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Policy implications of a weather-normalized indicator

Godet, Amandine Marie Clémence

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Monitoring Carbon Emissions of Ships – Policy implications of a weather-normalized indicator

Amandine Godet

PhD thesis – October 2023

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Author:	Amandine Godet
Supervisors:	Michael Bruhn Barfod, Associate Professor, DTU Management George Panagakos, Senior Researcher, DTU Management
University:	Technical University of Denmark
Department:	Department of Technology, Management and Economics
Division:	Division of Management Science
Address:	Akademivej Bygning 358, DTU 2800 Kgs. Lyngby, Denmark
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Summary

Maritime transportation is an essential pillar of modern societies, serving as the backbone of global trade. The shipping industry relies heavily on fossil fuels, significantly impacting the environment and contributing to climate change. The International Maritime Organization (IMO) has introduced a strategy to reduce greenhouse gas emissions from international shipping and decarbonize the industry to combat this issue. This strategy aims to accomplish energy efficiency gains, transition to alternative fuels, and implement market-based measures.

Various energy efficiency indicators are in use to monitor the performance of ships, both from technical and operational perspectives. Building upon previous research that identified shortcomings in these indicators, this thesis investigates alternative methods of assessing the energy efficiency of ships. Emphasizing the importance of a benchmarking tool, the primary objective of this thesis is to contribute to the policy debate on reducing emissions in international shipping by developing a comprehensive carbon intensity indicator.

The thesis comprises four articles addressing various approaches to monitoring ship carbon emissions. The first article focuses on the influence of weather conditions on a ship's energy efficiency, thereby contributing to the ongoing discussion on weather correction factors. Using model-based machine learning techniques, this article illustrates the diverse sea conditions encountered, their impact on energy efficiency, and the necessity of accounting for this diversity through multiple correction factors.

The second and third articles introduce and develop the concept of operational cycles for maritime transportation, drawing inspiration from the driving cycles employed in the automotive industry. The second article describes the process of generating operational cycles for the maritime sector as a novel

concept. It validates this concept using real-world data obtained from a fleet of container ships. Building upon this foundation, the third article extends the concept by elaborating more comprehensive cycles that better represent real-world indicators.

The fourth article explores voluntary reporting frameworks in the shipping industry. It focuses on the Clean Cargo case and investigates the needs and interests of its members regarding this private initiative and related reporting framework. The discussion revolves around the role of these voluntary frameworks as complementary approaches to regulatory frameworks towards maritime decarbonization.

Based on the methodology developments and analysis through the thesis, the following key findings and recommendations are presented:

- The weather impact on ships' fuel consumption prevents an accurate and real assessment of ships' efficiency. Multiple weather correction factors for energy efficiency indicators introduce a novel approach.

- Inspired by the automotive industry, maritime operational cycles improve the assessment of technical and operational aspects of a ship's energy efficiency. The cycles reduce the variability inherent to energy efficiency indicators and are suitable as benchmarking tools.

- Although the IMO regulatory framework remains at the core of the maritime decarbonization strategy, regional regulatory frameworks and private initiatives have demonstrated their capacity to enhance industry practices and facilitate regulatory developments.

This thesis contributes to enhancing carbon emissions monitoring in the maritime industry by introducing new methodologies and assessments. The resulting proposals are designed to enrich ongoing discussions within the IMO and complement the existing regulatory frameworks.

Resumé (Summary in Danish)

Maritim transport udgør en essentiel søjle i det moderne samfund og fungerer som rygraden i global handel. Shippingindustrien er stærkt afhængig af fossile brændstoffer, hvilket påvirker miljøet betydeligt og bidrager til klimaforandringer. Den Internationale Maritime Organisation (IMO) har introduceret en strategi for at reducere drivhusgasemissioner fra international shipping og af-karbonisere industrien for at bekæmpe dette problem. Strategien sigter mod at opnå højere energieffektivitet, en overgang til alternative brændstoffer, og implementering af markedsbaserede foranstaltninger.

Der anvendes forskellige indikatorer til at overvåge skibes energieffektivitet fra både tekniske og operationelle perspektiver. Denne afhandling, som viderebearbejder tidligere forskning, der har identificeret signifikante mangler i disse indikatorer, undersøger alternative metoder til at vurdere skibes energieffektivitet. Med fokus på vigtigheden af et benchmarking-værktøj er hovedmålet med denne afhandling at bidrage til politisk debat om at reducere emissioner inden for international skibsfart ved at udvikle en ny og mere retvisende indikator.

Afhandlingen består af fire artikler, der hver beskæftiger sig med forskellige tilgange til at overvåge skibes kulstofemissioner. Den første artikel fokuserer på vejrbetingelsernes indflydelse på et skibs energieffektivitet og bidrager dermed til den igangværende diskussion om vejrkorrektionsfaktorer. Ved hjælp af modelbaseret machine learning illustrerer artiklen de forskellige vejrforhold, der opleves, deres indvirkning på energieffektiviteten og nødvendigheden af at tage højde for dette gennem flere korrektionsfaktorer.

