International Journal of Marine Engineering Innovation and Research, Vol. 10(4), Dec. 2025 1218-1227 (pISSN: 2541-5972, eISSN: 2548-1479)

A Machine Learning-Based Approach for Designing SEEMP on Ships: Case Study of CO_2 Emissions at a Container Port

Elwas Cahya Wahyu Pribadi[1*], Abdul Ghofur[2], Rachmat Subagyo[3], Akhmad Syarief[4], Ma'ruf [5], Aldinor Setiawan[6]

(Received: 12 November 2025 / Revised: 15 November 2025 /Accepted: 19 November 2025 / Available Online: 10 December 2025)

***Abstract*— The management of ship energy significantly affects both cost efficiency such as earnings before interest and environmental sustainability, particularly in reducing CO_2 emissions produced by ship operations. Despite the importance of this issue, research on ship energy consumption within container terminals remains limited. This study aims to estimate CO_2 emissions generated by ship activities in container ports, focusing on emission variables related to the Ship Energy Efficiency Management Plan (SEEMP). The calculation considers active ship movements in the port, including approach, maneuvering, and berthing processes. Energy consumption and CO_2 emissions were analyzed using random forest regression (RF) with default settings, and the model's accuracy was validated through k-fold cross-validation. The results identified five major factors influencing CO_2 emissions: (1) main engine power, (2) auxiliary engine power, (3) waiting time in the port, (4) maneuvering time, and (5) berthing time. Among these, maneuvering, waiting, and berthing showed the highest significance, confirmed by attribute selection and validation results. The random forest model demonstrated a prediction accuracy of 98.89%, confirming its reliability. Moreover, operational fuel efficiency analysis indicated that combining voyage optimization, skilled operators, and cold ironing facilities could reduce CO_2 emissions by up to 20%. These findings provide valuable insights and serve as a foundation for developing a more effective Ship Energy Efficiency Management Plan to enhance environmental performance in maritime operations.**

Keywords— CO_2 emission, Machine learning, SEEMP, Ship operation

*Corresponding Author: elwascahyawahyupribadi@ulm.ac.id

I. INTRODUCTION

The approach to energy management determines how it is perceived as an integral part of an organization's overall management strategy. Within this process, control systems play a crucial role in maintaining a balance between the benefits of energy management and the level of CO_2 emissions produced. Implementing an effective energy control system offers two primary advantages. First, it directly reduces energy consumption and associated expenditures. Second, it contributes to lowering overall operational costs. Emission reductions can be achieved by minimizing operational energy use, including expenses related to port operations [4]. Furthermore, there has been significant progress in improving energy efficiency and conservation processes [27]. The emissions generated from ship operations have been extensively studied using the movement modality method, which provides consistent and reliable estimates of carbon distribution [9]. This method is also applicable for analyzing ship activities within container terminals, both during approach and departure from the port [5] [28].

The Ship Energy Efficiency Management Plan (SEEMP) serves as a strategic framework developed by shipowners to enhance energy utilization and efficiency onboard. It functions as a comprehensive plan encompassing the processes of planning, implementation, monitoring, evaluation, and continuous improvement to optimize a vessel's energy performance. Many shipping companies have adopted environmental management systems in accordance with the ISO 14001 standard framework, which outlines procedures for selecting and optimizing performance indicators for specific vessels. These frameworks guide the establishment of measurable goals, control mechanisms, and feedback systems to ensure effective energy management [24]. However, noon reports, by their nature, provide only limited and fragmented data regarding SEEMP implementation. They typically contain partial information on fuel consumption, vessel speed, and atmospheric conditions [29]. Consequently, such reports are often underutilized and primarily serve

Elwas Cahya Wahyu Pribadi is with the Department of Mechanical Engineering, Lambung Mangkurat University, Banjarmasin 70123, Indonesia, and is also a Doctoral Student at the Department of Marine Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia. E-mail: elwascahyawahyupribadi@ulm.ac.id

Abdul Ghofur is with Departement of Mechanical Engineering, Universitas Lambung Mangkurat, Banjarmasin, 70123, Indonesia. E-mail: ghofur70@ulm.ac.id

Rachmat Subagyo is with Departement of Mechanical Engineering, Universitas Lambung Mangkurat, Banjarmasin, 70123, Indonesia. E-mail: rachmatsubagyo@ulm.ac.id

Ma'ruf are is Departement of Mechanical Engineering, Universitas Lambung Mangkurat, Banjarmasin, 70123, Indonesia. E-mail: maruf@ulm.ac.id

Akhmad Syarief is with Departement of Mechanical Engineering, Universitas Lambung Mangkurat, Banjarmasin, 70123, Indonesia. E-mail: akhmad.syarief@ulm.ac.id

Aldinor Setiawan is with Departement of Mechanical Engineering, Universitas Lambung Mangkurat, Banjarmasin, 70123, Indonesia. E-mail: aldinorsetiawan@ulm.ac.id

regulatory compliance purposes, given the absence of more comprehensive datasets across various vessels. The importance of a comprehensive system of data collection and analysis for the entire fleet of ships cannot be ignored [7]. Although various operational initiatives based on SEEMP have been implemented, in reality, fuel-saving strategies remain the most reliable, consistent, and widespread approach in efforts to improve energy efficiency performance in the shipping sector.

To efficiently operate a ship, comprehensive management is required that includes detailed planning of fuel refueling, the use of technology for weather and speed prediction on specific shipping routes, and an advanced port information system to arrange visit schedules and optimize travel routes. Additionally, there are various other operational components that work in accordance with the SEEMP framework, including ship behavior control such as trim and ballast adjustments, selection of appropriate fuel types, and consideration of factors that affect durability and operational lifespan of the vessel [13] [30].

