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Analysis of Ship Fuel Efficiency and CO_2 Emissions

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Abstract. Ship fuel efficiency and CO_2 emissions analysis plays a vital role in enhancing the sustainability of maritime transportation and mitigating its environmental footprint. However, the traditional methods have difficulty in adapting real time data and the inability to capture complex and non-linear data because of relying on simplified assumptions and historical data. Fuel efficiency and CO_2 emissions are influenced by complex and nonlinear interactions between variables like weather conditions, engine performance, vessel load, and sea conditions. These traditional methods cannot easily model such intricate relationships, leading to simplified approximations that may not fully capture real-world dynamics. Deep learning (DL)-based methods could somewhat identify subtle, nonlinear dependencies between factors that influence fuel consumption and CO_2 emissions, leading to more accurate and reliable predictions. However, these models face limitations in training the noisy, sparse and turbulent data patterns, which reduces the accuracy of predicting the output and the computation time is increased. Therefore, this paper presents an Artificial Neural Networks using Adaptive Moment Estimation (ADAM) optimization algorithm to overcome the drawbacks faced due to noisy and sparse dataset. The ADAM optimizer enhances the learning process by adjusting learning rates based on first and second moments of gradients, offering faster convergence and improved resilience to noisy and sparse data. Using an ANN optimized with ADAM algorithm showed an improvement in prediction efficiency by 8% to 15% compared to Deep Learning Models.

Keywords: Artificial Neural Networks (ANN), ADAM, Deep learning, LSTM, Machine Learning.

1. Introduction

In global trade, the marine industry plays a vital role with thousands of ships transporting goods across the world's ocean. Although this industry is also a major cause of environmental damage, especially with regard to fuel consumption and carbon dioxide (CO_2) emissions. This immoderate and excessive burning of fossil fuels in ships leads to air pollution, climate change, and serious hazards to marine ecosystems. With the growing concerns over climate change and tightening international regulations such as IMO 2020 and MARPOL Annex VI, it has become imperative to adopt more accurate and adaptive techniques for monitoring and optimizing emissions and fuel consumption.

In order to effectively optimize energy usage in marine delivery, there is an urgent need for accurate and reliable models to predict specific fuel consumption (SFC). The method of predicting SFC is the center of the researcher. The exact predictions are important for achieving goals in strategic plans, regulatory requirements and the goals of sustainable development in the shipping industry. Till date, some reviews have been widely discussed about the potential application of machines and deep learning methods for predicting SFC. These articles discuss three main clusters of the commonly used algorithm, that is, (I) supervised machine learning method (MLMS), (II) unsupervised lea and (III) Deep learning method (DLM). Some previous studies were conducted to investigate a variety of machine learning and deep

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learning models for predicting SFC and CO_2 emissions of ships. For instance, Yan et al. random forest and gradient boosting machine models using AIS data, additional weather, operational parameters and obtained 88.4% and 90.1% accuracies, respectively. Fan et al. (2022) used an LSTM model based on time-series data like vessel speed, draft, wind speed, and wave height with an accuracy of about 70%, and complicated performance if inputting sparse or noisy data. Huang et al. (2022) proposed a deep neural network (DNN) model based on a single-year operational data from container and bulk carriers that achieved 92.3% accuracy, which also shows a good performance in nonlinear relationship modelling. Zhou et al. (2020) applied a Support Vector Regression (SVR) model and achieved 81% accuracy compared to six months of ship log data, although high dimensionality and noise were problematic. Liu et al. where they proposed a hybrid CNN-LSTM model with the use of AIS, weather, and engine monitoring data, which achieved 89.5% accuracy, but the complex structure of the model increased training times and prevented real-time use. In this article, we have worked on Artificial neural Network (ANN) with ADAM optimization algorithm which gives a better accuracy than the previous researches.

2. Related Work

Hansung Kin et al. [1] has proposed a hybrid system of the power plant. Using a linear interpolation method and a scaling approach, the electric load was analyzed based on the operating profile of large containers and carriers. The results show that during the port period, fuel consumption decreased by 18% and CO_2 emissions decreased by 61%, which suggests that similar hybrid systems can greatly increase emission efficiency. D. BOCCHETTI et al. [2] developed a statistical control system for fuel consumption of ships using multiple linear regression analysis. the model enables comparison between expected and actual fuel consumption, triggering management alerts when deviations occur. The model successfully predicted fuel consumption with 95% certainty and an error margin of ±5%. Nicholas bialistoki et al. [3] shows the operating system methodology for accurate evaluation of ship's fuel consumption and speed curve, considering the main influential factors such as projects, displacement, weather conditions, and roughness of propellers. This method, has been proved to be practical and important for increasing operational plans and efficiency. Zhi Yuan et al. [4] used Back Propagation Neural Network with double hidden layers (DBPNN) to create a model that predicts fuel consumption, reducing RMSE and MAE by 35.31% and 30.30%, respectively, while increasing R^2 to 0.9843. JAEWON Jang et al. [5] compares CO_2 emission predictions from an enhanced predictive model with those from a Life Cycle Assessment (LCA) simulation. The predictive model estimated emissions 83% higher than LCA results.

IBNA Zaman et al. [6] have developed an algorithm that uses real -time sensor data to analyze fuel statistical, theyused models based on the measured operational data. And got a result of R Squared value of 99.7%. Ivika skoko et al. [7] compares CO_2 emissions, fuel consumption, and operating costs of two similar dredger ships with different propulsion systems. The research was conducted through a combination of theoretical analysis of diesel and hybrid ships and experimental research, i.e., case studies. Wei Cao et al. [8] proposed a two-layer power allocation strategy for fuel cell ships to optimize fuel efficiency. this method reduces hydrogen consumption by up to 15.1% and decreases the power output of low-performing fuel cells by up to 15.7%. J. PRPIAN [9] used a zero-dimensional numerical model leading to a 10% reduction in both fuel consumption and CO_2 emissions.

