Brodogradnja Volume 77 Number 2 (2026) 77207

University of Zagreb Faculty of Mechanical Engineering and Naval Architecture

journal homepage: www.brodogradnja.fsb.hr

Brodogradnja

An International Journal of Naval Architecture and Ocean Engineering for Research and Development

Modelling maritime GHG emission measures impact assessment: A case study for container shipping by system dynamics

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ARTICLE INFO

Keywords:
GHG Emissions
Maritime Sector
Decarbonization
Emission Reduction Strategies
System Dynamics Modelling

ABSTRACT

The shipping industry is responsible for around 2% of carbon dioxide (CO_2) emissions worldwide. This research explores the interaction of technology change, operational approaches, and policy measures in achieving the target for reducing greenhouse gas (GHG) emissions. A simulation model based on the system dynamics of the maritime transport system has been created in accordance with International Maritime Organization (IMO) policies such as the Energy Efficiency Design Index (EEDI), the Ship Energy Efficiency Management Plan (SEEMP) and the Carbon Intensity Indicator (CII). Suggested actions to reduce the average speed of ships to 15 knots have shown significant reduction of CO_2 emissions in the short term. Further, the complete phase-out of High Fuel Oil (HFO) and the high uptake of Liquefied Natural Gas (LNG), methanol, and ammonia in an aggressive fuel transition scenario significantly lowers emissions by 2050. Market-based instruments such as fuel price mechanisms and carbon taxes are complementary methods that enable emissions reduction by encouraging the transition to cleaner fuels. The report calls for the harmonization of policies for the long-term sustainability of shipping. Future studies can expand the model by incorporating economy-related factors such as carbon prices and emissions trading mechanisms to help the industry achieve its 2050 net-zero target.

1. Introduction

Countries are implementing a range of technical and operational measures to reduce greenhouse gas emissions across all sectors. Global pacts, such as the Paris Agreement, set ambitious targets to mitigate climate change, calling on countries to adopt comprehensive emissions reduction strategies across all sectors. Among these sectors, shipping occupies a particularly critical position, as it supports more than 80% of international trade and accounts for around 2-3% of global CO_2 emissions. The International Maritime Organization (IMO) also defines the main target to achieve net-zero emissions in international shipping by 2050 [1]. Accordingly, the maritime sector's energy management practices need to be transformed through

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https://doi.org/10.21278/brod77207
Received 1 May 2025; Received in revised form 23 September 2025; Accepted 6 October 2025
Available online 7 November 2025
ISSN 0007-215X; eISSN 1845-5859

international and national regulatory measures, technological innovations, and operational strategies to achieve targeted levels and meaningful decarbonization outcomes [2].

IMO has adopted a phased approach to reducing greenhouse gas (GHG) emissions from international shipping, encompassing short-, medium-, and long-term measures. The short-term measures, effective since November 2022 under MARPOL Annex VI and implemented from January 2023, combine technical and operational requirements through the Energy Efficiency Existing Ship Index (EEXI), the Carbon Intensity Indicator (CII), and the enhanced Ship Energy Efficiency Management Plan (SEEMP) [3]. The guidelines stipulate benchmarks to be met with annual compliance carbon intensity assessments, along with action plans to be defined for lagging vessels, aiming to achieve a minimum of 40% reduction in carbon intensity by 2030 with respect to 2008 levels and a review scheduled by 2026. In this context, the 2023 GHG Strategy issued by the IMO shifts the focus with the addition of medium and long-term measures, in particular a ‘basket’ approach which includes a fuel dual for the lifecycle carbon intensity of marine fuels and a global economically-based system for offsetting emissions. Adoption of these measures during MEPC 83 in 2025, along with their implementation in 2027, is supported by the principles of equitable transition, along with guidelines for well-to-wake life cycle assessments, building of new capacities, and just transition measures [4]. While the suggested measures provide promising guidelines for the decarbonization of the maritime sector, the proposals put forth by the IMO will only achieve the desired effectiveness if a number of technological, economic and operational complexities are managed well. To understand the complexities in these interactions and analyse the impacts of these elements, experts have started to use modelling studies estimations of GHG emissions. These studies provide a comprehensive approach to outline the processes of emissions and examine the consequences of varying proposed regulatory and operational approaches [5].

GHG emission modelling in the maritime sector has been an important area of research in support of global efforts at carbon emission mitigation and meeting IMO targets. In the last 20 years, distributing work has been done to model emissions, developing future scenarios, and assessing mitigation effectiveness. The most accurate emission inventories remain bottom-up and activity-based emission models. These models use ship traffic, fuel spending, and emission components. Extremis, incorporating vessel specifications, is one of the first models scaled to regional and global intersections [6]. Later models incorporating more advanced techniques use machine learning to predict emissions and manage sparsely populated port datasets [7, 8]. While quantification of emissions is done efficiently with machine learning, the models remain static and devoid of responsive processes to changes in maritime systems. One such model is Mari-TEAM, which applies the “well-to-wake” framework to incorporate emissions from fuel and other ancillary shipping operations [9]. Other scenario studies have quantified the impacts of policies such as the Fuel-EU Maritime and the European Emission Trading System (EU-ETS) on the operations and technology of shipping companies [10]. At the organizational level, work done by UNCTAD attempting to relate policy changes on global trade patterns and GDP grows level through Computable General Equilibrium (CGE) models. This has shown policy change having uneven effects on different economies [11]. These models excel at demonstrating the impact of policies on various domains, yet they typically depend on fixed scenarios and linear cause-and-effect chains.

In light of that, a point of view that understands the regulatory policies, technological advances, market reactions, and operational tactics that influence the complexity of decarbonization of the shipping industry is beginning to reconcile. It understands that more advanced modelling techniques, going beyond static and linear tools, will be needed and utilized [12]. Using System Dynamics (SD) to approach these concerns is becoming more common. Unlike more conventional models, SD models systems with feedback loops, time lags, and changes in behavior, which provides better insights in the time evolution of interventions and the interaction of policies to operational and market dynamics. SD is particularly useful in studying GHG emissions in the maritime domain, where emissions are the result of numerous interrelated and competing stakeholders. There is a growing body of literature that documents the application of SD to maritime emission modelling with positive outcomes. For instance, the SD approach to projecting CO_2 emissions from Arctic shipping illustrates how various policies affect emission dynamics over the long term [13]. Similarly, an SD model was used to evaluate CO_2 mitigation strategies at Qingdao Port, capturing structural drivers of emissions and the effects of different control policies [14]. Kong et al. [15] applied a scenario-based SD framework to the maritime supply chain, integrating company-level decisions and policy influences on carbon abatement, while Gao et al. [16] employed SD to explore shipping industry carbon reduction strategies, demonstrating its ability to simulate various operational and regulatory pathways. Furthermore, Chen et al. [17] have shown that by explicitly modelling the relationships among economic growth, fishing fleet composition, and energy mix, system dynamics can evaluate the impact of interventions such as vessel modernization and fuel switching on long-term maritime carbon emissions. Liu et al. [18] merged technology innovation, regulatory enforcement, and operational optimization into a cohesive SD framework, demonstrating how synergistic interventions might expedite advancements toward mid- and long-term decarbonization objectives in the shipping industry.

Despite these applications, SD usage in the maritime sector remains limited when compared to its implementation in other domains such as energy systems, urban transportation, or industrial manufacturing. In these sectors, SD models have been extensively developed to analyse energy transitions [19, 20], assess long-term climate policies, and optimize emissions reduction strategies by integrating socio-economic and technological dimensions [21, 22]. In comparison, most of the SD models in the area of maritime transport tend to concentrate on specific, confined issues like port or route emissions, rather than providing integrated, multi-scale models that connect operational activities with international policy impacts. Additionally, several studies on maritime SD continue to be built on naive simplifications and do not incorporate the detailed bottom-up emission estimates and the operational activities in real time, thus minimizing their utility for policy formulation [23]. This limitation highlights the necessity for a more thorough system dynamics (SD) framework that not only captures the intricate interconnections within the maritime transport system but also integrates high-resolution data to improve model accuracy and relevance for policy-making. Building on this idea, the current study creates an SD model specifically aimed at assessing the effects of the International Maritime Organization's (IMO) greenhouse gas (GHG) mitigation strategies, using container shipping as a case study. This approach provides a stronger analytical tool to aid in evidence-based decision-making as we work towards decarbonizing the maritime sector. The research mainly focuses on carbon dioxide (CO_2) emissions, which represent between 55% and 84% of the total GHG emissions from shipping [24]. This consideration simplifies the accurate determination of the sector's principal source of emissions and aligns with the majority of existing policy and regulatory initiatives to curtail carbon emissions from vessels.

This study enhances the field of maritime SD applications both theoretically and statistically compared to prior research. Existing studies have predominantly focused on specific geographies however, our model embraces a global container shipping perspective in accordance with the IMO's 2050 decarbonization policy. This multi-scale methodology allows for the evaluation of fleet-wide CO_2 reduction strategies across diverse regulatory, operational, and technical contexts, beyond the localized focus prevalent in much of the current literature. Methodologically, prior research often evaluated single-measure scenarios such as the effects of policy regulation, technology adoption, or operational modifications whereas the current analysis integrates these within a multi-policy coupling framework. The model incorporates EEDI (Energy Efficiency Design Index), SEEMP, and CII regulations, the adoption of alternative fuels (liquefied Naturel Gas (LNG), methanol, ammonia), operational strategies (optimization of speed and load factor), and economic incentives (fuel pricing, carbon taxation) within a unified simulation framework, elucidating both synergistic and antagonistic effects. The current application concentrates on container vessels because of the accessibility of detailed operational and emissions data; however, the model's structural design is modular and adaptable, allowing for modifications to accommodate different vessel types and to explore various policy, technological, and operational scenarios. This study integrates localized case-study modelling with a globally representative, multi-policy simulation framework, offering a policy-relevant and empirically substantiated decision-support tool that addresses significant deficiencies in maritime sustainable development modelling and improves its ability to inform decarbonization pathways aligned with the IMO

After the introduction part, the system dynamic methodological approach chapter details the research design and describes the system dynamics modelling technique employed in this research to evaluate the effects of different GHG mitigation strategies. Lastly, the results and discussion chapter report the findings and their implications for policymakers and industry players, and provide recommendations for policy development and future research.

2. System dynamics modelling

The goal of system dynamics is to understand analyse, and model the behaviour of complex and evolving systems over time. Jay W. Forrester created this method in the 1950s at the Massachusetts Institute of Technology (MIT) for the management of industrial systems. Forrester developed this method to theoretically approach problem resolution in industrial systems by constructing models of dynamic structures. His groundbreaking book Industrial Dynamics (1961) established the basis for the core theory of the method and represented a breakthrough step forward in its evolution. Over time, the scope of system dynamics has significantly expanded, despite its initial focus on production and supply chain systems. Forrester's later books, Urban Dynamics (1969) and World Dynamics (1971) illustrated its use in areas such as urban planning and environmental sustainability. These books indicated how dynamic modelling allows policymakers to more accurately foresee the long-term consequences of policies as well as to come up with more integrated solutions to intricate difficulties [25-27].

System dynamics models exhibit several defining characteristics of complex systems. These include continuous transformation, where systems may appear stable yet exhibit fluctuations across multiple temporal scales; tight interconnections, in which variables are highly interdependent; governance through feedback, whereby reciprocal causal effects alter system states and generate new conditions; nonlinearity, characterized by disproportionate cause effect relationships; and path dependence, where past decisions constrain future options and delayed effects in stocks and flows add to system complexity. Such dependencies can be systematically examined using dynamic modelling [28]. System dynamics provides a systematic approach to the analysis and management of complex systems, typically implemented in six stages: problem definition, conceptual model development, mathematical model formulation, model analysis and validation, scenario development and policy analysis [29].

System dynamics is a rigorous approach to the study of the structural complexity of systems exhibiting interdependencies, feedback loops, and cumulative processes unfolding over time. Essentially, it portrays system behaviour through causal feedback mechanisms closed loop relationships between variables that often generate nonlinear and counterintuitive outcomes. At the model's core are stock and flow mechanisms, which capture accumulations (stocks) and rates of change (flows), thereby portraying inertia, delays, and long-term relationships inherent in real systems. Time is treated as a continuous variable, allowing for detailed temporal analysis and simulation of a wide range of policy options. The combination of structural representation and simulation capability allows system dynamics to reveal patterns such as growth, decline, oscillation, and policy resistance, where interventions generate paradoxical effects that undermine intended policy objectives [28, 29].

2.1 Theoretical foundations of system dynamics

This section has three fundamental steps of system dynamic modelling: feedback loops and causal loop diagrams, stock and flow structures and quantitative modelling, and time delays and nonlinear interactions.

2.1.1 Feedback loops and casual loop diagrams

Feedback loops constitute the foundational theoretical construct within system dynamics, encapsulating circular causal chains wherein the output of a process recursively influences its own input. There are two primary feedback types: reinforcing loops, which amplify system changes and often lead to exponential growth or collapse, and balancing loops, which counteract deviations thus promoting system stability or homeostasis These feedback structures explain how local interactions coalesce into global system behaviours, frequently resulting in nonlinear, counterintuitive dynamics that traditional linear reasoning cannot effectively capture. The identification and mapping of such loops allow modelers to uncover underlying causal mechanisms responsible for observed system patterns, such as oscillations, delays in response, or persistent imbalances [30].