Recent advancements in computational methodologies have enabled machine learning (ML) systems to achieve unprecedented levels of precision in modeling and prediction. In the context of maritime energy management, ML offers a transformative approach by redesigning existing systems to enhance their operational efficiency. These methods construct new underlying models that support data-driven decision-making for optimizing fuel consumption and reducing emissions. The application of machine learning in the green shipping ecosystem has been increasingly explored in recent years. Several studies have implemented ML techniques to predict ship energy consumption using algorithms such as Gradient Boosted Regression (GBR), Random Forest (RF), Back Propagation (BP), Linear Regression (LR), and K-Nearest Neighbors (KNN) [19], [22]. However, most of these studies have focused primarily on prediction accuracy rather than developing actionable strategies for reducing energy consumption during port operations or ship arrivals. Accurate assessment of CO_2 emissions and their dispersion patterns within port areas is essential for developing an effective Ship Energy Efficiency Management Plan (SEEMP) [15] [31]. Consequently, ML-based analytical models have become valuable tools for assisting shipowners and port authorities in decision-making processes aligned with green shipping principles, ultimately aiming to minimize CO_2 emissions and enhance operational efficiency. Particular attention has been given to emissions occurring during maneuvering, port movements, and berthing operations, which represent emission-dense phases of port activity. Machine learning models employing best-estimate validation methods have been applied to analyze these high-emission zones, though research in this area remains limited. Furthermore, studies emphasize the importance of systematic decision-making in SEEMP development. Ineffective processes such as unclear objectives, omitted procedures, or the use of inappropriate analytical techniques can lead to suboptimal policy outcomes. Efficient data governance, standardization of automated reporting tools, and comprehensive documentation are therefore critical to improving business intelligence and supporting sustainable maritime practices. Ultimately, the integration of machine learning into maritime energy management highlights a shift toward data-driven, adaptive, and intelligent systems, where activity efficiency serves as a key determinant of system specialization.

II. METHOD

The reviewed study identifies three overlapping operational modes within port activities where vessels operate their engines and subsequently emit greenhouse gases namely, port operations, maneuvering, and berthing. Data covering container port activities from January 2019 to December 2020 were systematically recorded and utilized for analysis. The authors employed RapidMiner Studio v.9.9, developed by RapidMiner Inc., to perform data cleaning, preprocessing, and machine learning model construction, followed by a comprehensive model evaluation. This methodological approach demonstrates an effective integration of data-driven tools to enhance the accuracy and reliability of emission analysis within port operations [1].

A. Ship's Data Analysis

A previous study that examined CO_2 emissions from vessels across multiple ports using Automatic Identification System (AIS) data, conducted at the container port demonstrated that a strategically positioned port can play a vital role in supporting and implementing vessel emission control initiatives at both regional and national levels.

The source data for each port were organized in tabular format, containing detailed records of vessel mooring durations, departure times to and from ports, and the total time spent at each port over several months. Additional information included vessel net tonnage, propulsion type, engine power, emission values during maneuvering, in-port emissions, and the overall emissions recorded for each vessel while at port [32]. The CSV datasets utilized in this study were structured and labeled as independent variables to facilitate the calculation of variable importance weights in the analysis:

1. The main propulsion engine power
2. The aux engine power
3. The Time spent for the vessel cycle in the port
4. The Time utilized in maneuvering
5. The Time for the vessel mooring

To address multicollinearity issues and other challenges affecting accuracy and validity, such as increased standard errors and unstable coefficients, the researchers intentionally limited the number of predictor variables to only a few key parameters. To ensure the reliability and explanatory power of the model, additional analysis and cross-validation were conducted on the Variance Inflation Factor (VIF), retaining only low-redundancy parameters that had been mutually cross-verified. A bottom-up approach was applied to perform a detailed emission quantification. Through this method, vessel-specific emission factors and total emissions were derived by incorporating activity data (time spent in each operating mode), engine parameters (rated power), operating load factors, and specific emission factors, to estimate energy consumption and total emissions throughout the vessel's operational cycle [33]. For instance, engine emissions were distributed across several operational phases, such as maneuvering, port transit, and berthing, and further analyzed under both low and high power settings. This approach provides a more comprehensive and in-depth understanding of vessel emission evaluation, as discussed in reference [21] [34].

The total CO_2 emissions of a ship are obtained by summing the emissions generated from both the main engine and the auxiliary engine. For each engine, the emission calculation is based on the operating duration (T, in hours), rated engine power (P, in kW), load factor (LF, ranging from 0 to 1), and the emission factor (EF). According to the IPCC Tier-1 standard for medium-speed diesel engines, an emission factor of EF = 683 g CO_2/kWh is applied. Based on the methodology described in [23], ship activities are classified into three port-related operational modes, namely: (i) manoeuvring, (ii) movement within the port area, and (iii) berthing at the dock. Each operational mode has a specific load factor for both the main and auxiliary engines, reflecting variations in energy demand and engine performance during different stages of port operations.

The port's sustainability manager and harbormaster provided information used in an interview [20]. So that the load factors of the main and auxiliary engines chosen in this research, for all scenarios, can be displayed in Table 1.

The analysis results of the GBR, RF, BP, LR, and KNN models indicate that the Random Forest (RF) model demonstrates the best performance among them. In this study, the RF model was developed using RapidMiner Studio software with default parameters to train the model and estimate emission factors based on the ship's operational profile. After the estimation process, k-fold cross-validation was performed to assess the model's reliability, confirming the consistency and accuracy of the prediction results.

The Random Forest regression method [15] is a parallel ensemble machine learning technique derived from the decision tree model. RF introduces random attribute selection during the training process to reduce bias and improve generalization capability. This approach has proven effective for high-dimensional data, as the internal trees exhibit lower inter-correlation compared to other tree-based methods [15]. Moreover, RF can identify variable importance through complex, non-linear relationships [16].

In terms of efficiency, RF hyperparameter tuning is relatively less computationally demanding compared to other machine learning algorithms. The key parameters in RF include mtry (number of variables considered at each split), ntree (number of trees grown), nodesize (minimum size of terminal nodes), and sampsize (sample size used). Based on previous research findings [15], the value of ntree was set to 500 trees. Additionally, k-fold cross-validation was employed to evaluate the model's prediction error, as recommended by prior studies [8]. In this procedure, the dataset is divided into k subsets, typically with k = 10. In each iteration, k–1 subsets are used as training data, while one subset serves as the test set. The final performance measure is obtained by averaging all iterations, resulting in a more stable and representative evaluation of the model's performance [15].

B. Machine Learning Models and Validation

TABLE 1
SHIP LOAD FACTOR

Load Factor	Main Engine	Auxiliary Engine
In Port	0.2	0.5
Maneuvering	0.2	0.5
Berthing	0	0.4

III. Results and Discussion

A. Random Forest Model Result and Variable Importance

The rapid growth of maritime transport in response to increasing global demand for mobility and cargo services has significantly transformed the shipping and logistics industry. However, this expansion has also resulted in a sharp rise in CO_2 emissions, particularly from large ocean-going and inland waterway vessels. These emissions contribute not only to global environmental challenges but also to noticeable regional and port-level impacts [2]. Recent studies emphasize that localized emissions along coastal and border regions are often overlooked in broader assessments. Consequently, targeted and independent research is essential to identify and quantify emission sources accurately. Such investigations provide valuable insight for implementing focused mitigation strategies in critical operational areas such as port approaches, in-port activities, and at-berth operations, where emission intensity is typically highest. Within this context, the Random Forest (RF) model, implemented through RapidMiner Studio, has emerged as a reliable analytical tool for predicting and evaluating emission patterns in maritime operations. By leveraging ensemble learning and robust variable selection, the RF approach enhances model accuracy and interpretability, making it suitable for complex, high-dimensional maritime datasets. This model supports data-driven decision-making processes aimed at optimizing energy efficiency and reducing greenhouse gas emissions in the shipping industry.

