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An Adaptive Prediction Framework of Ship Fuel Consumption for Dynamic Maritime Energy Management

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Abstract: Accurate prediction of fuel consumption is critical for achieving efficient and low-carbon ship operations. However, the variability of the marine environment introduces significant challenges, as it leads to dynamic changes in monitoring data, complicating real-time and precise fuel consumption prediction. To address this issue, the authors proposed an incremental learning-based prediction framework to enhance adaptability to temporal dependencies in fuel consumption data. The framework dynamically adjusts a dual adaption mechanism for input features and target labels while incorporating rolling retraining to enable continuous model updates. The effectiveness of the proposed approach was validated using a real-world dataset from an LPG carrier, where it was benchmarked against conventional machine learning models, including Random Forest (RF), Linear Regression (LR), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). Experimental results demonstrate that the proposed approach could significantly improve prediction accuracy in both offline and online scenarios. In offline mode, the proposed framework improves the R^2 of various machine learning models by at least 21.97%. In online mode, the proposed method increases R^2 by at least 17.97%. This work provides a new solution for real-time fuel consumption prediction in dynamic marine environments.

Keywords: ship fuel consumption; incremental learning; dual adaption; online prediction

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1. Introduction

With the continuous advancement of trade globalization, sea shipping has become the pillar of international trade, accounting for the vast majority of the global freight volume [1]. However, the shipping industry also contributes to global energy consumption and greenhouse gas emissions [2]. Therefore, accurate prediction of maritime fuel consumption is critical to improve operational efficiency, cost reduction, and environmental sustainability [3]. Despite significant progress, current online fuel consumption prediction methods still face some challenges that hinder their effectiveness.

The methods to predict ship energy consumption have been developed from traditional physical models to modern data-driven methods. Traditional physical models usually rely on domain knowledge, and can transparently explain prediction processes, such as white-box models [4]. Data-driven models include machine learning and deep learning models, which can automatically learn complex patterns and nonlinear relationships from large amounts of historical data, but with low interpretability, and are known as black-box models [5].

The white-box model is highly interpretable and provides a clear understanding of the potential factors influencing fuel consumption [6]. For example, the white-box model usually explicitly describes how a ship is affected by parameters such as wind speed, wave height, ship speed, and carrier weight during navigation [7]. These models predict the fuel consumption of ships by applying known physical laws, such as Newton's laws or hydrodynamic equations [8]. This domain knowledge-based modeling approach allows researchers and engineers to understand and interpret the output results of the models thoroughly, making the optimization and debugging of the model more intuitive. However, the white-box models are highly dependent on physical formulas and predefined relationships, which also limits their applicability [9]. These models are usually based on static assumptions and linear relationships, which may not fully fit into complex situations in practice. In the dynamic marine environment, changes in sea conditions, different operation modes, and differences in ship design may all lead to complex nonlinear interactions in fuel consumption [10]. Since the white-box model is usually not designed to cover all possible influencing factors and their complex relationships, it may appear inadequate when dealing with these nonlinear interactions and dependencies [11].

Machine learning (ML) techniques have significantly addressed the challenges faced by traditional white-box models in predicting marine fuel consumption. These advanced ML techniques are increasingly being used to improve prediction accuracy, using their ability to model complex nonlinear relationships in data to solve many problems that traditional white-box models cannot. Ref. [12] highlighted the development of an artificial neural network (ANN) model, which demonstrates superior performance to traditional methods for fuel consumption prediction [13]. The performance of ANN in fuel consumption prediction outperforms traditional methods. In addition, integrated learning approaches (e.g., stacked integrated learning) have been shown to significantly improve prediction performance. These methods combine multiple learning algorithms to improve robustness and accuracy. Refs. [14,15] showed that integrated models that integrate various algorithms outperform individual models by reducing bias and variance, thus providing more reliable predictions. These models typically use historical data and various ML techniques to predict future fuel consumption [16]. Despite these advances, a notable challenge remains: marine fuel consumption data are typically time series data, where observations are sequentially dependent. Traditional ML models, while powerful, may not be able to effectively capture the inherent temporal characteristics of such data.

Recent advances in ship energy prediction have also witnessed the application of deep learning models, with the emergence of many deep learning algorithms dedicated to the prediction of time series data. Refs. [17,18] utilize techniques such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) to capture temporal dependencies in the data, thus achieving high prediction accuracy. These models are adept at learning from sequential data and are therefore suitable for predicting fuel consumption, as past values and trends can significantly affect future consumption rates [19]. However, these models are not without limitations. They typically require large amounts of labeled data for training to achieve optimal performance, which can be a constraint in maritime applications where data collection is challenging and costly. In addition, without proper regularization, these models can be easily over-fitted and they perform well on training data but poorly on unseen data [20]. These models are often difficult to adapt to changing data distributions, requiring constant updating with new data [21]. Furthermore, most existing models fail to adequately address the dynamics and complexity of ship operations. For example, environmental conditions such as wind speed, wave height, and ocean currents can change significantly over time, which can affect fuel consumption rates. Models that fail to account for these variations may produce inaccurate predictions as [17,22] highlighted in their studies.

