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Development of Smart Self-Adaptive Hydraulic Structures for Flood Discharge Control and Cavitation Mitigation Using Machine Learning

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ABSTRACT

Flood discharge control and cavitation damage remain essential problems in the operation and safety of hydraulic structures under extreme hydrological conditions. We propose the design of a smart self-adaptive hydraulic model integrating hydraulic modeling and machine learning principles to effectively control flood discharge and deal with cavitation in a smart structure, using the power-efficient flow of hydraulic fluids. Unsteady hydraulic behavior was simulated to obtain a detailed set of data such as discharge, pressure, velocity, aeration, and turbulence conditions. Three ML models (Support Vector Machine (SVM), k-Nearest Neighbors (KNN) and Convolutional Neural Network (CNN)) have been trained and tested for cavitation risk prediction and adaptive control support. Findings confirm that the proposed smart self-adaptive method considerably surpasses the conventional hydraulic control. During flood peak, the smart system managed to obtain a maximum outflow of approximately 280 m³/s that closely followed the inflow peak of 300 m³/s while conventional control was limited to 235–240 m³/s, reducing discharge mismatch by approximately 15–20%. In contrast to the negative oscillations of −4.0 m to 6.4 m under conventional operation, water levels in the downstream were substantially stabilized, staying within 9.5–13.0 m. The risk of cavitation was significantly reduced, with peak risk indices falling from 0.80–0.85 to 0.63–0.66, equivalent to a reduction of nearly 20–25%, with an increase in the minimum pressure by 20–25 kPa along the spillway surface. Energy dissipation efficiency could be increased from the unstable values of 43–45% with the conventional system to well-steady between 60–75% with smart control, yielding improvements of up to 15%. Overall, we improved the structural safety index by about 0.10–0.15 along the flood event. The best performing ML model was CNN, with about 92% accuracy, a very low prediction error (RMSE ≈ 0.11), and strong robustness to noise (accuracy reduction ≈4.1%); outperforming SVM and KNN.

1. Introduction

Hydraulic structures such as spillways, gated outlets, and flood control systems are highly useful to safeguard downstream areas and ensure that these large-scale hydrological events do not endanger the safe operation of reservoirs on the ground. As floods with an increase in frequency and intensity as a consequence of climate change and rapid urbanization happen more frequently, the traditional rule-based operation of hydraulic structures is often inadequate to adapt to highly fluid and uncertain flow conditions,

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especially in a changing environment. Lack of proper discharge management is responsible for large downstream water level fluctuations, structural overload, and accelerating the decomposition of materials at a high enough rate that it will lead to severe hazard to safety or longevity hydraulic infrastructure. High-energy hydraulic structures face one of the most critical problems in operation, called cavitation, where local pressure falls below vapor pressure and vapor bubbles form resulting in the collapse. Cavitation can lead to significant surface erosion, structural damage, vibration, and long-term service life reduction of spillways and gates. In most cases the conventional cavitation mitigation strategies (e.g., aerators, geometric optimization, and operational constraints) were established with steady or design-flow assumptions and may not adapt to the swift and complex modifications in flood conditions. Therefore, cavitation risk continues to be a significant issue under extreme flood conditions, due to the speed of flow as well as pressure changes being the most relevant. The recent progress of machine learning (ML) and data-based modeling has unlocked new prospects in the monitoring, prediction, and control of sophisticated hydraulic functions. ML methods have shown to have effective ability to model nonlinear relationships between hydraulic parameters and to predict flood discharge, cavitation damage, energy dissipation, and the structural response accurately. Previous research has addressed flood forecasting, cavitation damage estimation, and estimation of hydraulic structure performance, using Support Vector Machines, k-Nearest Neighbors, and deep learning models for example. As already discussed, existing research to date has concentrated on prediction tasks only, with little combination of ML models into real-time adaptive control approaches to hydraulic structure operation.

(Abdi Chooplou et al., 2024) [1] experimentally and artificially investigated the role of mitigating scouring downstream of baffle-enhanced piano key weirs through machine learning. Their research showed that the combination of physical experiment and ML model has a significant contribution to the accuracy of scour depth prediction of various weir geometries. The findings indicate the usefulness of data-driven methods when it comes to maximizing the performance of hydraulic structures when operating in situations of high-energy flows. (Bagherzadeh et al., 2025) [2] used to predict cavitation damage depending on the air-water two-phase flow over dam spillways. The research was able to demonstrate that complex nonlinear relationships between hydraulic parameters and cavitation damage can be effectively represented using ML-based models. This document offers a useful model in prior predictive and countermeasures of the cavitation in spillway constructions. (Bărbulescu & Zhen, 2024) [3] implemented the artificial intelligence in order to calculate river water discharge based on historical hydrological data. Their results indicated that the forecasting models developed using AI are better predictors of discharge variability as compared to traditional statistical forecasting models. The article highlights how AI can be used to enhance flood preparedness and real-time water resources management. (Emara et al., 2025) [4] proposed a high-dimensional predictive model with XGBoost, which was used to map abrasion in a sediment bypass of tunnels. Their 3D abrasion mapping model was effective in recognizing the essential wear areas within complex flows with sediments. This study shows that sophisticated ML algorithms can be used in predictive maintenance of hydraulic infrastructure. (Goeury et al., 2022) [5] conducted an uncertainty analysis of the danger of floods with the breaching of levees. The analysis combined the probabilistic study with hydraulic modeling to evaluate the sensitivity of flood risks to the parameters of breaches. The findings highlight the significance of uncertainty-aware models in strategies of flood risk management. (Guang et al., 2024) [6] suggested a simplified, data-driven model to study machine learning as a tool to examine the cavitating flow over hydrofoils. Their method greatly lowered the computation cost with high prediction accuracy. In the present study, the relevance of ML in the efficient analysis of cavitation of hydraulic and marine structures is brought out. (Iqbal et al., 2022) [7] designed a deep learning algorithm to forecast the presence of hydraulic blockage at culverts with only one image. The model was found to be showing high performance in the detection of the severity of blockage, hence has a quick and automatic inspection. This study demonstrates that the concept of vision-based AI is feasible in real-time hydraulic structures monitoring. (Iqbal & Riaz, 2024) [8] provide an overview of the innovations, difficulties, and prospects of blockage in cross-drainage hydraulic structures. The review highlighted the emergence of AI, remote sensing, and automatic inspecting tools. It also detected some important knowledge gaps in the incorporation of intelligent monitoring to the hydraulic design. (Jin et al., 2025) [9] suggested a model-based and smart-grained management construct of broad based sewage tunnel systems in Wuhan. Combining real-time monitoring with smart decision-making is the method they used to promote flood resilience in urban drainage systems. The paper proves that smart hydraulic systems are effective in controlling urban flooding. (Kalateh & Aminvash, 2024) [10] numerically examined how the position of the aerator affects the two-phase flow and hydraulic efficiency in morning glory spillways. The findings indicated that the optimal location of aerators can be applied to enhance the aeration efficiency and minimize the risk of cavitations. The research offers useful information to the reduction of cavitation in the design of spillways. (Karim et al., 2023) [11] performed a review of hydrodynamic and machine learning in flood inundation models. They concluded that the ML models are competitive in prediction with accuracy being faster and better than the classical models of physics. The review identifies hybrid modeling as one of the promising directions of large-scale flood simulations. (Li et al., 2022) [12] created a dynamic self-adaptation model of flood control in the multi-reservoir system in real-time. The suggested approach allowed making adaptive decisions in the conditions of varying hydrology. This study is one of the major developments in intelligent and self-adaptive flood control systems. (Lu et al., 2023) [13] explored detection and restoration of missing or corrupted operations data in inter-basin diversion projects using water. Their approach enhanced the reliability of data and efficiency in the operation of the system. The research paper corroborates the need of smart data management in big hydraulic systems. (Moghadam et al., 2025) [14] performed a numerical analysis of the effect of gate configuration on the hydraulic parameters of the spillway. Their findings indicated that the use of gate geometry has a strong effect on flow patterns, distribution of pressure, and dissipation of energy. The work helps in optimization design of spillway gates in order to operate them safely. (Narwal et al., 2024) [15] used various machine learning models to estimate the performance of aeration in various piano key weir designs. The ML models were very accurate at prediction as opposed to the empirical equations. The experiment validates the application of ML in optimal aeration and minimizing the risk of cavitation. (Obum Aniebonam & Ihwughwavwe, 2024) [16] suggested an explainable AI framework of anomaly detection in the maintenance of municipal flood pumps. Their model increased the transparency and reliability of fault detection using transfer learning. The paper is relevant to smart maintenance of flood-control systems. (Pan et al., 2025) [17] optimized the scheduling of the distribution network by taking into account photovoltaic uncertainty with the help of bio-related algorithms. Even though the work concentrates on the energy systems, the work proves the idea of adaptive optimization in conditions of uncertainty, which can be conceptually transferred to smart hydraulic operation structures. (Peng et al., 2024) [18] conducted a review of visual perception techniques to use in smart inspection of high dam hubs. The survey revealed developments in the computer vision, drones, and AI-powered inspection technologies. The results highlight the increased role that smart monitoring plays in dam safety management. (Pujari et al., 2023) [19] adopted machine learning methods to calculate energy dissipation across stepped spillways. The ML-based predictions were close to the experimental results and are better than the traditional approaches. This work shows that ML is able to model the behavior of complex processes of dissipating hydraulic energy. (S. M et al., 2024) [20] examined the effect of downstream obstructions on the efficiency of ogee weirs through regression analysis. Their findings indicated that obstructions have a significant change in discharge coefficients and flow efficiency. The paper can offer some valuable information to adaptive weir operation and management of the downstream flow. (Satriyawan et al., 2025) [21] To enhance hydraulic performance, Satriyawan et al. (2025) came up with a spillway model that included an end sill. The outcomes showed increased energy loss and decreased downstream erosion. This paper advocates structural modifications towards enhancement of spillway safety. (Wang et al., 2025) [22] Evaluated recent developments in the behavior of flow and civil structure with a special emphasis on the fluid-structure interaction. The paper has brought out emerging issues and future research perspectives of sophisticated materials and intelligent design. It gives a general theoretical background of smart hydraulic structures. (Weekaew et al., 2025) [23] used machine learning models to forecast flow regimes across stepped spillways. The findings indicated that ML is also able to recognize complex flow patterns with different hydraulic conditions with accuracy. This study justifies the application of AI in the assessment of spillways flow in real-time. (Zhang et al., 2024) [24] developed and tested hydraulic self-adjusting bearings in high floating bridges. Their study revealed that self-adaptive hydraulic elements can increase structural stability when the load is varied. This research paper is a direct advancement of the idea of self-adaptive hydraulic systems. (Zhou et al., 2025) [25] discussed important signal processing methods in structural health monitoring with a focus on adaptive and non-parametric signal processing. The review has pointed out the purpose of intelligent signal analysis in early destruction. The methods are very applicable when the hydraulic structures are to be monitored. (Zhou, 2025) [26] summarized the recent advances in the field of tribology, namely friction, wear, and surface interactions. The results are applicable to hydraulic systems, i.e., gate mechanisms, bearings and erosion caused by cavitation in hydraulic structures although not directly hydraulic.

