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# A Deep Learning Method for the Prediction of Ship Fuel Consumption in Real Operational Conditions

**Abstract:** In recent years, the European Commission and the International Maritime Organization (IMO) implemented various operational measures and policies to reduce ship fuel consumption and related emissions. The effectiveness of these measures relies upon developing accurate predictive models encompassing the influence of real operational conditions. This paper presents a deep learning method for the prediction of ship fuel consumption. The method utilizes big data analytics from sensors, voyage reporting and hydrometeorological data, comprising of 266 variables made available following sea trials of a Kamsarmax bulk carrier of Laskaridis Shipping Co. Ltd. A variable importance estimation model using a Decision Tree (DT) is used to understand the underlying relationships in the available dataset. Consequently, a deep learning model is developed to understand the influence of sailing speed, heading, displacement/draft, trim, weather, sea conditions, etc. on ship fuel consumption (SFC). This is achieved by incorporating attention mechanism into Bi-directional Long Short-Term Memory (Bi-LSTM) network. The potential of the new method is demonstrated by training data streams corresponding to real ship fuel consumption rates as well as internal and external operational conditions. A comprehensive comparison with existing methods indicates that the Bi-LSTM with attention mechanism presents the best fit when using high frequency data. It is concluded that subject to further testing and validation the method could be used for the development of decision support systems for monitoring environmentally sustainable ship operations.

**Keywords:** Ship fuel consumption, decarbonization, big data science, deep learning, bulk carrier.

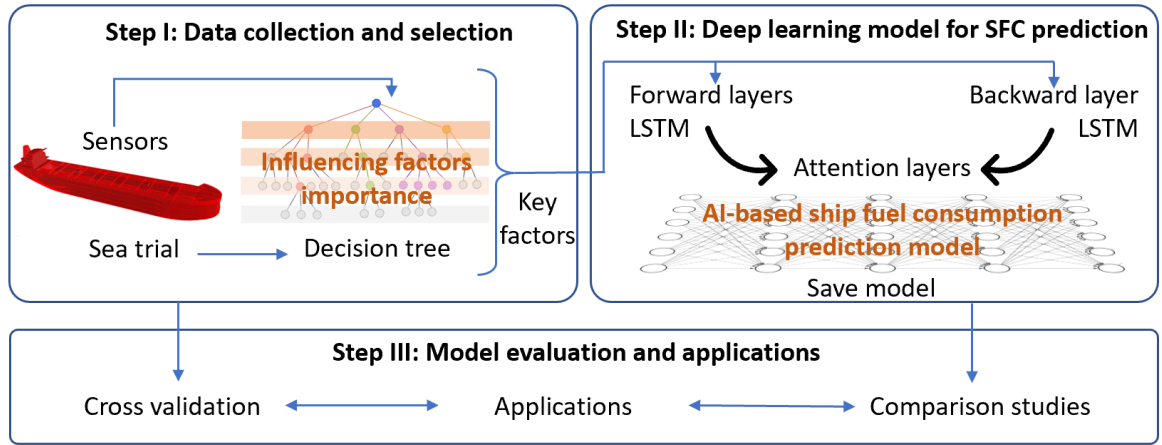


Fig. 1. The attention-based Bi-LSTM framework for the prediction of ship fuel consumption.

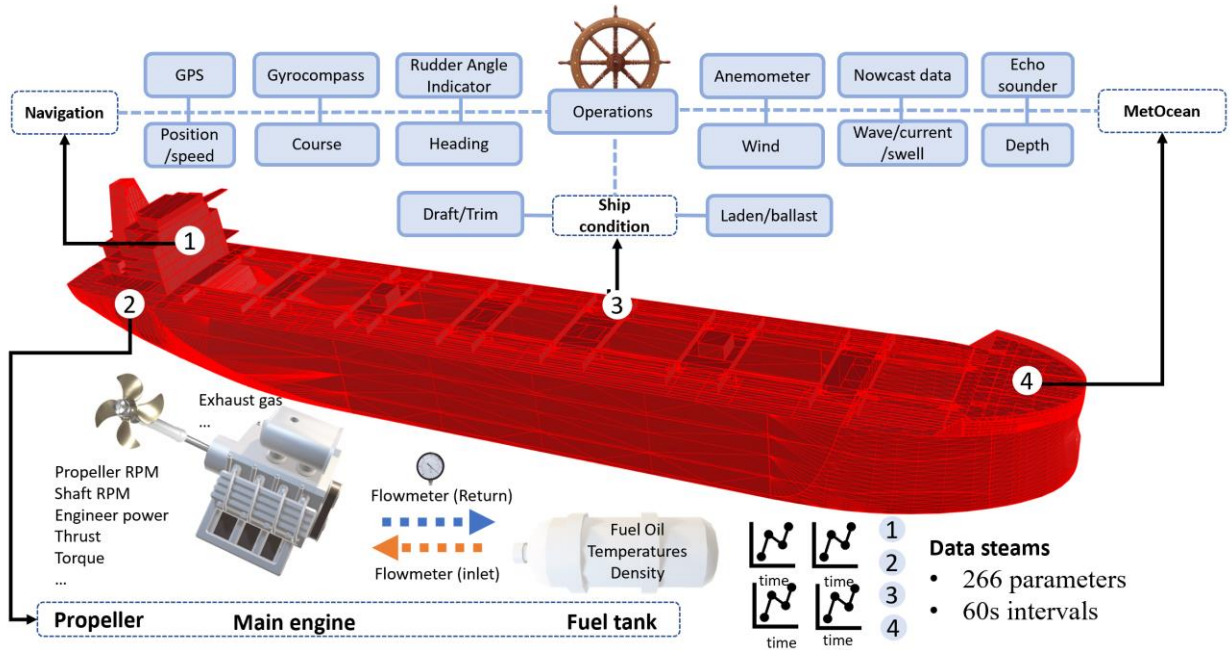


Fig. 2. Data collection and multisource-information fusion.

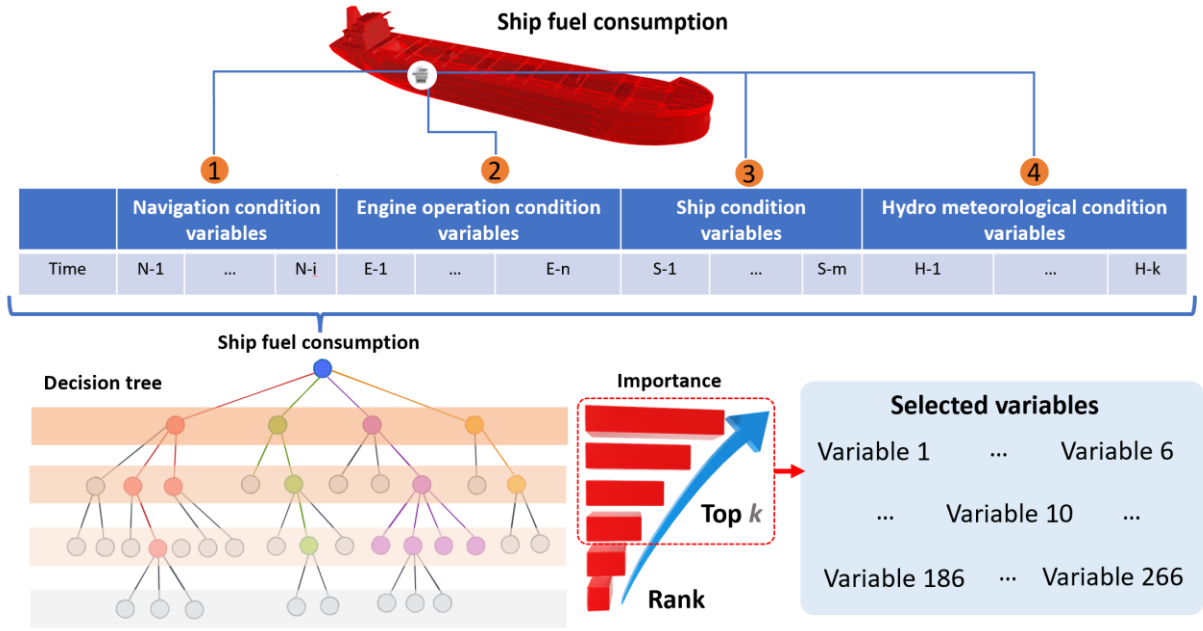


Fig. 3. Variable importance calculation for inputs selection of deep learning method.

