SciEn

Proceedings of 8th International Conference on Mechanical Engineering and Renewable Energy 2025
10-12 December, 2025, Chattogram, BANGLADESH

SciEn Conference Series: Engineering Vol. 4, 2026, pp 229-234 https://doi.org/10.38032/scse.2026.4.115

Predicting Ship Added Mass Coefficient with MACHINE LEARNING: Accuracy, Safety and Cost Savings

Md. Ahasanul Kabir, AL-Amin Hossain Seam, Zobair Ibn Awal*

Department of Naval Architecture & Marine Engineering, Bangladesh University of Engineering & Technology, Dhaka-5000, Bangladesh

ABSTRACT

Maritime accidents such as capsizing, storm-induced roll resonance, collisions and groundings continue to occur in Bangladesh's inland and coastal waterways. While these events are usually linked to overloading, weather conditions, and maintenance issues, another important hydrodynamic factor - the Added Mass Coefficient (AMC) is rarely examined. Traditional methods for calculating AMC are too slow for use in real operations. In this study, we explored how different machine learning (ML) models, including Random Forest (RF), Neural Networks (NN), Support Vector Regression (SVR), Linear Regression (LR), and Long Short-Term Memory (LSTM) networks can predict AMC values from basic vessel parameters. Our results show that AMC can be considered not only as a design variable but also as an operational safety parameter. By predicting AMC in advance the models provide a way to support safety actions such as adjusting heading, controlling load distribution and reducing risks in shallow-water navigation. We also suggest that future work should combine real-time data with hybrid approaches to strengthen the reliability of predictions.

Keywords: Added Mass Coefficient (AMC), Machine Learning (ML), maritime safety, hydrodynamic prediction, accident prevention.

1. Introduction

Inland and coastal shipping in Bangladesh is vital for transporting both passengers and cargo. Millions of people and large volumes of goods move through ferries, cargo vessels and barges every year, yet the safety record remains problematic. Over the decades, incidents such as the MV Shamia disaster in 1986 [7], the MV Nasrin-1 sinking in 2003 [7], the MV Shariatpur-1 collision in 2012 [7], the oil tanker grounding in the Shela River in 2014 [7], the MV Rupsa grounding in 2019 [7], and the MV Miraj-4 capsizing in 2014 [9] have exposed persistent vulnerabilities. More recently, the Karatoya River boat accident in 2022 once again highlighted that safety challenges remain unsolved [9]. While overloading, harsh weather and poor maintenance are commonly cited causes, another critical but less visible factor is the lack of monitoring of hydrodynamic safety parameters particularly the Added Mass Coefficient (AMC) [1,8].

The AMC quantifies the additional virtual water mass moving with a vessel compared to the water it displaces [1]. Elevated AMC values significantly influence ship dynamics: they increase resistance to maneuvering, extend turning radius and alter a vessel's natural roll frequency, potentially leading to resonance with prevailing wave patterns and capsizing [2][3]. In shallow waters, high AMC interacts with hydrodynamic suction to intensify squat effects, raising the risk of grounding [8].

Hydrodynamic mechanisms closely match the conditions observed in real-world maritime accidents involving overloading, storm-induced rolling, shallow-water operations and high-impact collisions.

Traditional methods of AMC estimation such as potential flow theory and numerical simulations though effective, are computationally intensive and often impractical for real-time decision-making [1][4]. With the emergence of machine learning (ML), researchers have demonstrated significant progress in ship motion prediction [3], added-wave resistance analysis [4] and accident severity assessment [7]. Advanced ML architectures, including neural networks [11], ensemble approaches [9], and hybrid frameworks [10], have proven capable of capturing complex hydrodynamic interactions with high accuracy while remaining computationally efficient for operational environments [6].

1.1 Novelty and Contributions:

- This study redefines AMC as a dynamic operational safety parameter that changes with operating conditions rather than a static value. Allow its real-time application and improve the prediction accuracy in better decision making.
- A data-driven machine learning based AMC prediction framework is introduced using experimentally derived datasets to predict AMC under various operational conditions, particularly beam-to-draft ratios (B/D).
- By reducing the possibilities of accidents, the proposed framework offers measurable economic benefits including lower insurance claims, repair costs and environmental remediation expenses.
- This paper demonstrates how real-time AMC predictions can be used into onboard decision support systems to enhance operational safety, improving both safety and efficiency in Bangladesh's waterways.