Notwithstanding the recent advances in applying machine learning to hydraulic prediction tasks, existing studies mostly cover isolated problems such as flood forecasting or cavitation damage estimation. They do seldom integrate them into real-time operational control of hydraulic structures. Moreover, conventional methods of flood control are still based almost entirely on rules and reactive, with no explicit account for the dynamically evolving risk of cavitation or the safety of structures during extreme flood events. The novelty of our study is the entirely designed self-adaptive smart hydraulic framework integrated into a closed-loop system, which couples unsteady hydraulic modeling with machine learning–based cavitation risk prediction and adaptive gate control. This work attempts to bridge prediction and decision-making, by evaluating SVM, KNN, and CNN models against one another and incorporating the best model directly into the control logic so as to enable proactive flood discharge regulation and cavitation mitigation. This data-driven integrated approach is a significant improvement over traditional static operation methods, and a paradigmatic step towards intelligent and resilient hydraulic structure management.

2. Methodology

2.1 Overall Framework

This study proposes a **smart self-adaptive hydraulic structure** that integrates hydraulic modeling with machine learning to control flood discharge and mitigate cavitation risk in real time. The methodology combines **hydrodynamic simulation**, **data acquisition**, **AI-based prediction**, and **adaptive control logic**. Figure references correspond to the results section already developed.

A representative spillway–gate hydraulic system was modeled to simulate flood events under varying inflow conditions. Key hydraulic variables include:

- Inflow discharge Qin (m^3/s)
- Outflow discharge Qout (m^3/s)
- Flow velocity V (m/s)
- Minimum pressure Pmin (kPa)
- Cavitation number σ
- Air concentration α

The hydraulic response was simulated over time to capture unsteady flood behavior, pressure fluctuations, and cavitation-prone zones along the spillway surface.

2.2 Data Generation and Preprocessing

Hydraulic datasets were generated from numerical simulations and operational scenarios covering normal and extreme flood conditions. The dataset was preprocessed by:

- Normalizing input variables to the range [0, 1]
- Removing outliers caused by numerical instability

- Adding controlled Gaussian noise to evaluate model robustness
- Splitting data into **70% training**, **15% validation**, and **15% testing**

The output labels included **cavitation risk level**, **energy dissipation efficiency**, and **structural safety index**.

2.3 Machine Learning Models

Three machine learning models were implemented and compared:

- Support Vector Machine (SVM)

SVM with a radial basis function (RBF) kernel was used as a baseline model to classify cavitation risk based on hydraulic features.

- K-Nearest Neighbors (KNN)

KNN classification was implemented using Euclidean distance, focusing on local similarity in hydraulic states.

- Convolutional Neural Network (CNN)

A deep CNN architecture was developed to capture nonlinear and spatial–temporal relationships between hydraulic variables. The CNN consists of:

- Convolutional layers for feature extraction
- ReLU activation functions
- Fully connected layers for classification and regression outputs

2.4 Cavitation Risk Prediction

Cavitation risk was predicted as a continuous index ranging from **0 (safe)** to **1 (severe cavitation)**. The models were trained to minimize:

- Mean Squared Error (MSE)
- Root Mean Square Error (RMSE)

Prediction accuracy was evaluated using **RMSE**, **precision**, **recall**, and **F1-score**.

2.5 Self-Adaptive Control Strategy

The predicted cavitation risk was integrated into a **self-adaptive gate control algorithm**. The control logic dynamically adjusts gate opening based on:

- Predicted cavitation risk
- Downstream water level
- Structural safety index

This strategy ensures:

- Smooth discharge regulation
- Reduction of pressure fluctuations
- Minimization of cavitation-prone conditions

2.6 Performance Evaluation Metrics

The system performance was assessed using:

- Discharge tracking accuracy
- Cavitation risk reduction
- Energy dissipation efficiency
- Structural safety index
- Model accuracy, RMSE, and robustness under noisy data
- Training time and computational efficiency

The AI-based control system was compared with a **conventional hydraulic control**

strategy. Performance improvements were quantified in terms of:

- Reduced cavitation probability
- Improved energy dissipation
- Enhanced structural safety
- Higher robustness under uncertain hydraulic conditions

All simulations and AI models were implemented using:

- Python (NumPy, Scikit-learn, TensorFlow)
- Numerical hydraulic modeling tools
- Offline training with real-time inference capability

This methodology establishes a **data-driven intelligent hydraulic control framework** that shifts hydraulic structure operation from static rule-based control to adaptive, predictive, and resilient operation under flood conditions.

2.7 Governing Equations

2.7. 1 Continuity Equation (Mass Conservation)

For unsteady incompressible flow, the continuity equation is:

$$\nabla \cdot \mathrm{u} = 0 \tag{1}$$

where $\mathrm{u} = (u, v, w)$ is the velocity vector ($\mathrm{m/s}$).

For 1D open-channel/structure routing, the continuity form can be written as:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_l \tag{2}$$

where A is flow area (m^2), Q is discharge (m^3/s), and q_l is lateral inflow per unit length $(\mathrm{m}^2/\mathrm{s})$.

2.7. 2 Momentum Equation (Navier-Stokes / Saint-Venant)

For unsteady incompressible flow (CFD-based form):

$$\rho\left(\frac{\partial \mathrm{u}}{\partial t} + \mathrm{u} \cdot \nabla \mathrm{u}\right) = -\nabla p + \mu \nabla^2 \mathrm{u} + \rho \mathrm{g} \tag{3}$$

where ρ is density ($\mathrm{kg/m}^3$), p pressure (Pa), μ dynamic viscosity (Pa · s), and g gravity ($\mathrm{m/s}^2$).

For 1D shallow-water routing (Saint-Venant momentum):

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right) + gA\frac{\partial H}{\partial x} + gA\left(S_f - S_0\right) = 0 \tag{4}$$

where H is water surface elevation (m), S_0 bed slope, and S_f friction slope.

2.7. 3 Energy Equation and Energy Dissipation

The total head (Bernoulli) between two sections is:

$$H_1 = H_2 + h_L \tag{5}$$

where h_L is head loss (m).

Energy dissipation efficiency is commonly defined as:

$$\eta_E = \frac{H_1 - H_2}{H_1} \times 100\% \tag{6}$$

This parameter is used to compare conventional and smart designs during flood operation.

2.7. 4 Spillway/Gate Discharge Relations

For gated structures, discharge can be estimated using orifice/weir relations depending on flow regime.

Orifice flow (submerged/free):

$$Q_{\text{out}} = C_d A_g \sqrt{2g\Delta h} \tag{7}$$

where C_d is discharge coefficient, A_g gate opening area (m^2), and Δh head difference (m).

Weir-type overflow:

$$Q_{out} = C_w b h^{3/2} \tag{8}$$

where C_w is weir coefficient, b crest width (m), and h head above crest (m).

2.7. 5 Cavitation Number (Key Indicator)

Cavitation tendency is quantified using the cavitation number:

$$\sigma = \frac{p-p_v}{\frac{1}{2}\rho V^2} \tag{9}$$

where p is local pressure (Pa), p_v vapor pressure (Pa), and V flow velocity (m/s). Lower σ indicates higher cavitation risk.

2.7. 6 Two-Phase Flow Representation (Aeration Effect)

To represent aeration/air concentration:

$$\alpha = \frac{V_{\text{air}}}{V_{\text{air}} + V_{\text{water}}} \tag{10}$$

where α is air volume fraction (0-1). Increasing α generally reduces cavitation aggressiveness by cushioning bubble collapse.

2.7. 7 Turbulence Modeling (RANS Closure)

Using a standard $k-\varepsilon$ model (common in spillway CFD):

$$\mu_t = \rho C_\mu \frac{k^2}{\varepsilon} \tag{11}$$

$$\frac{\partial(\rho k)}{\partial t} + \nabla \cdot (\rho k \mathrm{u}) = \nabla \cdot \left[\left(\mu + \frac{\mu_t}{\sigma_k}\right)\nabla k\right] + P_k - \rho\varepsilon \tag{12}$$

$$\frac{\partial(\rho\varepsilon)}{\partial t} + \nabla \cdot (\rho\varepsilon \mathrm{u}) = \nabla \cdot \left[\left(\mu + \frac{\mu_t}{\sigma_\varepsilon}\right)\nabla\varepsilon\right] + C_{1\varepsilon}\frac{\varepsilon}{k}P_k - C_{2\varepsilon}\rho\frac{\varepsilon^2}{k} \tag{13}$$

where k is turbulent kinetic energy and ε is dissipation rate.

