10.31653/smf49.2024.176-186

Miyusov M.V., Nikolskyi V.V., Levinskyi M.V., Levinskyi V.M., Saharov A.A.

National University «Odessa Maritime Academy»

DEVELOPMENT OF A COMPREHENSIVE MODEL FOR AS-SESSING GREENHOUSE GAS EMISSIONS FOR VARIOUS FUEL TYPES IN MARITIME TRANSPORT

Introduction

The maritime industry is the backbone of global trade, responsible for transporting approximately 80% of the world's goods by volume. Despite its efficiency in moving large quantities of cargo, the industry is a significant source of greenhouse gas (GHG) emissions, accounting for about 2.5% of global CO₂ emissions as reported by the International Maritime Organization (IMO) [1]. The combustion of fossil fuels in marine engines releases substantial amounts of carbon dioxide (CO₂) and nitrogen oxides (NO_x), contributing to climate change and air pollution [2].

Need for Alternative Fuels

Growing environmental concerns and stringent international regulations, such as the IMO's strategy to reduce GHG emissions from ships by at least 50% by 2050 compared to 2008 levels, have spurred interest in alternative fuels. Fuels like liquefied natural gas (LNG), hydrogen, methanol, and ammonia are being explored for their potential to reduce emissions compared to traditional marine diesel oil [3]. These fuels offer varying degrees of emission reductions and present unique challenges and opportunities for the maritime industry [4].

Objectives

The primary objective of this study is to develop a comprehensive model that assesses the GHG emissions associated with different fuel types used in maritime transport. The model aims to:

- Quantify CO₂ and NO_x emissions for various fuels under realistic operational conditions.
- Incorporate uncertainties in fuel consumption and emission factors using the Monte Carlo simulation method.
- Provide a comparative analysis of the environmental impacts of different fuels.
- Serve as a decision-making tool for stakeholders in the maritime industry to select optimal fuels for reducing GHG emissions.

Literature Review

Emission factors represent the average emissions associated with the consumption of a specific amount of fuel. They are essential for estimating total emissions from maritime activities. Studies have established emission factors for various marine fuels, indicating that alternative fuels can offer significant reductions in GHG emissions [5]. However, many of these studies provide deterministic values, not accounting for the variability in operational conditions that affect actual emissions.

Alternative fuels have been the subject of extensive research due to their potential to reduce GHG emissions:

- Liquefied Natural Gas (LNG): Offers lower CO₂ emissions compared to diesel and reduces NO_x emissions due to cleaner combustion [6].
- **Hydrogen**: Produces zero CO₂ emissions during combustion, presenting a promising zero-carbon fuel option [7].
- Methanol: Can be produced from renewable sources and offers reductions in CO₂ emissions, but may increase NO_x emissions [8].
- Ammonia: Like hydrogen, ammonia combustion does not produce CO₂, but challenges include toxicity and NO_x emissions that require control technologies [9].

Monte Carlo Simulation in Emission Modeling

Monte Carlo simulation is a statistical technique that allows for the modeling of uncertainties by running multiple simulations with random variables. In environmental studies, it is used to account for the variability in factors such as fuel consumption rates, emission factors, and operational conditions [10]. This method provides a probabilistic understanding of emissions, which is more informative for decision-making compared to deterministic models.

Methodology Overview of the Model

The developed model serves as a robust tool for comparing the environmental efficiency of different fuels used in maritime transport. It quantifies the emissions of CO_2 and NO_x resulting from the consumption of diesel, LNG, hydrogen, methanol, and ammonia, considering the uncertainties inherent in maritime operations.

Steps of the Model

1. Definition of Fuel Parameters

For each fuel type, the model defines essential parameters:

Emission Factors: average emissions of CO_2 and NO_x per unit of fuel consumed (e.g., kilograms per kilogram).

Consumption Rates: average fuel consumption per nautical mile (e.g., tons per nautical mile).

These parameters are derived from reputable sources and industry data, ensuring that the model reflects realistic operational conditions [1, 3, 7, 8, 9].