Causal Loop Diagrams (CLDs) offer a qualitative visual tool to represent these feedback networks by illustrating variables and their directional influences with polarity indicators (+ or -). CLDs support an early phase of model conceptualization by facilitating stakeholder understanding and hypothesis generation of systemic relationships [28]. Applied examples demonstrate the centrality of feedback loops in system dynamics. For instance, water pollution modelling incorporates balancing loops involving pollutant input and removal alongside reinforcing loops linked to population and industrial growth, which collectively define the evolving state of water quality [31]. In public health, models of chronic disease reflect feedback between patient behaviours, resource constraints, and health outcomes, revealing potential points of policy resistance and leverage [32]. These applications underscore the indispensability of feedback loop analysis for explaining and managing system dynamics.

2.1.2 Stock and flow structures and quantitative modelling

Stock-and-flow frameworks mathematicise dynamic conceptualizations of feedback loops by defining observable accumulations (stocks) and the rates over time of these accumulations (flows). Stocks are the state variables that hold quantities like populations, materials, or capital within the system, thus embodying the memory of the system. Flows are processes or rates that fill or drain these stocks, like birth rates, extraction of resources, recovery from disease, or trash generation. The translation of qualitative causal loop diagrams to quantitative stock-and-flow diagrams allows precise mathematical formulation through differential or difference equations, enabling computational simulation of system trajectories over time. The diagrams offer both conceptual clarity to modelers and operational usefulness for computer implementation [33, 34].

There are several empirical applications; for instance, hospital waste management in developing nations utilizes stocks to model various types of medical solid waste, with flows indicating generation and disposal rates of waste. This modelling overcomes data scarcity, facilitating forecasting and strategic planning for effective treatment processes [35]. Construction productivity models also quantify labour availability as a stock and completion of tasks as flows, illustrating the effects of change orders on workflow dynamics and labour efficiency in project stages [36]. These instances illustrate how stock-and-flow modelling represents system behaviour and facilitates scenario testing with empirical information, thus connecting theory and practice.

2.1.3 Time delays and nonlinear relationships

Time delays are crucial to system dynamics because they reflect the time gap between an activity or input and its consequent effect on other parts of the system. Delays, physical, informational, or institutional, strongly influence system behaviour by causing oscillations, overshooting, or prolonged disruption in system states. They often cause policy resistance when well-intentioned policies do not produce immediate desired effects, leading stakeholders to possibly drop policies prematurely or misinterpret system responses [37].

Nonlinear interactions reinforce delays by means of complicated dependencies, for instance, thresholds that generate sudden effects, saturation effects that lead to diminishing returns on additional input, or progressive effects that result in runaway processes. Such nonlinearities interfere with direct proportionality and require advanced modelling in order to formally represent emergent phenomena [38].

Nonlinearities and delays create complex dynamic patterns that mirror real systems. For example, water resource models that include extraction limits, recharge delays, and threshold effects show these complexities [39]. Public health models of chronic disease likewise reveal how nonlinear disease progression, combined with treatments that act slowly, shapes long-term population health trends [40]. Including these features is essential for realistic system projections and for avoiding overly simplistic policy recommendations.

2.2 VENSIM tool

Practical implementation of system dynamics (SD) theory becomes possible through advanced modelling and simulation software which supports the development of causal loop diagrams and stock-and-flow structures along with simulation execution together with optimization and sensitivity analyses [41, 42].

Vensim serves as the primary tool for both academic research and professional practice because of its exceptional capabilities for sensitivity analysis alongside calibration and detailed feedback structure assessment Its extensive modelling library and ability to process complex relationships together with broad format compatibility have made it the preferred tool for detailed policy design and decision support applications [43].While other platforms such as Stella/I Think, which is celebrated for educational usability [44], AnyLogic, for its hybrid modelling capability [45], Powersim, for strategic business modelling [46], and Insight Maker, for an intuitive web-based collaborative framework [47]. Demonstrate diverse strengths, Vensim's integration of analytical complexity and modeling adaptability enables practitioners to effectively combine conceptual system representations with empirically grounded, policy-relevant simulations [48]. Table 1 presents a comparative analysis of system dynamics software programs.

Table 1 System dynamic modelling software compare

Software	Primary Focus	Key Strengths	Typical Users	References
Vensim	System Dynamics modeling & analysis	Full sensitivity analysis, calibration tools, complicated feedback management, and the ability to work with many formats	Researchers, policy analysts, advanced SD practitioners	Vensim Ventana [43]
Stella/iThink	Educational SD modelling	Strong educational applications, an intuitive visual interface, and powerful narrative capabilities	Educators, students, policy communicators	Isee System [44]
AnyLogic	Hybrid modeling (SD, agent-based, discrete-event)	Multi-method modeling, Java extensibility, cross-domain flexibility	Supply chain modelers, transport planners, complex system analysts	Anylogic [45]
Powersim	Strategic business modeling & risk analysis	Scenario testing, strategic planning tools, business-oriented interfaces	Corporate strategists, risk managers	Powersim [46]
Insight Maker	Web-based collaborative SD modeling	Free, open-source, supports online collaboration, easy sharing	Educators, collaborative modeling groups	Insight Maker [47]

3. Modelling for GHG mitigation for container vessels

3.1 Problem definition and boundary setting

A clear and comprehensive articulation of the issue, together with a precise definition of system boundaries, is crucial for reliable system dynamics modelling. This phase involves specifying the priority issue and establishing the full environmental, social, and institutional context. Specifying the boundaries of the system (system context), limits the relevant stocks, flows, feedback loops and stakeholders, that are explored and included. Specifying the boundaries should reflect an appropriate trade-off between completeness and analytical tractability; the model can represent the ‘main’, the main dynamics without too much complexity. Also, it is best to involve stakeholders early because it can bring different forms of knowledge together, highlight implicit biases and assumptions, and assist the stakeholders' understanding of context, which may provide real elements of added value and therefore increase the validity, credibility and policy relevance of the model [38].

In this regard, the present study employs the System Dynamics (SD) methodology to assess the drivers of CO_2 emissions from container ships. The research problem is framed as a systematic identification and review of the operational, technological, economic, and liable regulatory restrictions that will drive CO_2 emissions pathways from container vessels around the world, and under the conditions of International decarbonization initiatives cut by IMO, the European Union (EU), and the divers flag state policies.

The system boundary is set to encompass the global container shipping sector, incorporating the relevant stocks, flows, feedback loops, and delays that drive emission dynamics. While the analysis focuses on container ships due to the availability of robust operational and emissions data, the model is designed to accommodate other vessel types and additional GHG species where necessary. The temporal scope extends to 2050 in alignment with IMO's Net Zero targets, while also considering external drivers such as fuel prices, technology innovation rates, and regulatory developments.

Developed in Ventana Vensim Professional 2023, the model begins with the identification of key variables directly or indirectly affecting CO_2 emissions, followed by the formulation of mathematical relationships that capture their interdependencies. This model occurred with these relationship variables and the system thinking model conceptualization and stock flow diagrams that underpin the model's dynamic behaviour. Assumptions are grounded in the operational realities of container shipping and the projected effects of existing and forthcoming IMO measures. The model is calibrated against historical data to ensure predictive accuracy, and its outputs are compared across a range of scenarios business as usual, IMO compliance, operational optimization, and technological uptake, including sensitivity analysis to ascertain the robustness of outcomes, with a view to evaluating the relative effectiveness of alternative mitigation trajectories towards achieving Net Zero CO_2 emissions by 2050.

As shown in Figure 1, firstly, key variables are identified, which directly or indirectly affect CO_2 emissions with regards to technological, operational, policy, and economic issues. After that, mathematical equations representing the relationships among these variables are developed. These equations formulate the causal feedback loops, stocks and flows, delays, and nonlinear interactions. Assumptions are based on model reliability by focusing on the operation of container ships, regulations set up by IMO up to 2050, and sensitivity to external drivers such as fuel price and technology development. The SD model is then calibrated with historical data for testing the accuracy of the model's forecast. Finally, there is a scenario analysis: business as usual, on target IMO, operational optimization, and technological adoption. Analysis would be conducted to explore the effectiveness of options in helping reach the IMO's Net Zero Emission by 2050 objectives to help its stakeholders enhance the initiatives taken on emission reduction.

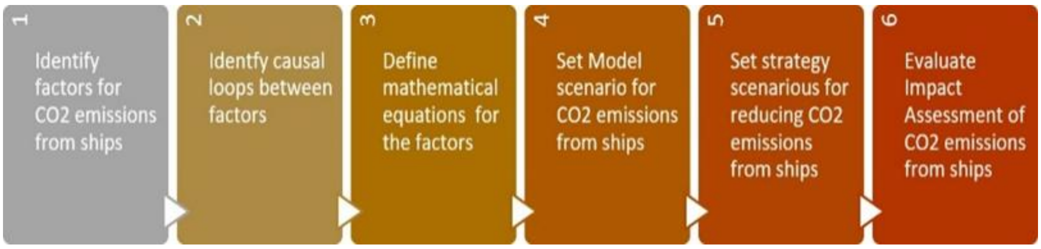

Fig. 1 System dynamics model flow chart

The fuel type in shipping plays a decisive role in the level of CO_2 emissions. The paper describes a System Dynamics (SD) model that encompasses various fuel alternatives, such as methanol, LNG, biofuels, and hydrogen, with different emission factors. The emission factors are relevant for determining the total amount of CO_2 emissions released during shipping activities. Switching to alternative fuels, such as biofuels and hydrogen, which exhibit lower carbon intensities compared to conventional fuels like High Fuel Oil (HFO) and MDO, can effectively curtail emissions. Incorporating these alternative fuels in the model enables the quantitative evaluation of their emissions mitigation potential. Past research has shown the potential of biofuels in cutting down carbon emissions substantially, thanks to their renewable nature and reduced lifecycle emissions [49]. The approach allows a detailed evaluation of available cleaner fuel alternatives within the system to examine the time-dependent behaviour of GHG measures the broader context of global maritime decarbonization

System thinking model conceptualization and diagram development is created to understand and analyse the initial conditions about the current state of the model. With this system thinking scenario, the accuracy of the positive and negative relationship. A model that can be taken as a reference for the creation of different scenarios is presented.

3.2 Systems thinking model conceptualization and diagram development

Following the definition of the problem and limits, conceptual model development involves iterative construction of causal loop diagrams (CLDs) to represent feedback dynamics and reveal causal pathways. The diagrams allow initial testing of model structural assumptions and encourage stakeholder and expert consensus. Iterations incorporate empirical information and participatory feedback to refine system representations.

Then, conceptual frameworks are translated into quantitative stock-flow diagrams, thus mathematically defining system structures for simulation. This procedure entails the conversion of symbolic causal relationships into mathematical equations, parameter calibration, and model implementation using simulation software tools. System thinking and model conceptualization created by assuming “CO2 emissions from container ships with the basic variables casual loop diagram”. The SD model framework of system thinking modelling is as in Figure 2. Firstly, system dynamic modelling approach framework and scope of the model are defined as below.

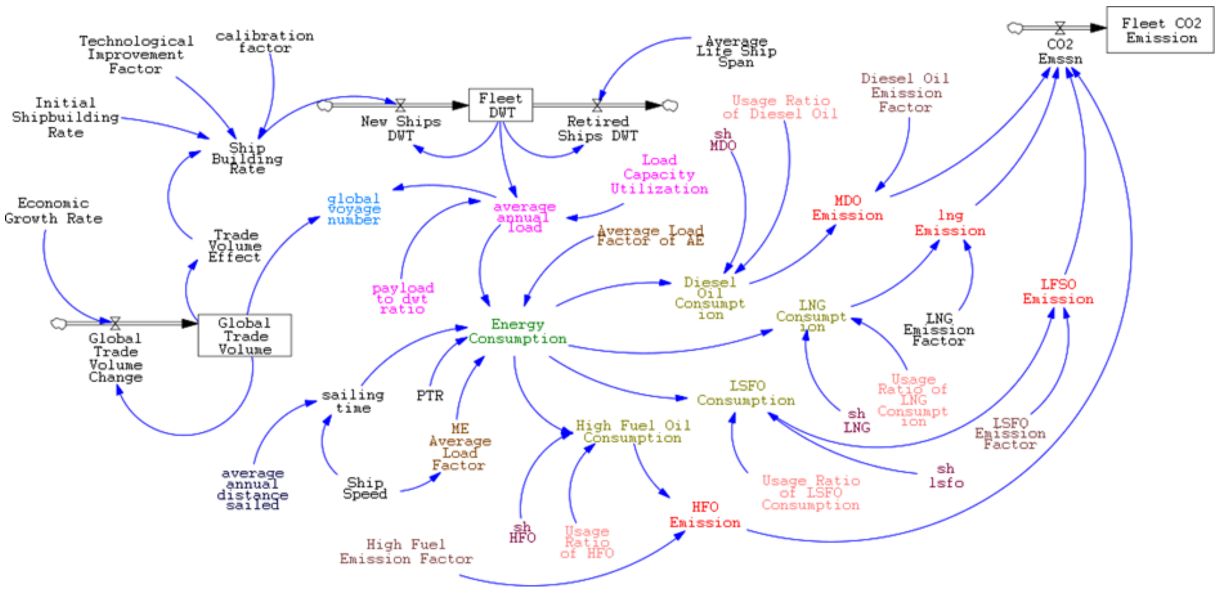

Fig. 2 System dynamics model flow chart

The variables for the dynamics used in system thinking framework are shown in Table 2. It will explain how the basic parameters used in the model were selected and defined. Table 2 gives the dynamics of the model for determining the system dynamic model variables. Table 2 describes the studies on which the variables of the model established on the reduction of emissions from the maritime sector are based. In this context, the stock, flow and variables decided on the model are classified.

