fluids

MDPI

Article

Machine Learning for Dynamic Pressure Coefficient Prediction in Vertical Water Jets

Amin Salemnia [1], Seyedehmaryam Hosseini Boldaji [2], Vida Atashi [3,*] and Manoochehr Fathi-Moghadam [4]

1 Department of Water Engineering, Shahid Chamran University, Ahvaz 6135743136, Iran; amin.salemnia@gmail.com
2 Department of Electrical and Computer Engineering, K. N. Toosi University of Technology, Tehran 163171419, Iran; smaryamhoseini@email.kntu.ac.ir
3 Faculty of Civil Engineering Department, University of North Dakota, Grand Forks, ND 58202, USA
4 Faculty of Water and Environmental Engineering Department, Shahid Chamran University, Ahvaz 6135743136, Iran; mfathi@scu.ac.ir
* Correspondence: vida.atashi@und.edu; Tel.: +1-701-885-2449

Abstract: Vertical water jets present significant challenges for hydraulic structures due to their potential to cause erosion and structural damage. This study aimed to predict the dimensionless pressure coefficient (C_p) of vertical water jets by examining the relationships between experimental parameters, such as Froude number, slope, and the ratio of waterfall height over the product of the Froude number and diameter, referred to as α, using machine learning models. Two hundred forty controlled experiments were conducted, with pressure data collected. To address the problem's non-linearity, six machine learning models were tested: linear regression, K-nearest neighbors, decision tree, support vector regression, random forest, and XGBoost. The XGBoost model outperformed others, achieving an R-squared of 0.953 and a Root Mean Squared Error (RMSE) of 0.191. Residual analysis validated its better performance, demonstrating that it delivered the most accurate predictions with minimal bias. Feature importance analysis revealed the Froude number was the most significant predictor, followed by slope and diameter. This study emphasizes the importance of the Froude number in predicting jet behavior and shows the efficacy of advanced machine learning models in capturing complex fluid dynamics, providing valuable insights for optimizing engineering applications such as water jet cutting and cooling systems.

Keywords: vertical water jets; machine learning models; pressure coefficient; Froude number

Citation: Salemnia, A.; Boldaji, S.H.; Atashi, V.; Fathi-Moghadam, M. Machine Learning for Dynamic Pressure Coefficient Prediction in Vertical Water Jets. *Fluids* **2024**, *9*, 205. https://doi.org/10.3390/fluids9090205

Academic Editors: Filippos Sofos and Ricardo Ruiz Baier

Received: 21 June 2024
Revised: 5 August 2024
Accepted: 28 August 2024
Published: 1 September 2024

1. Introduction

In hydraulic engineering, overflow spillways, particularly in high-head dams, generate vertical water jets that are critical to the system's function. These water jets, as exemplified in Figure 1, possess substantial energy that, if not properly managed, can cause significant damage to the dam structure and downstream environments. Traditional methods of understanding and mitigating the impact of these jets have primarily relied on physical models, which can be expensive, time-consuming, and limited in their scope [1–4].

In recent years, traditional approaches to understanding and mitigating the impact of vertical water jets, such as physical modeling, numerical methods, and hydraulics software, have been supplemented by emerging technologies in artificial intelligence and machine learning. However, despite advancements in numerical modeling, accurately predicting the properties of vertical water jets and dynamic pressure coefficients remains a challenge due to the complex nature of turbulent flow [5–7]. The application of machine learning methods in this context represents a novel and promising approach to address these challenges.

Figure 1. Photo of free-falling jet in Kariba Dam—Zambia [8].

Estimating dynamic pressure coefficients is vital for understanding jet behavior and optimizing hydraulic structures like plunge pools. Traditional models often fall short of accurately representing complex turbulent flows, especially at high velocities. Data-driven algorithms and machine learning methods offer a promising solution to these limitations.

By applying large datasets, machine learning approaches can improve prediction accuracy and efficiency while uncovering new insights into hydraulic dynamics. The benefits include more precise estimations, rapid analysis, adaptability to new data, and the potential revelation of novel design concepts. Integrating machine learning with traditional engineering can lead to more resilient and efficient hydraulic structures that are better equipped to handle high-velocity flows. Ultimately, this approach expands our capabilities in hydraulic structure management, potentially revolutionizing the field by combining data-driven methods with domain expertise.

Turbulent jets have been extensively studied through both laboratory experiments and numerical simulations. Numerous researchers have investigated the jets under various conditions [9–18], focusing on properties such as dynamic pressure coefficients and break-up length in laboratory settings. In contrast to extensive laboratory experimental studies, relatively few numerical investigations have explored under-pressure flows [19,20]. Taebi (2022) conducted a review of Recent Advances in Deep Learning for Computational Hemodynamics [21]. The main finding of this review is that deep learning (DL) approaches, particularly physics-informed neural networks (PINNs), show significant potential in accelerating and enhancing computational hemodynamics simulations. These models can reduce computational time, improve the prediction accuracy of complex flow patterns, and assist in quantitative flow pattern estimation based on sparse data. The review highlights several applications, such as predicting hemodynamics in aortic aneurysms, coronary artery bypass surgery, and cerebral aneurysms, demonstrating the feasibility and effectiveness of DL in these contexts.

Between numerical studies, relatively few investigations have explored the behavior of free-falling jets under various conditions. Jia et al. (2001) examined the scouring process caused by the dynamic pressure of jets in plunge pools using the CCHE 3D model and highlighted that pressure fluctuations, which are closely related to the velocity field, play a significant role in plunge pools, while Salehi Neyshabouri et al. (2003) conducted a similar study with a two-dimensional (2D) numerical model [22,23]. Neither study investigated the effect of jet air content on scour. Despite these efforts, the impact of jet air content and other variables remains underexplored.

Cui et al. (2012, 2014) performed numerical simulations to predict the mechanisms of sand-bed erosion [24,25]. Within a Lagrangian discrete framework, each particle can theoretically be tracked by considering force equilibrium. However, the computational demands for realistic sand-bed erosion simulations are substantial. Previous simulations used much larger particles to study granular behavior in the erosion process with reasonable accuracy. Due to computational limitations, the Lagrangian discrete approach is typically limited to a small number of particles [26]. Conversely, employing various machine learning methods based on artificial intelligence presents a more feasible alternative for simulating jet behavior. While various studies have explored jet behavior using numerical methods [27–30], there have been no detailed investigations utilizing machine learning techniques to predict dynamic pressure based on plunge pool pressure fluctuations and distributions.

This study marks a significant advancement in hydraulic engineering by applying various machine learning models to predict the dynamic pressure coefficients of vertical water jets. Our innovative approach leverages data from controlled experiments that were conducted at the hydraulic laboratory of Shahid Chamran University of Ahwaz, Iran. By comparing the performance of multiple machine learning algorithms, including linear regression, K-nearest neighbors, decision trees, support vector regression, random forest, and XGBoost, we aim to identify the most effective method for predicting jet behavior.

