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SCOUR DEPTH PREDICTION USING MACHINE-LEARNING (ML) ALGORITHM FOR OFFSHORE TRIPOD FOUNDATIONS

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Keywords: Scour, Tripod foundations, Adaptive Neuro-Fuzzy Interface System, Artificial Neural Network, Particle Swarm Optimization

Abstract

The instability of offshore structures is primarily affected by the scouring phenomenon around their foundations. This significantly contributes to the failure of offshore wind turbines that serve as critical energy infrastructure units. In the present study, three different machine-learning algorithms, viz. Adaptive Neuro Fuzzy Interface System (ANFIS), Artificial Neural Network (ANN), and ANN along with an optimization technique Particle Swarm Optimization (PSO), have been implemented to predict the scour depth around the tripod foundations. In exploring the prediction models, various parameters influencing the scour depth in the marine environment have been considered, such as current velocity (Uc), wave height (Hw), wave period (T), Froude number (Fr) and Keulegan-Carpenter number (KC). For training, testing, and validating the ML model's performance, 99 data points were collected from previously reported experimental studies. The effectiveness of all three machine-learning schemes, ANFIS, ANN, and ANN-PSO, has been evaluated using the statistical parameters, namely, coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MSE), Coefficient of Correlation (CC) and checked against those previously reported values in literature. Among all the machine learning models, the ANN-PSO results in good agreement with the reported outcomes and has better efficiency (R^2=0.99) for predicting the scour depth followed by ANN (R^2=0.98) and ANFIS (R^2=0.97) machine learning algorithms.

Keywords: Scour depth, Tripod foundations, Machine-Learning (ML) Adaptive Neuro-Fuzzy Interface System (ANFIS), Artificial Neural Network (ANN) and ANN-Particle Swarm Optimization (PSO)

1 INTRODUCTION

The burning of fossil fuels is the primary source of greenhouse gas emissions, which contribute to global warming and climate change. As a result, there is an increasing demand for renewable energy alternatives that can reduce carbon footprints and help in achieveing the global climate goals [1]. Therefore, wind energy provides sustainable energy in this transition, offering a scalable solution to meet the growing energy needs of the world's population while minimizing environmental harm. In order to do this, both onshore and offshore wind energy have become a pivotal component of the global renewable energy landscape and significantly contribute to reducing greenhouse gas emissions, which leads the transition towards a sustainable and low-carbon economy [2]. By harnessing the kinetic energy of wind over open seas, offshore wind turbines generate electricity with higher efficiency than their onshore counterparts and provide stronger and more consistent winds [3]. This characteristic enhances energy yield and makes offshore wind a viable solution for large-scale power generation, particularly in regions with extensive coastal areas. However, despite the promising potential of offshore wind turbines, several limitations pose challenges to their widespread deployment. One of the most critical issues is the problem of the formation of scour depth, which involves the erosion of seabed material around the foundations of wind turbines due to the action of ocean currents and waves [4]. Therefore, it is essential to accurately assess the interactions between offshore foundations and the surrounding wave and current environment. The simultaneous effect of coupled waves and currents can result in a significantly greater scour depth than when either currents or waves act independently [5]. Formation of the scour depth can compromise the structural integrity of the wind turbines, leading to increased maintenance costs and potentially jeopardising the safety of the installation. Hence proper assessment and mitigation of the scour depth is essential for offshore wind farm's long-term reliability and efficiency. Depending on the depth of water, the choice of foundation type for the offshore wind turbines plays a crucial role in addressing the formation of scour depth and other environmental challenges. To support the wind turbines, various types of foundations are employed in offshore wind turbine installations, including monopile, tripile, tripod, jacket, gravity-based, and floating foundations, as depicted in Figure 1.