Table 2 Model variables list

Variables	Explanation	References
Maritime GHGs	Maritime GHG emissions contribute to global warming, mainly from CO2, CH4, and N2O emissions.	Psaraftis.[50]
Alternative Fuels and Consumption	Alternative fuels like methanol and LNG can reduce emissions; biofuels and hydrogen are also explored.	Inal [51], Geng et al. [52]
Biofuel Blend	Biofuels are sustainable, renewable, and similar to conventional marine fuels, reducing emissions.	Kesieme et al. [53]
Emission Factors for Fuels	Emission factors for fuels are used to calculate CO2 emissions and are crucial for carbon accounting.	Geng et al. [52], Psaraftis. [50]
Well-to-Tank	WTT emissions arise from fuel extraction, production, and transportation, impacting total emissions.	Bouman et al. [54]
Speed	Reducing ship speed can significantly lower CO2 emissions; other factors like SOx are less impacted.	Geng et al. [52], Lu et al. [55]
Deadweight	Deadweight affects fuel consumption and emissions due to load capacity and water resistance.	Joung et al. [56]
Emission Control Areas (ECAs)	ECAs enforce strict emissions regulations to control SOx, NOx, and PM, promoting cleaner shipping.	Chen et al. [17]; Psaraftis & Zis [57]
Carbon Tax	Carbon taxes on fuels incentivize the use of eco-friendly alternatives and fund climate initiatives.	Christodoulou & Cullinane [58]
Technological Impact	Technologies like biofuels, speed optimization, and energy-efficient designs help reduce CO2 emissions.	Parry et al. [59]
Fuel Costs	Fuel costs impact the shift to cleaner fuels; higher costs initially affect operations.	Lindstad et al. [55]
Economic Growth	Economic factors like GDP influence global shipping demand and affect GHG emissions.	UNCTAD [11], Psaraftis & Zis [57]

The system thinking model quantifies the impact of ship speeds on emissions and fuel consumption. The non-linear correlation between ship speed and fuel consumption indicates that even reductions or increasing in speed can lead to changing in CO_2 emissions [52,55]. The use of speed optimization, in conjunction with operational strategies such as route optimization and effective load management, enhances the model's capacity to assess the impact of diverse tactics on emission results. Moreover, the model encompasses external factors such as economic development and fuel price fluctuations, which are key determinants of maritime emissions. The condition of the global economy, particularly GDP growth, impacts the demand for shipping services, hence affecting fuel consumption and emissions [57]. The model additionally assesses the impact of carbon taxes on the utilization of low carbon fuels. Imposing taxes on high-emission fuels might prompt a transition to alternate sources, such as biofuels, consistent with research that delineates the economic incentives necessary for effective decarbonization [58]. Furthermore, technology advancements are essential in reducing shipping emissions, and the SD model encapsulates the impact of innovations such as energy-efficient ship design, biofuel utilization, and speed-optimizing algorithms. This study examines the potential of various technologies to reduce emissions over the long run through simulation. A recent study underscores the significance of investing in green innovations, demonstrating how energy-efficient technologies may be incorporated into shipping operations to realize substantial emissions reductions [13, 16]. The interaction among these elements is depicted through cause trees and feedback loops in the SD model, which elucidate the dynamic relationships affecting maritime CO_2 emissions. The CO_2 Emission Cause

Tree delineates the impact of various fuel types (e.g., HFO, LNG, methanol, and ammonia) on total emissions, whereas the Energy Consumption Cause Tree identifies determinants such as deadweight tonnage, average load factors, and sailing duration that contribute to fuel consumption.

Table 3 Values for system thinking framework

Dynamics	Value	Unit	Reference
Technological improvement factor	0.03	dmnl	The Gold Standard Foundation [49]
Initial shipbuilding rate	0.056	1/year	UNCTAD [11]
Average annual distance sailed	6000	mil	Statista [60]
Ship speed	20	knots	Gunes [61], Geng et al. [52]
Payload to DWT (Deadweight)	0.5	loadston/dwt	Network for Transport Measures [62]
Load capacity utilization (Actual Payload) / (Deadweight)	0.47	dmnl	Network for Transport Measures [63]
HFO emissions factor	3.545	tons CO2/ton fuel	UNCTAD [11]
Usage ratio of HFO	0.8	dmnl	Psaraftis & Zis [57]
Low Sulphur Fuel Oil (LSFO) emissions factor	3.734	tons CO2/ton LSFO fuel	UNCTAD [11]
Usage ratio of LSFO	0,2	dmnl	Psaraftis & Zis [57]
LNG emissions factor	3.28	tons CO2/ton LNG fuel	Christodoulou & Cullinane, 2021 [58]
Diesel oil emission factor	3.782	tons CO2/ton Diesel oil fuel	UNCTAD [11]
Average load factor of AE	0.17	dmnl	UNCTAD [11]
Average load factor of ME (coefficient)	0.28	dmnl	UNCTAD [11]
Average life ship span	30	year	Psaraftis [50]

Unit values in Table 3 expressed as follows, ‘dmnl’ (dimensionless) refers to quantities that have no physical unit (usually defined as a ratio or coefficient). ‘1/year’ expresses a ratio corresponding to the inverse of time, while “mile” reflects the observed distance in nautical miles (1 nautical mile/hour = 1.852 km/hour). In maritime contexts, vessel speed is expressed in the unit ‘knots’ (nautical mile per hour). The term ‘loadstone/dwt’ refers to the situation where the amount of cargo (payload) is related to the deadweight (dwt) of the ship. ‘tons CO2/ton fuel’ refers to the tons of CO2 produced by the combustion of one ton of fuel; these values may vary for different fuel types (HFO, LSFO, LNG, etc.). Units such as ‘years’ usually refer to time-dependent quantities such as the average lifetime of the vessel.

Fixed parameters have been derived from recent literature or global reports, e.g., fuel prices, initial shipbuilding rates, efficiency coefficients, emission coefficients, and fuel costs. These fixed numbers have to be industry averages or generally accepted facts obtained from the relevant quarters. Numerical numbers used in the model have been gathered from the most well-known and reputable organizations, e.g., IMO reports, DNV-GL reports, and UNCTAD, to obtain maximum accuracy. Fixed parameters are model variables that directly affect the underlying dynamics and outcomes of the model. Increasing assumptions about fuel prices or the ship efficiency coefficient can cause an increase in cost calculations or emissions in a model, whereas lower fixed parameters can cause divergence in data.

4. Scenario development and analysis for maritime GHG emissions

This study has been enhancing clarity, a set of representative mathematical equations has been openly included for the purposes of revealing the logic of the simulation system. The fuel usage and the CO_2 emissions are computed by means of widely used energy-efficiency models:

$$Fuel\,Consumption_t = DWT \times LF \times Dist_t \times \left(Speed_t \,/\, Speed_{base}\right)^{\beta} \tag{1}$$

Subsequently, CO_2 emissions are obtained by multiplying fuel consumption with the corresponding emission factor (EF_f) for each fuel type:

$$CO_{2,t} = \sum\left(Fuel_{f,t} \times EF_f\right) \tag{2}$$

where EF_f is expressed in tons of CO_2 per ton of fuel, consistent with IMO and UNCTAD sources (e.g., 3.545 for HFO, 3.28 for LNG). Fuel usage during time t is determined by the ship's capacity (DWT) load factor (LF), and distance sailed distance while also capturing the nonlinear impact of speed. The ratio of the base speed to the actual speed, raised to the power of β reflects the fact that fuel consumption increases disproportionately with higher speeds.

The model developed over the base scenario allowed for the testing of the dynamics affecting various emissions. Using this model, it is possible to mathematically describe how the variables influence all of them. All model mathematical equations are in appendix section. The influence of the factors that will influence the decrease in emissions from the shipping industry on the entire system has been observed. Two baseline equations are provided below to illustrate the structure of the simulation.

Developed model is also used total carrying capacity of global fleet represented by Fleet DWT (Deadweight Tonnage) is the main stock variable, which is changed over time by ship retirements and new ships entering the fleet.

$$Fleet\,DWT = (1.69 \times 10^{8}) + \int (\mathrm{New\,Ships\,DWT} - \mathrm{Retired\,Ships\,DWT}) \tag{3}$$

It allows one to reproduce long-run transformations of the composition of the fleets, their efficiency, and emissions for other situations.

These exact formulations demonstrate how these causal relations are converted into algebraic terms of the model. Though the full set of equations is lengthy and given as a part of the Appendix, these few examples indicate the essence of the mechanisms governing fuel usage, emission formation, and vehicle population change.

Equation (3), the initial value of 1.69×10^{8} tons correspond to the baseline fleet DWT at the starting point of the simulation. Fleet DWT's change over time is determined by two flow variables acting in opposing directions: New Ships DWT, denoting the deadweight added annually via shipbuilding, and Retired Ships DWT, denoting the system capacity removed as ships reach the end-of-life. Due to this stock-flow format, the model can represent dynamically the growth or shrinking of the fleet for various policy and market situations.

IMO has developed a comprehensive strategy aimed at cutting down GHG emissions in the shipping universe. The pivot in the strategy entails the deployment of numerous alternative fuels like LNG, HFO, MDO, LSFO, ammonia, and methanol. All of these fuels present varying benefits and challenges in the areas of emissions reduction, discovery and infrastructure demands. LNG, for instance, has lower CO_2 emissions than conventional HFO, whereas MDO and LSFO lower the emission of sulphur oxides (SO_X) and particulate matter. Ammonia and methanol are the most notable options with its prospects of carbon emissions close to zero when generated from renewable sources. IMO's strategy not only promotes the use of such alternative fuels, but also adopts the EEDI and CII and works towards ensuring continuous improvement in global fleet energy efficiency and emissions reduction.

Based on these system thinking strategies, a new system dynamic model is designed by adding the stock and flow dynamics for GHG strategies into the model as in Figure 3.

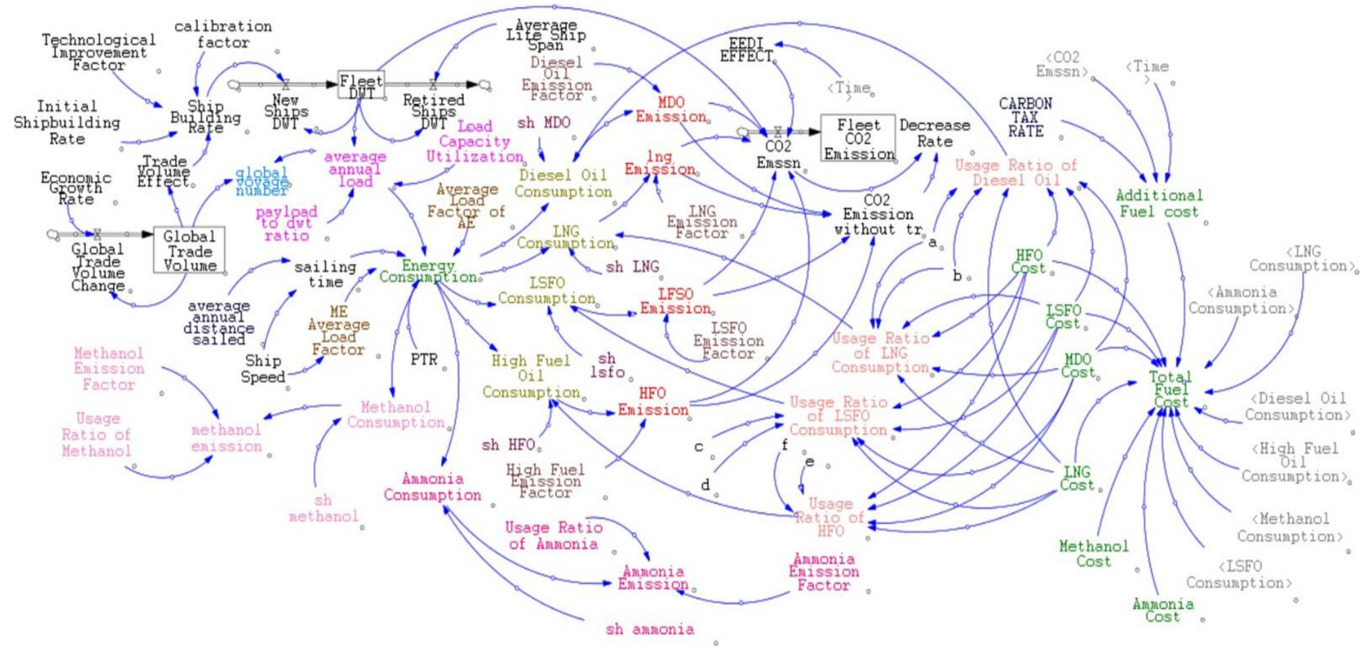

Fig. 3 SD model framework for scenarios with IMO GHG strategies

The constant values for the dynamics used in strategy scenarios are different from base scenario how in Table 4. The fuel prices utilized in our analysis are derived from average values over a certain time frame.

