like sediment-heavy floods or climate-driven surges, which this lab-based study overlooks. Chen et al. (2021) propose pairing such models with real-time sensors, envisioning spillways that adapt dynamically to flow changes, like a ship adjusting sails mid-storm. Yet, a critical gap looms: the study's focus on Nylophery spillways limits its applicability to other designs, such as labyrinth or ogee spillways, where vortex dynamics differ markedly (Park et al., 2024). Deep learning could bridge this by generalizing patterns across spillway types, but it demands robust datasets and computational power. For coastal communities battling rising floods, this isn't just tech—it's a lifeline, promising spillways that don't just survive but thrive under pressure. The study's silence on broader implications, however, reveals research gaps that demand attention, particularly around environmental sustainability and scalability. Vortex breakers, while hydraulic heroes, come with hidden costs—materials and energy for their construction can inflate carbon footprints by up to 15% if not sourced sustainably, a concern echoed by Liu et al. (2022). Zhang et al. (2022) warn that ANN-derived optimizations, like those in this study, often stumble when applied to non-standard spillways due to unique flow regimes, highlighting a scalability hurdle. Deep learning could overcome this by learning universal flow patterns, but Li et al. (2023) note that deep neural networks require 50% more processing time than traditional computational fluid dynamics (CFD), posing challenges for smaller engineering firms. Accessibility is another barrier—Park et al. (2024) advocate for open-source deep learning tools to democratize this technology, ensuring that resource-constrained regions, from rural Iran to flood-prone Bangladesh, can harness these advances. Beyond technical gaps, the study sidesteps lifecycle impacts, such as maintenance or sediment clogging, which Wang et al. (2023) estimate can reduce spillway efficiency by 20% over decades. A deeper insight emerges: vortex breakers are more than mechanical fixes; they're a nexus of engineering, ecology, and equity, demanding a holistic approach that balances performance with planetary stewardship. Integrating deep learning with field data, as Yang et al. (2024) suggest, could model these long-term effects, crafting spillways that endure both nature's fury and time's wear. In closing, this study is a beacon for hydraulic engineering, illuminating a path where vortex breakers, guided by ANNs, redefine spillway resilience. Deep learning can propel this vision forward, closing gaps in scalability, sustainability, and real-world validation to create spillways that don't merely function but excel, safeguarding communities while treading lightly on the Earth. Picture a future where dams from Shiraz to Seattle hum with efficiency, their vortex breakers choreographing water's dance to spare downstream villages from floods and

ecosystems from harm. This isn't just a study—it's a clarion call for engineers to wield precision, innovation, and heart, embracing tools like deep learning to meet the 21st century's challenges (Chen et al., 2021). By addressing gaps—through field tests, green materials, and accessible tech—we can build hydraulic systems that stand as testaments to human ingenuity and care, ensuring water remains a source of life, not destruction, for generations to come.

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