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A Data-Driven Model for Rapid CII Prediction

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Abstract: The shipping industry plays a crucial role in global trade, but it also contributes significantly to environmental pollution, particularly in regard to carbon emissions. The Carbon Intensity Indicator (CII) was introduced with the objective of reducing emissions in the shipping sector. The lack of familiarity with the carbon performance is a common issue among vessel operator. To address this aspect, the development of methods that can accurately predict the CII for ships is of paramount importance. This paper presents a novel and simplified approach to predicting the CII for ships, which makes use of data-driven modelling techniques. The proposed method considers a restricted set of parameters, including operational data (draft and speed) and environmental conditions, such as wind speed and direction, to provide an accurate prediction of the CII factor. This approach extends the state of research by applying Deep Neural Networks (DNNs) to provide an accurate CII prediction with a deviation of less than 6% over a considered time frame consisting of different operating states (cruising and maneuvering mode). The result is achieved by using a limited amount of training data, which enables ship owners to obtain a rapid estimation of their yearly rating prior to receiving the annual CII evaluation.

Keywords: marine machinery; machine learning; artificial intelligence

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1. Introduction

Greenhouse gas emissions from the maritime industry are primarily generated through the burning of fossil fuels for propulsion and power generation on ships. These emissions include carbon dioxide, methane, and nitrous oxide (N_2O), all of which contribute to the warming of the planet and the associated environmental consequences [1].

The environmental impact of these emissions is far-reaching. Greenhouse gas emissions from maritime transport contribute to air and water pollution, with negative effects on ecosystems and human health. Furthermore, these emissions are a significant driver of global warming, with the potential to disrupt weather patterns, rise sea levels, and cause other severe climate-related events [2].

In response to these concerns, the maritime industry has been engaged in the investigation of a range of strategies aimed at the reduction of its greenhouse gas emissions. In their study, Law et al. [3] provide a comprehensive overview of the various measures that can be employed to reduce fuel consumption and, consequently, emissions in the shipping sector. One approach involves the adoption of more energy-efficient technologies, such as combustion engines with improved injector design or novel energy converters with a higher overall efficiency, e.g., solid oxide fuel cells [4–7]. Additionally, wind-assisted propulsion represents a promising avenue for reducing fuel consumption. This approach, exemplified by Flettner rotors and aerofoils, has garnered increasing interest in recent years, leading to a notable rise in installations across diverse vessel types [8].

Nevertheless, the most significant means of reducing emissions resulting from ship operations is the utilization of alternative fuels, including hydrogen and its derivatives, such as ammonia or green methanol [3,9]. In previous years, suppliers have developed combustion engines that are capable of burning alternative fuels. Engine manufacturers have conducted extensive research and development activities pertaining to methanol engines, which have culminated in the advent of retrofit alternatives for conventional diesel engines, as well as options for new builds, which are currently available [10]. Furthermore, the maturity of hydrogen and ammonia engines has increased significantly in recent years. DNV anticipates the availability of 2-stroke and 4-stroke engines running on ammonia until 2026 and 4-stroke engines running on hydrogen until 2028 [11].

In addition to power conversion technologies, operational measures like speed optimization [12] have the potential to positively influence the CII rating. Slow-steaming is named as one of the most favorable approach to cut emissions in operation [13]. An operational efficiency optimization method is proposed to limit the CO_2 emissions and comply with CII ratings of an entire fleet while maximizing its total profit based on vessel and route characteristics [14].

In recent years, several governmental instruments have also been published by policy makers to facilitate the changeover from fossil to renewable fuels. The shipping sector was incorporated into the EU Emission Trading System (EU ETS) in October 2023. The EU ETS scheme aims to ramp up the utilization of renewable fuels of nonbiological origin (RFNBOs) and obliges the shipping industry to contribute to the EU goals of becoming the first climate neutral continent until 2050 [15]. In addition, since the beginning of 2023, the Energy Efficiency Ship Index (EEXI) and the Carbon Intensity Indicator (CII) have been required to be reported, in accordance with the adoptions set forth in MARPOL Annex VI [16].

The Carbon Intensity Indicator (CII) is a measure to track the CO_2 emissions of a vessel per nautical mile sailed in reference to its cargo. Ships will be rated in efficiency classes comparable to the EU energy labels. Each ship of the fleet will be evaluated on a yearly basis on a scale from A (major superior) to E (inferior performance level). Over time it will become harder to reach the efficient classes. Three years in a row with a rating of D or one year with a rating of E requires a corrective action plan [17]. These can range from simple measures, such as implementing power limitations for main engines [16], cleaning the hull and adjusting sailing speed, up to installing auxiliary solar/wind power production units [18].

