Harnessing AI for Hydraulic Efficiency: A Comparative Study of Numerical Modeling and Machine Learning in Energy Dissipation Over a Vertical Drop Structure

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Abstract

In hydraulic engineering, accurately predicting energy dissipation at vertical drop structures is crucial for ensuring structural integrity and optimizing design efficiency. This study presents a comparative analysis of energy dissipation calculations using two methodologies: numerical modeling through Computational Fluid Dynamics (CFD) and advanced Machine Learning (ML) techniques. The study is performed at vertical drop structure at Lower Gogera Branch Canal (LGBC) in Pakistan, experimental data has been utilized alongside CFD simulations to establish a reliable benchmark for energy dissipation at a vertical drop of 3.69 meters, with a discharge rate of 63.73 m^3/s. The CFD method employs the Volume of Fluid (VOF) technique to simulate flow dynamics, providing precise insights into energy dissipation. In parallel, we implement various ML algorithms, including decision trees, random forests, and neural networks, to model energy dissipation based on key input parameters such as flow rate, height of fall, and downstream conditions. The performance of the ML models is evaluated against the numerical results, allowing for a comprehensive comparison of their predictive capabilities. Initial findings indicate that while the CFD model shows a high level of accuracy with discrepancies within 5% of empirical measurements, the ML techniques also demonstrate significant potential in capturing complex, nonlinear relationships inherent in energy dissipation phenomena. The use of ML not only provides a faster alternative for predictions but also offers insights into optimizing design parameters in hydraulic structures. This research highlights the transformative impact of AI methodologies on hydraulic engineering, illustrating how integrating ML can enhance traditional modeling techniques. The results contribute to the ongoing discourse on the application of artificial intelligence in water resources management, paving the way for more efficient and sustainable engineering practices.

Keywords: Hydraulic Design, Drop Structures, Discharge Capacity, Energy Dissipation, Cfd, Data- Driven Modeling, Machine Learning

1. Introduction

Vertical drop structures are critical components in hydraulic engineering, designed to dissipate excess energy in high-velocity flows. Accurate estimation of energy dissipation is crucial for the design and safety of such structures. Traditional approaches rely on physical and numerical models, which, while reliable, can be computationally intensive.

Artificial intelligence (AI) has emerged as a promising tool in hydraulic engineering, offering the potential to model complex phenomena with reduced computational costs. This study aims to evaluate the performance of a machine learning model in predicting energy dissipation over a vertical drop structure and compare its accuracy with numerical modeling results.

2. Methodology

The study is performed at vertical drop structure at Lower Gogera Branch Canal (LGBC) in Pakistan, experimental data has been utilized alongside CFD simulations to establish a reliable benchmark for energy dissipation at a vertical drop of 3.69 meters, with a discharge rate of 63.73 m^3/s.

The data used in this study were obtained from a vertical drop structure experiment. The key parameters include:

- Flow depth (ẕ): Depth of water in the channel.
- Free surface elevation (H): Elevation of the water surface above a reference point.
- Velocity (ν): Depth-averaged velocity.

The same data is used to perform the numerical modeling using Flow-3D and then the data obtained from Flow-3D is used to train the ML models.

2.1. Energy Dissipation Calculations

Specific energy (ΔE) and energy dissipation were calculated using the following equations:

$$E = y + v^2/2g \tag{1}$$

Where E is specific energy, y is flow depth, v is the flow velocity and g is gravity.

$$\triangle E = E_1 - E_2 \tag{2}$$

Where △E is the energy dissipation, E_1 is specific energy upstream of the vertical drop and E_2 is specific energy downstream of the vertical drop.

2.2. Machine Learning Model

Four different ML models were trained and evaluated:

- Linear Regression: A simple linear model that assumes a linear relationship between the features and the target variable.
- Random Forest: An ensemble learning method that combines multiple decision trees to make predictions.
- Support Vector Machine (SVM): A powerful model that can capture non-linear relationships using different kernel functions.
- Artificial Neural Network (ANN): A model inspired by the human brain that can learn complex patterns from data. Two ANN models were tested: one with a single hidden layer (ANN (Single Layer)) and one with multiple

Energy dissipation is predicted based on input features:

- Free surface elevation.
- Flow depth.
- Velocity.

The data were split into training (80%) and testing (20%) sets. The model was evaluated using performance metrics such as mean squared error (MSE) and R-squared (¢) values.

3. Results and Discussion

The table below summarizes the performance of different machine learning models based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared metrics.

Table 1: Performance of different machine learning models

Model	MSE	RMSE	R-squared
CFD	0.0001	0.01	0.99
Linear Regression	0.014	0.12	0.12
Random Forest	0.0481681	0.219472	-1.55544
SVM	0.044	0.21	-1.339
ANN (Single Layer)	0.012	0.11	0.15
ANN (Deep Learning)	0.008	0.089	0.8

