

Article

Enhancing Ship Propulsion Efficiency Predictions with Integrated Physics and Machine Learning

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Abstract

This research develops a dual physics-based machine learning system to forecast fuel consumption and CO₂ emissions for a 100 m oil tanker across six operational scenarios: Original, Paint, Advanced Propeller, Fin, Bulbous Bow, and Combined. The combination of hydrodynamic calculations with Monte Carlo simulations provides a solid foundation for training machine learning models, particularly in cases where dataset restrictions are present. The XGBoost model demonstrated superior performance compared to Support Vector Regression, Gaussian Process Regression, Random Forest, and Shallow Neural Network models, achieving near-zero prediction errors that closely matched physics-based calculations. The physics-based analysis demonstrated that the Combined scenario, which combines hull coatings with bulbous bow modifications, produced the largest fuel consumption reduction (5.37% at 15 knots), followed by the Advanced Propeller scenario. The results demonstrate that user inputs (e.g., engine power: 870 kW, speed: 12.7 knots) match the Advanced Propeller scenario, followed by Paint, which indicates that advanced propellers or hull coatings would optimize efficiency. The obtained insights help ship operators modify their operational parameters and designers select essential modifications for sustainable operations. The model maintains its strength at low speeds, where fuel consumption is minimal, making it applicable to other oil tankers. The hybrid approach provides a new tool for maritime efficiency analysis, yielding interpretable results that support International Maritime Organization objectives, despite starting with a limited dataset. The model requires additional research to enhance its predictive accuracy using larger datasets and real-time data collection, which will aid in achieving global environmental stewardship.

Keywords: shipping industry; fuel consumption; machine learning; monte carlo simulations; maritime; sustainability



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1. Introduction

The international maritime industry is at a critical juncture, facing mounting pressure to reduce greenhouse gas (GHG) emissions in alignment with global sustainability goals. The International Maritime Organization (IMO) has implemented stringent regulations, such as the Energy Efficiency Design Index (EEDI) and the Energy Efficiency Operational

Indicator (EEOI), aimed at decarbonizing the shipping sector [1,2]. These initiatives aim to reduce ship fuel usage and carbon dioxide (CO₂) emissions [3]. In addition to these regulations, the Carbon Intensity Indicator (CII) has become mandatory for existing ships since January 2023 as part of MARPOL Annex VI. The CII measures the operational carbon intensity of ships and assigns an annual performance rating from A to E. This study's hybrid model, which predicts fuel consumption and CO₂ emissions under varying operational scenarios, provides a valuable tool to support compliance with CII by simulating emissions profiles and identifying design or operational modifications that improve a vessel's carbon intensity rating [4].

Moreover, ship design and propulsion systems have improved, and other initiatives in the industry struggle to achieve the IMO objectives [4]. Data-driven solutions are necessary to optimize fuel efficiency and reduce emissions, such as rising operating costs from fuel costs, regulatory compliance, and increased environmental scrutiny due to stricter emission standards, necessitating economic and environmental sustainability [5]. On the other hand, predicting the effects of technological measures on fuel usage and CO₂ emissions, which can be illustrated as a new approach to analyzing emissions for further mitigating activities, is challenging [6]. Traditional physics-based models, which follow International Towing Tank Conference (ITTC) procedures, perform well in controlled environments [7]. However, they do not effectively represent the intricate, non-linear connections between ship performance elements, such as speed, resistance, and propulsion efficiency, when operating in dynamic, real-world situations with changing sea states, cargo loads, and weather conditions.

The models continue to receive research improvements, yet their computational complexity and simplified assumptions restrict their ability to handle such variability [8]. The existing references are supported by recent studies that demonstrate a movement toward data-driven methods. Zhang et al. used deep neural networks to predict ship fuel consumption (FC) with high accuracy in real-time scenarios through the implementation of attention mechanisms in a Bi-LSTM network [8]. Jung and Chang investigated reinforcement learning methods for optimizing ship propulsion efficiency under various environmental conditions by developing a deep reinforcement learning-based energy management strategy for hybrid electric ship propulsion systems. The research demonstrates how machine learning (ML) continues to gain importance in maritime studies while supporting the hybrid method described in this study [9]. Recent research has used ML to estimate ship performance; however, these models often lack hydrodynamic principles, limiting interpretability and forecast accuracy [10,11].

The development of ship propulsion efficiency modeling has investigated multiple approaches, which include analytical techniques and computational modeling methods. Traditional physics-based models use ITTC procedures or computational fluid dynamics (CFD) to deliver precise resistance and power calculations, but fail to handle dynamic operational variations [12,13]. The early ML models that used support vector machines and basic neural networks enhanced flexibility but failed to establish physical connections [14,15]. The application of modern deep learning methods, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), demonstrates potential for understanding ship performance data patterns, but their black-box operation hinders interpretability [16,17].

Furthermore, advanced propellers (ship propellers with highly skewed blades, changeable pitch mechanisms, or biomimetic components designed to minimize FC, enhance efficiency, and mitigate environmental impact [18]), bulbous bows (a protruding bulb at a ship's bow just below the waterline, designed to reduce drag by altering water flow around the hull, improving fuel efficiency and stability [19]), and low-friction ship's hull coatings are often studied separately without considering their combined effects [20]. These studies

often employ static models that overlook the dynamic nature of ship operations, including sea conditions and cargo weights. This gap highlights the need for hybrid models that combine physics-based knowledge with powerful ML to assess ship performance more effectively in real-world settings.

The field of maritime FC prediction now relies more heavily on ML to overcome the limitations of traditional physics-based models. Hu et al. (2021) developed a sensor data-based hybrid FC prediction system that combined extremely randomized trees with random forest and XGBoost (XGB) to achieve better predictive results, demonstrating strong performance across multiple operational settings [21]. The research by Melo et al. (2024) showed that Random Forest, Gradient Boosting, and CatBoost performed well in optimizing FC under complex operational and environmental conditions [22]. Tran (2021) developed probabilistic FC models for bulk carriers by combining Monte Carlo (MC) simulations with Artificial Neural Networks (ANNs) to handle marine environmental uncertainties effectively [23]. Moreover, the research by Nguyen et al. (2023) utilized optimization algorithms in conjunction with ML models to optimize ship FC and operational efficiency, outperforming traditional models [24]. This work presents a hybrid model that combines MC simulations with an XGB regressor and physics-based hydrodynamic computations to estimate FC and CO₂ emissions accurately. The model encompasses nonlinear operational dynamics and outperforms simple data-driven approaches by incorporating physical properties, such as hull efficiency and propeller performance, and utilizing data augmentation.

In addition, by demonstrating the advantages of hybrid models that combine physics and ML to enhance emissions forecasting, the research closes a gap in the existing body of knowledge. It also emphasizes how better emission reductions result from combining hydrodynamic concepts with cutting-edge technology, such as low-friction coatings and improved propellers, than from single actions. The model supports efforts in decarbonization, operational planning, and enhanced ship design within the marine industry.

This research introduces a novel approach by combining physics-based hydrodynamic calculations with ML to predict ship propulsion efficiency and emissions under various operational conditions. This research addresses three specific questions: (1) Physics-based features enhance the accuracy of ML models when predicting FC and CO₂ emissions. (2) Which technical modifications (e.g., advanced propellers, hull coatings) most effectively reduce emissions under varying conditions? (3) How can this hybrid model support real-world maritime decarbonization efforts? This research addresses three key questions, leading to the development of a robust, interpretable tool for ship performance optimization that offers practical solutions for shipowners, designers, and policymakers.

This study provides fuel efficiency and operational planning tools to academics, researchers, engineers, ship equipment users, stakeholders, politicians, and shipowners to emphasize the maritime industry's vital role in global trade and sustainability. It advises shipbuilders on technical measures and regulators on policy. It promotes business and academic sustainability by supporting the IMO's decarbonization targets.

The following section of this paper describes the methodology, which includes physics-based calculations, ML model development, and data augmentation through MC simulations. The third section of this paper, titled "Findings and Results," presents the study's outcomes by evaluating model performance and comparative results and assessing the effects of technical measures on FC and CO₂ emissions. The fourth section of this paper, titled "Discussion," presents the research findings along with their implications. The fifth section, titled "Conclusions," summarizes the key results and suggests directions for future research.

2. Materials and Methods

This study employs a comprehensive methodology that integrates three distinct approaches to predict FC and CO₂ emissions for a specific oil tanker ship operating at speeds of 9 to 15 knots. The methods include physics-based calculations, ML model development and implementation, and data augmentation using MC simulations. The framework presented in Figure 1 outlines the entire process, from input data to validated predictions, through user simulation and scenario comparison, providing practical insights for optimization. Moreover, the arrows in Figure 1 illustrate the sequential flow within the Hybrid Physics-ML Framework. They show how physics-based data informs the training of various machine learning models to predict fuel consumption and CO₂ emissions. Crucially, the arrows also depict a feedback loop where prediction errors trigger MC simulations to augment data, leading to improved model accuracy.

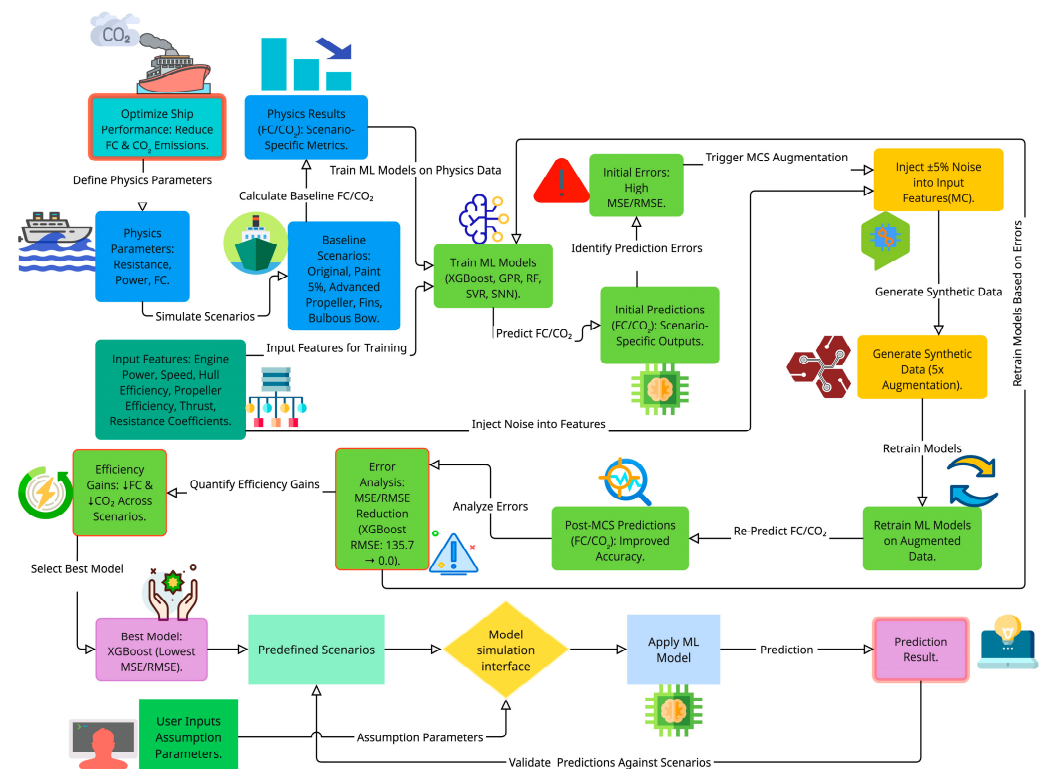


Figure 1. Hybrid Physics-ML Framework for Predicting FC and CO₂ Emissions.

The hybrid methodology combined physics-based calculations with advanced ML models to leverage hydrodynamic principles for interpretability and data-driven techniques for prediction, while addressing the limitations of individual approaches [21]. The MC simulation method was used for data augmentation to address dataset limitations by producing synthetic data points that represent real-world variability and measurement uncertainties, which improves model robustness and generalizability [23]. The integrated method yields precise predictions for FC and CO₂ emissions under various operational conditions.

2.1. Physics-Based Calculations

The research examines a 100 m long oil tanker with a 16.6 m width and 7966 tons displacement, which operates at speeds ranging from 9 to 15 knots. The tanker's dimensions and main characteristics are presented in Table 1, enabling performance simulation across various operational scenarios (complete specifications are provided in Appendix A, Table A1). Critical parameters, such as kinematic viscosity, seawater density, wetted surface

area, waterline length, wake fraction, and thrust deduction factors, were based on the specifications of the mentioned oil tanker to ensure accurate resistance and power calculations.

Table 1. Examined Oil Tanker Dimensions and Main Characteristics.

Parameter	Symbol	Unit	Value
Length overall	LOA	(m)	100
Length between perpendiculars	LBP	(m)	98.1
Breadth (at WL)	B	(m)	16.6
Draught (midship)	T	(m)	6.5
Displacement	Δ	(ton)	7965.9
Wetted surface area	AWS	(m ²)	2350
Block coefficient	C _B	-	0.72
Waterplane area coefficient	C _{WP}	-	0.862
Propeller diameter	-	m	4
Service speed	-	knots	13.5
Transmission efficiency	-	-	0.965
Brake Specific Fuel Consumption	BSFC	g/kWh	200
Model factor (k)	-	-	0.27

Additionally, regarding the BSFC which is mentioned in the table, it must be noted that while real-world BSFC (Brake Specific Fuel Consumption) values vary with engine load, typically increasing at low engine loads (<50% MCR) due to reduced combustion efficiency and auxiliary power overhead, the present study adopts a constant BSFC of 200 g/kWh for modeling purposes. MCR (Maximum Continuous Rating) is the maximum engine output (power) that a ship's main engine is certified to deliver continuously under standard service conditions, as defined by the engine manufacturer.

This simplification enables consistent comparison across technical scenarios while focusing on hull and propeller-induced hydrodynamic impacts. Marine diesel engines generally reach optimal fuel efficiency at 75–85% MCR, and deviations from this range are acknowledged as limitations. Nevertheless, this modeling assumption allows isolating and analyzing the effects of hull design and propulsion configurations on fuel consumption, without the confounding variability of engine-specific performance curves.

Furthermore, the model factor, representing additional viscous losses due to the ship's shape, was taken as 0.27 based on the tanker model's specific characteristics and empirical data for similar vessels. This value is supported by empirical studies and ITTC recommendations for full-form ships such as oil tankers, where form factors typically range between 0.25 and 0.3, depending on the block coefficient and hull shape [25]. This value reflects the form factor commonly observed in full-form ships, such as oil tankers, accounting for the additional resistance due to their bluff hull shapes. The test results of the oil tanker ship model examined, including wave resistance coefficients, thrust deduction factors, wake fractions, and relative rotative efficiencies at different speeds, are provided in Appendix A, Table A2.

Furthermore, the open-water propulsion efficiency for different types of propellers was analyzed. Table A3 in Appendix A presents the ship model test results, including the advance coefficient (J), thrust coefficient (K_T), and torque coefficient (K_Q) for both the original and advanced propeller designs. Original propeller designs feature simple, symmetrical shapes optimized for general performance. Advanced designs use optimized blade geometry, variable pitch, and advanced materials to enhance efficiency, reduce cavitation, and improve thrust. They meet modern demands for fuel efficiency, lower emissions, and quieter operation, leveraging CFD and advanced manufacturing for precision. These values are essential for calculating the propeller's performance and efficiency in different

scenarios. Then, to initiate the analysis, six distinct ship configurations were examined, with detailed descriptions and results provided in Section 3, Section 3.1 (Hydrodynamic Parameter Modifications):

- (a) *Original Scenario*: Served as the baseline for comparison, using the original ship specifications without any modifications.
- (b) *Paint Efficiency Scenario*: Modeled the application of advanced anti-fouling hull coating to assess its effect on frictional resistance.
- (c) *Advanced Propeller Scenario*: Modeled the use of an advanced propeller design to examine its effect on open-water efficiency.
- (d) *Fin Installation Scenario*: Modeled the addition of fins to the hull to evaluate their influence on propulsion efficiency.
- (e) *Bulbous Bow Scenario*: Models a bulbous bow addition to modify wave resistance and hull geometry.
- (f) *Combined Paint and Bulbous Bow Scenario*: Integrates the paint efficiency and bulbous bow modifications to assess synergistic effects.

For each scenario, calculations were performed to determine resistance coefficients, total resistance, adequate power, thrust required, propulsive efficiencies, delivered power (Pd), brake power (Pb), and FC. These calculations were based on the following key equations to ensure repeatability:

- Frictional Resistance Coefficient (CF): Calculated using the ITTC-1957 formula:

$$CF = \frac{0.075}{(\log_{10}(Re) - 2)^2} \quad (1)$$

where Re is the Reynolds number, defined as $Re = \frac{V \times L}{\nu}$ with V as velocity, L as ship length, and ν as kinematic viscosity.

- Total Resistance (Rt):

$$R_t = \frac{1}{2} \rho S V^2 C_T \quad (2)$$

where ρ is seawater density, S is the wetted surface area, V is the ship speed, and C_T is the total resistance coefficient ($C_T = C_F + C_W + kC_F$, with C_W as wave resistance coefficient and k as the model factor).

- Effective Power (Pe):

$$Pe = R_t \times V \quad (3)$$

The detailed equations for thrust, propulsive efficiencies, Pd, Pb, and FC are presented in Section 2.4 (Equations (5)–(25)) to ensure repeatable calculations across scenarios.

Polynomial regression was applied to derive equations for thrust and torque coefficients based on experimental data, enhancing the precision of propeller performance predictions.

The selection of quadratic polynomial regression occurred because experimental data (Appendix A, Table A3) showed smooth non-linear trends in propeller thrust (K_t) and torque (K_q) coefficients. The model achieved R^2 scores of 1.000 for both K_t and K_q for the original and advanced propellers with three parameters fitted to 17 data points. The model achieved perfect accuracy because of its simplicity, which was possible due to the high-quality, low-noise dataset and the consistent results for both propeller types, as shown in Figures A1–A4 in Appendix B.

The constants used in the resistance and power calculations were selected based on standard hydrodynamic modeling practices and empirical values reported in the literature.

The kinematic viscosity of seawater was taken as $1.188 \times 10^{-6} \text{ m}^2/\text{s}$, corresponding to a temperature of approximately 15°C and salinity conditions typical of open waters [26]. The form factor ($k = 0.27$) reflects additional viscous resistance associated with full-form hulls like oil tankers and aligns with values reported in Larsson and Raven (2010) for similar ship geometries [27]. Wave resistance coefficients were obtained from experimental results (Appendix A) and vary across speeds and scenarios. The transmission efficiency was assumed to be 96.5%, representative of a simplified direct-drive shaft system with minimal gearing losses, commonly used in medium-sized tanker configurations. These assumptions were necessary to ensure consistency across operational scenarios and to provide a baseline for evaluating the impact of technical modifications.

2.2. Machine Learning Model Development and Implementation

ML models were developed and implemented to capture the complex, non-linear relationships inherent in ship performance data. This process involves several key steps:

I. Data Enhancement and Feature Engineering

The dataset received advanced feature engineering methods to enhance its quality for ML model training. The independent variables (X) consist of physics-based operational parameters including engine power (P_e), rotational speed (n), thrust (T), hull efficiency (η_H), propeller efficiency (η_O), P_d , P_b , and ship speed (V) together with engineered features such as non-linear terms (V^2 , V^3) and interaction terms ($P_d \times \eta_H$, $\eta_O \times n$). The features capture physical ship performance mechanisms through their design, while differing from the quadratic polynomial regression in Section 2.1, which uses (K_t) and (K_q) coefficients ($R^2 = 1.000$) for physics-based calculations to provide additional predictive value without duplication.

The dependent variables (y) are FC and CO_2 emissions, calculated using physics-based equations (Section 2.4, Equations (27) and (28)). The dataset encompasses all scenarios (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, and Combined) to capture a wide range of operational conditions, enabling the models to predict FC and CO_2 emissions with enhanced accuracy across diverse maritime contexts.

II. Data Augmentation with MC Simulations

To address limitations posed by the small dataset and to prevent underfitting, MC simulations were applied for data augmentation. Controlled random noise within a $\pm 5\%$ range was introduced to key features such as engine power (P_e), rotational speed (n), thrust (T), hull efficiency (η_H), propeller efficiency (η_O), P_d , P_b , and ship speed (V). This process generated synthetic data points that simulated real-world variability and measurement uncertainties, effectively expanding the dataset and enhancing the models' generalization abilities.

The MC simulation involved generating additional synthetic samples for each original data point to expand the dataset. The steps in the augmentation process are as follows:

Random Noise Generation: For each feature x_{ij} in the feature vector $\mathbf{x}_i$, the authors generated a random noise ϵ_{ij} from a uniform distribution within the range $[-0.05, 0.05]$. As a result, $\epsilon_{ij} \sim \text{Uniform}(-0.05, 0.05)$ [28,29].