Vladimir bossed Igal. [10] evaluates the effects of slow steaming on fuel consumption and CO_2 emissions. A moderate 10% reduction in speed leads to a 19% drop in CO_2 emissions was acheived. Daniel Clark et al. [11] has developed a near-real-time database for tracking CO_2 emissions from global shipping using AIS data and vessel-level identifiers, using a random forest model giving a prediction accuracy of 86%. Xiaohe Li et al. [12] xplores multiple machine learning (ML) models to predict ship fuel efficiency, including decision trees, artificial neural networks (ANNs), support vector machines (SVMs), and gradient boosting models (GBMs) with R^2 values exceeding 0.96.

Jun Yuan et al. [13] Gaussian Process (GP) metamodel to predict ship energy consumption under various operational and weather conditions with results showing 10% speed reduction can lower fuel consumption by 19%. Zhihui Hu et al. [14] examined the effects of environmental factors (wind, waves, current) on prediction of fuel consumption using Back Propagation Neural Networks (BPNNs) and Gaussian Process Regression (GPR). While BPNN offers slightly lower accuracy than GPR, it operates significantly faster.

Zhihuan Wang et al. [15] introduces a model for shipping fuel consumption prediction using. It introduces a long short-term memory network with a self-control mechanism (SA-LSTM) using long-term short-term memory. Long Short-Term Memory network with a Self-Attention Mechanism (SA-LSTM). The model reduces the Mean Absolute Percentage Error (MAPE) by up to 20% compared to XGBoost and 12% compared to standard LSTM models. Mingyang Znag et al. [16] used a deep learning approach using a bidirectional long-term memory network (BI-LSTM) with attentional mechanisms to model SFC. Decision Tree (DT)-based variable evaluation models identify important influencing factors. Results show that over 90% of prediction errors are below 4%, with an average error of 0.98%. Shaohan Wang et al. [17] used the K-Means clustering approach to categorizes ship draught levels to better differentiate between empty and full-load conditions for fuel consumption modeling with an avrage R-squared of 0.94.

Tainrui Zhou et al. [18] introduced an advanced ship fuel consumption prediction model that integrates Gaussian process prediction with quantile regression acheiving a 95% confidence interval coverage probability of 0.98 and a prediction accuracy of 92%. Boazhi Sun et al. [19] developed both black box (machine learning) and white box (mathematics) models to predict ship fuel consumption. XGBoost and Random Forest models achieve R^2 values above 0.99, and after applying the Kwon method, accuracy reaches 0.9954. Anti Solons et al. [20] used a hierarchical Bayesian modelling approach to predict driving forces for multiple ships and assumed that similar vessels had closely related performance parameters. Using actual data from 64 cruise ships, the model shows that it surpasses traditional resistance-based calculations and improves prediction accuracy in fuel efficiency estimation.

Jasashwi Mandal et al. [21] passed the mixed-integer nonlinear programming (MINLP) model with two evolutionary algorithms, NSGA-II and OCEA, are used to create near-optimal solutions, and validate the approach across a variety of instances. Yang Yang Tung et al. [22] proposes an optimization model that considers both cruise speed and freight tonnage to enhance fuel efficiency in fleet deployment and bunker management. A "Most Promising Area Search" (MPAS) algorithm is developed to solve the model, ensuring convergence to a locally optimal solution.

Juhyang Lee et al. [23] developed a machine-based approach to predict fuel consumption and carbon emissions of multi-fuel-propelled smart ship using real-time onboard measurement data resulting in accuracy that varied by fuel model 81.5% for diesel and 91.2% for gas.Yongpeng Wang et al. [24] Deep learning was combined with AIS data to monitor vessel CO emissions in real time, resulting in LSTM having lower trajectory endpoint errors than RNN Zhihuan Wang et al. [25] focused on predicting ship fuel consumption and carbon strength index (CII) using self- Attention Long Short-Term Memory (SA-LSTM) which showed reduced fuel consumption prediction error by 20% compared to XGBoost and 12% compared to standard LSTM. Mingyang Zhang et al. [26] used a BI-LSTM network with attention mechanism to predict vessel fuel consumption (SFC) using 266 variables of data. The model reached an MSE of 2.04E-2, with over 90% of errors below 4%, and an average error rate of 0.98%.

3. Methodology

3.1 The Models used

3.1.1 Long Short-Term Memory (LSTM)

LSTM stands for Long Short-Term Memory, it is a type of RNN (Recurrent Neuronal Network) which defines the connect of long-term memory and short-term memory. A long-short time memory unit has typically three objectives:

- Forget Gate: It decides the information to be rejected from the previous state.
- Input Gate: The gate that decides what needs to be stored in the current cell state. This means the same system that should be used and then forgotten.
- Output Gate: This gate decides what information to be present in the current cell state by assigning information to 0:1, based on previous and current conditions.

The compact forms of the equations for the forward pass of an LSTM cell with a forget gate are:

$$f_t = \sigma_g\,(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$

$$\tilde{c} = \tanh_c(W_c x_t + U_c h_{t-1} + b_c) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{5}$$

$$h_t = o_t \odot \sigma_h(c_t) \tag{6}$$

where the initial values are $c_0 = 0$ and $h_0 = 0$ and the operator $\odot$ denotes the Hadamard product (element-wise product)

1. Forget Gate:

The forget gate will wipe out irrelevant information even in the cell state. Two inputs XT (input at some time) and HT1 (previous cell editing) are multiplied by a weight matrix, then some distortion is added. The outputs are binary and are obtained from the activation function. Missing cell states, such as issue 0, result in the omission of related data, preserves only the initially accepted and potentially harmful information.