The primary goal of this research is to overcome the limitations of traditional numerical and physical models in accurately representing complex turbulent flows, especially in high-velocity scenarios. By harnessing the power of machine learning, we seek to improve both the accuracy and efficiency of pressure coefficient predictions. This novel approach not only enhances our predictive capabilities but also has the potential to uncover new insights into hydraulic dynamics. Ultimately, our research aims to revolutionize hydraulic structure management by combining data-driven methods with domain expertise, leading to more resilient and efficient designs for better withstanding the challenges posed by high-velocity water jets.

2. Materials and Methods

In this section, we will outline the methodologies employed in our study, covering the theoretical framework, the experimental facility, data collection procedures, preprocessing techniques, and feature selection criteria. Additionally, we will describe the selection, training, evaluation, and hyperparameter tuning of various machine learning models used to predict dynamic pressures.

2.1. Theory

Water jets, characterized by turbulent flow resulting from a continuous momentum source, exhibit varied states upon impact with a surface or entry into a plunge pool, depending on their Froude numbers and falling heights. These jets may arrive fully broken up, termed as developed jets, presenting a fully turbulent form without a core, or they may retain a solid core, leading to higher impact pressure.

Currently, there are no widely accepted methods for predicting dynamic pressure coefficients or mean and fluctuating pressures on a plunge pool floor. Consequently, designers often have to develop solutions on a case-by-case basis. One major complication in developing a general solution is that plunging jets tend to partially or completely break up upon entry into the pool. The degree of jet break-up significantly influences both the extent and magnitude of pressure. Additionally, the jet tends to entrain substantial amounts of air, which mitigates pressure amplitudes.

Modeling falling jets is challenging due to the effects of surface tension and turbulence on jet break-up and air entrainment characteristics. Furthermore, the pressure fluctuation spectrum within the pool is influenced by the scale of turbulence, making it difficult to simulate these effects accurately in physical models. However, careful selection of model size and interpretation of results can help minimize or account for scale effects. The stability and internal turbulence of a free-falling jet are crucial determinants of its characteristics. Rayleigh (1892) [31] conducted pioneering investigations into jet stability, followed by more recent studies by researchers such as Baron (1949) [32], Chen and Davis (1964) [33], Hoyt and Taylor (1977) [34], McKeogh (1978) [35].

The experimental equation of the break-up length for circular jet, established by Ervine et al., 1997 [36], is as follows:

$$\frac{L_b}{D_0 F_0} = \frac{1.05}{C^{0.82}} \quad (1)$$

where L_b is the break-up length in meters, D_0 is nozzle diameter in meters, F_0 is Froude number at issuance conditions, and C is the turbulence parameter defined as follows:

$$C = 1.14 T_u F_0^2 \quad (2)$$

$$F_0 = \frac{U_0}{\sqrt{gD_0}} \quad (3)$$

where T_u is turbulent intensity. The mean dynamic pressure on the pool floor is described by a pressure coefficient, C_p, defined as follows:

$$Cp = \frac{H_m - y}{\sqrt{V^2{}_j/2g}} \quad (4)$$

$$V_j = \sqrt{U_0^2 + (2gH)} \quad (5)$$

where H_m and y are the mean head and depth at the plunge pool in meters, respectively, and V_j is the velocity of the impingement jet in m/s. It is worth mentioning that all the experiments were conducted in the absence of water depth in the plunge pool, so "y" is equal to 0 in Equation (4). The dynamic pressures were measured at the surface where the water jet directly impacted it. The parameters are shown in Table 1.

Table 1. An outline of the range of jet test conditions.

Fall Height (cm)	Diameter (cm)	Flow (lit/s)	Angle (Degree)	Mean Head Depth (cm)
8, 15, 25, 35, 45	7.9	11, 14, 17, 21	30, 45, 90	0
8, 15, 25, 35, 45	5.1	11, 14, 17, 21	30, 45, 90	0
8, 15, 25, 35, 45	4.3	11, 14, 17, 21	30, 45, 90	0
8, 15, 25, 35, 45	4.1	11, 14, 17, 21	30, 45, 90	0

2.2. Experimental Facility

Figure 2 illustrates the experimental configuration employed for circular jet experiments. The jets originated from elongated, smooth nozzles equipped with an upstream tube bundle designed to minimize turbulence. These nozzles were available in diameters of 4.1, 4.3, 5.1, and 7.9 cm. A recirculating pump facilitated flow rates of up to 21 L per second, yielding Reynolds numbers ranging from tens to 10^6. The vertical fall distance was adjustable, with a maximum height of 45 cm. Table 1 outlines the range of jet test conditions. There was no plunge pool depth because of the calculation of the maximum dynamic pressure.

In our study, the dynamic pressure of the flow was measured using a precision pressure sensor strategically placed at the center point of the jet. This sensor was instrumental in capturing accurate and detailed dynamic pressure data, which is critical for the training and validation of our machine learning models. By positioning the sensor at this central location, we ensured the collection of representative pressure readings that reflect the core behavior of the vertical water jet, thereby enhancing the reliability of our predictive analysis.

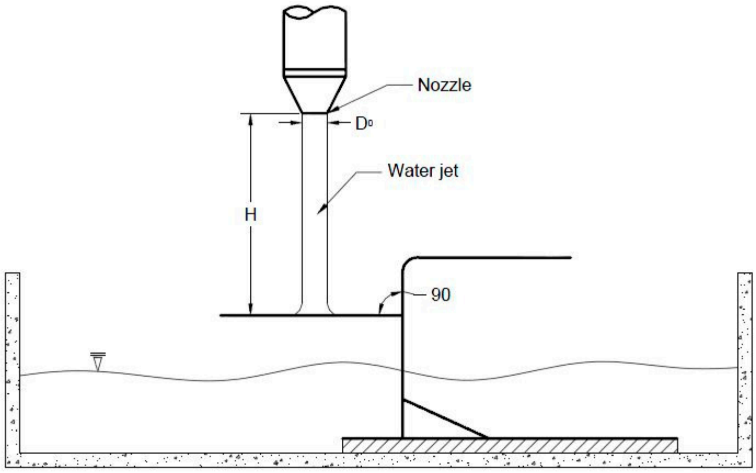

Figure 2. Schematic representation of the data capture model and influencing parameters.

2.3. Data Collection, Preprocessing, and Feature Selection

Data for this study were collected from 240 controlled laboratory experiments, each representing unique conditions of waterfall height (h), nozzle diameter (d), slope of the measuring surface (s), and flow rate from the nozzle (q). Each experiment was conducted over a 20-s period, with a pressure sensor recording the pressure (p(m)) every 0.02 s, resulting in 1000 samples per experiment.

In preprocessing, outliers were first identified and removed from each experiment using the 1.5xIQR criterion. Subsequently, the maximum pressure value from the filtered dataset of each experiment was selected to represent the maximum observed pressure for that setup. This selection was intended to focus analysis on peak pressure impacts, which are critical in the study of fluid dynamics under varying conditions.

