

Methodologies for cavitation prediction on high-head spillways: Review and propose a hybrid approach

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Abstract: Cavitation on high-head spillways can cause rapid concrete damage, posing serious threats to structural safety during flood releases. This review synthesizes methodologies for predicting cavitation inception, intensity, and damage risk across laboratory, field, numerical, and machine learning approaches. Both physical and numerical methods have been widely applied; however, they present limitations such as high cost, time consumption, and applicability restricted to individual case studies. The literature indicates that for spillways with similar configurations, the locations most at risk of cavitation damage are typically the same. Building on this insight, this study introduces a novel procedure for predicting cavitation risk by integrating advanced techniques including machine learning and 3D CFD modeling to develop a rapid prediction tool for quantifying the cavitation index.

Keywords: High-head spillway, procedure of prediction cavitation, 3D CFD, ML method.

1. Introduction

Cavitation in hydraulic structures can cause severe damage even when preventive design measures are in place (Lee, & Hoopes, 1996). Cavitation occurs when water flows at very high velocities in high-head spillways, forming vapor bubbles that collapse and generate intense shock waves. It is a primary cause of spillway surface deterioration and failure, leading to significant surface erosion and structural damage (Falvey, 1990). Among the various hydraulic issues that can occur on spillway surfaces, cavitation is often a primary cause of concrete surface failure in structures conveying high-velocity flows (Dehdar-Behbahani, & Parsaie, 2016; H. T. T. Le et al., 2023; Parsaie et al., 2016). Lee & Hoopes, (1996) summarized several challenges in studying cavitation damage on concrete surface. First, cavitation is a highly transient and three-dimensional phenomenon involving intense turbulence, making it difficult to capture and model with precision. Second, scale effects in laboratory models often hinder accurate reproduction of prototype conditions due to differences in Reynolds number, surface roughness, and air content. Third, direct measurement of cavitation inception, pressure fluctuations, and impact forces on spillway surfaces remains technically demanding and expensive. Fourth, the resistance of concrete to cavitation erosion is influenced by variability in mix design, aging, and maintenance history. Fifth, unpredictable operating conditions such as fluctuating reservoir levels, gate operations, and extreme flood events complicate the assessment of cavitation risk. Finally, the scarcity of long-term

field data limits the ability to validate and refine predictive models.

Investigation of cavitation risk is essential for both newly designed and aging hydraulic structures. Field observations at the Hoa Binh Hydropower Plant from 2000 to 2002 revealed severe erosion in the energy dissipation abutments and wing walls of 12 bottom outlets. The abutments exhibited erosion depths of 70÷80 cm and widths of 4÷6 m, while the wing walls suffered erosion up to 30 cm in depth and 2÷3 m in width. The damage was attributed to cavitation occurring in these locations (Thanh Bang Nguyen, 2012). In newly designed hydraulic structures, cavitation risk is commonly quantified through the cavitation index, which relates local pressure conditions to the vapor pressure of water $C_v = (p - p_v) / (\rho V^2 / 2)$, where p and p_v (N/m²) are absolute pressure and vapour pressure, respectively; V (m/s) is velocity; ρ (kg/m³) is water density. The classification of cavitation damage levels based on flow velocity and cavitation index was first introduced by (Kermani et al., 2013), providing a framework for assessing potential surface damage. Then this cavitation standard has been prevalently applying in several researches (H. T. T. Le et al., 2023); (Hien et al., 2024). For aging conveyance structures, variations in surface roughness often lead to the formation of localized cavitation zones. In such cases, the gasification index (K) is employed to predict gasification phenomena (TCVN, 2012). To determine both C_v and K , it is necessary to evaluate the pressure and velocity near the concrete surface. These parameters can be obtained through various approaches, including physical modeling, numerical modeling, and emerging machine learning techniques, enabling a more comprehensive quantification of cavitation risk.

In general, the purpose of predicting cavitation damage is to identify the location and assess the risk level of cavitation under alternative operating

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conditions. Table 1 summarizes previous studies that applied this flowchart to predict cavitation risk using

various methods across different spillway types and operating conditions.