Predictive analysis and intelligent decision making can be applied to improve and enhance the state of health of machinery items. The effective assessment of intelligent machinery and ship driving behavior by technicians will be impacted by the change in its operating state.

Gong et al. [19] proposed a novel approach, namely an improved convolutional neural network-support vector machine (CNN-SVM) method, to efficiently identify an incipient fault in rotating machinery. The outcome of this model verified that the suggested approach outperforms other intelligence diagnosis techniques currently in use, such as SVM, K-nearest neighbor, back-propagation neural network, deep BP neural network, and CNN. Mateev [20] focused on the design of a deep learning-integrated serialized monitoring system for engineering ship power machinery. Here, a deep learning-based approach for diagnosing ship shafting faults was put forth in an effort to increase the effectiveness and precision of this process. While machine learning is often applied in marine engineering for the calculation of wave height prediction, calculation of wind loads on ships, damage detection of offshore platforms, calculation of ship-added resistance [21], engine monitoring [22], wear fault diagnosis [23], and improving condition-based maintenance [24], its application for the prediction of the CII is rather limited.

The CII represents a novel measure introduced in the maritime industry. Therefore, the existing literature on this subject is rather limited.

In comparison to the work of Zhang et al. [25], the objective of the methodology presented in this paper is to predict the CII of the vessel using a minimal number of input parameters, with a particular focus on those that can be actively controlled by the vessel's management. Furthermore, given the positive correlation between the CII value and a ship's fuel consumption, extensive research has been carried out in the last years with the aim of developing methods to predict fuel consumption.

In general, ML methods have demonstrated their ability to predict operational parameters of ships. Shen et al. [26] established a prediction model of ship fuel consumption considering different marine weather conditions based on the Deep Belief Networks (DBNs) algorithm to dynamically predict ship fuel consumption under different marine weather conditions. Zhang et al. [25] found that the ANN model had the best performance compared to LASSO regression. Lang et al. [27] demonstrated the advantages of ML techniques in estimating propulsion power over physics-based models. The reason for the more accurate ML predictions in their study is the underestimation of modelling complex environmental effects in physical models. For instance, the propulsion power of ships can be underestimated due to the inaccurate implementation of physical models, which can include the effects of trim, added resistance, or propulsion efficiency.

Aim of the Research

The objective of the developed approach is to predict the CII rating of a vessel using the main operational parameters, namely speed and draft, in conjunction with the environmental parameters, specifically wind speed and direction, as inputs. The methodology is tested on a variety of operational scenarios, including sea passage conditions (cruising) and maneuvering.

The approach relies on data-driven models, which provide vessel management with an estimated emission rating in advance of receiving the yearly CII rating. This enables ship operators to select appropriate operational parameter values for planned routes, allowing them to take a proactive stance and react before receiving a potentially unfavorable CII rating.

2. Materials and Methods

This paper uses operational and environmental data collected and tracked for a representative container ship over the course of one year as input. The data have been preprocessed by performing a comprehensive correlation analysis to check the plausibility of the collected data set (see Section 2.1). Furthermore, cells containing no data have been excluded from this stage of the process. The DNN methodology (see Section 2.2) was then applied to predict the CII value of the ship. The results, presented in Section 3, are compared with the calculated CII rating, which serves as a benchmark for the predicted values (see Figure 1).

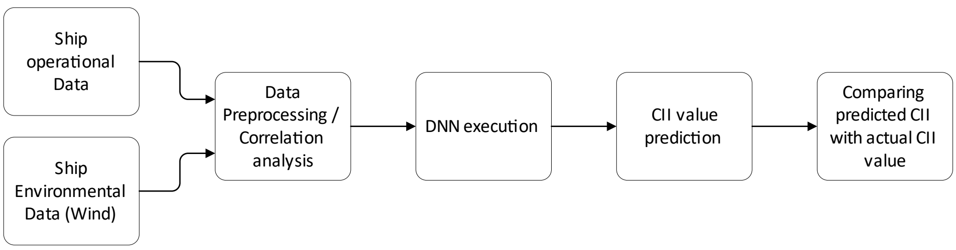

Figure 1. Schematic representation of the approach.