A mathematical model for forgetting is given as:

$$f_t = \sigma\,(W_f.[h_t - 1, x_t] + b_f) \tag{7}$$

where:

- W_f represents the weight matrix assigned to the forgetting gate.
- $[h_t - 1, x_t]$ indicates the current input chain and previous hidden state.
- b_f is a forgotten gate distortion.
- σ is the sigmoid activation function.

2. Input Gate:

The useful information of the cell state is then incorporated as another term. First, information is regulated in sigmoid functions; these inputs HT1 and XT, are used to filter values similar to the forget gates. Finally, we create the vector using the TANH function (gives -1 to +1 output) with all possible values for HT -1 (the Output HT-1) and XT. Thus, vector value is multiplied by adaptive value to get the useful information.

The equation for input-gate is:

$$i_t = \sigma\,(W_i\,.\,[h_t - 1, x_t] + b_i) \tag{8}$$

$C^t = tanh\ (W_c\ .\ [h_t - 1,\ x_t] + b_c)\ C^t = tanh\ (W_c\ .\ [h_t - 1,x_t]+b_c)$ (9)

$C_t = f_t \odot C_{t-1} + i_t \odot \widehat{C}_t$ (10)

where,

- $\odot$ denotes element-wise multiplication
- tanh is tanh activation function

3. Output gate:

This start gate takes on the task of seeking useful information from the current cell state exposed as output. The initial stage is the generation of a vector through the application of the TANH function to a cell. Next, the information accessed is limited by the SIGMOID function and the values stored are filtered by using the inputs HT 1, HT 1 and XT, XT, XT. Finally, the vector values and the restriction values are multiplied so that they are sent as output and input to the next cell.

The equation for the starting gate is:

$o_t = \sigma\ (\ W_o.[h_t - 1, x_t] + b_o)$ (11)

Figure 1 Shows the flowchart of the Methodology used.

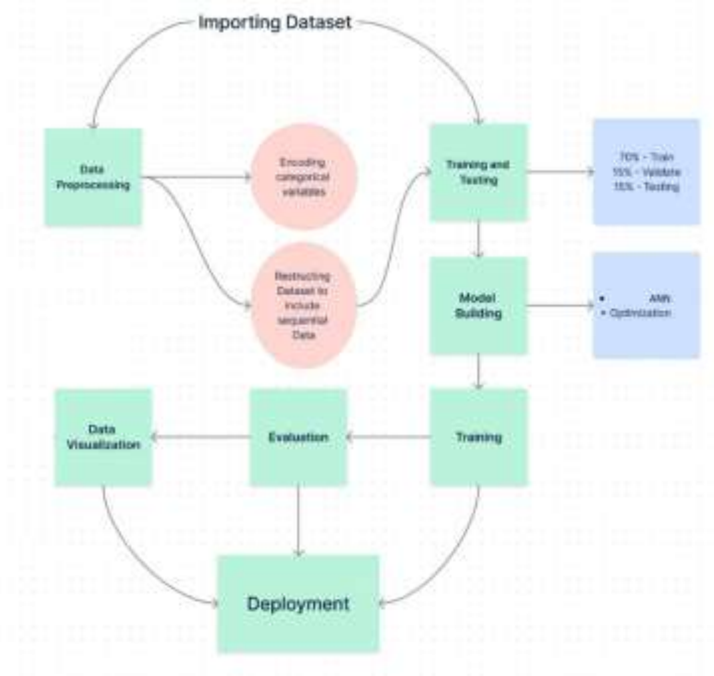

Figure 1: Methodology Flowchart.

3.1.2 Artificial Neural Networks

Neural networks (also known as ANNs or artificial neural networks) are a type of computer software inspired by biological neurons. The biological brain can solve difficult problems, but each neuron is responsible for solving very small parts of the problem. A neuronal network consists of cells that work together to achieve the desired outcome, although each cell is only responsible for solving a small part of the problem. This is a way to artificially create intelligent programs.

In a simple "feedforward" network, data processed by neurons pays for. Each neuron performs a weighted sum of the values of neurons in the previous layer. Next, add a constant value (indicates "bias"). Finally, apply a mathematical function to this value. This is called an "activation function." Activation functions are usually functioning that return values between 0 and 1, such as “tanh”.

The results of the activation function are sent to neurons in the next layer:

$$Y_j = Acyivation\ (\underbrace{\sum}_{i \in Inputs} \text{Weight}(\text{i}, \text{j}) * \text{X}_\text{i} + Bias\ (j)) \tag{12}$$

A very simple neural network, made of just one neuron that solves the same problem is represented in Figure 2.

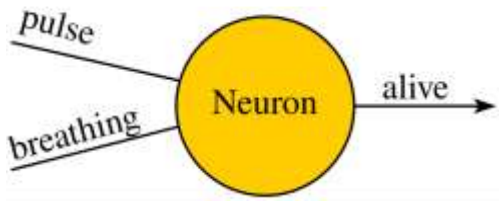

Figure 2: Simple Neuron and Synapse.