Another significant gap in current research is the lack of real-time adaptability. Traditional batch learning models are usually trained based on historical data and do not update their predictions based on new input data. This static approach may limit their effectiveness in dynamic marine environments where conditions and operating parameters are constantly changing. Refs. [23,24] highlighted that traditional batch learning models are designed to learn from a fixed dataset. These models do not adapt to new data after training until they are retrained on a newer dataset. This approach is problematic in a maritime environment as real-time data can significantly affect fuel consumption predictions [25]. For example, sudden changes in weather conditions, currents, and operating environments require immediate model adjustments to maintain prediction accuracy. If models are unable to adapt to new data, they may provide outdated or inaccurate predictions, leading to inefficient fuel usage and increased operating costs. Incremental learning (IL) and online learning techniques offer promising solutions to this problem [26]. Incremental learning models allow models to continually update their parameters as new data become available, and new data points can be merged without the need for complete retraining, making them more efficient and responsive to changes [27]. However, while these methods enhance adaptability, they may still struggle with capturing the intricate nonlinear dependencies and external influences affecting maritime fuel consumption. To overcome these limitations, researchers have explored hybrid modeling approaches that integrate multiple machine learning techniques. Among these, Artificial Neural Networks (ANNs) have gained attention for their ability to learn complex, nonlinear relationships directly from data.

Recent studies have demonstrated the considerable capability of ANN models in forecasting the behavior of complex energy systems, including maritime fuel consumption. The work reported in [28] shows that ANN-based approaches can effectively capture the intricate nonlinear dynamics inherent in such systems. In contrast to traditional physical or statistical models—which depend on pre-established relationships and assumptions—ANN models learn directly from data, thereby adapting to a wide range of operational scenarios and fluctuating environmental conditions.

In addition, recent research has underscored the promise of hybrid models that integrate the strengths of ANN with other machine learning techniques and physics-based approaches. For instance, [29] proposed a hybrid model combining ANN with support vector regression, achieving enhanced prediction accuracy and robustness compared to individual models. Similarly, [30] introduced a framework that incorporates physical constraints into a deep learning architecture, thereby improving both interpretability and adaptability in dynamic environments. Moreover, [31] presented a hybrid approach that merges ANN with a Kalman filter, facilitating real-time adaptation and error correction in system predictions.

Collectively, these studies demonstrate that hybrid models—by leveraging both data-driven learning and physical insights—can effectively mitigate challenges such as overfitting, limited interpretability, and the need for real-time adaptability. The integration of multiple modeling techniques not only enhances prediction accuracy but also improves the generalization capabilities of models in complex and dynamic energy systems. Such advancements make hybrid models particularly promising for maritime fuel consumption forecasting, where capturing nonlinear interactions and dynamic environmental variations is essential for optimizing operational efficiency and reducing costs.

Building on these promising findings, this study introduced a novel approach that further enhanced model adaptability and accuracy. Specifically, by incorporating incremental learning, the proposed method not only significantly improves prediction performance but also enables online forecasting of ship fuel consumption. The main contributions of this study are as follows:

1. Introduced the dual-adaption (DA) incremental learning into the ship fuel consumption prediction model. The framework employs incremental learning to capture the temporal dependencies in time series data, improving the prediction accuracy of maritime fuel consumption models.
2. The rolling retraining was applied to real-time prediction and can capture dynamic changes in time series data. By focusing on shorter and more manageable intervals, the rolling retraining approach enables the model to adapt to temporal changes quickly and accurately, improving its generalization ability and adaptability.
3. The combination of incremental learning and rolling retraining enables the model to be constantly updated with the emergence of new data, so as to realize real-time online prediction. This approach is effective in coping with data distribution changes over time and is particularly suitable for the task of predicting ship fuel consumption, which is constantly changing in response to environmental conditions and navigational states.

The proposed approach addressed the key issue of online prediction of ship fuel consumption. It introduced a novel integration of dual-adaption incremental learning with rolling retraining, thereby filling a gap in the existing literature on real-time forecasting in dynamic systems. By addressing both temporal dependencies and data distribution shifts, the proposed framework offers a robust theoretical foundation for future research in online prediction models across various domains. Dual adaption, incremental learning, and rolling retraining together enable real-time online prediction that can adapt to shifting data distributions, ensuring accurate and reliable forecasts. This capability supports more efficient fuel management and operational planning in the maritime industry by reducing fuel consumption, lowering costs, and minimizing environmental impact, thereby contributing to more sustainable maritime operations.

The rest of the paper is organized as follows: Section 2 details the dual adaption incremental learning and the use of rolling retraining; Section 3 describes the source and analysis of the dataset; Section 4 presents the experimental results and discussion of the various prediction methods; the conclusion is drawn in Section 5.

2. Methodology

2.1. Overall Framework of the Proposed Method

Accurate prediction of ship fuel consumption is critically important, yet the complex and variable sea conditions encountered during voyages can result in significant fluctuations in energy consumption. For ship operators, timely and accurate insight into fuel consumption is essential for optimizing sailing routes and speeds, as well as implementing effective energy-saving strategies. This not only reduces operational costs but also enhances overall economic efficiency. At the same time, fuel consumption prediction can also provide data support for environmental protection decision-making, reduce carbon emissions, and realize the goal of green shipping. To achieve reliable ship fuel consumption prediction, the authors developed an adaptive prediction framework for offline and online scenarios (Figure 1).