*Corresponding Author Email Address: ahasanulkabir643@gmail.com

Finally, it is visible that existing studies have only concentrated on predicting ship motions or wave resistance ignoring the link between AMC variability, real-time safety management and economic implications mostly unexplored.

Table 1 Multi Directional Flowchart from Accident to Cost Savings

<u>Accident Types</u> Overloading → reduced GM & stability Storm resonance → amplified roll Collisions → energy amplified by AMC Grounding → squat in shallow waters
<u>AMC Effects</u> Hydrodynamic inertia → slower maneuvering Higher inertia → stopping distance
<u>Model Prediction (RF/NN)</u> Trained with early stopping to avoid overfitting Predicts SAC range 0.50–0.80 from b/d ratio
<u>Risk Bands</u> Classification: High / Moderate / Low risk Based on SAC percentile thresholds High AMC = critical hydrodynamic risk
<u>Safety Actions</u> Pre-departure AMC-based safety check Speed/heading adjustments to reduce resonance Load restrictions in AMC stability ranges Shallow-water draft & speed limits

This paper connects inland and coastal accidents to AMC behavior using a practical risk framework (Table 1). It shows how high AMC values make problems like overloading, storm resonance, collisions and grounding. The machine learning-based system sorts ships into high, moderate, and low-risk categories, helping operators perform AMC checks before departure, adjust speed and heading and manage load in shallow waters. This approach helps operators and regulators to take action to prevent accidents.

2. Variability of the Added Mass Coefficient (AMC)

2.1. Background

Calculating the Added Mass Coefficient (AMC) is difficult because when a ship moves, it pushes and pulls surrounding water in complex ways. The result changes with hull shape, speed, wave direction and water depth and accurate calculation often requires costly experiments [1,2]. This "added mass" occurs because the vessel must also accelerate a certain volume of water around it effectively increasing the total moving mass. The relationship between added mass and vessel response can be expressed as:

$$m_{total} = m_{ship} + m_{added}$$

where $m_{added} = C_a \cdot \rho \cdot \nabla$, with C_a being the Added Mass Coefficient, ρ the water density and ∇ the displaced volume of the vessel. AMC is critical for predicting maneuvering behavior such as turning radius and stopping distance, for analyzing dynamic stability in roll, pitch and yaw motions, for estimating structural loads from slamming and collisions and for assessing safety risks from phenomena likes squat [3]. For example, a fully loaded crude oil tanker of approximately 250 m length and 17 m draft navigating a shallow channel at 7 knots may experience a substantial increase in AMC compared to deep water. In deep water, calculations might show $C_a \approx 0.85$, while in shallow water, due to the restricted water flow around the hull, C_a can rise to about 1.35. This increase means the effective inertia is roughly: $m_{total}, shallow/m_{total}, deep \approx 1.6$
indicating a 60% higher mass effect. Such changes alter stopping distances, roll frequency and squat behavior, making real-time AMC estimation essential for safe navigation [8]. The kinetic energy to be dissipated during stopping is given by:

$$E_k = ½\,(m_{ship} + m_{added})v^2$$

With a higher AMC, m_{added} increases, and therefore E_k grows, leading to significantly longer stopping distances. Changes in AMC also shift the vessel's natural roll frequency: $f_n = \left(\frac{1}{2\pi}\right)\sqrt{g \cdot \frac{GM}{(r^2 + a_{44})}}$

where GM is the metacentric height, r is the radius of gyration, and a_{44} is the added mass moment of inertia in roll. This shift can move the vessel closer to resonance speeds in beam seas, increasing roll amplitudes dangerously. Additionally, in shallow channels, high AMC enhances squat depth, increasing grounding risk:

$$Squat \propto \frac{V^2\left(\frac{B}{T}\right)}{}/Water\ Depth.$$

The effect of the Added Mass Coefficient (AMC) can be clearly seen when comparing deep and shallow water.