The primary propulsion power of the ship comes from a two-stroke, nine-cylinder diesel engine, model MAN 9G95. The main characteristics of the ship and its engine are listed in Table 1 below for the reference ship.

Table 1. Principal particulars and engine characteristics of the subject containership.

Ship Particulars and Engine Characteristics	
LOA [m]	367.0
LPP [m]	350.0
Breadth [m]	51.0
Depth [m]	30.4
Design draft [m]	14.5
Displacement at design draft [ton]	194,878
Scantling draft [m]	15.5
M/E cylinders	9

Twenty-three engine-related parameters were monitored to obtain continued measurements at fifteen-minute intervals of machinery-related conditions. These have already been described in [28] for the same vessel. However, in order to provide a very simplified approach, the operational parameters have been restricted to the below proposed list, since the fuel consumption is mainly affected by the limited operational and environmental parameters collected.

- shaft rpm [rpm]
- draft foreword [m]
- draft aft [m]
- relative/apparent wind speed [m/s]
- relative wind direction [deg]
- GPS speed [knots]
- log speed [knots]

In addition to the above features, the determination of the attained CII has been considered as part of the training data, considering the following formula:

$$CII = \frac{C_F \cdot (FC_{ME} + FC_{DG})}{DWT \cdot D} \quad (1)$$

where DWT is the deadweight, FC_{ME} and FC_{DG} the main engine and diesel generator fuel consumption, respectively, D the distance sailed and C_F the emission factor set equal to 3.114 for heavy fuel oil. It must be said that all these parameters were already part of the monitored data set but were not considered in the data-driven model.

The limit value to not overcome per year, defined as the required CII, is calculated as per Formula (2) below.

$$CII_{required} = \left(1 - \frac{Z}{100}\right) \cdot a \cdot DWT^{-c} \quad (2)$$

where a and c are constants related to the vessel type, and Z is a yearly increased correction factor. In order to contextualize the subsequent results, the requisite CII rating for the operational year 2024 is calculated. For the subject vessel in 2024, the CII rating required is 5.56.

2.1. Statistical Distribution and Data Analysis with Relative Distribution

A Pearson correlation analysis is performed in order to analyze the relationship between different environmental and operating parameters. The correlation Matrix shown in Table 2 helps in understanding the plausibility of the given data set and in finding correlations among the available data.

In general, the data show linear correlations, which are expected. A very strong correlation of 0.93 exists between the log speed and the fuel consumption, which means a higher ship speed strongly correlates with higher fuel consumption. Another noticeable correlation exists between a higher draft and Main Engine Fuel Consumption, at 0.72 and 0.64, respectively, which is also reasonable, since a higher draft leads to higher fuel consumption.

Table 2. Pearson analysis of environmental and operational parameters.

	Fuel Consumption ME	Draft Fore	Draft Aft	Log Speed	Relative Wind Speed	Relative Wind Direction
Fuel Consumption ME	1					
Draft fore	0.72	1				
Draft aft	0.64	0.94	1			
Log speed	0.93	0.70	0.63	1		
Relative wind speed	0.62	0.42	0.43	0.53	1	
Relative wind direction	−0.41	−0.27	−0.26	−0.38	−0.39	1

The relative wind direction (φ) in the data set is given in polar coordinates from 0° to 360°. The raw data are corrected to the range 0°–180° by Formula (3). This step ensures correct correlation findings. With this formulation given, a relative wind direction of 0° means head winds, which translates as added resistance. By contrast, wind at 180° means tails winds.

$$\varphi. = \begin{cases} if \\ else \end{cases} \begin{pmatrix} \varphi_{raw} > 180^\circ \ : \ 360^\circ - \varphi_{raw} \\ \varphi_{raw} = \varphi \end{pmatrix} \tag{3}$$

The medium strength negative correlation of −0.41 between relative wind direction and fuel consumption indicates a lowered fuel consumption with tail winds and vice versa a higher fuel consumption with head wind conditions. The correlation is rather weak for this effect, since the additional required fuel consumption due to tail winds influences the fuel consumption less than additional ship speed or a higher draft of the vessel.