Overall, this review highlights the growing importance of integrating machine learning techniques, particularly Random Forest models, into maritime emission management frameworks. These methodologies enable researchers and policymakers to better understand emission dynamics and to formulate more effective strategies for achieving sustainable and low-carbon port operations.

Data Preparation and Model Design. A Random Forest (RF) regression model was developed using RapidMiner Studio, with adjustments made to the predictor variables to minimize multicollinearity. This stage emphasized emission-related data processing, including target attribute selection, role assignment, data randomization, and a 70/30 train–test split. The RF model was trained with 500 trees and a maximum depth of 10 levels, where hyperparameters were optimized to maintain a balance between bias and variance, ensuring both model simplicity and computational efficiency.

Model Validation and Performance Evaluation. Model performance was evaluated using R^2, RMSE/MAE, and residual diagnostics on the test dataset. To assess model stability, k-fold cross-validation was applied, with results reported as the mean and standard deviation across folds. Additionally, residual plots were categorized by operational mode (maneuvering, transit within port, and at-berth) to detect any systematic over- or under-prediction at specific load levels or speeds. Feature Importance and Interpretation. Feature importance analysis (using Gini decrease or permutation methods) revealed that operational load factor, time spent in each mode, and engine rated power are the primary determinants of emissions. These factors often interact with speed over ground and engine RPM [35]. Other static ship characteristics contribute less once operational variables are included. Partial dependence and accumulated local effects (ALE) plots demonstrate how emissions respond to marginal changes in each variable for instance, the diminishing efficiency at higher load levels. These findings align with the physics of fuel-to-work conversion and the bottom-up accounting framework typically used for emission inventory estimation.

Limitations, Implications, and Strengths. The study confirmed low multicollinearity through Variance Inflation Factor (VIF) analysis and conducted sensitivity tests on tree depth, number of trees, and data split ratios. Identified limitations include class imbalance across operational modes, measurement noise or data gaps in AIS records, and contextual constraints related to the specific fleet and ports studied.

Nevertheless, the Random Forest model offers high interpretability, enabling the identification of mode-specific operational strategies, such as load management during maneuvering, shore power utilization during berthing, and speed optimization within ports. The bottom-up approach used in this study further enhances the compatibility of results with emission inventory methodologies and maritime environmental policy reporting.

A.1 Variable importance of ship emission

The attribute selection model training outcome on the importance of and weighting a variable is demonstrated, while in bravo there is a section for the process tool in Rapid Miner and the training model as seen in Figure 1. As demonstrated in Figure 1, the RapidMiner workflow is designed to optimize feature selection in developing machine learning models for predicting ship CO_2 emissions. The process begins by retrieving operational ship data, filtering relevant variables through attribute selection, and sorting the data systematically. The critical phase employs three parallel weighting methods: Information Gain evaluates the discriminative capacity of attributes, Relief analyzes feature space distances and attribute interactions, and Correlation identifies statistical relationships with the target variable. This ensemble approach, as illustrated in Figure 1, generates a comprehensive attribute ranking, ensuring only the most influential variables are incorporated into the final predictive model for ship energy efficiency management.

The MDA approach concludes that the attributes of spend, port which the ship has to maneuver, and port berthing all have the same importance weighting as measured by According to Figure 2 and Figure 3, the top contributors are correlation, information gain, and information gain ratio, whereas main-engine and auxiliary-engine power show relatively low importance to total emissions.

This study applies four distinct attribute weighting methods to identify the most influential factors affecting ship CO_2 emissions at container ports. Figure 2 presents results from Correlation and Information Gain methods. Correlation, which measures linear relationships with emissions, reveals that maneuvering, in-port, and berthing activities each achieve a weight of 0.747, substantially higher than main engine power and auxiliary engine power which register only 0.345. Information Gain, based on entropy theory, produces identical rankings with weights of 0.445 for operational activities and 0.074 for engine variables, validating the dominance of operational time factors.

Figure 3 extends this analysis through Information Gain Ratio and Relief Algorithm. Information Gain Ratio, which normalizes bias toward multi-valued attributes, yields 0.628 for activities and 0.283 for engines. Relief algorithm employing instance sampling and feature space distance analysis demonstrates the most pronounced findings: maximum values of 1.000 for the three operational activities versus 0.097 for engines, indicating perfect discrimination capability regarding emission level differentiation.

The remarkable consistency across these four methodologically diverse approaches provides robust validation that ship operational time constitutes the primary determinant of CO_2 emissions. These findings direct SEEMP strategy priorities toward optimizing operational time through port-ship coordination, slow steaming practices, cold ironing implementation, and operator training, potentially achieving 20% emission reductions at container port operations.