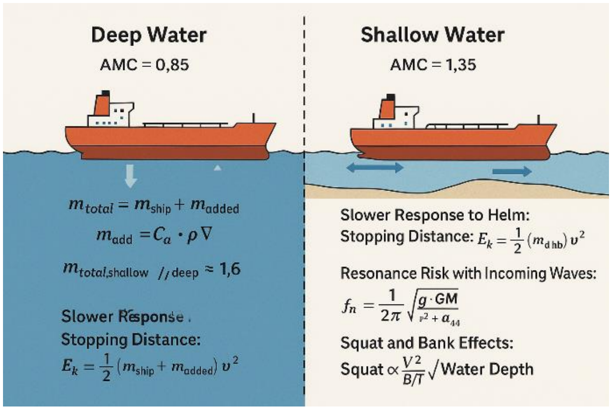

Fig.1 deep water vs. shallow water AMC effects

Figure 1 shows that in shallow water, the flow around the ship is restricted, so more water moves together with the vessel. This makes the ship feel heavier, which slows down steering, increases the turning circle and makes it harder to stop. It also changes the ship's natural roll frequency, which can match wave motion and cause dangerous rolling. In addition, high AMC in shallow water makes the ship sink deeper (squat), raising the chance of grounding. As seen in Figure 1, the same ship behaves very differently in deep water compared to shallow water, which is why predicting AMC correctly is important for safe operation.

2.2. what causes AMC to be different:

The AMC changes as operational and design factors alter the amount of surrounding water that moves with a vessel. In our study, we point out that the AMC does not remain constant but changes with several factors. Figure 2 highlights these variations clearly. Hull shape has a strong influence, as fuller hulls disturb more water and increase AMC, while slender hulls show lower values. Draft and loading also play a role with heavier loads raising AMC and lighter conditions reducing it. Water depth is another key factor. AMC rises in shallow water due to restricted flow but decreases in deep water where water moves more freely. In addition, ship speed and motion type (such as surge, sway, roll, or yaw) affect AMC, with sway often creating the highest values. As illustrated in Figure 2, these factors together explain why AMC varies across ships and operating conditions and why accurate prediction is essential for improving safety.

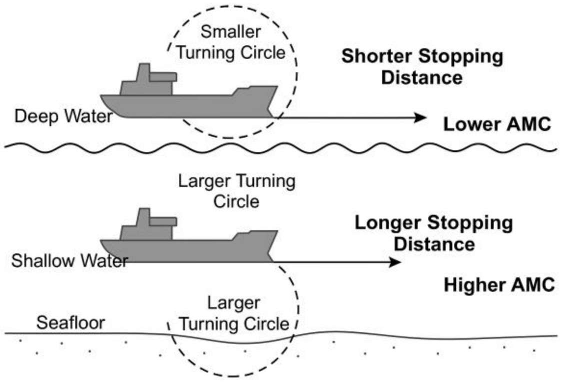

Fig.2 Change in AMC effects in deep vs. shallow water

3. METHODOLOGY

3.1. Data Source and Structure

The dataset used in this study was derived from a hydrodynamic table of the Ship Added Mass Coefficient (AMC) across a full operational range of beam-to-draft ratios (B/D) and AMC target levels from 0.05 to 1.00 in increments of 0.05. Each record contains: Feature, x = B/D, where B is the vessel beam (m) and D is the vessel draft (m). Targets, y_s = SAC at level s, s ∈ {0.05, 0.10, ..., 1.00}. All SAC values are dimensionless. The correlation between x and each y_s was computed as:

$$\rho_s = \Sigma(x_i - \bar{x})(y_{\{s,i\}} - \bar{y}_s) \Big/ \left[\sqrt{\Sigma(x_i - \bar{x})^2 \sqrt{\Sigma\left(y_{\{s,i\}} - \bar{y}_s\right)^2}}\right]$$

ensuring the observed relationship matches hydrodynamic theory. The dataset was divided into training and testing sets using stratified sampling over B/D: $n_{train} = 0.8 \times N$, $n_{test} = 0.2 \times N$.
This ensured balanced representation of both extreme and mid-range B/D values. For models sensitive to input magnitude (Neural Networks, SVR), standardization was applied: $x_{scaled} = \frac{(x - \mu_x)}{} \sigma_x$