Anden og tredje artikel introducerer begrebet operationelle cyklusser for maritime transport, hvilket er inspireret af de kørecyklusser, der anvendes i bilindustrien. Som et nyt koncept beskriver den anden artikel processen med at

genererere operationelle cyklusser for den skibe. Konceptet valideres igennem data indsamlet for en større flåde af containerskibe. Baseret på det grundlæggende princip om de operationelle cyklusser, udvider den tredje artikel konceptet ved at udarbejde mere omfattende cyklusser, der giver en bedre repræsentation af de reelle indikatorer. Endelig undersøger den fjerde artikel af-karbonisering af shipping fra interessenters perspektiv og udforsker, hvordan frivillige ordninger kan lette fremskridt inden for industrien.

Den fjerde artikel udforsker frivillige rapporteringsrammer i shippingindustrien. Den fokuserer på Clean Cargo-sagen og undersøger medlemmernes behov og interesser vedrørende dette private initiativ og tilhørende rapporteringsramme. Diskussionen drejer sig om disse frivillige rammers roller som komplementære tilgange til lovgivningsrammer for maritim af-karbonisering. Baseret på afhandlingens metodeudviklingen og analyse præsenteres følgende nøgleresultater og anbefalinger.

- Vejrpåvirkningen på skibes brændstofforbrug forhindrer en nøjagtig og reel vurdering af skibes effektivitet. Flere vejrkorrektionsfaktorer for energieffektivitetsindikatorer introducerer en ny tilgang.

- Inspireret af bilindustrien, forbedrer maritime driftscyklusser vurderingen af tekniske og operationelle aspekter af et skibs energieffektivitet. Cyklusserne reducerer variabiliteten, der er forbundet med energieffektivitetsindikatorer, og er velegnede som benchmarkingværktøjer.

- Selvom IMO-lovgivningsrammen forsat er kernen i den maritime af-karboniseringsstrategi, har regionale reguleringsrammer og private initiativer vist deres evne til at forbedre industripraksis og lette lovgivningsudviklingen.

Denne afhandling bidrager til at forbedre overvågningen af CO2-emissioner i den maritime industri ved at introducere nye metoder og vurderinger. De resulterende forslag er designet til at berige igangværende diskussioner inden for IMO og supplere de eksisterende lovgivningsrammer.

Preface

The following thesis completes my Ph.D. study entitled "Monitoring Carbon Emissions of Ships - Policy implications of a weather-normalized indicator." The study was conducted at the Division of Management Science, Department of Technology, Management and Economics at the Technical University of Denmark (DTU) to partially fulfill the requirements for acquiring the Doctor of Philosophy (Ph.D.) degree in Engineering.

The Danish Maritime Fond financially supported the thesis under the *Normalized Indicator for Carbon Emissions of ships (NICE)* project. I conducted the research between August 2020 and October 2023 under the supervision of Associate Professor Michael Bruhn Barfod and Senior Researcher George Panagakos. I also went for a research stay at the *Tyndall Centre for Climate Change Research*, University of Manchester, UK, between September and December 2022.

The thesis consists of an introduction and four research chapters. The introduction serves as the thesis guideline, introducing the context and motivations of the project and providing the thesis outline and conclusions. The research chapters consist of two chapters based on published academic papers and two others on submitted academic papers to international peer-reviewed journals. The four research chapters are co-authored and are each self-standing, with an introduction, conclusion, and separate bibliographies.

Kgs. Lyngby, October 2023

Amandine Godet

Acknowledgements

This Ph.D. journey has been an exciting and challenging experience. It started at a peculiar moment, in between lockdowns due to the pandemic in 2020, which made my first year of study a weird mix of online teaching and conferences, with fewer opportunities to meet colleagues, fellow Ph.D. students, and partners from the industry. Nevertheless, the next two years offered more opportunities for meeting people, traveling, and discussing my work. I have met many inspiring and highly skilled researchers who helped me in my work, and I am grateful for this journey.

I want to thank the people who have helped me during this project's three years; without their support, this thesis would not have been possible. First of all, I would like to thank my two supervisors, Associate Professor Michael Bruhn Barfod and Senior Researcher George Panagakos, for giving me the opportunity to pursue a Ph.D. study and trusting me to be skilled for the job. Thanks to George for his detailed feedback and great expertise from his many experiences and past positions, which were valuable and necessary. Special thanks go to Michael for his kindness, support, and listening ear, on top of his excellent academic skills. I would not have been through this journey without their complementary skills, and I thank Michael and George immensely.

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My thanks also go to my co-authors, starting with Professor Elizabeth Lindstad. I thank her for a great collaboration in the last months of my Ph.D. and for her valuable work in the field, which has guided me through my studies. I also had the chance to supervise Lukas Wallner, Jonas Thoustrup Saber, and Jacob Nurup, and their dedicated and serious work helped me significantly in my research.

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I am grateful to my colleagues at the Management Science division at DTU Management. To Christina Scheel Persson and Katrine Heide Sørensen for their great help with all the administrative processes. Big thanks to my office-mates Alastair, Baptiste, Bernardo, and Gaspard, with whom I shared most of the roller-coaster experience of the Ph.D. and who have always been cheerful and helpful. They made a solid foundation for my everyday Ph.D. life. To Alberto, Ali, and Sotiria for being great office-mates in the last months.