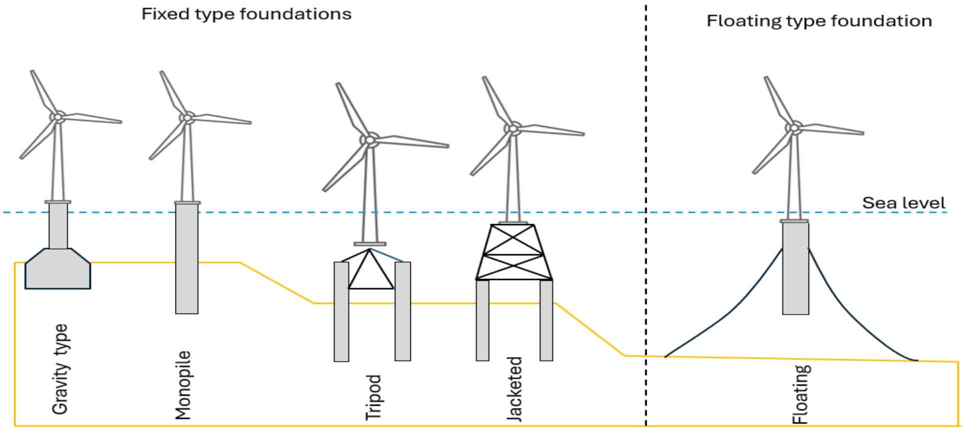


Figure 1: Different types of offshore foundations for different water depths

Among all these foundations, tripod foundations have emerged as a popular choice for supporting offshore wind turbines, particularly in regions with deep waters and strong tidal currents [7]. In cases where waves and currents are co-directional, the velocity on the wave-facing side of the foundation increases significantly compared to the opposite side [8]. This difference in velocity creates a substantial pressure gradient, leading to a deeper scour hole. Scouring around the foundations frequently occurs for offshore wind turbines due to the combined effects of waves and currents. Accurate scour depth estimation under these combined influences is crucial for both safety and practical applications. However, there is limited research on the prediction of scour depth for the tripod foundations involving combined waves and currents compared to those involving current alone. In recent years, integrating advanced machine learning algorithms into the design, operation, and maintenance of offshore wind turbines has marked a significant advancement. These algorithms are being used to optimise foundation design, predict and mitigate scour depth, enhance the structural health monitoring of turbines, and improve the overall efficiency of wind farm operations. Numerous studies have focused on assessing scour depth around circular piers under steady current conditions [9], [10], [11] [12] and wave action [13], [14]. However, as previously noted, no studies have explored the prediction of scour depth using Machine Learning (ML) algorithms in environments with coupled waves and currents for the tripod foundations. Furthermore, only a few studies have investigated scour depths around the tripod foundations through numerical and experimental approaches under such coupled conditions [15], [16], [17]. To the end, this paper aims to address the existing gaps in predicting scour depth around offshore tripod foundations by exploring the application of machine learning (ML) algorithms. The study aims to enhance the reliability and safety of offshore wind turbine installations by examining the current state of ML techniques and their limitations. Specifically, three machine learning algorithms, ANFIS, ANN, and ANN-PSO, are utilized to accurately predict the normalized scour depth (S/D), where S is the scour depth and D is the pile diameter, around tripod foundations under both current-only and combined waves-and-current conditions. The primary goal is to assess the significance and impact of various input parameters in the scouring process driven by the interaction of waves and currents. To verify the accuracy of these machine learning models, a statistical analysis is performed using multiple statistical metrics. Additionally, the predictions from these algorithms are compared with values reported in the literature through graphical plots. The outcomes of this research will provide valuable insights into the potential of ML for scour prediction and offer practical recommendations for improving the design and maintenance of offshore tripod foundations. Furthermore, the paper discusses the importance of offshore wind turbines in the context of global renewable energy goals, addresses the limitations related to the scour problem, reviews the different types of foundations used in offshore wind installations, and examines the latest advancements in machine learning algorithms that are shaping the future of this technology as per the guideline of the United Nations Sustainable Development Goals (UN SDG).