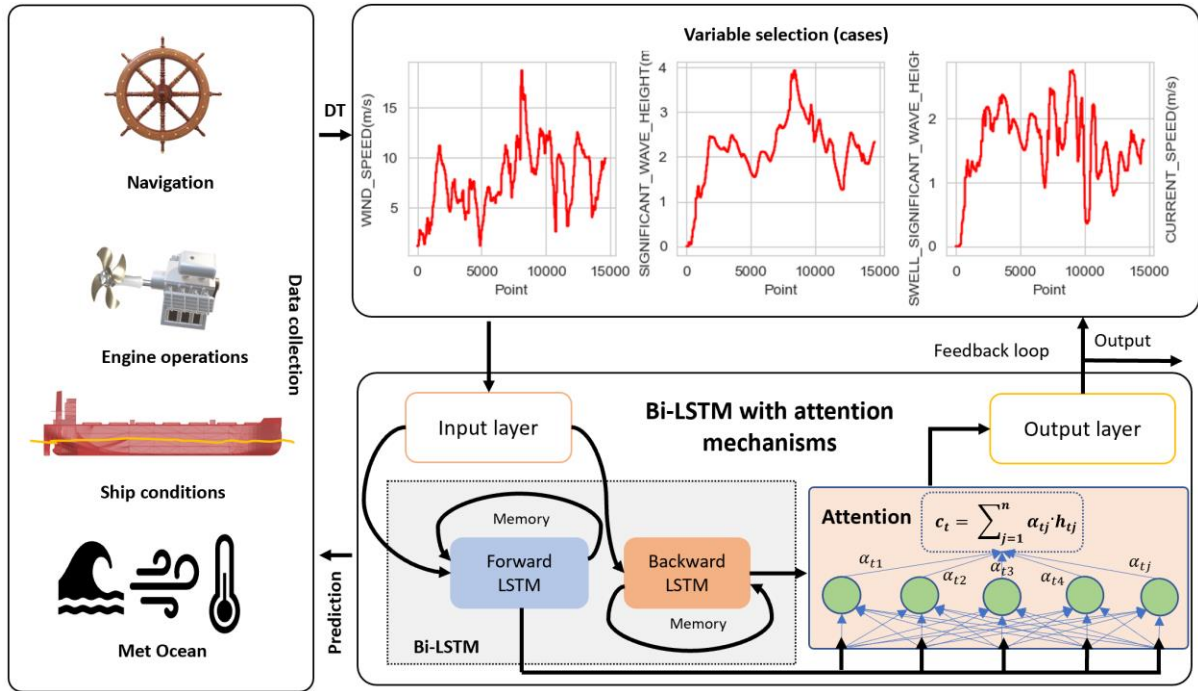


Fig. 4. The schematic of the deep learning method architecture for ship fuel consumption prediction.

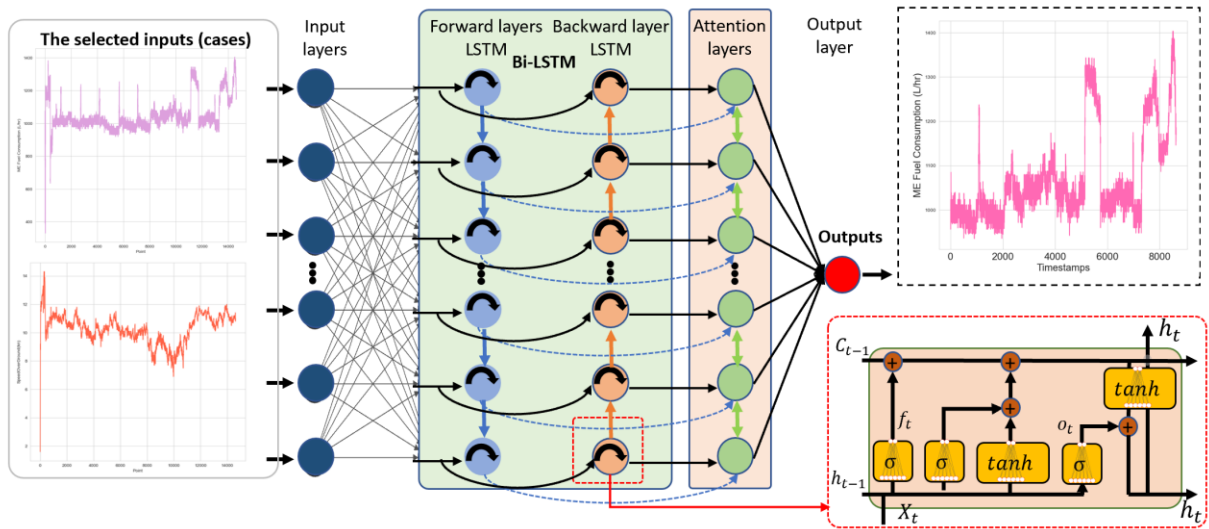


Fig. 5. The architecture of Bi-LSTM with attention mechanism for ship fuel consumption prediction.