To prepare the data for modeling, dimensionless inputs were calculated to standardize the data across different experimental setups. The Froude number and the ratio of waterfall height over the product of the Froude number and diameter as shown in Equation (6), referred to as alpha (α), were computed. Along with the slope, these parameters were selected based on expert opinions and their relevance to the physics of water jets as features for the machine learning models. All input features were then normalized using the StandardScaler from scikit-learn, which removes the mean and scales each feature to unit variance, ensuring a uniform scale across the dataset and enhancing model performance and comparability.

Initial visual analysis using scatter plots of the calculated C_p values revealed non-linear relationships between C_p and its controlling factors (Froude number and α) under different slope conditions. The data variability suggested that a simple linear modeling approach might be inadequate for capturing the underlying dynamics of jet behavior. To rectify this and improve model interpretability, a logarithmic transformation of the C_p values was applied. This transformation was aimed at linearizing the relationships, simplifying the statistical modeling,

$$\alpha = \frac{h}{F_0 \times d} \tag{6}$$

2.4. Model Selection, Training, Evaluation, and Hyperparameter Tuning

Six different machine learning models were evaluated: Ridge Regression, K nearest neighbors, Support Vector Machine (SVM), decision tree, random forest, and Extreme Gradient Boosting (XGBoost). The dataset was split into training (60% of the data), validation (20%), and test sets (20%) using a randomized approach to ensure the statistical independence of the test set. This was facilitated by employing scikit-learn's train_test_split function with a specified random_state to maintain reproducibility and prevent data leakage. The models were initially tuned and validated using the training and validation sets, optimizing for both R-squared and Root Mean Squared Error (RMSE). Extensive hyperparameter tuning was performed using random search, leading to the following optimized models:

- Ridge Regression: Ridge (alpha = 0.5)
- K nearest neighbors: KNeighborsRegressor (n_neighbors = 7)
- Decision tree: DecisionTreeRegressor (min_impurity_decrease = 0.0002)
- Support Vector Machine: SVR (kernel = 'rbf', gamma = 'auto', C = 5, epsilon = 0.06)
- Random forest: RandomForestRegressor (n_estimators = 2500, min_impurity_decrease = 0.0001)
- XGBoost: XGBRegressor (n_estimators = 2500, learning_rate = 0.01, max_leaves = 5, subsample = 0.7, colsample_bytree = 0.8)

Machine learning models have shown significant promise in predicting dynamic pressure coefficients and other fluid dynamics parameters, particularly in the context of vertical water jets. These models offer powerful tools for understanding and predicting complex flow behaviors, each with its unique strengths:

1. Ridge Regression has proven effective in fluid dynamics applications, especially for predicting pressure coefficients. Its ability to handle multicollinearity, a common issue in fluid dynamics data, makes it particularly valuable.
2. K-Nearest Neighbors (KNN), with its non-parametric nature, excels at capturing complex, non-linear relationships in fluid dynamics problems. It has been successfully used to predict flow characteristics and pressure distributions.
3. Support Vector Machine (SVM) has demonstrated its efficacy in predicting dynamic pressure across various fluid flow scenarios. Its capacity to manage high-dimensional data and model non-linear relationships has made it a popular choice among researchers.
4. Decision trees offer interpretability and can handle both numerical and categorical data, making them useful for understanding the factors influencing pressure coefficients. They have been effectively employed in flow prediction and classification tasks.
5. Random forest, an ensemble method based on decision trees, has shown excellent performance in predicting flow characteristics and pressure distributions. Its robustness against overfitting and ability to handle high-dimensional data have led to its increased adoption in fluid dynamics applications.
6. Extreme Gradient Boosting (XGBoost) has emerged as a powerful tool for predicting various fluid dynamics parameters, including pressure coefficients. Its high performance and ability to model complex relationships in data have made it increasingly popular in recent years.

The application of these machine learning models to vertical water jets represents an innovative approach to addressing the challenges in predicting dynamic pressure coefficients. By leveraging the strengths of each model, researchers can improve the accuracy and efficiency of predictions, potentially overcoming the limitations of traditional numerical and physical models. As these methods evolve, they promise to revolutionize hydraulic structure management by integrating advanced computation with domain expertise. This could lead to more resilient and efficient designs that are more suited for handling high-velocity water jets.

Each model was retrained on the combined training and validation dataset and evaluated on the test set using R-squared and RMSE. Additionally, the residuals of the predictions were analyzed through histogram plots to assess the distribution of prediction errors. To ensure the reproducibility of our results, the test dataset were kept separate and only used for final evaluation. The consistent performance of the models on both the validation and test datasets suggests the robustness and reliability of our findings. Data and model codes are available upon request to facilitate further research and verification by other researchers.

3. Results and Discussion

This section presents the results obtained from evaluating various machine learning models for predicting the dimensionless pressure coefficient (C_p) of vertical water jets. The performance of each model is assessed, and the impact of different features on model accuracy is analyzed. Additionally, insights into the behavior of vertical water jets based on the model predictions are discussed.

3.1. Performance of Machine Learning Models

Several machine learning models, including linear regression, K-Nearest Neighbors (KNN), decision tree, support vector regression (SVR), random forest, and XGBoost, were evaluated to predict the pressure coefficient (C_p) based on experimental conditions characterized by the Froude number, slope, and alpha. The performance of each model was assessed using root mean squared error (RMSE) and R-squared (R^2) as evaluation metrics.

Root Mean Squared Error (RMSE) measures a model's error in predicting quantitative data by representing the square root of the average squared differences between predicted and observed values. A smaller RMSE indicates that predicted values are closer to observed data points, reflecting better model performance. R-squared (R^2), or the coefficient of determination, indicates the proportion of variance in the dependent variable explained by the independent variables in a regression model. An R^2 of 1 signifies perfect prediction accuracy. Generally, a higher R-squared value indicates a better model fit.

These metrics are crucial for evaluating and comparing the efficacy of different machine learning models. Each model's performance was systematically compared to determine which most effectively predicts water jet pressure dynamics under varied experimental conditions.

The quantitative results of the model evaluations are presented in Table 2 and Figure 3. XGBoost outperformed all other models, achieving the highest R-squared value of 0.953 and the lowest RMSE of 0.191, indicating its superior ability to capture complex relationships and variations within the data accurately.

Table 2. Model performance metrics for predicting C_p.