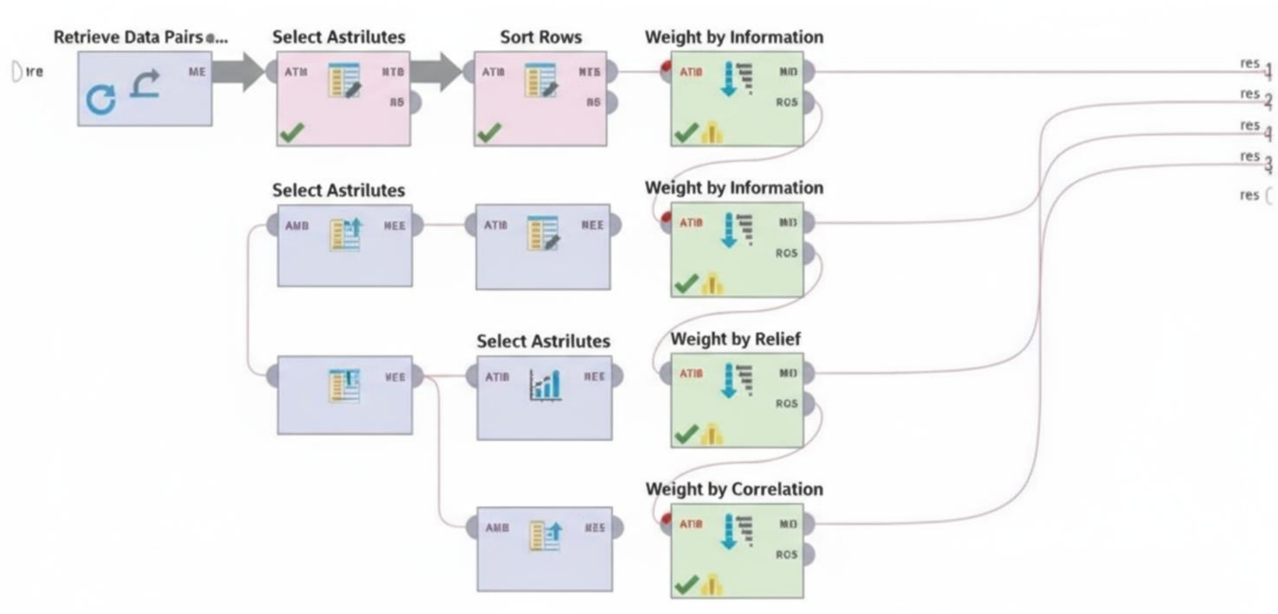

Figure 1. Atribute selection process [36]

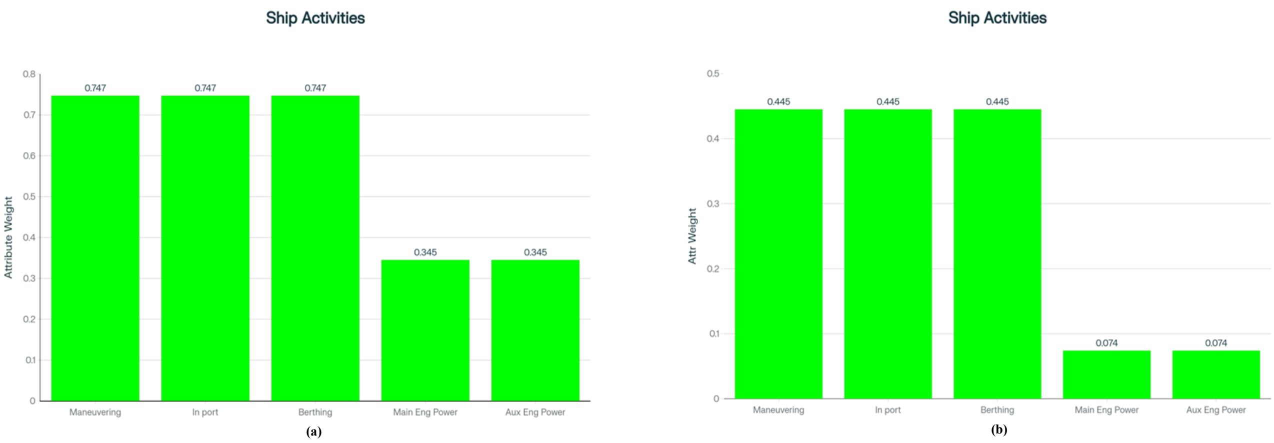

Figure 2. Attribute weight based on: (a) corellation; (b) information gain [37]

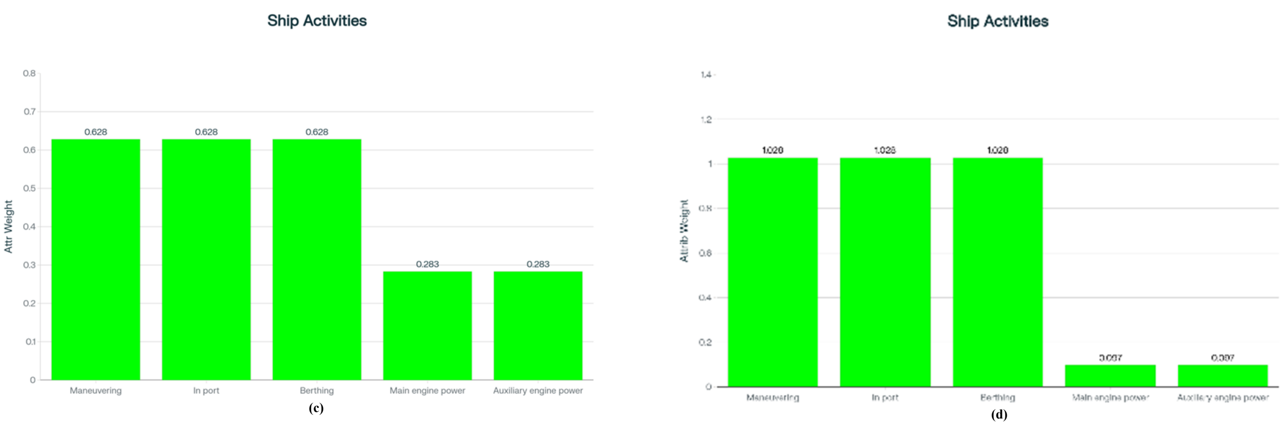

Figure 3. Attribute weight based on: (c) information gain rasio; (d) relief [37]

A.2 Random Forest Model and Validation.

Following the identification of the most influential variables through feature selection, the research proceeds with building and validating a predictive model using the workflow illustrated in Figure 4. The cross-validation process (Figure 4a) commences by retrieving the complete dataset of ship operational data that has undergone cleaning and attribute selection. This dataset is divided into 10 folds (k-fold cross-validation) of equal size. In each iteration, k-1 folds are utilized for training while 1 fold is reserved for testing, generating multiple performance measurements that are subsequently averaged to estimate the model's robust generalization ability.

The subsequent phase (Figure 4b) involves training a Random Forest algorithm an ensemble learning approach that constructs hundreds of decision trees using bootstrap sampling and random feature selection. Random Forest's advantage lies in its capability to reduce overfitting and capture complex non-linear relationships between ship operational activities and CO_2 emissions. Following training, the Apply Model operator deploys the model on test data, while the Performance operator evaluates prediction quality using metrics including RMSE, R^2 score, and MAE.