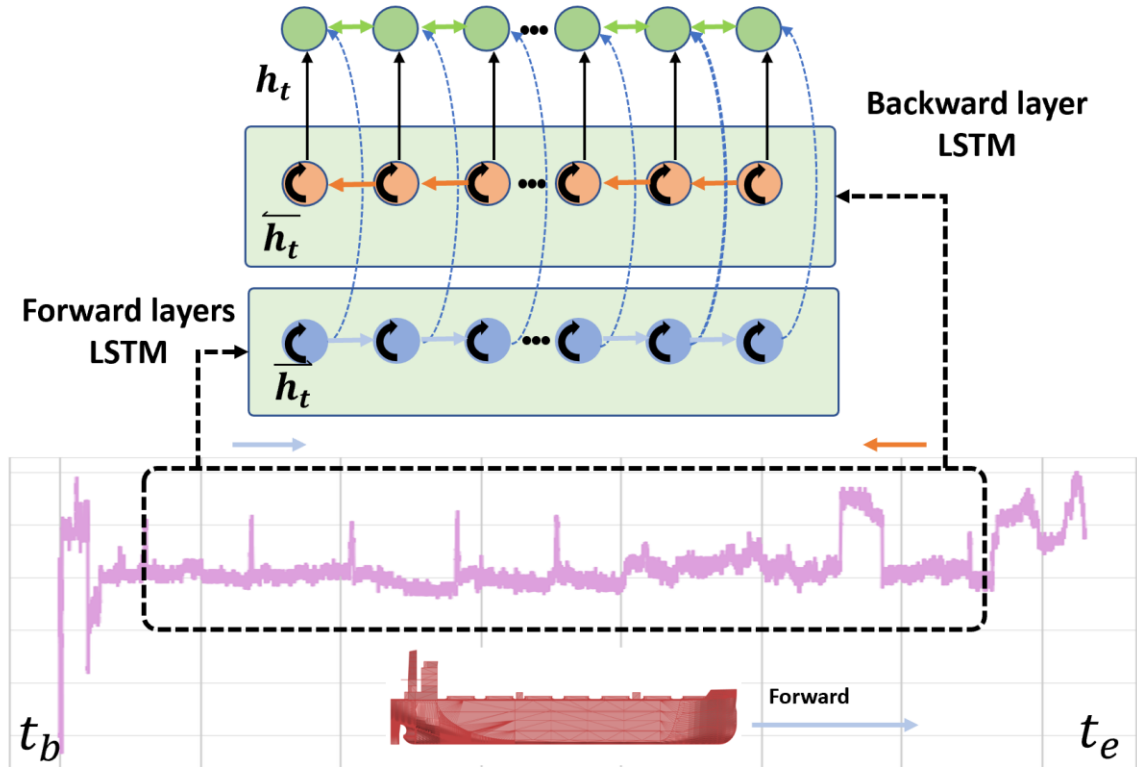


Fig. 6. Capturing and utilizing information from both forward and backward directions.

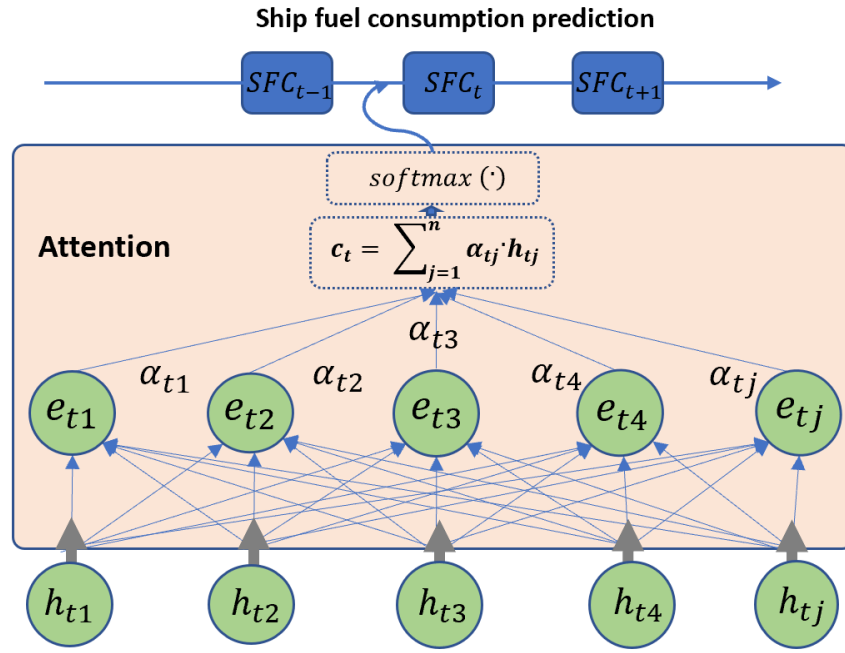


Fig. 7. Attention mechanism for ship fuel consumption prediction.

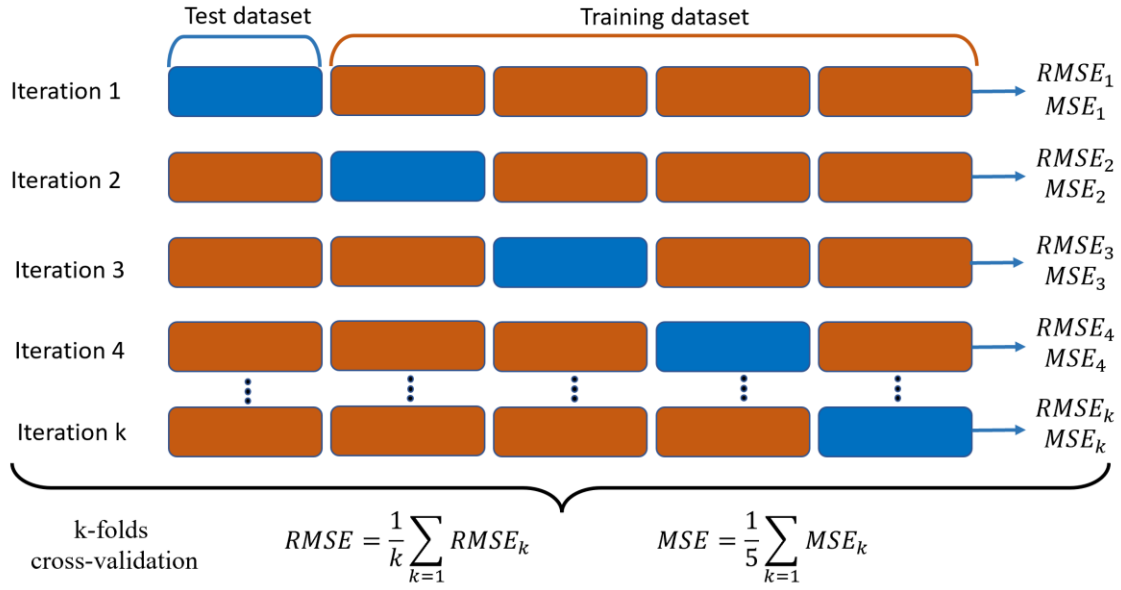


Fig. 8.  $k$  folds cross-validation for model evaluation.

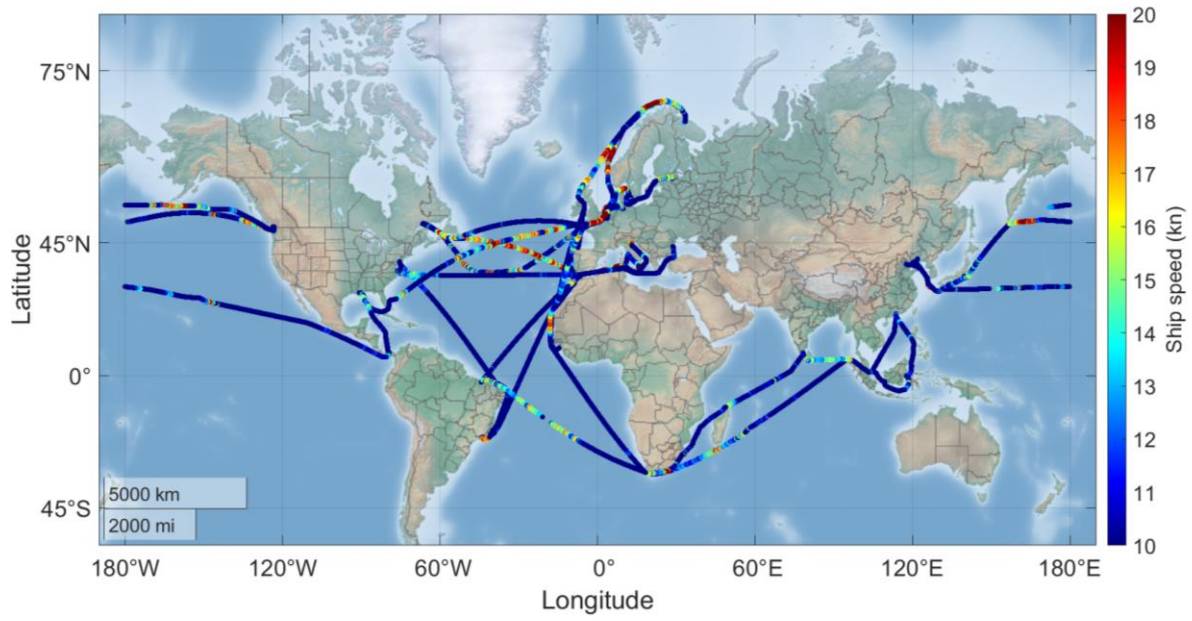


Fig. 9. Ship trajectories of sea trial data of a bulk carrier from 01.2021 to 02.2023.