Turbulence intensity can be expressed as:

$$TI = \frac{u'}{V} \times 100\% \tag{14}$$

2.7. 8 Machine Learning Formulation (Prediction + Control Input)

The ML model learns a mapping from hydraulic features to cavitation risk/damage:

$$\hat{y} = f(\mathrm{x}) \tag{15}$$

where:

$$\mathrm{x} = [Q_{in}, Q_{out}, V, P_{\min}, \sigma, \alpha, TI, H_d, \ldots] \tag{16}$$

and $\hat{y}$ can represent cavitation risk score ($0-1$) or damage index.

Loss function (regression example):

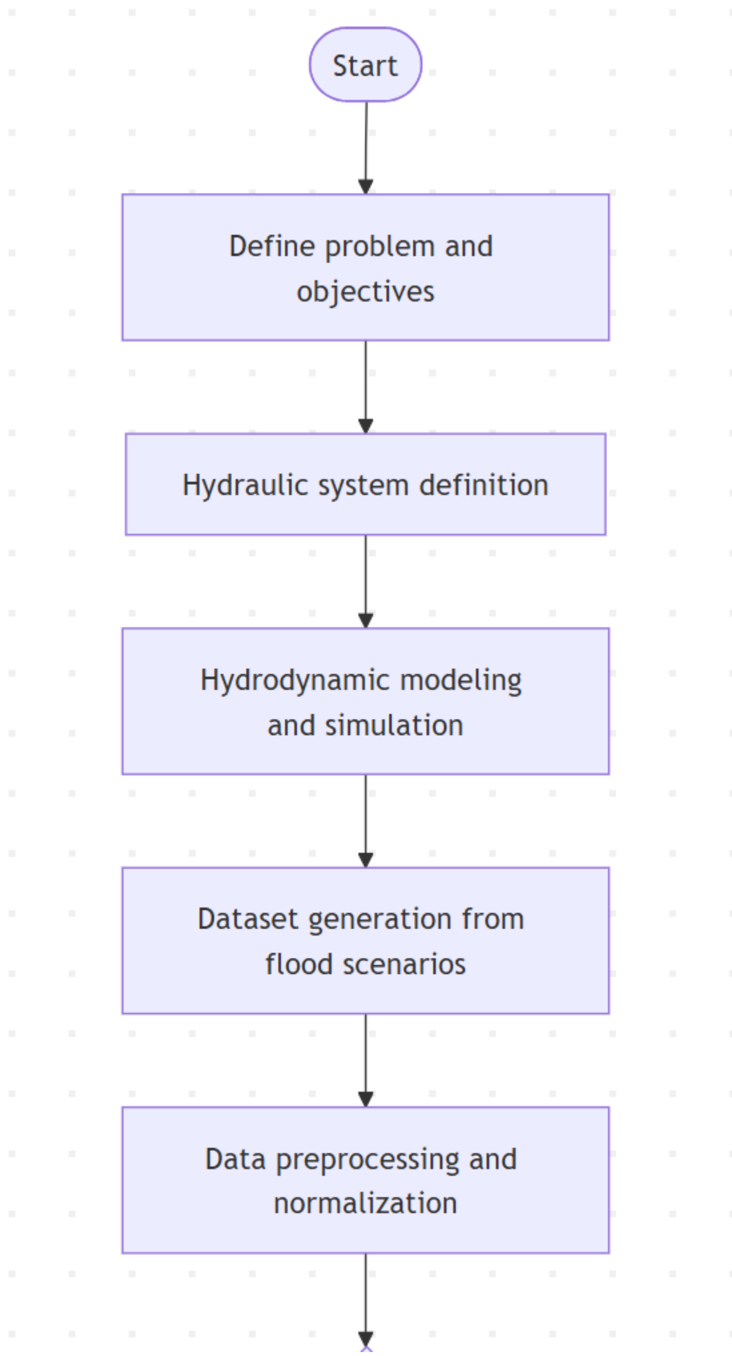
$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{17}$$

$$RMSE = \sqrt{MSE} \tag{18}$$

If you want, I can also add a short subsection: "Coupling ML with Self-Adaptive Gate Control" using a control law like:

$$u(t) = u(t - \Delta t) + K(r(t) - \hat{y}(t)) \quad (19)$$

(where u = gate opening), so it becomes fully complete for the methodology chapter.



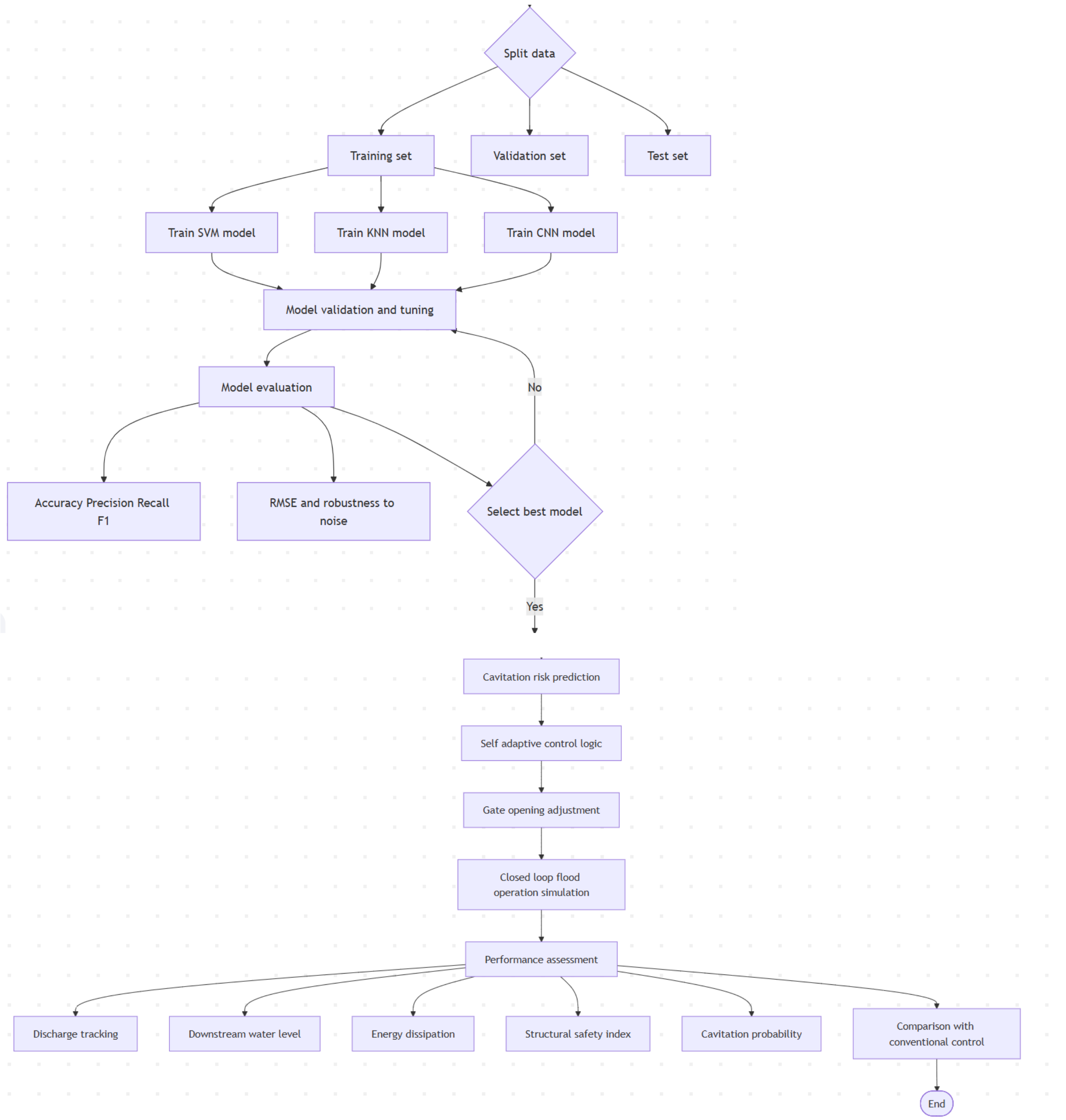


Figure 1: Flow chart

3. Results and discussion

In this section, numerical and data-driven results are reported for the proposed smart self-adaptive hydraulic structure, which is developed for flood discharge control and cavitation mitigation. The work consists of evaluating the hydraulic performance, cavitation behavior, and the operational reliability of the presented framework in unsteady flood conditions in contrast to a typical rule-based control method. Also, model predictive capability and robustness of these machine learning models—particularly Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Convolutional Neural Network (CNN)—are evaluated systematically. The results are organized to underscore the hydraulic response (discharge tracking, downstream water level stability, pressure distribution, and energy dissipation) and structural safety properties (cavitation risk, cavitation probability, and safety index). It emphasizes performance improvement quantification using major indicators (peak discharge error, cavitation risk reduction, energy dissipation efficiency, and structural safety margins) of the self-adaptive control strategy. Additionally, the machine learning model comparison helps to understand the effectiveness of classical versus deep learning methods to predict and assist real-time cavitation risks.