The Clean Cargo and BSR teams, among which I did an internship before starting my Ph.D., also deserve to be mentioned here. I learned a lot during the five months of my internship, where I was introduced to the maritime sector. Special thanks to Victor Gancel, my manager and mentor, who encouraged me to pursue this Ph.D. project.

Then, I would like to express my gratitude to the association *The Shifters* and all its members for being so committed and inspiring. It has been a comforting shelter to have this group of like-minded people. Special thanks to the collective "Une vision pour demain" for all our great moments, especially to Clément for his great friendship. Thanks to the *Climate Fresk* team for the great moments and commitment to spreading climate awareness in Denmark. I have grown in many aspects with these years of associative experience, and it now occupies an essential part of my life.

Regarding another significant part of my life, I thank my fellow training mates from AFUK, Pole Republic, and Akroyoga København. Many of them became my friends here in Denmark. I also had the opportunity to start teaching my passion for circus, which has been a rewarding experience. Thanks to Vivi and Maibrit for their trust and mentorship and Klaus for being a fabulous co-teacher and training partner. Warmest thanks to Aurélie, who believed in me in the first place and had a decisive impact on my life. Thanks also to all my students for their warm welcome, positive feedback, and attitude, who helped me grow as a teacher.

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List of Acronyms

The following abbreviations, presented alphabetically, are employed multiple times throughout this thesis. Their full name introduces them for their first occurrence in each chapter. The list is provided for the reader's convenience if a quick reminder of any abbreviation becomes necessary.

AE Auxiliary engine

AER Annual Efficiency Ratio

BF Beaufort

CFD Computational Fluid Dynamics

cgDIST Cargo-distance

CII Carbon Intensity Indicator

CSR Corporate Social Responsibility

DCS Data Collection System

DWT Deadweight

EEDI Energy Efficiency Design Index

EEOI Energy Efficiency Operational Index

EEXI Energy Efficiency eXisting ship Index

elpd Expected log pointwise predictive density

EMS Environmental Management System

ETS Emissions Trading Scheme

EU European Union

GAM Generalized additive model

GFS GHG Fuel Standard

GHG Greenhouse gas

GT Gross tonnage

HDV Heavy-Duty Vehicles

IMO International Maritime Organization

LNG Liquefied natural gas

MARPOL International Convention for the Prevention of Pollution from Ships

MBM Market-Based Measure

MCR Maximum Continuous Rate

ME Main engine

MEPC Marine Environment Protection Committee

MRV Monitoring Reporting and Verification

NEDC New European Driving Cycle

NICE Normalized Indicator for Carbon Emissions of ships

PM Particulate matter

SDG Sustainable Development Goal

SEEMP Ship Energy Efficiency Management Plan

TEU Twenty-foot Equivalent Unit

TTW Tank-to-wheel

UN United Nations

UNFCCC United Nations Framework Convention on Climate Change

US United States

VECTO Vehicle Energy Consumption Calculation Tool

WLTC World harmonized Light vehicles Test Cycles

WTW Well-to-wheel

1 Introduction and thesis outline

Climate change is one of the most significant challenges humanity faces. Global climate action started in the 1990s, with the creation of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 and its operationalization in 1997 by ratifying the Kyoto Protocol (UN, 1997). In 2015, the UNFCCC ratified the Paris Agreement, a legally binding treaty aiming to hold 'the increase in the global average temperature to well below 2°C above pre-industrial levels' and pursue 'efforts to limit the temperature increase to 1.5°C above pre-industrial levels' (UNFCCC, 2015). The same year, the United Nations (UN) introduced the 17 Sustainable Development Goals (SDGs) in its 2030 Agenda for Sustainable Development and included a specific Goal on Climate Action (UN General Assembly, 2015).

The maritime industry plays a foundational role in the global transportation of goods and is crucial for modern societies and industries. However, it mainly relies on fossil fuels, the combustion of which results in greenhouse gas (GHG) emissions that contribute to global warming. Shipping GHG emissions accounted for 1,076 million tons-CO_2e in 2018, being 2.89% of the GHG anthropogenic emissions (Faber et al., 2020). The emissions accounted for 977 million tons in 2012, representing a 9.6% increase in six years (Faber et al., 2020). Recent studies have expected this number to grow in the coming decades, with an estimated increase of 90-130% in 2050 compared to 2008 levels (Faber et al., 2020). The United Nations Conference on Trade and Development forecasts an annual growth of 2.1-2.2% for the seaborne trade in the coming years and around 3% for the containerized trade (UNCTAD, 2023).

The expected shipping emissions increase combined with the climate urgency put a strong imperative for the maritime industry to decarbonize. To deal with this enormous challenge, the International Maritime Organization (IMO) (the UN organization for maritime-related matters) adopted in 2018 its *Initial* *strategy on reduction of GHG emissions from ships*, revised in 2023 (IMO, 2018, 2023a). Through a number of short–, medium– and long-term measures, the IMO Member States intend to decarbonize the shipping industry by or around 2050.