Table 1. Literature review on cavitation prediction of high-head spillways

N ^o	Investigators	Spillway type	Methodologies	Operating conditions	Location of cavitation risk
1	(Kermani et al., 2013)	Spillway chute	Physical model	Extreme floods	At the end of chute
2	(Bagherzadeh et al., 2025)	Spillway chute	CFD+ML	Extreme floods	At the end of chute
3	(Foroudi & Barati, 2022)	Spillway chute with different contraction angle	Physical model	Extreme floods	Near end of chute
4	(Hien et al., 2024)	Ogee spillway with flip bucket	3D CFD	Extreme floods+ different opening control gate	At flip bucket
5	(Dong et al., 2019)	Stepped spillway	3D CFD	Different opening control gate	At some steps near spillway's toe
6	(Yusuf & Micovic, 2020)	Stepped spillway	Physical+3D CFD	Extreme floods	Step
7	(H. T. T. Le et al., 2023)	Ogee spillway and bottom outlet	CFD	Extreme floods	Crest and slopping segment
8	(N.Chiến, 2013)	Ogee spillway with flip bucket	1D CFD	Extreme floods	At flip bucket
9	(Wan et al., 2018)	Spillway chute	3D CFD	Extreme floods	At the end of chute

2. Cavitation prediction methodologies

2.1. Experimental study

Experimental testing in physical models is a traditional and widely used method for investigating hydraulic mitigation objectives, such as enhancing energy dissipation capacity, reducing local scour depth, and minimizing cavitation risk. Physical modeling remains a reliable and extensively applied technique for predicting cavitation in conveyance structures, including spillways, tunnels, and chutes, due to its ability to accurately replicate complex flow phenomena such as turbulence and air-water interactions, allowing direct visualization and validation of actual cavitation sites. Moreover, it is valuable for assessing the effectiveness of mitigation measures, such as aerators or stepped spillway geometries. In general, experimental prediction of the cavitation index involves measuring water depth, pressure, and velocity. (Kermani et al., 2013) and (Foroudi & Barati, 2022) conducted several experiments on spillways with channel chutes (Table 1), revealing that the highest cavitation risk typically occurs near the end of the chute. However, limitations in laboratory capacity, workforce availability, and experimental costs as well as the inability of physical models to address all design and operational scenarios, which led to the increasing use of numerical models as a flexible and cost-effective alternative.

2.2. Numerical methods

With advances in computational power and numerical algorithms, numerical modeling has become an indispensable tool for predicting cavitation risk in hydraulic structures. Compared to physical modeling, numerical simulations offer greater flexibility in evaluating a wide range of design configurations, operational conditions, and geometric modifications without the constraints of laboratory scale or cost. By

using Computational Fluid Dynamics (CFD) techniques, researchers can estimate key hydraulic parameters such as velocity fields, pressure distribution. These parameters enable the calculation of the cavitation index and the identification of potential cavitation zones with high spatial resolution. Moreover, numerical models allow for the detailed investigation of flow features that are difficult to measure experimentally, including transient bubble dynamics and localized pressure fluctuations, thus providing valuable insights for both design optimization and damage mitigation strategies.

Table 1 indicates that 3D numerical modeling has been widely recognized as an effective tool for assessing the hydraulic characteristics of flow under various operating conditions (Bagherzadeh et al., 2025); (Hien et al., 2024); (Dong et al., 2019); (Yusuf & Micovic, 2020). Simulating the cavitation index along the spillway surface enables the quantification of both the location and intensity of cavitation risk. However, these studies have been limited to individual case analyses. Both physical and numerical methods remain time-consuming and costly for investigating cavitation damage, as not all structures will experience the same level of damage under identical design conditions. Variations in operating schedules and construction details can significantly influence structural performance (Lee, & Hoopes, 1996). For spillways with the same configuration, the locations most prone to cavitation risk are usually in the same positions (Table 1). In addition, the magnitude of cavitation index often depends on the magnitude of inflow or extreme flood level (H. T. T. Le et al., 2023). The minimum value of cavitation index often appears at location that vacuum pressure or maximum velocity occurs. These limitations have motivated the exploration of advanced prediction techniques, particularly machine learning (ML)

approaches, which can leverage historical data and simulation outputs to rapidly estimate cavitation risk. By identifying patterns and relationships between hydraulic parameters and observed damage, ML models can provide fast, cost-effective, and scalable predictions without the need for exhaustive physical or numerical simulations for each case.