2 METHODOLOGY

In the present study, three machine learning algorithms, namely ANFIS, ANN, and ANN, along with the Particle Swarm Optimization (PSO) technique, are employed for the accurate prediction of the scour depth (*S*) normalized by pile diameter (*S/D*) for the tripod foundations under coupled wave-current environment. The primary objective of this study is to determine the influence of input parameters on the scouring process induced by the combined effects of waves and currents. This analysis aims to inform future research by identifying the key physical variables that dominate the scouring process. To predict the normalized scour depth (*S/D*) for tripod foundations subjected to coupled wave and current conditions, 99 datasets were collected from the previously reported numerical and experimental studies [16]. The data utilized in this study includes both dimensional and non-dimensional parameters, as outlined in Equations (1) and (2).

$$S = f(H, T, U_c, U_{cw}) \tag{1}$$

$$\frac{S}{D} = f(KC, F_r) \tag{2}$$

Where H is the wave height, T is the wave period, U_c is the current velocity, and U_{cw} is the combined current and wave velocity. Among the total datasets, 70% of the data were allocated for training the machine learning models, while the remaining data were used for the testing and validation of the prediction model. The range of all the datasets for the various parameters is detailed in Table 1. To check the accuracy of the predicted model, statistical indices, namely: Root Mean Square Error (RMSE), Correlation Coefficient (CC) and Mean Absolute Error (MAE) were used, and the final predicted values were compared against the reported values in the previous literature.

Table 1: Range of dataset used in the Machine-Learning (ML) models

Parameter	Symbol	Mínimum value	Máximum value
Period of wave (s)	T	0	2.0
Height of wave (m)	H	0	0.06
Current velocity (m/s)	U_c	0	0.4
Velocity ratio	U_{cw}	0	0.35
KC number	KC	0	6.04
Froude number	F_r	0.2	0.88
Normalised scour depth	*(S/D)*	0.03	1.61

3 MACHINE LEARNING ALGORITHAMS

3.1 Artificial Neural Network

Artificial Neural Networks (ANNs) have become a significant and adaptable tool in artificial intelligence (AI) and Machine Learning (ML), drawing its inspiration from the architecture and functionality of the human brain. An ANN model is a computational framework consisting of interconnected units known as neurons, which are systematically arranged into layers. The ANN architecture is typically composed of three primary layers: the input layer, hidden layers, and the output layer. The input layer is responsible for receiving raw data, which is then transmitted to the hidden layers via neurons, where the core computational processes occur. The final output is produced in the output layer, as illustrated in Figure 2.

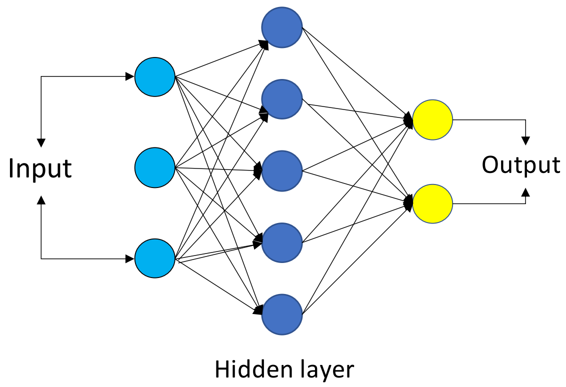


Figure 2. Schematic illustration of the architecture of Artificial Neural Network (ANN) model

The training of an ANN model involves fine-tuning the weights and biases of the connections between neurons to minimize the discrepancy between predicted and actual results, as detailed in Equation 3.

$$y = \left[\sum(x_1 w_1 + x_2 w_2 + x_3 w_3, \dots\dots\dots) + \beta\right] \tag{3}$$

Where, y is the output, x_1, x_2, x_3… Input from the neurons, w_1, w_2, w_3 …weight, and β is the bias. This is generally accomplished through backpropagation, in conjunction with optimization techniques such as gradient descent. In this network, each neuron in each layer is linked to neurons in the adjacent layer through weighted connections,