In the context of decarbonizing the shipping industry, this PhD thesis focuses on measuring and assessing ships' carbon emissions and energy efficiency. The overall objective is to contribute to the policy debate on reducing emissions in international shipping by developing a comprehensive carbon intensity indicator.

This chapter introduces background information on the maritime sector (Section 1.1), looking at the shipping emissions and energy efficiency (Section 1.1.1) and the weather impact on efficiency (Section 1.1.2). It also introduces the policy frameworks for the decarbonization of the shipping industry (Section 1.1.3), along with private initiatives and voluntary frameworks (Section 1.1.4). Section 1.2 then formalizes the scope and research objectives of this Ph.D. thesis, while Section 1.3 describes each chapter's dissemination and scientific contributions. The conclusions of the thesis are exposed in Section 1.4, along with directions for future research.

1.1 Background

Maritime transportation is nowadays the backbone of the global trade. While shipping has always been essential for transporting goods, containerization in the latter half of the previous century significantly intensified maritime transportation (Levinson, 2016). Ships now transport more than 80% of global trade (UNCTAD, 2022). Maritime transportation can be divided into international and domestic shipping (Faber et al., 2020). This thesis only deals with international shipping. Among the many ship types existing in international shipping (e.g., tankers, cruise ships, Roll-on Roll-off ships), the three major ones in fuel consumption are container ships, bulk carriers, and oil tankers (Faber et al., 2020). For their significant role and proximity to end consumers, container ships are the main focus of this thesis.

Container shipping is a significant segment of international shipping. While it transported around 65 million Twenty-foot Equivalent Unit (TEU) in 2000, it increased to approximately 163 million of TEU in 2022, as shown in Figure 1.1 (UNCTAD, 2023). While the long-term growth rate was around 7% for the past three decades, it has dropped to 1 to 3% in the last few years due to the COVID-19 pandemic and Ukraine war, and a rate of around 3% is expected for the coming years (UNCTAD, 2023).

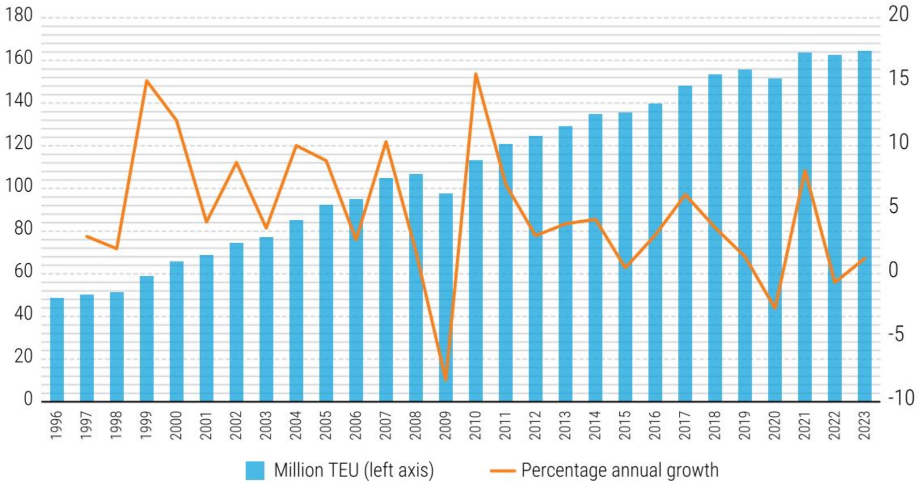

Figure 1.1: Global containerized trade, 1996-2023. Source: UNCTAD (2023)

The UN established the IMO in 1948, which entered into force in 1958. This international body aims to regulate maritime transportation for 'safe, secure and efficient shipping on clean oceans' (IMO, 2013). The International Convention for the Prevention of Pollution from Ships (MARPOL) is the main regulatory instrument to prevent pollution by ships, including Annex VI, which covers air pollution from ships (i.e., sulfur and nitrogen oxides, particulate matter). Annex VI entered into force in 2005, supplemented in 2011 with a chapter on energy efficiency measures for reducing GHG emissions from ships. The following section gives an overview of the carbon emissions from ships, while Section 1.1.3 further elaborates on energy efficiency measures and the policy framework.

1.1.1 Shipping emissions

As previously introduced, international shipping is responsible for approximately 3% of anthropogenic GHG emissions due to the sector's dependence on heavy fuel oil as the main fuel used (Faber et al., 2020). The fuel combustion releases different gases, including carbon dioxide (CO_2), sulfur oxide (SO_X), nitrogen oxide (NO_X), particulate matter (PM), and various other exhaust gases. SO_X, NO_X and PMs are air pollutants harmful to human health. Regulations have been developed to reduce the emissions of these pollutants. A limit of 0.5% m/m (mass by mass) sulfur present in the fuels has been introduced since the 1^{st} of January 2020. This limit falls to 0.1% m/m in Emission Control Areas (ECAs) (IMO, 2019). NO_X depend on the combustion temperature (Faber et al., 2020) and are regulated under the NO_X Technical Code 2008, with stricter requirements in ECAs (IMO, 2014). As PMs correlate with fuel sulfur content, the sulfur regulation indirectly limits the PM emissions (Faber et al., 2020).