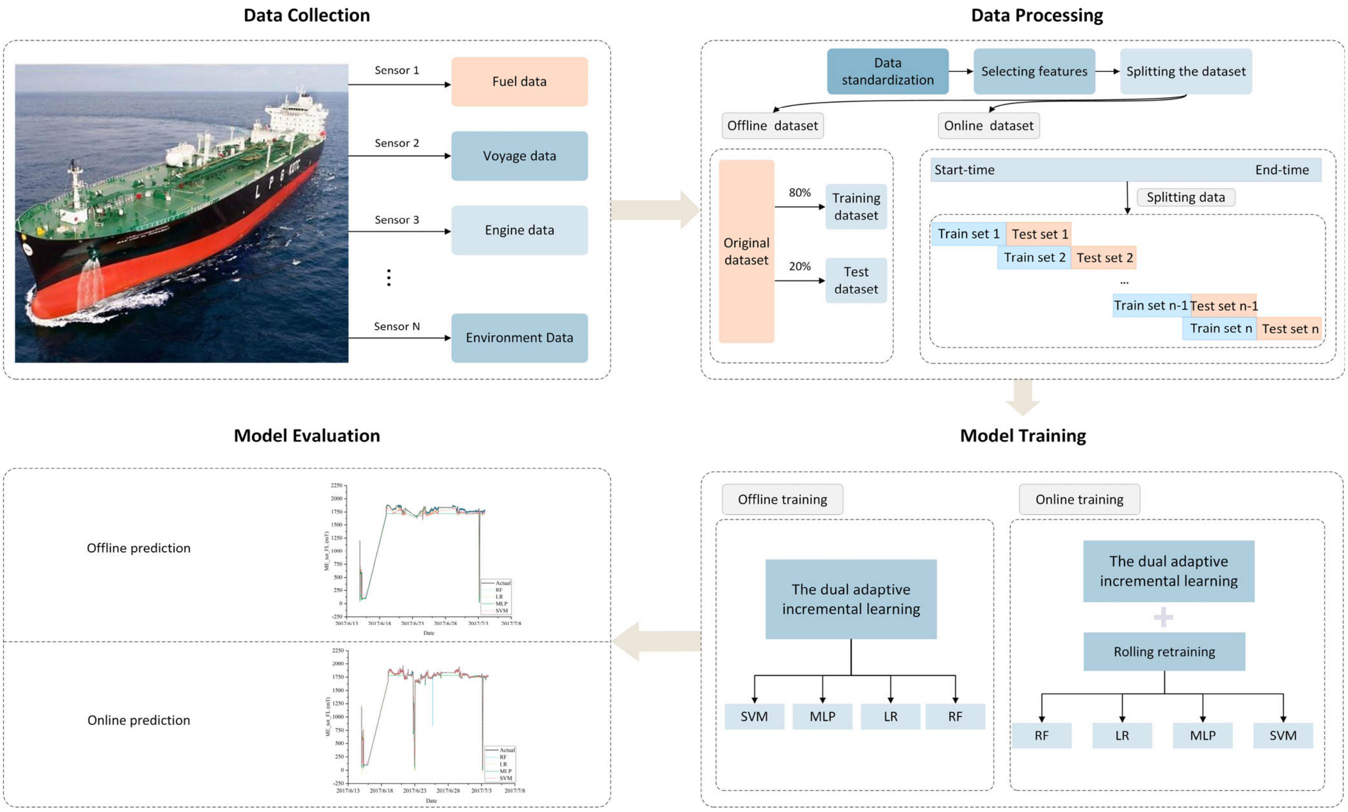

Figure 1. Structure of the proposed framework.

The proposed model structure introduces incremental learning of dual adaption, containing dual adaption to features and targets to data. This incremental learning process enhances the model's ability to capture potential patterns and trends in time series data, thus improving prediction performance. By continuously adjusting the incremental task, the model effectively learns the time dependence during training, thus producing more accurate predictions during testing. Moreover, the online prediction is promoted through the rolling retraining mechanism, where the data are divided into multiple parts for dynamic updating. This is conducted through a combination of incremental learning methods and rolling learning, allowing the model to be updated with newly available data without full retraining, thus enabling real-time prediction capabilities. Through offline and online training, the model can dynamically adjust the prediction models to ensure that it can provide highly accurate fuel consumption prediction under different sailing conditions, which helps ship operators to keep abreast of the fuel consumption characteristics and thus optimize energy-saving voyages.

2.2. Incremental Learning Module

Incremental learning, also known as online learning or sequential learning, is a machine learning paradigm where models are trained incrementally as new data arrives. This method is particularly useful for dealing with large-scale data streams and non-stationary environments where the data distribution varies over time [32]. By updating parameters with each new data point or batch, incremental learning enables adaptation to evolving patterns, making it crucial for real-time analysis and streaming data. In this study, incremental learning is integrated into the adaptive prediction framework to effectively handle data distribution shifts in maritime fuel consumption modeling, improving prediction accuracy across different operational conditions. The key steps in this approach are as follows:

1. Data pre-processing:

Rolling data extraction: the authors extract data in a rolling window to ensure that the model always has the most up-to-date information.

Function scaling and translation: function scaling and translation to maintain consistency across time windows.

2. Model update:

Online training: model parameters are updated incrementally using new batches of data. The model parameters θ are updated iteratively based on each new batch of data (X_i, y_i):

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(f(X_i; \theta_t), y_i) \tag{1}$$

where θ_t are the model parameters at the time step t. η is the learning rate. L is the loss function. $f(X_i; \theta_t)$ is the model prediction given the features X_i and parameters θ_t. $\nabla_\theta L$ is the gradient of the loss with respect to the model parameters.

For models like the RF, which do not support direct incremental updates, partial fitting can involve re-training on both old and new data:

$$D_{combined} = D_{old} \cup D_{new} \tag{2}$$

The model is then re-fitted on the combined dataset $D_{combined}$.

3. Dealing with conceptual drift:

Adaption mechanisms: To accommodate potential conceptual drift, the authors employed mechanisms such as sliding windows and decay factors that prioritize recent data over older data. The preparation of data for rolling retraining involves organizing the dataset into smaller, manageable segments that the model can process incrementally. To evaluate the performance of incremental learning methods, the authors use a rolling evaluation framework in which the models' predictions are continuously evaluated based on incoming data.