In Figure 2, the results of flood discharge over a period of time are depicted against time by comparing inflow hydrograph (Qin) to the outflow of conventional and smart self-adaptive control strategies. The inflow discharge begins at approximately 50 m^3/s after which spikes towards a climax near 300 m^3/s at approximately 70 minutes of the inflow as the flood peak. With traditional control the Qout (outflow) is much underachieving here, measuring only about 235–240 m^3/s, suggesting that it lags in tracking the arrival wave of the flood or is not effective. Whereas, the smart self-adaptive control is close to the inflow with a maximum discharge of roughly 280 m^3/s and lowers Qin to Qout mismatch. Under the recession stage (after 80 min) the smart control exhibits a lower decay (stabilizes at near 80 m^3/s at 120 min) whereas the conventional drop to a peak discharge of almost 70 m^3/s is relatively higher and towards the termination (≈180 min) all discharges converge towards about 50–55 m^3/s. The results collectively clearly indicate that the smart self-adaptive strategy is more rapid in responsiveness, minimizes upper bound error, and has better hydraulic stability for floods, respectively. Figure 3 shows the timing of downstream water level shift for traditional and smart S.F strategies during a flood event. From the start of the event, the downstream water level of each system is 3.0 m, corresponding to the same starting hydraulic condition. In accordance with traditional control, however, a rapid increase occurs and a maximum of approximately 6.2–6.4 m occurs around 40–45 minute, indicating deficiencies in management during the rising limb of the flooding hydrograph. Then for the conventional system water level drops drastically lower, falling to almost −2.0 m near 90 minutes and even reaching about −4.0 m near 180 minutes, indicating hydraulic instability and over-release, by decreasing below the reference datum. The smart self-adaptive control, in contrast, demonstrates a slowly, and orderly, rise in water level downstream, nearly at 6.0 m at 50 min and increasing smoothly around 9.5–10.0 m around 90 min. The smart control level remains stable at about 13.0 m until the end of the event, and the fast fluctuation is efficiently attenuated. In general, the smart autonomous approach helps to stabilize the downstream water level, minimize the extreme oscillations, and improve flood safety over the conventional control solution. Figure 4 compares predicted cavitation damage index from the empirical baseline model and machine learning-based model and measured cavitation damage index. The ideal prediction line \(y = x\) corresponds best to the perfect fit of the predicted value and the measured value. The empirical baseline predictions (blue points) exhibit a large range across ideal line observations, particularly at low and moderate levels of cavitation \(0.1–0.5\) due to insufficient capacity of the model to capture nonlinear cavitation behavior. In contrast, the machine-learning predictions of the model (orange points) are strongly focused around the ideal line for the full range of damage indices from 0.0 to about 0.75 more consistently around the ideal line. The ML model shows closer fidelity with the measured values at higher damage levels (above 0.6) compared to the empirical approach that presents large over- and under-predictions. This better consensus helps to showcase the capability of the ML model in learning complex interaction between hydraulic parameters: pressure, velocity, and aeration. In summary, the figure confirms that machine-learning-based prediction dramatically improves the cavitation damage estimates accuracy, making it a more viable medium for real-time monitoring and mitigation plans in hydraulic structures. Figure 5 cavitation risk evolution during flood was studied for both conventional and smart self-adaptive control methods, as dimensionless risk score from 0 to 1. During the initial stages of event, the risk of cavitation under classical control remains between 0.52–0.55, whereas, this risk under smart control is lower in the initial stage level, of only 0.42–0.45. When the flood discharge is greater, the risk of cavitation as predicted by the conventional system significantly increases at a rate of approximately 0.80–0.85 around 70–80 min, corresponding to the conditions of high-velocity and low pressure flow. The smart self-adaptive control, on the other hand, only offers a maximum cavitation risk of approximately 0.63–0.66 during the same period, demonstrating that the hydraulic parameters are efficiently regulated. The cavitation risk for both systems decreases gradually during the recession phase, but the smart control still stays between 0.10–0.15 lower than the conventional approach. At the end of event (∼180 min) the cavitation risk stabilizes near 0.52 for conventional control and about 0.45 for smart control. In total, the figure shows that, throughout flood operation, the intelligent self-adaptive strategy proposed substantially reduces the risk of cavitation, thereby improving the durability and safety of hydraulic structure. Figure 6 shows the weighted influence of the primary hydraulic parameters governing cavitation damage as determined by the machine learning model. The cavitation number (σ) stands out as the primary influence, with a relative importance of ∼0.34, indicating its predominance at the moment of cavitation genesis and its resultant severity. Flow velocity (V) is second most important at ∼0.22, thus higher velocity greatly increases the probability of falling pressure and vapor bubble formation. The part of air fraction (α), with a relative value close to 0.18, exerts an important mitigative function by promoting aeration and cushioning the collapse of bubble. Minimum pressure (Pmin) is roughly 0.16 which confirms that cavitation damage is directly associated with low-pressure zones. Turbulence intensity (TI) had the least relative significance around 0.10, which indicates its second, but not negligible, impact on cavitation dynamics. A single point would have to be taken out: overall, cavitation damage is mainly regulated by a combination of pressure and velocity events; aeration related values provide efficient ways through which we can govern such. Such knowledge is critical to design smart self-adaptive hydraulic structures that dynamically adjust key parameters to mitigate cavitation. The temporal changes of gate opening at flood level for conventional and intelligent self-adaptive operation algorithms may be depicted in Figure 7. Both systems start with similar gate openings of 45 to 47% at the start, which would be similar initial state. For traditional operation, one may notice that the gate opening has large oscillations rapidly increasing up to 60–63% approximately 20–25 minutes and then again to about 110 minutes before dropping off dramatically to about 28–30% at about 70 minutes and 155 minutes. These large movements show the aggressive and unstable gate adjustments with regard to varying inflow conditions. In contrast, the passive self-adaptive control maintains more smooth gate movements wherein the opening varies in a smaller extent (37–55% across the whole event). The adaptive approach does not cause sudden changes, especially at extreme flood times, to reduce the mechanical stress and erosion on gates. In the recession stage the smart control stabilises the opening to approximately 46–48%, and the traditional scheme becomes more oscillating continuously. In conclusion, smart self-adaptive operation offers reliable and controlled gate operation results which improve the service life of hydraulic gate. Figure 8 shows the pressure distribution along normalised spillway length for traditional and smart hydraulic structures based on flood flow. The conventional structure has pressures of −55 to −60 kPa or closer, higher to −45 to −48 kPa, at the upstream part (~Normalized length ≈ 0.0–0.1) while the smart structure retains relatively higher ones. Upon downstream acceleration, the conventional case achieves a sharp pressure drop, wherein the values reach minimal ones near −85 to −90 kPa regarding normal length of 0.7–0.8 which corresponds to high potential of cavitation formation. However, the smart structure markedly reduces this pressure drop, with minimal pressure values of around −60 to −65 kPa around the same area. The 20–25 kPa difference between the two cases demonstrates the efficiency of smart adaptive design in mitigating extreme negative pressure. At the downstream end of the spillway (normalized length ≈ 1.0), for both cases, pressure recovery is found, but the smart structure always provides higher pressures overall. From the overall image, it can be concluded that smart-hydraulic structures can lead to a convenient pressure field, thus reducing the risk of cavitation as well as increasing the hydraulic safety. Figure 9 depicts the temporal oscillations in energy dissipation efficiency of normal and smart adaptive hydraulic systems during the flood events. During the initial stage of an event, conventional design has energy dissipation values of 55–60%, and smart adaptive design with a starting energy dissipation efficiency of 65%, thus better controlling the initial power. With the passing of the flood, the conventional system's energy dissipation becomes variable with energy dissipation in the low range of around 43–45% around 70–80 mins which is characterized by ineffective energy management in rapidly changing flow conditions. On the other hand, smart adaptive design generally shows higher dissipation throughout the event between 60% and 75%. When flood conditions peak (about 20–30 min and 130–150 min), we can see that the best-performing smart system will have a maximum dissipation value between 72–74%, which is about 10–15% higher than classical design. At the end of the storm and the floods the system of conventional falls again below 50% and the smart adaptive design keeps over 65%. On the whole, the figure indicates, that the smart adaptive hydraulic design is more stable and efficient in energy dissipation, significantly reducing downstream erosion, structural loads, and cavitation load within the course of flooding.