- Diesel:

- Emission Factor CO₂: 3.17 kg CO₂ per kg of fuel
- Emission Factor NO_x: 0.02 kg NO_x per kg of fuel
- Consumption Rate: 0.18 tons per nautical mile
- LNG (Liquefied Natural Gas):
- Emission Factor CO₂: 2.75 kg CO₂ per kg of fuel
- Emission Factor NO_x: 0.015 kg NO_x per kg of fuel
- Consumption Rate: 0.15 tons per nautical mile

- Hydrogen:

- Emission Factor CO₂: 0 kg CO₂ per kg of fuel
- Emission Factor NO_x: 0 kg NO_x per kg of fuel (assuming fuel cells)
- Consumption Rate: 0.20 tons per nautical mile

- Methanol:

- Emission Factor CO₂: 1.37 kg CO₂ per kg of fuel
- Emission Factor NO_x: 0.02 kg NO_x per kg of fuel
- Consumption Rate: 0.22 tons per nautical mile

- Ammonia:

- Emission Factor CO₂: 0 kg CO₂ per kg of fuel
- Emission Factor NO_x: 0.01 kg NO_x per kg of fuel
- Consumption Rate: 0.25 tons per nautical mile

2. Incorporation of Uncertainty Using Monte Carlo Simulation

To capture the variability in real-world operations, the model employs the Monte Carlo simulation method. This involves:

Number of Simulations: The model runs 10,000 iterations for each fuel type to ensure statistical robustness.

Variables Considered:

Fuel Consumption Variability (CV): Accounts for changes in fuel consumption due to factors such as engine efficiency, vessel load, weather conditions, and maintenance status. A variability percentage (e.g., $\pm 5\%$) is applied to the average consumption rate.

Emission Factor Variability (EV): Considers fluctuations in emission factors due to differences in fuel quality, combustion efficiency, and en-

gine technology. A variability percentage (e.g., $\pm 10\%$) is applied to the average emission factors.

Simulation Process:

For each iteration:

Randomly generate a fuel consumption rate within the specified variability range using a normal distribution centered around the average consumption rate.

$$FCR_i = FCR_{mean} + \delta_{FCR} \times Z_{FCR}$$

Randomly generate emission factors for CO₂ and NO_x within their respective variability ranges.

$$\begin{split} EF_{CO2,i} &= EF_{CO2,mean} + \delta_{EF_{CO2}} \times Z_{EF_{CO2,i}} \\ EF_{NOx,i} &= EF_{NOx,mean} + \delta_{EF_{NOx}} \times Z_{EF_{NOx},i} \\ \delta_{FCR} &= FCR_{mean} \times CV \\ \delta_{EF_{CO2}} &= EF_{CO2,mean} \times EV \\ \delta_{EF_{NOx}} &= EF_{NOx,mean} \times EV \end{split}$$

where $FCR_{mean}, EF_{CO2,mean}, EF_{NOx,mean}$ – average fuel consumption rate and emission factors;

CV – consumption variability percentage;

EV – emission variability percentage;

Z – values of standard normal random variables (mean 0, standard deviation 1). Z is generated using a random number generator that produces values following a standard normal distribution.

Calculate the emissions $(E_{CO2,i}, E_{NOx,i})$ for that iteration using the formulas:

$$E_{CO2,i} = Distance \times FCR_i \times EF_{CO2,i}$$
$$E_{NOY,i} = Distance \times FCR_i \times EF_{NOY,i}$$

Store the calculated emissions for statistical analysis.

3. Calculation of Mean Values and Confidence Intervals

After completing the simulations, the model performs statistical analysis to determine:

Mean Emissions: The average emissions of CO_2 and NO_x across all simulations for each fuel type.

$$\overline{E}_{CO2} = \frac{1}{N} \sum_{i=1}^{N} E_{CO2,i}$$

$$\overline{E}_{NOx} = \frac{1}{N} \sum_{i=1}^{N} E_{NOx,i}$$

95% Confidence Intervals: The range within which the true mean emissions are likely to fall with 95% confidence. This is calculated by:

- Sorting the emissions data.

- Determining the lower and upper bounds corresponding to the 2.5th and 97.5th percentiles.

4. Comparison with Baseline Diesel Scenario

Diesel fuel serves as the baseline for evaluating the environmental benefits of alternative fuels. The model calculates:

Baseline Emissions: The mean emissions of CO_2 and NO_x for diesel fuel.

Emission Reductions: The percentage reduction in emissions for each alternative fuel compared to diesel, calculated using:

$$ER(\%) = \left(\frac{BE - AFE}{BE}\right) \times 100$$

ER – emissions reduction, BE – baseline emissions, AFE – alternative fuel emissions.

This comparison highlights the effectiveness of each alternative fuel in reducing GHG emissions relative to the conventional diesel fuel.

5. Visualization of Results

To facilitate interpretation and comparison, the model visualizes the results using bar charts:

Mean Emissions: Each fuel type is represented by a bar indicating its mean emissions of CO_2 and NO_x .

Confidence Intervals: Error bars on each bar represent the 95% confidence intervals, illustrating the variability and uncertainty in emissions.

Emission Reductions: Percentage reductions are displayed alongside the charts to provide a quick reference for the environmental benefits of each fuel.

Implementation Details

Functionality of the Model

The model operates through a series of computational steps, designed to simulate real-world variability and provide statistically significant results.