3.2 Adaptive Neuro-Fuzzy Interface System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) machine learning algorithm, initially developed by Jang (1993), represents a computational approach that integrates neural networks and fuzzy logic to address nonlinear problems and establish mathematical relationships between input and output parameters. ANFIS's ability to merge fuzzy inference systems with neural network features, such as learning, optimization, and connectionist structures, makes it a highly accurate predictive tool [18]. In this study, a Sugeno-type Fuzzy

Inference System (FIS) is combined with a Feed-Forward Neural Network (FFNN) to address the challenge of selecting input variable membership functions. To optimize this selection, a hybrid function is employed [19]. The FIS comprises three main components: (1) a set of if-then rules; (2) a mechanism to define Membership Functions (MF) based on the database; and (3) a system output generation component that integrates fuzzy rules. The use of if-then rules offers a practical method for making predictions and analyzing uncertainties. The training techniques of the ANN can minimize prediction errors, which are further refined by the FIS rules. Initially, fuzzy membership functions derived from the input are converted and integrated into the ANFIS input. The desired output is then obtained using an averaging method to generate the output membership functions. In this study, a constant type membership function [20] is used to produce the outputs.

3.3 ANN-Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm is inspired by the simulation of social behaviors found in nature. Its fundamental principle is that individual particles within a swarm communicate and modify their movements based on their own experiences and the experiences of others in the group [21]. This collective behavior helps the swarm to converge towards optimal regions within the search space. The PSO technique is modeled after natural processes such as bird flocking and fish schooling, where individuals coordinate their movements toward a common goal while navigating obstacles and avoiding predators. In these scenarios, each individual makes decisions based on its own observations and the actions of nearby peers. In PSO, particles represent potential solutions, and their movement toward an optimal solution is driven by a combination of individual and group knowledge. A swarm in PSO is composed of multiple particles, each with a specific position and velocity in the search space. The position denotes a candidate solution, while the velocity determines the particle's direction and speed. The movement of particles is influenced by two main factors: the cognitive component, which guides particles toward their personal best-known position (Pbest), and the social component, which steers them towards the global best-known position (Gbest) [22]. The position $\boldsymbol{x_i}$ and velocity $\boldsymbol{v_i}$ of particle i at time t are updated using the following equations (4) and (5):

$$v_i^{k+1} = wv_i^k + c_1r_1\left(pbest_i - x_i^k\right) + c_2r_2\left(gbest_i - x_i^k\right) \tag{4}$$

$$\boldsymbol{x_i(t+1) = x_i(t) + v_i(t+1)} \tag{5}$$

Where:

- $\boldsymbol{w}$ is the inertia weight that controls the influence of the previous velocity,
- $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are cognitive and social coefficients,
- $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ are random values uniformly distributed between 0 and 1

4 RESULTS AND DISCUSSION

4.1 Artificial Neural Network (ANN)

In this section, the author's discuss the results obtained from the Artificial Neural Network (ANN) machine learning model and evaluate its performance. During the training process, the Mean Squared Error (MSE) on the training dataset was continuously monitored, and training was halted when the MSE dropped below a predefined threshold value. After 1,000 epochs, the model achieved its optimal validation performance with an MSE of 0.08. The corresponding ANN weights from this epoch were saved and subsequently used to forecast the training sample data. This approach effectively mitigates overfitting and underfitting, which is a common challenge in various machine-learning algorithms. In the training phase, the model achieved an RMSE of 0.12, a correlation coefficient (CC) of 0.97, and a Mean Absolute Error (MAE) of 0.08. During testing, the model reported an RMSE of 0.16, a CC of 0.95, and an MAE of 0.14. Figure 3(a) shows the linear regression analysis comparing the observed (*S/D*) values with the predicted (*S/D*) values, yielding an R^2 value of 0.98. Whereas Figure 3(b) depicts the error histogram of the total datasets. To further assess the model's accuracy, a comparative plot of the observed versus predicted (*S/D*) values was constructed, as shown in Figure 3(c). This plot indicates a strong agreement between the predicted and observed values.

