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Predicting Icebreaker Resistance Using Machine Learning and Scale Model Testing

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ABSTRACT

Icebreakers are essential assets to enable safe Arctic and subarctic operations. These specialized ships have strengthened hulls and robust propulsion systems to enable them to manage ice and open shipping lanes through sea ice. Accurately predicting icebreaker performance is critical for designing vessels that are fit for purpose. A key factor in icebreaker performance prediction is understanding ice resistance, which determines an icebreaker's capability to operate effectively in icy conditions. In recent years, Machine Learning (ML) methods have been increasingly utilized to predict ship efficiency, typically using parameters such as length, beam, draft, and speed. This study expands on this approach by integrating both fundamental vessel parameters and environmental factors, including ice thickness, along with detailed hull geometry data into ML models. The objective is to assess how these factors enhance the accuracy of ice resistance predictions. The dataset includes ten different icebreakers, with model tests conducted by the National Research Council of Canada's Ocean, Coastal, and River Engineering Research Centre (NRC-OCRE). We trained boosting models to predict total ice resistance. This study demonstrates how data-driven approaches can result in novel multivariate regressions of ice resistance and highlights the improvements in prediction accuracy achieved by incorporating hull geometrical characteristics.

KEYWORDS: Icebreakers; Machine learning; Ice resistance

1. INTRODUCTION

The ability to navigate through ice-covered waters is crucial for Arctic and subarctic operations, where icebreakers play an essential role in maintaining safe and efficient maritime transit. These specialized vessels are designed with reinforced hulls and powerful propulsion systems to break and clear ice, ensuring accessibility for commercial and research missions. Predicting the performance of icebreakers in such extreme conditions is fundamental for optimizing vessel design, operational efficiency, and safety (Xue, et al., 2024, Zhou, et al., 2023).

One of the key challenges in icebreaker design is accurately estimating ice resistance, which directly influences power requirements, fuel consumption, and overall maneuverability.

Traditional methods for predicting ice resistance rely on empirical formulas, scale model testing, and computational fluid dynamics (CFD) simulations (Dick, et al.,1989). While these approaches provide valuable insights, they can be time-consuming, expensive, and limited in their ability to generalize across different vessel designs and ice conditions (Bassam, et al., 2022).

Recent advancements in data-driven methodologies, particularly Machine Learning (ML), offer new opportunities for improving ice resistance predictions. ML models have demonstrated success in various maritime applications, from ship performance optimization to automated navigation (Yan et al., 2022; Islam, 2021). However, most existing ML models utilize fundamental ship parameters—such as length, beam, draft, and speed—without fully incorporating the detailed hull geometry (Zhou et al., 2023; Kim et al., 2020).

In recent years, ML approaches have been applied to predict ship performance metrics, including ice resistance. A study proposed an artificial neural network (ANN) model to estimate ship resistance in ice-covered waters, demonstrating the potential of ML in this domain (Sun et al., 2022). Another research effort combined the challenges of predicting ice resistance and propulsion power for polar ship design. The study focused on developing an ANN model to predict the propulsion power of polar ships, considering traditional requirements and test data to select appropriate input features and training datasets (Zhou, et al. 2023). Furthermore, a study explored the use of an ANN to predict ice resistance for ice-going ships in level ice, highlighting the applicability of ML techniques in this field (Kim, et al., 2020). These studies collectively indicate a growing interest in leveraging ML to improve the prediction of ice resistance and the overall performance of icebreaking vessels. However, there remains a need for further research that integrates detailed hull geometry as well as ice flexural strength and ice thickness into ML models to enhance predictive accuracy.

This study leverages an ML technique to enhance the predictive accuracy of ice resistance by integrating ice thickness and flexural strength, fundamental vessel parameters, and detailed hull geometrical characteristics. Using a dataset of ten icebreaker scale model tests conducted by the National Research Council of Canada's Ocean, Coastal, and River Engineering Research Centre (NRC-OCRE), we developed a boosting learning model to estimate total ice resistance. By incorporating hull geometrical characteristics alongside traditional parameters, this research demonstrates the potential of ML-based approaches to refine ice resistance predictions. The findings contribute to the ongoing evolution of ship design methodologies, supporting the development of more efficient and capable icebreakers.

2. METHODOLOGY

This study utilizes a data-driven approach based on machine learning to predict icebreaker resistance. The methodology encompasses data acquisition, feature engineering, model training, and validation.