2.3. Dual Adaptive Incremental Learning Module

In ML-related fields, adapting models to different tasks or datasets is critical for improving performance and generalization [33]. Traditional adaption methods usually focus on feature adaption or target adaption respectively [34]. However, in scenarios involving multiple tasks or meta-learning, simultaneous adaption of input features and targets is crucial for optimal performance. In this study, an adaptive prediction framework is employed to address distribution shifts in maritime fuel consumption modeling. Incremental learning uses a multi-head feature and target adaption layers to adjust incremental and test data to a locally stationary distribution, which can help reduce the impact of distribution shifts. The pseudocode for the feature and the target adaption layer is shown in Algorithm 1.

The following are the meanings of the parameters in Algorithm 1:

θ: The model's parameters that are initialized at the beginning and updated iteratively during training.

X_{new}: the new input features from the data stream that are subject to adaption.

y_{new} : the new target values from the data stream that may exhibit drift or inconsistencies.

f_{adapt} : the feature adaption function that transforms X_{new} based on historical input features X_{hist}.

X'_{new}: the adapted new input features after applying f_{adapt} .

g_{adapt}: the target adaption function that adjusts y_{new} using historical target values y'_{new}.

y'_{new}: the adapted target values after applying g_{adapt}.

X_{hist}: the historical input features that the model has already seen and learned from.

y_{hist}: the historical target values associated with X_{hist}.

$\{X_{inc}', y_{inc}'\}$: the incremental dataset, which combines historical data and the newly adapted data for training.

η: the learning rate, a hyperparameter controlling the step size of model updates.

$L(\theta; X_{inc}', y_{inc}')$: the loss function that measures the difference between the model's predictions and the actual target values on the incremental dataset.

$\theta_{updated}$: the updated model parameters after minimizing the loss function L.

$\nabla L(\theta; X_{inc}', y_{inc}')$: the gradient of the loss function with respect to θ, used to guide the parameter update step.

Algorithm 1 Dual adaptive Incremental Learning

1. Initialize model parameters: \(\theta\)
2. Loop through the incoming data stream:
3. Apply feature adaption to the new input features \(X_{new}\):
    \(X'_{new} = f_{adapt}(X_{new}, X_{hist})\)
4. Apply target adaption to the new target values \(y_{new}\):
    \(y'_{new} = g_{adapt}(y_{new}, y_{hist})\)
5. Combine historical data and adapted new data for incremental learning:
    5.1 Create incremental dataset:
        \(\{X'_{inc}, y'_{inc}\} = \{X_{hist}, y_{hist}\} \cup \{X'_{new}, y'_{new}\} \)
    5.2 Update model parameters:
        \(\theta_{updated} = \theta − \eta \nabla L(\theta; {X'_{inc}, y'_{inc})\)
        where \(L\) is the loss function of the model
6. Update historical data:
    \(X_{hist} \leftarrow X_{hist} \cup X_{new}\)
    \(y_{hist} \leftarrow y_{hist} \cup y_{new}\)
7. Return updated model parameters: \(\theta_{updated} \)

The double adaption framework addresses issues of feature distribution inconsistencies and target variable drift through feature adaption and target adaption. f_{adapt} uses regularized adversarial training to align the distribution and transform X_{new} to be consistent with historical data. g_{adapt} applies weighted adjustments to the y_{new} to mitigate the impact of target changes. On this basis, incremental learning combines the adapted new data with historical data, dynamically updating θ, ensuring continuous learning from streaming data and addressing concept drift, while maintaining the robustness and adaptability of the classifier in both online and offline scenarios.

This method adapts the input features and targets as specified, then trains the models using the adapted data and applies the learned adaption to new data points for inference, ensuring consistency with the training process. In this study, this approach is integrated into the adaptive prediction framework for maritime fuel consumption modeling, allowing the model to dynamically adjust to distribution shifts. By seamlessly incorporating adapted features and targets into the training and prediction process, it enhances prediction accuracy and generalization across varying operational conditions. The following are its basic mathematical expressions and principles:

1. Feature adaption:

The input feature after the feature adaption process can be represented as follows:

$$\hat{X} = A_X \bullet X \tag{3}$$

where X represents the input features with n samples and d features. A_X is an adaption matrix or adaption vector of the same dimension as the input features, which is used to scale or transform the input features. $\hat{X}$ is the adapted feature set.

2. Target adaption:

The target can be represented as after the target adaption process:

$$\hat{y} = A_y \bullet y \tag{4}$$

where y represents the input features with samples and features. A_y is an adaption matrix or adaption vector of the same dimension as the input features, which is used to scale or transform the input features. $\hat{y}$ is the adapted feature set.

The adaption matrices A_X and A_y are learned using meta-learning or domain adaption strategies to minimize the loss function across different tasks or domains.

2.4. Rolling Retraining for Online Prediction

Rolling retraining is a technique for periodically updating a model using an expanding dataset that integrates historical and recent data to maintain accuracy and adapt to distribution shifts [35]. This dynamic updating mechanism is especially crucial for online real-time prediction, as it enables the model to promptly reflect the most current data trends and maintain prediction accuracy in rapidly changing environments. It employs a sliding window approach, continuously refreshing the training set by removing outdated data and incorporating new samples. This ensures the model remains aligned with evolving patterns. The process of rolling retraining is shown in Figure 2. Extract specific features from the raw data and construct the rolling retraining data structure, extract necessary features for each time point, selectively process sequence features, add them to the rolling dataset along with corresponding targets, and divide the data into training and testing sets based on the research design to evaluate the performance of rolling retraining model.