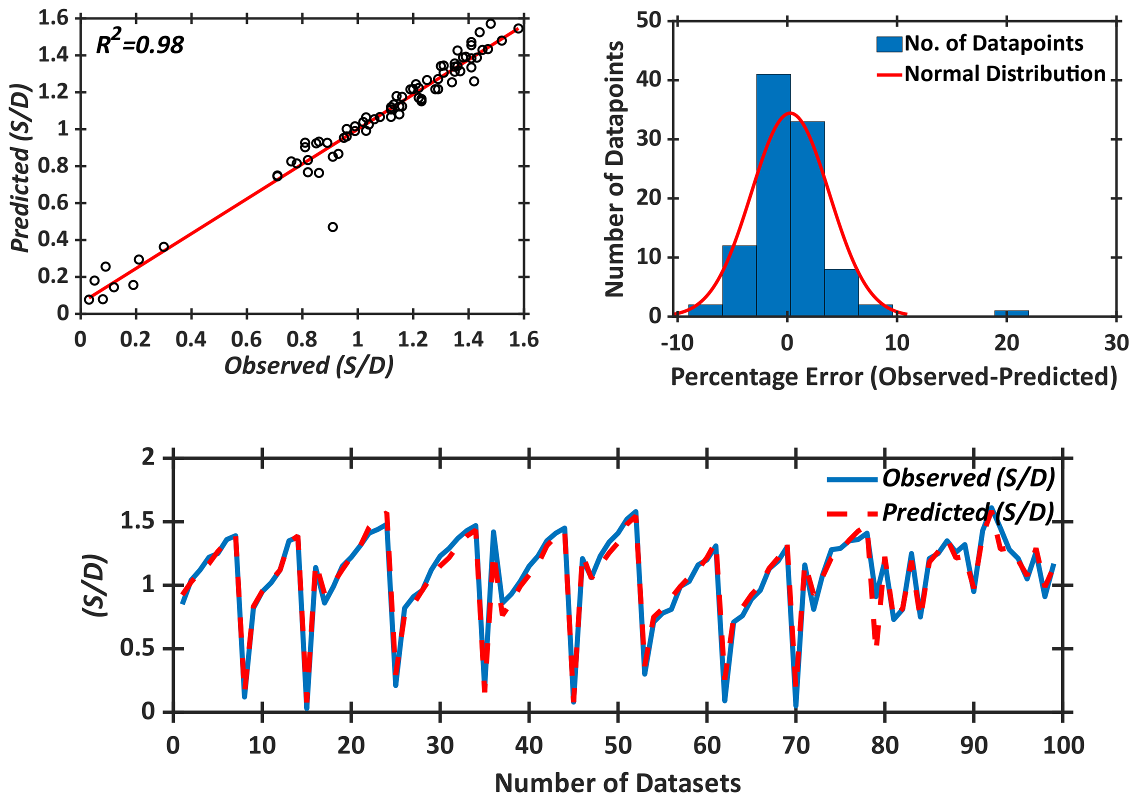


Figure 3: (a) Regression plot for observed and predicted (*S/D*), (b) Error histogram of predicted values, (c) Comparison plot for predicted and observed *(S/D*) for ANN model