This range introduces a variation of up to $\pm 5\%$ for each feature, simulating measurement errors and natural fluctuations.

Synthetic Feature Calculation: The synthetic feature x_{ij}^* was calculated by applying the random noise to the original feature [30]:

$$x_{ij}^* = x_{ij} \times (1 + \epsilon_{ij}) \quad (4)$$

Synthetic Sample Creation: The authors created five synthetic samples for each original data point, resulting in an augmented dataset that is six times larger than the original (including the original data). The synthetic feature vectors $\mathbf{x}_i^{(j)}$ were paired with the original target values to form new data points [30]:

$$\mathbf{x}_i^{(j)} = [x_{i1}^*, x_{i2}^*, \dots, x_{in}^*], \quad \text{for } j = 1, 2, \dots, 5 \quad (5)$$

To ensure that MC augmentation involved checking synthetic samples against hydrodynamic principles to verify that the original data distribution and model fidelity remained intact. The Kolmogorov–Smirnov test results showed that the feature distributions of the augmented dataset (Pe, V, η O) matched those of the original data distribution (p -values > 0.05), indicating no significant degradation. The R^2 scores for FC predictions remained at 0.95 when comparing the original and augmented datasets, confirming that predictive accuracy was preserved. The validation results for specific scenarios, including Paint at 14.5 knots, are presented in Section 3.5 and Appendix B, Table A5, which demonstrate that synthetic data match physics-based calculations while maintaining essential data characteristics.

The validation of synthetic data points as a subset was performed to ensure hydrodynamic principles, with detailed results presented in Section 3, Section 3.7 (Comparative Analysis of ML Model Performance).

III. Model Training and Verification

Several ML algorithms were evaluated for their predictive performance:

Support Vector Regression (SVR): Effective in high-dimensional spaces and capable of modeling complex relationships using kernel functions, SVR is suitable for capturing the non-linear dynamics between ship performance variables and FC [31,32].

Gaussian Process Regression (GPR): GPR provides probabilistic predictions with uncertainty estimates, which is valuable for assessing. The probabilistic predictions generated by GPR include uncertainty estimates that help evaluate prediction confidence in maritime applications that operate under changing conditions. The uncertainty estimates from GPR help evaluate prediction reliability by quantifying the impact of imperfect training samples, which may contain measurement errors or model approximations.

Random Forest Regressor (RF): As an ensemble method, RF reduces overfitting by averaging multiple decision trees, making it robust against outliers and noise in the data [33].

XGBoost Regressor (XGB): Known for its speed and performance, XGB efficiently handles large datasets and complex patterns, making it ideal for modeling the intricate effects of technical modifications on ship performance [34].

Shallow Neural Network (SNN): SNNs can approximate complex, non-linear functions and capture intricate patterns in the data through their layered architecture, even with a relatively simple network structure [35].

The first dataset for ML training originated from physics-based calculations (Section 2.1, Appendix C), which included operational parameters (e.g., Pe, V, η O) and FC/CO₂ values for all scenarios at speeds of 9–15 knots. The augmented dataset was split into training and testing sets using an 80–20 (80% for training and 20% for testing) ratio, randomly partitioned to ensure representative sampling. This approach ensured sufficient data for learning while retaining a subset for evaluating predictive capabilities. The training and evaluation split was used to balance the data; however, future studies could employ k -fold cross-validation (e.g., 5-fold) to further reduce potential biases from data splitting and improve the model's robustness.

The models received training using the expanded dataset, which included engine power (Pe), ship speed (V), and propeller efficiency (η O) features, along with MC aug-

mentation for improvement of robustness. The training dataset included all scenarios (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, and Combined) to support FC prediction and reduction goals, while covering FC values ranging from 103.77 kg/h for Advanced Propeller at 9 knots to 863.18 kg/h for Bulbous Bow at 15 knots. The scenarios based on physics-based calculations show optimized conditions with reduced FC where the Advanced Propeller reaches 729.31 kg/h and the combined reaches 771.04 kg/h at 15 knots, while the original reaches 814.84 kg/h. The models SVR, RF, and XGB may struggle to predict FC values below 61.41 kg/h at 8 knots because their learned patterns are limited to the 9–15 knot range. The MC simulations enhance predictions throughout this range yet fail to generate new minimum FC conditions. The uncertainty estimates from GPR provide a partial answer to the reliability of extrapolation predictions by showing results in Appendix B, Table A6, which tests model performance at 8 knots beyond the training data range. Future research should investigate additional low FC scenarios to improve extrapolation capabilities for optimal fuel efficiency.

To ensure model validity, the ML predictions were benchmarked against physics-based calculations derived from ITTC-recommended hydrodynamic formulas and propeller test data. These physics-based outputs provided the ground truth for both training and testing the ML algorithms, allowing for direct quantitative comparison of model performance across all operational scenarios.

2.3. Evaluation of Model Performance and Implementation

The training process used separate ML models for FC and CO₂ emissions because these objectives require different predictive approaches. The fixed emission factor (EF) of 3.114 kg CO₂/kg fuel (Equation (27)) creates a near-perfect correlation between FC and CO₂ emissions, but separate models provide flexibility to handle scenario-specific variations in operational conditions across the Original, Paint, Advanced Propeller, Fin, Bulbous Bow, and Combined scenarios.

The ML models (SVR, GPR, RF, XGB, SNN) were evaluated using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to assess predictive accuracy for FC and CO₂ emissions across all scenarios (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, Combined) [28,34]. These metrics quantify the difference between predicted and physics-based values, enabling a comprehensive comparison of model performance. Predictions were assessed before and after MC data augmentation. This process enhances model robustness by generating synthetic data points to simulate real-world variability and measurement uncertainties, as detailed in Section 2.2. MC augmentation involves adding controlled random noise ($\pm 5\%$ range) to key features such as engine power (P_e), ship speed (V), and propeller efficiency (η_O), expanding the dataset and improving generalization across diverse operational conditions. This process, previously referred to as model correction, significantly reduces prediction errors, as evidenced by lower MSE and RMSE values post-augmentation, particularly for XGB and GPR models, across all evaluated scenarios.

The models were evaluated based on their predictive accuracy and robustness across various scenarios. The XGB model demonstrated superior performance, effectively capturing complex, non-linear relationships between features and showing robustness to scenario variations, achieving near-zero MSE values (e.g., mean MSE of 3.50×10^{-8} across scenarios, Table A13). The models RF and GPR demonstrated overfitting or underfitting problems in particular cases, yet SVR and SNN faced challenges with maritime dataset complexity because their error metrics were high (SVR mean MSE of 6730.93, SNN mean MSE of 442.88, Appendix D, Tables A13 and A14), which shows their difficulties with non-linear interactions and dataset variability compared to XGB and GPR.

The novelty of the hybrid physics-ML approach can be justified by comparing the XGB model with physics-based features (e.g., Pe , V , ηO , V^2 , $Pd \times \eta H$) and MC augmentation to a conventional XGB model trained solely on raw operational data (e.g., Pe , V , ηO) without physics-derived features or MC augmentation. The hybrid model achieved significantly lower mean MSE (3.50×10^{-8} vs. 50.67) and RMSE (0.0001871 vs. 7.12) for FC predictions across all scenarios (Appendix D, Table A13), demonstrating enhanced accuracy due to physically informed features and robust data augmentation. This comparison underscores the hybrid model's ability to capture complex maritime dynamics, outperforming purely data-driven models that struggle with non-linear interactions and limited datasets.

2.4. Formulas and Calculations

The mathematical framework presented in this subsection facilitates a seamless integration with the hybrid methodology for physics-based calculations described in Section 2.1. The equations used for resistance, power, and emissions calculations were applied to all scenarios (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, Combined) and speed ranges (9–15 knots) to train the ML model (Section 2.2.K). Let $X = [x_1, x_2, \dots, x_m]$ be the original dataset with m samples and n features, including engine power (Pe), ship speed (V), thrust (T), hull efficiency (ηH), propeller efficiency (ηO), Pd , Pb , and engineered features (e.g., V^2 , V^3 , $Pd \times \eta H$) as described in Section 2.2. The corresponding target values $y = [y_1, y_2, \dots, y_m]$ represent FC or CO_2 emissions.

The augmented dataset X_{aug} and y_{aug} are constructed as:

$$X_{aug} = \{x_i\} \cup \left\{x_i^{(j)} \mid j = 1, 2, \dots, k\right\}_{i=1}^m \quad (6)$$

$$y_{aug} = \{y_i\} \cup \left\{y_i^{(j)} = y_i \mid j = 1, 2, \dots, k\right\}_{i=1}^m \quad (7)$$

where $k = 5$ is the number of synthetic samples per original data point. To initiate the calculations, the authors utilized formulas from the International Towing Tank Conference (ITTC) Recommended Procedures, which provide standardized methods for resistance and propulsion calculations in naval architecture [36].

The following formulas were employed for all speed ranges and scenarios:

1. *Conversion of Speed (V)*: Initially, the ship speed was converted to meters per second in knots.

$$V(\text{m/s}) = V(\text{knots}) \times 0.5144 \quad (8)$$

2. *Reynolds Number (Re)*: This dimensionless number characterizes the flow regime around the ship's hull, indicating whether the flow is laminar or turbulent.

$$Re = \frac{V \times L}{\nu} \quad (9)$$

V is the velocity in m/s, L is the ship's length, and ν is the kinematic viscosity.

3. *Frictional Resistance Coefficient (C_F)*: Represents frictional resistance due to water viscosity acting on the ship's hull surface. Calculated using the ITTC-1957 formula:

$$C_F = \frac{0.075}{(\log_{10}(Re) - 2)^2} \quad (10)$$

Different scenarios include adjustments to C_F to reflect efficiency changes, such as a 5% reduction in the Paint Efficiency Scenario.

4. *Viscous Resistance Coefficient (C_V)*: Accounts for the total viscous resistance, including frictional resistance and form effects due to the ship's shape.

$$C_V = (1 + k) \times C_F \quad (11)$$

where k is the form or model factor, representing additional viscous losses (taken as 0.27 in this study).

5. *Wave Resistance Coefficient* (C_W): Obtained from scenario-specific data, accounting for the resistance due to wave generation. Values for C_W are provided in Appendix A, Table A3.

6. *Total Resistance Coefficient* (C_T):

$$C_T = C_V + C_W \quad (12)$$

7. *Total Resistance* (R_T): The total resistance exerted by the water is:

$$R_T = C_T * \frac{\rho}{2} \times S \times V^2 \quad (13)$$

where " ρ " is the seawater density, S is the wetted surface area, and V is the ship's speed.

8. *Effective Power* (P_e):

$$P_e = R_T \times V \quad (14)$$

9. *Advance Speed* (V_A):

$$V_A = V \times (1 - w) \quad (15)$$

where " w " is the wake fraction.

10. *Thrust Required* (T_{req}):

$$T_{req} = \frac{R \times T}{(1 - t)} \quad (16)$$

where " t " is the thrust deduction factor.

By utilizing the data from Table A3 in Appendix A, the authors generate charts of the advance coefficient (J) versus the thrust coefficient (K_T) and torque coefficient (K_Q) for both the original and advanced propellers. These charts were used to derive equations representing each graph, essential for calculating propeller performance at different operating conditions.

Figures illustrate the relationships between J and K_T , and between J and K_Q for both propeller types are provided in Appendix B. Figures A1 and A2 show the J - K_T and J - K_Q charts for the original propeller, respectively. In contrast, Figures A3 and A4 present the corresponding charts for the advanced propeller. The equations representing the relationships between J and K_T , and between J and K_Q were derived using polynomial regression from the charts. For the original propeller, these equations are as follows:

11. *Thrust coefficient* (K_T):

$$K_T = -0.1417J^2 - 0.2161J + 0.3115 \quad (17)$$

12. *Torque coefficient* (K_Q):

$$K_Q = -0.2320J^2 - 0.1428J + 0.3750 \quad (18)$$

On the other hand, for the advanced propeller, the equations are:

13. *Thrust coefficient* (K_T):

$$K_T = -0.1491J^2 - 0.2276J + 0.3279 \quad (19)$$

14. *Torque coefficient* (K_Q):

$$K_Q = -0.2211J^2 - 0.1359J + 0.3572 \quad (20)$$

Furthermore, the following equations were used to calculate the thrust and torque coefficients at various advanced coefficients, enabling the determination of propeller performance for each scenario.

15. *Advance Coefficient (J)*: Calculated to find the operating point of the propeller at a given speed.

$$J = \frac{V_A}{n \times D} \quad (21)$$

where n is the propeller rotation speed (revolutions per second), and D is the propeller diameter.

16. *Propeller Thrust (T)*: Calculated using the thrust coefficient.

$$T = K_T \times \rho \times n^2 \times D^4 \quad (22)$$

17. *Hull Efficiency (η_H)*:

$$\eta_H = \frac{1 - t}{1 - w} \quad (23)$$

18. *Propeller Open Water Efficiency (η_O)*:

$$\eta_O = \frac{J}{2\pi} \times \frac{K_T}{K_Q} \quad (24)$$

19. *Delivered Power (P_D)*:

$$P_D = \frac{P_e}{\eta_H \times \eta_O \times \eta_{RR}} \quad (25)$$

where η_{RR} is the relative rotative efficiency.

20. *Brake Power (P_B)*:

$$P_B = \frac{P_D}{\eta_{TR}} \quad (26)$$

where η_{TR} is the transmission efficiency.

$$\text{Loss (\%)} = 1 - \text{efficiency (\%)}$$

21. *Fuel Consumption (FC)*:

$$FC = \text{BSFC} \times P_B \quad (27)$$

where Brake Specific Fuel Consumption (BSFC) is considered 200 (g/kW-h). As mentioned in Section 2.1, in practice, marine engine BSFC fluctuates based on load, typically increasing at low loads due to combustion inefficiencies and auxiliary demand. Nevertheless, for modeling simplicity and comparability, this study assumes a constant BSFC of 200 g/kWh—representative of efficient load conditions (75–85% MCR). This allows isolating the effects of hydrodynamic and technical modifications on fuel demand while acknowledging that real-world variability may require further consideration in future work.

22. *CO₂ emissions*:

$$\text{CO}_2 \text{ (kg)} = FC \times 3.114 \quad (28)$$

where 3.114 kg CO₂/kg fuel is the EF for Heavy Fuel Oil (HFO), representing the amount of CO₂ emitted per kilogram of fuel consumed. This factor is based on the carbon content

of HFO and the stoichiometry of the combustion process, as specified by the IMO [37]. It accounts for the complete combustion of the fuel, where the carbon in the fuel combines with oxygen to form CO₂. Using this standardized EF ensures consistency in calculating and comparing CO₂ emissions across different vessels and operational scenarios.

3. Results

The research findings from experiments on technical modifications (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, Combined) for FC and CO₂ emissions reduction in a sample oil tanker (Appendix A, Table A1) and development of a reliable hybrid physics-based ML model for accurate predictions, extensible to other oil tankers. The primary objectives were to identify the optimal scenario for FC and CO₂ reduction and to develop a reliable ML model for predictive accuracy under various operational conditions. The experiments were performed at a speed range of 9 to 15 knots, involving physics-based calculations of FC and CO₂ emissions (Appendix C) and training of ML models (SVR, GPR, RF, XGB, SNN) using an 80–20 train–test split, as described in Section 2.2.

The results were validated by comparing ML predictions with physics-based calculations, using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to assess accuracy across all scenarios, as detailed in Section 3.5. The XGB model demonstrated the best predictive accuracy, while the Advanced Propeller scenario exhibited the most substantial FC reduction, followed by the Combined scenario, indicating significant potential for CO₂ emission reductions. The MC data augmentation improved the model's generalizability, as discussed in Section 2.2. The extrapolation performance at 8 knots, relevant for minimal FC, is presented in Appendix B, Table A6, further validating the model's robustness. The detailed physics-based calculations, including resistance coefficients and adequate power, are provided in Appendix C.

3.1. Hydrodynamic Parameter Modifications

The scenarios modeled modifications to hydrodynamic parameters affecting ship resistance and propulsion efficiency, as detailed below:

- *Frictional Resistance Coefficient (CF)*: Frictional Resistance Coefficient (CF) determines frictional resistance ($R_{t_f} = CF \cdot (\rho/2) \cdot S \cdot V^2$) where $\rho = 1025 \text{ kg/m}^3$, $S = 2350 \text{ m}^2$, V is speed. The Paint Efficiency Scenario simulated a 5% CF reduction through advanced anti-fouling coatings that decrease hull surface roughness.
- *Wave Resistance Coefficients (CW)*: Wave Resistance Coefficients (CW) define the resistance resulting from wave formation ($R_{t_w} = CW \cdot (\rho/2) \cdot S \cdot V^2$). The Bulbous Bow Scenario used CW values ranging from [0.444, 0.448, 0.495, 0.538, 0.574, 0.623, 0.684, 0.829, 1.027, 1.786] $\times 10^{-3}$ for speeds between 9–15 knots and extended the waterline length to 103 m and increased the wetted surface area to 2400 m² to represent changes in hull shape.
- *Thrust and Wake Fraction*: Thrust (T) and wake fraction (w) affect P_d and hull efficiency ($\eta_H = (1 - t)/(1 - w)$), where (t) is the thrust deduction factor). The Fin Installation Scenario assumed a 2% thrust increase and 4% wake fraction improvement to enhance flow to the propeller.
- *Open Water Efficiency*: Propeller open water efficiency ($\eta_O = (J/2\pi) \cdot (K_t/K_q)$), where J is the advance coefficient, K_t and K_q are thrust and torque coefficients, as detailed in Appendix A impacts P_d . The Advanced Propeller Scenario simulated an enhanced η_O curve to represent modern propeller engineering.
- *Combined Modifications*: The Combined Paint and Bulbous Bow Scenario integrated Paint's 5% CF reduction with Bulbous Bow's CW values, waterline length, and wetted surface area changes to assess synergistic effects.

It will be relevant to consider that the frictional resistance reduction modeled in this scenario assumes an optimal, freshly coated hull surface. In real conditions, the effectiveness of antifouling paint tends to decline over time, typically within 3 to 6 months, due to marine biofouling and environmental exposure (Notti et al. 2019) [38]. As such, the long-term impact of hull coatings on fuel consumption requires consideration of performance degradation over the operational cycle.

3.2. Scenario Comparison Results

The Combined Paint and Bulbous Bow Scenario achieved FC reductions at every speed compared to single modifications, with cuts between 5.23% at 9 knots (108.59 kg/h) and 5.37% at 15 knots (771.04 kg/h) compared to the Original Scenario. These percentage reductions are calculated relative to the Original Scenario at each corresponding speed. The slightly greater savings at higher speeds reflect the increased influence of wave-making resistance, which the bulbous bow helps to mitigate more effectively at higher Froude numbers.

The Combined Scenario recorded 260.12 kg/h of FC at 12 knots, which was lower than the 263.48 kg/h (Paint Efficiency), 284.26 kg/h (Bulbous Bow), and 276.27 kg/h (Original) values. The Fin Installation and Advanced Propeller Scenarios decreased FC, but their effects were less significant than those of other modifications. The Combined Scenario demonstrated a strong negative relationship ($r = -0.99$) between ship speed and relative FC reduction, which indicates more significant efficiency gains at higher speeds. The combined effect of reduced frictional and wave-making resistance demonstrates how integrated hydrodynamic improvements can create synergistic benefits. Detailed FC comparisons across speeds appear in Table A4 and Figure A8 of Appendix B, while Figure A9 shows CO₂ emissions.

3.3. Graphical Results

Graphical analysis, shown in Figure 2a, revealed that total resistance increases with ship speed across all scenarios, driven by hydrodynamic drag. Efficiency modifications showed notable benefits: the Paint (5%) scenario achieved the lowest resistance, highlighting reduced drag from enhanced hull coatings.

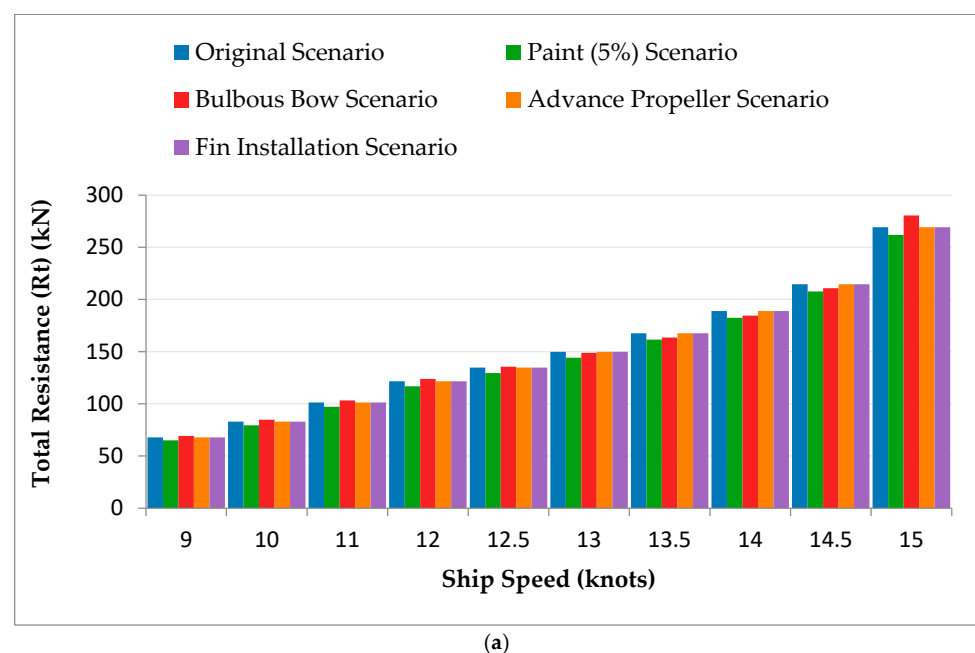


Figure 2. Cont.