On climate pollutants, Faber et al. (2020) list the following GHG emitted during fuel combustion: CO_2, methane (CH_4), nitrous oxide (N_2O), carbon oxide (CO), Black Carbon (dependent on the fuel type, engine type, and engine load). Besides, the following GHG can be emitted onboard: hydrofluorocarbon (HFC) from refrigeration systems, perfluorocarbon (PFC) used in firefighting foams (now prohibited by the Montreal Protocol), sulfur hexafluoride (SF_6), nitrogen trifluoride (NF_3) and non-methane volatile organic compound (NMVOC) (Faber et al., 2020). SF_6 and NF_3 leakages are judged negligible, while HFCs and NMVOCs are unrelated to fuel combustion. The climate impact of all these gases depends on their global warming potential and their lifetime in the atmosphere. By definition, CO_2 is the reference (global warming potential equal to one), and the potential of other gases is estimated as CO_2-equivalent. For oil and diesel fuels, CO_2 accounts for the most significant global warming potentials, both from tank-to-wheel (TTW) (during the combustion phase) and well-to-wheel (WTW) (from the extraction to the combustion) emissions (Comer and Osipova, 2021).

While some research estimates the overall emissions the shipping industry generates (e.g., Faber et al. (2020)), this thesis primarily focuses on comparing emissions among various ships. As a result, we typically only consider CO_2

emissions by using its emission factor (e.g., 3.114 grams of CO_2 per gram of heavy fuel oil). Accounting for all GHG emissions would change the absolute figures when assessing global warming potentials over 20 or 100 years. However, this would not affect the relative values or energy efficiency evaluation.

There are three ways to reduce GHG emissions from shipping: improve the energy efficiency of ships (using less fuel for the same transport work), switch to decarbonized fuels and energy sources, and reduce the transport work (the amount of cargo transported, and the distances covered). Regarding the latter point, it extends beyond the scope of the shipping industry alone, as global cargo transport depends on the requirements of other sectors. Nevertheless, the *Review of Maritime Transport 2023* noted that ’on the supply side, container shipping may have entered an overcapacity phase, meaning that carriers will aim at managing capacity using tools such as slippage, idling of vessels or demolition,’ showing the dependency with the other sectors (UNCTAD, 2023). Regarding the transition to alternative fuels and energy sources, stakeholders actively discuss and examine various available fuel options, their associated technologies, supply chains, safety considerations, and future costs (see, e.g., Kołakowski et al. (2022); Lagouvardou et al. (2023); Rivarolo et al. (2023)).

The definition of ships’ energy efficiency relates to the amount of energy required to transport a specific quantity of cargo across a specified distance. In the context of decarbonization, it can be characterized as the carbon emissions associated with a particular transport work (cargo shipment over a defined distance). This definition aligns with the one of the Energy Efficiency Operational Index (EEOI), expressed in CO_2 emissions per ton-mile. Nonetheless, the precise tonnage of cargo on board is often considered sensitive commercial information. Consequently, the energy efficiency is commonly estimated using the ship’s deadweight (DWT), becoming the Annual Efficiency Ratio (AER). Chapters 3 and 4 dive deeper into these energy efficiency indicators with their definition, advantages, and flaws.

Figure 1.2 shows the GHG emissions of international shipping, which have increased since 1990 with a peak in 2008. The financial crisis of the late 2000s led to higher fuel prices, causing ships to slow down, a practice known as ’slow steaming.’ Consequently, due to the cubic relation between speed and fuel consumption, the GHG emissions decreased for the same transport work (Cariou, 2011; Psaraftis and Kontovas, 2013).

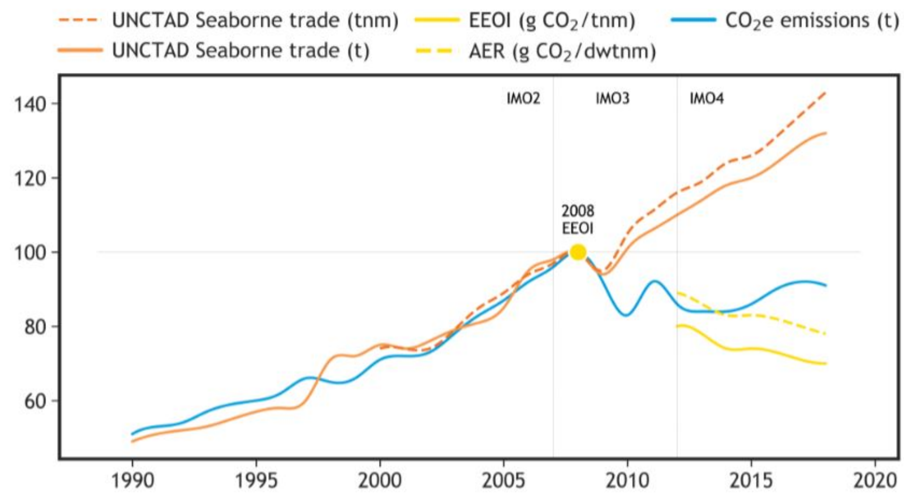

Figure 1.2: International shipping GHG emissions and trade metrics, indexed in 2008, for the period 1990-2018, according to the voyage-based allocation of international emissions. Source: Faber et al. (2020)

The energy efficiency indicators (EEOI and AER) demonstrate enhanced efficiency resulting from ongoing advancements in both technical and operational aspects and the deployment of bigger ships. The discussion on efficiency improvements has been a subject of interest among policymakers for over a decade (see Section 1.1.3). Efficiency depends on many factors, including external parameters that operators cannot control, with weather conditions being one of these significant factors, further discussed in Section 1.1.2.