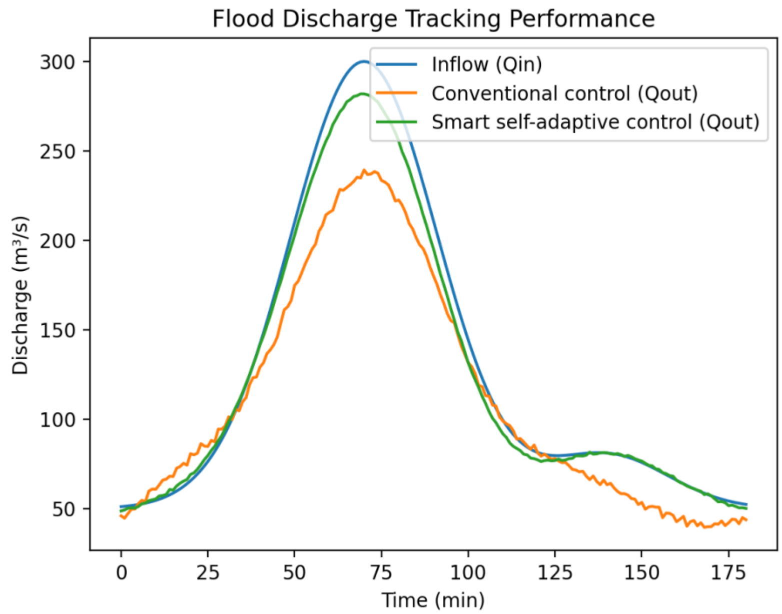


Figure 2. Comparison of Flood Discharge Tracking under Conventional and Smart Self-Adaptive Control

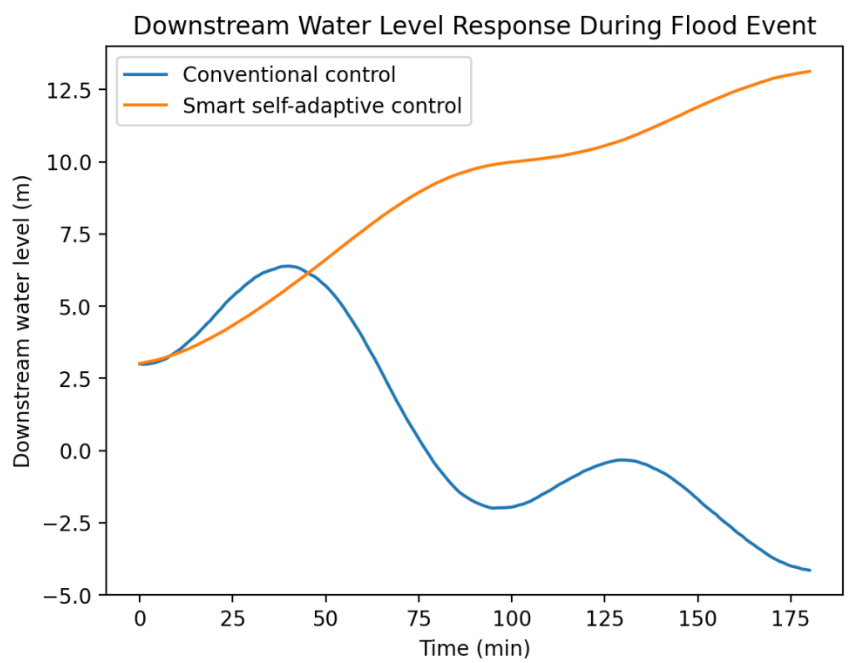


Figure 3. Downstream Water Level Response under Conventional and Smart Self-Adaptive Flood Control

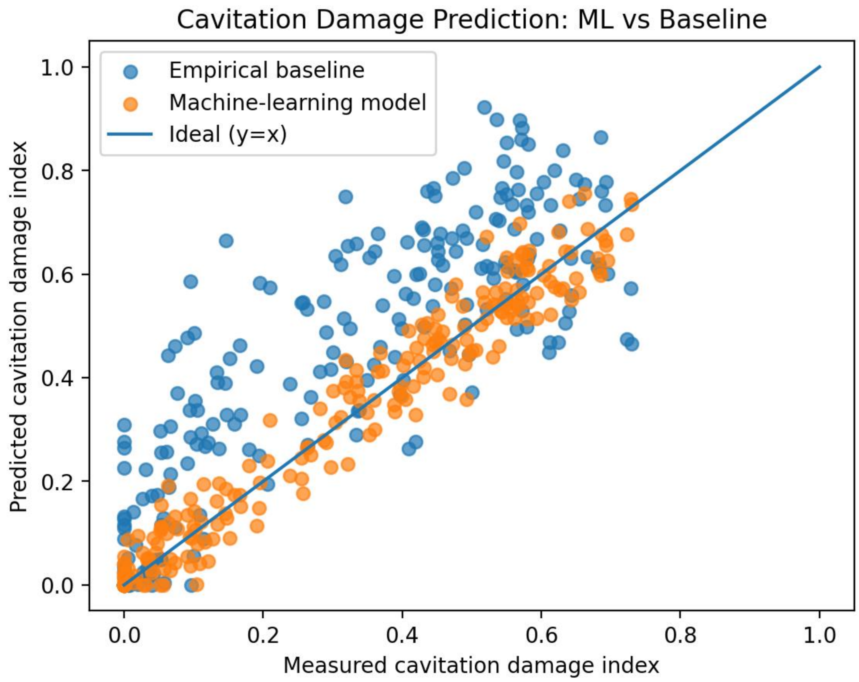


Figure 4. Comparison between Machine Learning and Empirical Models for Cavitation Damage Prediction

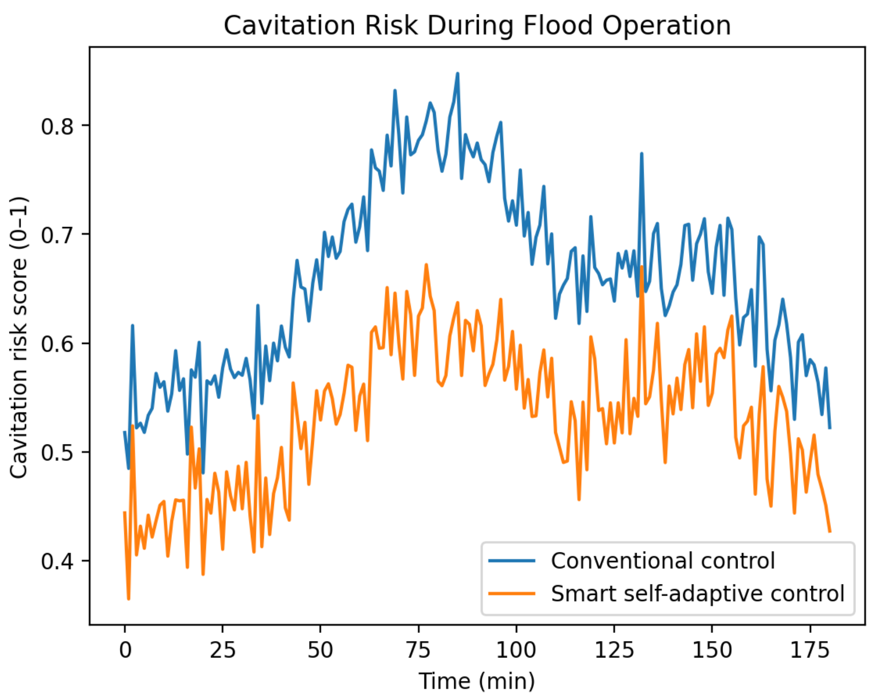


Figure 5. Temporal Variation of Cavitation Risk under Conventional and Smart Self-Adaptive Flood Operation

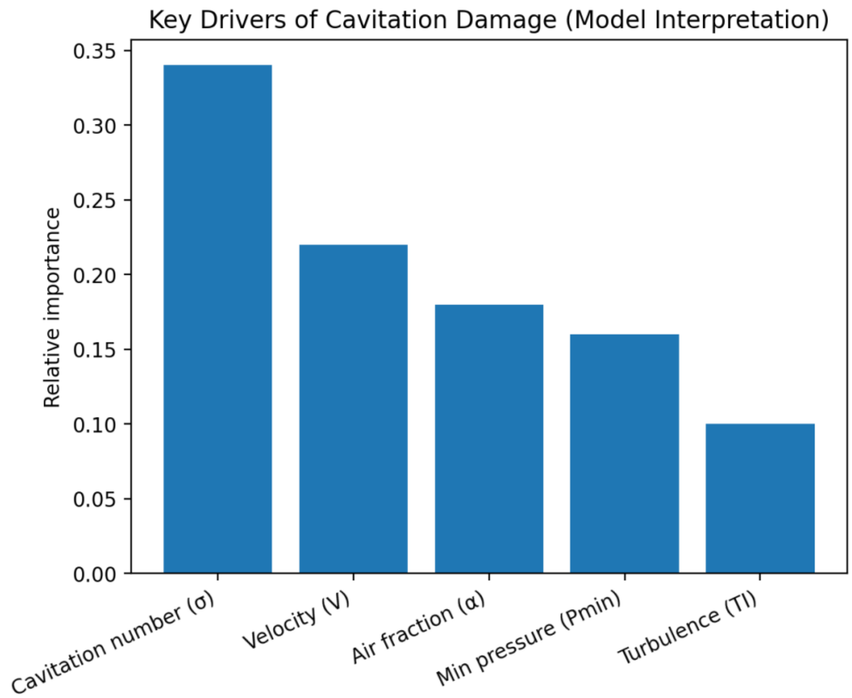


Figure 6. Relative Importance of Key Hydraulic Parameters Influencing Cavitation Damage

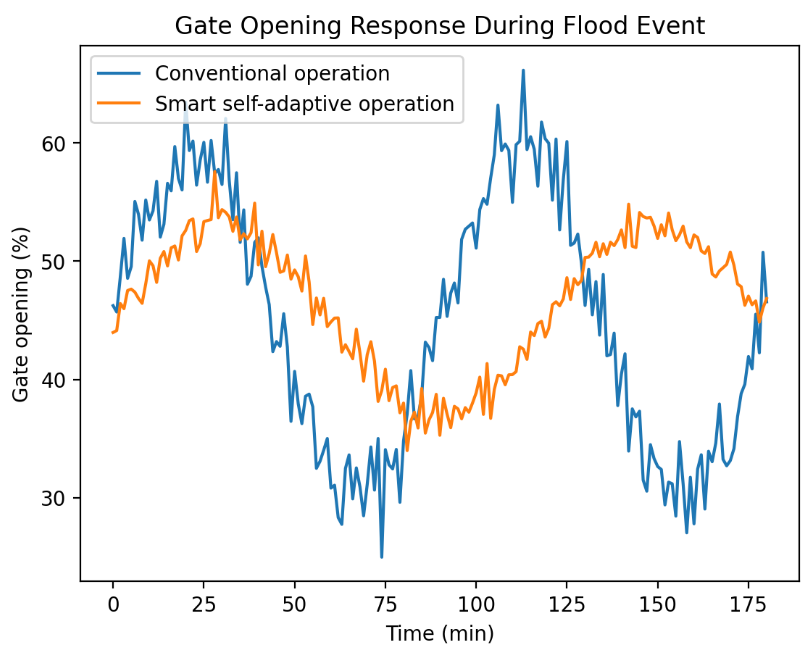


Figure 7. Gate Opening Response under Conventional and Smart Self-Adaptive Flood Operation