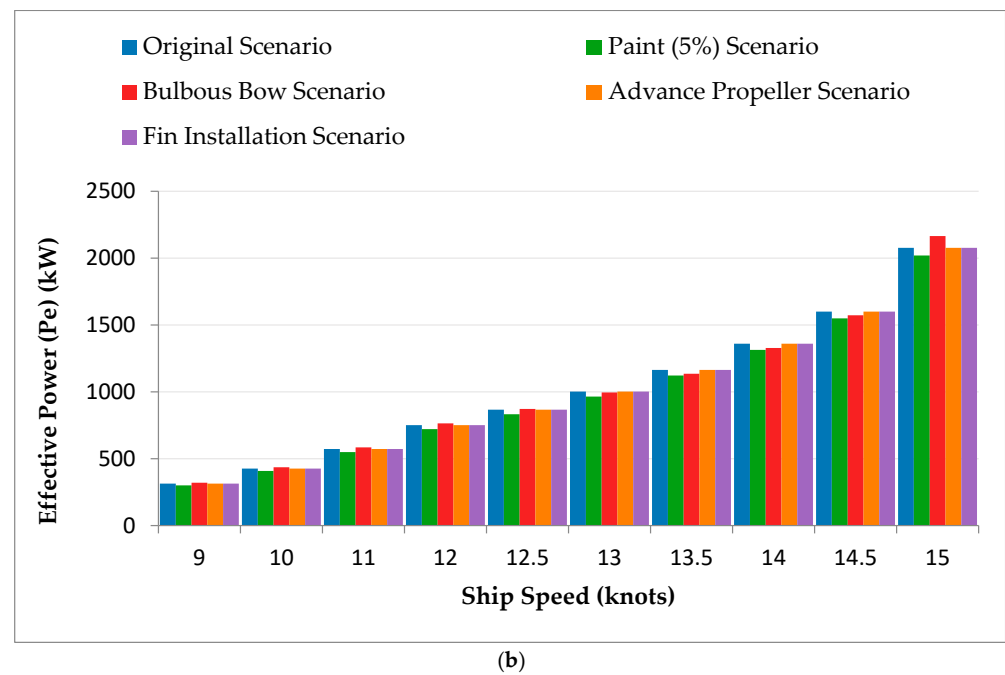


Figure 2. (a). Total Resistance (R_t) vs. Ship Speed for Different Scenarios (Excl. Combined). (b). Adequate Power (P_e) vs. Ship Speed for Different Scenarios (Excl. Combined).

The Advanced Propeller and Fin (2–4%) scenarios followed similar resistance trends to the baseline but with noticeable reductions. The Bulbous Bow scenario showed higher resistance at low speeds but improved efficiency at higher speeds, aligning with its established performance advantages. Figure 2b highlights effective power (P_e) requirements across scenarios, with the Original Scenario demanding the most power. The Paint (5%) and Advanced Propeller Scenarios demonstrated substantial reductions in power needs. Although the Bulbous Bow Scenario initially required more power due to increased resistance, it improved at higher speeds as wave resistance decreased.

Figure 3 illustrates the thrust required (T_{req}) across various scenarios, reflecting trends in resistance. The Paint (5%) Scenario showed the lowest T_{req} due to reduced hull resistance, while the Advanced Propeller Scenario minimized thrust needs through optimized performance. The Fin (2–4%) Scenario also reduced T_{req} , enhancing propulsion efficiency. The Bulbous Bow Scenario required the highest thrust at lower speeds due to increased wet surface area. However, its thrust demand decreased relative to the Original Scenario at higher speeds, reflecting benefits of wave resistance.

The Bulbous Bow scenario required the highest thrust due to its increased wetted area, while the Advanced Propeller scenario minimized thrust needs through optimized performance. The Paint (5%) scenario also showed reduced thrust demands compared to the original, highlighting the effectiveness of improved hull coatings. These graphical results indicate that different modifications have a significant impact on the ship's hydrodynamic performance. Scenarios focusing on drag reduction (e.g., Paint (5%) and Advanced Propeller) provided the most direct improvements in resistance, power, and thrust requirements. In contrast, the Bulbous Bow scenario shows benefits primarily at higher speeds.

The comparison between R_t , P_e , and T_{req} for Original, Paint (5%), Bulbous Bow, and Combined Paint and Bulbous Bow Scenarios is presented in Figures A5–A7 of Appendix B. The Combined Scenario had the lowest R_t , P_e , and T_{req} at all speeds (e.g., at 12 knots, $R_t = 116.21$ kN, $P_e = 717.23$ kW, $T_{req} = 153.07$ kN, compared to 121.61 kN, 750.69 kW, 160.02 kN for the Original). This synergy, combining Paint's frictional resistance reduction

with Bulbous Bow's wave resistance optimization, highlights the potential for integrated modifications to enhance efficiency, particularly at higher speeds where wave-making resistance dominates.

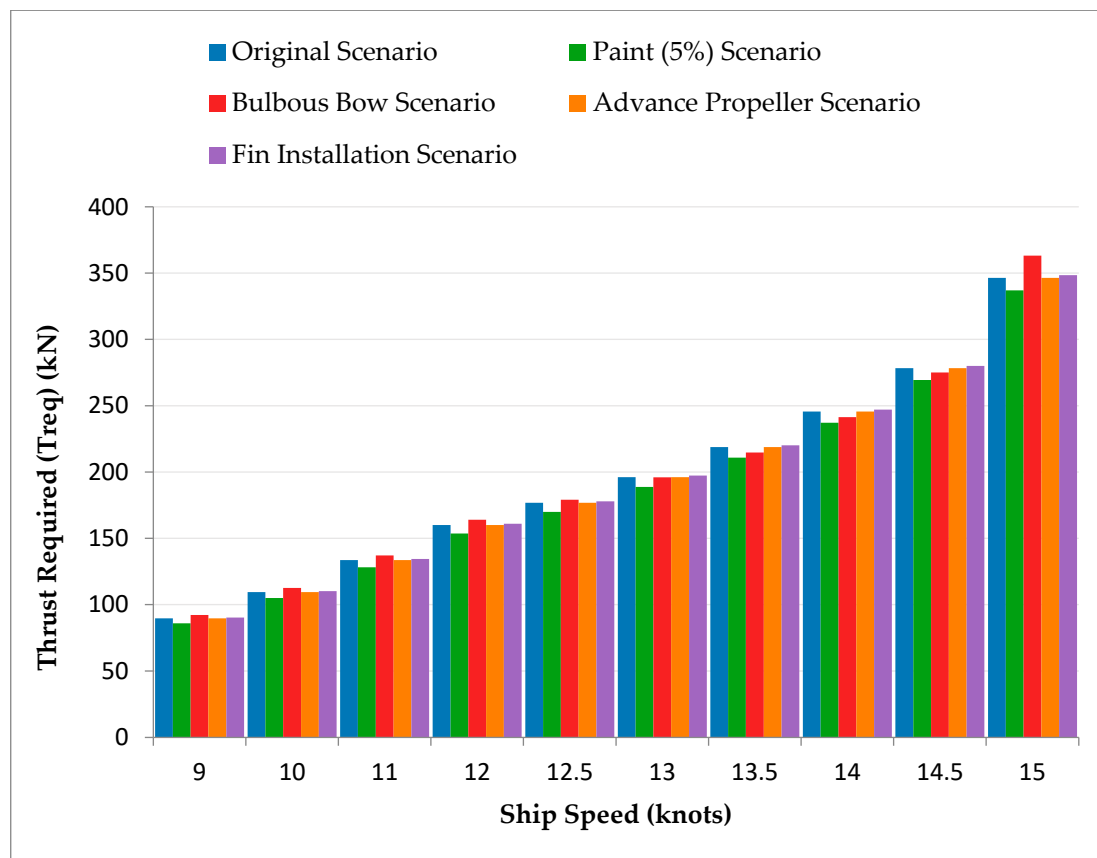


Figure 3. Thrust Required (Treq) vs. Ship Speed for Different Scenarios (Excl. Combined).

While the Combined scenario consistently reduces fuel consumption across all speeds, the relative gain at 15 knots is modest. This indicates that although wave resistance becomes more significant at higher speeds, the synergistic effect of the combined modifications produces steady rather than sharply increasing benefits.

3.4. Evaluation of Technical Modifications Before Machine Learning

Based on the calculation and analysis presented in the previous section, including the graphical results depicted in Figure 2a,b and Figure 3, the baseline analysis (Original Scenario) revealed high energy demands and environmental impact, with Pd reaching 1174.59 kW at 90 rpm and FC at 352.99 kg/h, resulting in significant CO₂ emissions. Comparatively, the Paint (5%) Improvement Scenario reduced hull resistance, leading to decreased FC (276.26 kg/h at 12 knots) and Pd (1211.81 kW), showcasing enhanced energy efficiency. Similarly, the Advanced Propeller Design improved hydrodynamic efficiency, increasing propeller efficiency (η_O) from 0.464 to 0.579 at 12 knots, reducing Pb requirements.

The Fin (2–4%) Scenario demonstrated drag reduction, lowering thrust requirements to 160.02 kN at 12 knots and improving hull efficiency (η_H). The Bulbous Bow Scenario optimized flow at the bow, achieving significant efficiency gains, with Pd dropping to 1174.59 kW and FC to 267.78 kg/h at 12 knots. The Combined Paint and Bulbous Bow Scenario further reduced FC to 260.12 kg/h at 12 knots, demonstrating synergistic efficiency

gains. These modifications highlight the potential for reduced energy use and emissions through targeted design enhancements.

3.5. Comparative Analysis of Modifications

Regarding comparison scenarios related to the research, FC and CO₂ emissions showed significant reductions in all modified scenarios compared to the baseline. The Paint Improvement scenario effectively lowered both metrics by reducing hull resistance. The Advanced Propeller and Fins scenarios improved efficiency, consistently lowering Pb requirements. Among all modifications, the Bulbous Bow proved the most effective, achieving consistent reductions in FC and emissions across all ship speeds. Figure 4a shows FC comparisons in different scenarios, and Figure 4b demonstrates a comparison of CO₂ emissions between different scenarios as follows:

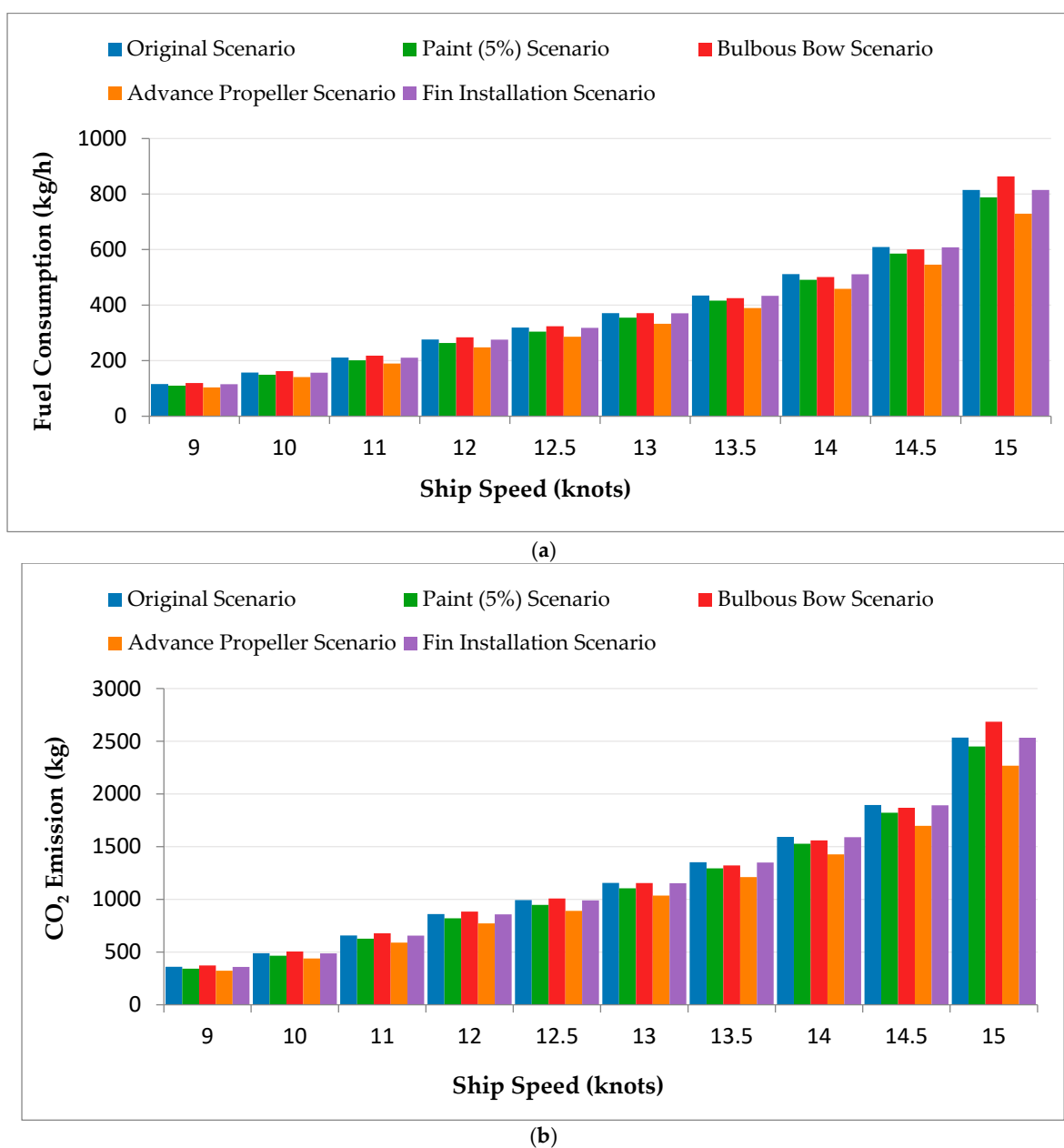


Figure 4. (a) Comparative FC Trends for Original and Modified Scenarios (Excl. Combined). (b) CO₂ Emission Trends Across Scenarios (Excl. Combined).

The Combined Paint and Bulbous Bow Scenario achieved consistent FC reductions at every speed point compared to single modifications, with cuts between 5.23% at 9 knots (108.59 kg/h) and 5.37% at 15 knots (771.04 kg/h) compared to the Original Scenario. The Combined Scenario produced 260.12 kg/h of FC at 12 knots, which was lower than the 263.48 kg/h (Paint Efficiency), 284.26 kg/h (Bulbous Bow), and 276.27 kg/h (Original). The Fin Installation and Advanced Propeller Scenarios decreased FC, but their effects were less significant. The Combined Scenario demonstrated a strong negative correlation ($r = -0.99$) between ship speed and relative FC reduction, indicating that efficiency gains were more significant at higher speeds. The combined effect of reduced frictional and wave-making resistance demonstrates how integrated hydrodynamic improvements can work together to achieve better results. The detailed FC comparisons across speeds are presented in Table A4 and Figure A8 of Appendix B, and CO₂ emissions are illustrated in Figure A9.

Finally, it is pertinent to mention that the accuracy of the ML models was evaluated by comparing their predictions with independently computed physics-based values, serving as a validation baseline. This comparison confirmed that the models—particularly XGB and GPR—achieved high agreement with theoretical predictions, supporting the robustness of the hybrid framework.

3.6. Scenario-Specific Performance Insights

The efficiency gains across ship speeds (9 to 15 knots) are illustrated in Figure 5a,b, which show the percentage reduction in FC and thrust required (Treq) relative to the Original Scenario. Among all configurations, the Advanced Propeller achieved the largest FC reduction, ranging from 4.9% to 6.2%, due to its higher open water efficiency ($\eta_o = 0.579$), which represents a 24.78% improvement over the baseline propeller ($\eta_o = 0.464$). This improvement is calculated as follows: $(0.579 - 0.464)/0.464 \times 100$.

The Combined Scenario (Paint + Bulbous Bow) followed, yielding consistent FC reductions of 3.3% to 4.9%, while the Paint (5%) Scenario achieved reductions of 10.3% to 10.5% across all speeds. Although the Paint Scenario models only a 5% reduction in the frictional resistance coefficient (CF), its impact on fuel consumption is amplified at higher speeds where resistance increases non-linearly.

In contrast, the Fin Installation Scenario produced negligible FC savings (0.06% to 0.26%). The Bulbous Bow Scenario exhibited mixed results: at low speeds (e.g., 9 knots), fuel consumption increased by 3.36% due to greater wetted surface area and added resistance. However, at mid-range speeds (e.g., 13.5 knots), it reduced FC by 2.17%, demonstrating its benefit in mitigating wave resistance. At 15 knots, however, fuel consumption increased again by 5.93%, indicating diminishing returns at higher speeds.

Moreover, Figure 5b presents the Treq changes. The Combined Scenario showed the greatest Treq reduction (2.7% to 4.2%), followed by the Advanced Propeller (3.0% to 4.8%). The Paint Scenario yielded no change in Treq (0%), while the Fin Scenario slightly increased Treq by 0.58% to 0.65%. The Bulbous Bow Scenario increased Treq at lower speeds (e.g., 2.81% increase at 9 knots) but produced reductions at higher speeds (e.g., 1.83% decrease at 13.5 knots and 4.83% decrease at 15 knots), reflecting its speed-dependent hydrodynamic performance.

The efficiency of open water (η_o) plays a crucial role, especially in the Advanced Propeller Scenario, where higher η_o reduces Pd and FC, especially at higher speeds. However, η_o remains constant for Paint, Bulbous Bow, Fin, and Combined Scenarios ($\eta_o = 0.464$), so η_o increase is excluded from Figure 5a,b to avoid uninformative zero bars, with FC and Treq reductions providing more precise insights. These modifications show that hydrodynamic improvements can reduce FC and CO₂ emissions, but their effects

depend on operating conditions. The Combined Scenario performs better than individual modifications, as explained in Section 3.2.

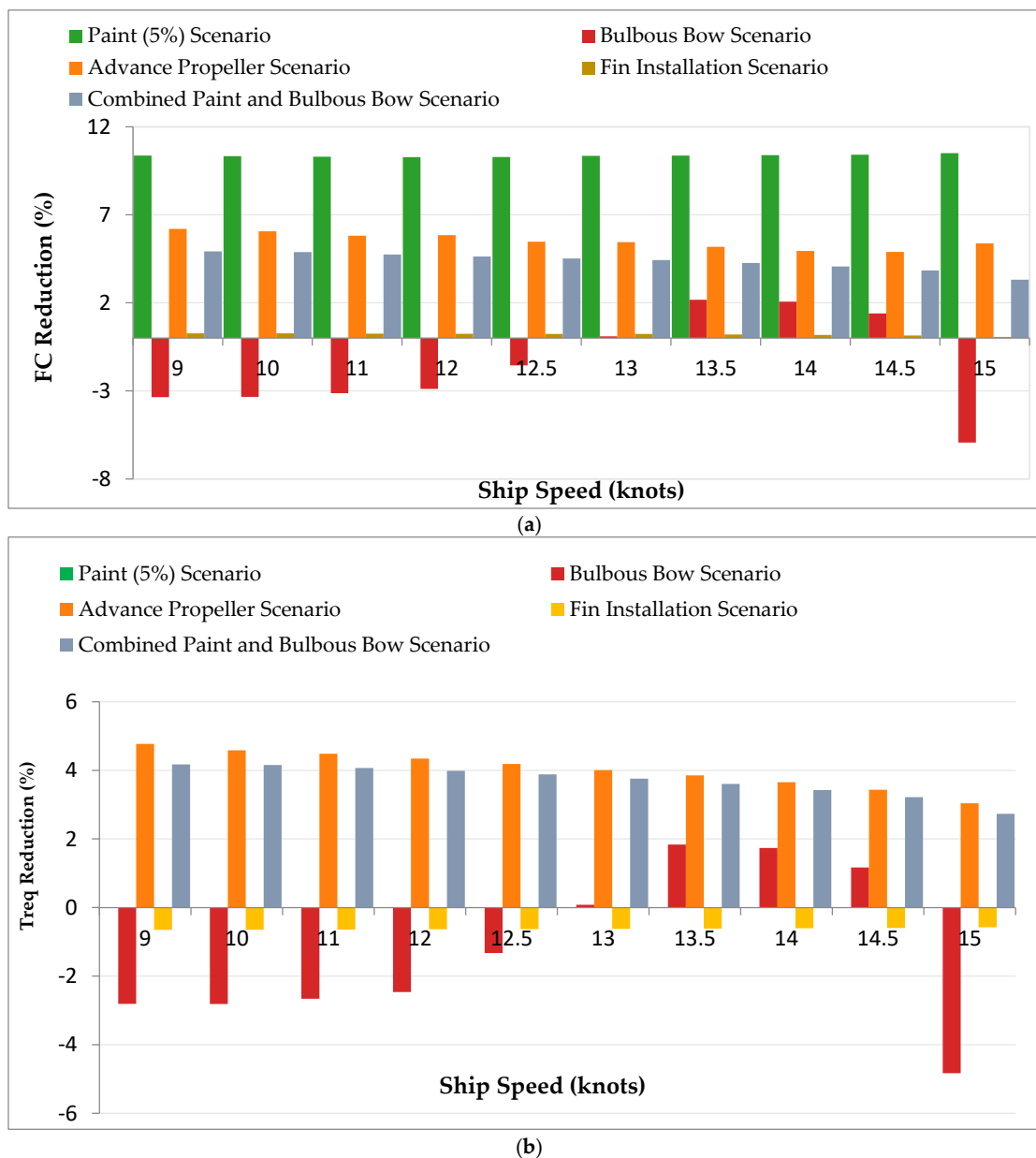


Figure 5. (a) FC Reduction Across Speeds. (b) Treq Reduction Across Speeds.