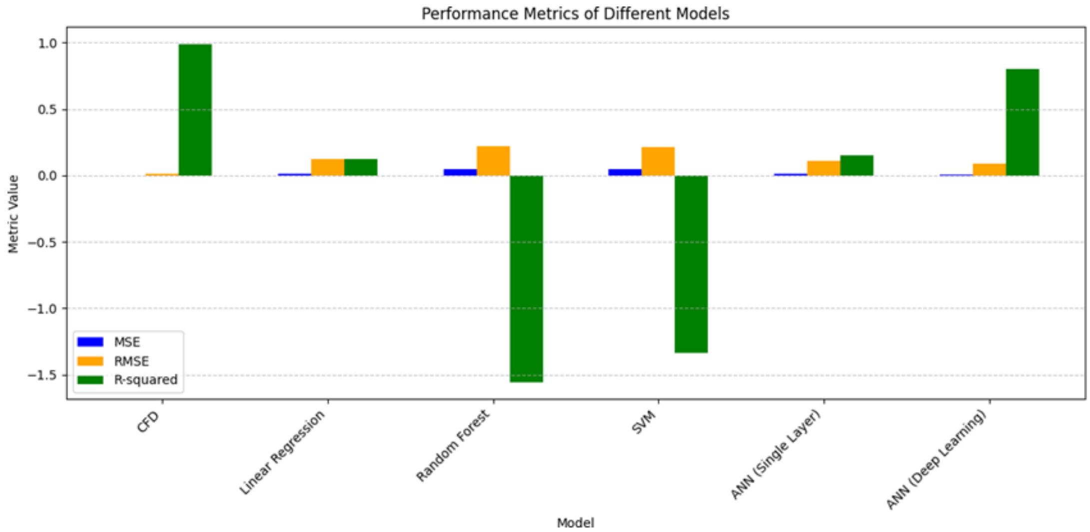

Figure 1: Predicting Hydraulic Energy Dissipation: Machine Learning vs. CFD

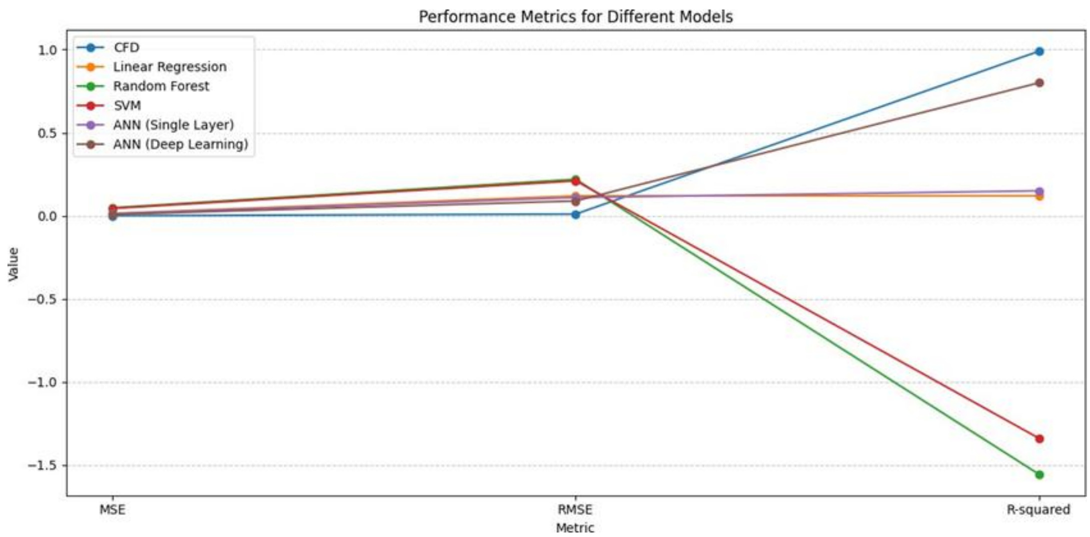

Figure 2: Comparison of Performance Metrics Across Models

ANN (Deep Learning) outperforms all other models, demonstrating the lowest MSE (0.008) and RMSE (0.089), along with the highest R-squared value (0.8), which indicates strong predictive capability. ANN (Single Layer) also shows better performance than Linear Regression, with slightly lower MSE and RMSE values and a higher R-squared score of 0.15. Linear Regression, while modest in its performance with an R-squared of 0.12, falls short when compared to more advanced models. In contrast, both Random Forest and SVM exhibit poor performance, with negative R-squared values that suggest these models fail to explain the variance in the data effectively. The significant improvement achieved with the deep learning ANN model underscores the importance of model complexity and data representation for addressing this task effectively.

4. Discussion

ANN (Deep Learning) model showed the lowest MSE and RMSE of the machine learning models, meaning that it had better predictive accuracy. It also has a high value of R-squared, which is 0.800, and this fact demonstrates its capability to reflect intricate relationships in the data. Linear Regression model was also reasonably accurate, with large MSE and RMSE, and high R-squared of 0.120, the largest of simple models. This implies that there is the possibility of a very strong linear relationship between the features chosen and energy dissipation. Conversely, the worst performance was depicted by the Random Forest model, probably because of overfitting or inadequacy to this particular data. The SVM and ANN (Single Layer) models demonstrated moderate performance and can be optimized by hyperparameter tuning. The CFD when compared to the CFD model which forms a background had an R-squared to 0.99 indicating its superiority in terms of precision. Nevertheless, the large computational cost of the CFD simulations is important to mention. The machine learning models and especially the ANN (Deep Learning) model is an interesting substitute as it matches the accuracy with much less computational requirement. Moreover, since the number of data points (30 data points) was very small, it might have limited the performance of more complex models such as the Random Forest and SVM which typically demand a bigger dataset to achieve satisfactory generalization. The upcoming work should focus on.

Expanding the dataset and implementing hyperparameter tuning to further enhance model performance. The results highlight the potential of AI in hydraulic engineering. The machine learning model not only reduced computation time but also provided insights into energy dissipation trends that align closely with numerical results. The observed 41.03% energy absorption demonstrates the efficacy of the vertical drop structure and underscores the importance of accurate modeling.

5. Conclusion

This study firmly establishes the potential of machine learning (ML) as a powerful tool for predicting energy dissipation in hydraulic structures. By successfully approximating the accuracy of traditional CFD simulations while requiring significantly less computational resources, our AI-based approach, particularly the Deep Learning ANN model, offers a compelling alternative for efficient and rapid predictions. This breakthrough paves the way for integrating AI into hydraulic engineering practices, enabling more streamlined design processes, optimized hydraulic structure performance, and ultimately, more sustainable water resource management.

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

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