Model	R-Squared	RMSE
Linear Regression (LR)	0.774	0.421
K-Nearest Neighbors (KNN)	0.900	0.280
Decision Tree	0.902	0.277
Support Vector Regression (SVR)	0.914	0.260
Random Forest	0.941	0.215
XGBoost	0.953	0.191

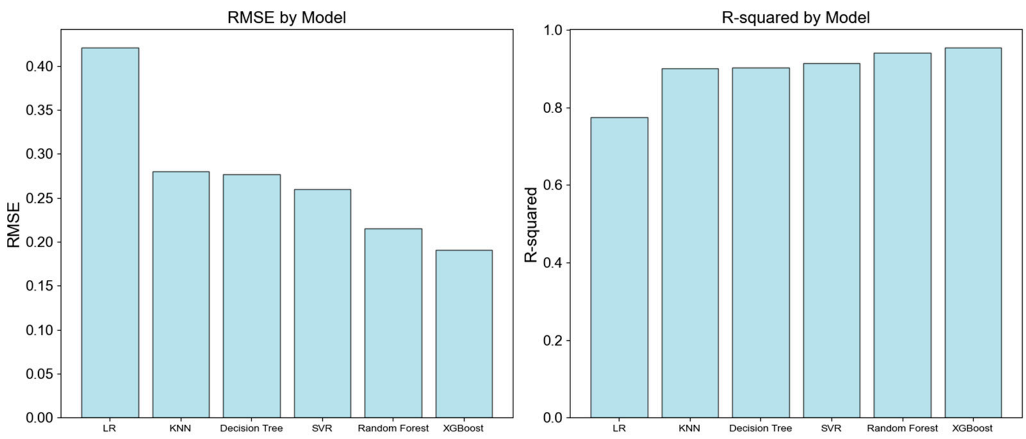

Figure 3. Comparison of model performance for predicting C_p: RMSE and R-squared values across different machine learning models.

Linear regression exhibited the least favorable performance with an R-squared value of 0.774 and an RMSE of 0.421, suggesting that the model's assumptions of linearity did not hold true for the complex dynamics of fluid pressure in this setting. Conversely, models like SVR and random forest showed strong performance with R-squared values above 0.9, underscoring their ability to handle non-linear data more effectively.

The scatter plot of predicted versus actual values (Figure 4) visually confirms the quantitative assessments. XGBoost's predictions are notably closer to the diagonal line, demonstrating its higher precision and consistency across various test cases.

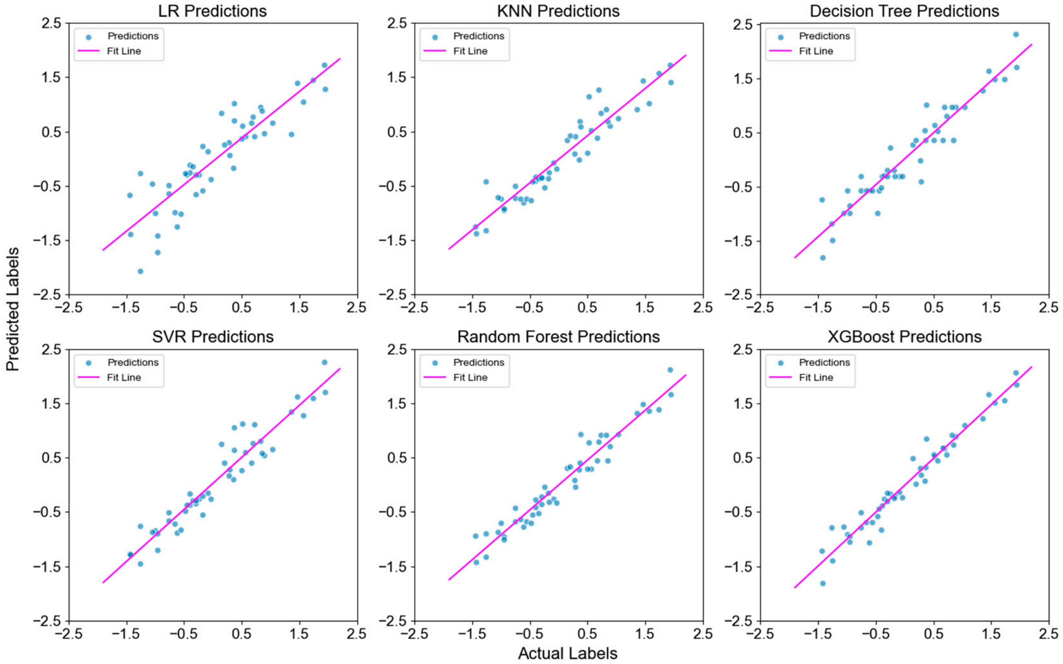

Figure 4. Scatter plots of predicted vs. actual values for C_p with fitted lines across different machine learning models.

3.2. Analysis of Feature Impact and Importance

Understanding the relative importance of each feature used in the predictive models is crucial for interpreting model behavior and guiding further model improvements. This analysis focuses on evaluating how each feature contributes to the predictive accuracy of the models, particularly the random forest and XGBoost models, both of which provide an explicit measure of feature importance.

The random forest model's ability to quantify the importance of each feature offers valuable insights into which variables most significantly impact the model's predictions. Similarly, the XGBoost model also provides built-in functionality for assessing feature importance, allowing for comparative analysis across models. Table 3 demonstrates the relative importance of different features in predicting the pressure coefficient (C_p) as estimated by the random forest model. Figure 5 presents the estimated importance of the Froude number, slope, and alpha (α), which were identified as key predictors in our study.

Table 3. Relative Feature Importance for predicting C_p estimated by the random forest model.

Feature	Importance (%)
Froude number	57
Slope	23
alpha	20

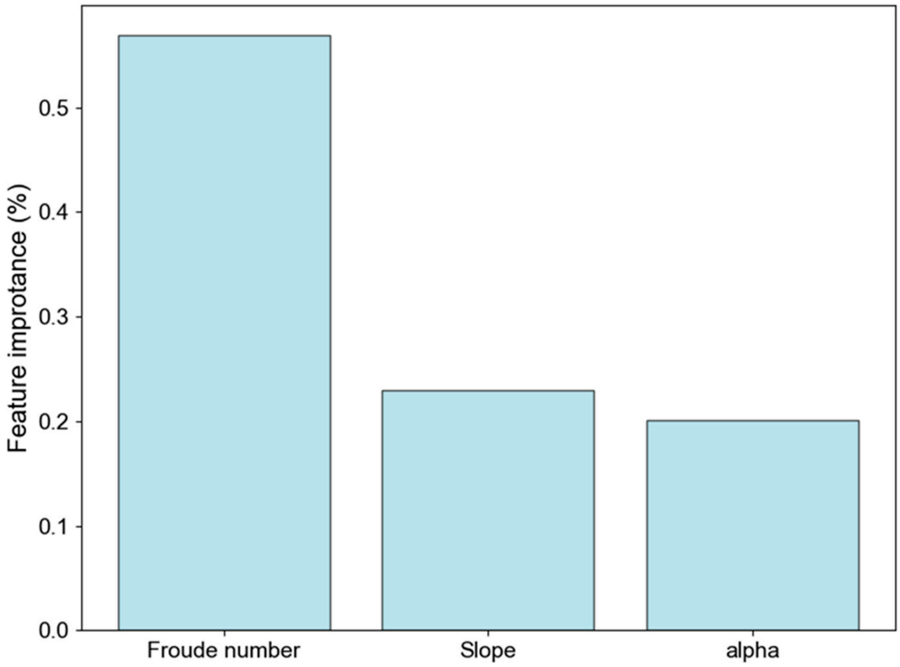

Figure 5. Relative Feature Importance estimated by the random forest model for predicting C_p of vertical water jets, expressed as percentages.