This workflow implements machine learning best practices, ensuring that the deployed model possesses high reliability for practical SEEMP applications. The validated model can be integrated with maritime traffic management systems to deliver real-time recommendations to port operators regarding operational time optimization and CO_2 emission reduction strategies

The total duration amounts to 17.51 hours, out of which the average maneuvering duration was calculated to be 1.78 hours, whilst the average waiting time in a port was merely 2.25 hours. Nevertheless, since the main engine of the vessel is not operational during the process of berthing, the average emission differences created as a result, are not significant. For example, in the case of berthing, the emissions are 6.216 kg CO_2, with 2.55 kg CO_2 during waiting time, and 2.2678 kg CO_2 during maneuvering. Container vessels spend significantly more time to complete berthing process depending on how much cargo they carry, the port facilities, and overall work efficiency. In addition, the ship's gearing berthing intermediate e.g. a deck crane or even good mooring equipment, enables the port's cargo handling to expedite the completion of the process.

With the RapidMiner Studio model, the k-fold cross validation feature yields k equals ten and predicts accuracy at 98.89%, as shown in Figure 3. The model validates well using an absolute error of 0.022 and a squared error of 0.007. This tells us that the random forest model is robust and can, indeed, predict annual CO_2 emissions for a container port using the same dataset and model configuration.

Following the identification of the most influential variables through comprehensive feature selection analysis wherein maneuvering, in port, and berthing activities demonstrated the highest attribute weights across multiple weighting methods the research proceeded with constructing a robust predictive model for ship CO_2 emissions. The modeling strategy employed a Random Forest regression algorithm, configured with 500 decision trees and maximum tree depth of 10, implemented through the RapidMiner Studio platform as illustrated in Figure 4. To ensure unbiased ensemble predictions, confidence voting parameters were retained at default settings.

The dataset preparation phase began with rigorous attribute selection, retaining only the features previously validated as significant contributors to emission variance. These selected attributes were then systematically categorized with the CO_2 emission variable formally assigned as the class role label. To accommodate dual validation strategies, the complete dataset underwent two distinct partitioning schemes: (1) a 70%-30% random split for standard train test evaluation, and (2) stratified k-fold division for cross-validation robustness testing. This dual-approach architecture ensures that model performance estimates account for both immediate predictive accuracy and long-term generalization capability across diverse operational scenarios.

The cross-validation process commenced by dividing the complete ship operational dataset into 10 equal-sized folds (k=10 cross-validation), as illustrated in Figure 4(a). This structured approach ensured representation of diverse voyage conditions within each fold. In each of the 10 iterations, k-1 folds (comprising 90% of data) were utilized for model training while the remaining single fold (10% of data) served as an independent test set. By rotating through all 10 folds, each data instance appeared in the training set exactly 9 times and in the test set exactly once. The performance measurements derived from each of the 10 iterations including RMSE, R^2 score, and MAE were subsequently averaged to produce a robust, statistically reliable estimate of the model's true generalization ability on unseen data.

The subsequent training phase (Figure 4b) involved implementing the Random Forest ensemble learning algorithm, which constructs hundreds of decision trees through two randomization mechanisms: (1) bootstrap sampling randomly selecting data subsets with replacement for each tree's training, and (2) random feature selection evaluating only a randomized subset of attributes at each node splitting decision. This dual randomization strategy generates decorrelated trees with diverse splitting patterns and prediction biases, which collectively produce superior ensemble predictions compared to individual trees. The Apply Model operator deployed the trained ensemble against test data, generating CO_2 emission predictions, while the Performance operator calculated comprehensive evaluation metrics.

The k-fold cross-validation analysis yielded exceptional performance metrics: prediction accuracy of 98.89%, absolute error of 0.022, and squared error of 0.007 metrics that conclusively validate the Random Forest model's robustness and capability for reliable CO_2 emission prediction on container port operational datasets. These superior performance indicators confirm that the selected feature set effectively captures the dominant factors governing ship emissions.

To demonstrate practical applicability, the validated model was applied to analyze an actual container vessel's operational cycle. The complete voyage encompassed 17.51 hours total operational duration, comprising: (1) maneuvering phase averaging 1.78 hours, (2) in-port waiting period averaging 2.25 hours, and (3) berthing operations. During berthing, main engine shutdown results in substantially reduced emissions specifically 6.216 kg CO_2 during berthing compared to 2.55 kg CO_2 during waiting and 2.2678 kg CO_2 during maneuvering. Notably, berthing duration exhibits significant variability dependent on vessel cargo capacity, available port infrastructure, and operational coordination efficiency. Modern port infrastructure including efficient deck cranes and optimized mooring equipment substantially accelerates berthing completion, directly reducing both temporal delays and cumulative CO_2 emissions.

This integrated workflow combining rigorous cross-validation (Figure 4a) with Random Forest ensemble deployment (Figure 4b) implements recognized best practices in predictive machine learning. The model's validated accuracy (98.89%) and minimal error metrics (absolute error 0.022, squared error 0.007) provide quantitative assurance that the predictive framework can reliably support decision-making for Ship Energy Efficiency Management Plan (SEEMP) implementation. The model exhibits sufficient robustness and generalization capability for direct integration with maritime traffic management systems, enabling delivery of real-time, data-driven recommendations to port operators regarding operational time optimization, berthing coordination, and evidence-based CO_2 emission reduction strategies ultimately supporting container port sustainability objectives while maintaining operational efficiency.