Figure 2 visualizes the calculated CII value depending on relative wind direction and speed. In order to facilitate the interpretation of the data, points corresponding to periods in harbor have been excluded. The different bars give the average CII value of the wind condition sections. Consequently, the number of values determining the CII value of one section differs. The color code spans from green to red, with green indicating a favorable CII value and darker yellow to red signifying a high CII value. The requisite CII rating for the exemplar vessel in 2024 can be calculated as 5.56 (please see Section 2.1 for further details). A mid-yellow color tone represents this value. Higher bars and, correspondingly, darker colors denote a high CII rating, while greener tones indicate a favorable rating.

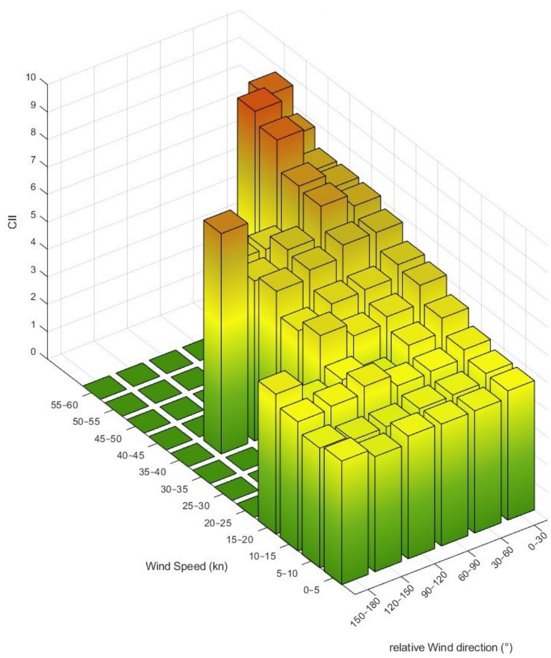

Figure 2. CII value depending on wind conditions.

The wind conditions mentioned here strongly correlate with ship speed. If the ship speed is higher, the wind facing the vessel comes mainly from head-on. For some of the combinations of wind conditions, there is no matching data available in the data set, which is understandable. For example, for high wind speed, the matching relative wind direction is mainly in the region of head winds.

The trend of higher wind speeds and winds facing the vessel predominantly from a head-on direction lead to higher fuel consumption of the main engine and, consequently, also to higher CII values. Despite this fact, the influence of wind speed on the CII value is greater than the influence of the wind direction, which also fits to the linear correlations of the Pearson analysis.

The CII value at wind speeds of 35–40 knots and a relative wind direction of 120–150° is an outlier, which can be explained with only one data point available for that parameter combination.

In addition to the correlations identified with environmental conditions, operational conditions also exert an influence on the CII value, as illustrated in Figure 3. A low ship speed of up to six knots, which falls within the area of maneuvering, has been observed to result in high fuel consumption and, consequently, an increase in CII values. However, excluding the two bars in this area, a correlation between increasing ship speed and growing CII values is evident. Additionally, an increase in draft has been observed to lead to higher CII values, although this influence is comparatively smaller than that of ship speed.

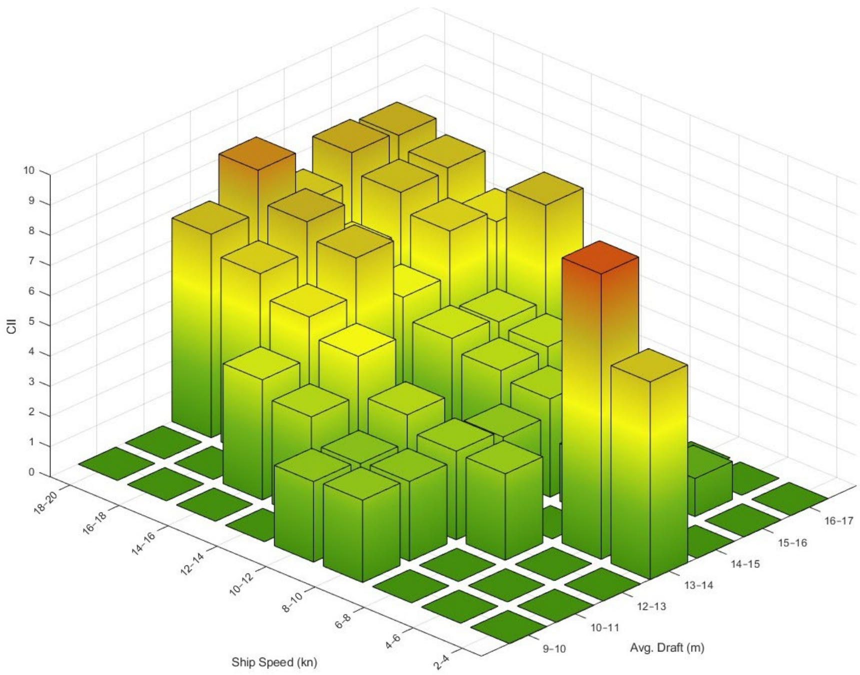

Figure 3. Operational influences on the CII value.