Figure 3 Represents neural network having Input layer, Hidden layer and Output layer

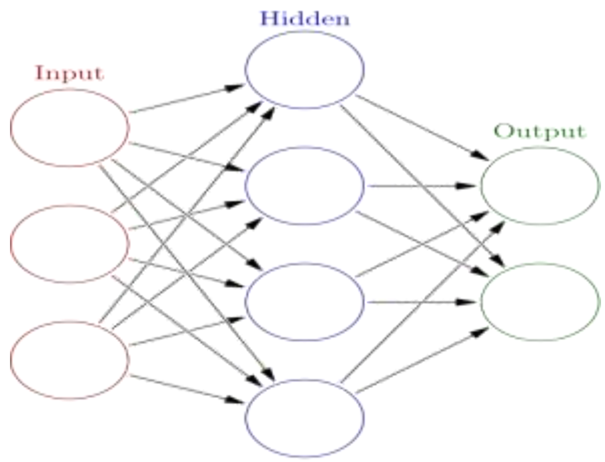

Figure 3: Neural Network representing Input layer, Hidden layer and Output layer.

3.1.3 Adaptive Moment Estimation (ADAM)

ADAM (Adaptive Moment Estimation) is an optimization algorithm used for training deep learning models, such as Artificial Neural Networks (ANN). In the training scheme for LSTM and ANN models for predicting ship fuel consumption and CO_2 emissions in this project the Adam optimizer was used. Especially because Adam benefits from fast convergence that allows speeding up the training on complex emission data, and its adaptive learning rates are helpful when the input features vary greatly. It is memory-efficient, allowing it to scale well to large datasets, and it is robust to the specific choice of hyperparameters, providing stable performance when little or no tuning is applied. These benefits make Adam a simple yet highly effective option for our prediction problem.

ADAM adjusts the learning rate for each model parameter based on the first and second moments of the gradients:

- The first moment is the average of the derivatives (i.e., how much and in which direction the model's weights change).
- The second moment is the uncentered variance of the gradients (i.e., how much is the gradient changing). ADAM adjusts how much each parameter should be shifted during training by monitoring these moments. They enable faster and more accurate convergence, particularly with noisy or sparse datasets.

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * g_t \tag{13}$$

$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * g_t^2 \tag{14}$$

$$\widehat{m_t} = m_t/(1 - \beta_1^t) \tag{15}$$

$$\widehat{v_t} = v_t/(1 - \beta_2^t) \tag{16}$$

$$\theta = \theta - (\alpha * m_t/\sqrt{(\widehat{v_t} + \varepsilon)}) \tag{17}$$

where,

m_t is first moment estimate

v_t is second moment estimate

g_t is gradient at time step

β_1 and β_2 are the decay rates

$\widehat{m_t}$ is bias-corrected first moment estimate

$\widehat{v_t}$ is bias-corrected second moment estimate

α is learning rate

θ are the model parameters

ε is small constant typically 10^{-8}

4. Results and discussions

Figure 4 shows different data visualization techniques used to understanding the dataset. Figure 4 shows a bar graphs the mean engine efficiency of the engines; it can be noted that the mean engine efficiency is similar for all four types of ships. Figure 4 shows a bar graph that represents mean CO_2 emission of each ship; it can be seen that the tanker ship emits the most amount of CO_2 whereas surfer boat emits the least. Figure 4 shows a bar graph that represents mean distance travelled of each ship; it can be seen that the tanker ship travelled the most distance whereas oil surfer boat travelled the least. Figure 4 shows a bar graph that represents mean ratio of distance travelled to the CO_2 emissions of each ship; the graph shows that the tanker ship emits less CO_2 per unit distance whereas surfer boat emits the most CO_2 per unit distance. Figure 4 shows bar plot for fuel type vs CO_2 emissions.

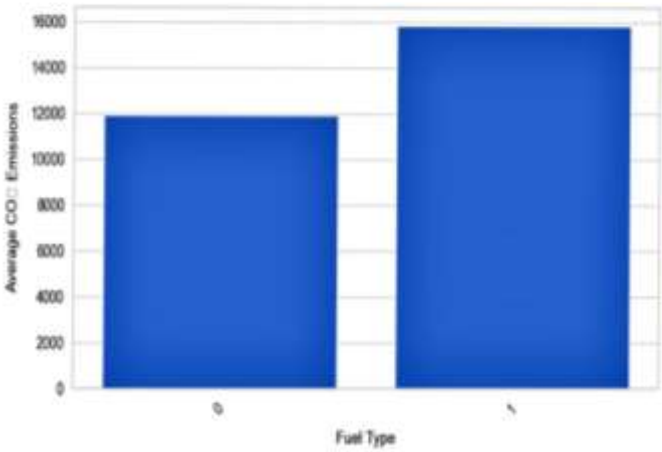

Figure 4: Fuel type vs CO_2 emissions.

The graph shows the average CO_2 emissions for different fuel types, highlighting that Fuel Type 0 is more eco-friendly, where Fuel Type 0 is Diesel and Fuel Type 1 is Heavy Fuel Oil (HFO). Average Co_2 Emission for Diesel is 11,800 unit and for HFO is 15,800 unit. Fuel Type 0 is more efficient, producing 25% less CO_2 than Fuel Type 1 . Figure 5 shows heat map for various routes.

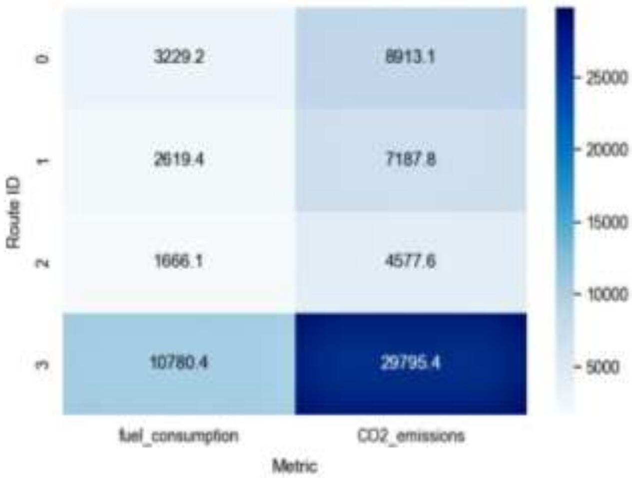

Figure 5: Route Efficiency (Fuel & CO_2).