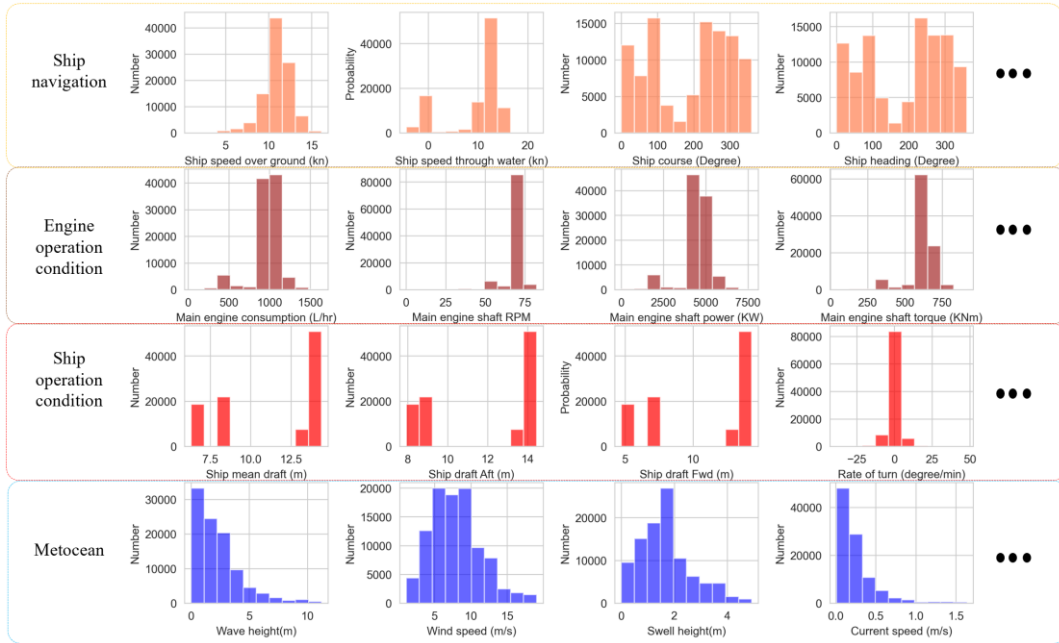
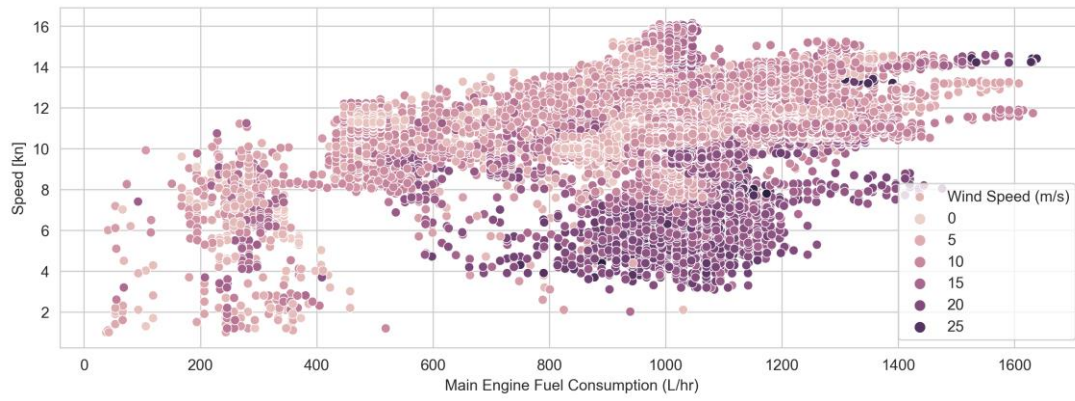
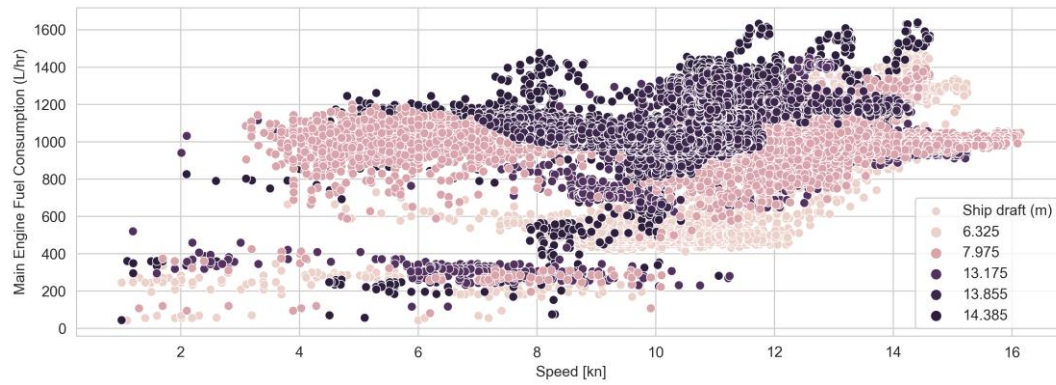


Fig. 10. Visual representation of the collected data samples.





(a) ship fuel consumption distribution under different ship speed and wind speed conditions.



(b) ship fuel consumption distribution under different ship speed and draft conditions.

Fig. 11. The relationship between ship fuel consumption and external conditions (speed, draft, wind).