Table 4 Values for base scenario

Variables	Value	Unit	Reference
Ammonia emissions factor	1.6	tons CO_2/ton ammonia fuel	Yüzbaşıoğlu, Tatarhan, & Gezerman [64]
Specific heat consumption of ammonia	0.194	tons/kWh	Di Micco, Cigolotti, Mastropasqua, Brouwer, & Minutillo [65]
Methanol emissions factor	1.375	tons CO_2/ton methanol fuel	IMO [66]
Specific heat consumption methanol	0.183	tons/kWh	Di Micco, Cigolotti, Mastropasqua, Brouwer, & Minutillo [66]
HFO Cost	500	\$/ton fuel for considered type	Ship & Bunker [67]
LSFO Cost	600	\$/ton fuel for considered type	Ship & Bunker [67]
MDO Cost	700	\$/ton fuel for considered type	Ship & Bunker [67]
LNG Cost	800	\$/ton fuel for considered type	Federal Reserve Bank of St. Louis [68]
Methanol Cost	300	\$/ton fuel for considered type	Chemanalyst [69]
Ammonia Cost	200	\$/ton fuel for considered type	Shiozawa [70]
EEDI	0.17	tons/dwt	IMO [71]

4.1 Fuel type based scenarios analysis and findings

Three scenarios (i, ii, iii) are developed from the scope of the study to understanding change in fuel usage attitude of the shipping sector.The parameters for fuel type-based scenarios are shown in Table 5.

Table 5 Type of scenarios and parameters

Parameter	Scenario i - Business as Usual	Scenario ii - IMO Based	Scenario iii - Aggressive
Usage Ratio of HFO	0.8	0.65	0
Usage Ratio of MDO	0	0.1	0
Usage Ratio of LSFO	0.2	0.1	0.2
Usage Ratio of LNG	0	0.1	0.3
Usage Ratio of Ammonium	0	0.025	0.25
Usage Ratio of Methanol	0	0.025	0.25
EEDI Effect	X	X	X
Carbon Tax	-	50	50
Speed (knots)	23	18	15

Table 5 was therefore used to assess the future expected trend of carbon emission under different fuel usage rates, speed changes, and various economic policies for container ships under three scenarios: Business as Usual, IMO Based, and Aggressive. In the BAU case, it is assumed that HFO would reach an 80% utilization rate, which will yield an annual CO_2 emission of 347,778 million tons by 2050. BAU describes the continued rise in the current levels of emission without interventions. The IMO-based scenario decreases HFO use to 65%, while elevating marine diesel oil (MDO) usage to 10%, and raising LSFO and LNG consumption by 10% each. Emission of CO_2 will increase to reach 260,376 million tons by the year 2050. This would help comply with the GHG reduction goals set by the International Maritime Organization while allowing room for further reduction with carbon tax implementation and the speed of vessel slowdown to a speed of 18 knots. With that in mind, for this, in the Aggressive scenario, HFO is not utilized at all; MDO usage has gone to 0%, while LSFO, LNG, ammonium, and methanol go up to 20%, 30%, 25%, and 25%, respectively. This proactive policy aims at annually reducing CO_2 emissions to 135,957 million tons by 2050. The reduction in the speed of ships to 15 knots and the imposing of a 50% carbon tax greatly reduces the emissions.

The overall results of scenarios shown as in Figure. 4 and the values of the C02 emissions changes are shown in Table 6. According to the results shown in Figure 4, it is seen that there is a sharp increase trend from 2025 until 2030 and 2050 when no GHG reduction strategy is applied on GHG emissions from ships.

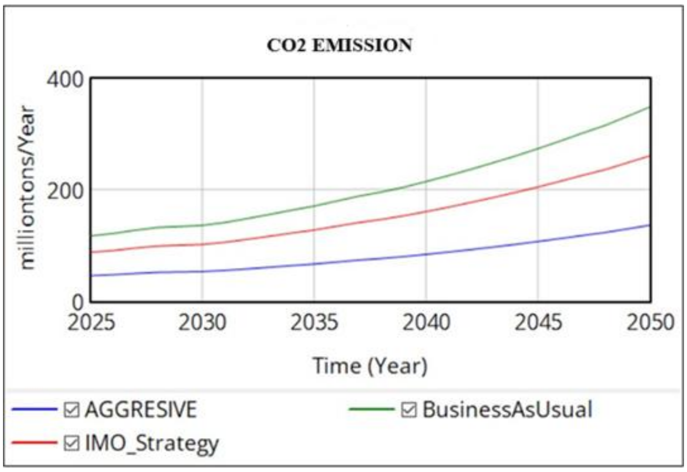

Fig. 4 The result of fuel type-based scenarios

Table 6 The result of (i) scenario – Change of CO2 Emissions (million tons CO2 per year)

Time (Year)	2025	2030	2035	2040	2045	2050
CO2 Emission: Aggressive	45.7228	53.0657	66.6021	83.7799	106.846	135.957
CO2 Emission: IMO Strategy	87.5654	101.628	127.552	160.45	204.625	260.376
CO2 Emission: Business As Usual	116.959	135.742	170.368	214.309	273.312	347.778

Table 6 shows the change of CO2 emissions and scenario results as below:

- In Scenario 1 – Business as Usual, CO2 emissions show a steady and sharp increase by 2050. This scenario reflects the implications of maintaining current practices without implementing additional measures to mitigate GHG emissions. The sharp upward trend highlights the critical need for effective mitigation strategies, as continuing this path results in the highest emissions levels, thereby exacerbating the impacts of climate change.
- In Scenario 2 – IMO Strategy based change in fuel type usage, emissions increase gradually till to 2047 before slightly declining by 2050. This scenario illustrates the impact of existing and proposed actions by the IMO to mitigate GHG emissions. While there has been a large increase over the years, the peak and then slight decline demonstrate that these actions are somewhat successful but not enough to create a noticeable decline in emissions in the long term.
- Under Scenario 3 – Aggressive Strategy change in fuel type consumption, emissions increase over time but at a much slower rate compared to the IMO Strategy. In 2050, emissions would be considerably less than under the IMO Strategy. This scenario reflects more aggressive policies and measures being taken to mitigate CO2 emissions. The reduced rate of growth and the reduced overall emissions indicate the potential benefits of more ambitious decarbonization policies in shipping, possibly through stricter regulations, new technology, and a switch to cleaner fuels.

Accordingly, it can be concluded the current IMO strategies, although targets for 2050 have been set, need clear to be strengthen and should be accelerated the implementation of these policies to achieve better results. The significant reduction in emissions under the Aggressive Strategy highlights the necessity of adopting more stringent measures, such as stricter emissions regulations, greater investment in clean technologies, and a transition to low-carbon fuels. It is also essential to regularly monitor emissions levels and adjust strategies as needed to ensure that targets are met. This includes integrating new technologies and best practices promptly to adapt to changing conditions and opportunities for improvement.

4.2 Speed based scenarios analysis and findings

System Dynamics model has been run to understand the effect of change in average speed attitude of the vessels in general. In these scenarios, the speed value, which is set 20 knots in the base setting, is changed to 18 knot and 15 knots. The results have been presented in Figure 5 and Table 7.

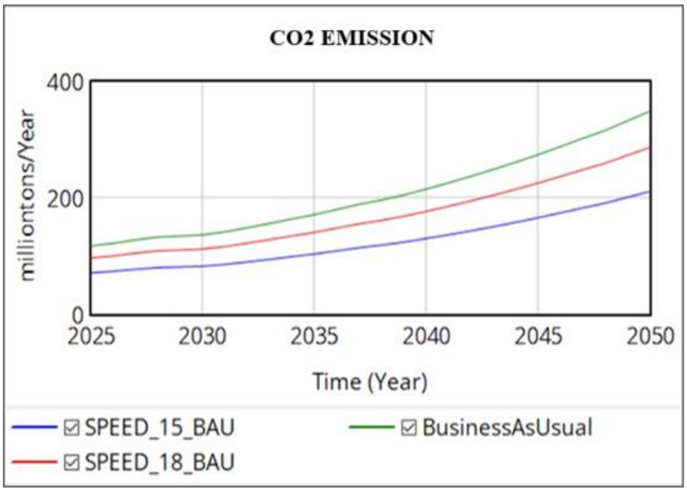

Fig. 5 The results of speed-based scenario

Table 7 The result of (ii) scenario – Change of CO_2 Emissions (million tons CO_2 per year)

Time (Year)	2025	2030	2035	2040	2045	2050
CO2 Emission: SPEED_18_BAU	96.1031	111.537	139.989	176.094	224.576	285.763
CO2 Emission: SPEED_15_BAU	70.692	82.0448	102.974	129.532	165.195	210.203
CO2 Emission: Business As Usual	116.959	135.742	170.368	214.309	273.312	347.778

The second set of data from the system dynamics model examines how varying ship speeds impact CO2 emissions under a business as usual (BAU) scenario, with a focus on the potential benefits of speed reduction as recommended by the International Maritime Organization (IMO). When ships operate at a speed of 15 knots, emissions show a gradual increase over the period from 2025 to 2050. This lower speed scenario leads to significantly reduced emissions compared to scenarios with higher speeds, demonstrating that speed reduction within a BAU context can effectively lower CO2 emissions. Increasing the speed to 18 knots results in a higher emissions profile than the 15-knot scenario but still maintains lower emissions compared to the standard BAU scenario with higher speeds. This shows that even moderate reductions in speed can benefit emissions, albeit not to the same extent as more considerable reductions. In the business-as-usual scenario, in which vessels continue to travel at 20 knots, emissions rise steeply from 2025 to 2050. This is the highest emissions scenario of those considered, highlighting the environmental cost of retaining present operational methods without instituting speed reductions or other mitigation measures. The results highlight that speed reduction of ships can play a significant role in emissions reduction. The evidence unequivocally illustrates that a slowdown to 15 knots leads to significantly reduced emissions, and even a moderate slowdown to 18 knots achieves significant cuts relative to the BAU case. This implies that speed reduction may be used as an effective measure by the shipping sector to mitigate emissions.

The study proposes that the IMO may table speed reduction measures as a part of its emissions reduction policy. The efficacy of speed reduction measures is backed by evidence, which demonstrates that even small reductions in speed can translate into substantial savings in emissions. Furthermore, the application of system dynamics modelling has been useful to determine the long-term effect of various strategies on CO2 emissions. It offers a practical framework for assessing the impacts of different policy alternatives, aiding evidence-based decision-making in regulatory development.

From these conclusions, a number of recommendations can be made. The IMO may consider making or lowering speed limits in order to curtail emissions, incorporating these measures within a comprehensive approach that also encompasses technological enhancements and efficiency gains. Ongoing research and monitoring will also be essential. By updating models and strategies on a regular basis with emerging data and technological improvements, it will be feasible to modify policies in a dynamic way to achieve long-term sustainability targets. Lastly, adopting an integrated approach that combines speed reduction with other measures, such as enhancing fuel efficiency and investing in cleaner technologies, will be essential for achieving global emissions targets in the maritime industry.

4.3 Fuel Cost based Scenarios Analysis and Findings

This study investigates how HFO and LNG price volatility affects the shipping sector through developing a series of scenarios-all with different price conditions to form the basis of reviewing how changes in the relative cost profiles of HFO and LNG impact operations and total costs. Figure 6 and Table 8 present the results of that analysis.

CO2 emissions exhibit a consistent increase from 2025 to 2050. This scenario assesses the impact of economic variables on emissions through alterations in the prices of HFO and LNG. An increase in HFO costs, in conjunction with LNG, leads to a substantial reduction in emissions relative to the business-as-usual scenario. LNG represents a more cost-effective and environmentally sustainable alternative fuel, characterized by reduced emissions that suggest a higher preference for various fuel types. Pricing strategies hold significant importance in this context. The business-as-usual scenario indicates a continuous increase in emissions without intervention, reflecting the highest emissions trajectory among all analysed scenarios. This situation underscores the necessity of implementing proactive measures to curtail emissions growth and stresses the urgency of mitigation strategies. Data from scenario indicates that incentives for economic activity can promote the shift to cleaner fuel sources. An increase in HFO costs, in conjunction with LNG, may lead to substantial emissions reductions. Policymakers, including the IMO, can utilize economic mechanisms such as taxes, subsidies, or pricing regulations to promote the adoption of lower-emissions fuels.

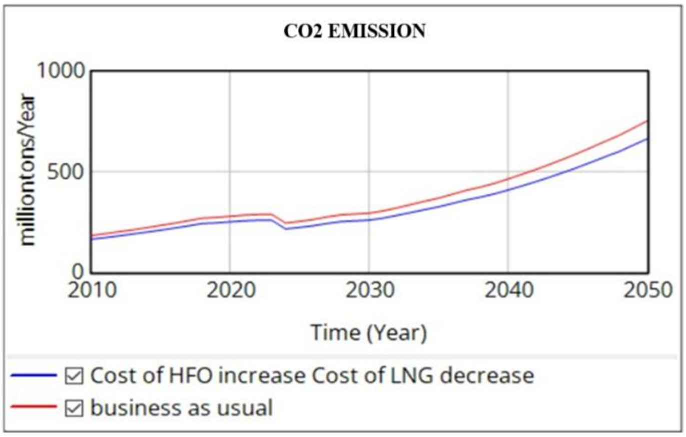

Fig. 6 The result of cost of HFO increase cost of LNG decrease scenario(iii)

Table 8 Cost of HFO Increase cost of LNG decrease scenario(iii) – Change of CO2 Emissions (million tons CO2 per year)

Time (Year)	2025	2030	2035	2040	2045	2050
CO2 Emission: Cost of HFO Increase Cost of LNG decrease _BAU	87.5727	101.636	127.563	160.463	204.642	260.398
CO2 Emission: Business as Usual	116.959	135.742	170.368	214.309	273.312	347.778

The incremental rise in fuel prices may contribute to a reduction in emissions; however, it lacks sufficient evidence to demonstrate that economic measures alone are adequate for attaining sustainability. Further efforts are required to advance cleaner technologies, enhance vessel operations, and refine regulatory frameworks to sustain progress.