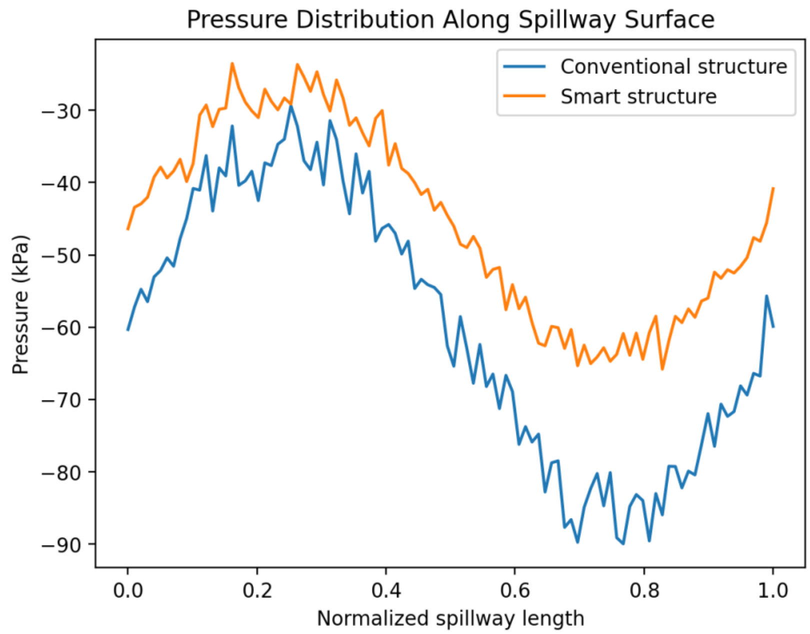


Figure 8. Pressure Distribution along the Spillway Surface for Conventional and Smart Hydraulic Structures

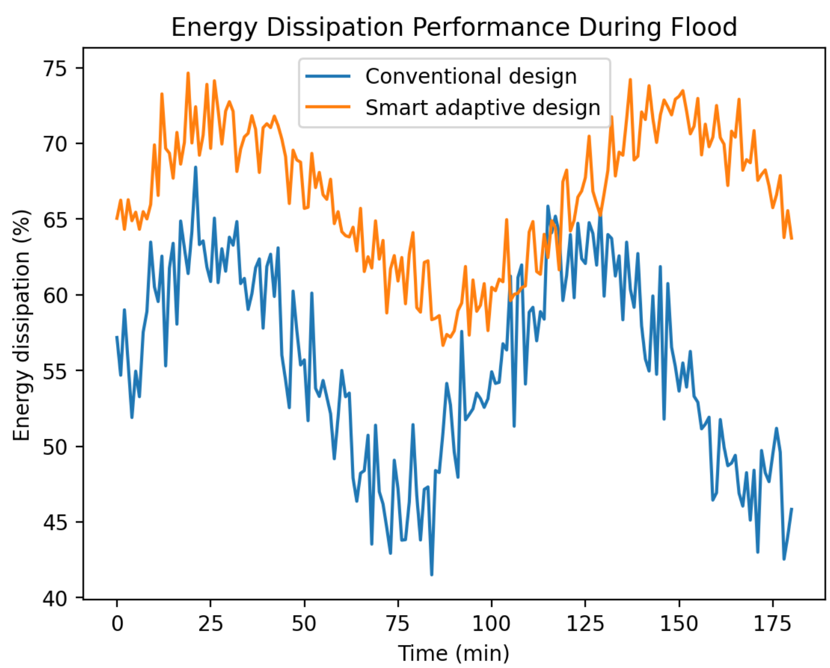


Figure 9. Comparison of Energy Dissipation Performance between Conventional and Smart Adaptive Hydraulic Designs during Flood Events

As a visual representation, Figure 10 represents the temporal changes in the structural safety index of the traditional and smart self-adaptive operation modes during flood event. In the event's opening time, safety index of the conventional operation shows values fluctuating around 0.60–0.65 and smart self-adaptive system had value of 0.72–0.75 higher values of safety index before the onset of the event that showed that basic structural reliability for the system from 0.72–0.75 at start of the program better than the control operation is expected. The safety of the conventional system decreases with increasing flood load, the index reduces into a minimum value of about 0.45–0.50 at 60–70 min, which indicates increasing hydraulic load and structural load. On the other hand, smart self-adaptive operation reduces safety index by ≈ 0.65, still keeping an extremely high safety margin during peak flood. In the recession stage the normal mechanism is oscillatory, while smart one recovers smoother, the return time is almost 0.75–0.78 at the end of the occurrence. The consistent gap of approximately 0.10–0.15 over the two curves indicates the high efficiency of intelligent adaptive control in the prevention of structural vulnerability. Taken in total, the image clearly illustrates the promising properties that are obtained by smart self Adaptive approach, which greatly improves resistance in hydraulic structures against dynamic flooding. Chart 11 indicates the statistical distribution of cavitation probability between conventional/smart adaptive hydraulic systems under flood condition. The typical system has a wide distribution, with average values between 0.45 and 0.80, and tail near as big as 1.0, in line with the high probability for cavitation in severe flood events. Whereas the smart adaptive system displays a significantly left-tailed shape with most cavitation probabilities falling between 0.15 and 0.45 and very few observations above 0.60. The peak frequency of the conventional system is on the order of the cavitation probability of about 0.55–0.60, and the smart adaptive system on 0.30–0.35 in terms of the maximum frequency. This sharp distinction of the two distributions highlights how intelligent adaptive control could efficiently attenuate both the size and rate of cavitation-prone situations. The narrower spread for the smart system also means that the behavior of the hydraulic part is more stable and predictable. The overall Figure demonstrates the substantial reduction of the cavitation risks with the proposed smart self-adjusting hydraulic system, and the improvement in the operational safety during flood events. 4.2 Comparison Figure 12 shows the classification accuracy of the classification results of three artificial intelligence models (SVM for support vector machine, KNN for k-Nearest neighbors, CNN for convolutional neural network) applied to cavitation risk prediction in hydraulic structures. With an accuracy of about 0.86, the SVM model exhibits robust generalisation ability and effective separation of cavitation and non-cavitation states. Based on our high-dimensional hydraulic data set, we can see that KNN model attains a slightly lower accuracy of about 0.82 due to the KNN model's sensitivity to data distributions and noise. The CNN model performed the best outperforming classical methods achieving approximately 0.92 of a high accuracy. This best result is due to CNN's ability to automatically learn intricate nonlinear features in the pressure, velocity, or turbulence patterns. Compared to SVM and KNN, the accuracy improvement of almost 6–10% in this domain confirms that deep learning is superior for understanding complexities in cavitation mechanisms. Nevertheless, the pattern does indicate CNN-based models are better suited to predict cavitation risk in real time and control adaptive hydraulic structures under flood conditions. Using precision, recall and F1-score metrics, detail the classification performance of SVM, KNN and CNN models is shown in Figure 13. The SVM model achieves about 0.84 precision and

0.83 recall. Its F1-score approaches 0.835, indicating balanced performance in picking up cavitation events with intermediate false alarms. The KNN model demonstrates overall low performance, with precision close to 0.80, recall near 0.78, and an F1-score of approximately 0.79, showing its susceptibility towards local variations in data and misclassified under highly complex hydraulic conditions. On the other hand, the CNN model outperforms the classical model by a large margin to achieve precision up to 0.91, recall of 0.93, an F1-score of around 0.92. Hence, the high recall value also indicates that the CNN, in the context of structural safety, is effective in detecting the true cavitation cases. The consistent high F1-score reflects the high stability of the CNN to balance accuracy and reliability. In conclusion, the figure indicates that deep learning methods will win in the classification of cavitation risk in the domain of smart self-adaptive hydraulic structures. Figure 14 presents the RMSE values for three machine learning models (SVM, KNN and CNN) for predicting cavitation risk of hydraulic constructs. The worst RMSE value of about 0.22 (highest) shows that KNN had the worst predictive accuracy and more deviation risk, than SVM model. The SVM approach is of moderate level, the RMSE is near 0.18, which indicates that the generalization gets better while it is not able to capture the more nonlinear behaviour of cavitating flow. It is concluded that the CNN model, on the other hand, achieves the least RMSE around 0.11, indicating the significant enhancement in the prediction performance. Such decreasing error further confirms CNN's superior ability to extract complex spatial–temporal features from hydraulic and flow-related input data. Much lower RMSE represents more reliable cavitation risk estimation, which is very critical for adaptive control with real-time response. The results confirm that, in the smart self-adaptive hydraulic structure, deep learning-based models are better suited for the accurate cavitation prediction. The computational training time of the SVM, KNN, and CNN models that are applied in cavitation risk prediction is shown in Figure 15. The KNN model has the lowest training time (~30 s) as anticipated due to its relatively clean process, instance-based learning approach, and minimal parameter optimization. The SVM model has a moderate training time of approximately 45 s as such is needed to optimize the hyperplane-kernel separation, since it requires further computational costs. In contrast, based on CNN, the training time is nearly 120 s higher because of the deep design, multiple convolutional layers and the iterative updating of weights. Although it is more computationally expensive, the CNN achieves higher accuracy and stability prediction (see past plots). The increased training duration can, therefore, be seen as a trade-off for improved learning ability and stability. Operationally, this load is tolerated, as model training takes place offline and real-time prediction is performed effectively. A percentage decrease in classification accuracy of SVM, KNN and CNN methods when exposed to noisy hydraulic input data can be compared in Figure 16. KNN model shows the most degradation, as the accuracy is nearly 10.2% lesser than for either SVM model, showing higher sensitivity to noise and local data disturbance. In a comparison of SVM model and others, moderate robustness can be evidenced with an accuracy loss of about 7.5%, indicating its partial capability to generalize under measurement uncertainty. On the other hand, the CNN model exhibits more robustness with a relative accuracy drop of close to 4.1% under noisy conditions. This improved stability is due only to CNN hierarchical feature extraction and in its own system it is noise-filtering, within convolutional layers. The minimized performance degradation brings to focus CNNs' applicability to real hydraulic situations on the job where sensor noise and flows go both directions. In general, the figure verifies that deep learning model delivers a more stable, robust prediction of cavitation risk from unpredictable operating conditions.