1.1.2 Weather impact on efficiency

Weather and sea conditions significantly impact ships' fuel consumption. Indeed, the added resistance from waves and wind compared to calm sea conditions increases the required power and thus impacts energy efficiency. Although calm seas are relatively infrequent, calculating ship resistance in calm water is usually a reference point for assessing ships' efficiency. To estimate the weather impact, Faber et al. (2020) adopted the value found by Prpić-Oršić and Faltinsen (2012), who modeled a container ship in the North Atlantic. They assume an additional power requirement of 15% (referred to as the sea margin) compared to theoretical propulsion requirements and consider this value to be 10% for coastal ships.

The weather effect consists of more than waves and wind. Additional parameters include currents, water depth, air and sea temperatures, and sea salinity. Directions also matter for waves, wind, and currents, as the wind from the stern can decrease fuel consumption while the headwind increases it. Different types of waves can also be studied: wind waves, caused by local wind, and swells, which are waves transported over a long distance (Toffoli and Bitner-Gregersen, 2017).

Weather and sea conditions have been described and categorized using different scales to include these aspects. The Beaufort scale classifies sea states based on wind speed, ranging from calm (0 on the scale, with an average wind velocity below 1 knot) to hurricane conditions (12 on the scale, over 64 knots), with middle conditions being a strong breeze (6 on the scale, averaging 22-27 knots) (ISO, 2015). From a more theoretical approach, irregular waves (as opposed to regular waves, described as sinusoids) are usually characterized by wave energy spectra of different types (e.g., Bretschneider, Pierson-Moskowitz) and parameters (significant wave height and peak period) (Stansberg et al., 2002).

The study of the weather impact on ship added resistance, speed loss, or fuel consumption usually approaches the problem either theoretically or empirically. Among theoretical studies, different methods exist for the calculation of the calm water resistance (e.g., Holtrop and Mennen method used in Lu et al. (2015), Guldhammer and Harvald's method used in Taskar and Andersen (2020)), the calculation of the added resistance in waves (e.g., Gerritsma and Beukelman used in Bøckmann and Steen (2016) and Tezdogan et al. (2016), Kwon's method (Kwon, 2008) used in Medina et al. (2020)), the use of Computational Fluid Dynamics (CFD) (e.g., used in Yoo et al. (2020), Cho et al. (2023) and Islam and Guedes Soares (2022)), and much more. Regarding empirical studies, the interest in machine learning models using actual operational data is growing, especially in neural networks (e.g., Bal Beşikçi et al. (2016); Bassam et al. (2023); Cepowski and Drozd (2023); Senteris et al. (2019); Tarelko and Rudzki (2020); Valčić et al. (2020)).

Weather conditions at sea can be somewhat predicted, with global models utilizing historical data to provide estimates for most regions across the globe. Among databases commonly employed in research, the European Centre for Medium-Range Weather Forecasts, particularly its ERA5 model (fifth generation atmospheric reanalysis of the global climate), includes wave and wind information dating back to 1940, with a resolution of 30km (ECMWF, 2023). Additionally, the Global Wave Statistics database, as introduced by Hogben (1988), finds application in various studies such as those by Riesner and el Moctar (2018), Degiuli et al. (2019) and Prpić-Oršić and Faltinsen (2012). These worldwide databases are essential for statistics across different regions, as Figure 1.3 illustrates. For example, the averages reveal that the North Atlantic and Pacific experience more severe conditions than the South Atlantic and Pacific. Seasonal variations also play a role, typically resulting in calmer sea conditions during the summer months (MAN Energy Solutions, 2018).

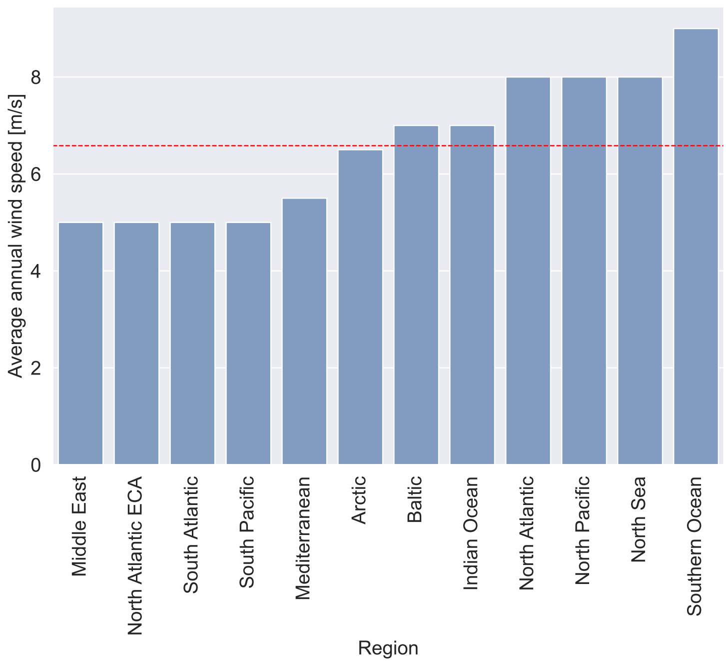

Figure 1.3: Average wind speeds in different sea regions. The red dashed line indicates the average value. Source: own representation based on Rehmatulla et al. (2017)