4.2 Adaptive Neuro-Fuzzy Interface System (ANFIS)

This section discusses the results obtained from the Adaptive Neuro-Fuzzy Inference System (ANFIS) machine learning model, along with its performance evaluation. The enhanced predictive capability of ANFIS is attributed to its integration of Neural Networks (NN) and the Fuzzy Inference System (FIS), leveraging the strengths of both approaches. The models were trained using data from existing literature, and their performance was assessed using statistical metrics. During the training phase, the ANFIS model achieved an RMSE of 0.11, a correlation coefficient (CC) of 0.94, and a Mean Absolute Error (MAE) of 0.10, while in the testing phase, it recorded an RMSE of 0.19, a CC of 0.92, and an MAE of 0.12. Figure 4(a) presents the results of the linear regression analysis between the observed normalized scour depth (*S/D*) and the predicted scour depth (*S/D*), yielding an R^2 value of 0.97. To further evaluate the accuracy of the trained model, a comparison plot was generated between the reported (*S/D*) values from studies and the corresponding predicted (*S/D*) values, as shown in Figure 4(c). These findings underscore the significant potential of ANFIS for accurately predicting scour depth around tripod foundations.

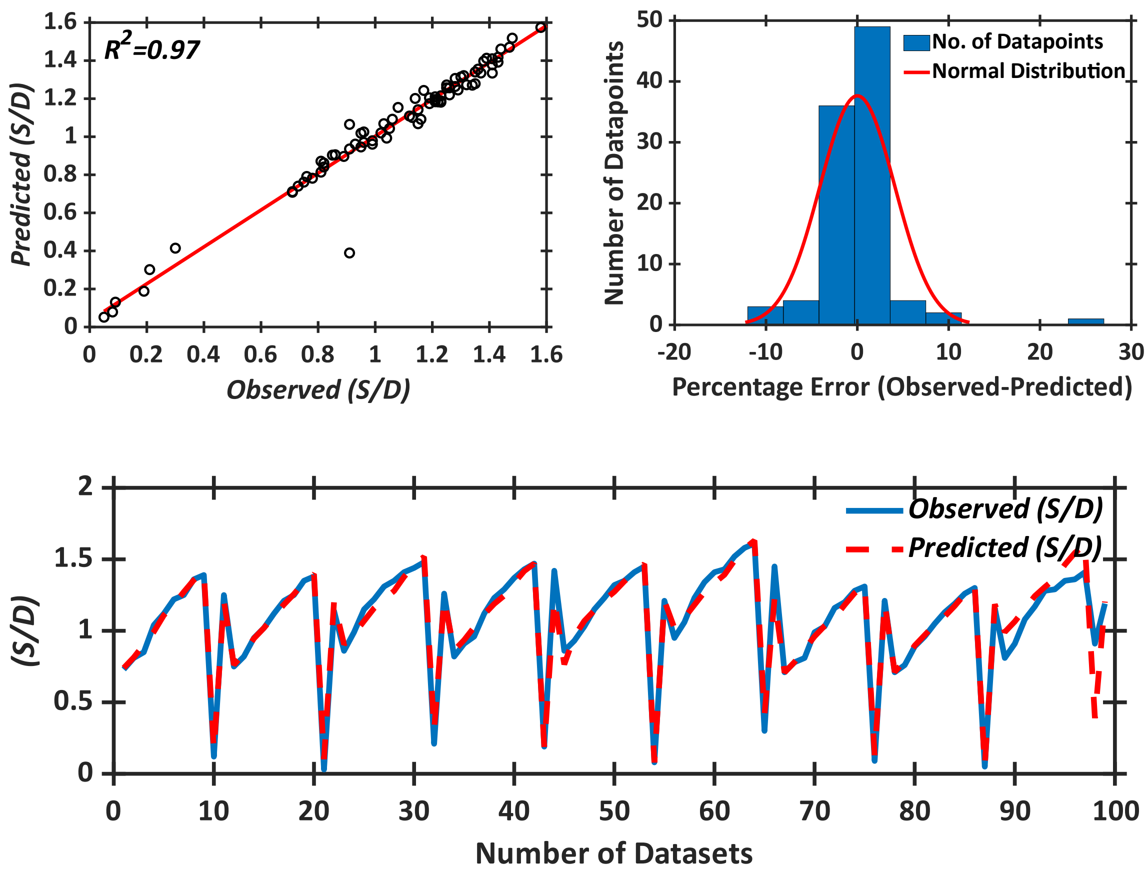
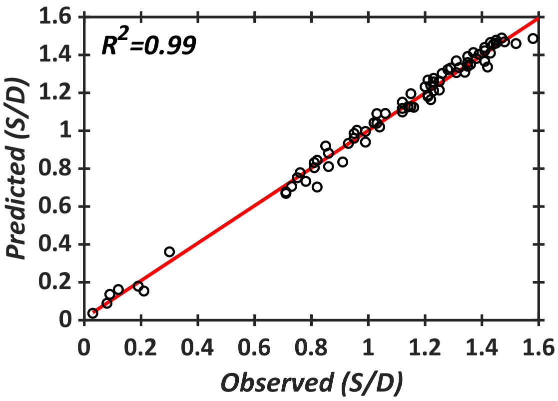
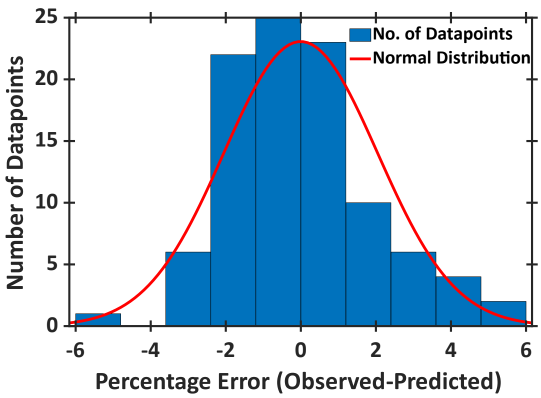