The findings indicate that market mechanisms may effectively reduce emissions. Financial incentives promoting cleaner fuels can drive industry-wide transformations. A comprehensive approach integrating economic, technological, and regulatory strategies is essential to achieve long-term emission reduction targets in the maritime industry.

5. Sensitivity analysis and model validation

The system dynamics model validation process used two separate modules to assess its efficacy and investigate sensitivity to a range of factors. The study recorded results from sensitivity analysis to show how a wide range of parameters affected model results in order to help to identify the drivers of maritime greenhouse gas emissions. The model validation system consisted of two validation procedures to validate the degree to which causal loop diagrams and stock-flow structures adequately modelled the dynamic relationships between regulatory and technological and operational layers. Through the combination of these measures, a reliable simulation output was produced, whereupon policy development and strategic decision-making would occur.

5.1 Sensitivity analysis

The system dynamics model created by this investigation was subjected to a sensitivity test to assess its robustness and reliability by assessing key input parameters affecting emissions and cost results. The study evaluated three principal variables of which are fleet deadweight tonnage and average ship lifespan and ship velocity for a greater fuel economy. The study simulated four scenarios all starting from the same business-as-usual baseline values for each variable at -20%, -10%, +10% and +20% while keeping other variables at their respective values.

The model shows strong sensitivity to changes in vessel speed and fuel costs according to the results. The research demonstrated that operational speed optimization functions as an efficient decarbonization method through its ability to lower total CO2 emissions by 17.6% in 2050 when average sailing speeds drop by 20%. The rise of LNG prices by 20% caused the market to accept LNG at a lower rate which produced a 9.4% increase in total emissions compared to the baseline projection. Alterations in the carbon tax rate significantly influenced fuel-switching behaviour, underscoring its function as a policy instrument. The impact of technological enhancement factors was rather limited, suggesting that technological advancement alone may be insufficient without additional policy measures to achieve significant emission reductions.

The results underscore the significance of policy stability and market certainty in shaping long-term decarbonization pathways, bearing crucial implications for policymakers and industry stakeholders involved in regulatory formulation and fleet investment strategies. In a subsequent version of the analysis, emphasis was placed on three principal variables: average vessel longevity, total fleet deadweight tonnage (DWT), and the technological enhancement factor. In the original configuration, the BAU values of each parameter were varied by −20%, −10%, +10%, and +20%, while all other inputs remained constant. Table 9 shows that this facilitated the evaluation of how departures from baseline assumptions could affect emission trajectories and cost-related consequences, thereby identifying the parameters that exert the greatest influence on system behaviour.

Table 9 Sensitivity analysis

CO_2 EMISSIONS SENSITIVITY ANALYSIS						
CRITICAL VARIABLE	2025	2030	2035	2040	2045	2050
Fleet DWT (BAU)	116.959	135.742	170.368	214.309	273.312	347.778
Fleet DWT %+20	99.5215	108.594	136.295	171.447	218.649	278.222
Fleet DWT %+10	105.263	122.168	153.331	192.878	245.981	313.000
Fleet DWT %-10	128.655	149.316	187.405	235.740	300.643	382.555
Fleet DWT %-20	140.351	162.890	204.442	257.171	327.974	417.333
Average Life Ship Span (BAU)	116.959	135.742	170.368	214.309	273.312	347.778
Average Life Ship Span%+20	116.959	130.34	157.177	189.971	232.810	284.663
Average Life Ship Span%+10	116.959	133.319	164.387	203.154	254.547	318.225
Average Life Ship Span%-10	116.959	137.75	175.406	223.859	289.635	373.900
Average Life Ship Span%-20	116.959	139.442	179.707	232.118	303.940	397.098
Ship Speed (BAU)	116.959	135.742	170.368	214.309	273.312	347.778
Ship Speed %+20	78.337	90.918	114.11	143.541	183.06	232.937
Ship Speed %+10	96.103	111.537	139.989	176.094	224.576	285.763
Ship Speed %-10	140.733	163.334	204.999	257.871	328.868	418.470
Ship Speed %-20	167.311	194.18	243.714	306.571	390.976	497.500

The sensitivity analysis of 2050 CO_2 emissions shows that operational conditions have the biggest effect on long-term decarbonization results. When the average speed of a ship goes down by 20% (from 20 to 16 knots), emissions go down by 32.9%. When the speed goes down by 10%, emissions go down by 17.8%. This shows that speed is a very flexible factor that affects emissions. The fleet's capacity shows almost perfectly proportional responsiveness: a 20% decrease in deadweight tonnage leads to a 19.9% decrease in emissions, while a 20% increase leads to a 20.0% increase. Changes to the average ship's lifespan have moderate effects (–18.1% for a 20% decrease and +14.2% for a 20% increase). The sensitivity analysis employed the +20% and -20% standard criterion around the base vessel speed of 20 knots (between 16–24 knots) for the purpose of model robustness testing and ensuring that small deviations from the base scenario. In contrast, the scenario analysis was intentionally designed. In particular, the "Aggressive scenario" used 15 knots as the reference speed, outside the sensitivity test range. Reason of these, the industry and literature surveys considering "slow steaming" as a feasible short-term shortening of the carbon tonne-mile for the sector, and it provides a sound basis upon which the cumulative effect of slower speed, switching of fuels, and taxation of carbon can be evaluated.

All of these results point to the same thing: focusing on managing speed and fleet size will lead to big drops in emissions right away. However, to make bigger cuts in maritime CO_2 emissions, average life ship span must be supported by new laws.

5.2 Model validation

The model validation was performed through structure and behaviour testing to assess the dependability of the simulation results. The model structure was built upon accepted system dynamics principles and was supported by other peer-reviewed literature, industry literature and professional opinion. The causal loop diagrams and stock-flow structures accurately depict the dynamic interplay among regulatory, technological, and operational factors influencing maritime GHG emissions.

Historical data on worldwide container fleet DWT is 2008 to 2022 were utilized for model calibration and testing in behavioural validation. Also, historical data on CO_2 emissions 2018-2022 were utilized for model calibration and testing in behavioural. The simulation findings demonstrated a strong correlation with the reported trends in fleet expansion and emission patterns, with variations within ±5% of empirical data during the calibration phase. Additionally, the model's principal outputs, such as energy consumption, emissions reductions under IMO policy, and the ramifications of fuel switching, were compared with reference studies and scenario analyses performed by the IMO and the International Council on Clean Transportation (ICCT).

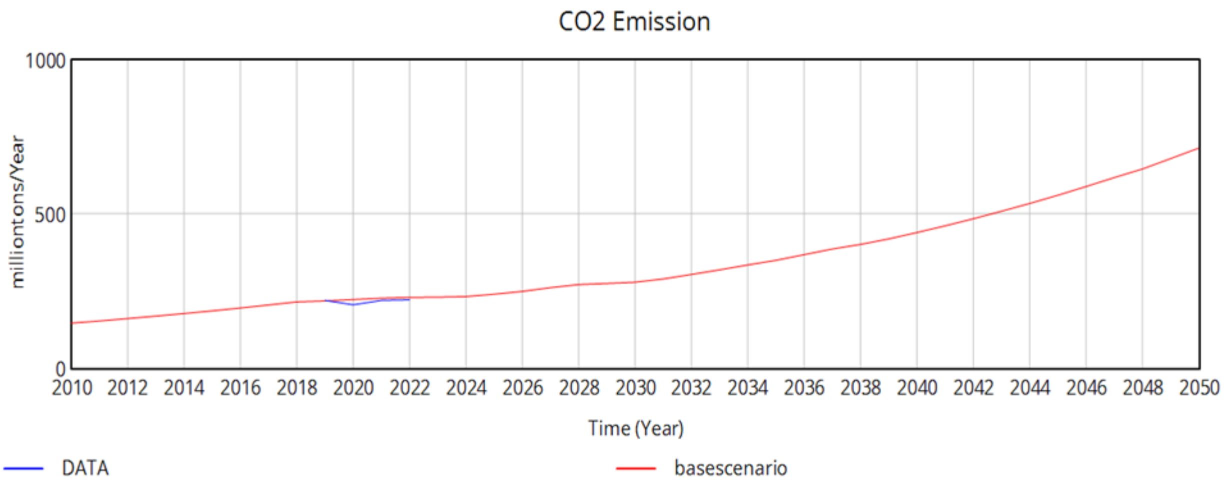

Fig. 7 Results for CO_2 emissions from container ships in the base scenario model

In recent years, carbon emissions have become a major environmental issue with the activities of container ships and increased world trade and maritime transport. In the past, the fuel that most ships used was heavy fuel oil, HFO, which has a high carbon density, hence leading to an increase in carbon emissions. With the rise of environmental awareness and international regulations in the 2000s, the industry has been focusing more on lower carbon fuels, such as LNG and methanol, and energy efficiency measures. Figure 7, shows that the latest forecasts also show that if carbon reduction plans are not applied in the maritime industry, container ships will emit 278 million tons of carbon in 2030 and 712 million tons in 2050. Hence, alternative fuel consumption and operation strategies will need to be followed in order to achieve goals related to sustainability.

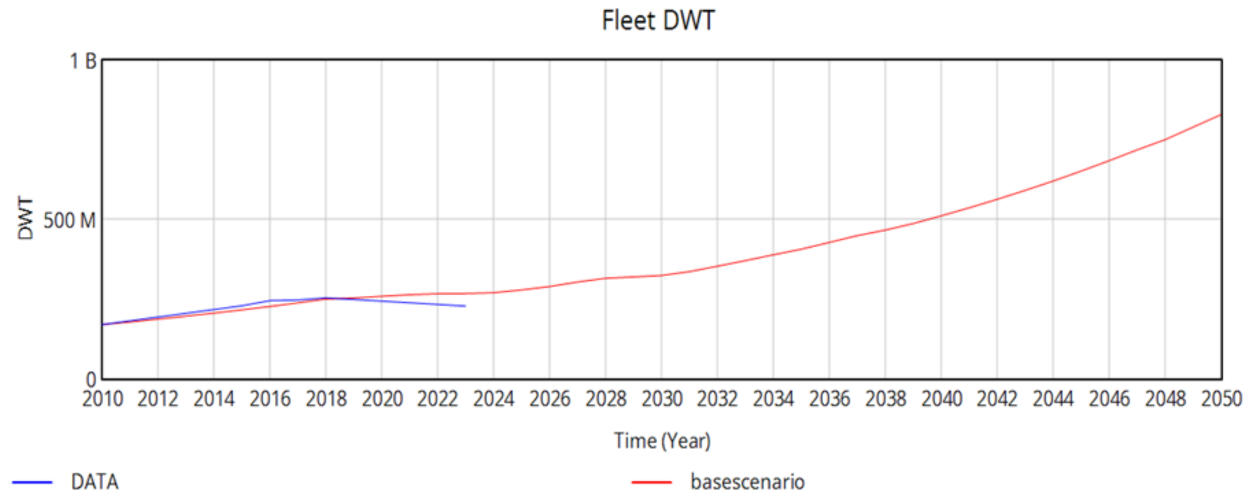

Fig. 8 Results for Fleet DWT for container ships in the base scenario model

Figure 8, shows that the total DWT of vessels worldwide is likely to grow significantly between 2010 and 2050, consistent with the growth in global trade volume and economic expansion. By 2010, the shipping industry had the tendency to increase existing vessel tonnage to facilitate world trade, therefore contributing to growth in the overall fleet carrying capacity. While DWT growth continued into the 2020s, environmental sustainability and carbon emissions reduction brought new ship designs and efficiency measures to the fore. Projections indicate that global fleet DWT capacity will go up significantly by 2050. Such growth must be further balanced with low-carbon fuels, energy-efficient technologies, and more sustainable operations. Based on this fact, the capacity of the world's fleet is expected to be 3.6 times larger by 2050, with fewer environmental impacts

For behavioural validation, we compared the model's conclusions to historical CO_2 emissions data for the global container fleet from 2018 to 2022. This data comes from the IMO Fourth GHG Study (2020) and UNCTAD marine statistics. We utilized two widely established performance criteria to see how closely the observed and simulated values matched up.

We used the Coefficient of Determination (R^2), which is given in Eq. (3), and the Root Mean Square Error (RMSE), which is defined in Eq. (4), to measure how well the observed and simulated values agreed. These equations (4) and (5) are include O_i is observed value and P_i is predicted value.