3.7. Comparative Analysis of Machine Learning Model Performance

The evaluation of ML models—Support Vector Regression (SVR), Gaussian Process Regression (GPR), Random Forest (RF), Extreme Gradient Boosting (XGB), and Neural Networks (NN)—takes place before and after MC simulations to assess their prediction capabilities for FC and CO₂ emissions across ship modification scenarios, including Paint, Advanced Propeller, and the Combined Scenario, which incorporates all optimizations. The selected graphs present the most important findings, while Table A12 in Appendix D provides detailed results for the original and paint scenarios and ML models. The following observations reveal the effects of applying MC simulation for dataset augmentation and its impact on model accuracy.

The XGB model generates FC predictions for the Combined Scenario, which are compared to the Original Scenario in Figure 6. XGB produced highly accurate predictions

for the 771.04 kg/h FC at 15 knots without MC simulation because it matched the actual value of 771.04 kg/h. The XGB model achieved near-perfect alignment after MC simulation with a prediction of 771.04 kg/h while demonstrating better fuel efficiency than the Original Scenario's 814.84 kg/h.

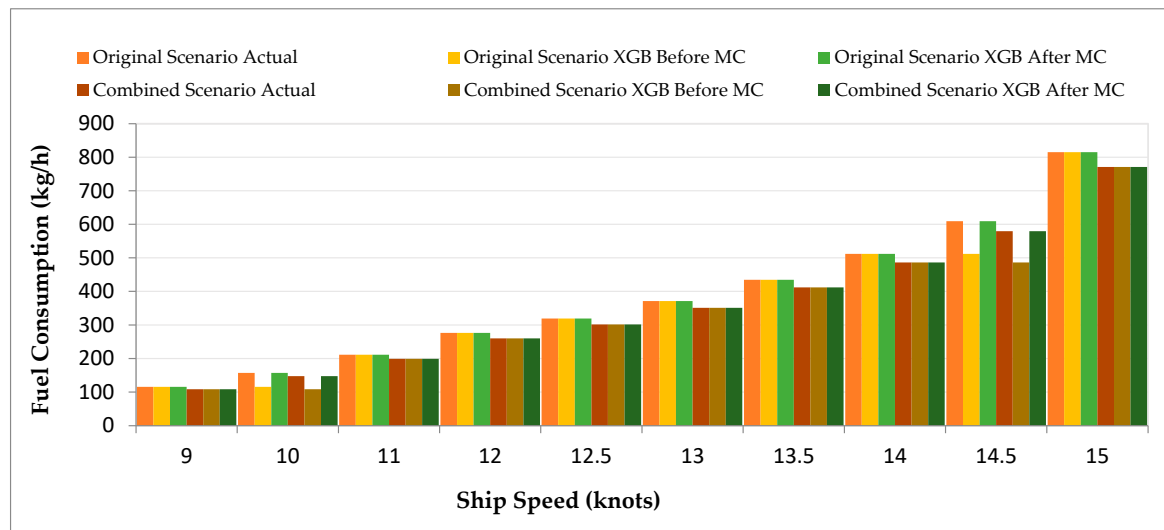


Figure 6. FC Comparison Before and After ML (XGB) and After ML with MC for Combined Scenario.

The GPR results for FC in the Advanced Propeller Scenario are shown in Figure 7. The original calculations showed better alignment with GPR than SVR before MC simulation (e.g., FC of 638.46 kg/h at 15 knots vs. actual 729.31 kg/h). The accuracy of GPR improved substantially after MC simulation to reach 633.07 kg/h, especially in cases such as the Advanced Propeller Coefficients, demonstrating GPR's capability to handle intricate data patterns.

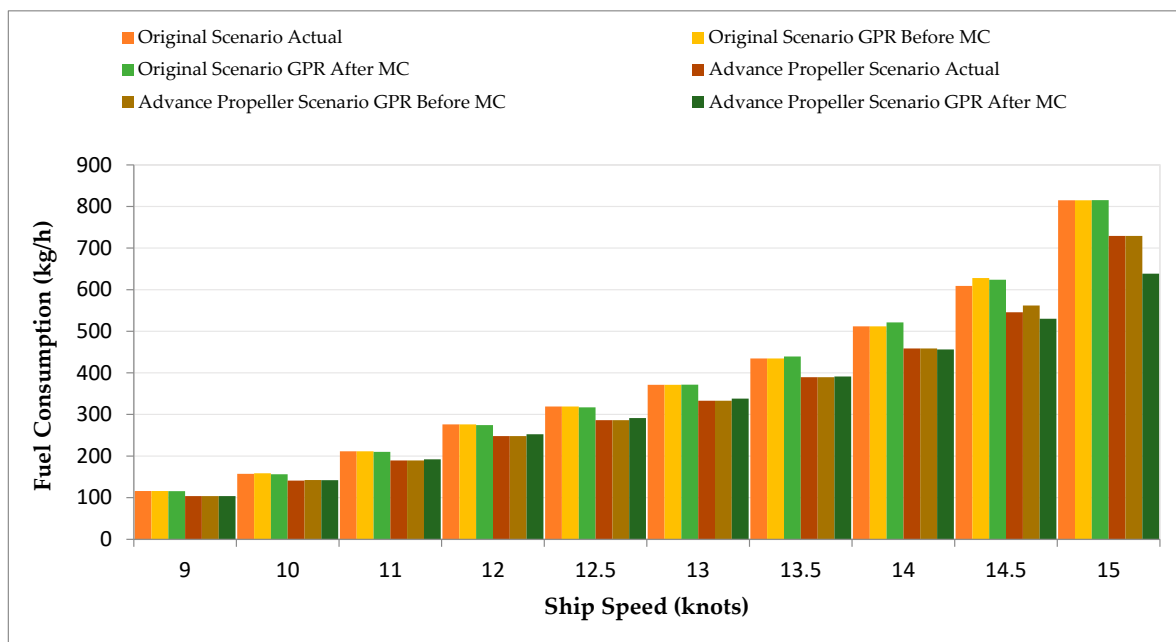


Figure 7. FC Comparison Before and After ML (GPR) and After ML with MC for Advanced Propeller Scenario.

The evaluation of RF through FC reveals its performance, as shown in Figure 8. The predictive performance of RF was acceptable before MC simulation, but it performed worse than GPR and XGB (e.g., 772.47 kg/h at 15 knots vs. 787.84 kg/h in Paint). MC simulation yielded moderate improvements in RF, resulting in predictions of 682.38 kg/h, indicating its potential for more straightforward applications.

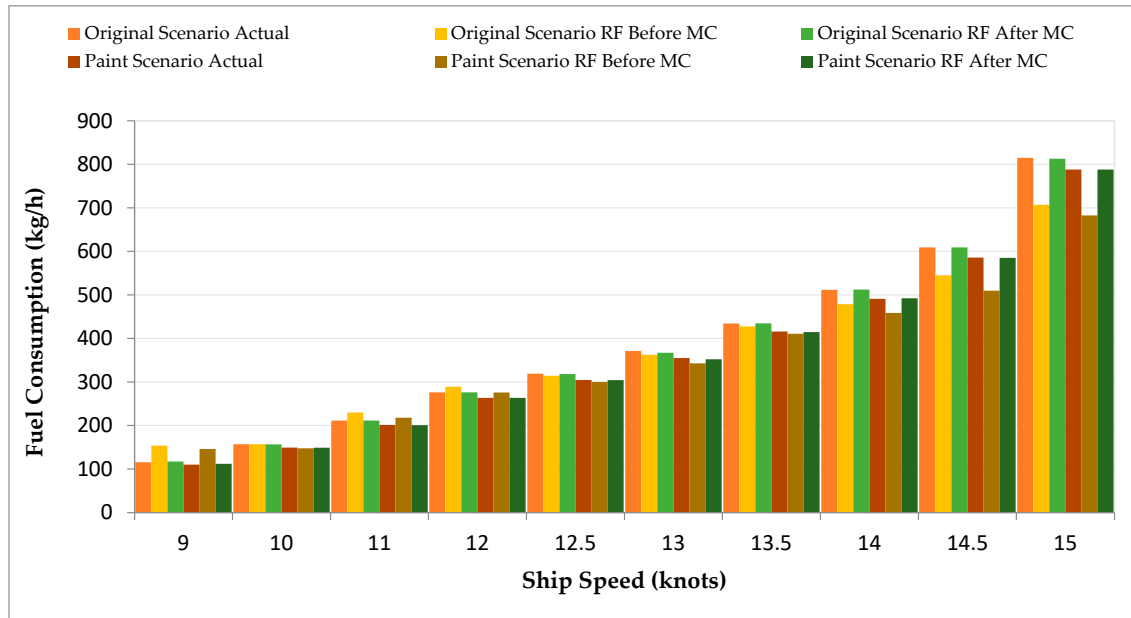


Figure 8. FC Comparison Before and After ML (RF) and After ML with MC for Paint Modification Scenario.

The Paint Modification Scenario in Figure 9 shows XGB as the top-performing model. XGB produced highly accurate predictions without MC simulation because its results matched the original values precisely (e.g., 788.36 kg/h at 15 knots vs. 787.84 kg/h). The model achieved near-perfect alignment in Paint Modifications and the Combined Scenario after undergoing MC simulation.

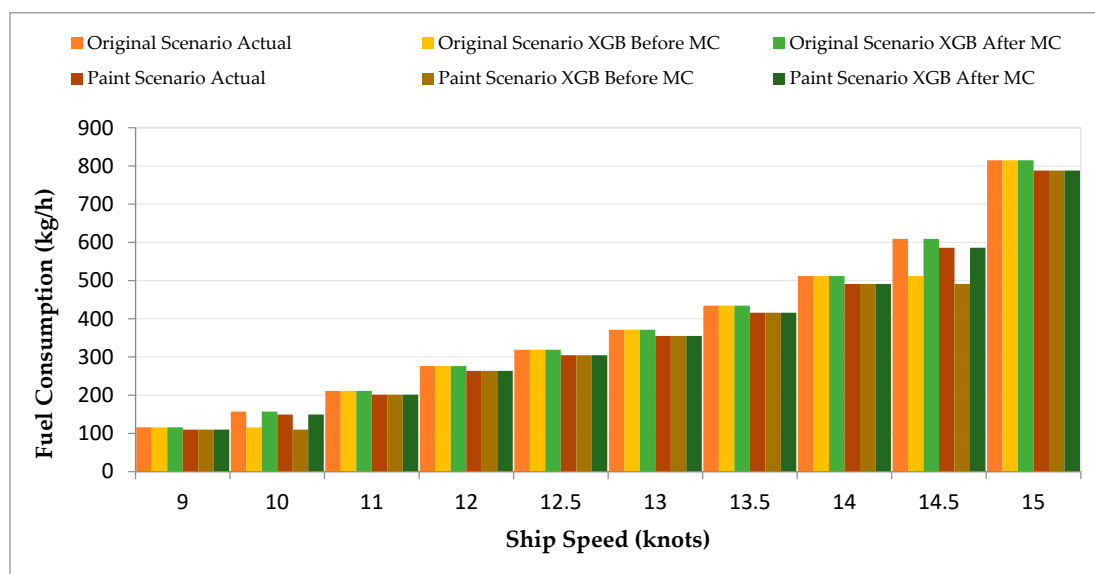


Figure 9. FC Comparison Before and After ML (XGB) and After ML with MC for Paint Modification Scenario.

The performance of NN is shown in Figure 10. NN showed some improvement after MC simulation, but its predictions were not consistent across different scenarios (e.g., FC of 806.87 kg/h at 15 knots vs. actual 771.04 kg/h in Combined). This variability indicates the need for more optimization and hyperparameter tuning when using NN for this application.

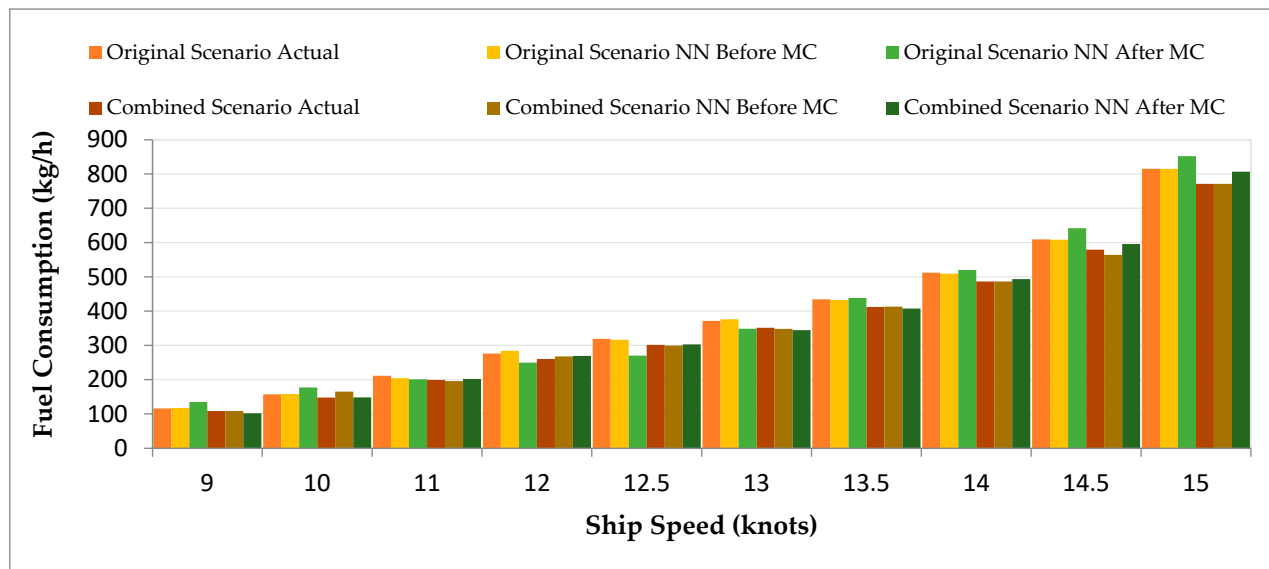


Figure 10. FC Comparison Before and After ML (NN) and After ML with MC for Combined Scenario.

Figure 11 shows the predicted FC using SVR. SVR predictions were far from the original physics-based calculations without MC simulation, especially at higher speeds (e.g., FC of 327.78 kg/h at 15 knots vs. actual 771.04 kg/h in Combined). However, after MC simulation, the augmented dataset helped to reduce these discrepancies but only to a limited extent (e.g., FC of 334.31 kg/h), indicating limited improvement in SVR's predictive capabilities.

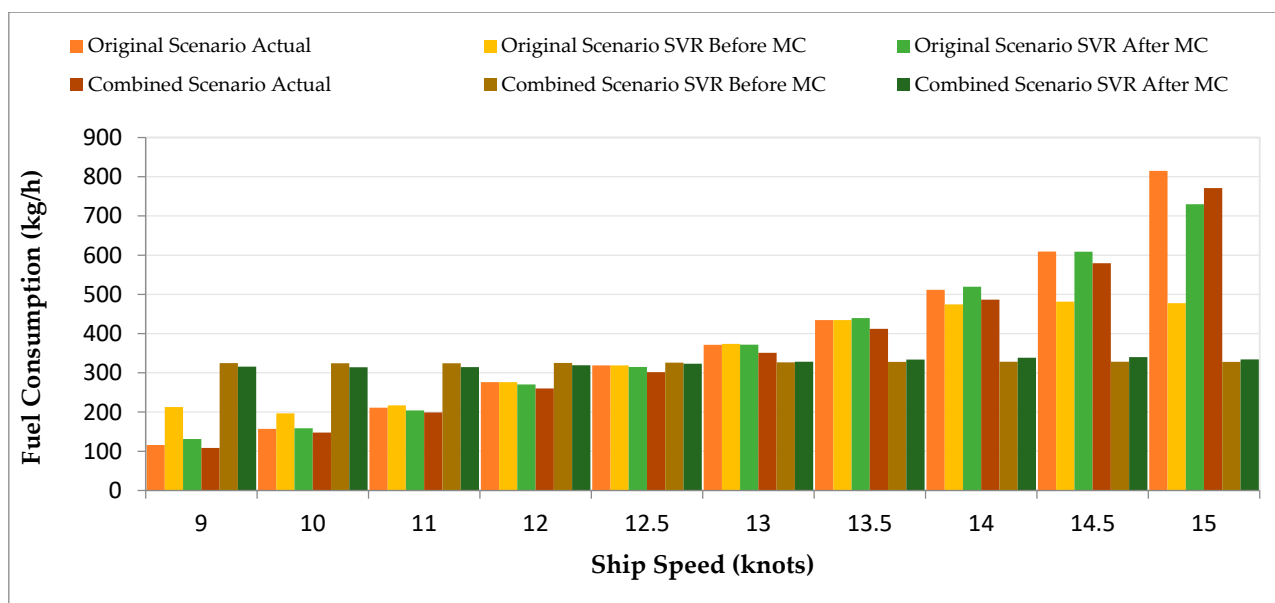


Figure 11. FC Comparison Before and After ML (SVR) and After ML with MC for Combined Scenario.

a. CO₂ Emissions Analysis

The Advanced Propeller Scenario CO₂ emission predictions from GPR are presented in Figure 12. The model provided accurate results before MC simulation (e.g., CO₂ 1949.72 kg at 15 knots vs. actual 2268.14 kg) and achieved major improvements after MC (e.g., CO₂ of 1968.83 kg), resulting in reliable emission predictions.

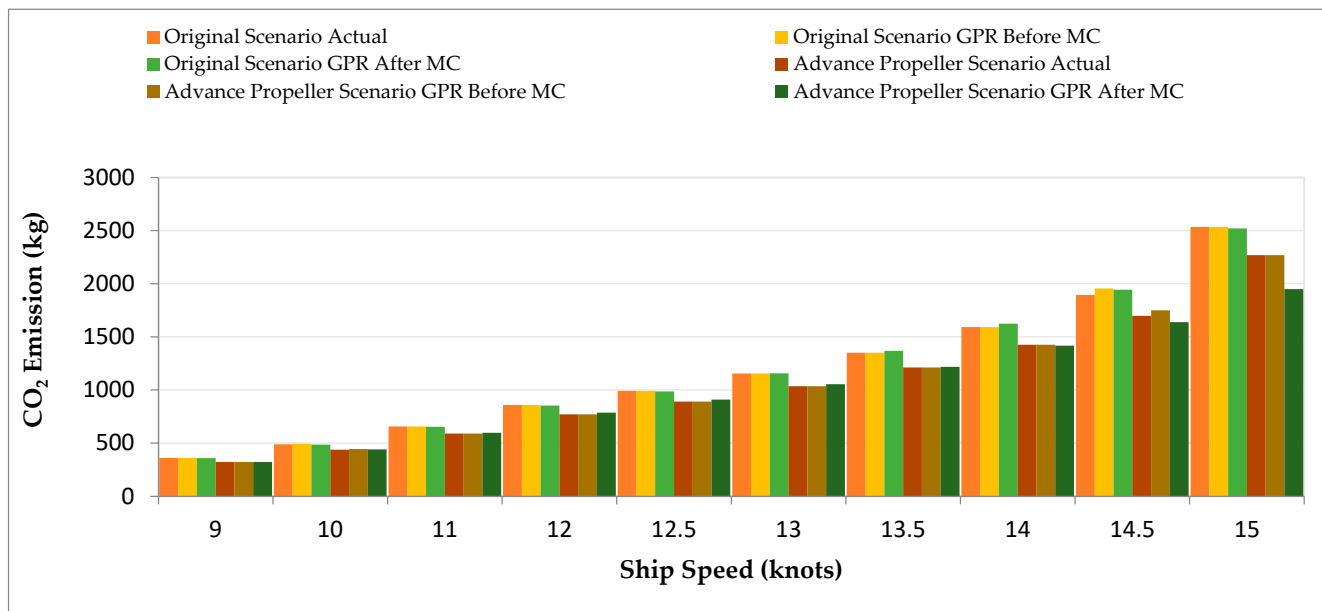


Figure 12. CO₂ Emission Comparison Before and After ML (GPR) and After ML with MC for Advanced Propeller Scenario.