This heatmap compares fuel consumption and CO_2 emissions across routes. Route 2 is the most efficient; Route 3 has 6.5 X more fuel use and CO_2 output identifying Route 2 as the most efficient because it covers relatively less distance and the weather condition for that route was calm. Figure 6 shows scatter plot for CO_2 Emissions vs. Engine Efficiency.

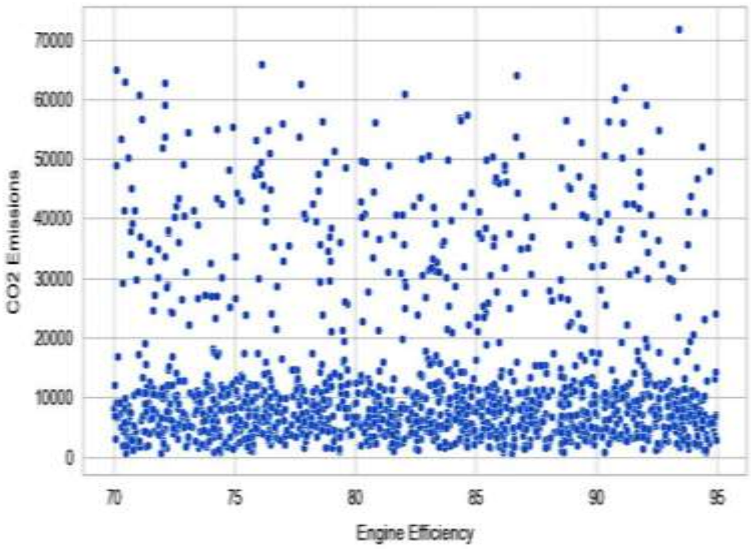

Figure 6: CO_2 Emissions vs. Engine Efficiency.

This scatter plot displays the lack of strong correlation between engine efficiency and CO_2 emissions. The lower portion of the graph is more crowded and this signifies that low efficiency engines still produce a wide range of CO_2. High efficiency engines can still emit large CO_2. This indicates that improvements in engine efficiency alone do not consistently lead to lower emissions. Figure 7 Shows Line graph of comparison of Training Loss and Validation Loss.

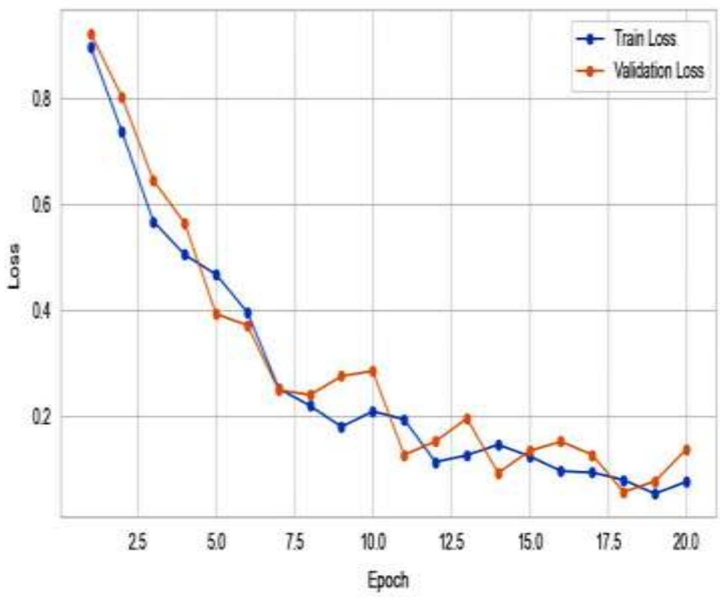

Figure 7: Training & Validation Loss.

Training Loss drops from 0.9 to 0.05 in 20 Epochs. Validation Loss also follows a similar trend, which indicates that the model has learned well with minimal overfitting and performs reliably on unseen data. Figure 8 Shows a Box Plot studying weather conditions based on Fuel consumption.

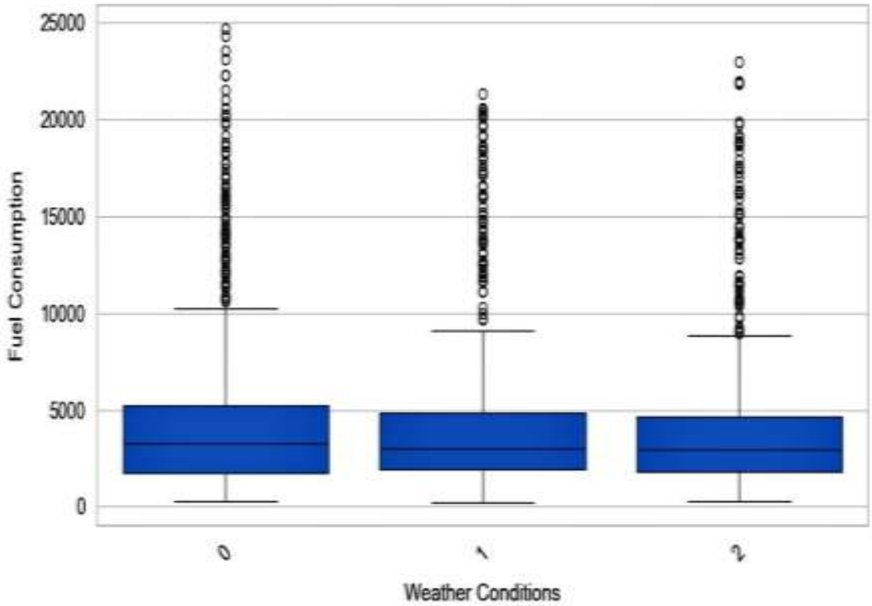

Figure 8: Weather Conditions vs Fuel Consumption.