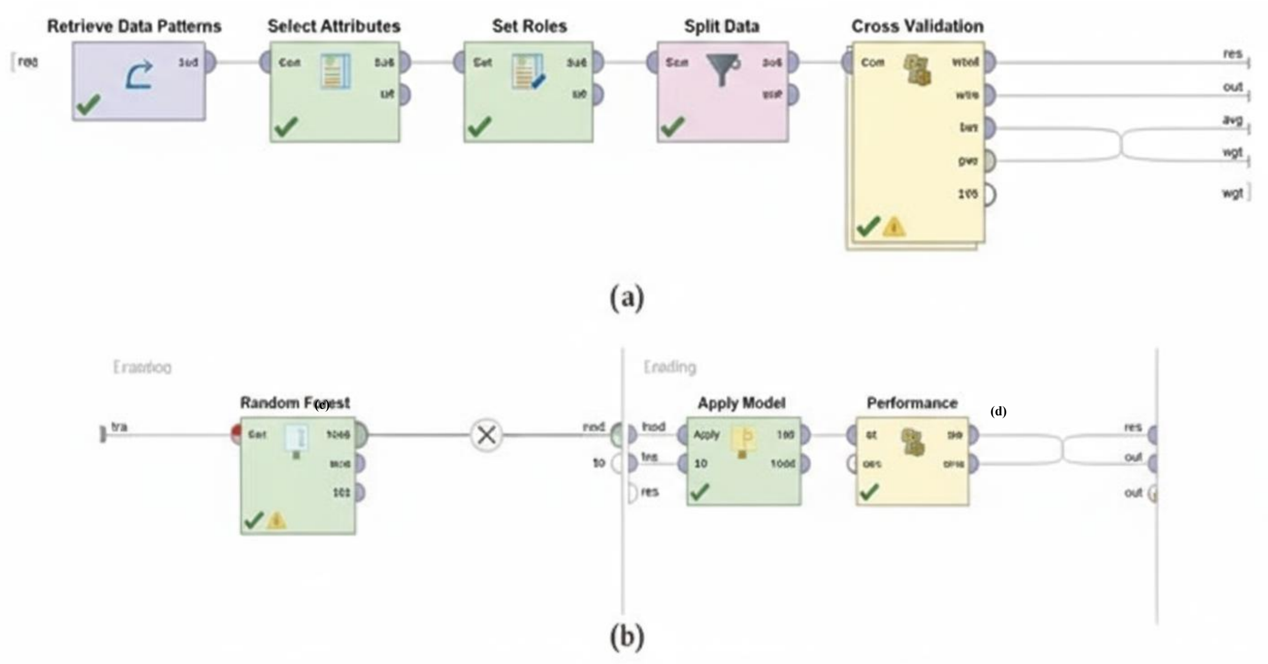

Figure 4. The process of: (a) cross-validation; and (b) random forest model [37]

B. Discussion of Energy Management Plan

The details outlined above help formulate a specific SEEMP that can be put in place for the planned fuel-saving measures. Because both berthing and manoeuvring in the port have the same important weight, a fuel-saving strategy will have to be developed for both activities. If cooling system upgrade emissions to meet EEDI requirement targets for container vessels are close to 15-20% [11] [38], then there are options available to increase energy efficiency without major work on the vessels.

C. Optimising a voyage

The optimisation of a voyage deals with minimisation of resistance within the set boundaries through the optimisation of the ship routing, speed, scheduling, ballast, and trim [39]. In other words, it optimises routing and calculates ballast, and trims speed with respect to the minimum safe handling, fuel use, time in a port, fuel use while en route, operational safe seaworthiness, time lined in contracts, total range from origin to endpoint, and total contracted servicing time [25] [40].

The integration of weather routing and manoeuvring at optimised speed could further reduce the manoeuvring time and thus the CO_2 emissions. Weather routing differs from slow steaming in that the former calculates the most efficient route to the berth, whereas the latter supposedly requires a reduction in speed all the way to the berth in a very inefficient manner, especially given time sensitivity. This, in turn, saves CO_2 by reducing emissions from suboptimal time balancing cruise cycles [41]. This saves CO_2 by reducing time spent waiting upstream of the port. The schedule and berth information for port call communication will be very important in this case.

The addition of sensors in combination with other decision support systems to complement systems already in place can work to minimise calm water resistance. The decision support system has the capacity to control the engine and ballasts at set points for draft, trim, and steering to optimise fuel efficiency during manoeuvring [42]. The system could help with manoeuvring which has the potential to lower the total estimated CO_2 emissions from the voyage by up to 10%, as estimated [25]. There is a significant amount of research which demonstrates the ability of manoeuvring time to optimise time efficiency when exhaustive use of sensors and the decision support system is employed [7].

D. *Cold ironing*

Cold ironing is the practice of providing the ship with an electrical source from the shore. During the berthing process, the ship is able to disengage the diesel generators. This process, which happens at the most time at the port, will significantly reduce the CO_2 emissions of the ship [43]. With the source of ironing able to come from low-carbon and zero-carbon energy sources like wind and solar energy, it can even considerably lessen CO_2 emissions of ships at port by as much as 40 [17]. Port authorities recommend the ship owner as much as possible to support the use of cold ironing at berth which is most available as it will reduce the most time spent manoeuvring and waiting in the port. This will mean incresed CO_2 emissions and incresed fuel cost.

E. Operator Skill

The non-technical elements underpinning operational readiness hinge on having the appropriate training and expertise. Fuel-saving measures can only be effectively integrated and managed by the ship control operators if proper training and knowledge are provided. Training systems on the operation of the vessels should be continuously updated as new systems are integrated into the fleet for both new operators and those already on board [43]. The ship operators must also be skilled enough to influence the correct amounts of time spent on the vessel and port activities. It is possible to lower net CO_2 emissions by up to 10% through heightened operational and energy-conscious awareness [18] [44].

F. Type of Auxiliary Engine

Utilization of dual-fuel engines on ships is steadily increasing for both the main engines and the auxiliary engines. within this configuration, the LNG is used as the dominant fuel, while very small quantities of solar (marine diesel) are injected for pilot ignition. The system is capable of operating in a gas dominant mode, and then automatically switching to full diesel mode, should the gas supply be interrupted. [3] are optimistic that this approach will be able to sustain or even increase power output, and improve overall operational effectiveness (for example, through cleaner combustion and better operational efficiency), as long as the actual performance is affected by engine calibration, gas quality, and load control. In the case of retrofitting (where dual-fuel is added to an existing diesel engine) the ISO type LNG tank is a focal point in the critical architecture for fuel management [14] [45].

IV. Conclusion

RapidMiner Studio as the primary tool for achieving data modelling and analysis, its destructive fore method approach allows for the execution of recursive machine learning that emphasises the importance of predicting the variable usage for CO_2 emissions in importance prediction modelling. Subsequently, a random forest model is generated from a set of five features, from which the pertinent free variables are computed. The curiosity of the model, within which the importance of individual ship variables factors attention and its engagements, is then obtained as outputs. As part of the implementation of SEEMP, the trained model results support ways to reduce CO_2 emissions for pirate manoeuvring, port, and berthing. It is imperative to mention that within the frameworks of cold ironing, there is a port which recaptures a substantial amount of CO_2 emissions, but fails to provide, hence voyage optimisation techniques trained operators are a blend imperative to lower EEDI reduction standards. Emissions cease as intervals dwindle and punctuality is achieved by the voyage, but, in port, rigorous studies are conducted to reduce CO_2 emissions by assessing facilities that provide cold ironing and increase work productivity. Throughout, too, support can be garnered primarily during the berthing moments which necessitate coordination such as the control of cold ironing and data sharing for timely arrivals. The designed concurrency from this document can be employed to construct.