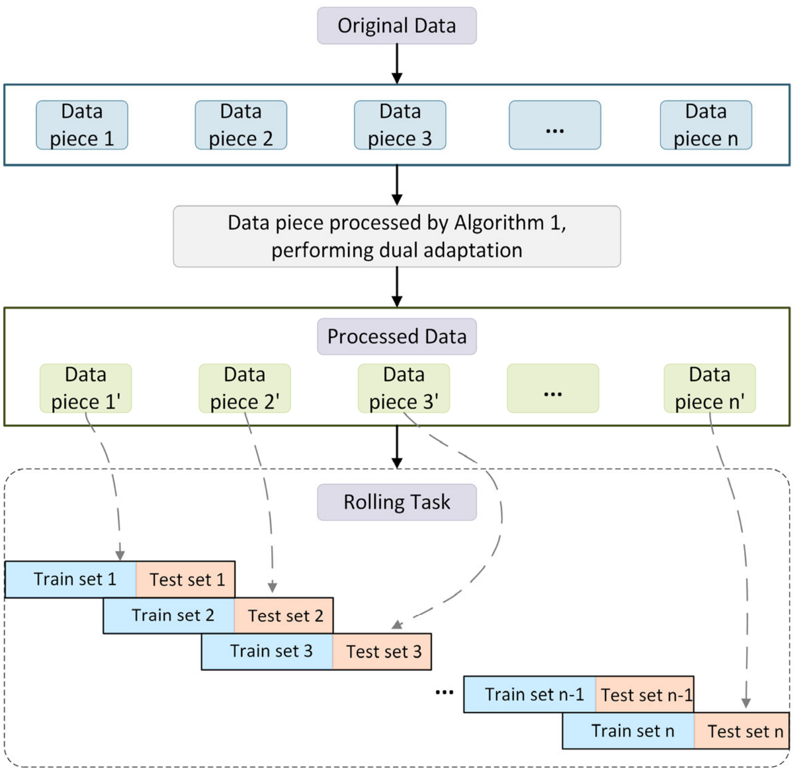

Figure 2. Process of rolling retraining.

The basic principle of rolling retraining is to adapt to the changing nature of data over time by acquiring and processing data dynamically. A rolling window is applied to the dataset to generate a series of tasks or samples.

$$T_i = \{(X_i, y_i) \mid X_i = X[t_i : t_i + \Delta t], y_i = y[t_i + \Delta t]\} \quad (5)$$

where T_i represents the i-th task in a rolling window. $X[t_i : t_i + \Delta t]$ is the featured over the time interval $[t_i, t_i + \Delta t]$. $y[t_i + \Delta t]$ is the target label at the end of the window. Δt is the length of the time window.

Rolling retraining allows the model to handle time series forecasting or prediction tasks in an online manner, adapting to recent changes in data. In this study, the training set and test set in each data piece consist of 40 samples and 10 samples, respectively.

3. Case Study

3.1. Data Description

This study utilized a public dataset from a Liquefied Petroleum Gas (LPG) carrier for experiments [36]. The vessel specifications are shown in Table 1. The data were collected over 12 months and contains four sets of data sources, i.e., (1) measurements from the ship's automated system as the primary source, (2) data from the Electronic Chart Display and Information System (ECDIS), (3) data from midday reports, and (4) meteorological and oceanographic information available based on geographic location and sailing time. This public dataset has been pre-processed to exclude highly irrelevant variables and variables for which complete data are not available (even if from alternative sources) through pre-processing such as correlation analyses, and the public dataset contains 20 variables (Table 2). The authors of [36] demonstrated the impact of the number of features on prediction results, and when the model construction time is not critical, it is recommended to use all input variables. Therefore, in this study, all features are selected as input features, with ME total FO consumption (ME_tot_FL) as the output target.

Table 1. Specifications of the LPG carrier.

Parameter	Value	Units
Length	225	m
Breadth	37	m
capacity	54,340	DWT
maximum output power	12,400	kw
Service speed	16.8	kn
Main engines	MAN B&W 6G60ME-C9.2	—

Table 2. Features and description of the dataset.

No	Features	Description
1	Pickup11	ME revolutions per minute (min^{-1})
2	ME_tot_FL	ME total FO consumption (mT)
3	Nav_02	Ship's speed over ground (knots)
4	Nav_04	Wind speed from anemometer (knots)
5	MS114	Ambient air temperature (°C)
6	MW014	Sea water temperature (°C)
7	List in degrees	(°)
8	Draft—mean	(m)
9	ECDIS COG	course over ground (deg)

Table 2. *Cont.*

No	Features	Description
10	ECDIS	wind direction (deg)
11	Uwind	(m/s)
12	Vwind	(m/s)
13	Wind gust	(m/s)
14	Significant wave height	(m)
15	Wave direction	(°)
16	Wave period	(s)
17	Sea direction	(°)
18	Sea current speed	(m/s)
19	Sea	Douglas sea scale (DSS) (ship's logbook) (the Douglas sea scale is a measure of the height of the waves and the state of the swell. The scale is expressed from 0 to 9)).
20	Wind	Beaufort scale (Bft) (ship's logbook) (the Beaufort scale is used to evaluate wind strength in the scale from 0 to 12))

3.2. Evaluation Metrics

To objectively evaluate the accuracy of the prediction results, appropriate evaluation metrics must be selected to provide a precise and comprehensive description of the prediction performance. The selected indicators include mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R^2). The specific formulae for these indicators are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad (6)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \quad (9)$$

In the Formulas (6)–(9), n represents the total number of samples, y_i denotes the actual value of the *i-th* sample, $\hat{y}_i$ is the predicted value of the *i-th* sample, and $\overline{y}$ is the mean of the actual values.