The analysis of RF's CO₂ emission predictions appears in Figure 13. The model achieved better results after MC simulation, but its performance remained less reliable than GPR and XGB (e.g., CO₂ of 2122.20 kg at 15 knots vs. actual 2450.20 kg in Paint).

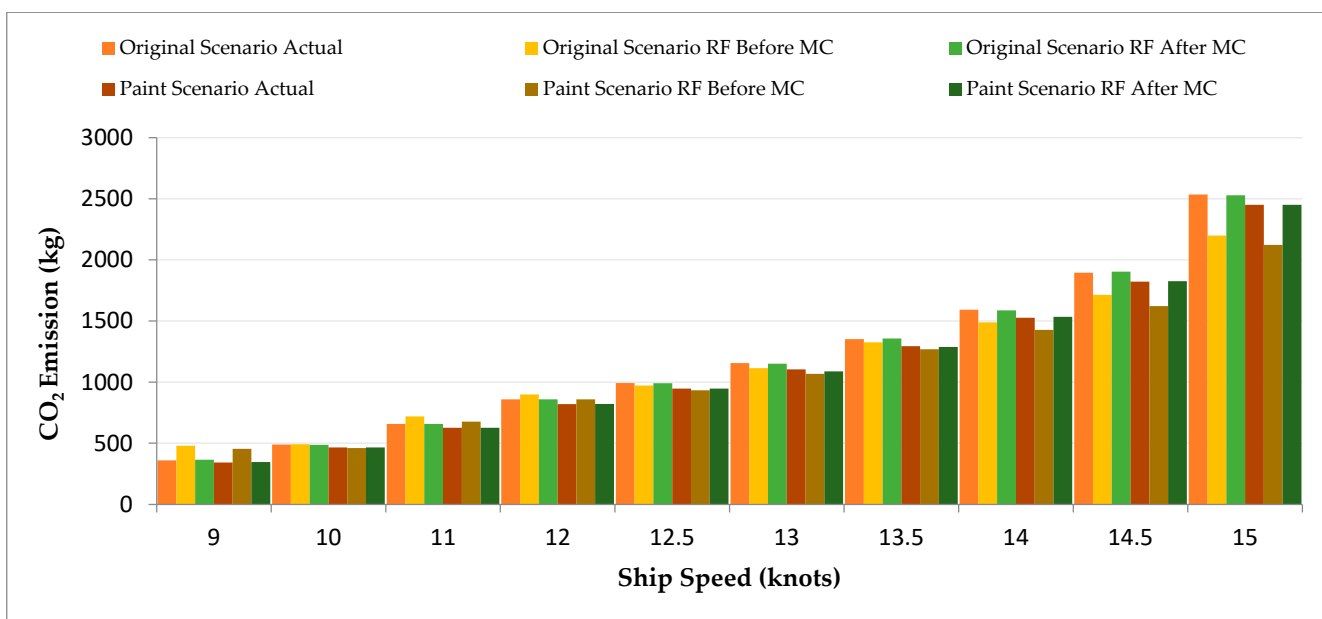


Figure 13. CO₂ Emission Comparison Before and After ML (RF) and After ML with MC for Paint Modification Scenario.

The XGB model demonstrates outstanding accuracy in its CO₂ predictions for the Combined Scenario, as shown in Figure 14 (e.g., CO₂ of 2397.93 kg at 15 knots vs. actual 2397.93 kg), representing a substantial decrease from the Original Scenario's 2534.16 kg. The model delivered superior results across all scenarios, especially when making exact predictions such as Paint Modifications (e.g., CO₂ of 2454.72 kg at 15 knots vs. actual 2450.20 kg post-MC).

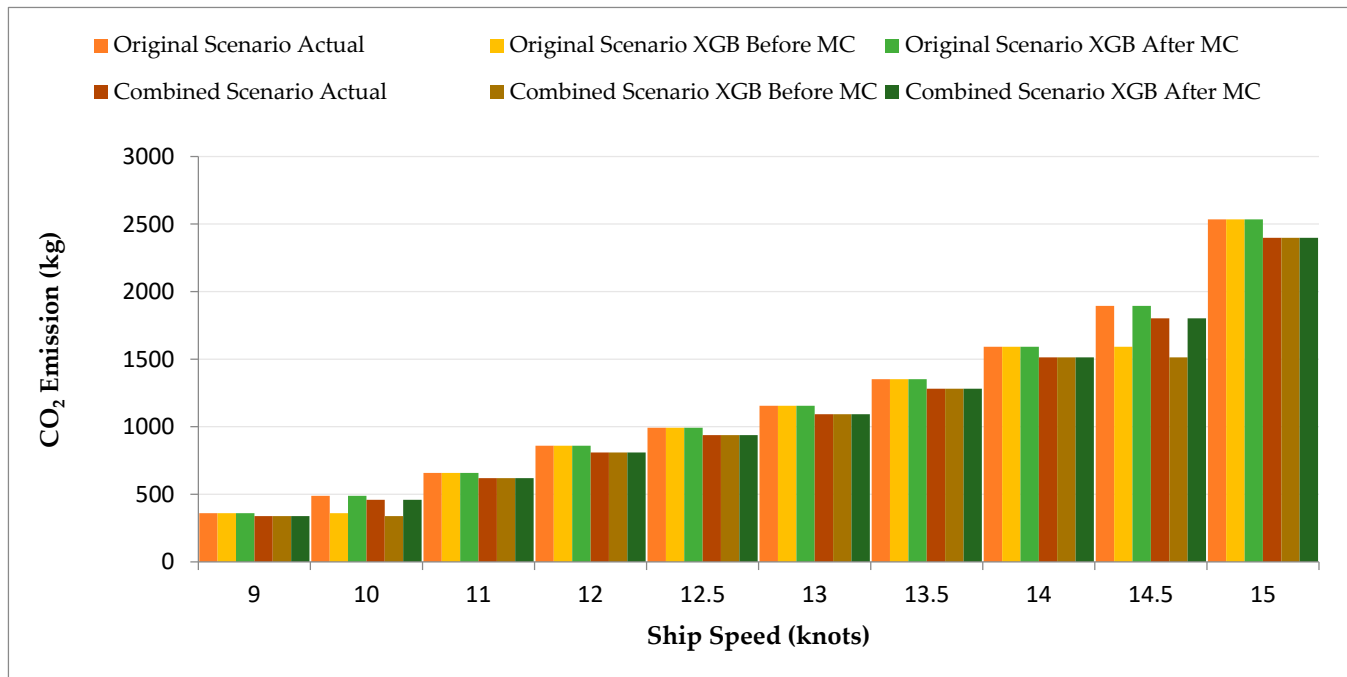


Figure 14. CO₂ Emission Comparison Before and After ML (XGB) and After ML with MC for Combined Scenario.

The SVR model failed to reach acceptable accuracy levels at both pre- and post-MC simulation stages (e.g., CO₂ of 1016.35 kg at 15 knots vs. actual 2397.93 kg before MC, improving to 1022.88 kg post-MC in Combined), indicating its unsuitability for such applications. NN's CO₂ predictions improved after MC simulation but remained inconsistent (e.g., CO₂ of 2510.53 kg at 15 knots vs. actual 2397.93 kg in Combined), indicating a need for further enhancements to achieve robust predictions. The detailed results of all simulations, including all scenarios (Original, Paint, Fin, Advanced Propeller, Bulbous Bow, and Combined) and ML models after MC sampling, are presented in Table A14 of Appendix D, providing a comprehensive reference for model performance.

MC simulation produced positive effects across all models, improving the match between predicted values and the original physics-based calculations. The XGB and GPR models proved to be the most reliable, producing accurate predictions for FC and CO₂ emissions, particularly in the Combined Scenario, demonstrating the potential of integrated ship modifications to enhance efficiency and reduce emissions. The strength of ML methods lies in their ability to capture non-linear relationships and adapt to dynamic operational conditions, as demonstrated by real-time input simulations (e.g., engine power: 870 kW, ship speed: 12.7 knots, Section 4.3), which physics-based models alone struggle to model accurately due to their reliance on static assumptions. In contrast, SVR and NN demonstrated limited effectiveness, even after the dataset was augmented through MC simulation. The following section delves deeper into quantitative evaluations using Mean Squared Error (MSE) plots to comprehensively assess the models' predictive accuracy and identify the most effective approach for specific scenarios.

The synthetic data points produced by MC simulations underwent validation through physics-based calculations of a selected subset of augmented samples. The SVR model evaluated one synthetic sample for each original data point to verify that the generated values for thrust (T), Pd, and FC stayed within the oil tanker specifications (Appendix A, Table A1). The Paint scenario at 14.5 knots receives validation through Table 2, which shows the original FC value against SVR model predictions before and after MC augmentation. The MC-augmented prediction shows substantial improvement, which verifies the physical accuracy of synthetic data. The validation samples for Advanced Propeller, Bulbous Bow, Combined, and Fin scenarios are presented in Appendix B, Table A5. The SVR model trained on the augmented dataset produced FC predictions with an R^2 score of 0.95 across all scenarios, demonstrating substantial predictive accuracy and low overfitting, as the model performs well on new test data.

Table 2. Sample Validation of Augmented Data for Paint Scenario (14.5 knots).

Data Types	Fuel Consumption (FC, kg/h)
Original (Physics-Based)	586
SVR (Before MC)	464
SVR (After MC)	581

b. Model Evaluation Based on MSE Metrics

SVR consistently showed high MSE and RMSE values before and after MC simulations. Despite significantly reducing errors post-simulation, SVR's values remained relatively high compared to other models, indicating its limited suitability for accurate predictions in this application. Specifically, in the “Bulbous Bow” scenario, RMSE for FC decreased from approximately 135.70 before MC to 33.99 after MC, demonstrating improvement but still lagging behind other models in terms of accuracy. The Combined Scenario showed similar patterns for SVR, with high MSE values before MC simulation that decreased significantly after MC but remained less competitive than the XGB and GPR models. This further underscores SVR's challenges in achieving high precision across diverse scenarios. Table 3 shows SVR's performance across all scenarios, emphasizing its relative lack of reliability. Mean MSE and RMSE values for FC predictions across all models are provided in Appendix D, Table A13.

Table 3. MSE Performance for FC and RMSE Performance for CO₂ Emissions of SVR Across Scenarios.

Scenario	MSE_FC_Before_MC	MSE_FC_After_MC	RMSE_CO ₂ _Before_MC	RMSE_CO ₂ _After_MC
Original	14,243.8	766.1	524.3	172.7
Paint	13,107.6	613.4	505.4	163.4
Advanced Propeller	10,150.3	623.4	457.2	148.2
Fin	14,247.4	773.8	524.3	182.7
Bulbous Bow	18,415.7	1155.6	559.2	215.1
Combined	39,046.2	614.1	617.4	610.7

XGB and GPR emerged as the most accurate models. XGB demonstrated low MSE values after MC simulations across all scenarios, even reaching zero MSE in some cases, indicating a perfect fit for those conditions.

In scenarios such as “Paint (5%)” and “Bulbous Bow,” XGB's RMSE values effectively became zero after MC simulations, highlighting its robustness and ability to handle variability. This is further described in Figure 15 and 16, which compares XGB's performance against GPR, RF, and SNN. GPR also demonstrated strong predictive capabilities, particularly in the “Advanced Propeller” scenario, where it outperformed XGB in terms of MSE

and RMSE. This suggests that GPR can be advantageous in specialized contexts with more complex underlying dynamics. Overall, GPR maintained low RMSE values, particularly in scenarios with increased complexity, demonstrating its flexibility and adaptability.

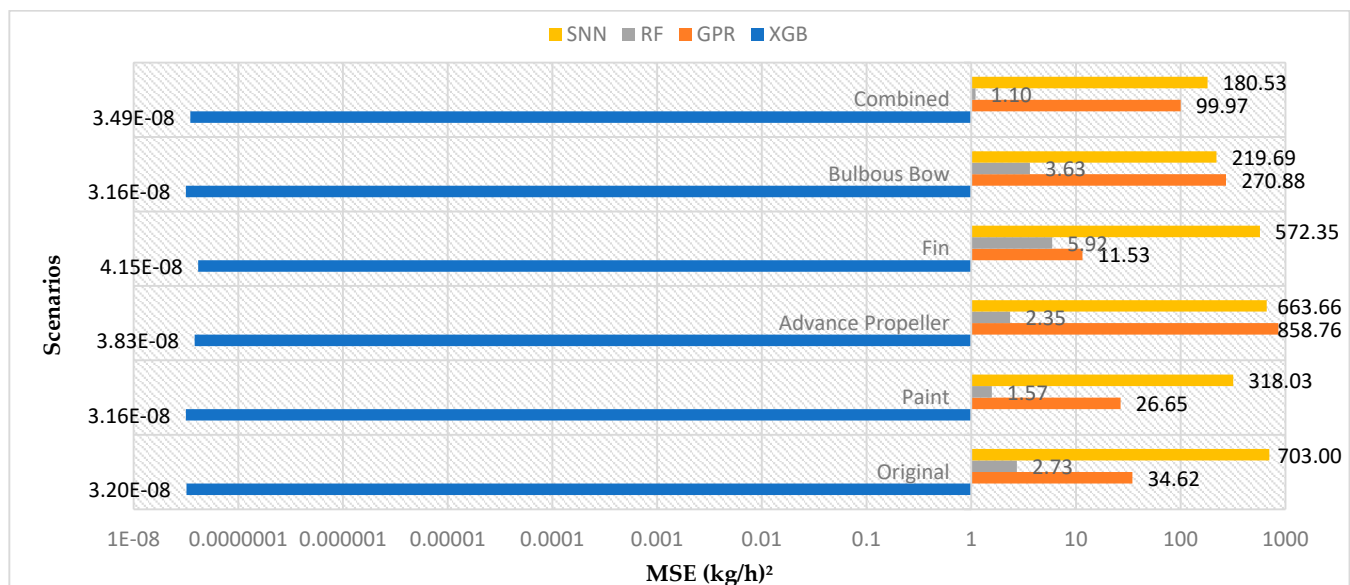


Figure 15. MSE performance comparison of XGB, GPR, RF, and SNN for FC across scenarios.

RF and SNN models performed moderately well but did not achieve the same levels of accuracy as XGB or GPR. While demonstrating error reduction after MC simulations, the RF model still had higher MSE values than the top-performing models. For instance, in the “Bulbous Bow” scenario, MSE for RF dropped from approximately 2512.84 to 3.63 after MC simulations. Yet, RMSE remained comparatively high at 1.90, indicating a need for more generalizability. This trend was evident across multiple scenarios, suggesting that RF is less consistent in reducing prediction errors when compared to GPR and XGB. SNN improved after MC simulations, with reduced MSE values across many scenarios. However, their performance could have been better. In particular, in the “Fin (2–4%)” scenario, RMSE for FC decreased from approximately 10.92 to 8.04, indicating improvement; however, it still falls short of the results achieved with GPR or XGB. The inconsistencies in SNN performance render it less reliable for predictions that require high accuracy across varying conditions. Figure 15 highlights the comparative performance of XGB, GPR, RF, and SNN models, illustrating SNN’s moderate yet inconsistent improvements. Detailed MSE performance for the other models is available in Appendix D, Table A14.

It is relevant to note that the MSE values shown may reflect differences in internal scaling between models. While the relative performance trends are valid, the absolute values should be interpreted with caution.

c. Detailed Scenario-Based Analysis

Evaluating different scenarios provides a more granular view of each model’s behavior under varying conditions. Below is a detailed discussion of model performance for specific scenarios:

- i. *Original Scenario:* This scenario served as a baseline for comparison. XGB and GPR both demonstrated the best performance, achieving low MSE and RMSE values, especially after MC simulations. While showing error reductions post-simulation, the SVR model still had high RMSE values of approximately 27.68, indicating its lack of precision.

- ii. *Paint (5%) Scenario*: In this scenario, XGB continued to demonstrate excellent performance, with an MSE value of zero post-simulation, indicating that the model effectively generalized the new conditions introduced by the paint modification. GPR also showed strong performance, while RF and SNN showed moderate levels of error reduction.
- iii. *Advanced Propeller Scenario*: The Advanced Propeller scenario demonstrated GPR's ability to handle complex modifications. GPR achieved the lowest MSE and RMSE compared to other models, making it the best performer in this context. XGB also performed well, but not as consistently as GPR, particularly before the MC simulation.
- iv. *Fin (2–4%) Scenario*: In this scenario, XGB and GPR were again the most effective, while SNN showed improvements but still lagged. The RF model exhibited moderate improvements but failed to match the performance levels of XGB and GPR. This scenario highlighted the limitations of RF and SNN in scenarios with minor, more nuanced changes.
- v. *Bulbous Bow Scenario*: In the Bulbous Bow scenario, XGB and GPR maintained high performance, with XGB achieving perfect accuracy (MSE of zero post-simulation). SVR showed improvements but had higher error levels, making it the least effective for this scenario. SNN performed inconsistently, suggesting sensitivity to the modifications in this particular scenario.
- vi. *Combined Scenario*: The Combined Scenario tested the models' ability to generalize across diverse conditions by integrating multiple modifications. XGB achieved near-zero MSE, reinforcing its robustness, while GPR maintained low MSE values, though higher than XGB's. RF performed moderately, with MSE values lower than those of SNN, which showed higher errors, indicating inconsistent performance in complex scenarios.

3.8. Implementation of the XGB Model and Summary of Results

Building upon the comparative analysis of ML models, where XGB demonstrated superior predictive performance, this section details the implementation of the XGB model and summarizes the key results obtained. By integrating the XGB model into the hybrid framework, the authors aimed to enhance predictive accuracy for FC and CO₂ emissions under various operational scenarios. A single XGB model was trained on a combined dataset from all scenarios (Original, Paint, Advanced Propeller, Fin, Bulbous Bow, Combined) to enable flexible predictions for diverse ship configurations.

The following subsections discuss the user interface development, visualization, and comparative analysis of predictions across different scenarios; key insights derived from the results; quantitative evaluation of the model's predictions; and an assessment of XGB's overall performance in capturing complex maritime operational dynamics.

i. Visualization and Comparative Analysis

Predictions were visualized across a range of ship speeds (9 to 15 knots) using a single model trained on all scenarios. Graphs illustrated the relationship between ship speed and predicted metrics:

- **Fuel Consumption**: The bar chart demonstrates how the combined model predicts FC (after MC augmentation) at different speeds, exhibiting similar FC reduction patterns to efficiency-based scenarios such as "Advanced Propeller" and "Bulbous Bow" at higher speeds.
- **CO₂ Emissions**: The bar chart of CO₂ emissions mirrored the FC pattern, showing reduced emissions in configurations that matched the "Advanced Propeller" and "Fin (2–4%)" scenarios.

- **MC-augmented:** The MC-augmented predictions matched the scenario-specific trends, demonstrating the model's ability to capture parameter effects accurately. The visualization illustrates how different configurations align with the aggregated scenario trends, enabling practical interpretation.

ii. Key Insights

- **Fuel Consumption:** The combined model captured efficiency gains consistent with scenarios like “Advanced Propeller” at higher speeds, where propeller efficiency improvements reduce FC. The “Bulbous Bow” scenario also improved FC significantly at high speeds by reducing wave resistance.
- **CO₂ Emissions:** The model predicted CO₂ emissions through efficiency-driven scenarios such as “Advanced Propeller” and “Fin (2–4%)”, which matched expected hydrodynamic improvements.