2.1 DATA ACQUISITION

The foundation of our dataset comprises data from ten distinct icebreaker designs. The data is derived from model tests conducted by the National Research Council of Canada's Ocean, Coastal, and River Engineering Research Centre (NRC-OCRE). One of the NRC's standard ice model tests, described by Wang (2023), addresses the data acquisition process. These ice model tests consist of three different tests—open water, level ice, and presawn tests—in order to derive the ice resistance regression equation. A full description of the test and analysis method can be found in Wang (2023). The ice resistance data for the study was derived from the regression equations in Wang (2023). It is noted that each hull form has a unique ice resistance regression equation. The range of ice conditions, as well as the ship speed, are shown below:

- Speed: 3-7 knots
- Flexural strength of ice: 300 KPa to 700 KPa
- Ice thickness: 0.5 m to 1.5 m

2.2 FEATURE ENGINEERING

This study goes beyond parameters like external environmental factors and fundamental vessel parameters by incorporating detailed hull geometry characteristics. In addition to basic vessel parameters (such as length and draft), the following geometric features were extracted or calculated for each icebreaker design:

- *Stem Angle:* The angle of the stem at the waterline influences the initial ice impact.
- *Flare Angle:* The angle of the hull plating relative to the vertical, affecting the ice-breaking process.
- *Waterline Angle:* The angle of the waterline at the bow influences the interaction between the hull and the ice sheet.

This study emphasizes ship geometry input, expanding to include 39 points of waterline angles, 8 flare angles, and two stem angles for each vessel. Figure 1 is an illustration of the ship's angles, generated using SpaceClaim. This expanded feature set aims to capture the influence of hull shape on ice resistance more comprehensively. The relationship between hull form parameters, including angles and ship resistance, is often non-linear. To address these non-linearities, we employed polynomial feature engineering, a technique commonly used to model complex relationships (Zheng, et al., 2018, Yang, et al., 2021). In terms of feature engineering, we opted for two-degree polynomial features, which allow us to generate new features from existing ones. For example, if the dataset contains two features, x and y, the polynomial transformation generates the following new features: $[x, y, x^2, y^2, x \cdot y]$. This transformation increases the feature count from two to five.

2.3. MACHINE LEARNING MODELS

We employed a machine learning model to predict total ice resistance. We used *XGBoost (Extreme Gradient Boosting)* a gradient boosting algorithm known for high accuracy and efficient training, particularly in regression tasks with complex, non-linear relationships. In this study, predicting total ice resistance (RTP) involves many interacting vessel geometry and environmental parameters, and XGBoost's tree-based structure effectively captures these interactions. XGBoost builds an ensemble of decision trees sequentially, with each tree correcting the errors of its predecessors. Hyperparameter tuning was performed using cross-validation to optimize model performance, which will be described in the following subsections. The model was implemented using Python 13.12.2 and the scikit-learn 1.5.1 and XGBoost 2.1.3 libraries (Chen, et al., 2016).