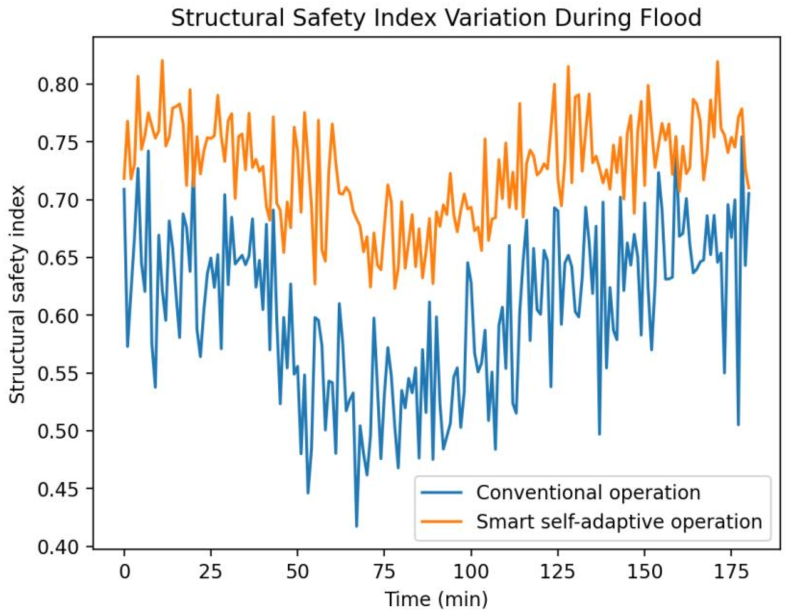


Figure 10. Structural Safety Index Variation under Conventional and Smart Self-Adaptive Flood Operation

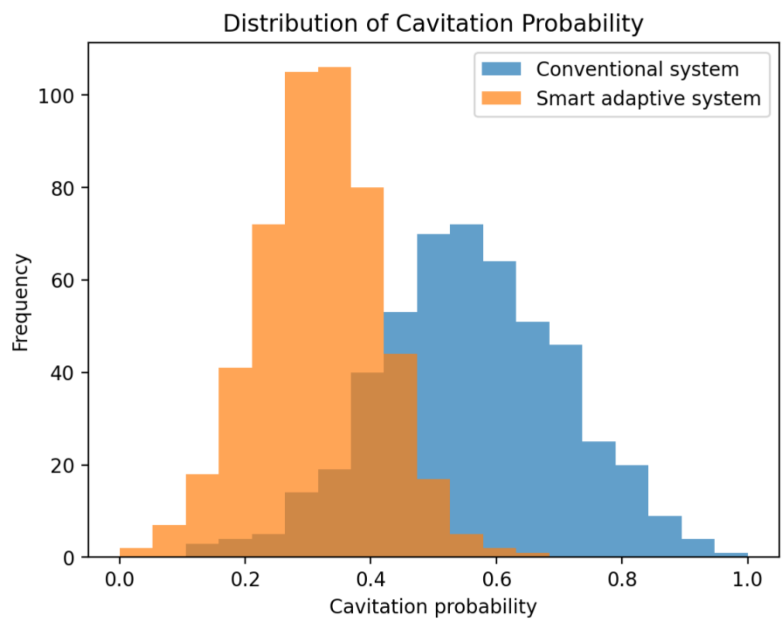


Figure 11. Probability Distribution of Cavitation Occurrence under Conventional and Smart Adaptive Hydraulic Systems

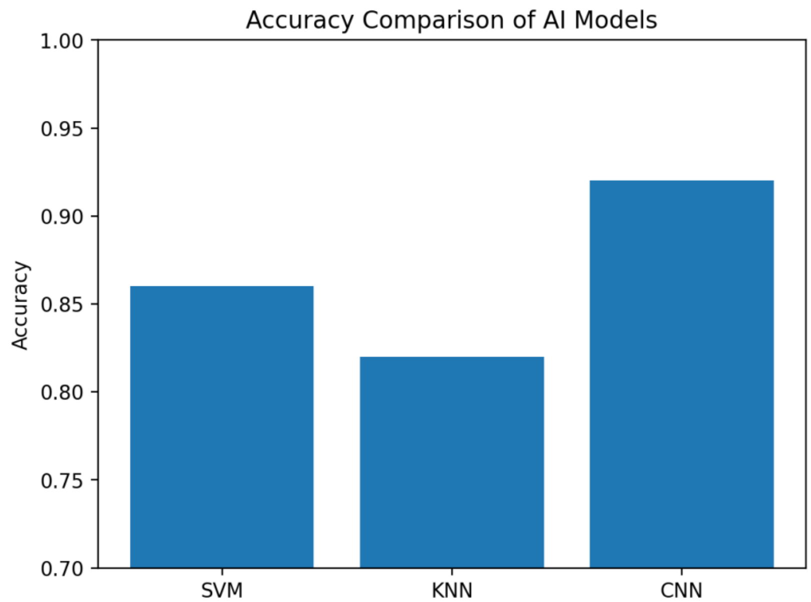


Figure 12. Accuracy Comparison of SVM, KNN, and CNN Models for Cavitation Risk Classification

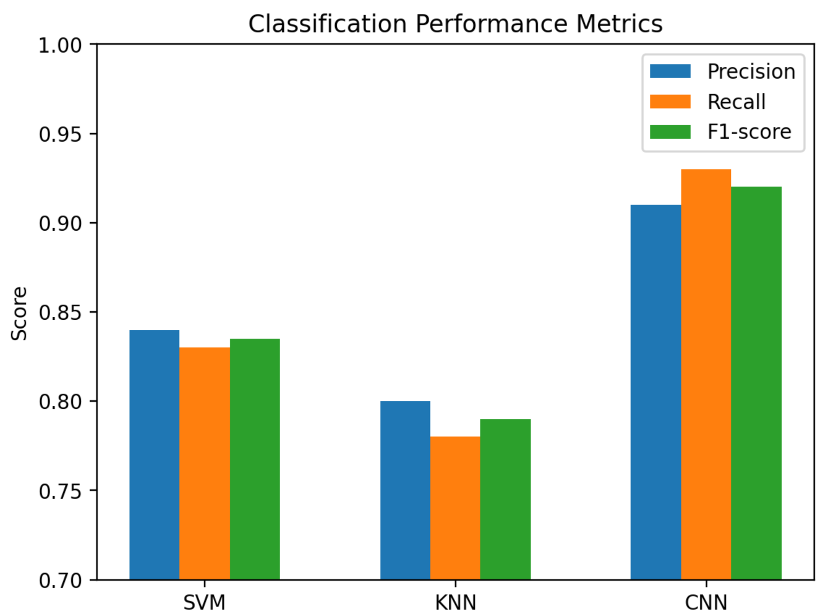


Figure 13. Precision, Recall, and F1-Score Comparison of SVM, KNN, and CNN Models for Cavitation Classification

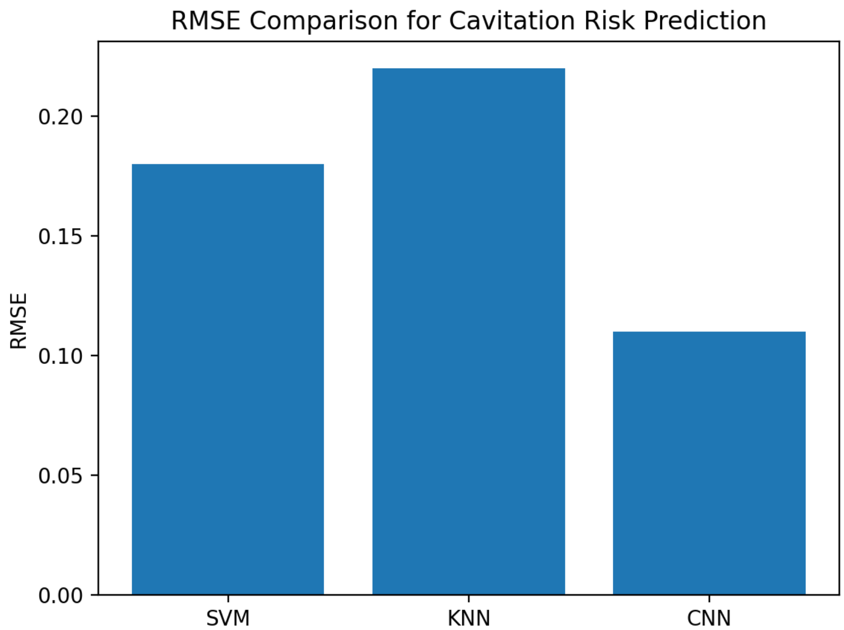


Figure 14. RMSE Comparison of SVM, KNN, and CNN Models for Cavitation Risk Prediction