The XGB model demonstrated its ability to handle operational condition variability, thus proving its effectiveness for real-world deployment. The combined FC and CO₂ prediction trends are shown in Figure 16, with user input overlay.

iii. Quantitative Evaluation of Predictions

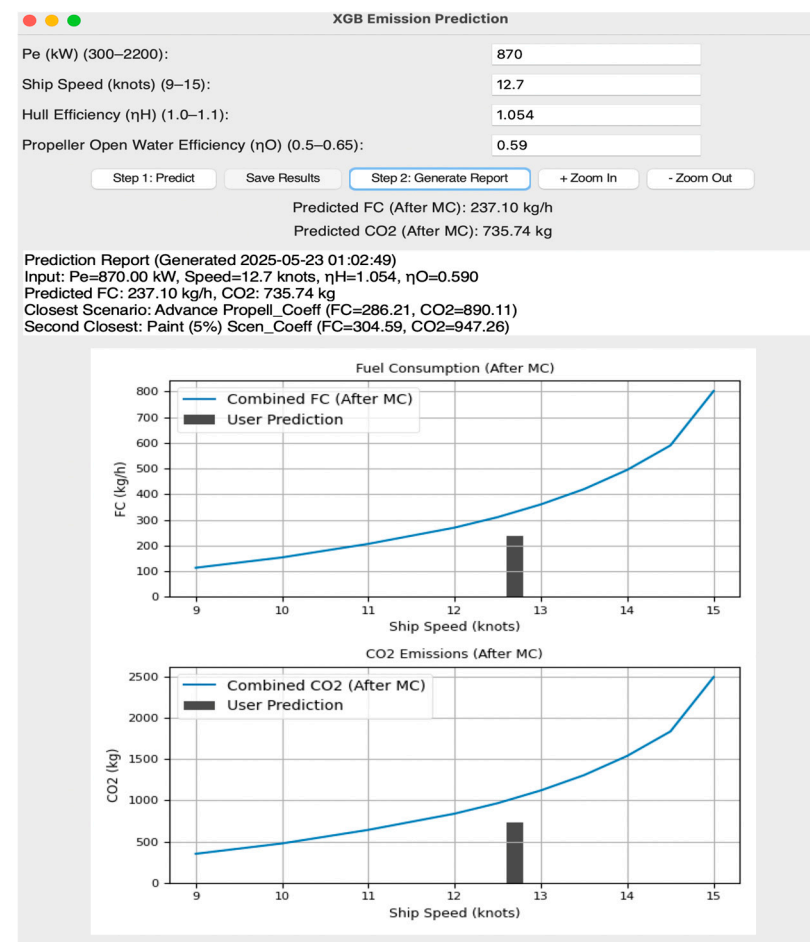


Figure 16. Combined FC and CO₂ prediction across speeds with sample parameters input.

The XGB model predicted an FC of 237.10 kg/h and CO₂ emissions of 735.74 kg after MC augmentation, using the following sample operational inputs: engine power (Pe: 870 kW), ship speed (12.7 knots), hull efficiency (η_H : 1.054), and propeller efficiency (η_O : 0.590). The configuration shows the closest match to the “Advanced Propeller” scenario (FC: 286.21 kg/h, CO₂: 890.11 kg) followed by the “Paint (5%)” scenario (FC: 304.59 kg/h,

CO₂: 947.26 kg). The setup with its high propeller efficiency ($\eta_O = 0.590$) benefits from efficiency improvements that are similar to those in the “Advanced Propeller” scenario, which focuses on enhanced propeller design. The predicted values are lower than expected (FC: 284.26 kg/h, CO₂: 884.04 kg), which may indicate underestimation, possibly due to the model’s generalization across diverse scenarios. To achieve further reductions in FC and CO₂, the model suggests improvements similar to the “Advanced Propeller” scenario, such as adopting advanced propeller technologies to enhance η_O .

iv. Evaluation of XGB Model Performance

XGB demonstrated superior performance to other ML models, such as RF and GPR, which struggled with overfitting or underfitting in specific scenarios. Its ability to capture non-linear relationships between features and robustness to scenario variations made it the most effective model for predicting FC and CO₂ emissions. With hyperparameters optimized (e.g., 100 estimators for a balance of efficiency and accuracy), XGB effectively generalized across operational scenarios, providing reliable predictions.

4. Discussion

This study’s comprehensive evaluation of technical modifications and ML approaches provides significant insights into enhancing ship efficiency and reducing emissions for maritime operations. Integrating physics-based calculations with advanced ML models, supplemented by data augmentation through MC simulations, has demonstrated the potential for accurate and reliable predictions of FC and CO₂ emissions under various operational scenarios. The study trains a single XGB model on a combined dataset from all scenarios to enable flexible predictions for assumption-defined configurations, which addresses real-world scenarios where ship designs may not align with predefined modifications.

4.1. Effectiveness of Technical Modifications

The analysis of different technical modifications before the application of ML models highlighted the tangible benefits of targeted design enhancements:

- **Advanced Propeller Design:** This modification consistently improved thrust requirements and effective power across varying speed ranges. By increasing the propeller’s open water efficiency (η_o) from 0.464 to 0.579 at 12 knots, it effectively reduced energy consumption, particularly at higher speeds. This demonstrates the propeller’s ability to enhance hydrodynamic efficiency and operational performance under diverse conditions.
- **Paint Efficiency Improvement (5% Reduction):** The application of advanced hull coatings reduced the frictional resistance coefficient (CF), leading to decreased hull resistance. This resulted in lower FC (e.g., 276.26 kg/h at 12 knots) and Pd, showcasing enhanced energy efficiency through drag reduction. The findings validate the benefits of high-quality hull coatings in improving fuel economy.
- **Fin Installation:** By enhancing thrust by 2% and improving the wake fraction by 4%, fins lowered thrust requirements (T_{req}) to 160.02 kN at 12 knots and improved hull efficiency (η_H). This modification contributed to overall operational efficiency, highlighting the potential of appendages in optimizing propulsion.
- **Bulbous Bow Addition:** The bulbous bow scenario optimized flow at the bow, achieving the most significant efficiency gains, particularly at higher speeds. Although it increased wetted surface area and resistance at lower speeds, the bulbous bow reduced wave-making resistance at higher speeds, aligning with established naval architecture principles. This modification reduced FC to 267.78 kg/h at 12 knots and demonstrated its effectiveness for vessels operating at moderate to high speeds.

4.2. Impact of Data Augmentation with Monte Carlo Simulations

The use of MC simulations for data augmentation has shown significant efficacy in enhancing the performance of ML models. This method enhanced the dataset by introducing controlled variability and modeling real-world uncertainties, enabling the models to more effectively discern the intricate correlations between operational factors and target variables. Data augmentation significantly mitigated overfitting, enabling models such as XGB and GPR to generalize more proficiently across various contexts. After data augmentation, the decrease in MSE and RMSE values underscored the significant improvement in predictive accuracy, particularly for models susceptible to data fluctuation. The XGB model achieved better generalization through the combined dataset approach with $3\times$ MC augmentation, which enabled it to predict FC and CO₂ emissions for various user configurations while minimizing the overfitting risk that scenario-specific models exhibited.

The hybrid model is built on a succession of controlled simplifications, yet it does provide an organized and repeatable foundation. The authors did not dynamically model environmental circumstances, including the state of the sea, wind forces, uneven loads, and long-term impacts of hull fouling. Instead, the authors employed idealized hydrodynamic characteristics. Marine biofouling can make hull coatings and other treatments less effective over time, which can have a big effect on resistance and fuel use.

The authors also used constant BSFC and transmission efficiency values to provide an idea of how the engine will perform in different operational modes. Future versions of the model will try to include these changing, real-world aspects by using sensor-based empirical data, time-dependent degradation models, and probabilistic simulations that better show how the environment changes.

4.3. Practical Implications and Applications

The findings of this study offer significant practical implications for reducing FC and CO₂ emissions in oil tanker operations, with applicability extending to other similar vessels. The XGB model, identified as the most accurate predictor of FC and CO₂ emissions (Section 3.5), provides a reliable tool for forecasting operational performance across diverse conditions, enabling data-driven decision-making for tanker operators and designers.

For example, a simulated operational scenario with $P_e = 870$ kW, 12.7 knots, $\eta_H = 1.054$, and $\eta_O = 0.590$ resulted in predicted FC of 237.10 kg/h and CO₂ emissions of 735.74 kg, which is close to the Advanced Propeller scenario, indicating that adopting advanced propeller designs could optimize efficiency (Section 3.8). The Advanced Propeller scenario achieved the most significant FC reduction (e.g., 729.31 kg/h at 15 knots compared to 814.84 kg/h for the Original scenario), followed by the Combined scenario (771.04 kg/h), which demonstrates effective modifications for enhancing fuel efficiency and reducing emissions.

Ship operators can utilize these insights to adjust operational parameters, such as selecting optimal speeds or installing advanced propellers, to reduce emissions. Designers can use scenario comparisons to determine which modifications should be prioritized, such as improving propeller efficiency or investigating hybrid configurations during ship design to achieve sustainability goals. The model's precise emission projections enable the achievement of global sustainability targets while supporting environmental preservation and compliance with international regulations. The model's robustness results from MC data augmentation (Section 2.2) and validation at 8 knots for minimal FC (Appendix B, Table A6), which enables its application to other oil tankers to expand its maritime sustainability impact. The study does not address the monetary aspects of modifications, but the technical performance data would allow stakeholders to perform cost-benefit analyses.

This study assumes a constant BSFC of 200 g/kWh for simplicity; however, actual engine performance fluctuates with load. Marine engines generally achieve optimal efficiency

at 75–85% of Maximum Continuous Rating (MCR). In contrast, operating at lower loads (<50% MCR) may lead to increased Brake Specific Fuel Consumption (BSFC) due to suboptimal combustion, higher auxiliary power requirements, and increased oil consumption. Future model enhancements should integrate variable BSFC profiles and investigate the potential of machine learning to identify optimal operating points that reconcile propulsion improvements with slow steaming and energy efficiency goals.

This study assumes a constant transmission efficiency of 96.5%, representing a simplified model of a direct-drive shaft system typically employed in medium-sized oil tankers. This value, although supported by high-efficiency propulsion configurations with minimal mechanical losses, fails to account for the variability introduced by differing propulsion layouts or operating conditions. Transmission efficiency is influenced by factors such as shaft speed, load, and the incorporation of reduction gears or intermediate couplings. Future developments of the model should incorporate a load-dependent transmission efficiency profile and a modular representation of the propulsion chain to enhance realism and predictive accuracy.

5. Conclusions

The research developed a physics-based ML hybrid system to forecast oil tanker FC and CO₂ emissions through hydrodynamic modeling and sophisticated ML algorithms, advancing maritime sustainability. The study trained one XGB model to predict various ship configurations through a combined dataset from Original, Paint, Advanced Propeller, Fin, Bulbous Bow, and Combined scenarios, which handles real-world design and operational variations. The research aimed to assess technical modifications for reducing FC and CO₂ emissions while developing an ML model that could be applied to other oil tankers. The XGB model achieved superior performance compared to Support Vector Regression, Gaussian Process Regression, Random Forest, and Shallow Neural Network models by demonstrating high predictive accuracy when validated against physics-based calculations. The Advanced Propeller scenario produced the largest FC reduction, followed by the Combined scenario, indicating substantial potential for reducing CO₂ emissions.

The model's predictions enabled scenario comparisons, which provided practical insights into how operators should prioritize advanced propeller designs or hull coatings to maximize efficiency, thereby helping operators optimize vessel operations and designers achieve sustainability targets. The research results directly inform operational planning and design choices through simulated predictions (e.g., a flow rate of 237.10 kg/h for specific inputs, Section 3.8), providing practical utility without requiring an interface. The research supports IMO decarbonization targets through its data-driven maritime efficiency solution.

The research has made progress, but it faces two main challenges and limitations: the initial dataset is small, necessitating the use of MC data augmentation, and the predictions are sometimes underestimated, which could be improved by incorporating features such as paint properties or wave resistance. Future research should expand empirical datasets to include diverse ship types, optimize models such as Shallow Neural Networks, and explore deep learning techniques. Real-time sensor data integration would enable dynamic monitoring, thereby enhancing operational efficiency. The development of innovative, sustainable ship performance solutions that meet global environmental regulations requires transdisciplinary collaboration between naval architects, oceanographers, and AI experts.

Future studies should focus on integrating real-time operational data from multiple vessel types to validate and enhance model generalizability. Incorporating advanced hybrid algorithms with adaptive learning capabilities could further improve predictive accuracy under variable marine conditions. Additionally, exploring environmental and economic trade-offs of combined technical modifications across different ship classes would broaden

the applicability of this framework. Lastly, deeper integration of sensor-based IoT systems may support continuous emissions monitoring and optimization.

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

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

Appendix A. Ship Characteristics and Test Results

Table A1. Examined oil tanker dimensions and main characteristics.

Parameter	Symbol	Unit	Value
Length overall	LOA	(m)	100
Length between perpendiculars	LBP	(m)	98.1
Waterline length	LWL	(m)	100
Wetted length	LWS	(m)	100
Breadth (at wl)	B	(m)	16.6
Draught (midship)	T	(m)	6.5
Draught (AP)	TA	(m)	6.5
Draught (FP)	TF	(m)	6.5
Displacement volume	∇	(m ³)	7771.6
Displacement	Δ	(ton)	7965.9
Wetted surface area	AWS	(m ²)	2350
The surface area of the rudder(s)	A _R	(m ²)	58.5
Total surface area of appendages	A _A	(m ²)	41
Bulbous sectional area	A _B	(m ²)	0
Centre of bulbous sectional area	H _B	(m)	0
Transom area	A _T	(m ²)	1.9
Centre of the transom area	H _T	(m)	6.25
Block coefficient	C _B	-	0.72
Prismatic coefficient	C _P	-	0.73
Midship area coefficient	C _M	-	0.986
Waterplane area coefficient	C _{WP}	-	0.862
Longitudinal center of buoyancy	LCB	(m) (from AP)	48.1
Longitudinal center of floatation	LCF	(m) (from AP)	45.12
Service speed	-	knots	13.5
Propeller diameter	-	M	4
Number of blades	-	-	4
Blade area ratio	-	-	0.4
Pitch/diameter ratio	-	m	0.74
Transmission efficiency	-	-	0.965
Water density	-	kg/m ³	1025
Water temperature	-	°C	15
Kinematic viscosity	ν	m ² /s	1.18831 10 ⁻³
Brake Specific Fuel Consumption	BSFC	g/kWh	200

Table A2. Oil Tanker Ship Model- Examined Test Results.

Ship Speed (Knots)	Wave Resistance Coefficient 1000 (Without Bulbous Bow)	Wave Resistance Coefficient 1000 (with Bulbous Bow)	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency
6	0.44	0.462	0.247	0.289	1.012
7	0.461	0.479	0.245	0.287	1.012
8	0.451	0.465	0.245	0.287	1.012
9	0.435	0.444	0.244	0.286	1.012
10	0.439	0.448	0.243	0.285	1.012
10.5	0.457	0.462	0.243	0.284	1.012
11	0.49	0.495	0.242	0.283	1.012
11.5	0.538	0.538	0.240	0.281	1.012
12	0.604	0.574	0.238	0.279	1.012
12.5	0.692	0.623	0.236	0.276	1.012
13	0.805	0.684	0.234	0.272	1.012
13.5	0.953	0.829	0.231	0.268	1.012
14	1.141	1.027	0.229	0.264	1.012
14.5	1.385	1.385	0.226	0.260	1.012
15	1.701	1.786	0.223	0.255	1.012

Table A3. Propulsion Open Water Efficiency for Different Types of Propellers.

Original Propeller			Advanced Propeller	
J	Kt	10·Kq	Kt	10·Kq
0.05	0.2993	0.3696	0.3151	0.35196
0.1	0.2882	0.359	0.3034	0.34191
0.15	0.2762	0.3479	0.2907	0.33129
0.2	0.2632	0.336	0.277	0.32002
0.25	0.2493	0.3234	0.2624	0.30803
0.3	0.2346	0.31	0.2469	0.29523
0.35	0.219	0.2956	0.2305	0.28155
0.4	0.2026	0.2803	0.2133	0.26692
0.45	0.1855	0.2638	0.1953	0.25126
0.5	0.1678	0.2462	0.1766	0.2345
0.55	0.1492	0.2274	0.1571	0.21656
0.6	0.1302	0.2072	0.137	0.19735
0.65	0.1105	0.1857	0.1163	0.17682
0.7	0.0903	0.1626	0.095	0.15488
0.75	0.0694	0.138	0.0731	0.13145
0.8	0.0482	0.1118	0.0507	0.10646
0.85	0.0264	0.0838	0.0278	0.07983

Appendix B. Propeller Performance Charts

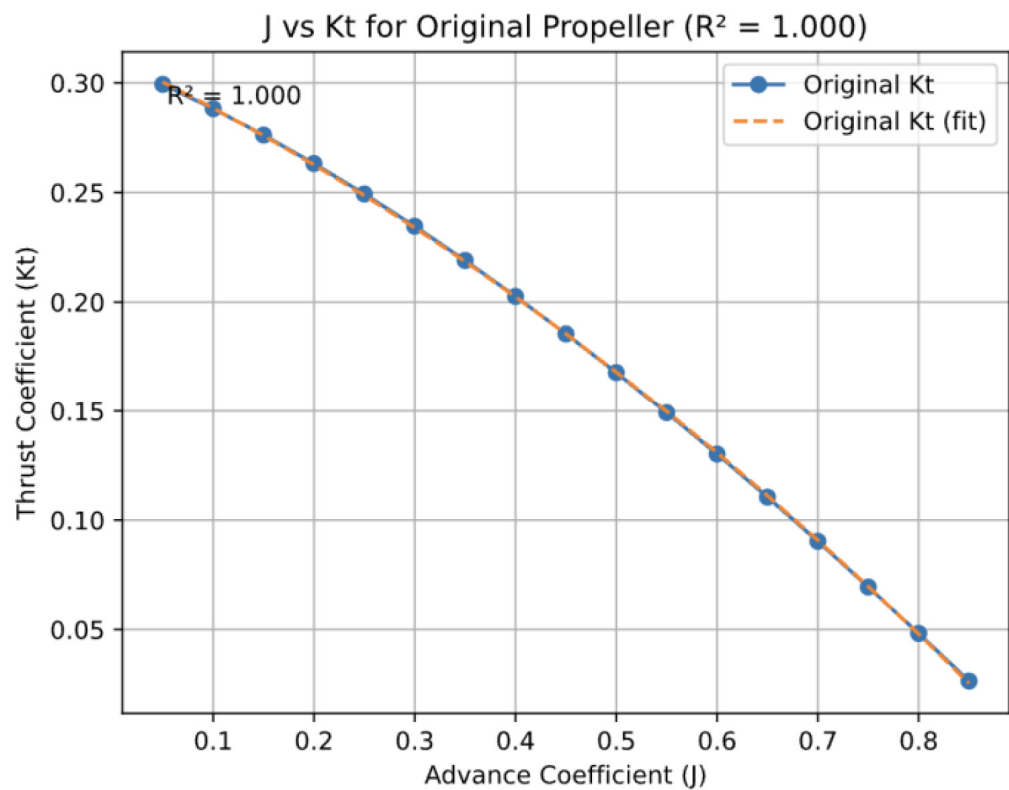


Figure A1. K_t vs. J for original propeller with quadratic fit ($R^2 = 1.000$).

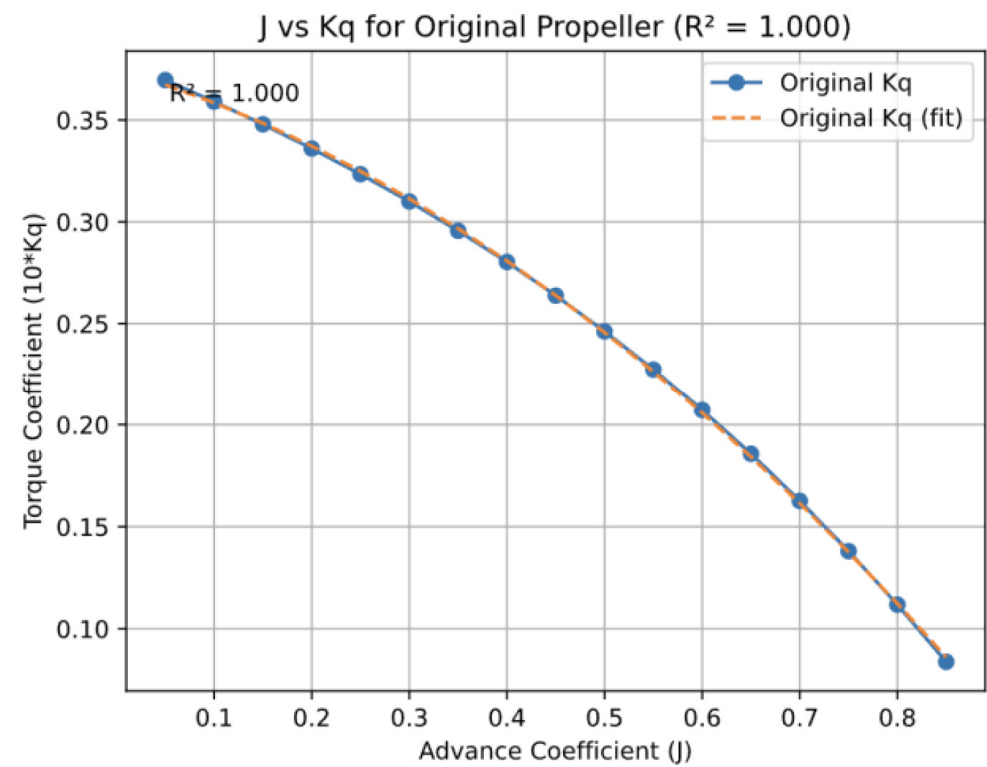


Figure A2. K_q vs. J for original propeller with quadratic fit ($R^2 = 1.000$).