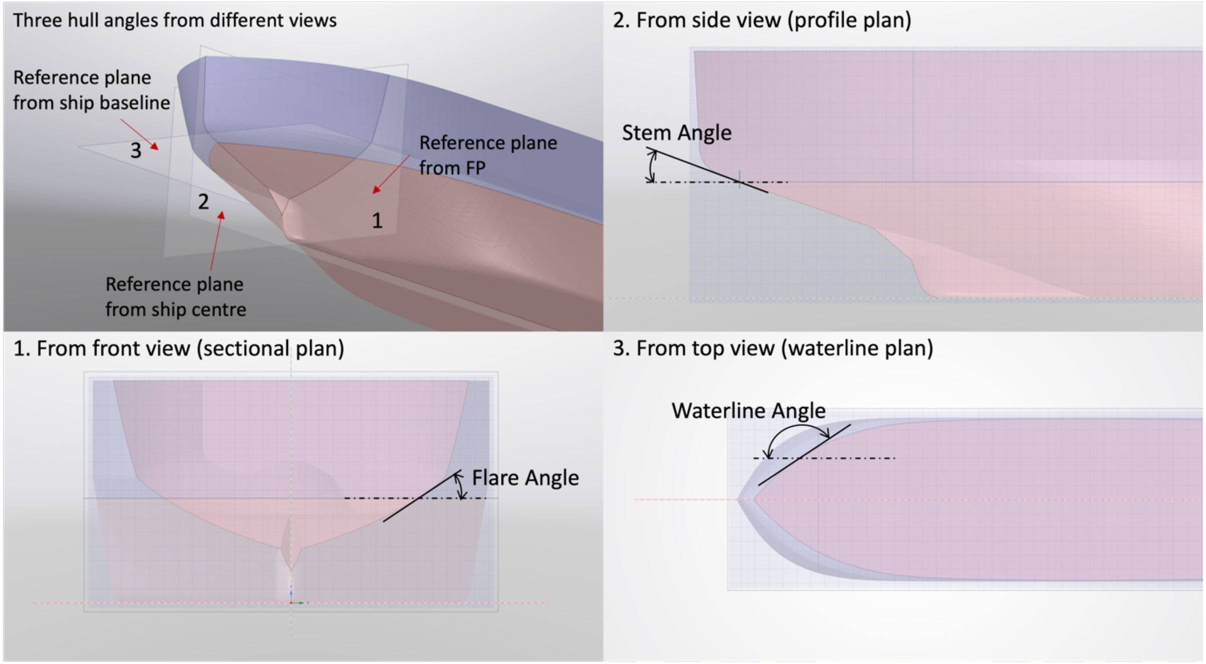


Figure 1. Ship's angles, generated using SpaceClaim

2.4 TRAINING AND VALIDATION

The dataset was split into training and testing sets. The number of instances (rows) is 8415, and the number of features (columns) is 57 before applying the polynomial feature and 1710 after applying the polynomial feature engineering. The training set was used to train the XGBoost model, while the testing set was used to evaluate their performance. We performed grid-search cross-validation for parameter tuning. The process was as follows.

2.4.1 CROSS-VALIDATION STRATEGY

In our study, we employed a cross-validation strategy to ensure the robustness and generalizability of our model. We utilized a total of ten vessels, denoted as M1 to M10, in our experimental design. In our block cross-validation, each block is a vessel, and each vessel has about 800 instances. The cross-validation process was structured as follows:

1) We reserved one vessel (M1) with all its instances for final validation, setting it aside to assess the model's performance on completely unseen data after the training and testing phases.

2) The remaining nine vessels (M2 to M10) were used in a block cross-validation scheme (Valavi, et al., 2018).

3) Each vessel data is a “block” and the process was to leave one block for testing and train on the remaining blocks. For example, for the first block cross-validation iteration we test on M2, and train on M3 to M10.

This approach allowed us to maximize the use of our limited dataset, with each vessel (M2 to M10) serving as a test set once while the model was trained on the remaining vessels. This strategy provided an assessment of our model's performance across different subsets of the data, enhancing the reliability of our results.

Upon completion of the nine rounds, we utilized the held-out vessel (M1) for final validation, obtaining an estimate of our model's performance on entirely unseen data. This cross-validation strategy ensured a thorough evaluation of our model's capabilities and generalizability. In each round, we calculated the Mean Squared Error (MSE) to measure the average squared difference between predicted and actual values. The MSE scores from all nine rounds were averaged to provide an overall performance metric for that set of parameters.

2.4.2 GRID SEARCH IMPLEMENTATION

After completing the block cross-validation process for one set of parameters, we adjusted a single parameter according to our predefined grid. We then repeated the entire block cross-validation process with the new parameter set. This procedure was iterated for all parameter combinations in our grid with the following parameter ranges:

‘max_depth’ set to {3, 4, 5}, which controls the maximum depth of each tree;

‘learning_rate’ set to {0.05, 0.1, 0.2}, which determines the step size at each iteration to minimize loss;

‘n_estimators’ set to {100, 200, 300}, representing the number of trees in the ensemble;

‘colsample_bytree’ set to {0.3, 0.5}, specifying the fraction of features randomly selected for each tree.

- *Parameter Selection:* We compared the average MSE scores across all parameter combinations. The parameter set yielding the lowest average MSE was selected as optimal.
- *Final Validation:* After identifying the optimal parameters through this grid search process, we trained a final model using these parameters on all the data from vessels M2 to M10. We then evaluated this model on the held-out validation set (M1) to obtain an assessment of our model’s performance on entirely unseen data.

This approach allowed us to explore the parameter space while avoiding data leakage. By implementing the grid search, each parameter combination was evaluated across all data subsets.

3. RESULTS

The features and the target considered in the results are stated in Table 1. The angles are illustrated in Figure 1.

Table 1. Feature identifiers and descriptions.