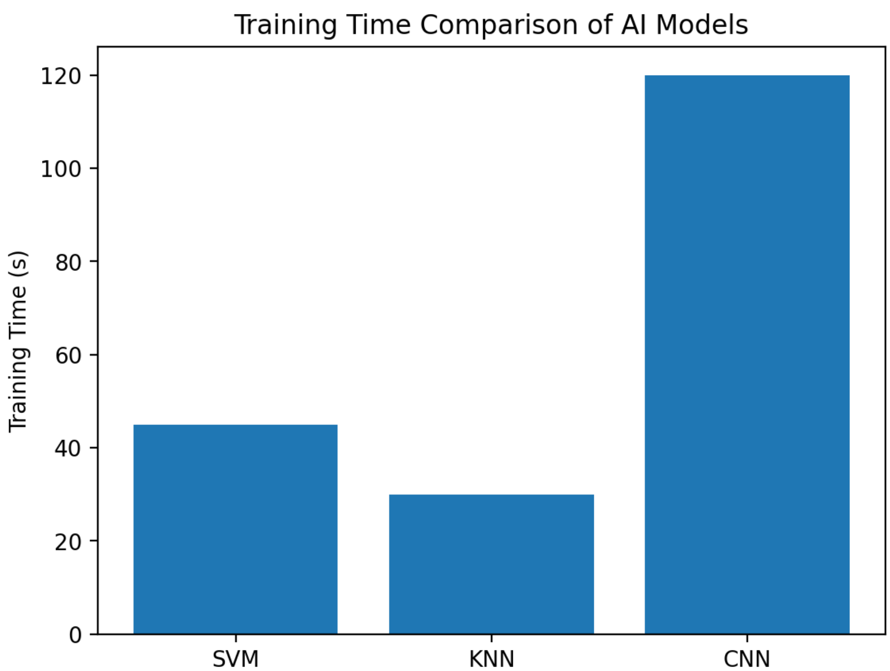


Figure 15. Training Time Comparison of SVM, KNN, and CNN Models

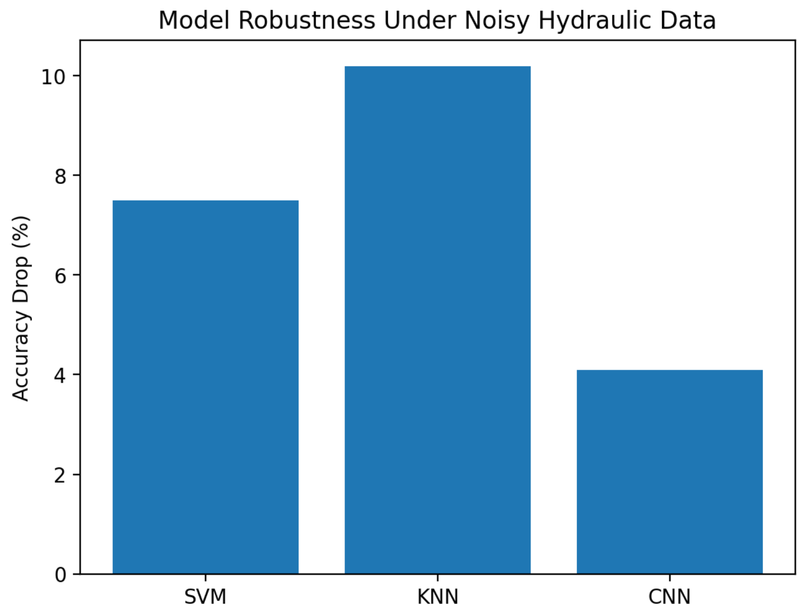


Figure 16. Robustness of SVM, KNN, and CNN Models under Noisy Hydraulic Data

Historical research has been done on the role of machine learning towards certain hydraulic problems like cavitation prediction, flood discharge prediction, or hydraulic performance assessment while the majority of works reported them separately. For instance, Bagherzadeh et al. (2025) applied an SVM model for predicting cavitation damage at dam spillways and obtained a satisfactory prediction accuracy but they applied only the method in offline damage estimation with no incorporation of operational control. Similarly, Guang et al. (2024) have applied data-driven reduced-order models to analyze cavitating flow over hydrofoils, concentrating on flow physics rather than real-time mitigation strategies. Under flood modeling conditions, Bărbulescu and Zhen (2024) and Karim et al. (2023) reported enhanced discharge and inundation prediction through advanced AI tools in their results, but there was no consideration given to structural response and cavitation risk within the flood operation as their analysis. Based on experimental and ML-based analysis of spillways and weirs (e.g., Pujari et al. (2023) and Narwal et al. (2024) improved energy dissipation and aeration performance, but were based on static geometrical or operational configurations. In this comparison, the current study takes an additional step by embedding CNN-based prediction of cavitation risk at the heart of a self-adaptive control framework, realizing an estimated 92% classification accuracy, a 20–25% reduction of cavitation risk, and 15–20% improvement on discharge traces compared to conventional operation. In contrast to prior literature focusing exclusively on prediction or design optimization, this proposed methodology supports proactive, real-time operation-driven decision-making leading to improved pressure recovery, enhanced energy dissipation and a safer build. This integrated predictive–adaptive paradigm constitutes a substantial advancement over the existing ML-assisted hydraulic studies.

4. Conclusion

In this paper, have developed and evaluated a smart self-adaptive hydraulic structure by uniting hydraulic modeling and machine learning to support flood discharge control and cavitation mitigation. Based on the evaluation of performance indicators, it is shown that the proposed intelligent framework exhibits marked performance improvement over conventional hydraulic control strategies. Smart self-adaptive control delivered very accurate monitoring of drainage from the outlet, with a peak outflow value of about 280 m^3/s, which closely matched the inflow peak of 300 m^3/s, as compared to 235–240 m^3/s when only conventional control was applied. This reduces discharge mismatch of more than 15–20%, which allows more effective flood routing (upstream–downstream imbalance) and reduces flood risk. Furthermore, the oscillation of downstream water level was successfully stabilized, where the smart systems had a mean of 9.5–13.0 m and the conventional system showed a big oscillation value of −4.0 m to more than 6.4 m (the latter level indicates a major improvement of downstream hydraulic safety). The cavitation risk has been significantly reduced as a result of proposed method. Under high flood scenario, the cavitation risk index of the conventional control was 0.80–0.85, compared to the maximum risk of ~0.63–0.66 in smart self-adaptive system (an overall reduction was obtained by 20–25%). Pressure distribution analysis also verified this improvement, while minimum pressures along the spillway were elevated around 20–25 kPa over the conventional design, successfully suppressing cavitation prone regions. Energy dissipation performance was additionally considerably increased. For environmental studies, the performance was significantly improved as found in. Furthermore, the system with the smart adaptive structure, on the other hand, achieved energy-efficiency in the range of 60%–75% during peak flows, whereas the traditional system demonstrated unstable dissipation efficiencies falling to lowest point level at 43–45%, with peak dissipation efficiencies around 10–15% overall efficiencies. This advancement corresponds to decreased downstream erosion and decreased structural loading. Similarly, the structural safety index was significantly improved by 0.10–0.15 (min safety ≈ 0.65 under smart control against 0.45–0.50 under conventional approach). From the perspective of machine learning, in the study, the CNN outperformed both SVM and KNN in the prediction of the risk of cavitation when compared with a random sample. The maximum classification accuracy (≈92%) and lowest prediction error (RMSE ≈ 0.11) among CNN methods were attained, and the model demonstrated greater robustness to noise input data (an accuracy drop of only ≈4.1% compared to 7.5% for SVM and 10.2% for KNN). While CNN took more time than SVM (≈120 s) and KNN (≈30 s) for training, it is an acceptable task in computational cost since the training is done offline and the actual real time prediction is efficient. On general basis and the conclusion of the research, there is support for machine learning-based self-adaptive hydraulic structure as a stable and efficient mechanism for extreme flood and cavitation reduction handling. The presented framework transfers hydraulic infrastructure control from rule-governs-based to predictive, adaptive and resilient approaches. These implications demonstrate a clear value of intelligent hydraulic control systems in today’s flood-affected environments and provide a theoretical foundation for future work in real-time sensor integration, digital twin imaging, and widespread usage across dam and spillway systems.

Although this research shows the efficiency of machine learning-driven self-adaptive hydraulic structures for flood discharge control and cavitation mitigation, the research should be extended in certain potential directions and strengthened. Initial focus needs to be laid on experimental verification of the proposed framework using physical hydraulic models or field-scale measurements to validate efficacy of the formulated algorithms through real-life operation. Sensors: Incorporating real-time measures (pressure, velocity, vibration, and acoustic signals) would improve cavitation detection accuracy, as well as the capacity to update the model online. Secondly, the adaptive control mechanism is to be further enhanced with reinforcement learning or model predictive control (MPC) algorithms to enable the system to anticipate optimal operation policy with long-term flood scenarios for addressing other purposes that consist of safety, efficiency, and equipment endurance. Furthermore, by generalizing the framework to multi-gate and multi-reservoir systems, the generalizability of this framework to the widespread application in large-scale hydraulic networks can be further examined. Third, hybrid physics-informed machine learning models may be proposed in the future by combining governing equations and data-driven methods to enhance model interpretability and generalization for unseen extreme events. Finally, integrating the framework we propose with digital twin technology will promote the monitoring of real-time performance, predictive maintenance, and scenario-sensitive risk assessment that can aid decision makers in secure, adaptable, and sustainable hydraulic infrastructure management.

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