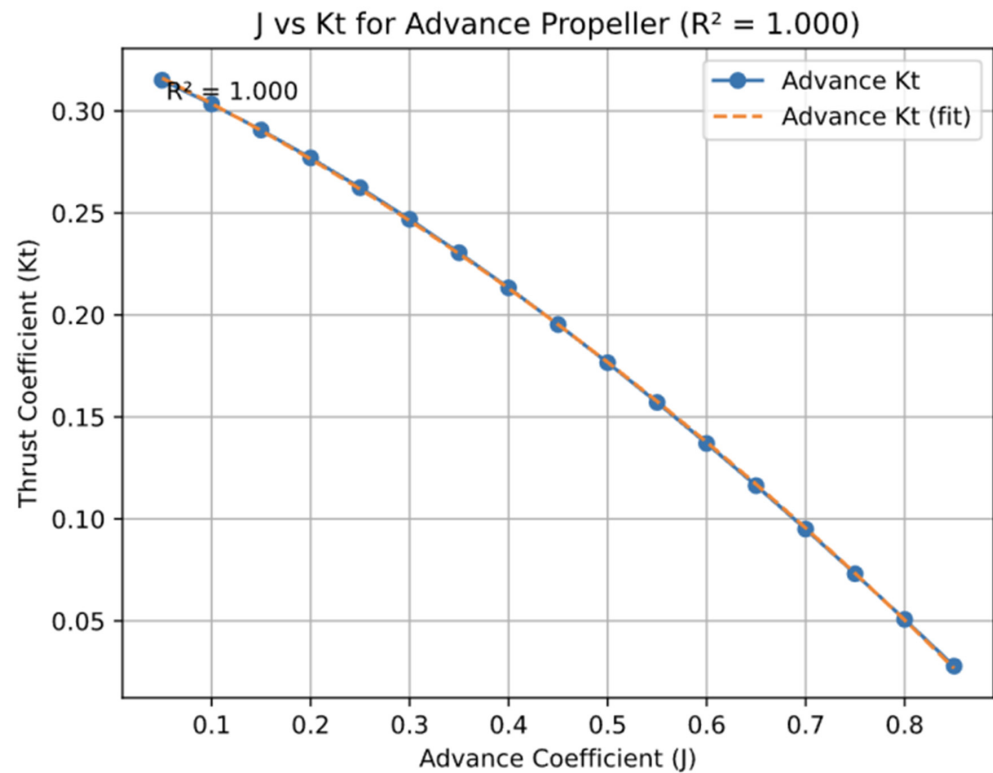


Figure A3. Kt vs. J for advanced propeller with quadratic fit ($R^2 = 1.000$).

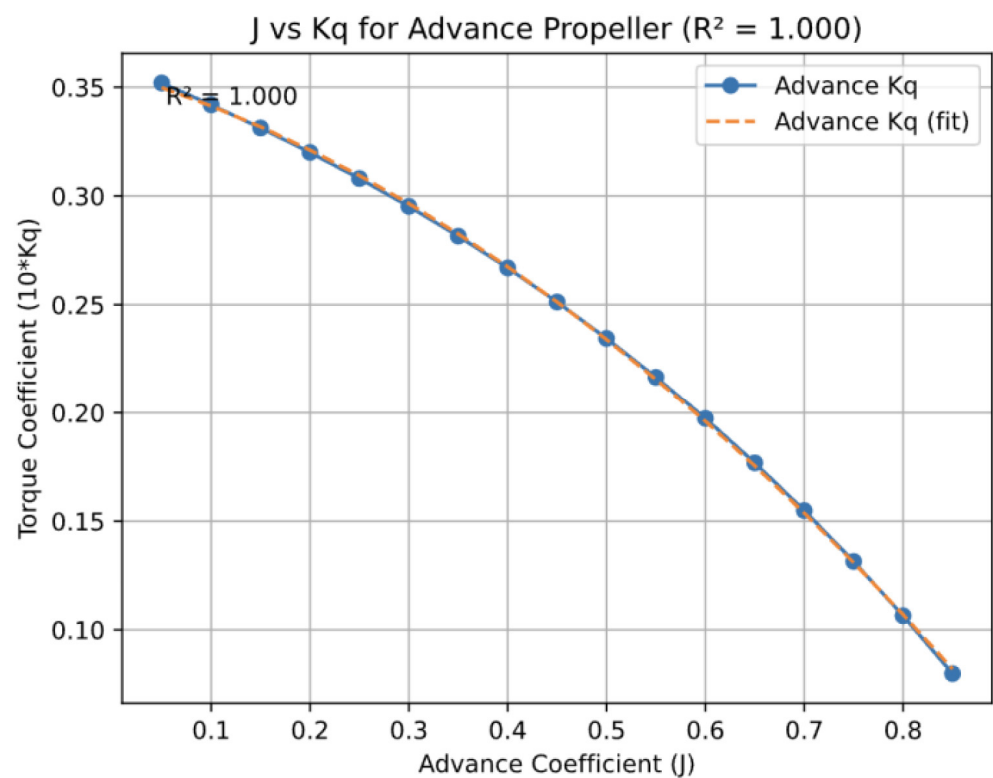


Figure A4. Kq vs. J for advanced propeller with quadratic fit ($R^2 = 1.000$).

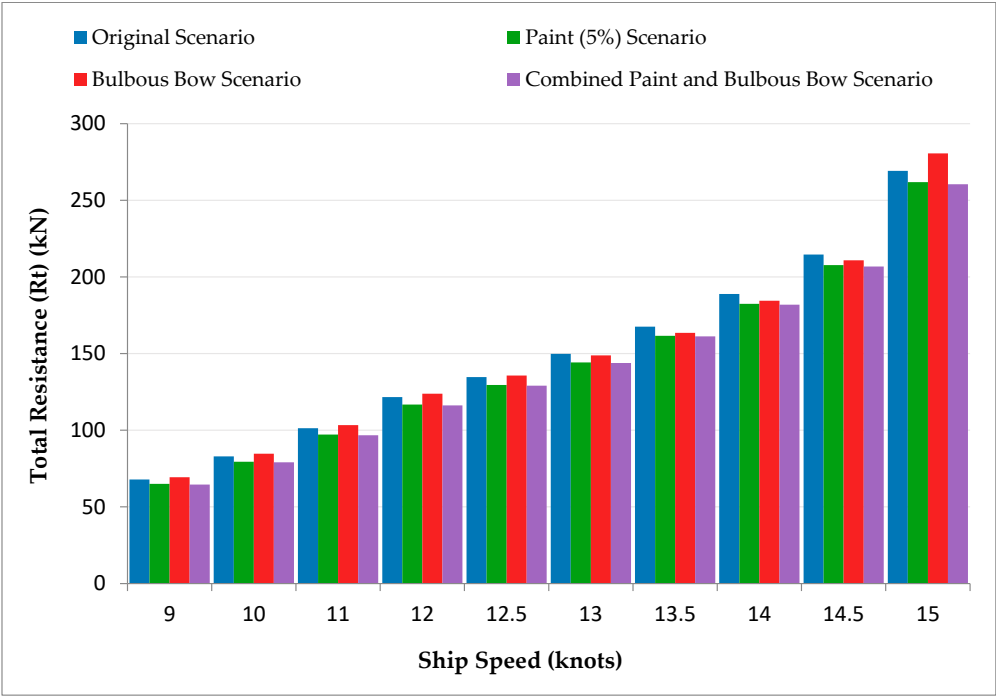


Figure A5. Total resistance (R_t) vs. ship speed including combined scenario.

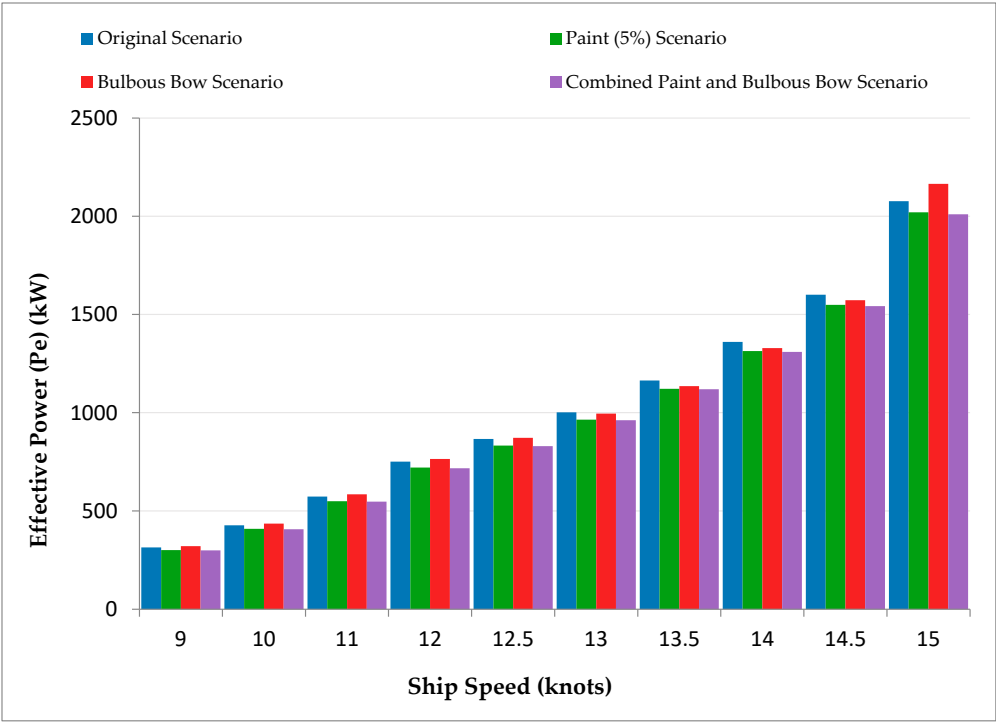


Figure A6. Effective power (P_e) vs. ship speed including combined scenario.

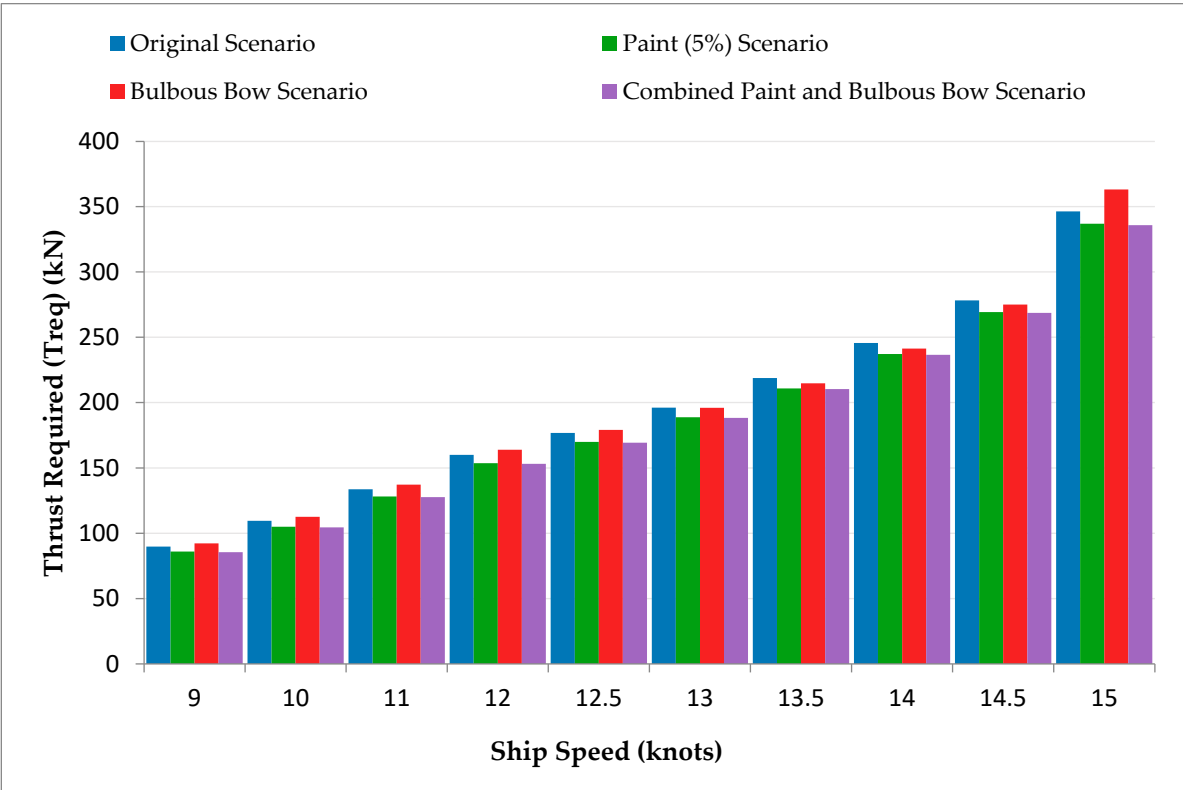


Figure A7. Thrust required (Treq) vs. ship speed including combined scenario.

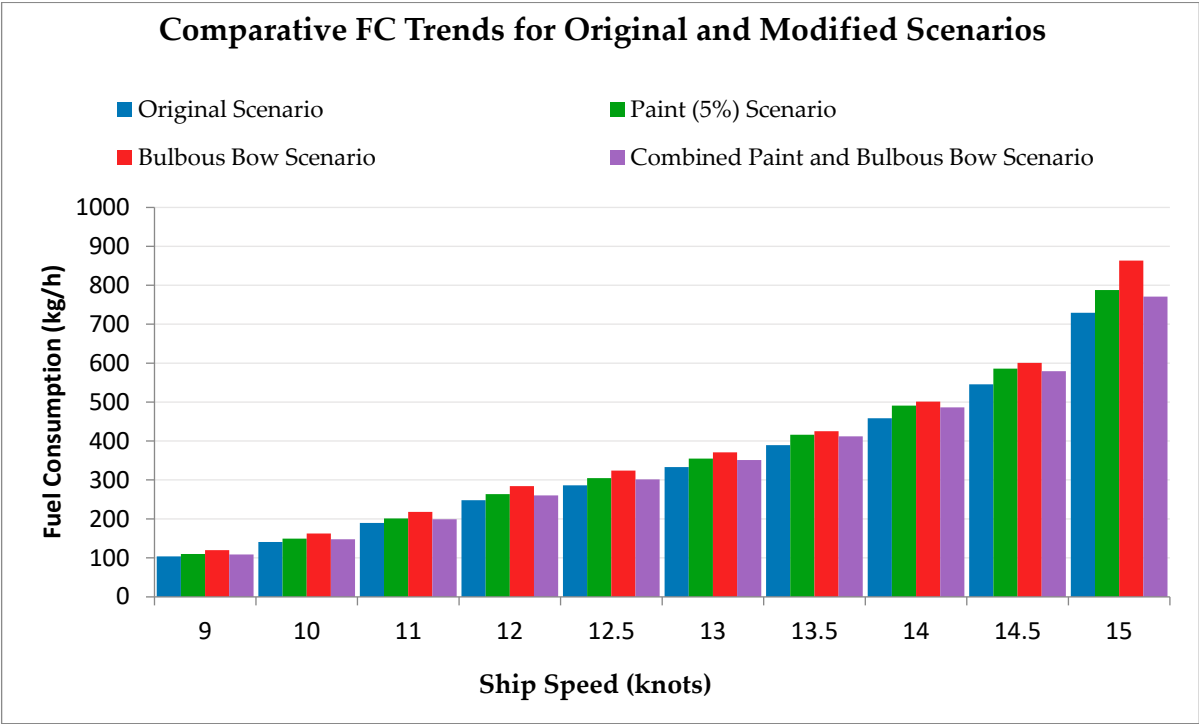


Figure A8. FC vs. ship speed including combined scenario.

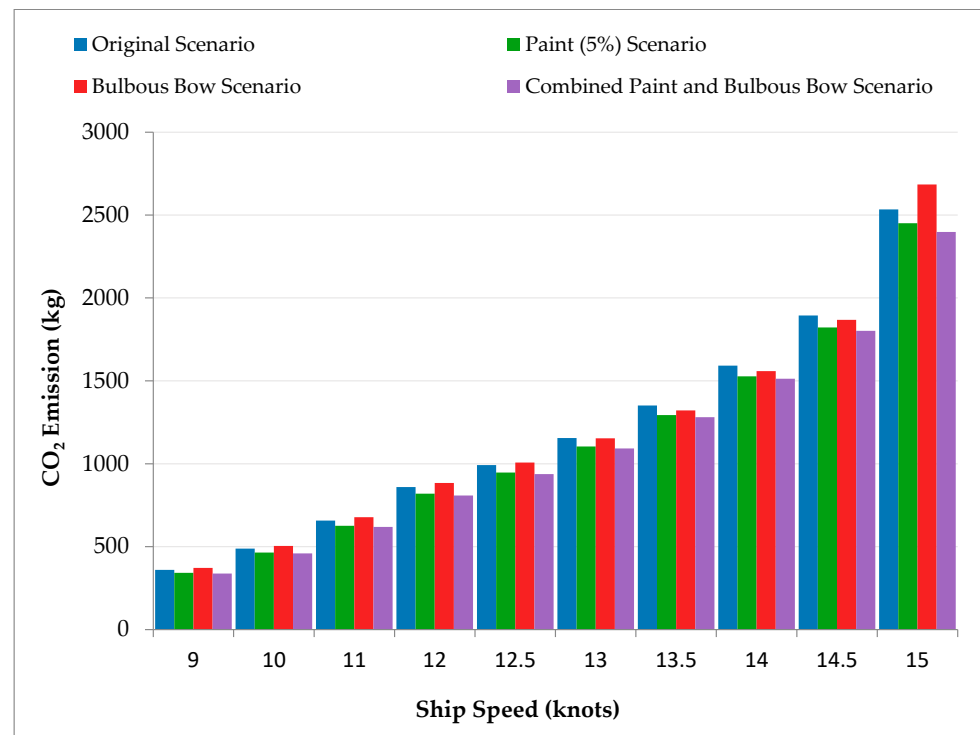


Figure A9. CO₂ emission vs. ship speed including combined scenario.

Table A4. Combined Paint and Bulbous Bow Scenario Parameters.

Ship Speed (knots)	Rt (kN)	Pe (kW)	Treq (kN)	FC (kg/h)	CO ₂ Emission (kg)
9	64.54	298.91	85.45	108.59	337.71
10	79.02	406.47	104.51	147.58	459.08
11	96.68	547.37	127.60	199.03	619.18
12	116.21	717.23	153.07	260.12	808.97
12.5	129.01	829.45	169.36	301.54	937.79
13	143.87	961.24	188.28	351.13	1092.01
13.5	161.23	1119.50	210.34	411.98	1281.26
14	181.84	1309.58	236.62	486.46	1512.90
14.5	206.82	1542.61	268.74	579.32	1801.67
15	260.44	2009.38	335.85	771.04	2397.93

Table A5. Additional Validation Samples for Augmented Data at 14.5 knots.

Scenario	Data Type	Fuel Consumption (FC, kg/h)
Advanced Propeller	Original (Physics-Based)	545.6961681
	Neural Network (Before MC)	559.4786360
	Neural Network (After MC)	529.9805960
Bulbous Bow	Original (Physics-Based)	600.5953901
	Random Forest (Before MC)	527.8524522
	Random Forest (After MC)	577.0773365
Combined	Original (Physics-Based)	579.3200000
	XGB (Before MC)	486.4600525
	XGB (After MC)	579.3199463
Fin	Original (Physics-Based)	608.2600070
	GPR (Before MC)	615.8368798
	GPR (After MC)	608.2599487

Table A6. Sample Model Performance for Extrapolation at 8 knots.