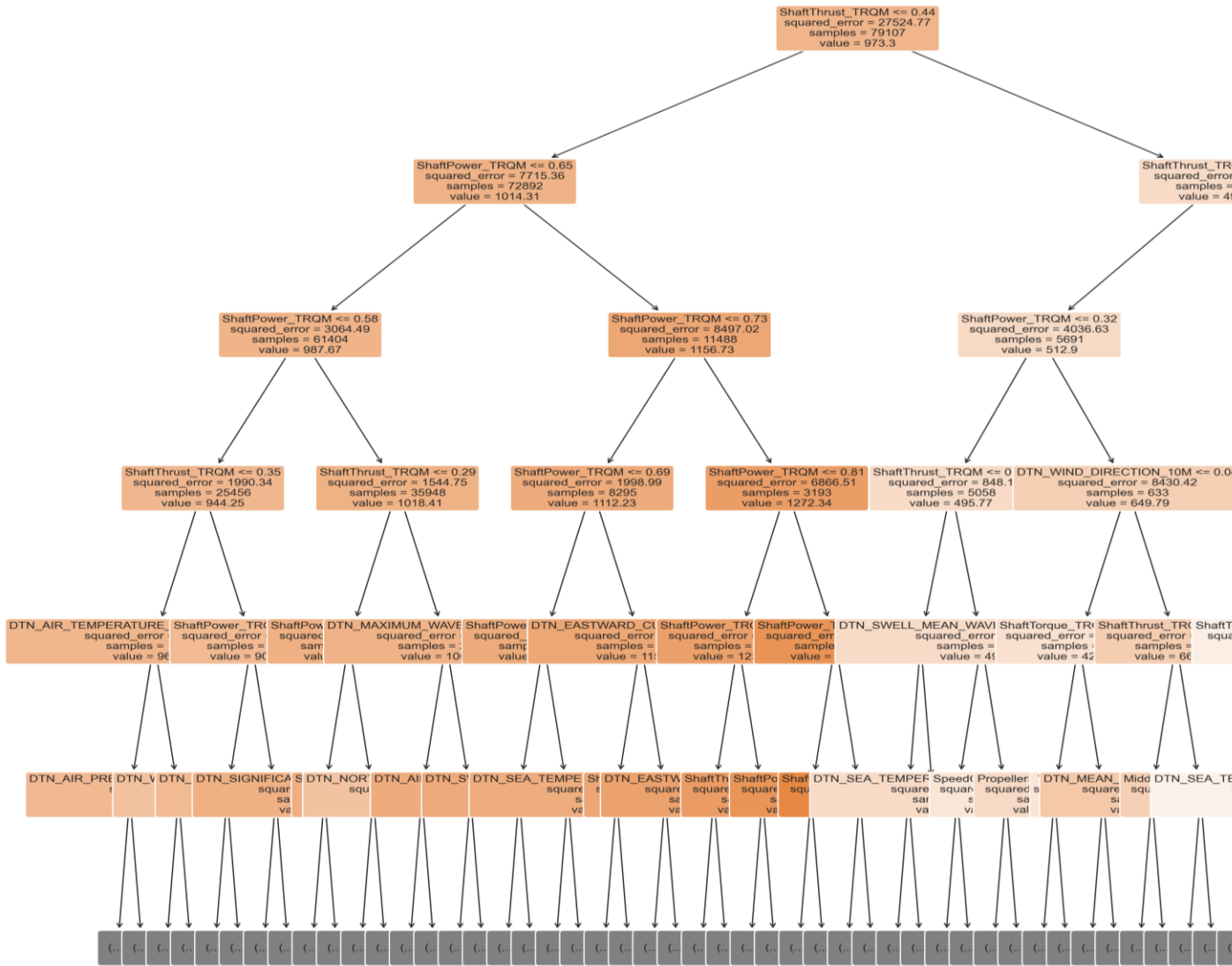


Fig. 12. Visualization of the decision tree model with the best-performing hyperparameters obtained from the grid search (the tree includes 90 levels (depths), and only the first five levels of the tree are displayed here).



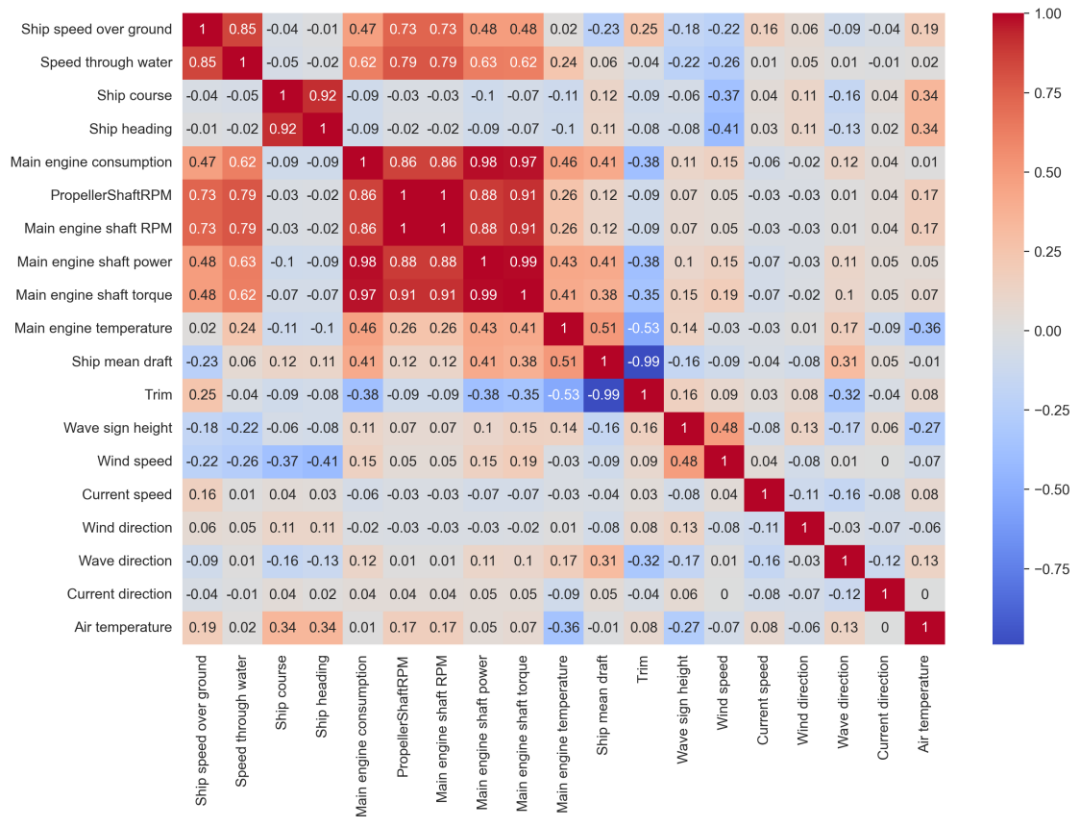


Fig. 13. The correlation relationships between the selected key influencing factors on ship fuel consumption using the collected data streams.

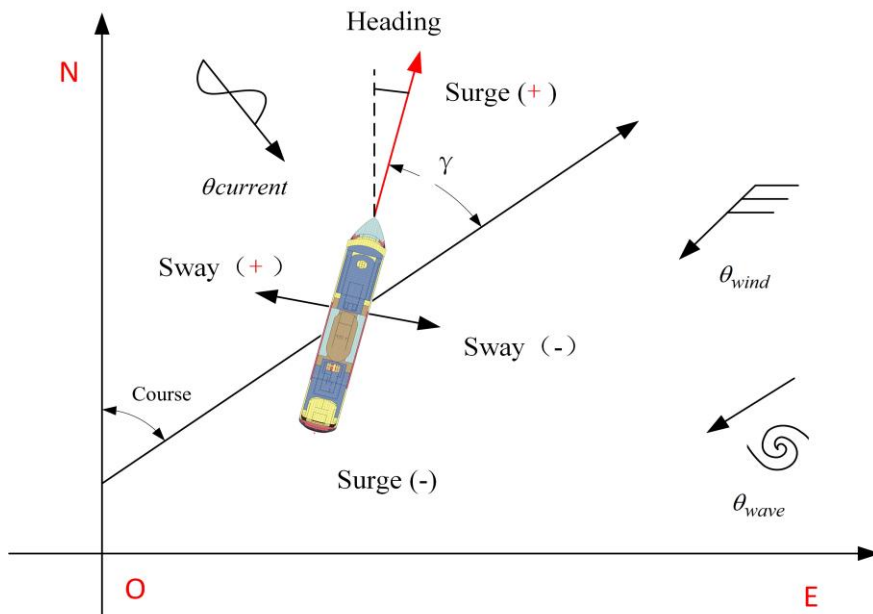


Fig. 14. The relationship between hydrometeorological factors and ship motions in real operational conditions (Zhang et al., 2023 b).