Data Input and Initialization User Inputs:

Distance: The voyage distance in nautical miles (e.g., 1,000 nautical miles).

Number of Simulations: The total iterations for the Monte Carlo simulation (e.g., 10,000).

Consumption Variability: The percentage variability in fuel consumption rates (e.g., $\pm 5\%$).

Emission Variability: The percentage variability in emission factors (e.g., $\pm 10\%$).

Fuel Selection: Users can select which fuels to include in the simulation from the available options.

Baseline Fuel: Diesel is typically used as the baseline for comparison. If diesel is not selected, the first fuel in the selection serves as the baseline.

Simulation Process

Random Sampling:

For each fuel type and each simulation iteration:

- Generate a random fuel consumption rate using a normal distribution centered on the average consumption rate, with the specified variability.
- Generate random emission factors for CO₂ and NO_x using normal distributions centered on their respective average emission factors, with the specified variability.

Emission Calculation:

Calculate the emissions for each iteration

Data Storage:

Store the calculated emissions for each iteration in arrays for further statistical analysis.

Statistical Analysis

Mean Emissions:

Calculate the mean emissions of CO_2 and NO_x for each fuel type by averaging the emissions across all simulations.

Confidence Intervals:

Sort the emissions data for each fuel type.

Determine the 2.5th and 97.5th percentiles to establish the 95% confidence intervals.

Emission Reductions:

Compare the mean emissions of alternative fuels with the baseline fuel to calculate the percentage reduction in emissions.

Results Presentation

Generate bar charts displaying the mean emissions and confidence intervals for CO_2 and NO_x for each fuel type.

Use consistent color schemes and labeling to enhance readability.

Results Interpretation:

Provide a summary of the findings, highlighting the fuels that offer the most significant reductions in emissions.

Discuss the trade-offs between different fuels, such as reductions in CO_2 versus potential increases in NO_x emissions.

Results

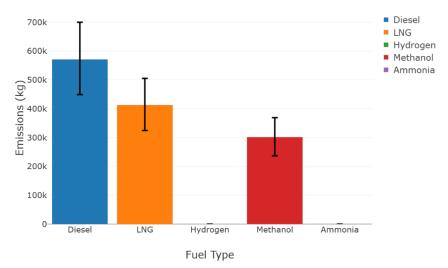
The model's simulations yield the following results (see fig. 1, fig. 2, table 1, table 2) for a voyage distance of 1,000 nautical miles, considering 10,000 simulations with specified variability in consumption and emission factors.

Fuel	Mean CO ₂ Emissions (kg)	95% Confidence Interval (kg)	CO ₂ Reduction (%)
Diesel	570,600	445,514 - 695,686	0.00
LNG	412,500	322,146 - 502,854	27.72
Hydrogen	0	0 - 0	100.00
Methanol	301,400	235,336 - 367,464	47.17
Ammonia	0	0 - 0	100.00

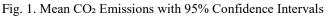
Table 1. CO₂ Emissions

Table 2. NO_x Emissions

Fuel	Mean NO _x Emis- sions (kg)	95% Confidence Interval (kg)	
Diesel	3,600	2,812 - 4,388	
LNG	2,250	1,756 - 2,744	
Hydrogen	0	0 - 0	
Methanol	4,400	3,435 - 5,365	
Ammonia	2,500	1,951 - 3,049	



CO2 Emissions with Confidence Intervals



NO_x Emissions with Confidence Intervals

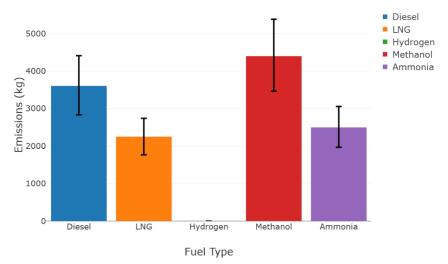


Fig. 2. Mean NO_x Emissions with 95% Confidence Intervals

Discussion

The model's simulations reveal significant differences in emissions among the various fuel types:

- Hydrogen and Ammonia: Both fuels result in zero CO₂ emissions during combustion, offering a 100% reduction compared to diesel. However, ammonia produces NO_x emissions (mean: 2,500 kg) that are lower than those of diesel (mean: 3,600 kg) but higher than LNG and hydrogen, which may necessitate additional emission control measures.
- Methanol: Provides a substantial reduction in CO₂ emissions (47.17%) compared to diesel but exhibits higher NO_x emissions (mean: 4,400 kg vs. diesel's 3,600 kg), which may necessitate additional emission control measures.
- LNG: Offers a moderate reduction in CO₂ emissions (27.72%) and lower NO_x emissions compared to diesel, making it a cleaner alternative within the fossil fuel category.
- **Diesel**: Serves as the baseline, highlighting the potential emission reductions achievable by switching to alternative fuels.