MAE provides the average absolute value of the prediction error, MSE, and RMSE emphasize the impact of large errors, and R^2 measures the models' ability to explain data variation. Using a combination of these metrics provides a more comprehensive assessment of model performance.

3.3. Model Evaluation

Ship fuel consumption prediction models were developed by using Python 3.12.1. All experiments were conducted on a 64-bit Windows 10 Professional operating system and an Intel Core i5-10210U CPU (Santa Clara, CA, USA), and the models were developed using the Scikit-learn 1.4.2 library. The optimal model parameters were obtained by grid search and five-fold cross-validation, set as shown in Table 3.

Table 3. Parameters of the models.

Model	Hyperparameter Set
RF	N_estimators: 50; Random_state: 42; Max_depth: 10; Min_samples_leaf: 4; Min_samples_split: 10
MLP	Hidden_layer_sizes: (150, 100, 50); Max_iter: 3000; Learning_rate_init: 0.001; Solver: adam; Alpha: 0.0001; Activation: logistic;
SVM	Kernel: rbf, C: 100; Gamma: 0.01; Epsilon: 0.5
LR	Alpha = 0.1, L1_ratio = 0.7

The first step of our analysis is to develop a prediction model that estimates the fuel consumption models while considering both operational and environmental factors. Based on the time series, the data were divided into the training set (first 80%) and the test set (last 20%). In the offline mode, the dataset was used for separate training and testing. In the online mode, the test set is transmitted through each rolling task, and incremental learning is used to update the model. Through this method, real-time data flow is simulated to achieve continuous model updates and predictions. To test the effectiveness of the prediction methods introducing dual adaption incremental learning and real-time prediction, the performance of four machine learning methods (RF, MLP, LR, SVM) is compared in both offline and online modes, with and without dual adaption incremental learning, and the prediction results of each model were evaluated.

After data normalization, a total of 18,500 samples with 20 features were obtained. In this experiment, all features were selected as input features, with ME_tot_FL as the output target. By establishing and comparing the prediction performance of each marine fuel consumption prediction model, the effectiveness of incremental learning of dual adaption is verified experimentally.

4. Results and Discussion

4.1. Offline Prediction

Four common machine learning algorithms, such as RF, MLP, SVM, and GLM, were selected to predict fuel consumption according to the time series. Table 4 presents and contrasts the offline prediction results of each model for not introducing and introducing dual adaptive incremental learning. It can be found that when dual adaptive incremental learning is not introduced, SVM performs the best, with the lowest prediction error, and the highest best fit (R^2 = 0.8027), followed by RF, MLP, and LR.

Table 4. Offline prediction results of different ML models.

Model	With the Proposed Framework	MAE	MSE	RMSE	R^2
RF	No	95.2363	13,699.8254	117.0463	0.7793
	Yes	**0.4543**	**2.1446**	**1.4645**	**0.9999**
LR	No	138.2928	22,931.0330	151.4300	0.6307
	Yes	**37.0782**	**1653.6943**	**40.6656**	**0.9734**
SVM	No	105.5878	12,250.2684	110.6809	0.8027
	Yes	**52.1895**	**3012.3372**	**54.8848**	**0.9515**
MLP	No	114.7771	18,095.3891	129.3816	0.7091
	Yes	**58.6082**	**5010.9688**	**70.3570**	**0.9213**

The experimental results indicate that the incorporation of dual adaptation and incremental learning leads to substantial improvements in prediction performance across various machine learning models. For instance, in the RF model, the MAE decreased from 95.2363 to 0.4543, the MSE dropped from 13,699.8254 to 2.1446, and the RMSE was reduced from 117.0463 to 1.4645, with the R^2 increasing from 0.7793 to 0.9999. Similar performance enhancements were observed with LR, SVM, and MLP models. It supports the conclusion that the dual adaptation mechanism combined with incremental learning effectively captures the dynamic variations inherent in marine fuel consumption data.

In comparison to previous studies that have primarily relied on static models, our dynamic approach outperforms these earlier methods. Compared to the relatively lower performance metrics reported in [37,38], the results in this study are significantly superior. Moreover, while [39,40] addressed the limitations of static models, our method overcomes these challenges by dynamically adapting to changes in the data stream. Especially, our approach achieves near-perfect prediction accuracy (R^2 up to 0.9999 in the RF model), demonstrating significant improvements over the traditional static methods.

4.2. Online Prediction

Unlike the offline mode, the online mode is no longer predicted by batch training of the entire model. After applying the rolling retraining to process the new data, the model is rolling-updated and predicted according to the simulated data flow of the incremental learning task to realize the online prediction.

This section validates the online predictive performance of four ML models combining rolling retraining and dual-adaption incremental learning. Rolling retraining divides the temporal data into countless sessions, with each session serving as a rolling task, and then divides each session into a training set and a test set. The data are input into the downloaded model as rolling tasks, which are then continuously updated through incremental learning and predicted during training. Continuous prediction according to time, thus realizing the function of online prediction.

To validate the online predictive performance of the four ML models combining rolling retraining and dual adaption incremental learning, a control group was established. The control group uses the batch update method, combined with the rolling window method, to simulate the process of real-time data arrival and model update. In order to ensure the reliability of the experiment, the rolling window is the same as the rolling retraining, each window is ten steps, and the machine learning parameters are consistent.

Table 5 presents the online real-time prediction results of the four machine learning algorithms without introducing dual adaptive incremental learning and when introducing dual adaptive incremental learning, respectively. When dual adaptive incremental learning is not introduced, the best fitting effect is LR (R^2 = 0.9617), while the other three species did not obtain a relatively good fitting effect, and the error was large, especially for MLP.