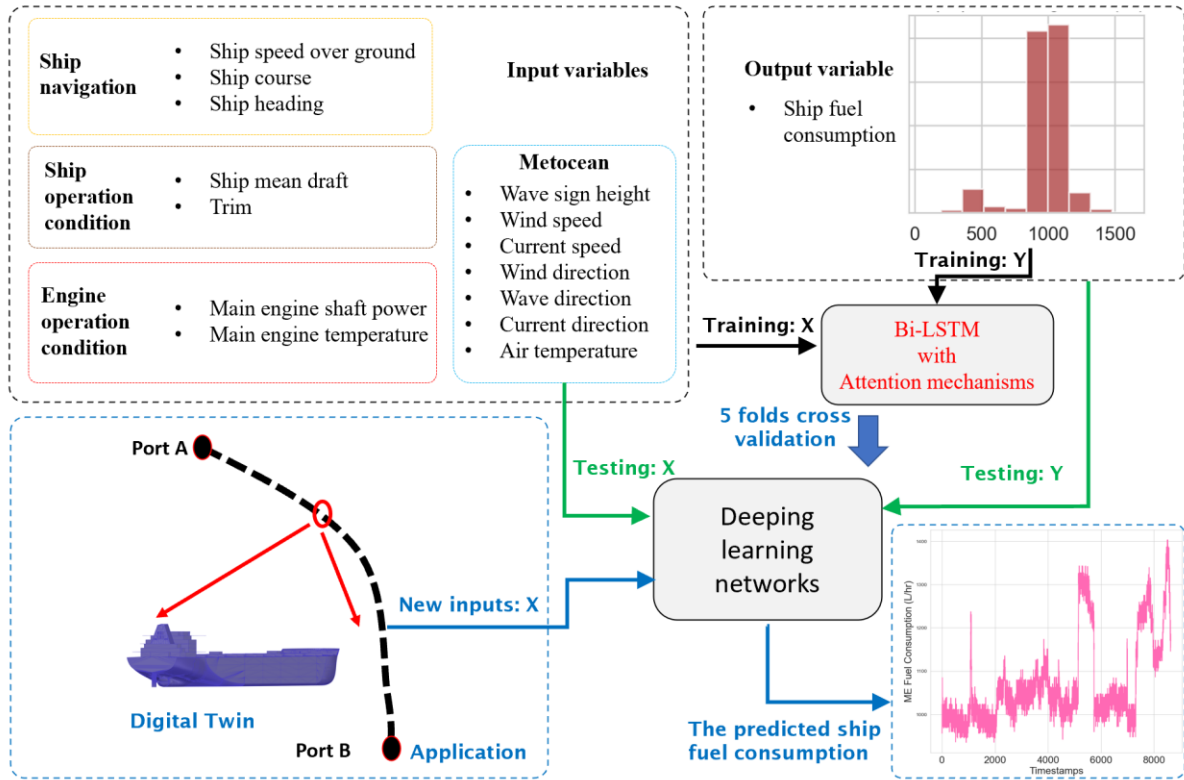


Fig. 15. The deep learning processing of ship fuel consumption prediction for model training, testing and application.

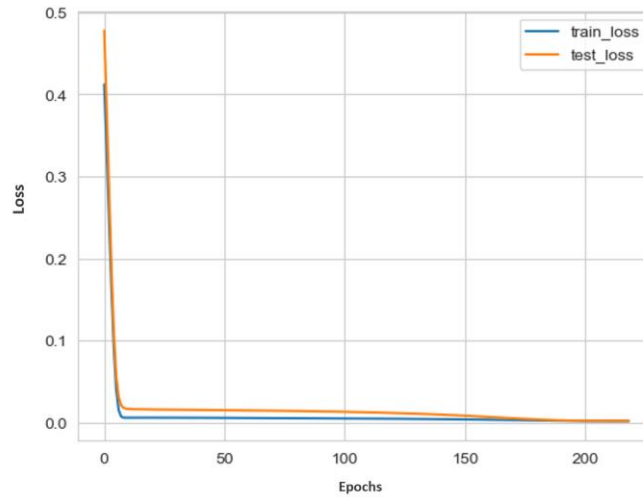


Fig. 16. The model performance evaluation.

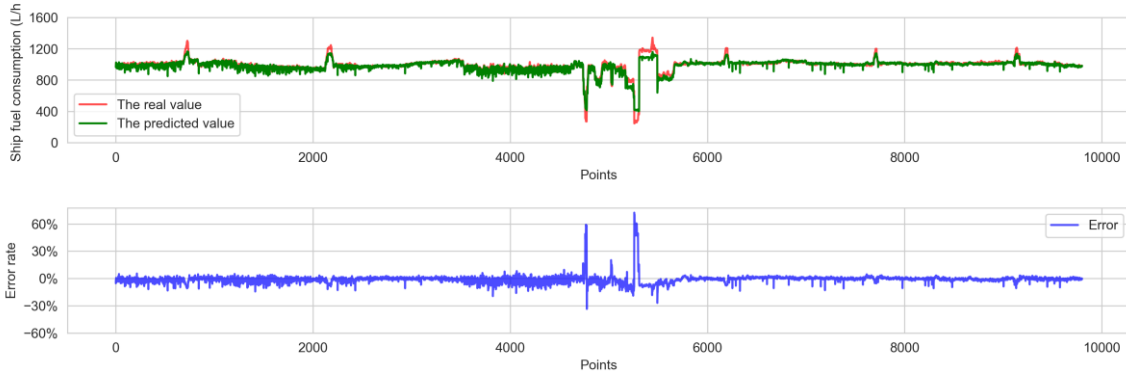


Fig. 17. The results of ship fuel consumption prediction (In the upper figure, the red line represents the real values of ship fuel consumption, while the green line represents the predicted results. In the bottom figure, the blue line represents the error rate in the time domain.)