2.3. Machine learning approaches

Recently, machine learning (ML) has emerged as a

robust and effective approach for forecasting various hydraulic parameters, such as discharge coefficients and maximum scour depth (T. H. Le et al., 2025); (X.-H. Le & Hien, 2025). Table 2 demonstrates the advantages of integrating numerical simulations with advanced ML techniques can significantly improve the prediction and analysis of hydraulic structures in comparison with purely applying numerical or experimental methods.

Table 2. Advantages of integrating 3D CFD and ML methods

N ^o	Advantages of the proposed hybrid approach	Only 3D CFD model or physical model	Integrating 3D CFD, physical model and ML
1	Faster predictions after training	Every new scenario are expensive and time-consuming.	Once trained, the ML model can instantly predict cavitation indices, intensity levels, and zones for new flow conditions.
2	Ability to generalize beyond simulated cases	CFD and physical results are limited to the specific scenarios.	ML can learn patterns from CFD outputs (and experimental data) to interpolate between simulated conditions and extrapolate to new situations within reasonable limits.
3	Enhanced use of historical and experimental data	Impossible	ML can combine data from: 3D CFD simulations; scale model experiments. This fusion improves prediction reliability and reduces dependence on purely numerical or experimental approaches.
4	Reduced computational cost for large-scale parametric studies	Impossible	ML can rapidly evaluate several combinations, enabling optimization of spillway design to minimize cavitation risk.
5	Scalability for different spillway types	Impossible	The same ML framework can be retrained or fine-tuned for different types of spillways, leveraging existing CFD/experimental datasets.

However, this approach has rarely been applied to develop a formula capable of predicting both the location and intensity of cavitation. Bagherzadeh et al. (2025) employed the Flow-3D model for the Gelevard–Neka spillway and validated the results against available field data. Based on the analysis of key hydrodynamic parameters, they proposed a method to predict cavitation damage location and intensity using a support vector machine (SVM) model. Nevertheless, no practical prediction tool was provided for rapid assessment of cavitation risk, limiting the applicability of their approach to other case studies.

Integrating 3D CFD with ML provides advanced tools for modeling and prediction, yet it introduces several technical and practical disadvantages. The high computational cost of generating large CFD datasets and training ML models often limits scalability. Data quality and representativeness also pose challenges, as biased or limited CFD data can reduce model accuracy and generalization. Furthermore, ML models may lack physical interpretability and sometimes violate fundamental conservation laws, undermining trust in their predictions. Finally, integrating and validating CFD–ML frameworks requires complex data handling and interdisciplinary expertise, making their implementation difficult in real-world engineering applications.

2.4. Future research

Building on these developments, this study proposes an integrated framework that combines 3D CFD modeling with machine learning algorithms to rapidly quantify the cavitation index and identify high-risk zones under various operating conditions. This approach aims to overcome the limitations of conventional physical and purely numerical methods. A novel procedure consisted of three main steps is developed to achieve this objective:

Step 1: Categorization and data collection.

High-head spillways are classified into three main types: (i) spillway channel chutes, (ii) stepped spillways, and (iii) ogee spillways with flip buckets. For each type, geometric configurations and operational conditions (e.g., extreme flood elevations, gated operations) are collected and systematized.

Step 2: 3D CFD simulations and cavitation index computation.

A validated 3D CFD model is employed to simulate hydraulic characteristics under different operating conditions, including pressure distribution, depth-averaged velocity, bottom velocity, and flow depth. The model is calibrated and validated against observed data. From the simulations, the cavitation index (C_v) is computed along the spillway surface.