Table 5. Online prediction results of different ML models.

Model	With the Proposed Method	MAE	MSE	RMSE	R^2
RF	No	23.8757	10,738.8680	103.6285	0.8270
	Yes	**1.6439**	**357.6750**	**18.9123**	**0.9955**
LR	No	11.8387	2375.9733	48.7440	0.9617
	Yes	**9.3015**	**325.0524**	**18.0292**	**0.9959**
SVM	No	23.1797	12,257.62	110.7142	0.8026
	Yes	**13.7633**	**149.5871**	**12.2306**	**0.9981**
MLP	No	142.0444	26,132.2602	156.5376	0.5791
	Yes	**59.4512**	**5874.1083**	**74.1779**	**0.9257**

The model optimized by introducing dual adaptive incremental learning has a very good online prediction effect. The optimized RF achieved the best prediction effect, with MAE reduced by 22.2318 mT and 84.7162 mT by RMSE. The other three models also showed a significant improvement. The MAE of LR, SVM, and MLP decreased by 2.5365 mT, 9.4164 mT, and 82.5932 mT, and the RMSE decreased by 30.7148 mT, 98.4836 mT, and 82.3597 mT, respectively.

After the models were optimized by introducing dual-adaptive incremental learning, they realized online prediction functions well, with a high fitting degree and small error, and can achieve accurate real-time prediction effect. Compared to previous studies, our results are superior to those reported in [41]. The dual adaptive learning approach delivers even better performance. This underscores the effectiveness of dual adaptive learning mechanisms in enhancing predictive accuracy for maritime fuel consumption.

4.3. Ablation Study

Ablation studies are experimental techniques used to evaluate the significance of individual modules or features within a model. To demonstrate the impact of the incremental learning method and the dual adapted incremental learning method on improving fuel consumption prediction accuracy, ablation studies were conducted in this section. The ablation experiments were performed in both offline and online modes, respectively.

Table 6 illustrates the performance of the four algorithms in the offline mode across three scenarios. Both IL and DA-IL enhance the performance of the four models to varying extents. Notably, IL and DA-IL show significant improvements for RF and LR, with comparable optimization levels. However, DA-IL outperforms IL in significantly boosting the performance of SVM and MLP. Overall, DA-IL demonstrates greater stability in enhancing model prediction accuracy than IL. This may be attributed to its dual adaption mechanism, which enables the model to better adapt to the dynamic changes in the distribution of ship data.

Table 6. Ablation study results of each offline model.

Model	Schema	MAE	MSE	RMSE	R^2
RF	Unimproved	95.2363	13,699.8254	117.0463	0.7793
	Improved with DA	0.5344	2.7499	1.6583	0.9999
	Improved with DA-IL	**0.4543**	**2.1446**	**1.4645**	**0.9999**
LR	Unimproved	138.2928	22,931.0330	151.4300	0.6307
	Improved with DA	40.0765	1709.3676	41.3445	0.9115
	Improved with DA-IL	**37.0782**	**1653.6943**	**40.6656**	**0.9734**
SVM	Unimproved	105.5878	12,250.2684	110.6809	0.8027
	Improved with DA	23.1791	12,257.6341	110.7142	0.8026
	Improved with DA-IL	**52.1895**	**3012.3372**	**54.8848**	**0.9515**
MLP	Unimproved	114.7771	18,095.3891	129.3816	0.7091
	Improved with DA	67.1491	5987.5406	77.3732	0.9029
	Improved with DA-IL	**58.6082**	**5010.9688**	**70.3570**	**0.9213**

Similar to its performance in offline mode, IL in online mode does not consistently stabilize the optimization effect across the four models. In contrast, DA-IL provides a more stable performance improvement than IL (Table 7). For RF, while IL achieves slightly lower error and higher prediction accuracy compared to DA-IL, the extent of optimization is relatively modest. For the other three models, DA-IL demonstrates more significant improvements, resulting in clearer and more accurate prediction outcomes. Therefore, the overall optimization performance of DA-IL on the model is superior to IL.

Table 7. Ablation study results of each online model.

Model	Schema	MAE	MSE	RMSE	R^2
RF	Unimproved	23.8757	10,738.8680	103.6285	0.8270
	Improved with DA	1.2125	28.5872	5.3467	0.9996
	Improved with DA-IL	**1.6439**	**357.6750**	**18.9123**	**0.9955**
LR	Unimproved	11.8387	2375.9733	48.7440	0.9617
	Improved with DA	34.1168	1521.5695	39.0073	0.9808
	Improved with DA-IL	**9.3015**	**325.0524**	**18.0292**	**0.9959**
SVM	Unimproved	23.1797	12,257.62	110.7142	0.8026
	Improved with DA	17.0881	1528.8256	39.1002	0.9916
	Improved with DA-IL	**13.7633**	**149.5871**	**12.2306**	**0.9981**
MLP	Unimproved	142.0444	26,132.2602	156.5376	0.5791
	Improved with DA	72.9789	7558.9635	86.9423	0.9039
	Improved with DA-IL	**59.4512**	**5874.1083**	**74.1779**	**0.9257**

Through the two sets of ablation experiments, it is evident that both incremental learning and dual adaption play essential roles in enhancing the accuracy of fuel consumption prediction. Incremental learning enables the model to effectively capture the temporal dependencies in fuel consumption data, while dual adaption enhances the stability of incremental learning's impact. Together, these approaches are well-suited for handling the dynamic nature of fuel consumption data in real-world navigation scenarios, offering a reliable solution for accurate fuel consumption prediction.