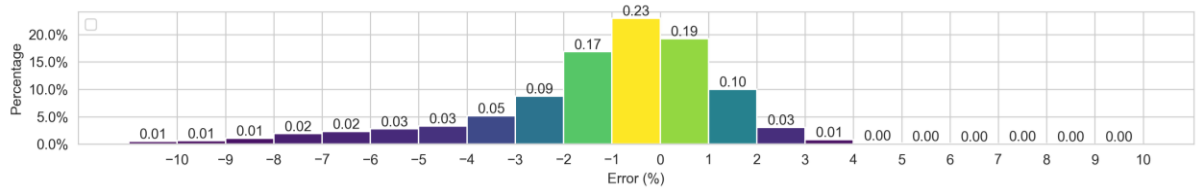


Fig. 18. The analysis of prediction errors using the adopted model.

```
Save model: model.save('Ship fuel consumption model.h5')
Load model: loaded_model = load_model('Ship fuel consumption model.h5')
Use the model: Predictions = loaded_model.predict(New_inputs)
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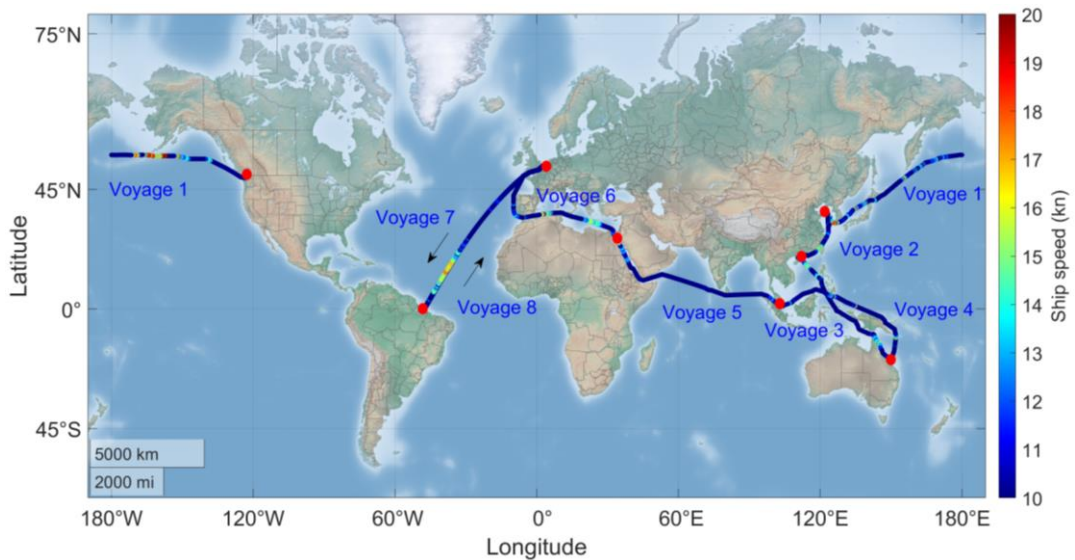


Fig. 19. Ship fuel consumption prediction by calling the trained model. (Ship trajectories of new data of a bulk carrier from 01.2023 to 06.2023.)



Fig. 20. The error analysis of ship fuel consumption prediction for a whole voyage 1 (In the upper figure, the red line represents the real values of ship fuel consumption, while the green line represents the predicted results. In the middle figure, the blue line represents the error rate in the time domain. The bottom figure presents the prediction error distributions.)

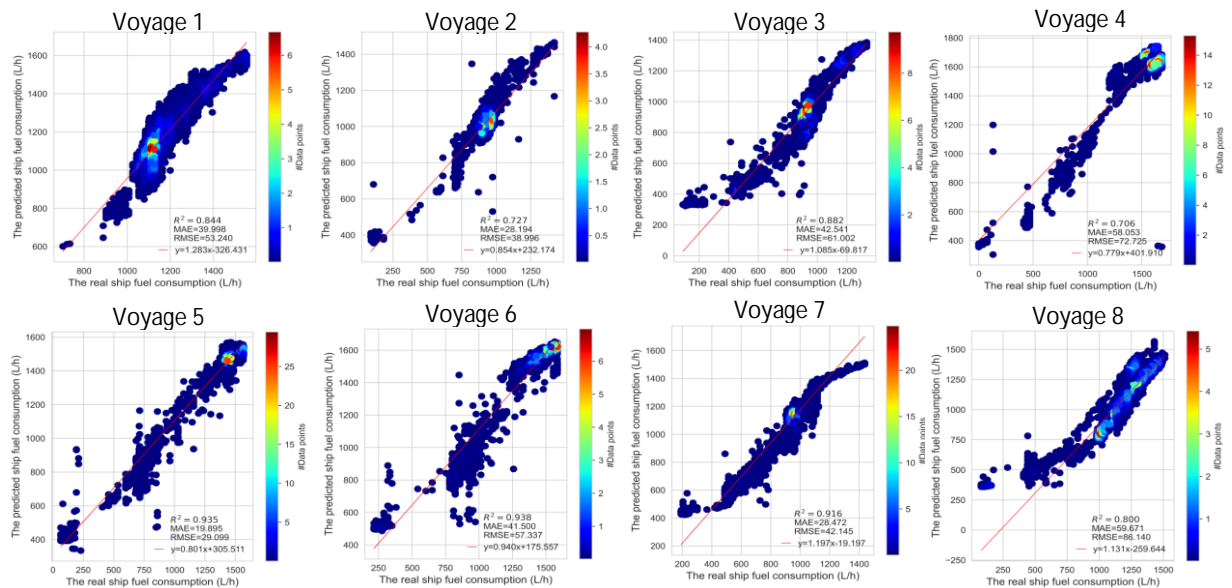