Step 3: Dimensional analysis and machine learning prediction.

i) The dataset of cavitation index values is analyzed using the Buckingham π theorem. C_v distributions along the spillway surface are examined for their correlation with governing variables, such as upstream head (H , m), discharge (Q , m³/s), spillway geometry (surface coordinates (x , z), height P , roughness), Froude number (F), water density (ρ , kg/m³), and gravitational acceleration (g , m/s²).

ii) Machine learning approaches are then employed to establish predictive models for C_v . Cavitation risk levels along the spillway surface are categorized based on established cavitation standards. The predictive accuracy of the models is validated against observed C_v data. Finally, an independent case study is simulated numerically to generate C_v values, which are compared with machine learning predictions to assess the accuracy and generalizability of the proposed predictive framework.

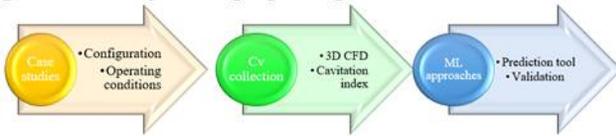


Figure 1. Procedure of cavitation prediction on high-head spillways

Vietnam has several high-head dams, which regulates water level in large reservoirs (Figure 2). Two prevalent categories of high-head spillways are: i) Spillways coupling with bottom culverts: Ta Trach, Son La and Tuyen Quang; ii) Spillways with flip buckets to dissipate energy: Canh Tang, Lai Chau, Chay 5, Song Bung 4, Ban Ve, Long Song. Their configurations and dimension such as spillway height (P), the width (B) and the height (H) of each bay significantly affected to form cavitation risk zones and cavitation intensity (Table 3). Besides, different upstream water depths corresponding with extreme flood scenarios have been used as the input data of numerical model. In order to apply the procedure, numerical result of cavitation index along spillway surface corresponding with each categories are simulated by a 3D CFD model. These data are training and testing by the proposed ML so that building a formula to predict cavitation index (C_v). The application of this procedure to the two aforementioned spillway types will be presented in a subsequent study.