Additionally, the feature importance analysis using the XGBoost model has shown similar trends, with the Froude number, slope, and alpha contributing 43%, 35%, and 22%, respectively. These results are presented in Table 4, providing a consistent view across both high-performing models.

Table 4. Relative Feature Importance for Predicting C_p Estimated by the XGBoost Model.

Feature	Importance (%)
Froude number	43
Slope	35
alpha	22

The analysis shown in Tables 3 and 4 revealed that the Froude number is the most significant predictor, accounting for approximately 57% and 43% of the importance in the random forest and XGBoost models, respectively. This underscores its critical role in the dynamics of fluid motion and pressure in vertical water jets. The slope of the surface impacts the pressure measurements as well, contributing about 23% and 35% to the model's predictions in random forest and XGBoost, respectively. Alpha, while less influential than the other two features, still plays a notable role by accounting for 20% and 22% of the importance in these models.

These findings have implications for both model optimization and engineering design decisions related to fluid jets and hydraulic systems. Knowledge of feature importance can be used to refine model architectures, potentially simplifying models by eliminating less important variables or focusing on interaction effects between the most critical features. Additionally, understanding which factors most significantly affect pressure can inform design decisions in applications involving fluid jets, such as in hydraulic systems or water-based cooling technologies.

3.3. Residual Analysis

Residual analysis is a crucial step in assessing the fit of a model and understanding any underlying patterns that might suggest bias or inefficiency in the predictions. The residuals from the SVM, random forest, and XGBoost models were analyzed to evaluate how well these models capture the underlying dynamics of the data and to identify any systematic errors.

SVM model residuals: The residuals for the SVM model (Figure 6) were examined to assess model fit. The plot shows a distribution that appeared relatively normal. To quantitatively assess this observation, we conducted a Shapiro–Wilk test. The Shapiro–Wilk test resulted in a statistic of 0.948, with a p-value of 0.034, indicating that the normality assumption is not fully supported at the 5% significance level. This suggests that while the SVM model generally performs well, there might be non-normally distributed errors, which implies the presence of minor systematic errors under specific conditions that could be further explored.

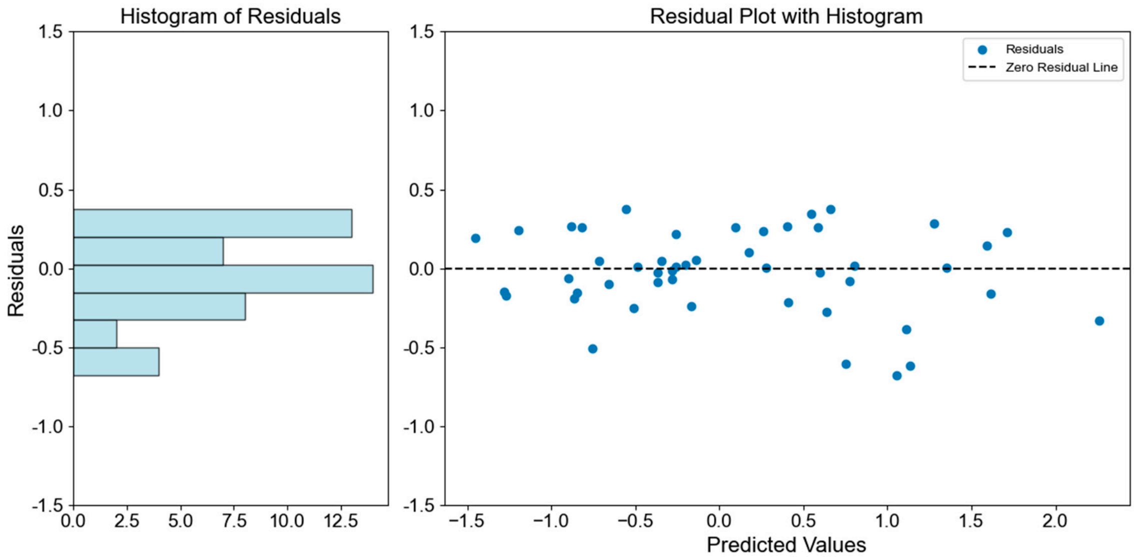

Figure 6. Residual Analysis for the SVM model: Histogram of residuals and residual plot against predicted values.

Random forest model residuals: The residuals plot for the random forest model (Figure 7) illustrates the distribution of residuals associated with predictions of the pressure coefficient. The histogram alongside the scatter plot indicates a normal distribution of residuals, which suggests that the model adequately captures the variability in the data without systematic errors or biases. To further validate this observation, a Shapiro–Wilk test was performed, yielding a test statistic of 0.976 and a p-value of 0.425, confirming the residuals' normal distribution at the conventional significance levels.

XGBoost Model Residuals: The XGBoost model's residuals (Figure 8) demonstrate an excellent fit, with the histogram closely resembling a normal distribution. This indicates a highly effective model in terms of accuracy and consistency across different scenarios. The minimal deviation from normality suggests that the XGBoost model efficiently handles the non-linear complexities of the dataset. Further quantitative analysis using the Shapiro–Wilk test confirms this observation, yielding a test statistic of 0.968 and a p-value of 0.208, which do not reject the hypothesis of normality at the conventional alpha levels (e.g., 0.05).

The analysis of residuals plays a critical role in validating the assumptions of the modeling process and ensuring the robustness of the predictions. The normal distribution of residuals across these models, particularly in the random forest and XGBoost, confirms that they are well-suited for this type of predictive task, capturing the essential patterns without being affected by non-systematic fluctuations. However, the slight deviations observed in the SVM model's residuals suggest areas for model tuning, possibly through parameter adjustments or by incorporating additional data preprocessing steps. Such refinements could further improve the model's performance and reduce any minor biases that could affect its predictions in real-world applications.

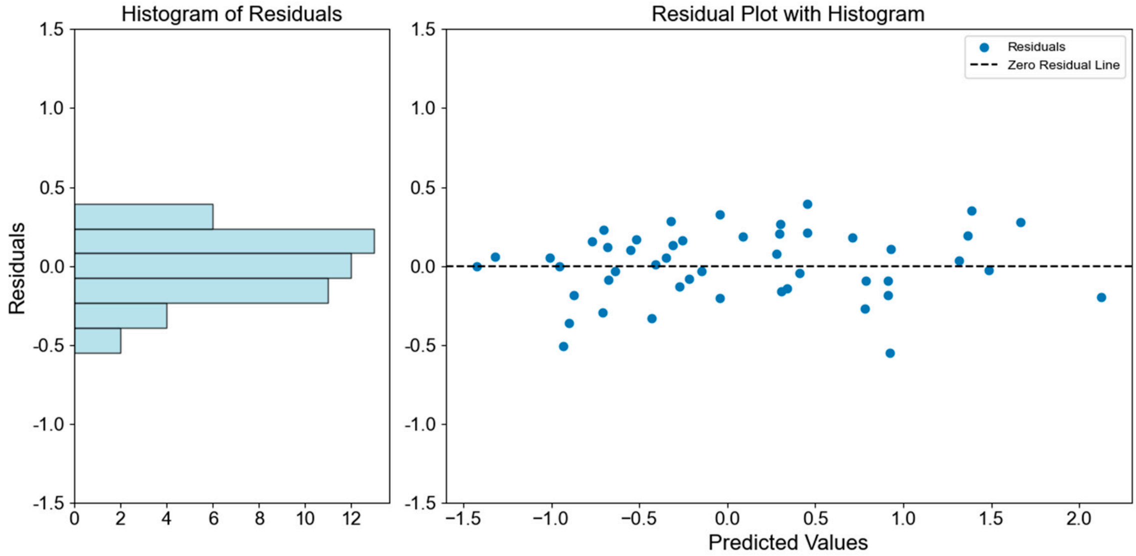

Figure 7. Residual Analysis for the random forest model: Histogram of residuals and residual plot against predicted values.