Emphasis on fuel-efficient manoeuvres at ports for the development of SEEMP's anywhere in the world, particularly in developing nations like Indonesia where environmental concerns have taken a back seat, is warranted.

References

[1] Z. S. Chen, J. S. L. Lam, and Z. Xiao, “Prediction of harbour vessel emissions based on a machine-learning approach,” *Transportation Research Part D: Transport & Environment*, vol. 131, art. no. 104214, Jun. 2024.

[2] E. C. W. Pribadi, R. O. S. Gurning, and E. Susanto, “Warehouse Inventory Management System for the Smooth Delivery of Cargo to Reduce Dwelling Time at the Port of Tanjung Emas Semarang,” *IPTEK Journal of Proceedings Series*, no. 4, ISSN 2354-6026, Jul. 2020. DOI: 10.12962/j23546026.y2020i4.7938

[3] M. A. Budiyanto and T. Shinoda, “Energy efficiency on the reefer container storage yard: An analysis of thermal performance of installation roof shade,” *Energy Reports*, vol. 6, suppl. 2, pp. 686–692, 2020.

[4] M. A. Budiyanto, M. H. Huzaifi, and S. J. Sirait, “Estimating of CO_2 emission in a container port based on modality movement in the terminal area,” *International Journal of Technology*, vol. 10, no. 8, pp. 1618–1625, 2019.

[5] M. A. Budiyanto, M. H. Huzaifi, S. J. Sirait, and P. H. N. Prayoga, “Evaluation of CO_2 emissions and energy use with different container terminal layouts,” *Scientific Reports*, vol. 11, pp. 1–14, 2021.

[6] M. A. Budiyanto, A. S. Pamitran, H. T. Wibowo, and F. N. Murtado, “Study on the performance analysis of dual fuel engines on the medium speed diesel engine,” *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, vol. 68, no. 1, pp. 163–174, 2020.

[7] E. B. Beşikçi, O. Arslan, O. Turan, and A. L. Ölçer, “An artificial neural network based decision support system for energy efficient ship operations,” *Computers & Operations Research*, vol. 66, pp. 393–401, 2016.

[8] E. C. W. Pribadi, E. S. Koenhardono, and A. Kurniawan, “Simulation of speed and maneuver control of trimaran ship model with neural network based hybrid propulsion system,” in *Proc. 3rd International Conference on Engineering, Technology and Innovative Researches (ICETIR 2021)*, Virtual, Indonesia, Sept. 1–3, 2021, AIP Conf. Proc., vol. 2482, p. 130001, Feb. 21 2023, doi: 10.1063/5.0111422.

[9] M. H. Huzaifi, M. A. Budiyanto, and S. J. Sirait, “Study on the carbon emission evaluation in a container port based on energy consumption data,” *Evergreen*, vol. 7, no. 1, pp. 97–103, 2020.

[10] C. Iris and J. S. L. Lam, "A review of energy efficiency in ports: Operational strategies, technologies and energy management systems," *Renewable and Sustainable Energy Reviews*, vol. 112, pp. 170–182, 2019.

[11] E. C. W. Pribadi, S. Semin, A. Santoso, B. Cahyono, A. Iswantoro, H. Prasutiyon, dan F. M. Felayati, "Lateral Swirl Combustion System Development of Dual Fuel Diesel Engine Piston to Improve Efficiency and Reduce NO_x Emission: A Brief Review," *International Journal on Engineering Applications*, vol. 12, no. 4, pp. 218-225, 2024, doi:10.15866/irea.v12i4.23008.

[12] L. Mengxiao, S. Hu, Y. Ge, G. B. M. Heuvelink, Z. Ren, and X. Huang, "Using multiple linear regression and random forests to identify spatial poverty determinants in rural China," *Spatial Statistics*, vol. 42, 2021, doi: 10.1016/j.spasta.2020.100461.

[13] E. C. W. Pribadi, S. Semin, A. Santoso, and M. I. Saihilmi, "Static Structural Simulation on a 47-mm-Crown-Diameter Lateral Swirl Combustion System (LSCS) Piston Modified," in *Proc. International Conference on Environmental Design, Material Science, and Engineering Technologies (EDMSET 2024)*, Dubai, UAE, 22–24 Apr. 2024, *Advances in Science, Technology & Innovation*, vol. xx, pp. 135-141, Springer Nature, 2025, doi:10.1007/978-3-031-76837-8_14.

[14] A. S. Pamitran, M. A. Budiyanto, and R. D. Y. Maynardi, "Analysis of ISO-tank wall physical exergy characteristic – case study of LNG boil-off rate from retrofitted dual fuel engine conversion," *Evergreen*, vol. 6, no. 2, pp. 134–142, 2019.

[15] Y. Peng, H. Liu, X. Li, J. Huang, and W. Wang, "Machine learning method for energy consumption prediction of ships in port considering green ports," *Journal of Cleaner Production*, vol. 264, 2020, doi: 10.1016/j.jclepro.2020.121564.

[16] R. M. Mohana, C. K. K. Reddy, P. R. Anisha, and B. V. R. Murthy, "Random forest algorithms for the classification of tree-based ensemble," *Materials Today: Proceedings*, 2021, doi: 10.1016/j.matpr.2021.01.788.

[17] E. A. Sciberas, B. Zahawi, D. J. Atkinson, A. Juandó, and A. Sarasquete, "Cold ironing and onshore generation for airborne emission reductions in ports," *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, pp. 67–82, 2016.

[18] S. Jensen, M. Lützen, L. L. Mikkelsen, H. B. Rasmussen, P. V. Pedersen, and P. Schambya, "Energy-efficient operational training in a ship bridge simulator," *Journal of Cleaner Production*, vol. 171, pp. 175–183, 2018.

[19] J. Singh and G. Dhiman, "A survey on machine-learning approaches: Theory and their concepts," *Materials Today: Proceedings*, 2021, doi: 10.1016/j.matpr.2021.05.335.

[20] L. Styhre, H. Winnes, J. Black, J. Lee, and H. Le-Griffin, "Greenhouse gas emissions from ships in ports – case studies in four continents," *Transportation Research Part D: Transport and Environment*, vol. 54, pp. 212–224, 2017.

[21] M. Tsagrisa and N. Pandis, "Multicollinearity," *American Journal of Orthodontics and Dentofacial Orthopedics*, vol. 159, no. 5, pp. 695–696, 2021.