4.4. Uncertainty Analysis

In this study, all experiments were conducted with ten repeated trials to assess the stability and reliability of the results. To assess the stability of different models across various data folds, we computed the mean and standard deviation of R^2 values obtained from ten-fold cross-validation (Time Series CV). In online mode, data are continuously updated, making it impossible to perform fixed ten-fold cross-validation. Moreover, the model used in online mode is identical to that in offline mode, with the only difference being that online mode trains and predicts simultaneously. Therefore, uncertainty analysis is conducted solely on the offline model.

As shown in Table 8, significant differences in fitting ability and stability are observed among the models. This study adopts a dual adaptive learning approach to dynamically adjust the models' ability to adapt to changes in data distribution across different time windows. However, although dual adaptive learning can to some extent improve the models' generalization, the results indicate that the MLP still exhibits the highest R^2 standard deviation (0.1849), suggesting that its predictive performance varies considerably across different time windows. This may be due to the fact that neural networks are highly dependent on the training data; even with dual adaptive learning, they may not completely eliminate errors under dramatic shifts in data distribution.

Table 8. R^2 Mean and standard deviation for different models improved with proposed framework.

Model	R^2 Mean ± Std
RF	0.9853 ± 0.0310
LR	0.8814 ± 0.1287
SVM	0.8749 ± 0.1672
MLP	0.7951 ± 0.1849

In contrast, after applying dual adaptive learning, the Random Forest (RF) maintains the lowest R^2 standard deviation (0.0310), demonstrating that its ensemble learning strategy has an advantage in reducing model uncertainty. Both LR and SVM still show relatively high R^2 standard deviations (0.1287 and 0.1672, respectively) after applying dual adaptive learning, indicating that these models remain somewhat unstable in the face of changing data distributions, and may require further optimization in feature engineering or adjustments in the adaptive learning strategy to more effectively cope with variations across different time windows.

Overall, the adaptive learning method has improved the models' adaptability to a certain extent, but different models respond differently to adaptive learning. Future research could further explore combining adaptive learning with other regularization strategies (such as Dropout and Batch Normalization) or ensemble methods (such as Stacking) to reduce model uncertainty and enhance prediction stability.

5. Conclusions

5.1. Contributions of This Study

In the course of ship navigation, monitoring systems accumulate substantial amounts of data, enabling data-driven approaches for predicting ship fuel consumption. This study introduces innovative methods to enhance the accuracy and adaptability of ship fuel consumption prediction models, effectively addressing challenges posed by dynamic data distributions.

The proposed incremental learning of dual adaptation dynamically adjusts input features and targets during training, improving the model's ability to capture temporal dependencies in fuel consumption data. Experimental results demonstrate significant improvements in both offline and online prediction scenarios. In the offline setting, the RF model's MSE decreased from 13,699.83 to 2.14, while R^2 improved from 0.7793 to 0.9999, indicating near-perfect predictive capability. In online prediction, the MSE for RF reduced from 10,738.87 to 357.68, and R^2 improved from 0.8270 to 0.9955, demonstrating the model's adaptability to new data. The results further confirm that rolling retraining effectively updates the model in real time, substantially enhancing predictive performance, particularly in scenarios with shifting data distributions.

Additionally, the combination of incremental learning and rolling retraining enables real-time online prediction by continuously updating the model with new data while capturing dynamic changes in time series patterns. By focusing on shorter, manageable time intervals, the model adapts more quickly and accurately to temporal variations. Experimental results verify the strong real-time prediction performance of four machine learning models, demonstrating the generalization and adaptability of the proposed approach.

Overall, these methods significantly enhance the predictive performance and reliability of ship fuel consumption models in real-world maritime applications. The results indicate that the combination of incremental learning and rolling retraining effectively addresses challenges posed by dynamic data environments, paving the way for more efficient, accurate, and adaptive fuel consumption forecasting in shipping operations.

5.2. Research Gaps and Future Work

Despite its promising results, this study has some limitations that warrant further exploration. One key limitation is that while the proposed method effectively handles dynamic data distributions, it does not fully account for the complex interactions among environmental and operational factors. For instance, wind speed, wave height, and ship speed likely interact in ways that influence fuel consumption, but treating these variables independently may overlook their synergistic effects. Future research could explore multifactor interaction modeling using techniques such as deep learning or physics-informed machine learning to capture these complex dependencies.

Additionally, while the model adapts well to new data within the same operational environment, its ability to generalize across different vessel types and routes remains an open question. Cross-domain transfer learning techniques could be investigated to enable models trained on one vessel's data to be effectively applied to different ship types or operational regions with limited retraining. Another important future direction is the integration of real-time sensor feedback from ship monitoring systems to further enhance predictive accuracy and operational decision-making.

5.3. Application in the Maritime Industry

The findings of this study have practical implications for the maritime industry, particularly in fuel efficiency optimization and emissions reduction. The proposed method can be integrated into existing ship energy management systems (SEMS) to provide real-time fuel consumption forecasts, enabling operators to make data-driven decisions on speed adjustments, engine settings, and route optimizations. Furthermore, shipping companies can utilize this framework for predictive maintenance, identifying anomalies in fuel consumption that may indicate engine inefficiencies or hull fouling. Regulatory bodies and fleet managers could also adopt such adaptive predictive models to support compliance with IMO's decarbonization targets, such as the Energy Efficiency Existing Ship Index (EEXI) and Carbon Intensity Indicator (CII) requirements.

By enabling more accurate and adaptive fuel consumption predictions, this research contributes to enhancing operational efficiency, reducing fuel costs, and minimizing environmental impact in maritime transportation. Future work will focus on extending this approach to broader vessel categories, integrating additional environmental factors, and refining real-time deployment strategies to maximize its practical applicability in the shipping industry.

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