Fuel consumption remains fairly consistent across different weather conditions, with medians around 4,000–5,000 units. Weather Condition 0 signifies Stormy weather, while 1 and 2 respectively signify Moderate and Calm. Weather has limited average effect, but extreme conditions cause spikes. Figure 9 Shows Line graph of Fuel efficiency over Months.

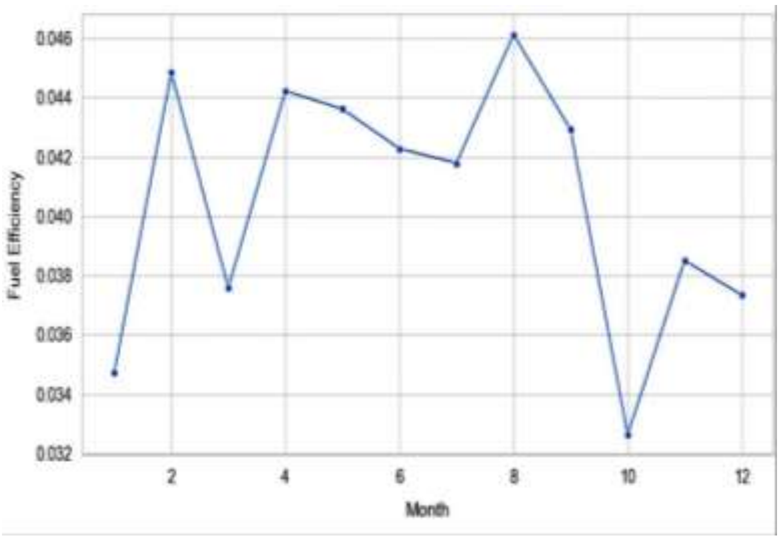

Figure 9 : Fuel Efficiency over months.

This line graph tracks monthly fuel efficiency trends which shows peak efficiency in August(0.046) and the lowest in October(0.032). There is a 30% variation in efficiency across months. Figure 10 Shows a Scatter Plot of Fuel Consumption varying with Distance.

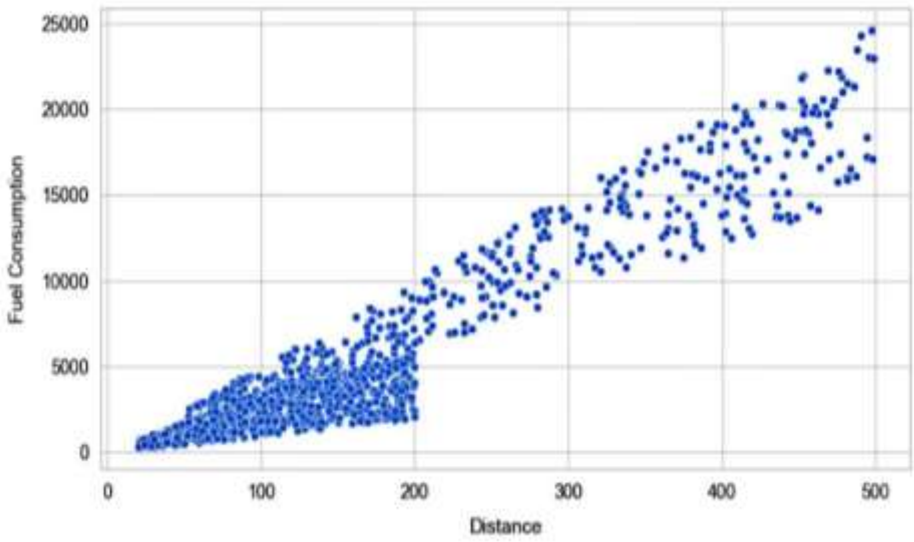

Figure 10: Fuel Consumption vs Distance.

The plot depicts a strong linear trend up to 25,000 unit fuel at 500 km. It shows a clear positive linear relationship between distance and fuel consumption which confirms that longer trips naturally consume more fuel, and the data aligns with real-world expectations. Most trips in the dataset are short distance trips, under 200km, This area has the high data density which indicates that it is the most common operational raange for ships and beyond 200km longer trips are less frequent. Figure 11 Shows a Scatter Plot comparing predicted and actual CO_2 emissions.

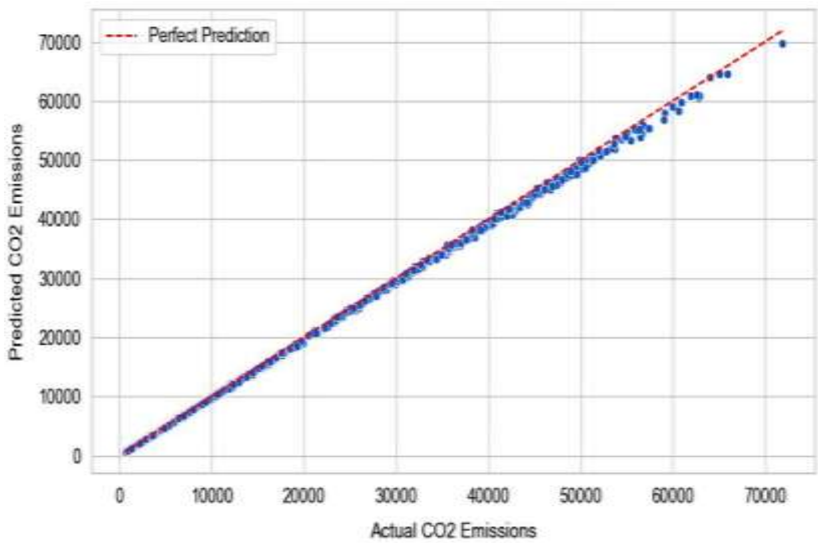

Figure 11: Predicted vs. Actual CO_2 Emissions.