Where $\mu_x = \left(\frac{1}{n}\right) \Sigma\, x_i$, $\sigma_x = \sqrt{\left[\left(\frac{1}{n}\right) \Sigma\, (x_i - \mu_x)^2\right]}$.
Tree-based models (Random Forest) were trained on unscaled B/D values to retain interpretability.

3.2. Data Augmentation (Extended for 0.05–1.00)

To make the dataset more diverse and balanced, we applied different data generation and preservation methods. These included curve-based generation, bootstrap residual sampling, mix-up interpolation, and ordering preservation across targets. Each method helped expand SAC values while keeping realistic hydrodynamic patterns. Table 2 summarizes these methods, showing how synthetic data was created and controlled. By using these techniques, we ensured that extreme and mid-range SAC levels were properly represented, improving both training and testing reliability for the machine learning models.

Table 2 Data Generation and Preservation Methods

Method	Formula / Process
1. Curve-Based Generation	$\hat{y}_s(x) = a_s + b_s x + c_s x^2$ $\tilde{y}_s(x) = \hat{y}_s(x) + \varepsilon_s, \varepsilon_s \sim N(0, [\lambda^0{,}_s + \lambda^1{,}_s \hat{y}_s(x)]^2)$
2. Bootstrap Residual Sampling	$\tilde{y}_s(x*) = \hat{y}_s(x*) + r_s*$, $r_s* \sim Bootstrap(\{y_{s,i} - \hat{y}_s(x_i)\})$
3. Mix-up Interpolation	$x' = \lambda x_i + (1 - \lambda) x_j$ $y'_s = \lambda y_{i,s} + (1 - \lambda) y_{j,s}$ $\lambda \sim Beta(\alpha, \alpha)$
4. Ordering Preservation Across Targets	For each x, enforce $\tilde{y}_{1.00} \geq \tilde{y}_{0.95} \geq \ldots \geq \tilde{y}_{0.05}$ via isotonic regression

3.3. Model Development & Model Validation

In this study, five machine learning models were developed to predict the Ship Added Mass Coefficient (AMC) based on the beam-to-draft ratio (B/D). These models included Random Forest, Neural Networks, Support Vector Regression (SVR), Linear Regression, and Long Short-Term Memory (LSTM). The models were trained using a dataset of AMC values under various operational conditions. To prevent overfitting 5-fold cross-validation was applied. Hyperparameters for each model were tuned using grid search for models like SVR and Random Forest. Neural Networks and LSTM were optimized with early stopping to prevent overfitting, ensuring that the models performed well across both training and testing datasets.

From Figure 3, Random Forest proved to be the most reliable model for predicting the Ship Added Mass Coefficient (AMC), offering the best balance of accuracy and stability. This makes it the most suitable choice for real time safety management applications.

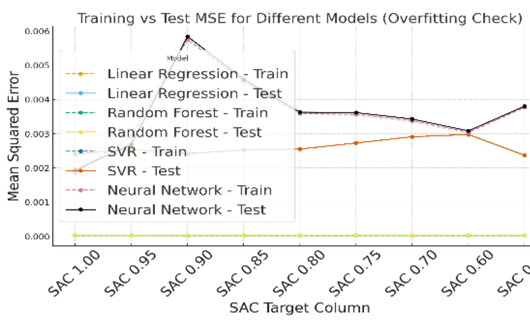

Fig.3 Overfitting Check

All models used the same 80–20 training-testing split within the 5-fold structure to maintain data balance across beam-to-draft ratios and AMC values.