Figure 4: (a) Regression plot for observed and predicted (*S/D*), (b) Error histogram of predicted values, (c) Comparison plot for predicted and observed (*S/D*) for ANFIS model

4.3 ANN-Particle Swarm Optimization (PSO)

The ANN-based PSO technique exhibited strong predictive capabilities, as demonstrated by the high correlation coefficients and low RMSE values during both the training and testing phases. During the training phase, the model achieved an RMSE value of 0.06, a correlation coefficient (CC) of 0.98, and a Mean Absolute Error (MAE) of 0.07. In the testing phase, the model recorded an RMSE value of 0.14, a CC of 0.97, and an MAE of 0.13. Figure 5(a) depicted a linear regression analysis between the observed and predicted normalized scour depth (*S/D*), yielding an R^2 value of 0.99. The close alignment between the observed and predicted (*S/D*) values, as indicated by the R^2 value, underscores the model's ability to accurately capture the underlying data patterns. Additionally, the comparative plot in Figure 5(b), which compares the model's predictions with previously reported (*S/D*) values, further supports the model's accuracy. The use of PSO to optimize the ANN model's parameters significantly contributed to its robust performance. The ANN-based PSO model demonstrates considerable potential for accurate scour depth prediction for the tripod foundations. Nonetheless, future research could investigate the integration of PSO with other optimization techniques or deep learning models to further enhance its performance.