Nevertheless, weather forecasts and hindcast data (historically analyzed data) come with some uncertainties. For example, Vettor and Guedes Soares (2022) highlighted the importance of accounting for uncertainties when estimating the performance of ships in seaways, especially when using weather forecasts for route planning. Research is ongoing to improve these models, such as Mounet et al. (2023), who used ships as wave buoys to improve the reliability and availability of regional sea state information. Chen et al. (2020) compared the accuracy of two of these databases (European Centre for Medium-Range Weather Forecasts (ECMWF) and National Centers for the Environmental Prediction (NCEP)) on eight routes and found that the NCEP showed better results for higher wind speeds.

Furthermore, weather and sea conditions affect different types of ships in varying ways. For instance, with their superstructure and container layout, container ships are more susceptible to additional wind resistance. For example, Andersen (2013) found that variations in the height of container bays increased the longitudinal force caused by the wind. Due to the complexity of wind resistance calculations, Valčić et al. (2020) proposed a pattern recognition method that uses images of various cargo layouts to estimate the wind loads on ships.

Due to the added resistance from waves and wind resulting in additional fuel consumption, a great interest in weather routing algorithms has emerged in the past years, enhanced by the development of machine learning techniques, data availability, faster calculation potentials, and the improvements of weather forecast models. Ship weather routing can be defined as 'the development of an optimum sailing course and speed for ocean voyages based on nautical charts, forecasted sea conditions, and possibly the individual characteristics of a ship for a particular transit' (Simonsen et al., 2015). In their bibliometric review of route optimization in maritime transportation, Mollaoglu et al. (2023) showed the importance of routing under different weather conditions. Grifoll et al. (2022) implemented a comprehensive software for weather routing, using the wave predictions of Copernicus Marine Environment Monitoring Service. Regarding other examples of applications, Ormevik et al. (2023) looked at a scheduling problem for a given route and optimized the speed with the weather. Ulsrud et al. (2022) introduced a time-dependent routing problem to account for the changes in weather forecasts. Although weather routing algorithms play an essential role in enhancing the operational efficiency of ships, they fall beyond the scope of this thesis.

In conclusion, the impact of weather on ships varies significantly across regions, ship layouts, and seasons. The calculation of these ships' energy efficiency depends significantly on weather conditions. To establish a benchmark for ships' energy efficiency unaffected by these variations, it is necessary to nullify these weather-related influences. Chapter 2 addresses this specific challenge.

1.1.3 Policy frameworks for reduction of carbon emissions

The IMO is the main regulatory body for shipping transportation and the only one to apply to all ships globally. Within the IMO, the Marine Environment Protection Committee (MEPC) is in charge of the environmental issues, including air pollutants and GHG emissions, covered by the MARPOL treaty. The committee usually convenes twice a year, and several working groups treat different subjects. The MEPC 80^{th} session marked a big step in the decarbonization journey, with the adoption of the 2023 IMO strategy on reduction of GHG emissions from ships (IMO, 2023a), revising its 2018 version (IMO, 2018). The strategy will be revised again in 2028. This strategy also falls in the broader context of the UN 2030 Agenda for Sustainable Development (IMO, 2023a). The 2023 IMO GHG strategy includes four levels of ambition, as follows:

1. reduce the carbon intensity of ships by improving the energy efficiency;
2. reduce 'CO_2 emissions per transport work, of international shipping, by at least 40% by 2030, compared to 2008;'
3. increase the 'uptake of zero or near-zero GHG emission technologies, fuels and/or energy sources to represent at least 5%, striving for 10%, of the energy used by international shipping by 2030;'
4. peak GHG emissions as soon as possible and 'reach net-zero GHG emissions by or around, i.e., close to, 2050, taking into account different national circumstances.'

Additionally, two indicative checkpoints have been established to assess the progress toward achieving the net-zero trajectory (IMO, 2023a):

1. 'reduce the total annual GHG emissions from international shipping by at least 20%, striving for 30%, by 2030, compared to 2008;'

2. ’reduce the total annual GHG emissions from international shipping by at least 70%, striving for 80%, by 2040, compared to 2008.’