Scenario	Data Type	Fuel Consumption (FC, kg/h)
Advanced Propeller	Physics-Based (Calculated)	61.41
	SVR (Before MC)	106.81
	SVR (After MC)	70.43
	RF (Before MC)	81.33
	RF (After MC)	62.03
Combined	Physics-Based (Calculated)	63.94
	XGB (Before MC)	64.27
	XGB (After MC)	64.27
	GPR (Before MC)	64.27
	GPR (After MC)	63.80 (Uncertainty: ± 15)
Paint	Physics-Based (Calculated)	64.67
	NN (Before MC)	64.53
	NN (After MC)	61.33

Note: Physics-based FC values at 8 knots are calculated using a power-law model ($FC = a \cdot V^b$) fitted to 9–15 knot data (Appendix C). ML model FC predictions are extrapolated from 9-knot values using the physics-based FC ratio (8 knots/9 knots), as 8-knot ML data are unavailable. GPR uncertainty estimates indicate prediction reliability for extrapolation.

Appendix C. Detailed Calculations and Results

Table A7. Physics-based calculations—original scenario.

Ship Speed (knots)	Wave Resistance Coefficient · 1000	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency	Speed m/s	Re	CF	Cv	Ct	Rt (kN)	Pe(kW)	Va (m/s)	Treq (kN)
9	0.435	0.244	0.286	1.012	4.6296	389,595,307.6	0.001726671	0.002192872	0.002627872	67.83484964	314.0482199	3.3055344	89.7286371
10	0.439	0.243	0.285	1.012	5.144	432,883,675.1	0.001702942	0.002162737	0.002601737	82.91383244	426.5087541	3.67796	109.5295012
11	0.49	0.242	0.283	1.012	5.6584	476,172,042.6	0.001681896	0.002136008	0.002626008	101.2616638	572.9789987	4.0570728	133.5905855
12	0.538	0.24	0.281	1.012	6.1728	519,460,410.2	0.001663021	0.002112037	0.002650037	121.6124557	750.6893668	4.4382432	160.0163891
12.5	0.604	0.238	0.279	1.012	6.43	541,104,593.9	0.001654275	0.002100929	0.002704929	134.6913255	866.0652227	4.63603	176.7602696
13	0.692	0.236	0.276	1.012	6.6872	562,748,777.7	0.001645937	0.00209034	0.00278234	149.8513221	1002.085761	4.8415328	196.140474
13.5	0.805	0.234	0.272	1.012	6.9444	584,392,961.4	0.001637973	0.002080226	0.002885226	167.5756882	1163.712609	5.0555232	218.767217
14	0.953	0.231	0.268	1.012	7.2016	606,037,145.2	0.001630353	0.002070549	0.003023549	188.8585755	1360.083917	5.2715712	245.5898251
14.5	1.141	0.229	0.264	1.012	7.4588	627,681,328.9	0.001623051	0.002061275	0.003202275	214.5647195	1600.39533	5.4896768	278.2940591
15	1.701	0.223	0.255	1.012	7.716	649,325,512.7	0.001616043	0.002052375	0.003753375	269.1337357	2076.635905	5.74842	346.3754643

Table A8. Physics-based calculations—paint Efficiency Scenario (5% Reduction).

Ship Speed (knots)	Wave Resistance Coefficient · 1000	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency	Speed m/s	Re	CF	Cv	Ct	Rt (kN)	Pe(kW)	Va (m/s)	Treq (kN)
9	0.435	0.244	0.286	1.012	4.6296	389,595,307.6	0.001640337	0.002083228	0.002518228	65.00455308	300.945079	3.3055344	85.98485858
10	0.439	0.243	0.285	1.012	5.144	432,883,675.1	0.001617795	0.0020546	0.0024936	79.46765766	408.781631	3.67796	104.9770907
11	0.49	0.242	0.283	1.012	5.6584	476,172,042.6	0.001597801	0.002029208	0.002519208	97.14332675	549.6758001	4.0570728	128.1574232
12	0.538	0.24	0.281	1.012	6.1728	519,460,410.2	0.00157987	0.002006435	0.002544435	116.7662969	720.7749977	4.4382432	153.6398644
12.5	0.604	0.238	0.279	1.012	6.43	541,104,593.9	0.001571561	0.001995883	0.002599883	129.4605611	832.4314076	4.63603	169.8957494
13	0.692	0.236	0.276	1.012	6.6872	562,748,777.7	0.00156364	0.001985823	0.002677823	144.2222434	964.442986	4.8415328	188.7725699
13.5	0.805	0.234	0.272	1.012	6.9444	584,392,961.4	0.001556074	0.001976215	0.002781215	161.5346485	1121.761213	5.0555232	210.8807421
14	0.953	0.231	0.268	1.012	7.2016	606,037,145.2	0.001548836	0.001967021	0.002920021	182.3919873	1313.514136	5.2715712	237.1807377
14.5	1.141	0.229	0.264	1.012	7.4588	627,681,328.9	0.001541899	0.001958211	0.003099211	207.6590523	1548.887339	5.4896768	269.3372922
15	1.701	0.223	0.255	1.012	7.716	649,325,512.7	0.001535241	0.001949756	0.003650756	261.7755133	2019.85986	5.74842	336.9054225

Table A9. Physics-based calculations—dvanced Propeller Scenario.

Ship Speed (knots)	Wave Resistance Coefficient · 1000	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency	Speed m/s	Re	CF	Cv	Ct	Rt (kN)	Pe(kW)	Va (m/s)	Treq (kN)
9	0.435	0.244	0.286	1.012	4.6296	389,595,307.6	0.001726671	0.002192872	0.002627872	67.83484964	314.0482199	3.3055344	89.7286371
10	0.439	0.243	0.285	1.012	5.144	432,883,675.1	0.001702942	0.002162737	0.002601737	82.91383244	426.5087541	3.67796	109.5295012
11	0.49	0.242	0.283	1.012	5.6584	476,172,042.6	0.001681896	0.002136008	0.002626008	101.2616638	572.9789987	4.0570728	133.5905855
12	0.538	0.24	0.281	1.012	6.1728	519,460,410.2	0.001663021	0.002112037	0.002650037	121.6124557	750.6893668	4.4382432	160.0163891
12.5	0.604	0.238	0.279	1.012	6.43	541,104,593.9	0.001654275	0.002100929	0.002704929	134.6913255	866.0652227	4.63603	176.7602696
13	0.692	0.236	0.276	1.012	6.6872	562,748,777.7	0.001645937	0.00209034	0.00278234	149.8513221	1002.085761	4.8415328	196.140474
13.5	0.805	0.234	0.272	1.012	6.9444	584,392,961.4	0.001637973	0.002080226	0.002885226	167.5756882	1163.712609	5.0555232	218.767217
14	0.953	0.231	0.268	1.012	7.2016	606,037,145.2	0.001630353	0.002070549	0.003023549	188.8585755	1360.083917	5.2715712	245.5898251
14.5	1.141	0.229	0.264	1.012	7.4588	627,681,328.9	0.001623051	0.002061275	0.003202275	214.5647195	1600.39533	5.4896768	278.2940591
15	1.701	0.223	0.255	1.012	7.716	649,325,512.7	0.001616043	0.002052375	0.003753375	269.1337357	2076.635905	5.74842	346.3754643

Table A10. Physics-based calculations—Fin Installation Scenario.

Ship Speed (knots)	Wave Resistance Coefficient · 1000	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency	Speed m/s	Re	CF	Cv	Ct	Rt (kN)	Pe(kW)	Va (m/s)	Treq (kN)
9	0.435	0.24888	0.29744	1.012	4.6296	389,595,307.6	0.001726671	0.002192872	0.002627872	67.83484964	314.0482199	3.25257177	90.31160087
10	0.439	0.24786	0.2964	1.012	5.144	432,883,675.1	0.001702942	0.002162737	0.002601737	82.91383244	426.5087541	3.6193184	110.237233
11	0.49	0.24684	0.29432	1.012	5.6584	476,172,042.6	0.001681896	0.002136008	0.002626008	101.2616638	572.9789987	3.99301971	134.449073
12	0.538	0.2448	0.29224	1.012	6.1728	519,460,410.2	0.001663021	0.002112037	0.002650037	121.6124557	750.6893668	4.36886092	161.0334424
12.5	0.604	0.24276	0.29016	1.012	6.43	541,104,593.9	0.001654275	0.002100929	0.002704929	134.6913255	866.0652227	4.5642712	177.8713822
13	0.692	0.24072	0.28704	1.012	6.6872	562,748,777.7	0.001645937	0.00209034	0.00278234	149.8513221	1002.085761	4.76770611	197.3597647
13.5	0.805	0.23868	0.28288	1.012	6.9444	584,392,961.4	0.001637973	0.002080226	0.002885226	167.5756882	1163.712609	4.97996812	220.1120268
14	0.953	0.23562	0.27872	1.012	7.2016	606,037,145.2	0.001630353	0.002070549	0.003023549	188.8585755	1360.083917	5.19437004	247.074198
14.5	1.141	0.23358	0.27456	1.012	7.4588	627,681,328.9	0.001623051	0.002061275	0.003202275	214.5647195	1600.39533	5.41091187	279.9570986
15	1.701	0.22746	0.2652	1.012	7.716	649,325,512.7	0.001616043	0.002052375	0.003753375	269.1337357	2076.635905	5.6697168	348.3751466

Table A11. Physics-based calculations—Bulbous Bow Scenario.

Ship Speed (knots)	Wave Resistance Coefficient · 1000	Thrust Deduction	Wake Fraction	Relative Rotative Efficiency	Speed m/s	Re	CF	Cv	Ct	Rt (kN)	Pe(kW)	Va (m/s)	Treq (kN)
9	0.444	0.24888	0.286	1.012	4.6296	401,283,166.9	0.001719964	0.002184354	0.002628354	69.29085975	320.7889643	3.3055344	92.25005292
10	0.448	0.24786	0.285	1.012	5.144	445,870,185.4	0.001696373	0.002154394	0.002602394	84.699344	435.6934255	3.67796	112.6111415
11	0.495	0.24684	0.283	1.012	5.6584	490,457,203.9	0.001675448	0.002127819	0.002622819	103.2905863	584.4594532	4.0570728	137.1429527
12	0.538	0.2448	0.281	1.012	6.1728	535,044,222.5	0.001656681	0.002103985	0.002641985	123.8226029	764.3321633	4.4382432	163.9600144
12.5	0.574	0.24276	0.279	1.012	6.43	557,337,731.7	0.001647985	0.002092941	0.002666941	135.6252412	872.0703012	4.63603	179.1046976
13	0.623	0.24072	0.276	1.012	6.6872	579,631,241	0.001639695	0.002082412	0.002705412	148.8083127	995.1109488	4.8415328	195.9860825
13.5	0.684	0.23868	0.272	1.012	6.9444	601,924,750.3	0.001631776	0.002072355	0.002756355	163.4970007	1135.388572	5.0555232	214.7546376
14	0.829	0.23562	0.268	1.012	7.2016	624,218,259.5	0.001624199	0.002062733	0.002891733	184.4681193	1328.465608	5.2715712	241.3303844
14.5	1.027	0.23358	0.264	1.012	7.4588	646,511,768.8	0.001616939	0.002053512	0.003080512	210.7977341	1572.298139	5.4896768	275.0420581
15	1.786	0.22746	0.255	1.012	7.716	668,805,278.1	0.00160997	0.002044662	0.003830662	280.5197137	2164.490111	5.74842	363.1135134

Appendix D.

Table A12. Sample FC and CO₂ Emissions detailed results for original and paint scenarios and ML models.

Scenario		Original Scenario (FC)			
ML Model	GPR FC Before MC	NN FC Before MC	RF FC Before MC	SVR FC Before MC	XGB FC Before MC
Ship Speed (knots)					
9	115.7696693	117.476855	153.8689349	212.5441426	115.7706909
10	158.6434913	157.8509436	157.1669438	196.6363757	115.7706909
11	211.3112914	204.0828663	229.842333	216.8806122	211.3114166
12	276.2684182	283.9687245	289.2304312	276.369045	276.2680664
12.5	319.0039009	316.2486729	314.198828	318.903584	319.0044556
13	371.3694974	375.8887913	362.3647279	373.6568423	371.3694458
13.5	434.4792596	431.9160264	427.659364	434.378943	434.479126
14	511.7771533	509.1980774	478.5193559	474.5461671	511.7771301
14.5	628.1440622	608.4019767	545.0306977	481.4836737	511.7771301
ML Model	GPR FC After MC	NN FC After MC	RF FC After MC	SVR FC After MC	XGB FC After MC
Ship Speed (knots)					
9	115.5215296	134.6166003	117.4227306	131.1508187	115.7701187
10	156.3614339	177.0100822	156.6829376	158.6310184	157.0962982
11	210.0374382	200.7464994	211.3112914	204.0135631	211.3114014
12	274.3117836	249.6234641	276.2684182	270.2385251	276.2684326
12.5	317.0237926	269.8809941	318.2454924	315.0517762	319.0038757
13	371.4828272	348.4123989	366.9677781	371.653	371.3694763
13.5	439.2622737	437.9602642	434.6211409	439.5563096	434.4792175
14	521.3440264	520.1257762	512.177922	519.5712447	511.7770691
14.5	623.9973716	641.5809365	609.1134837	608.8219948	609.1134033
Scenario		Original Scenario (CO ₂)			
ML Model	GPR CO ₂ Before MC	NN CO ₂ Before MC	RF CO ₂ Before MC	SVR CO ₂ Before MC	XGB CO ₂ Before MC
Ship Speed (knots)					
9	360.0436715	358.8237916	479.5619646	916.5662006	360.0446777
10	493.713828	435.609839	491.4473423	870.0368642	360.0446777
11	657.1781161	611.9956983	719.1216592	859.0989233	657.1782837
12	859.1947808	918.0395544	899.5066409	929.6611844	859.1941528
12.5	992.1021319	1006.558513	972.180545	1011.335582	992.1025391
13	1154.959137	1125.634976	1113.764349	1135.725684	1154.959351
13.5	1351.230497	1324.754651	1325.653944	1255.635094	1351.230347
14	1591.626947	1597.243742	1488.195197	1298.03187	1591.626953
14.5	1955.396435	1950.373941	1713.64544	1259.176407	1591.626953
15	2534.163236	2539.708027	2199.086615	2199.086615	2534.162109

Table A12. Cont.

Scenario		Original Scenario (CO ₂)			
ML Model	GPR CO ₂ After MC	NN CO ₂ After MC	RF CO ₂ After MC	SVR CO ₂ After MC	XGB CO ₂ After MC
Ship Speed (knots)					
9	358.813239	448.428842	365.1846923	447.1187997	360.0441284
10	485.6354766	537.1271601	487.2839359	526.2801538	488.5692749
11	653.5278652	630.8712249	657.1781162	660.4106049	657.1781616
12	853.706109	775.7901294	859.1947807	855.6961727	859.1948242
12.5	986.6739402	835.7401571	991.0725549	988.4495129	992.1021118
13	1156.820535	1076.905761	1150.741714	1156.598379	1154.959106
13.5	1368.183743	1355.812357	1356.479677	1350.774585	1351.230469
14	1624.497932	1617.521944	1586.819018	1566.882446	1591.626831
14.5	1943.520796	1992.570497	1904.11218	1786.114488	1894.342773
15	2519.773601	2607.000819	2527.765033	2007.914881	2534.163086
Scenario		Paint Scenario (FC)			
ML Model	GPR FC Before MC	NN FC Before MC	RF FC Before MC	SVR FC Before MC	XGB FC Before MC
Ship Speed (knots)					
9	110.0681824	109.7261409	145.9697979	198.9500958	110.0694275
10	151.1317976	136.466916	147.7941416	184.4212582	110.0694275
11	201.2853668	190.9735841	217.9306678	205.5268493	201.2854462
12	263.4790258	280.0992688	275.9635875	263.5794429	263.4786377
12.5	304.5852633	305.8465382	299.9679622	304.4850525	304.5857544
13	354.9289312	347.0132561	342.6251478	356.7247847	354.9288025
13.5	415.9640576	411.2245197	410.7555031	415.8638479	415.9638672
14	490.9831319	493.1734249	458.7298578	456.1786509	490.9830627
14.5	604.0632426	603.0627193	509.7395255	464.3280106	490.9830627
ML Model	GPR FC After MC	NN FC After MC	RF FC After MC	SVR FC After MC	XGB FC After MC
Ship Speed (knots)					
9	110.9468804	104.3293647	112.0365167	122.5078835	110.0686035
10	150.4267954	159.4908743	149.0412014	148.252523	149.434967
11	202.1326087	197.0763132	200.7668618	191.8302572	201.2854309
12	264.4943841	237.5931262	263.4790258	254.4450196	263.479126
12.5	305.9407542	267.2496331	304.3589495	297.0075927	304.5852661
13	356.5729771	328.4503802	352.1221403	352.766029	354.928894
13.5	417.0407844	417.1987376	414.6594368	423.01583	415.9640808
14	491.9418897	493.8534728	492.1279181	503.15546	490.9830322
14.5	581.251839	587.7390545	585.0367962	594.70329	585.7319946

Table A12. Cont.

Scenario		Paint Scenario (CO ₂)			
ML Model	GPR CO ₂ Before MC	NN CO ₂ Before MC	RF CO ₂ Before MC	SVR CO ₂ Before MC	XGB CO ₂ Before MC
Ship Speed (knots)					
9	342.3120472	341.3546769	453.9660716	868.3139517	342.3130493
10	470.3726079	417.9267183	459.6397804	821.9489526	342.3130493
11	625.9974908	585.9480329	676.4859729	811.4365762	625.9974976
12	819.4197703	873.3001888	858.2467571	882.4097629	819.4193726
12.5	947.2601688	957.7176548	932.9003626	964.1036723	947.260498
13	1103.828976	1078.978708	1067.093867	1086.98547	1103.829102
13.5	1293.648219	1271.538847	1268.987043	1207.031549	1293.648193
14	1526.95754	1531.564039	1426.649858	1249.671125	1526.957642
14.5	1880.573319	1871.194434	1621.449695	1210.609411	1526.957642
15	2450.197529	2454.717365	2122.1974	1164.175625	2450.196289
ML Model	GPR CO ₂ After MC	NN CO ₂ After MC	RF CO ₂ After MC	SVR CO ₂ After MC	XGB CO ₂ After MC
Ship Speed (knots)					
9	345.827258	369.3603125	345.984959	406.610355	342.3125305
10	469.3596164	472.5635381	464.7424402	484.2087486	464.7426147
11	630.0039312	579.7292394	625.9974908	618.5010343	625.9976196
12	823.901072	673.9866465	820.6981743	811.3285214	819.4199219
12.5	952.9826716	753.8638453	946.2690489	941.239089	947.2601929
13	1110.169015	944.3038956	1087.226196	1106.209366	1103.828979
13.5	1295.161495	1196.729475	1287.257755	1302.449508	1293.648193
14	1527.291712	1480.261427	1533.464514	1515.700765	1526.95752
14.5	1799.758685	1836.58612	1825.357815	1734.062779	1821.626343
15	2402.145048	2465.61085	2450.197529	1945.897448	2450.197266

Table A13. Mean MSE and mean RMSE for FC predictions across scenarios.

Model	Mean MSE (After MC)	Mean RMSE (After MC)
SVR	6730.9338	55.0255
GPR	217.0695	14.7333
RF	2.8845	1.6984
XGB	3.49927×10^{-8}	0.0001871
SNN	442.8756	21.0446

Table A14. ML models performance metrics for FC after MC.

Scenario	XGB-Model Performance Reference		SNN-Model Performance Reference		RF-Model Performance Reference		GPR-Model Performance Reference		SVR-Model Performance Reference	
	MSE FC After (kg/h) ²	RMSE FC After (kg/h)	MSE FC After (kg/h) ²	RMSE FC After (kg/h)	MSE FC After (kg/h) ²	RMSE FC After (kg/h)	MSE FC After (kg/h) ²	RMSE FC After (kg/h)	MSE FC After (kg/h) ²	RMSE FC After (kg/h)
original	3.20129 × 10 ⁻⁸	1.78921 × 10 ⁻⁴	702.9967199	26.51408531	2.726694526	1.651270579	34.61564091	5.883505835	766.08926	27.67831751
Paint	3.16396 × 10 ⁻⁸	1.77875 × 10 ⁻⁴	318.0265551	17.83329905	1.572330678	1.253926105	26.65448824	5.162798489	613.36023	24.76611051
Advanced Propeller	3.82875 × 10 ⁻⁸	1.95672 × 10 ⁻⁴	663.6611939	25.7616225	2.350944354	1.533278955	858.7625862	29.30465127	623.48086	24.96959872
Fin	4.14829 × 10 ⁻⁸	2.03674 × 10 ⁻⁴	572.3498592	23.92383454	5.924156541	2.433959026	11.53390635	3.396160531	773.8736	27.81858372
Bulbous Bow	3.16116 × 10 ⁻⁸	1.77797 × 10 ⁻⁴	219.6918737	14.8220064	3.632037997	1.905790649	270.8768963	16.4583382	1155.59246	33.99400624
Combined	3.49193 × 10 ⁻⁸	1.86867 × 10 ⁻⁴	180.5276211	13.43605675	1.100682394	1.049134116	99.97322306	9.998661063	614.06277	24.78069

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