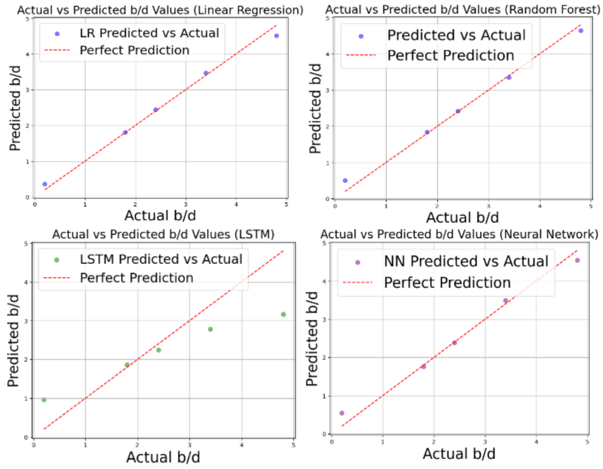

Fig. 4 Model prediction results against actual data (a) Linear Regression, (b) Random Forest Regression, (c) Long Short Term Model (LSTM) and (d) Neural Network (NN)

Machine learning models were tested to predict AMC from beam-to-draft ratio. Random Forest gave the best accuracy, Linear Regression and Neural Networks performed well, while Support Vector Regression and Long Short-Term Memory were weaker, as shown in Figure 4.

3.4. Model Training and Evaluation Metrics

We divided the dataset into 80% for training and 20% for testing so that both high and low SAC values were included properly. For Neural Networks, we used validation splits and early stopping to stop overfitting, while Random Forest and other tree-based models were trained directly since they do not need scaling. To check how well the models worked, we used four measures: R^2 (fit of the model), MAE (mean average error), MSE (mean squared error), and RMSE (root mean of squared error). Figure 5 shows the results of these measures for all models. It can be seen that Random Forest gave the best results with the highest R^2 and lowest errors, while Linear Regression and Neural Networks also gave good performance. From this, we found Random Forest to be the most suitable model for predicting AMC (Figure 5).

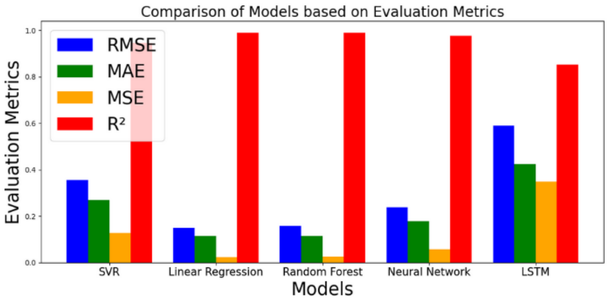

Fig. 5 Evaluation Metrics Comparison

3.5. Risk Assessment Integration

We built a risk framework using Random Forest predictions, classifying SAC values into low, moderate, and high bands. Figure 6 shows risk distribution across beam-to-draft ratios, marking zones of higher hydrodynamic danger. This helps crews to detect risks before departure and take actions like adjusting speed, heading, or load, making machine learning directly useful for safer ship operations.

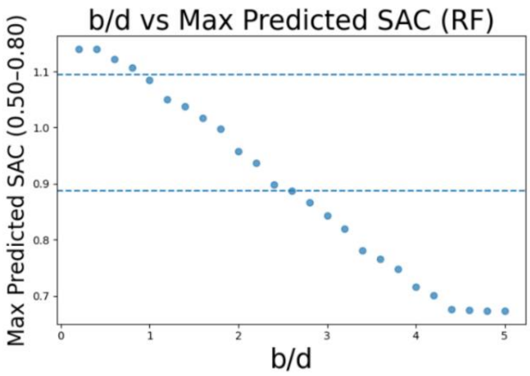

Fig. 6 Risk Assessment Integration against b/d

3.6. Model Comparison and Selection

All models were evaluated on the same dataset using R^2, MAE, MSE, and RMSE. Figure 7 compares their performance at SAC levels 0.55 and 0.80. Random Forest achieved the highest accuracy with the lowest errors, while Linear Regression and Neural Networks showed consistent results. LSTM and SVR were less reliable. Therefore, Random Forest was chosen as the best model for AMC prediction.