2.2. The DNN-Based Method

Our main method to perform the computation was a data-driven model, specifically a DNN, which is one of the most well-liked and effective machine learning techniques. The advantages of using a DNN against other methods, for instance physics-based models, have been demonstrated already by the authors for the same vessel type [28], where an extensive explanation of this kind of methodology was given. In addition, the superiority of the ANN methods in the framework of ship fuel consumption against other regressors has been shown by Jeon et al. [29] or by Gkerekos et al. [30].

Numerous domains and applications have seen their successful implementation. Multiple hidden layers are present inside of these Artificial Neural Networks (ANNs). It is worth mentioning that the idea behind the predicted output is described by a linear combination of an adjustable input and a bias [31]. After the computation, it is activated by a nonlinear function [32].

Deep learning represents a generalization of ANNs where more than one hidden layer is applied, which also implies that more neurons are utilized for implementing the model [33]. For this reason, an Artificial Neural Network with multiple hidden layers is called a DNN.

The term 'deep' in this context refers not only to the number of layers that contribute to the model but also to the high number of activation units, as in this case. Indeed, a DNN exhibits a greater degree of complexity in its interlayer connectivity than a conventional ANN, utilizing a larger number of neurons to capture the nonlinear aspects of complex data structures [33]. The DNN presents the presence of multiple inner layers considered inside the network. The modeling method for a DNN is based on the back-propagating learning algorithm used in the backward step with two hidden layers [34]. One layer of our suggested neural network had 8192 action units, while the other layer (second) had 4096 activation units.

The same neural structure (comprising two layers) has been employed to predict both ship fuel consumption and brake power, as demonstrated by La Ferlita et al. [28,35]. Representatively, the DNN architecture illustrating the same architecture characteristics (but with a different input layer) has been already provided in La Ferlita et al. [35].

A variety of architectural approaches have been considered prior to the development of this particular configuration. These include alterations to the layer type, the addition of new layers, and the application of regularization or normalization techniques. Nevertheless, when evaluated in comparison to the final output, these methods did not demonstrate superior performance. By transitioning from a low-dimensional space to a projection of the data into a higher-dimensional nonlinear space, this configuration has enhanced the neural network's capacity to generalize the problem.

The ADAM optimization algorithm was incorporated into the system. In order to achieve an exponential decay rate of 0.96 over ten epochs, we reduced its learning rate of 0.001. The training process comprised 100 epochs. The sigmoid-weighted linear unit function, a continuous smooth function that permits some insignificant weights to propagate in the network, was the source of the nonlinear swish function [32], which served as the activation function. The output is described by a linear combination of a bias and an adjustable input. After the computation, a nonlinear function turns it on. This algorithm allows for the dynamic adjustment of each parameter's learning rate.

In terms of software, the same tensorFlow version 2.16.1 and Google Colab Python version 3.10 [28] were used in the neural network development process. Google offers a product called Google Colab that enables the execution of any Python code that is appropriate for machine learning. TensorFlow is a computational toolkit for deep learning. DNNs use input features and understand both the input and output values. These models include processes for training and learning. The training and the validation steps were performed by splitting the training dat a set, consisting of the usual 80/20 approach.

In addition, preprocessing intended as a correlational analysis was performed in advance, as shown in Section 2.1. According to Jiao et al. [36], it is a common practice to conduct a data transformation beforehand by examining the distribution and statistical characteristics of the input features.

Nevertheless, the DNN method is itself an optimization procedure. Since each feature's weight is updated separately until the algorithm discovers the right pattern, we did not consider further filtering in our analysis (considering also the reduced number of samples).

According to the different scenarios for cruising and maneuvering, two different data sets have been considered. Afterwards, the neural network was put to the test in brand new situations that were unknown to the algorithm, which were, respectively, the cruising and the maneuvering condition.

As performance metrics to understand the DNN capabilities, four main parameters were considered, such as RMSE, MAE, MSE [35], and the addition of the R-Squared value [37]. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression analysis evaluation.