Coefficient of Determination (*R*²) – calculates the percentage of the model that explains the variation in the observed data:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(O_i - P_i\right)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \tag{4}$$

Root Mean Square Error (RMSE) – calculates the average magnitude of prediction errors:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(O_i - P_i\right)^2}{n}} \tag{5}$$

The behavioural validation outcomes show strong consensus between model outputs and past CO_2 emission statistics of the world container fleet for the 2018–2022 timeframe. Based on the observed dataset of 0.997 and root mean square error (RMSE) of 2.28 million tons. value near unity demonstrates that the model explains almost all the variance in observed data, and low RMSE confirms that deviations are within the ±5% range employed in the calibration process. Collectively, these measures confirm that the system dynamics model formulated herein can accurately reproduce historical emission trajectories, thereby underlining its validity for scenario-based policy-making and strategic decision-making in maritime decarbonization.

6. Conclusion and future works

This paper represents the preliminary analysis of the use of a system dynamics model for the assessment of a set of GHG mitigation strategies in container shipping. While EEDI, SEEMP, and CII at present are good foundations, they may not be adequate to meet the ambitious decarbonization goals of 2050. To this effect, the system dynamics model evaluated the future trend of carbon emissions under three scenarios: Business as Usual, IMO Based, and Aggressive. In the BAU scenario, it is assumed that the HFO utilization rate is 80%, and the annual CO_2 emissions will reach 347,778 million tons in 2050. Under the IMO Based scenario, HFO use is reduced to 65%, MDO is increased by 10%, LSFO and LNG by 10% and emissions are expected to fall to 260.376 million tons. In the Aggressive scenario, HFO is phased out completely, MDO increased by 0%, LSFO by 20%, LNG by 30%, and ammonium and methanol by 25%; in this case, CO_2 emissions are targeted to decrease to 135,957 million tons in 2050. These scenarios indicate that the use of alternative fuels like LNG, methanol, and hydrogen will result in huge cuts in emissions, but these need huge investments in infrastructure and technology.

One measure that could be effective in the short run is the reduction of speed. The model indicates that without any near-term technological innovations, the reduction of fleet speed by about 15 knots would reduce the emissions of CO_2 sharply. It then shows that such operational strategies as speed reduction set a low-cost short-term option for emissions reduction. Projections based upon cost permit long-term adaptability by consistently offering opportunities for shifting to cleaner fuel options. However, such financial mechanisms by themselves are insufficient for realizing sustainable reductions and require a complementary regulatory framework and continuing technological innovation. The system dynamic approach provides a novel framework for analysis of decarbonization strategies inasmuch as it offers many advantages. The approach provides a complete view encompassing the relationships between technological development and technological advancements and operational strategies and economic incentives and policy considerations. The ability of the model to impose a wide variety of scenarios allows for the examination of many different pathways and the respective emissions yielded by various emitting parties. The use of long-term impacts in such a way can improve the strategic planning and policymaking process by allowing bottlenecks or potential unintended impacts in the long term. The analysis based upon the results of the model suggests the wisdom for policymakers in terms of combining the use of robust regulatory regimes (such as EEDI, SEEMP, and CII) and market mechanisms such as carbon pricing in terms of allowing for important clean-fuel use and operational efficiencies and being prepared for the use of alternative infrastructure for the fuel. The analysis for shipping lines suggests the use of operational strategies such as speed optimization as highly low-cost short-term interventions and the development of early capabilities for the use of alternative fuels as a strategic move for the reduction of the impact of carbon cost in the years ahead. For the authorities responsible for infrastructure planning and ports, the scenarios stress the point of making timely investments in storage and bunkering infrastructure in preparing for anticipated fuel transitions and avoiding supply bottlenecks.

As exploratory research, there are some limitations to this study. The model is mainly aimed at container ships and thus the generalizability of the findings to other types of ships such as bulk carriers and tankers is limited. Subsequent research is invited to incorporate other segments into the model to further inform the understanding of the emissions profile in the shipping sector. Second, the assumptions made in the model, like average historical fuel costs, simplified operational parameters, and combined fleet characteristics, don't take into consideration short-term market fluctuations, technology interruptions, or differences between ship segments. Third, several factors, such the age distribution of the fleet, delays in retrofitting, preparedness of port facilities, and capacity limits, are shown in a simplified way, so they may not fully show how complicated things are in the real world. Because of these boundary conditions, the results should be seen as examples of what could happen.

In comparison to the forecasts of the IMO's Fourth GHG Study (2020), the results of the current model exhibit both convergence and notable divergences. The IMO study estimates that total CO_2 emissions from international shipping could range from approximately 794 to 1,039 million tonnes by 2050 under various policy and market scenarios. However, our modelled trajectories for alternative fuel adoption and operational optimization for container ships indicate the potential to decrease emissions by over 40% relative to a business-as-usual scenario, thereby narrowing the gap to the IMO's absolute reduction targets for 2050. Nonetheless, the study reveals that, even under the most optimistic scenarios examined, sectors target consistent with complete decarbonization remain challenging without broader use of zero-emission energy sources across all vessel categories. The robustness of our system dynamics model lies in its integration of multiple policy levers namely, EEDI, SEEMP, CII compliance, alternative fuel adoption, speed reduction, and carbon pricing within a unified dynamic framework, thereby considering both cumulative and interactive effects of interventions over time. This facilitates a more precise identification of policy combinations that can diminish the gap between present trends and the IMO's long-term decarbonization objectives.

Another preliminary study highlights the promise of system dynamics modelling as a robust tool in strategy analysis aimed at lowering greenhouse gas emissions. The IMO's points on decarbonization can be achieved only by an integrated approach consisting of operational modifications, capital enhancements, economic stimuli, and regulation having consistent performance review inbuilt. Updating the model periodically by repeated interaction with the players in the industry in the country and tracking performance data will make the new strategy continue along the same lines as global developmental objectives for sustainability. The research possesses practical value, yet it adds value to scholarship by showing how the system dynamics approach can aggregate a myriad of variables such as policy handles, feedback links, and customized constraints and apply them in commercial sectors in research opportunity. The research work shall contribute towards the possibilities the researchers can avail themselves for the study of marine decarbonization and give a modelling template which the research can tailor in the rest of the shipping business.

The fuel prices used in this study are average over a time period. At this stage, the examples given are typical applications to show how the model can produce outputs in probable future situations. So, we want to stress that the forecasts here should not be considered as ‘exact projections’ or ‘policy recommendations’ but rather a framework to show the potential of the model. We will also do model applications for different ship types. This way we will increase the general validity and sectoral applicability of the model and provide more general recommendations for academia and industry. This study estimated the reduction effect of CO_2 emissions from maritime operations. The model is based on the influence of indicators of a potential of emission reduction, such as fuel-specific emission factors, fuel consumption, and fleet capacity. The area of adaptation of maritime machinery, storage tanks, or other related facilities; accessibility of port infrastructure and bunkering stations. These issues need more detailed research by further investigation for comprehensive assessments of the sustainability of alternative fuels and their long-term impacts.

ABBREVIATIONS

BAU	Business As Usual
CGE	Computable General Equilibrium
CII	Carbon Density Indicator
CLD	Casual Loop Diagrams
DML	Dimensionless
DWT	Deadweight
EEDI	Energy Efficiency Design Index
EEXI	Energy Efficiency Existing Ship Index
EU	European Union
EU-ETS	European Emission Trading System

GDP	Gross Domestic Product
GHG	Greenhouse Gas
HFO	High Fuel Oil
ICCT	International Council on Clean Transportation
IMO	International Maritime Organization
LNG	Liquefied Natural Gas
LSFO	Low Sulphur Fuel Oil
MDO	Marine Diesel Oil
SD	System Dynamic
SEEMP	Ship Energy Efficiency Management Plan
UNCTAD	United Nations Conference on Trade and Development

ACKNOWLEDGEMENTS

This study is presented in the 29th International Maritime Lecturers Association (IMLA29) Conference.

FUNDING

The project discussed within the scope of this study is a project funded by The IAMU as Organizational Development Project FY2023's, Theme 3 Sustainable Shipping Research Project Number: 20230307

APPENDIX

The following is a list of variables and equations from the project that The International Association of Maritime Universities (IAMU) paid for under the Organizational Development Project FY2023, Theme 3 Sustainable Shipping Research, Project Number: 20230307.

System Dynamic Model Variable and Equations List

NO	TOOL TYPE	VARIABLE NAME	EQUATIONS	UNIT	DEFINITION	REFERENCES
1	Stock	Fleet DWT	$(1.69 \times 10^8) + \int (\text{New Ships DWT} - \text{Retired Ships DWT})$	DWT	The aggregate Deadweight Tonnage (DWT) of the fleet, denoting the total carrying capacity of all vessels within the fleet.	Lazarev [72]
2	Flow	New Ships DWT	$\text{Fleet DWT} \times \text{Ship Building Rate}$	DWT/Year	The Deadweight Tonnage of newly incorporated vessels in the fleet.	BRS Group [73]
3	Flow	Retired Ships DWT	$\text{Fleet DWT} \times \text{Average Life Ship Span}$	DWT/Year	The deadweight tonnage of retired vessels.	BRS Group [73]

4	Variable	Ship Building Rate	$\text{Initial Shipbuilding Rate} \times (1 + \text{Technological Improvement Factor}) \times (1 + \text{Trade Volume Effect}) \times \text{Calibration Factor}$	1/Year	The frequency of new ship construction.	BRS Group [73]
5	Variable	Average Life Ship Span	30	Year	The mean operational lifespan of vessels in the fleet.	BRS Group [73]
6	Variable	Technological Improvement Factor	0.03	Dmnl	A variable denoting advancement in technology over time.	Gold Standard [49]
7	Variable	Initial Shipbuilding Rate	0.056	1/Year	The initial rate of shipbuilding at the start of the model period.	Gao et al. [16]
8	Variable	Trade Volume Effect	$\frac{\text{Global Trade Volume}}{\text{DELAY1(Global Trade Volume, 1)}} - 1$	Dmnl	The impact of trade volume changes on the fleet and operations.	-
9	Stock	Global Trade Volume	$(1.3 \times 10^9) + \int (\text{Global Trade Volume Change})$	Loadston/Year	The total volume of global trade.	Statista [60]
10	Flow	Global Trade Volume Change	$\text{Global Trade Volume} \times \text{Economic Growth Rate}$	Loadston/Year	The rate of change in global trade volume.	-
11	Variable	Economic Growth Rate	Historical Data Imported	Dmnl	The rate of economic growth, influencing trade and shipping demand.	BRS Group [73]
12	Variable	Global Voyage Number	$\frac{\text{Global Trade Volume}}{\text{Average Annual Load}}$	Dmnl	The total number of voyages made by the global fleet.	-
13	Variable	Average Annual Load	$(\text{Fleet DWT} \times \text{Payload to DWT Ratio}) \times \text{Load Capacity Utilization}$	Loadston	The average load carried by ships annually.	-
14	Variable	Payload to DWT Ratio	0.5	Loadston/DWT	The ratio of the actual payload to the ship's DWT.	UNCTAD [11]
15	Variable	Load Capacity Utilization	0.47	Dmnl	The extent to which the fleet's carrying	Network for Transport Measures [63]

					capacity is utilized.	
16	Variable	Energy Consumption	(ME Average Load Factor + Average Load Factor of AE) × Sailing Time × Average Annual Load × PTR	KWh	The total energy consumption by the fleet.	-
17	Variable	Average Annual Distance Sailed	6000	mil	The average distance sailed by ships annually.	UNCTAD [11]
18	Variable	Sailing Time	$\frac{\text{Average Annual Distance Sailed} \times 0.9}{\text{Ship Speed}}$	hour	The total time spent sailing.	-
19	Variable	PTR	0.2	KW/Loadston	Propulsive thrust demand refers to the force necessary to propel a vessel through water.	N. P. Najeeb [74]
20	Variable	Ship Speed	20	knot	The average speed at which ships travel.	Geography, T. [75]
21	Variable	ME Average Load Factor	$0.28 \times \left(\frac{\text{Ship Speed}}{13.44}\right)^3$	Dmnl	The average load factor of the main engine.	Gao et al. [16]
22	Variable	Average Load Factor of AE	0.17	Dmnl	The average load factor of auxiliary engines.	Gao et al. [16]
23	Variable	High Fuel Oil Consumption	Energy Consumption × sh HFO × Usage Ratio of HFO	Millionton	The consumption of high fuel oil by the fleet.	Gao et al. [16]
24	Variable	sh HFO	175×10^{-10}	Millionton/KWh	Specific fuel consumption value for low high sulphur fuel oil.	Comer, B. & Osipova, L. [76]
25	Variable	Usage Ratio of HFO	$\text{IFTHENELSE}(\text{HFO Cost} < \text{LSFO Cost} \wedge \text{HFO Cost} < \text{MDO Cost} \wedge \text{HFO Cost} < \text{LNG Cost}, f, e)$	Dmnl	The usage ratio of high fuel oil.	Kong et al. [15]
26	Variable	High Fuel Emission Factor	3.545	Dmnl	The emission factor associated with high fuel oil.	International Council on Clean Transportation, [76]
27	Variable	HFO Emission	High Fuel Emission Factor × High Fuel Oil Consumption	Millionton	The total emissions from high fuel oil consumption.	-