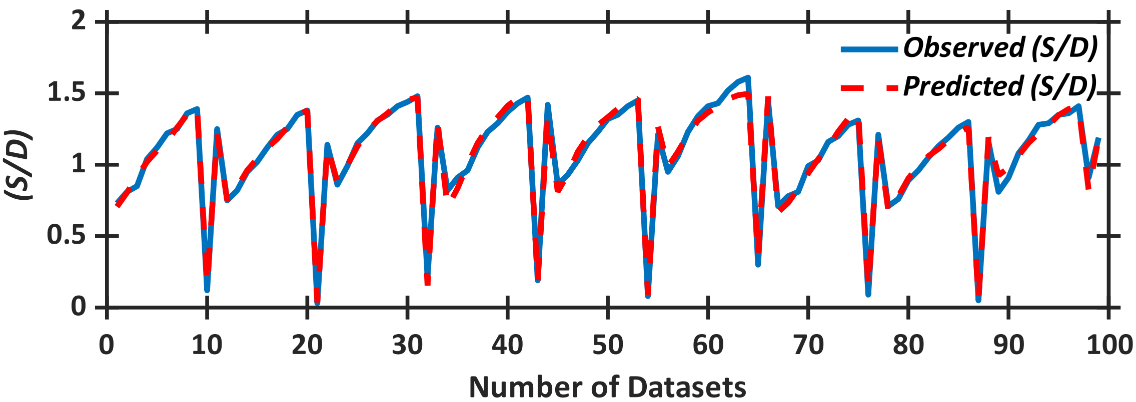


Figure 5: (a) Regression plot for observed and predicted (*S/D*), (b) Error histogram of predicted values, (c) Comparison plot for predicted and observed (*S/D*) for ANN-PSO model

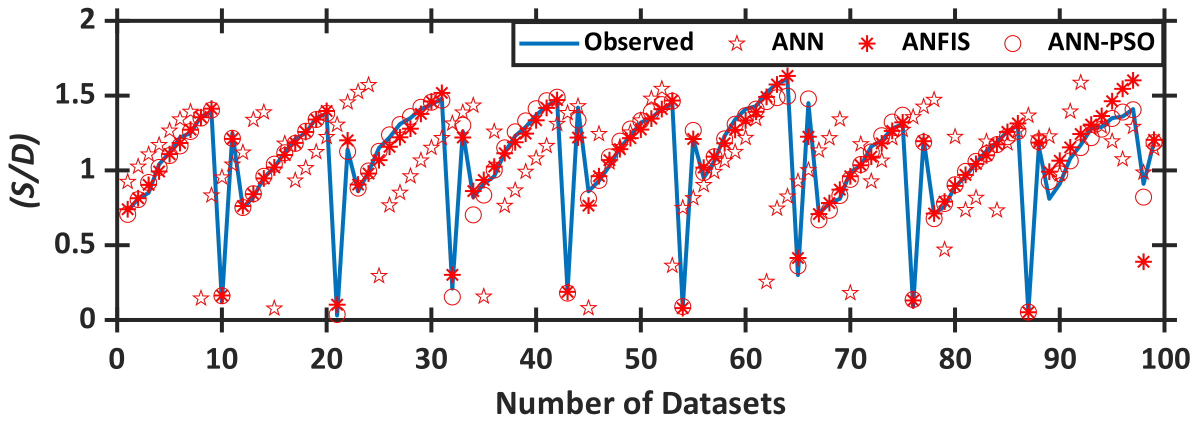


Figure 6: Comparison plot for all the ML models for predicted and observed (S/D) values

5 CONCLUSION

The present study employs a novel approach for predicting the normalized scour depth (*S/D*) using machine-learning algorithms in coupled waves and the current environment for the tripod foundations. The validation of these machine-learning algorithms was conducted through statistical indices and comparisons with the previously reported studies. The results from the machine-learning algorithms showed a strong correlation between previously reported values and the predicted values generated by the algorithms. The effectiveness of three machine learning techniques, ANFIS, ANN, and ANN-PSO, was evaluated for predicting scour depth. Among these, the ANN-PSO model demonstrated the highest accuracy, achieving a correlation coefficient (CC) of 0.98 and a low root mean square error (RMSE) of 0.06 during both the training and testing phases as depicted in figure 6. These findings indicate that data-driven models can be reliably used to predict scour depth. During the testing phase, the ANN-PSO model outperformed as compared to the other models. Although the ANN model's performance declined during testing, it still performed relatively well, with a CC of 0.97 and an RMSE of 0.12, compared to the ANFIS model. Overall, all these models performed well in the prediction of the scour depth. These findings suggest that these machine learning techniques can effectively estimate scour depth in both current-only and combined waves-and-current environments. Additionally, incorporating optimization techniques can help identify key parameters, such as wave velocity, wave period, current and wave velocity to reduce model computation time, and enhance prediction accuracy.

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