The Root Mean Square Error (RMSE) is one of the most often used performance metrics in deep learning [38,39]. The Root Mean Square Error (RMSE) provides an indication of the average magnitude of errors in a set of predictions. The Mean Absolute Error (MAE), on the other hand, is a good metric that might be more resilient to outliers [40]. Another important performance metric in deep learning is the Mean Squared Error (MSE), which measures the average of the squares of the errors. MSE is particularly useful for identifying and penalizing large errors, making it a valuable complement to RMSE and MAE in certain deep learning applications. The R-squared can offer support as a direct estimator of the population parameter, providing a straightforward way to compare the performance of different models [41].

3. Results and Discussion

This paper considered the two operational scenarios, cruising and maneuvering, to test the deep learning approach. It is important to clarify that these scenarios are based on the vessel status as stated by the reporting system. Thus, we can expect the presence of some transient phenomena in the 'cruising' conditions and some steady phases in the 'maneuvering' conditions. These conditions were selected to cover the situations where the main fuel consumption of the vessel occurs. During maneuvering, the fuel consumption varies significantly more than during cruising, which is associated with steady sailing speed. Thus, the model is tested in both steady state and transient conditions.

Figure 4 presents a comparison of the calculated and predicted CII values for cruising conditions. The vertical axis illustrates the CII value, while the horizontal axis represents sample points as a subset of the data set. In general, the predicted CII values align well with the calculated ones, as can be seen clearly in the illustration below. The sea passages are distinguished by relatively stable operations. The CII amplitudes are present in the majority of the sample points. At sample point 590, the vessel commences a transient operation. In this region, the predicted values also demonstrate a high degree of alignment with the calculated ones. A sudden drop in CII right before sample point 100 can be credited to bad data reporting.

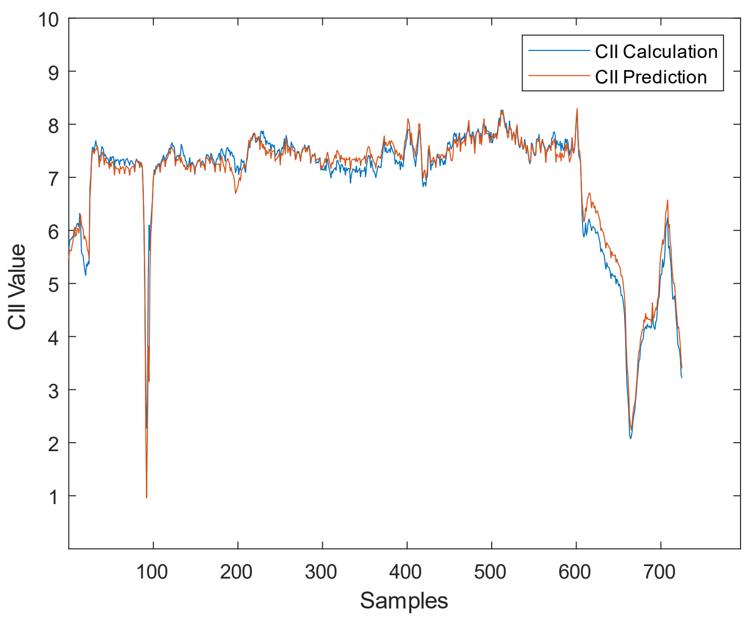

Figure 4. Calculated and predicted CII value for cruising conditions.

Figure 5 gives an extract of the CII prediction in maneuvering conditions. The major difference compared to the sea passage is the very transient change in the CII value, resulting from heavy accelerations of the main engine and, consequently, also a fluctuating fuel consumption and CII rating. The predicted value can follow the calculated one, especially if the CII stays constant over a period of time. An example of the phenomenon is the period between sample point 120 and 130. What also becomes visible is that the predicted values do not reach the peaks of a CII with 35, e.g., at the sample points of 180–190. However, it is also not clear if these sudden increases in the calculated CII are due to the use of bad data or real physical phenomena. Overall, there is a good alignment of predicted and calculated values.