28	Variable	LSFO Consumption	$\text{Energy Consumption} \times \text{sh LSFO} \times \text{Usage Ratio of LSFO Consumption}$	Millionton	The consumption of low sulphur fuel oil.	-
29	Variable	sh LSFO	167×10^{-10}	Millionton/KWh	Specific fuel consumption value for low sulphur fuel oil	International Council on Clean Transportation [76]
30	Variable	Usage Ratio of LSFO Consumption	$\text{IFTHENELSE}(\text{LSFO Cost} < \text{HFO Cost} \land \text{LSFO Cost} < \text{MDO Cost} \land \text{LSFO Cost} < \text{LNG Cost}, c, d)$	Dmnl	The usage ratio of low sulphur fuel oil.	Kong et al. [15]
31	Variable	LSFO Emission Factor	3.734	Dmnl	The emission factor associated with low sulphur fuel oil.	International Council on Clean Transportation, [76]
32	Variable	LSFO Emission	$\text{LSFO Consumption} \times \text{LSFO Emission Factor}$	Millionton	The total emissions from low sulphur fuel oil consumption.	-
33	Variable	LNG Consumption	$\text{Energy Consumption} \times \text{sh LNG} \times \text{Usage Ratio of LNG Consumption}$	Millionton	The consumption of liquefied natural gas.	-
34	Variable	sh LNG	156×10^{-10}	Millionton/KWh	Specific fuel consumption value for liquefied natural gas.	International Council on Clean Transportation [76]
35	Variable	Usage Ratio of LNG Consumption	$\text{IFTHENELSE}(\text{LNG Cost} < \text{HFO Cost} \land \text{LNG Cost} < \text{MDO Cost} \land \text{LSFO Cost} < \text{LSFO Cost}, a, b)$	Dmnl	The usage ratio of liquefied natural gas.	Kong et al. [15]
36	Variable	LNG Emission Factor	3.28	Dmnl	The emission factor associated with liquefied natural gas.	International Council on Clean Transportation [76]
37	Variable	LNG Emission	$\text{LNG Consumption} \times \text{LNG Emission Factor}$	Millionton	The total emissions from liquefied natural gas consumption.	-
38	Variable	Diesel Oil Consumption	$\text{Energy Consumption} \times \text{sh MDO} \times \text{Usage Ratio of Diesel Oil}$	Millionton	The consumption of diesel oil.	-

39	Variable	sh MDO	165×10^{-10}	Dmnl	Specific fuel consumption value for marine diesel oil.	International Council on Clean Transportation, [76]
40	Variable	Usage Ratio of Diesel Oil	$\text{IFTHENELSE}(\text{MDO Cost} < \text{HFO Cost} \wedge \text{MDO Cost} < \text{LNG Cost} \wedge \text{MDO Cost} < \text{LSFO Cost}, a, b)$	Dmnl	The usage ratio of diesel oil.	Kong et al. [15]
41	Variable	Diesel Oil Emission Factor	3.782	Dmnl	The emission factor associated with diesel oil.	International Council on Clean Transportation [76]
42	Variable	MDO Emission	$\text{Diesel Oil Consumption} \times \text{Diesel Oil Emission Factor}$	Millionton	The total emissions from diesel oil consumption.	-
43	Variable	Methanol Consumption	$\text{Energy Consumption} \times \text{sh Methanol}$	Millionton	The consumption of methanol.	-
44	Variable	sh Methanol	0.186×10^{-10}	Millionton/KWh	Specific fuel consumption value for methanol.	Di Micco et al. [65]
45	Variable	Usage Ratio of Methanol	0.01	Dmnl	The usage ratio of methanol.	Kong et al. [15]
46	Variable	Methanol Emission Factor	1.375	Dmnl	The emission factor related to methanol.	IMO [5]
47	Variable	Methanol Emission	$\text{Methanol Consumption} \times \text{Methanol Emission Factor} \times \text{Usage Ratio of Methanol}$	Millionton/KWh	The total emissions from methanol consumption.	-
48	Variable	Ammonia Consumption	$\text{Energy Consumption} \times \text{sh Ammonia}$	Millionton	The consumption of ammonia.	-
49	Variable	sh Ammonia	0.194×10^{-10}	Millionton/KWh	Specific fuel consumption value for ammonia.	Di Micco et al. [65]
50	Variable	Usage Ratio of Ammonia	0.01	Dmnl	The usage ratio of ammonia.	Kong et al. [15]
51	Variable	Ammonia Emission Factor	1.6	Dmnl	The emission factor associated with ammonia.	Yüzbaşıoğlu et al. [65]
52	Variable	Ammonia Emission	$\text{Ammonia Consumption} \times \text{Ammonia Emission Factor} \times \text{Usage Ratio of Ammonia}$	Millionton/KWh	The total emissions	-

					from ammonia consumption.	
53	Variable	a	0	Dmnl	Usage ratio	-
54	Variable	b	0.1	Dmnl	Usage ratio	-
55	Variable	c	0.2	Dmnl	Usage ratio	-
56	Variable	d	0.3	Dmnl	Usage ratio	-
57	Variable	e	0.6	Dmnl	Usage ratio	-
58	Variable	f	0.8	Dmnl	Usage ratio	-
59	Variable	CO2 Emission Without tr	$(\text{HFO Emission} + \text{LSFO Emission} + \text{LNG Emission} + \text{MDO Emission} + \text{Ammonia Emission} + \text{Methanol Emission}) - \text{Fleet DWT} \times \text{EEDI Effect}$	Millionton	The total CO2 emissions from all fuel types without CO2 emission treatment.	-
60	Variable	Decrease Rate	$\frac{\text{CO2 Emission} - \text{CO2 Emission Without tr}}{\text{CO2 Emission Without tr}}$	Dmnl	The rate of decrease in CO2 emissions.	-
61	Flow	CO2 Emission	$(\text{HFO Emission} + \text{LSFO Emission} + \text{LNG Emission} + \text{MDO Emission} + \text{Ammonia Emission} + \text{Methanol Emission}) - \text{Fleet DWT} \times \text{EEDI Effect}$	Millionton	The total CO2 emissions from all fuel types.	Gao et al. [16]
62	Stock	Marine Fleet CO2 Emission	$0.277 + \int(\text{CO2 Emission})$	Millionton	The total CO2 emissions from the entire marine fleet.	UNCTAD [11]
63	Variable	Carbon Tax Rate	50	$/ton	The rate of carbon tax.	Czermański et al. [77]
64	Variable	Additional Fuel Cost	$\text{IFTHENELSE}(\text{Time} < 2024, 0, \text{Carbon Tax Rate} \times \text{CO2 Emission} \times 100)$		Additional cost due to carbon tax on CO2 emissions.	Gao et al. [16]
65	Variable	HFO Cost	500	$/ton	The cost of high sulphur fuel oil.	Ship & Bunker [67]
66	Variable	LSFO Cost	600	$/ton	The cost of low sulphur fuel oil.	Ship & Bunker [67]
67	Variable	MDO Cost	700	$/ton	The cost of marine diesel oil.	Ship & Bunker [67]
68	Variable	LNG Cost	800	$/ton	The cost of liquefied natural gas.	Global price of LNG [68]
69	Variable	Methanol Cost	300	$/ton	The cost of methanol.	Methanol Prices Monitor News Market

						Analysis & Demand [69]
70	Variable	Ammonia Cost	200	$/ton	The cost of ammonia.	Shiozawa, B. [70]
71	Variable	Total Fuel Cost	(HFO Cost × High Fuel Oil Consumption + LNG Cost × LNG Consumption + LSFO Cost × LSFO Consumption + MDO Cost × Diesel Oil Consumption) × 100 + Additional Fuel Cost + Methanol Consumption × Methanol Cost + Ammonia Consumption × Ammonia Cost	$	The total cost of all types of fuel consumed, including additional costs due to carbon tax.	Gao et al. [16]
72	Variable	EEDI Effect	IFTHENELSE(Time < 2024,0,1.7×10^{-7})	Millionton/DWT	The effect of the Energy Efficiency Design Index (EEDI) regulation on emissions.	Czermański et al. [77]

REFERENCES

[1] International Maritime Organization (IMO), 2023. IMO Strategy on Reduction of GHG Emissions from Ships: Resolution MEPC.377(80). London, UK: International Maritime Organization. https://wwwcdn.imo.org/localresources/en/MediaCentre/PressBriefings/Documents/Resolution%20MEPC.377(80).pdf (accessed 31st May 2024)

[2] The International Energy Agency, 2023. Tracking Clean Energy Progress. https://www.iea.org/reports/tracking-clean-energy-progress-2023 (accessed 25th December 2024)

[3] International Maritime Organization (IMO), 2025. Index of MEPC Resolutions and Guidelines related to MARPOL Annex VI. https://www.imo.org/en/ourwork/environment/pages/index-of-mepc-resolutions-and-guidelines-related-to-marpol-annex-vi.aspx (accessed 10st June 2025)

[4] International Maritime Organization (IMO), 2025. IMO Approves Net-Zero Regulations For Global Shipping. https://www.imo.org/en/mediacentre/pressbriefings/pages/imo-approves-netzero-regulations.aspx (accessed 10st July 2025)

[5] International Maritime Organization (IMO), 2020. Fourth Greenhouse Gas Study 2020 https://www.imo.org/en/ourwork/environment/pages/fourth-imo-greenhouse-gas-study-2020.aspx (accessed 10st July 2025)

[6] Schrooten, L., De Vlieger, I., Panis, L. I., Chiffi, C., Pastori, E., 2009. Emissions of maritime transport: A European reference system. *Science of the Total Environment*, 408(2), 318-323. https://doi.org/10.1016/j.scitotenv.2009.07.037

[7] Meng, L., Gan, H., Liu, H., Lu, D., 2025. Deep learning-based research on fault warning for marine dual fuel engines. *Brodogradnja*, 76(3), 1-28. https://doi.org/10.21278/brod76303

[8] Huang, I. L., Lee, M. C., Nieh, C. Y., Huang, J. C., 2023. Ship classification based on ais data and machine learning methods. *Electronics*, 13(1), 98. https://doi.org/10.3390/electronics13010098

[9] Kramel, D., Muri, H., Kim, Y., Lonka, R., Nielsen, J. B., Ringvold, A. L., Nouman, E. A., Steen, S., Strømman, A. H., 2021. Global shipping emissions from a well-to-wake perspective: the MariTEAM model. *Environmental science & technology*, 55(22), 15040-15050. https://doi.org/10.1021/acs.est.1c03937

[10] Psaraftis, H. N., Kontovas, C. A., 2014. Ship speed optimization: Concepts, models and combined speed-routing scenarios. *Transportation Research Part C: Emerging Technologies*, 44, 52-69. https://doi.org/10.1016/j.trc.2014.03.001

[11] UNCTAD, 2023. Review of Maritime Transport 2023. United Nations Conference on Trade and Development. https://unctad.org/webflyer/review-maritime-transport-2023 (accessed 8th August 2025)

[12] Bortuzzo, V., Bertagna, S., Braidotti, L., Bucci, V., 2025). An innovative tool for the evaluation of energy efficiency of merchant ships. *Brodogradnja*, 76(3), 1-27. https://doi.org/10.21278/brod76304

[13] Jing, D., Dai, L., Hu, H., Ding, W., Wang, Y., Zhou, X., 2021. CO_2 emission projection for Arctic shipping: A system dynamics approach. *Ocean and Coastal Management*, 205, 105531. https://doi.org/10.1016/j.ocecoaman.2021.105531

[14] Mamatok, Y., Huang, Y., Jin, C., Cheng, X., 2019. A system dynamics model for CO_2 mitigation strategies at a container seaport. *Sustainability*, 11, 2806. https://doi.org/10.3390/su11102806

[15] Kong, Y., Liu, J., Chen, J., 2022. Exploring the carbon abatement measures in maritime supply chain: A scenario-based system dynamics approach. *International Journal of Production Research*, 61(18), 6131–6152. https://doi.org/10.1080/00207543.2022.2088427

[16] Gao, X., Zhu, A., Yu, Q., 2023. Exploring the carbon abatement strategies in shipping using system dynamics approach. *Sustainability*, 15, 13907. https://doi.org/10.3390/su151813907

[17] Chen, X., Di, Q., Hou, Z., Yu, Z., 2022. Measurement of carbon emissions from marine fisheries and system dynamics simulation analysis: China's northern marine economic zone case. *Marine Policy*, 145, 105279. https://doi.org/10.1016/j.marpol.2022.105279

[18] Liu, G., Xu, Y., Ge, W., Yang, X., Su, X., Shen, B., Ran, Q., 2022. How can marine fishery enable low carbon development in China? Based on system dynamics simulation analysis. *Ocean and Coastal Management*, 231, 106382. https://doi.org/10.1016/j.ocecoaman.2022.106382

[19] Hafner, S., Gottschamer, L., Kubli, M., Pasqualino, R., Ulli-Beer, S., 2024. Building the bridge: How system dynamics models operationalise energy transitions and contribute towards creating an energy policy toolbox. *Sustainability*, 16(19), 8326. https://doi.org/10.3390/su16198326

[20] Kostidi, E., Nikitakos, N., 2024. Revolutionizing the Marine Spare Parts Supply Chain through Additive Manufacturing: A System Dynamics Simulation Case Study. *Journal of Marine Science and Engineering*, 12(9), 1515. https://doi.org/10.3390/jmse12091515

[21] Weitzel, M., Vandyck, T., Los Santos, L. R., Tamba, M., Temursho, U., Wojtowicz, K., 2023. A comprehensive socio-economic assessment of EU climate policy pathways. *Ecological Economics*, 204, 107660. https://doi.org/10.1016/j.ecolecon.2022.107660

[22] Tong, D., Cheng, J., Liu, Y., Yu, S., Yan, L., Hong, C., Qin, Y., Zhao, H., Zheng, Y., Geng, G., Li, M., Liu, F., Zhang, Y., Zheng, B., Clarke, L., and Zhang, Q., 2020. Dynamic projection of anthropogenic emissions in China: methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios. *Atmospheric Chemistry and Physics*, 20(9), 5729-5757. https://doi.org/10.5194/acp-20-5729-2020

[23] Mahía Prados, J. M., Arias Fernández, I., Romero Gómez, M., Naveiro Parga, M., 2024. The decarbonisation of the maritime sector: Horizon 2050. *Brodogradnja*, 75(2), 1-26. https://doi.org/10.21278/brod75202

[24] Nong, D., Simshauser, P., & Nguyen, D. B. (2021). Greenhouse gas emissions vs CO2 emissions: Comparative analysis of a global carbon tax. *Applied Energy*, *298*, 117223. https://doi.org/10.1016/j.apenergy.2021.117223

[25] Forrester, J.W., 2012. Industrial Dynamics: A Major Breakthrough for Decision Makers. In The Roots of Logistics. *Springer*, Berlin/Heidelberg, Germany, 141–172. https://doi.org/10.1007/978-3-642-27922-5_13

[26] Forrester, J.W., 1997. Industrial Dynamics. *Journal of the Operational Research Society,* 48(10), 1037-1041. https://doi.org/10.1057/palgrave.jors.2600946

[27] Forrester, J. W., 1970. Urban dynamics. *IMR; Industrial Management Review (pre-1986)*, 11(3), 67.