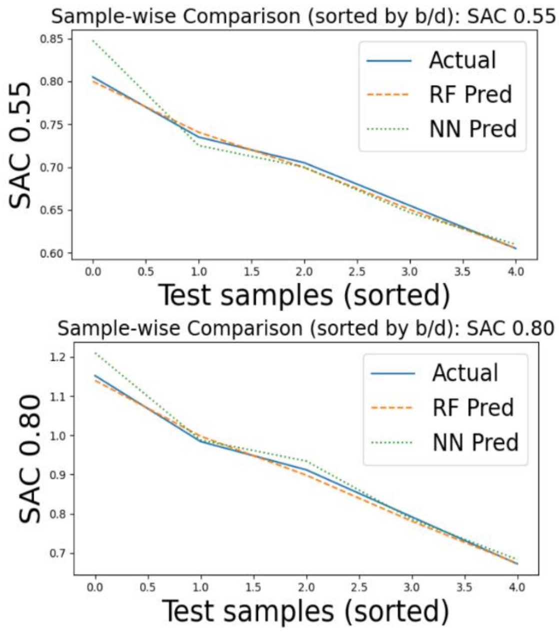

Fig. 7 Model Comparison (SAC 0.55 and 0.8)

4. RESULTS AND DISCUSSION

The results from our dataset confirm that machine learning can effectively estimate the Ship Added Mass Coefficient (AMC) under different conditions. We compared five models - Linear Regression, Random Forest, Support Vector Regression, Neural Network, and Long Short-Term Memory using R^2, MAE, MSE, and RMSE. Table 3 shows that Random Forest and Linear Regression gave the best accuracy, Neural Network and Support Vector Regression also performed well, while Long Short-Term Memory was less consistent due to data limitations.

Table. 3 Performance Metrics of Machine Learning Models

Model	R^2	MSE	RMSE	MAE
Random Forest	0.989	0.0249	0.158	0.0065
Linear Regression	0.990	0.0251	0.1585	0.0067
SVR	0.981	0.0295	0.1718	0.0081
Neural Network	0.977	0.0320	0.1789	0.0090
LSTM	0.889	0.0482	0.2195	0.0127

Table 3 presents the performance of all tested models. The Random Forest algorithm gave the most reliable results, with an R^2 above 0.989 and very low errors, showing strong accuracy and stability. Linear Regression performed at a similar level, confirming the linear trend in the dataset. Neural Networks also reached good accuracy (R^2 above 0.977) after proper training. Long Short-Term Memory models were less consistent due to limited data but improved with extended training. These findings suggest that ensemble methods like Random Forest, combined with neural models, can provide powerful tools for accurate and safe hydrodynamic prediction.

5. RECOMMENDATION

To make this work more practical and useful in real operations, several follow-up steps are needed. These steps are aimed at improving model accuracy, widening the range of vessels covered and making sure the results can be applied in real time:

1. **Expand the training dataset:** Collecting more AMC values from different ships and conditions will make the models fairer and more reliable.
2. **Include environmental factors:** Parameters such as wave spectrum, currents and variable water depths should be added to the prediction process to better represent real operating environments.
3. **Onboard implementation:** Random Forest models can be used in ship support systems to quickly classify risks and work alongside vibration and fatigue monitoring tools.
4. **Develop hybrid models:** Combining physics-based knowledge with machine learning could make SAC prediction more adaptive and reliable in both routine and extreme operating conditions.
5. **strengthen validation with real data:** Validate model predictions using full-scale measurements and accident case studies to ensure reliability and increase confidence in real-world applications.
6. **Adopt Online Learning:** Use real-time learning to update models with voyage data, keeping predictions accurate in changing conditions.

6. CONCLUSION

This research shows that machine learning methods can effectively predict the Ship Added Mass Coefficient (AMC) and these predictions can play a practical role in improving operational safety. Among the tested models, Random Forest produced the most reliable results and appears suitable for integration into onboard decision support tools. The framework connects AMC prediction with risk evaluation and shows how preventive strategies can reduce accident risks and operational costs. Importantly, the study indicates that AMC should no longer be considered only as a fixed value but as a parameter that changes with operating conditions. Using it in this way allows crews to anticipate vessel behavior more accurately and to make proactive decisions in real time. These findings ensure marine safety systems that link prediction with monitoring of vibration and other operational factors, which could improve both safety and efficiency in Bangladesh's waterways.

7. ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial and device-based support received under the Basic Research Grant (Office Order No. 9238, dated 17 June 2025), which enabled access to the computational resources necessary for this research. The academic environment provided by the Department of Naval Architecture and Marine Engineering of Bangladesh University of Engineering and Technology (BUET) was supportive, played a vital role in this paper. The authors express their sincere appreciation to Professors of Naval Architecture and Marine Engineering department for their continuous guidance, insightful feedback, and encouragement throughout the research process. Special thanks are also extended to the faculty members and peers at BUET whose constructive discussions and suggestions enriched the quality of this work. Finally, the authors thank the ICMERE 2025 organizers for giving them the opportunity to share this work.

8. REFERENCES

[1] D. D. T. S. a. T. C. T. C. Vinh, "Determination of Added Mass and Inertia Moment of Marine Ships Moving in 6 Degrees of Freedom," *International Journal of Transportation Engineering and Technology,* vol. 2, no. 1, p. 8–14, 2016.

[2] G. D. W. a. D. K. P. Yue, "Physics-based learning models for ship hydrodynamics," Jan 2014. [Online]. Available: https://arxiv.org/abs/1401.3816.

[3] X. Z. X. T. X. L. a. W. L. X. Guo, "arXiv preprint," Predicting heave and surge motions of a semi-submersible with neural networks, jul 2020. [Online]. Available: https://arxiv.org/abs/2007.15973.

[4] U. D. N. a. H. B. B. M. Mittendorf, "Data-driven prediction of added-wave resistance on ships in oblique waves—A comparison between tree-based ensemble methods and artificial neural networks," *Applied Ocean Research,* vol. 118, p. 102964, 2022.

[5] J. X. e. al., "Machine learning in maritime safety for autonomous shipping: a bibliometric review and future trends," *Journal of Marine Science and Engineering,* vol. 13, p. 746, 2025.

[6] P. M. Madsen, "Using near misses, artificial intelligence, and machine learning to predict maritime accidents," *Risk Analysis,* 2025.

[7] Y. F. e. al., "Prediction of the severity of marine accidents using improved machine learning," *Transportation Research Part E: Logistics and Transportation Review,* vol. 188, no.

10.1016/j.tre.2024.103647, p. 103647, jul. 2024.

[8] S. X. X. W. a. D. Q. X. Wang, "Numerical simulation and analysis of added mass for the underwater variable-speed motion of small objects," *Journal of Marine Science and Engineering,* vol. 12 no.4, no. 10.3390/jmse12040686, p. 686, 2024.

[9] H. Lan, "Predicting types of human-related maritime accidents with selective ensemble learning," *Marine Safety Journal,* 2024.

[10] E. A. Balas, "Maritime risk assessment: A cutting-edge hybrid model," *Journal of Marine Science and Engineering,* vol. 13 no.5, p. 939, 2025.

[11] F. H. J. P.-O. a. J. L. D. Selimović, "Estimation of sea state parameters from ship motion responses using attention-based neural networks," arXiv preprint, jan 2023. [Online]. Available: https://arxiv.org/abs/2301.08949.

9. NOMENCLATURE

Symbol	Definition
AMC	Added Mass Coefficient (dimensionless hydrodynamic parameter)
SAC	Ship Added Mass Coefficient (dimensionless, used for prediction)
B	Vessel beam (m)
D	Vessel draft (m)
B/D	Beam-to-draft ratio (dimensionless)
ρ	Water density (kg/m^3)
∇	Displaced volume of vessel (m^3)
C_a	Added mass coefficient used in hydrodynamic equations
$\hat{y}$	Predicted SAC value
β_0, β_j	Intercept and regression coefficients
ε	Error or tolerance margin
w, b	Weight vector and bias (SVR, NN)
σ	Activation / sigmoid function
tanh	Hyperbolic tangent activation
C_t	Cell state in LSTM
h_t	Hidden state output in LSTM