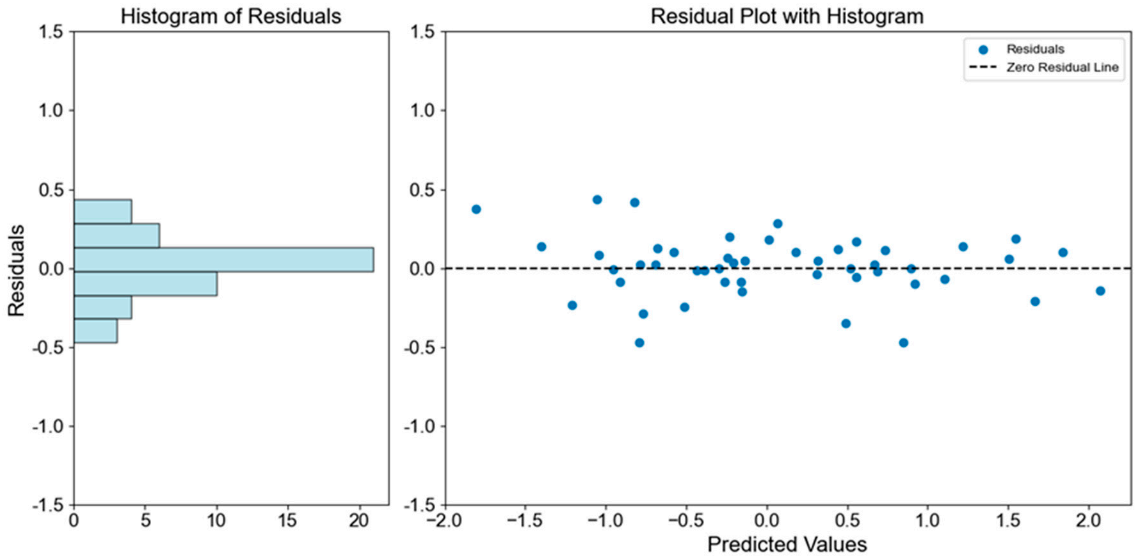

Figure 8. Residual analysis for the XGBoost Model: Histogram of residuals and residual plot against predicted values.

3.4. Insights into Jet Behavior

The behavior of vertical water jets, as characterized by the pressure coefficient (C_p), exhibits complex dynamics that are influenced by several factors, including the Froude number, the slope of the impact surface, and the ratio of height over the Froude number times the diameter (alpha), which serves as a dimensionless parameter relevant to the physics of water jets and is used as one of the features for machine learning models in predicting the behavior of vertical water jets. Our analysis has provided profound insights into how these factors interact and influence the resulting pressure dynamics.

Non-linear Relationships and Transformations: Initial observations from the scatter plot of calculated C_p from p(m) (Figure 9) demonstrate that the relationship between C_p and the controlling factors (Froude number, alpha) is inherently non-linear. This plot shows varied behaviors under different slope conditions, which are marked by triangle, square, and circle symbols representing slopes of 90, 60, and 30 degrees, respectively. This variability suggests that a simple linear approach may not adequately capture the underlying physics of jet behavior.

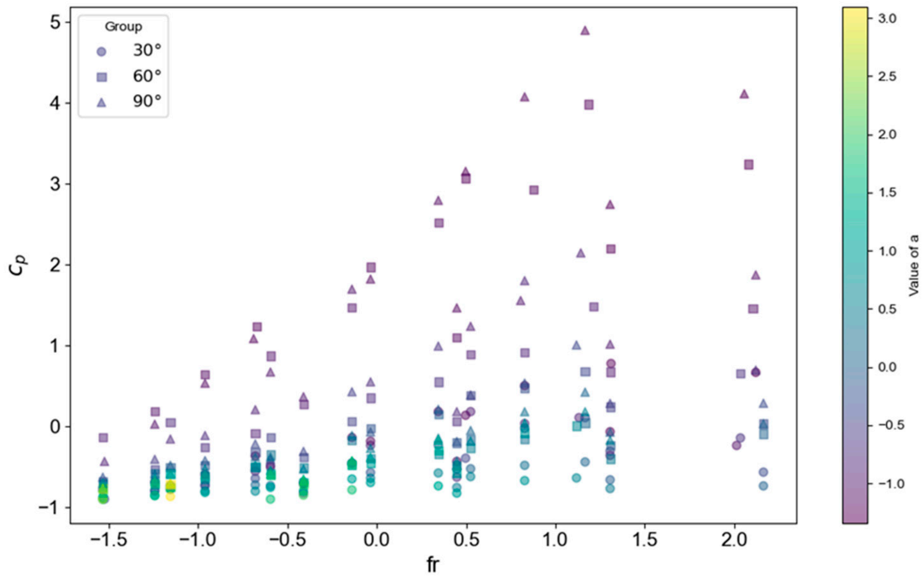

Figure 9. Scatter plot of Normalized Dimensionless Pressure Coefficient (Cp) against Normalized Froude Number, color-coded by Alpha Values and marked by Slope Angles.

To address the non-linearity observed, a logarithmic transformation of C_p values was applied. Figure 10 displays the log-transformed values of C_p, plotted against the Froude number and alpha, with the slope still indicated by distinct markers. This transformation reveals a more linear relationship, simplifying the interpretation and subsequent modeling. The transformed data not only align better with linear assumptions but also enhance the model's ability to predict with greater accuracy.