The predicted line (Red) closely overlaps actual values (Blue). The model's predictions closely align with actual CO_2 emission values, demonstrating high prediction accuracy and confirming the model's effectiveness in emission forecasting. Figure 12 Shows a bar graph of Mean Engine Efficiency of different Ship Types.

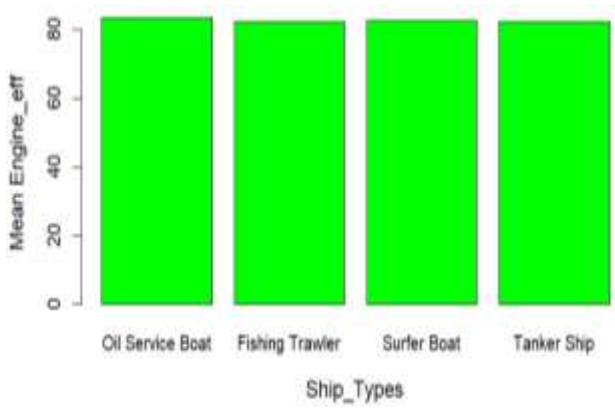

Figure 12: Mean Engine Efficiency.

This graph compares the mean engine efficiency which is almost same for all ship types because we are not comparing individual data points. This is the mean engine efficiency and hence remains the same. Figure 13 Shows a bar graph of Mean Distance of different Ship Types.

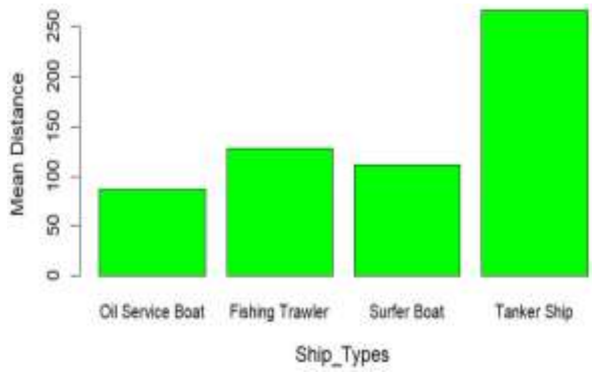

Figure 13: Mean Distance.

This graph compares the mean distance travelled by different types of ship, tanker ship covered the highest diatance. Oil Service boat covered the least distance. Figure 14 Shows a bar graph of Mean CO_2 Emissions of different Ship Types.

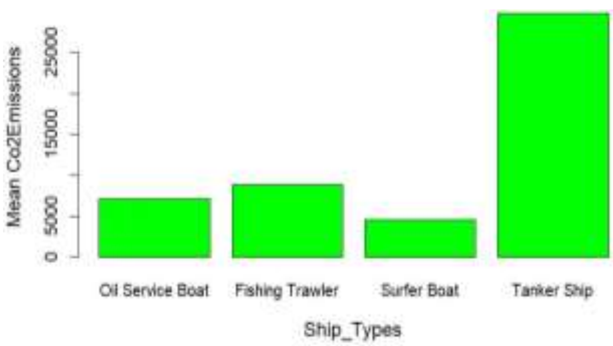

Figure 14: Mean CO_2 emissions.

This graph compares the mean CO_2 emissions, tanker ships produced highest amount of CO_2. Figure 15 Shows a bar graph of Distance of different Ship Types.

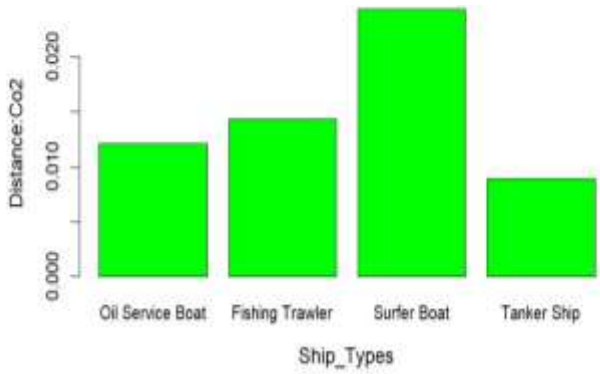

Figure 15: Distance To CO_2 Emissions Ratio.

This graph compares the distance to CO_2 emissions of different ships, tanker ships have the least ratio which makes it more efficient compared to other ships. Surfer boat has highest ratio which makes it less efficient. Figure 16 Shows a Heatmap of relationships between four variables: CO_2 emissions, Fuel consumption, Distance, Engine efficiency.