[22] T. Uyanık, Ç. Karatuğ, and Y. Arslanoğlu, "Machine learning approach to ship fuel consumption: A case of container vessel," *Transportation Research Part D: Transport and Environment*, vol. 84, 2020, doi: 10.1016/j.trd.2020.102389.

[23] J. Weng, K. Shi, X. Gan, G. Li, and X. Huang, "Ship emission estimation with high spatial-temporal resolution in the Yangtze River Estuary using AIS data," *Journal of Cleaner Production*, vol. 248, 2020, doi: 10.1016/j.jclepro.2019.119297.

[24] D. Priyanta, H. Prastowo, R. Nurrahman, N. Siswantoro, T. Pitana, M. B. Zaman, S. Semin, and Y. H. Parluhutan, "Digital Twin Monitoring System for Diesel Engine Based on Arduino, Case Study: RPM and Exhaust Gas Temperature," in *SpringerBriefs in Applied Sciences and Technology*, Springer, 2024, pp. 75–82.

[25] H. Xing, S. Spence, and H. Chen, "A comprehensive review on countermeasures for CO_2 emissions from ships," *Renewable and Sustainable Energy Reviews*, vol. 134, 2020, doi: 10.1016/j.rser.2020.110222.

[26] I. D. Dawangi and M. A. Budiyanto, "Ship Energy Efficiency Management Plan development using machine learning: Case study of CO_2 emissions of ship activities at container port," *International Journal of Technology*, vol. 12, no. 5, pp. 1048–1057, 2021, doi: 10.14716/ijtech.v12i5.5183.

[27] E. C. W. Pribadi, R. Subagyo, A. Ghofur, and R. C. Ariesta, "A Critical Review of Performance Improvement Techniques in Compression Ignition Engines," *International Journal of Marine Engineering Innovation and Research (IJMEIR)*, vol. 10, no. 3, pp. 998–1006, Sep. 2025

[28] Y. Qi, L. Zhang, and H. Wang, "Spatial-temporal analysis of carbon emissions from ships under different operating modes," *Science of The Total Environment*, vol. 2024, pp. –, 2024.

[29] Y. C. Shih, "Speed optimization in bulk carriers: A weather-sensitive approach using historical noon report data," *Journal of Marine Science and Engineering*, vol. 11, no. 10, 2023.

[30] M. Bayraktar, et al., "Scientometric Analysis of Energy Efficiency Indicators in Shipping," *Sustainability*, vol. 17, no. 8, 2025.

[31] R. C. Ariesta, A. Sulisetyono, T. Yulianto, and E. C. W. Pribadi, "Reliability Analysis of Passenger Ship Structure Conversion in Bali Straits," *International Journal of Marine Engineering Innovation and Research (IJMEIR)*, vol. 7, no. 4, pp. 335–342, Dec. 2022, doi: 10.12962/j25481479.v7i4.5562.

[32] E. BenHakoun, A.-B. Author, and C.-D. Author, "The daily port and shoreline emission inventory model," *Maritime Policy & Management* (or similar journal), 2024.

[33] X. Gao, et al., "Analysis of emission characteristics associated with vessel ingress/egress and in-port activities using AIS data," *Marine Pollution Bulletin*, 2024.

[34] F. M. Felayati, H. Prasutiyon, S. Janah, D. H. Wijaya, M. B. Saputra, & Semin, "Performance and carbon emissions of a diesel/oxy-hydrogen dual-fuel engine with oxy-hydrogen injection variation under low and medium load conditions," *Int. J. Renewable Energy Development*, vol. 13, no. 2, pp. 235–244, Mar. 2024, doi:10.61435/ijred.2024.57983.

[35] E. C. W. Pribadi, E. S. Koenhardono, and A. Kurniawan, "Simulation of speed and maneuver control of trimaran ship model with neural network based hybrid propulsion system," in *Proc. 3rd International Conference on Engineering, Technology and Innovative Researches (ICETIR 2021)*, Virtual, Indonesia, Sept. 1–3, 2021, *AIP Conference Proceedings*, vol. 2482, p. 130001, Feb. 21, 2023, doi: 10.1063/5.0111422.

[36] M. Shantal, Z. Othman, A. Abu Bakar, "A Novel Approach for Data Feature Weighting Using Correlation Coefficients and Min–Max Normalization," *Symmetry*, vol. 15, no. 12, p. 2185, Dec. 2023.

[37] M. Zhang, N. Tsoulakos, P. Kujala, S. Hirdaris, "A deep learning method for the prediction of ship fuel consumption in real operational conditions," *Engineering Applications of Artificial Intelligence*, vol. 130, Apr. 2024, art. no. 107425. DOI: 10.1016/j.engappai.2023.107425.

[38] J. Barreiro, A. Theotokatos, and P. He, "Review of ship energy efficiency technologies — propulsion, WHR and electrical systems," *Renewable and Sustainable Energy Reviews*, vol. 157, p. 112054, 2022.

[39] Y. Yu, "Trim and engine power joint optimization of a ship based on operational trimming and voyage planning," *Journal of Marine Science and Engineering*, vol. 12, no. 3, art. no. 475, 2024

[40] X. Xie, J. Zhang, and Y. Liu, "Joint optimization of ship speed and trim based on optimal trim voyage window," *J. Mar. Sci. Eng.*, vol. 12, no. 3, art. no. 475, 2024.

[41] J.-O. Eom, J.-H. Yoon, J.-H. Yeon, and S.-W. Kim, "Port Digital Twin Development for Decarbonization: A Case Study Using the Pusan Newport International Terminal," *Journal of Marine Science and Engineering*, vol. 11, art. no. 1777, 2023, doi:10.3390/jmse11091777.

[42] . Tadros, "Review of the Decision Support Methods Used in Ship Energy Efficiency and Voyage Optimisation," *Journal of Marine Science and Engineering*, vol. 11, no. 4, art. no. 835, 2023.

[43] A. Kelmalis, D. F. Lekkas, A. Dimou, et al., "Cold ironing and the study of renewable energy sources utilization for maritime electrification: A case-based assessment," *Environments*, vol. 11, no. 4, art. 84, 2024.

[44] M. Tadros et al., "Technological, Operational and Energy Pathways for Maritime Transport to Reduce Emissions Towards 2050," final report for OGCI/Concawe, Jan. 2022.

[45] H. K. Lim, A. F. Rahman, and S. H. Lee, "Assessing LNG dual-fuel retrofitting: feasibility and environmental impact for an intermediate-size ship," *Journal / Elsevier (article)*, 2024.