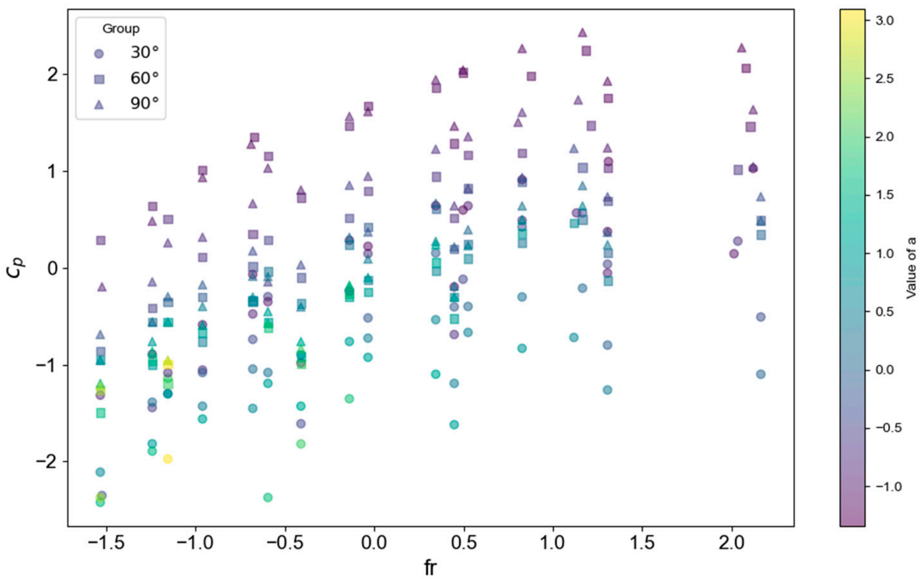

Figure 10. Scatter plot of Normalized Log-Transformed Dimensionless Pressure Coefficient (log (C_p)) against Normalized Froude Number, color-coded by Alpha Values and marked by Slope Angles.

Rationale and Implications of Logarithmic Transformation: The decision to employ a logarithmic transformation of the C_p values stems from the exponential nature of the changes observed in pressure dynamics as influenced by the Froude number and alpha. In fluid dynamics, especially in scenarios involving jet behavior, pressures can increase exponentially with slight changes in velocity or height parameters, making it challenging to model these effects linearly. By transforming C_p to a logarithmic scale, we linearize these exponential relationships, thus fitting a linear model more effectively and reducing the impact of extreme values. This not only improves the interpretability of the data by reducing skewness and stabilizing variance but also aligns the statistical modeling process more closely with the physical phenomena under study. Moreover, achieving a more linear relationship enhances the robustness of the models, improving predictive accuracy across a range of conditions and facilitating the use of linear regression techniques, which are generally less complex and computationally intensive than their non-linear counterparts. This methodological approach ensures that our models reflect both the theoretical understanding of jet behavior and provide practical tools for engineers and practitioners to manage fluid dynamics effectively.

Model Interpretation and Jet Behavior Insights: The transformed data provide a clearer view of how specific changes in the experimental setup affect the pressure dynamics of vertical water jets. For instance, increasing the Froude number generally results in higher C_p values, indicating higher impact pressures. Similarly, changes in the slope significantly alter the pressure dynamics, which is critical for applications involving spray dynamics or fluid impact studies.

Implications for Fluid Dynamics and Engineering: The insights gained from these analyses are valuable for engineering applications where precise control of fluid dynamics is necessary. Understanding the impact of non-linear relationships and the conditions under which they manifest allows engineers to better design systems for optimal performance, such as in water jet cutting, cooling systems, or hydraulic machinery. Additionally, these findings can guide further experimental designs for exploring other aspects of jet behavior that may not have been fully captured in the initial studies. Such follow-up studies could investigate the effects of varying environmental conditions or material properties on the behavior of jets.

4. Conclusions

This study explored the complex dynamics of vertical water jets by investigating the relationships between various experimental parameters such as the Froude number, slope, and alpha, and the resultant pressure coefficient (C_p). Through a rigorous evaluation of multiple machine learning models, the research identified the critical factors influencing jet behavior and demonstrated the efficacy of advanced predictive models in capturing these complexities.

Key Findings:

- Non-linear Dynamics and Transformations: The study highlighted the non-linear nature of the relationship between the input features and the target variable. The logarithmic transformation of the C_p values helped linearize this relationship, enhancing model performance and providing clearer insights into the underlying physical processes.
- Feature Importance: The analysis revealed that the Froude number is the most critical predictor, which influences jet dynamics more significantly than other variables. Understanding the impact of the Froude number, along with the slope of impact and the dimensionless parameter alpha, is crucial for predicting and manipulating jet behavior in practical applications.
- Model Performance: Among the evaluated models, the XGBoost model exhibited outstanding performance with an R-squared value of 0.953 and an RMSE of 0.191. This high level of accuracy attests to the model's capability to handle the non-linear interactions between the input features effectively.

The findings from this research have direct applications in fields such as hydraulic engineering, environmental science, and industries where precise control of fluid dynamics is critical. For instance, in water jet cutting applications, the ability to predict and manipulate jet behavior based on the Froude number and slope can lead to improved cutting efficiency and precision. Similarly, in cooling systems or erosion control mechanisms, understanding the impact of these parameters can guide the design and optimization of fluid impact processes.

Further investigations could explore additional variables that may affect jet behavior, such as temperature, viscosity, and material properties of the impacted surface. Additionally, extending the study to include the effects of external environmental factors like wind and ambient pressure could provide more comprehensive models of jet dynamics. Incorporating computational fluid dynamics (CFD) simulations or conducting validation experiments with real-world scenarios could further strengthen the predictive capabilities of the models developed in this study.

Overall, this research demonstrates the synergy between advanced machine learning techniques and traditional engineering principles in solving complex problems. By successfully applying these methods to the study of vertical water jets, we have advanced our understanding of fluid dynamics and showcased the practical utility of predictive modeling in various engineering domains. The methodologies developed and insights gained from this study offer a valuable framework for future research and application in related fields, ultimately contributing to more efficient and sustainable solutions in fluid systems engineering.