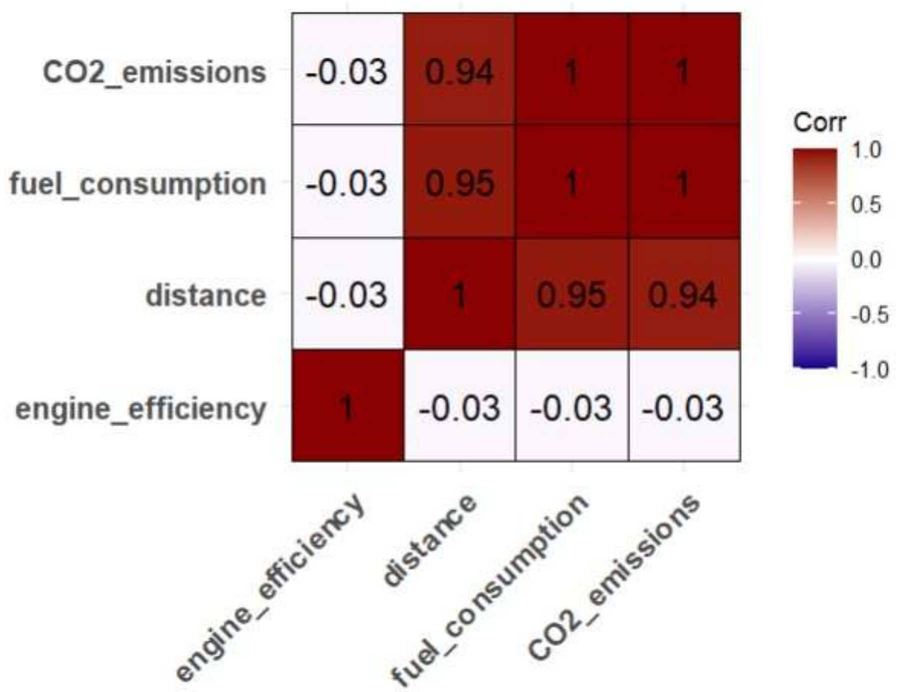

Figure 16: Correlation Heatmap.

The heatmap shows a strong positive correlation between distance, fuel consumption, and CO_2 emissions - 1.00, indicating perfect positive correlation as they increase together. Engine efficiency has almost no correlation with the other variables, suggesting it operates independently. Correlation between Distance and Fuel consumption -0.95 indicates longer distances result in more fuel usage. Distance vs CO_2 emissions -0.94 show that longer trips produce more CO_2. Engine efficiency has a correlation of -0.03 with all three other variables, indicating almost no linear relationship. Various models were made and tested with the dataset. For each model, the ship fuel and CO_2 emissions were taken as the dependent variables whereas all other variables are taken as independent variables. Table 1 shows the accuracy of each model used for analysis.

It can be noted that accuracy of MLR is 9%, hence we can conclude that the data is noisy and turbulent. Hence, due to noisy data, traditional regression models such as SLR, MLR, logistic regression, etc. cannot be used for the analysis. Deep learning models were taken as the next step for analysis. LSTM and SA-LSTM are best used for time-series forecasting hence, the data is fit analysis. Testing on various parameters and complexity of the LSTM model the model performed best at an accuracy of 52.45%. SA-LSTM performed better than traditional LSTM model, the SA-LSTM model discarded the insignificant columns such as the region and ship id. This helped the model achieve better accuracy of 62.36%. The deep learning models have very less accuracy. This is because instead of leaning from the data, the models are memorizing. Hence, machine learning models were opted as the better solution to train the data. Artificial Neural Network was implemented for the analysis. Improving the complexity and adding more neurons helped increase the accuracy of the model. The maximum accuracy was obtained at 94.70%. Hence, machine learning model like ANN were best suited for the turbulent and noisy data.

Table 1: Accuracy of each model used.

Methods	Accuracy
Non linear programming (NLP)	80 %
Random forest	92%
MLR	9%
LSTM	52.45%
SA-LSTM	62.36%
ANN using FNN	93%
ANN using ADAM (Our optimized Model)	**94.70%**

Table 2 shows Accuracy ANN with number of neurons in each layer.

Table 2: Accuracy of ANN.

Sr. No.	**Accuracy (%)**	**Epochs**	**Batch Size**	**Early Stop**	**Input Layer**	**Hidden Layer 1**	**Hidden Layer 2**	**Output Layer**	**Optimizer**
ANN1	69.74	200	20	Yes	128	64	32	2	ADAM
ANN2	90.29	200	16	Yes	128	64	32	2	ADAM
ANN3	**94.70**	**500**	**8**	**Yes**	**256**	**128**	**64**	**2**	**ADAM**

Multiple iterations and changes were made to the ANN network as shown in Table 2. For the first model, the input layer comprised of 128 layers and two hidden layers were made with 64 and 32 neurons respectively, finally the output layer comprised of two neurons, one for fuel efficiency and other for CO_2 emissions. Later the model was improved with 500 epochs, 256neurons, 128 neurons, 64 neurons, 2 neurons in Input, hidden layers and output layer respectively. This performed the best with an accuracy of 94.70%.

5. Conclusion

In this study, we addressed this critical challenge with accurate prediction of ship fuel efficiency and CO_2 emissions by utilizing Artificial Neural Networks (ANN). Both classical methods and the previous deep learning methods (e.g., Long Short-Term Memory (LSTM) networks) resulted in unacceptably high output when working with distorted, sparse, non-linear marine data. Firstly, the LSTM model was trained and achieved a prediction accuracy of only 52.45%. We compared different types of ships in LSTM model. Then, SA-LSTM achieved an accuracy 62.36%. By using an ANN using ADAM algorithm we achieved more robustness and accurate predictions. The ANN model delivered the best accuracy of 94.70%, well above LSTM performance, indicating its ability to learn complex variable relationships of engine performance with the vessel load, weather conditions, and sea state. This type of data-driven method not simply boosts predictive performance but also contributes to the greater objective of promoting environmental sustainability in the maritime transportation sector through decision-making improvement and operational efficiency.

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