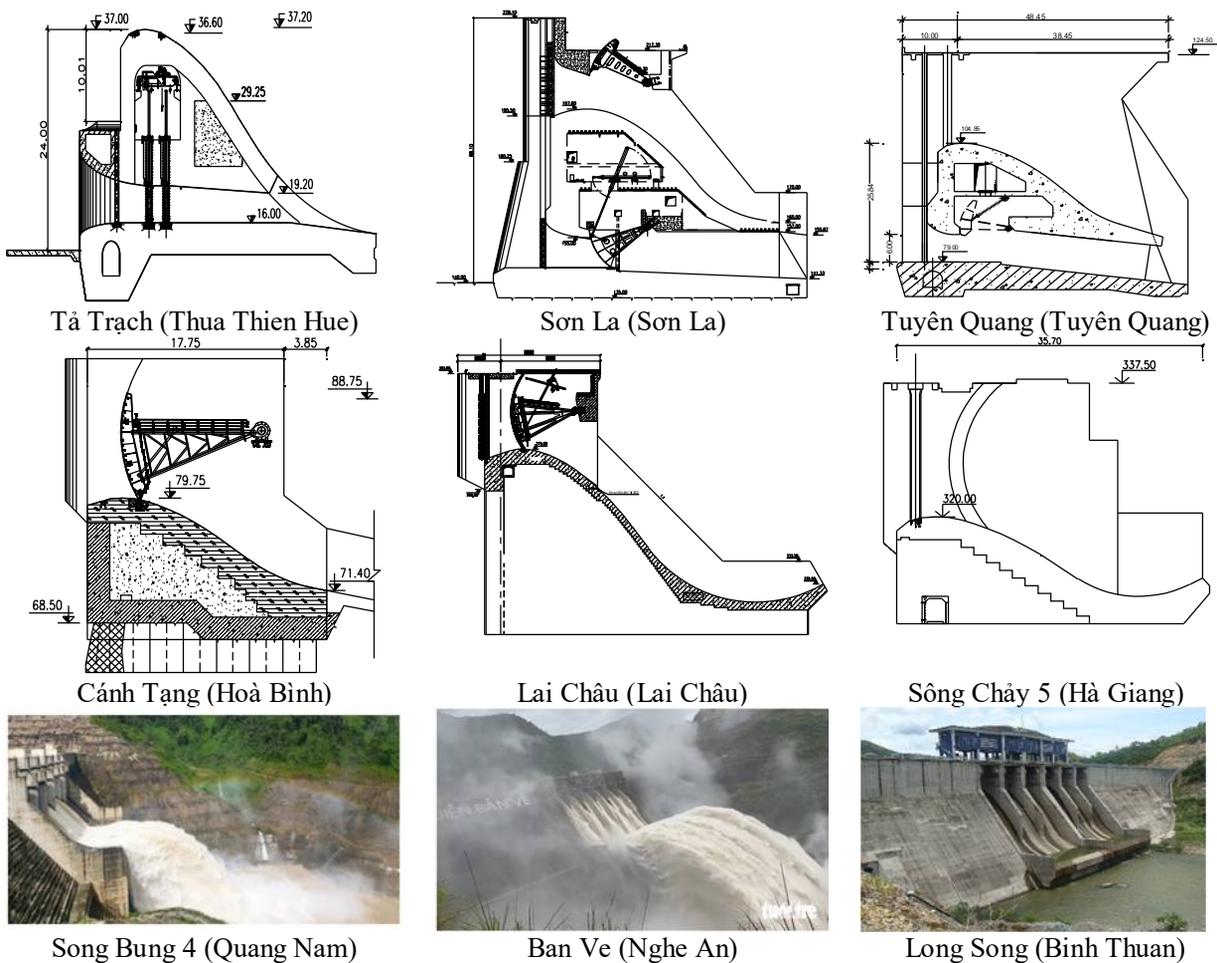


Figure 2. Configurations of spillway cross sections of some high-head spillway in Vietnam

Table 3. Hydraulic parameters of some high-head spillways

N°	Spillways	Hydraulic parameters of spillway		Upstream water depth (m)			PMF
		n(B×H) (m)	P (m)	Normal water depth	Design flood	Extreme flood	
1	Ta Trach	5(9×8.0)	24.00	8.0	11.27	13.0	16.07
2	Son La	6(15×11.2)	57.80	17.2	20.30	21.38	30.27
3	Tuyen Quang	4(15×15.15)	27.35	15.15	16.55	19.04	
4	Canh Tang	2(9×9.0)	21.75	9.0	10.05	10.89	11.73
5	Lai Chau	6(14.5×2.0)	59.50	20.0	22.52	27.75	
6	Chay 5	3(9×10.0)	14.00	10.0	13.0	15.31	

3. Conclusion

This study provides a comprehensive review of three methodologies for predicting cavitation risk on spillway surfaces. Traditionally, experimental investigations and numerical simulations have been the predominant tools for such predictions. While physical model experiments offer valuable empirical insights and allow for direct observation of cavitation onset, they are often constrained by high costs, substantial time requirements, and scaling effects. Similarly, conventional numerical modeling approaches, though capable of capturing complex flow phenomena, tend to be case-specific and require significant computational resources.

Recent advancements in 3D CFD have enhanced the capability to resolve high-fidelity, physics-based flow fields, enabling detailed analysis of parameters critical to cavitation assessment. In parallel, ML techniques have emerged as a complementary approach, offering rapid prediction, adaptability to diverse hydraulic conditions, and scalability across multiple spillway configurations. The integration of 3D CFD and ML leverages the strengths of both methodologies: CFD provides accurate, physics-grounded datasets for model training, while ML facilitates fast and generalized predictions. This synergy enables the development of robust, efficient, and practical prediction tools, with significant potential for application in both design optimization and real-time operational decision-making.

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