Author Contributions: Conceptualization, A.S.; methodology, A.S. and S.H.B.; software, A.S. and S.H.B.; validation, A.S. and S.H.B.; formal analysis, A.S. and S.H.B.; investigation, A.S. and S.H.B.; data curation, A.S. and S.H.B.; writing—original draft preparation, A.S. and S.H.B.; writing—review and editing, V.A.; visualization, A.S. and S.H.B.; supervision, V.A. and M.F.-M.; project administration, V.A. and M.F.-M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lu, S.; Wang, C.; Wang, W.; Li, M.; Zhang, D. Analysis on the Shape and Impact Pressure of the High-Pressure Water Jet during the Hydraulic Flushing Cavity Technique. *Geofluids* **2021**, *2021*, 7496540. [CrossRef]
2. Dong, C.; Yu, G.; Zhang, H.; Zhang, M. Scouring by submerged steady water jet vertically impinging on a cohesive bed. *Ocean Eng.* **2020**, *196*, 106781. [CrossRef]
3. Godasiaei, S.H.; Kamali, H. Water jet angle prediction in supersonic crossflows: Euler–Lagrange and machine learning approaches. *Eur. Phys. J. Plus* **2024**, *139*, 251. [CrossRef]
4. Wei, W.; Xu, W.; Deng, J.; Liu, B. Experimental study of impact pressures on deep plunge pool floors generated by submerged inclined jets with controlled aeration. *J. Hydraul. Eng.* **2020**, *146*, 04020021. [CrossRef]
5. Wang, H.; Qian, Z.; Zhang, D.; Wang, T.; Wang, C. Numerical study of the normal impinging water jet at different impinging height, based on Wray–Agarwal turbulence model. *Energies* **2020**, *13*, 1744. [CrossRef]
6. Luo, X.; Ye, W.; Huang, R.; Wang, Y.; Du, T.; Huang, C. Numerical investigations of the energy performance and pressure fluctuations for a waterjet pump in a non-uniform inflow. *Renew. Energy* **2020**, *153*, 1042–1052. [CrossRef]
7. Carvalho, R.F.; Lopes, P.M.; Beg, M.N.A. Digital Flow in a Pool Induced by a Vertical Jet. *Water* **2024**, *16*, 1386. [CrossRef]
8. Siamilandu, O. Excavation Work on Kariba Dam Complete. 2023. Available online: https://www.newsday.co.zw/thestandard/local-news/article/200021415/excavation-work-on-kariba-dam-complete (accessed on 27 August 2024).
9. Xu, G.; Antonia, R. Effect of different initial conditions on a turbulent round free jet. *Exp. Fluids* **2002**, *33*, 677–683. [CrossRef]
10. Mistry, D.; Dawson, J.R. Experimental investigation of entrainment processes of a turbulent jet. In *APS Division of Fluid Dynamics Meeting Abstracts*; APS Division of Fluid Dynamics: College Park, MD, USA, 2014.
11. Lemanov, V.; Terekhov, V.; Sharov, K.; Shumeiko, A. An experimental study of submerged jets at low Reynolds numbers. *Tech. Phys. Lett.* **2013**, *39*, 421–423. [CrossRef]
12. Rajaratnam, N.; Khan, A. Intersecting circular turbulent jets. *J. Hydraul. Res.* **1992**, *30*, 373–387. [CrossRef]
13. Raiford, J.P.; Khan, A.A. Investigation of circular jets in shallow water. *J. Hydraul. Res.* **2009**, *47*, 611–618. [CrossRef]
14. Ead, S.; Rajaratnam, N. Plane turbulent wall jets in shallow tailwater. *J. Eng. Mech.* **2002**, *128*, 143–155. [CrossRef]
15. Bhuiyan, F.; Habibzadeh, A.; Rajaratnam, N.; Zhu, D.Z. Reattached turbulent submerged offset jets on rough beds with shallow tailwater. *J. Hydraul. Eng.* **2011**, *137*, 1636–1648. [CrossRef]
16. Hussein, H.J.; Capp, S.P.; George, W.K. Velocity measurements in a high-Reynolds-number, momentum-conserving, axisymmetric, turbulent jet. *J. Fluid Mech.* **1994**, *258*, 31–75. [CrossRef]
17. Salemnia, A.; Fathi Moghodam, M. Effect of nozzle diameter and falling height on the dynamic pressure coefficient of vertical free water jets. *Water Soil Sci.* **2015**, *24*, 185–195.

18. Salemnia, A.; Fathi, M.M. Investigation of break up length of free water jet. *Iran. J. Irrig. Drain.* **2019**, *13*, 309–318.
19. Carraro, M.; De Vanna, F.; Zweiri, F.; Benini, E.; Heidari, A.; Hadavinia, H. CFD modeling of wind turbine blades with eroded leading edge. *Fluids* **2022**, *7*, 302. [CrossRef]
20. Cravero, C.; De Domenico, D.; Marsano, D. The use of uncertainty quantification and numerical optimization to support the design and operation management of air-staging gas recirculation strategies in glass furnaces. *Fluids* **2023**, *8*, 76. [CrossRef]
21. Taebi, A. Deep learning for computational hemodynamics: A brief review of recent advances. *Fluids* **2022**, *7*, 197. [CrossRef]
22. Neyshabouri, A.S.; Da Suva, A.F.; Barron, R. Numerical simulation of scour by a free falling jet. *J. Hydraul. Res.* **2003**, *41*, 533–539. [CrossRef]
23. Jia, Y.; Kitamura, T.; Wang, S.S. Simulation of scour process in plunging pool of loose bed-material. *J. Hydraul. Eng.* **2001**, *127*, 219–229. [CrossRef]
24. Cui, X.; Li, J.; Chan, A.; Chapman, D. A 2D DEM–LBM study on soil behaviour due to locally injected fluid. *Particuology* **2012**, *10*, 242–252. [CrossRef]
25. Cui, X.; Li, J.; Chan, A.; Chapman, D. Coupled DEM–LBM simulation of internal fluidisation induced by a leaking pipe. *Powder Technol.* **2014**, *254*, 299–306. [CrossRef]
26. Taghipour, F.; Ellis, N.; Wong, C. Experimental and computational study of gas–solid fluidized bed hydrodynamics. *Chem. Eng. Sci.* **2005**, *60*, 6857–6867. [CrossRef]
27. Aziz, T.; Raiford, J.; Khan, A. Numerical simulation of turbulent jets. *Eng. Appl. Comput. Fluid Mech.* **2008**, *2*, 234–243. [CrossRef]
28. Islam, M.R.; Zhu, D.Z. A numerical study of confined wall jets in a shallow basin. *J. Hydraul. Res.* **2011**, *49*, 595–600. [CrossRef]
29. Ghahremanian, S.; Moshfegh, B. Evaluation of RANS models in predicting low Reynolds, free, turbulent round jet. *J. Fluids Eng.* **2014**, *136*, 011201. [CrossRef]
30. Faghani, E.; Saemi, S.D.; Maddahian, R.; Farhanieh, B. On the effect of inflow conditions in simulation of a turbulent round jet. *Arch. Appl. Mech.* **2011**, *81*, 1439–1453. [CrossRef]
31. Rayleigh. XXXVI. Investigations in Capillarity:—The size of drops.—The liberation of gas from supersaturated solutions.—Colliding jets.—The tension of contaminated water-surfaces. *Lond. Edinb. Dublin Philos. Mag. J. Sci.* **1899**, *48*, 321–337. [CrossRef]
32. Baron, T.; Comings, E.W.; Johnstone, H. *Atomization of Liquid Jets and Droplets*; Engineering Experiment Station, University of Illinois: Champaign, IL, USA, 1949.
33. Chen, T.-F.; Davis, J.R. Disintegration of a turbulent water jet. *J. Hydraul. Div.* **1964**, *90*, 175–206. [CrossRef]
34. McKeogh, E.J.; Elsawy, E.M. Air retained in pool by plunging water jet. *J. Hydraul. Div.* **1980**, *106*, 1577–1593. [CrossRef]
35. Hoyt, J.W.; Taylor, J. Waves on water jets. *J. Fluid Mech.* **1977**, *83*, 119–127. [CrossRef]
36. Ervine, D.; Falvey, H.; Withers, W. Pressure fluctuations on plunge pool floors. *J. Hydraul. Res.* **1997**, *35*, 257–279. [CrossRef]