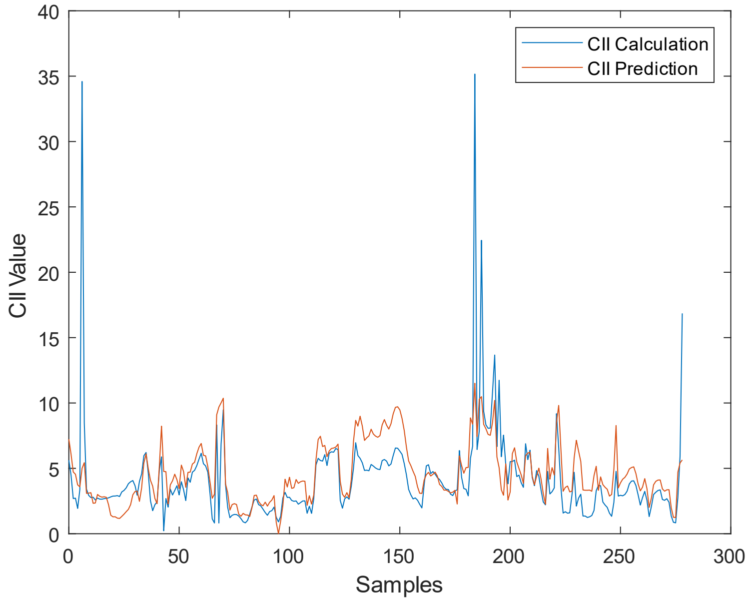

Figure 5. Calculated and predicted CII values for maneuvering conditions.

Furthermore, the satisfactory alignment in sea conditions is corroborated by the values for RMSE, MAE, MSE, and R^2, which serve to evaluate the quality of AI methods. The results for the sea passages are particularly noteworthy (see Table 3). The methodology is demonstrated to be capable of reliable prediction of the CII value in sea passages, with an RSME value of 0.23 and an MAE value of 0.05. Furthermore, the values of RMSE (2.90) and MAE (1.47) in maneuvering conditions indicate a satisfactory result in transient operations.

Table 3. MSE, RMSE, MAE, and R2 of the predicted values under multiple scenarios.

Scenarios	**RMSE**	**MAE**	**MSE**	$\mathbf{R^2}$
Sea Passage Condition	0.23	0.15	0.05	0.96
Maneuvering Condition	2.90	1.47	8.43	0.33

Finally, using the available data, the CII value is calculated for three time periods: 1 month, 2 months, and 3.5 months. By comparing these values to the results of the model, its capability to predict the CII value of the vessel over longer time periods, which include a combination of various conditions like cruising, maneuvering and anchoring, is evaluated. For the inputs of the model, average values taken from the corresponding time period of the data were used. For the averaging, anchoring conditions were ignored to avoid skewing the input data. The three distinct time periods were selected by dividing the available data into three approximately equal sets and combining one, two and three sets, respectively (see Table 4 below).

Table 4. Results of CII prediction periods.

Scenarios	Actual Value	Prediction	Deviation (%)
1 Month	6.55	6.2	5.34
2 Months	5.54	5.44	1.80
3 Months	5.91	5.56	5.92

The ability of DNN generalization against other ship topology vessels was not tested in the current work due to lack of data. It is of paramount importance to mention that that the carbon emissions depend on the operational design and profile of the vessel considered.

In this respect, the speed and the deadweight of the vessel can influence the CII. In general, deep learning models have demonstrated a strong ability to generalize new and different scenarios. Their capacity to learn abstract representations of data, together with their adaptability, make them suitable for predicting patterns of unseen data (wild data). Therefore, despite the fact that this aspect has not been directly tested, a certain level of confidence can be taken into account.

4. Conclusions

The proposed method demonstrated that it is feasible to forecast the CII value of a vessel with a high degree of accuracy from the outset of its operational period, based on the analysis of fundamental environmental and operational parameters.

The AI algorithm demonstrated its capacity to predict the CII value with an uncertainty of only 5.92% for the given data set of a container vessel in a time period of 3.5 months of continuous operation, encompassing a range of ship operational modes. The data-driven approach yielded precise results for the prediction of the CII value, as evidenced by the favorable RMSE, MAE, and R-squared values. The methodology demonstrates particularly high levels of accuracy, particularly in the context of sea passages.

The method has been found to be a valuable tool for ship operators, enabling an early investigation of CII values in their respective fleets and facilitating prompt action before a poor rating is received and the adoption of ship operations is necessitated.

It is reasonable to posit that the methodology is effective for vessels that operate primarily under steady state conditions. As these conditions were extensively covered by the training data, such an outcome seems logical. In a subsequent step, the model will be applied to data sets representing types of vessels that spend a significant amount of time in maneuvering mode, such as cruise ships and ferries, aiming to further assess its predictive capabilities when provided with more diverse training data.

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