Identifier	Description
stem_at_draft	Stem Angle
flare_p_i	Flare Angle
waterline_beam_p_i	Water line Angle
hP (m), σfP (Pa)	Ice Thickness, Ice Flexural Strength
VP (knots)	Vessel Speed
RTP (KN)	Total Resistance (target)
SN, FN, TP	Strength Number, Thickness Froude Number, Draft

The flare angles, shown as flare_p975 to p799, are taken along the ship's length (LPP) from 97.5% from the stern to 79.9% (or 2.5% to 20.1% from the bow), providing insight into the curvature of the hull in these sections (a total of 8 data points). The waterline beam angles, presented as waterline_beam_p1 to p40, represent the angles measured from the center of the beam and extending outward to cover up to 40% of the beam's width (a total of 39 data points). These measurements help describe how the waterline changes from the centerline. Additionally, two stem angles at the front of the ship are measured: one at the full draft and another at 90% of the draft. Please see Wang (2023) for SN and FN definitions.

3.1 FEATURE IMPORTANCE

To gain further insights into the impact of individual features on the model's predictions, we employed SHapley Additive exPlanations (SHAP). SHAP can present feature contributions for the prediction. A positive SHAP value indicates that the feature contributed to increasing the prediction, while a negative SHAP value indicates that the feature contributed to decreasing the prediction (Lundberg, et al., 2017). By analyzing the SHAP values for each target variable, we can identify the features that have the most significant influence on the model's predictions, providing a more granular understanding of the relationships between the features and ship resistance components (Figure 2).

3.2. PERFORMANCE METRICS

The performance of the machine learning models was evaluated using two key metrics: Mean Squared Error (MSE) and R-squared (R^2). MSE quantifies the average squared difference between the predicted and actual ice resistance values, providing a measure of the overall prediction accuracy. R^2 indicates the proportion of variance in the ice resistance that is explained by the model, reflecting the goodness of fit. When incorporating all angle-related features, the model achieved an MSE of 9456.448 and an R^2 value of 0.953 for predicting total resistance, RTP (KN). In contrast, when excluding angle-related features, the MSE increased to 28300.743, and the R^2 value decreased to 0.861, demonstrating the significant contribution of hull geometry information to improving prediction accuracy.

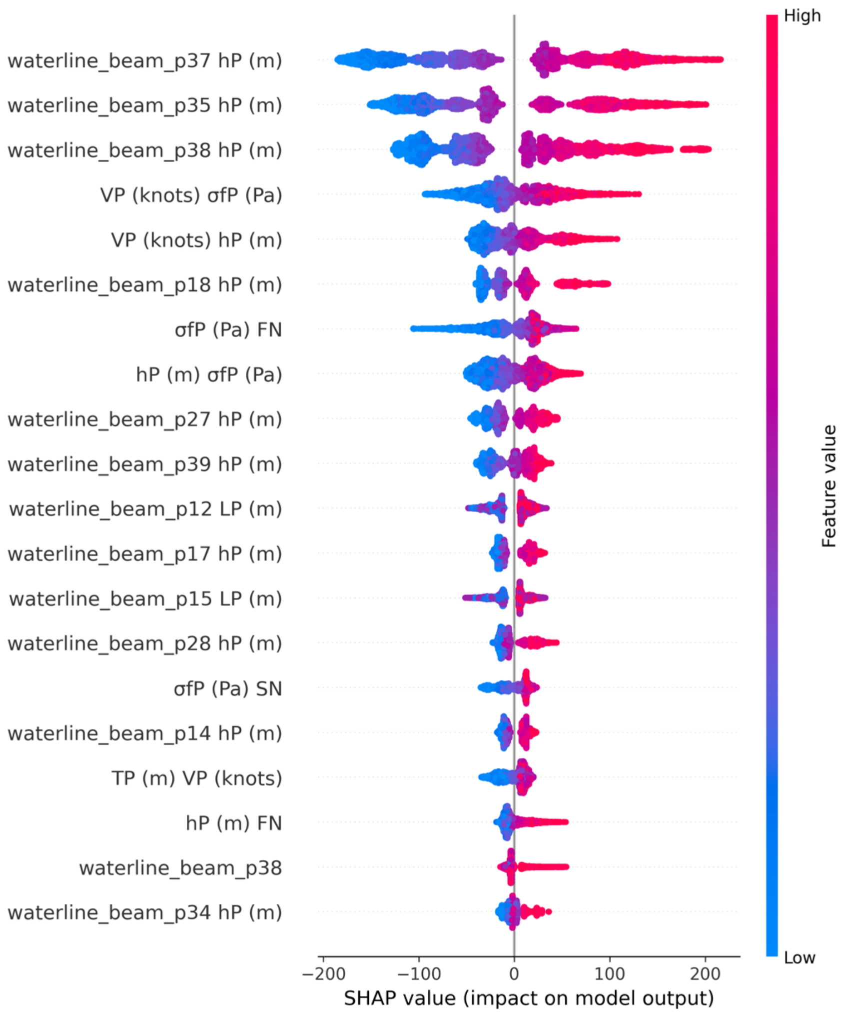
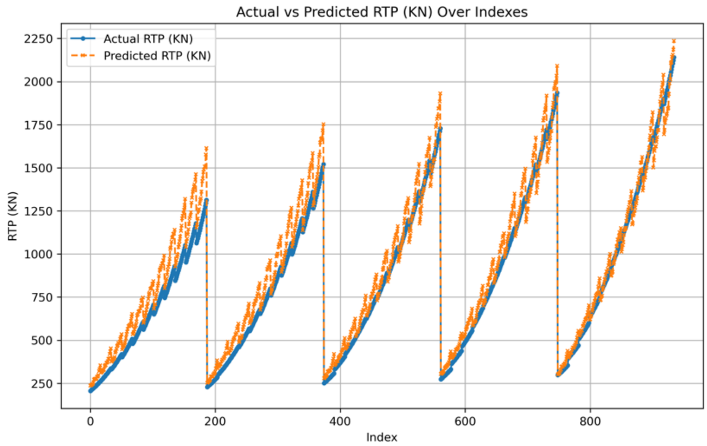