Implications for the Maritime Industry

The results have several important implications:

- Adoption of Zero-Carbon Fuels: Hydrogen and ammonia present significant opportunities for decarbonizing maritime transport. However, challenges such as fuel storage, handling safety, and the need for new infrastructure must be addressed.
- Balancing NO_x Emissions: While some alternative fuels reduce CO₂ emissions, they may increase NO_x emissions. Technologies like selective catalytic reduction (SCR) systems can mitigate NO_x emissions but add complexity and cost.
- **Incremental Improvements with LNG**: LNG offers a viable transition fuel, providing emissions benefits without requiring extensive modifications to existing infrastructure.
- Limitations of the Model
- **Data Accuracy**: The model relies on average emission factors and consumption rates, which may not capture the full range of operational variability.
- Scope of Variables: While the model includes variability in consumption and emission factors, it does not account for other influ-

ential factors such as engine age, maintenance practices, or specific vessel designs.

• Assumption of Normal Distribution: The use of normal distributions in the Monte Carlo simulations assumes that variations are symmetric around the mean, which may not reflect real-world skewness.

Recommendations for Future Research

- Enhanced Data Collection: Gathering more detailed and specific data on fuel properties and engine performance can improve the accuracy of the model.
- Inclusion of Additional Emissions: Incorporating other pollutants such as sulfur oxides (SO_x) and particulate matter (PM) can provide a more comprehensive environmental assessment.
- Life-Cycle Analysis: Extending the model to consider the full lifecycle emissions of fuels, including production, transportation, and disposal, would offer a holistic view of environmental impacts.

Conclusion

The comprehensive model developed in this study effectively assesses the GHG emissions associated with various fuel types used in maritime transport. By incorporating uncertainties through Monte Carlo simulations, the model provides realistic estimates of emissions under varying operational conditions.

Key Findings

- **Significant Emission Reductions**: Alternative fuels, particularly hydrogen and ammonia, can substantially reduce CO₂ emissions, potentially achieving zero emissions during combustion.
- **Trade-offs in Emissions**: While some fuels reduce CO₂ emissions, they may increase NO_x emissions, highlighting the need for balanced environmental strategies.
- **Decision-Making Tool**: The model serves as a valuable tool for stakeholders in the maritime industry to evaluate the environmental benefits of different fuels and make informed decisions.

Implications

• **Policy Development**: Regulators can use the model's findings to formulate policies and incentives that encourage the adoption of cleaner fuels.

- **Industry Adoption**: Maritime companies can leverage the model to assess the environmental and potential economic benefits of transitioning to alternative fuels.
- **Future Innovations**: The model can be adapted to evaluate emerging fuels and technologies, supporting ongoing efforts to decarbonize maritime transport.

References

1. International Maritime Organization (IMO). Fourth IMO GHG Study. London: IMO, 2020.

2. Sagin S. V., Kuropiatnyk O. A. Using exhaust gas bypass for achieving the environmental performance of marine diesel engines. *Austrian Journal of Technical and Natural Sciences*. 2021, № 7–8 (July–August). P. 36–43.

3. Smith T. W. P., Jalkanen J. P., Anderson B. A., Corbett J. J., Faber J., Hanayama S., et al. Third IMO GHG Study 2014. London: IMO, 2015.

4. Sagin S. V., Sagin S. S., Madei V. Analysis of methods of managing the environmental safety of the navigation passage of ships of maritime transport. *Technology Audit and Production Reserves*. 2023. \mathbb{N}_{2} 4 (3(72)). P. 33–42.

5. Eide M. S., Longva T., Hoffmann P., Endresen Ø., Dalsøren S. B. Future cost scenarios for reduction of ship CO₂ emissions. *Maritime Policy & Management*. 2011. Vol. 38, № 1. P. 11–37.

6. Balcombe P., Anderson K., Speirs J., Brandon N., Hawkes A. The natural gas supply chain: The importance of methane and carbon dioxide emissions. *ACS Sustainable Chemistry & Engineering*. 2017. Vol. 5, №. 1. P. 3–20.

7. International Energy Agency (IEA). The Future of Hydrogen. Paris: IEA, 2019.

8. Methanol Institute. Methanol as a Marine Fuel Report. Washington, D.C.: Methanol Institute, 2018.

9. Brown T., Caldwell M. Ammonia as a zero-carbon fuel: An assessment of potential scenarios. *Energy Research & Social Science*. 2020. Vol. 65. 101455.

10.Rubinstein R. Y., Kroese D. P. Simulation and the Monte Carlo Method. 3rd ed. Hoboken, New Jersey: John Wiley & Sons, 2016.