Fig. 21. The comparison of the real and the predicted ship fuel consumption.

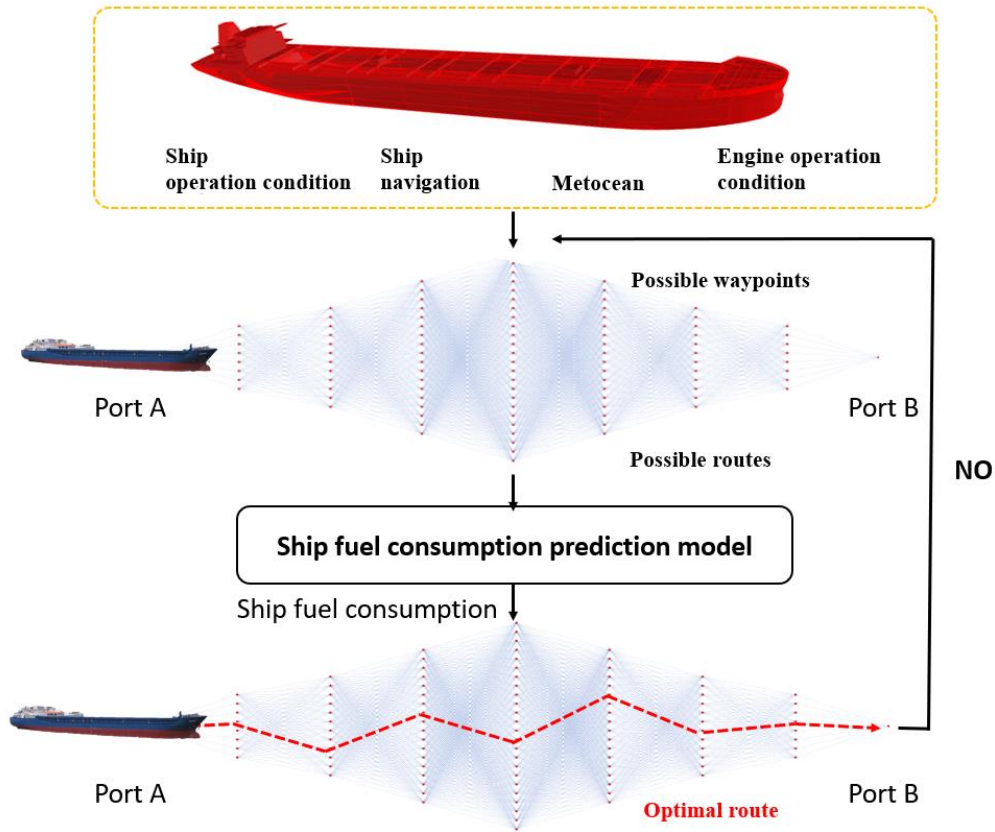


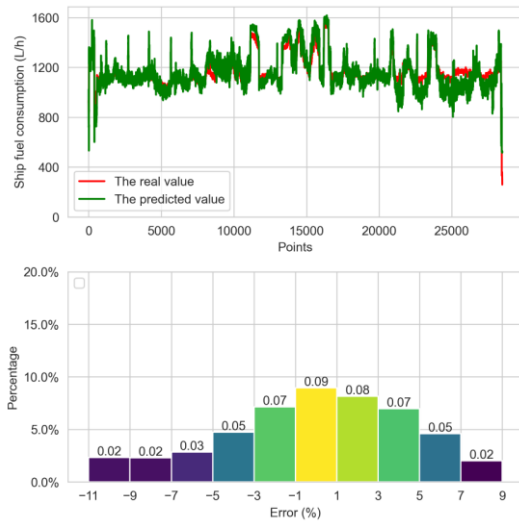
Fig. 22. A flowchart of multi-objective optimization method for ship fuel consumption reduction based on prediction model.

## Appendix A: Word cloud of 266 parameters of the collected data streams.

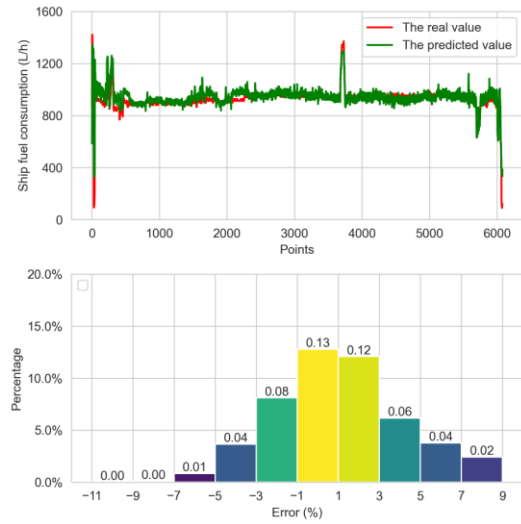


Fig. A1. Word cloud of 266 parameters of the collected data streams from sea trials.

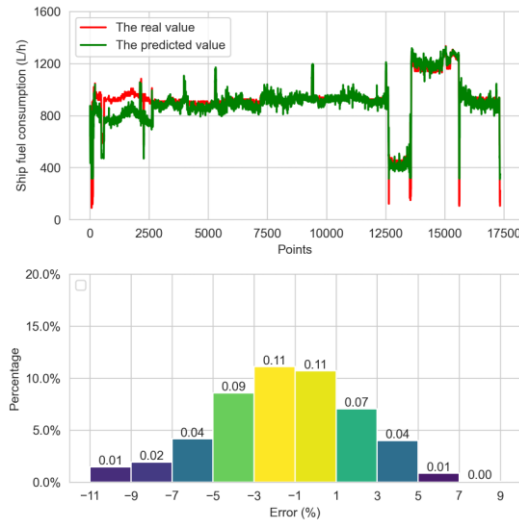
## Appendix B: The error analysis of ship fuel consumption prediction for 8 whole voyages.



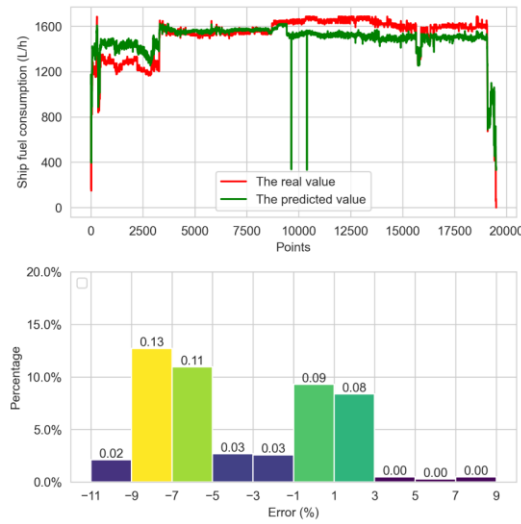
(a) Voyage 1



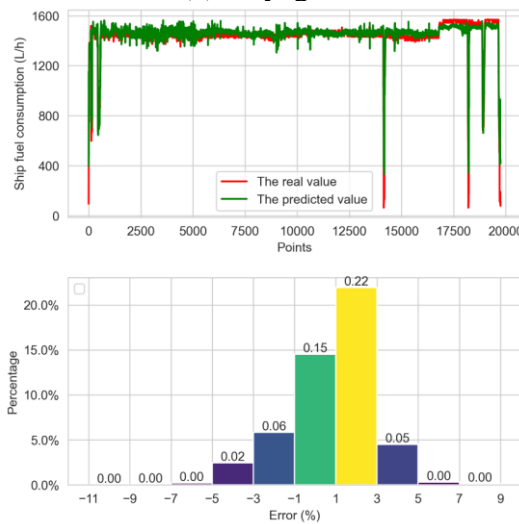
(b) Voyage 2



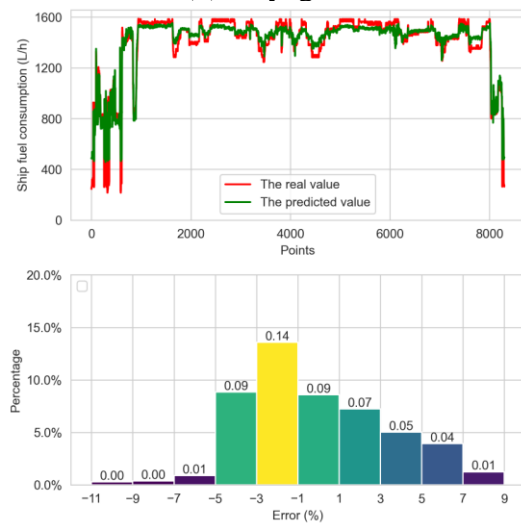
(c) Voyage 3



(d) Voyage 4

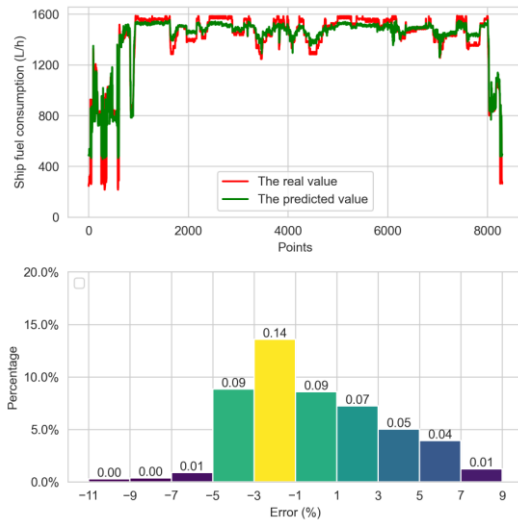


(e) Voyage 5

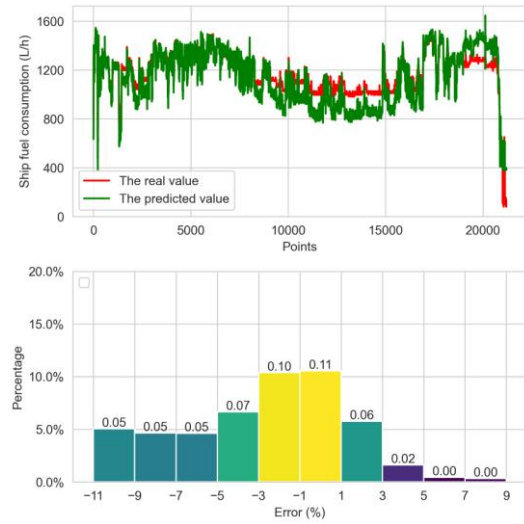


(f) Voyage 6





(g) Voyage 7



(h) Voyage 8

**Fig. B1.** The error analysis of ship fuel consumption prediction for 8 whole voyages.