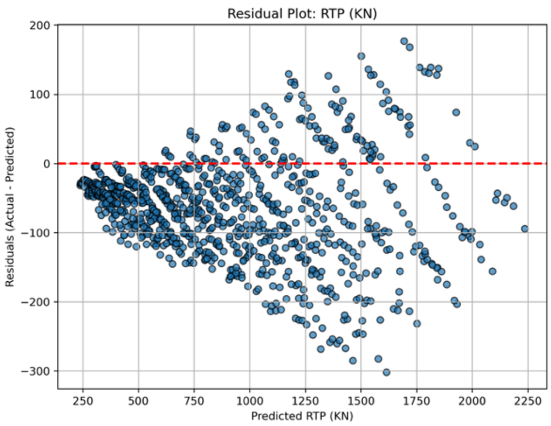
Figure 2. SHAP values for total resistance.

3.3 PREDICTION AND ACTUAL

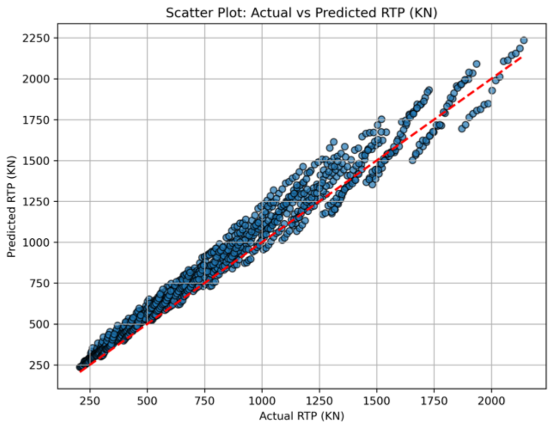
Figure 3 describes the following: In (a), the time series plot compares actual and predicted total resistance (RTP) values across the instances, which is the number of rows (indexes). The model closely tracks the actual resistance patterns, capturing many of the fluctuations of ice resistance. These show significant variance, but the variance is properly captured in the model. In (b), the residual plot displays the distribution of residuals (the difference between actual and predicted RTP values) against the predicted RTP. Ideally, residuals should be randomly distributed around zero. In (c), the scatter plot of actual versus predicted RTP values demonstrates a strong positive correlation, indicating that the model effectively captures the overall trend in ice resistance. Data points cluster closely around the red dashed line, which represents perfect predictions.



(a)



(b)



(c)

Figure 3. (a) Actual vs. Predicted Total Resistance Over Indexes (b) Residual Plot: RTP (KN) (c) Actual vs. Predicted RTP (KN)

CONCLUSION

This research has shown the potential of machine learning to advance the prediction of icebreaker resistance, a critical factor in the design and operation of these specialized vessels. The integration of hull geometry, specifically multiple stem angles, flare angles, and waterline angles, alongside traditional parameters and environmental conditions, led to an improvement in prediction accuracy. The XGBoost model, trained on data from ten icebreaker scale model tests, effectively captured the complex, non-linear relationships between these factors and ice resistance. In future work, we want to look in more detail at the sub-resistances, whose summation contributes to the overall ice resistance. Additionally, we plan to apply a min-max scaler to features with a large dynamic range and to the target variables.

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