[28] Sterman, J. D., 2000. Business Dynamics: Systems thinking and modeling for a complex world. MacGraw-Hill Company.

[29] Barlas, Y., 2007. System dynamics: systemic feedback modeling for policy analysis. *System*, 1(59), 1-68.

[30] Richardson, G. P., 2013. System dynamics. In *Encyclopedia of operations research and management science*, 1519-1522. Springer, Boston, MA. https://doi.org/10.1007/978-1-4419-1153-7_1030

[31] Mousavi, S. H., Kavianpour, M. R., Alcaraz, J. L. G., Yamini, O. A., 2023. System dynamics modeling for effective strategies in water pollution control: insights and applications. *Applied Sciences*, 13(15), 9024. https://doi.org/10.3390/app13159024

[32] Zahedi, R., Yousefi, H., Aslani, A., Ahmadi, R., 2024. System dynamic model of water, energy and food nexus for policy implementation. *Applied Water Science*, 14(10), 213. https://doi.org/10.1007/s13201-024-02279-z

[33] Baez, J. C., Li, X., Libkind, S., Osgood, N. D., Redekopp, E., 2023. A categorical framework for modeling with stock and flow diagrams. In *Mathematics of Public Health: Mathematical Modelling from the Next Generation*, 175-207. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-40805-2_8

[34] De Assis, R. F., de Santa-Eulalia, L. A., Ferreira, W. D. P., Armellini, F., Anholon, R., Rampasso, I. S., Santos, J. G. C. L. D., 2021. Translating value stream maps into system dynamics models: a practical framework. *The International Journal of Advanced Manufacturing Technology*, 114(11), 3537-3550. https://doi.org/10.1007/s00170-021-07053-y

[35] Zeinalnezhad, M., Alavi, S., Mirmohammadsadeghi, S., Gunasekaran, A., Kabir, G., 2025. Circular economy modelling for healthcare waste management by integrating system dynamics and analytical network process. *Operations Management Research*, 1-26. https://doi.org/10.1007/s12063-025-00553-0

[36] Al-Kofahi, Z. G., Mahdavian, A., Oloufa, A., 2022. System dynamics modeling approach to quantify change orders impact on labor productivity 1: principles and model development comparative study. *International journal of construction management*, 22(7), 1355-1366. https://doi.org/10.1080/15623599.2020.1711494

[37] Meadows, D., 2008. Thinking in systems: International bestseller. Chelsea green publishing. Chelsea, Vermont, USA.

[38] Sterman, J., 2002. System Dynamics: systems thinking and modeling for a complex world. Massachusetts Institute of Technology. Massachusetts, USA.

[39] Naugle, A., Langarudi, S., Clancy, T., 2024. What is (quantitative) system dynamics modeling? Defining characteristics and the opportunities they create. *System Dynamics Review*, 40(2), e1762. https://doi.org/10.1002/sdr.1762

[40] Darabi, N., Hosseinichimeh, N., 2020. System dynamics modeling in health and medicine: a systematic literature review. *System Dynamics Review*, 36(1), 29-73. https://doi.org/10.1002/sdr.1646

[41] Ford, A., 2018. System dynamics models of environment, energy, and climate change. In *Encyclopedia of complexity and systems science*, 1-25. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-27737-5_541-4

[42] Sterman, J., Oliva, R., Linderman, K., Bendoly, E., 2015. System dynamics perspectives and modeling opportunities for research in operations management. *Journal of Operations Management*, 39, 1-5. https://doi.org/10.1016/j.jom.2015.07.001

[43] Vensim Ventana, (n.d). Vensim software: History. https://vensim.com/software/#History (accessed 01st July 2025)

[44] Isee Systes, (n.d). Isee systems software. https://www.iseesystems.com/ (accessed 01st July 2025)

[45] Anylogic (n.d). Why use simulation modelling?. https://www.anylogic.com/use-of-simulation/ (accessed 01st July 2025)

[46] Powersim (n.d). Powersim About us. https://powersim.com/about-us/ (accessed 01st July 2025)

[47] Insight Maker. Insight Maker System Dynamics. https://insightmaker.com/docs/systemdynamics (accessed 01st July 2025)

[48] Eberlein, R. L., Peterson, D. W., 1992. Understanding models with Vensim™. European journal of operational research, 59(1), 216-219. https://doi.org/10.1016/0377-2217(92)90018-5

[49] The Gold Standard Foundation, 2021. Methodology for retrofit energy efficiency measures in shipping; The Gold Standard Foundation: Geneva, Switzerland. Available online. https://globalgoals.goldstandard.org/standards/422_V2.0_TC_EE_Shipping_Retrofit-Energy-Efficiency-Measures-in-Shipping.pdf (accessed 31st May 2024).

[50] Psaraftis, H.N., 2019. Decarbonization of Maritime Transport: To Be or Not to Be? *Maritime Economics and Logistics*, 21, 353–371. https://doi.org/10.1057/s41278-018-0098-8

[51] Inal, O. B., 2024. Decarbonization of shipping: Hydrogen and fuel cells legislation in the maritime industry. *Brodogradnja*, 75(2), 1-13. https://doi.org/10.21278/brod75205

[52] Geng, X., Wen, Y., Zhou, C., Xiao, C., 2017. Establishment of the sustainable ecosystem for the regional shipping industry based on system dynamics. *Sustainability*, 9(5), 742, https://doi.org/10.3390/su9050742

[53] Kesieme, U., Pazouki, K., Murphy, A., Chrysanthou, A., 2019. Biofuel as an alternative shipping fuel: technological, environmental and economic assessment. *Sustainable Energy & Fuels*, 3(4), 899-909. https://doi.org/10.1039/C8SE00466H

[54] Bouman, E.A., Lindstad, E., Rialland, A., Strømman, A.H., 2017. State-of-the-art technologies, measures, and potential for reducing GHG emissions from shipping–a review. *Transportation Research Part D: Transport and Environment*, 52, 408–421. https://doi.org/10.1016/j.trd.2017.03.022

[55] Lu, D., Wang, A., Gan, H., Su, Y., Ao, X., 2025. A multi-objective collaborative optimization method of ship energy efficiency based on NSGA-II and TOPSIS. *Brodogradnja*, 76(3), 1-23. https://doi.org/10.21278/brod76301

[56] Joung, T.H., Kang, S.G., Lee, J.K., Ahn, J., 2020. The IMO initial strategy for reducing greenhouse gas (GHG) emissions, and its follow-up actions towards 2050. *Journal of International Maritime Safety, Environmental Affairs, and Shipping*, 4(1), 1-7. https://doi.org/10.1080/25725084.2019.1707938

[57] Psaraftis, H.N., Zis, T., 2021. Impact assessment of a mandatory operational goal-based short-term measure to reduce GHG emissions from ships: The LDC/SIDS case study. International Environmental Agreements: Politics, Law and Economics, 21, 445–467. https://doi.org/10.1007/s10784-020-09523-2

[58] Christodoulou, A., Cullinane, K., 2021. The fuel EU maritime policy and its implications for shipping decarbonization. *Marine Policy*, 131, 104620. https://doi.org/10.1016/j.marpol.2021.104620

[59] Parry, I., Heine, M.D., Kizzier, K., Smith, T., 2018. Carbon taxation for international maritime fuels: Assessing the options. *International Monetary Fund*, 2018(203). https://doi.org/10.5089/9781484374559.001

[60] Statista, 2024. Global maritime trade carried by containers 1980–2023. https://www.statista.com/statistics/253987/international-seaborne-trade-carried-by-containers/ (accessed 16 April 2024)

[61] Gunes, U., 2023. Estimating bulk carriers' main engine power and emissions. *Brodogradnja*, 74 (1), 85-98. https://doi.org/10.21278/brod74105

[62] The Network for Transport Measures, n.d. 7.3 Payload – Network for Transport Measures. https://www.transportmeasures.org/en/wiki/manuals/sea/payload/ (accessed 31st May 2024).

[63] The Network for Transport Measures, n.d. 7.4 Load capacity utilisation – Network for Transport Measures. https://www.transportmeasures.org/en/wiki/manuals/sea/load-capacity-utilisation/ (accessed 31st May 2024).

[64] Yüzbaşıoğlu, A.E., Tatarhan, A.H., Gezerman, A.O., 2021. Decarbonization in ammonia production, new technological methods in industrial scale ammonia production and critical evaluations. *Heliyon*, 7(10), e08257. https://doi.org/10.1016/j.heliyon.2021.e08257

[65] Di Micco, S., Cigolotti, V., Mastropasqua, L., Brouwer, J., Minutillo, M., 2024. Ammonia-powered ships: Concept design and feasibility assessment of powertrain systems for a sustainable approach in maritime industry. *Energy Conversion and Management: X*, 22, 100539. https://doi.org/10.1016/j.ecmx.2024.100539

[66] International Maritime Organization (IMO), 2022. Resolution MEPC.346(78): 2022 guidelines for the development of a ship energy efficiency management plan (SEEMP). IMO, London, UK.

[67] Ship & Bunker, 2025. World Bunker Prices, https://shipandbunker.com/prices. (accessed 10st July 2025)

[68] International Monetary Fund, 2024. Global price of LNG, Asia. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/PNGASJPUSDM (accessed 7th May 2024).

[69] ChemAnalyst, 2024. Methanol Prices Monitor News Market Analysis & Demand 2024. https://www.chemanalyst.com/Pricing-data/methanol-1 (accessed 22nd April 2024.

[70] Shiozawa, B. The Cost of CO_2-Free Ammonia. Ammonia Energy Association 2020. https://ammoniaenergy.org/articles/the-cost-of-co2-free-ammonia/ (accessed on 31 May 2024).

[71] International Maritime Organization (IMO), 2014. Resolution MEPC.245(66). IMO, London, UK. https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/MEPCDocuments/MEPC.245(66).pdf (accessed 31st May 2024).

[72] Lazarev, V. A., 2021. Development Trends of World Commercial Fleet during 2001-2018. *IOP Conference Series. Materials Science and Engineering*, 1079(6), 062092. https://doi.org/10.1088/1757-899X/1079/6/062092

[73] BRS Group, 2020. Shipping & Shipbuilding Markets 2020 Annual Review. https://www.isemar.org/wp-content/uploads/2020/07/brs_review_2020.pdf (accessed: 31st May 2024).

[74] Najeeb, N. P., 2016. The Design of a Containership Propulsion System. https://matheo.uliege.be/bitstream/2268.2/6199/1/PARAVILAYIL%20NAJEEB%20-%20Full%20Thesis%205th%20Cohort%2C%20Feb%202016%20%20%28UGAL%29.pdf (accessed: 31st May 2024).

[75] Fuel Consumption by Containership Size and Speed-The Geography of Transport Systems, 2022. The Geography of Transport Systems-The spatial organization of transportation and mobility. https://transportgeography.org/contents/chapter4/transportation-and-energy/fuel-consumption-containerships/ (accessed: 31st May 2024).

[76] Osipova, L., Georgeff, E., Comer, B., 2021. Global scrubber washwater discharges under IMO's 2020 fuel sulfur limit. *International Council on Clean Transportation Europe*, 10-12.

[77] Czermański, E., Oniszczuk-Jastrząbek, A., Spangenberg, E. F., Kozłowski, Ł., Adamowicz, M., Jankiewicz, J., Cirella, G. T., 2022. Implementation of the Energy Efficiency Existing Ship Index: An important but costly step towards ocean protection. *Marine Policy*, 145, 105259. https://doi.org/10.1016/j.marpol.2022.105259