Regarding the first level of ambition, the IMO aims to strengthen ships’ energy efficiency design requirements. In 2011, the IMO adopted the first set of international mandatory measures to enhance ships’ energy efficiency, which included the Energy Efficiency Design Index (EEDI) and the Ship Energy Efficiency Management Plan (SEEMP). The EEDI sets specific efficiency standards for new ships, while SEEMP aims to monitor and improve the operational efficiency of ships. The EEDI requirements have different phases, progressively introducing stricter efficiency standards. Figure 1.4 shows the timeline for the different mandatory measures, with their implementation and the EEDI phases. The figure also displays the implementation of the IMO Data Collection System (DCS), which requires a yearly reporting of fuel consumption for each ship over 5,000 gross tonnage (GT) (IMO, 2016).

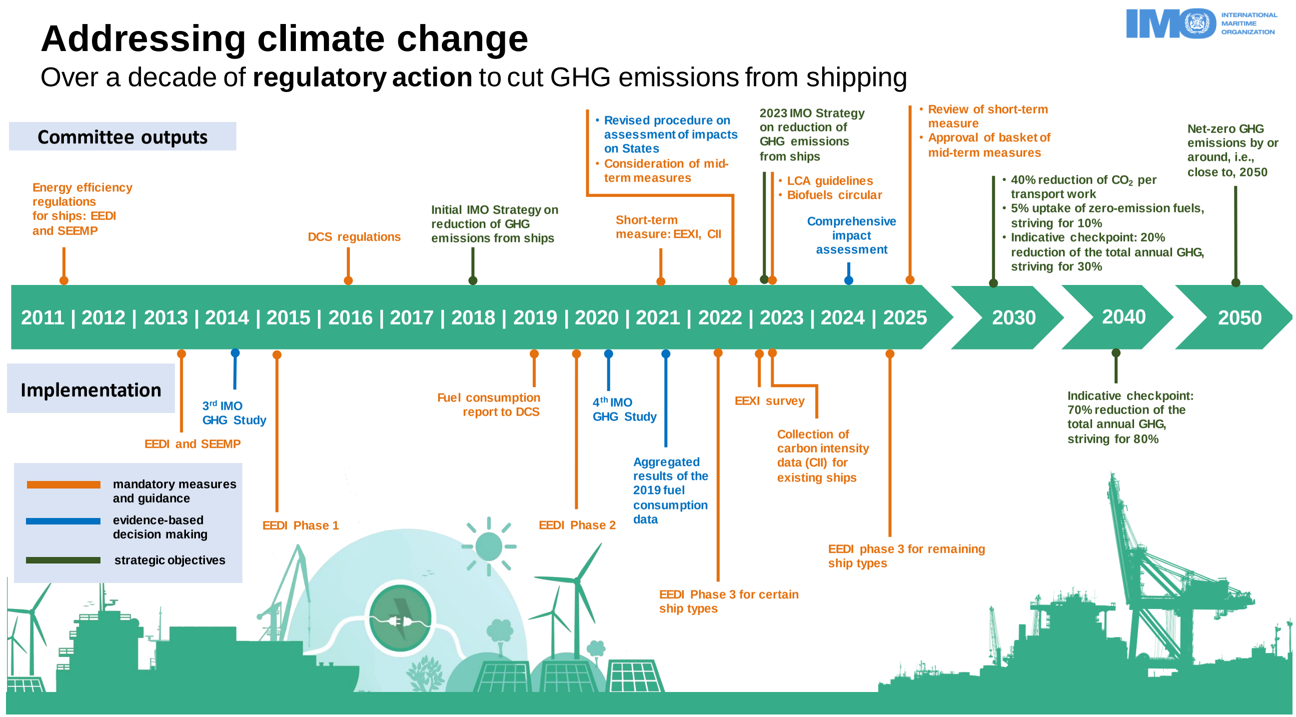

Figure 1.4: Overview of IMO regulatory action to cut GHG emissions from shipping. Source: IMO (2023c)

As part of its GHG reduction strategy, the IMO adopted short-term measures in 2021, introducing the Carbon Intensity Indicator (CII) and the Energy Efficiency eXisting ship Index (EEXI) and strengthening the SEEMP. The EEXI, with a similar formulation to EEDI, set energy efficiency requirements for all existing ships as of the 1^{st} of January 2023. These new requirements lead to adopting different compliance options, such as power limitation and wind assistance, as shown in Figure 1.5. The CII is an annual operational efficiency rating system using a scale from A to E. The initial ratings are scheduled to be issued starting in 2024, based on 2023 data. Ships receiving an E rating for one year or a D rating for three consecutive years must submit a corrective action plan. Stakeholders, e.g., administrations and port authorities, are encouraged to provide incentives to ships rated A or B. The required CII thresholds will progressively decrease by 2% each year between 2023 and 2027. This reduction aims to raise energy efficiency standards and enhance compliance options, e.g., speed optimization and biofouling management (see Figure 1.5).

Returning to Section 1.1.2, the weather plays an ongoing role in the policy discussions regarding energy efficiency indicators. A weather correction factor, f_w, was introduced for the EEDI (alongside other correction factors) to account for the sea conditions, different from the calm water conditions specified for the EEDI baseline and trial tests. There is no mandatory requirement to apply the correction factor, but comprehensive guidelines have been developed for its calculation (IMO, 2012). Discussions regarding including weather corrections for the CII are also ongoing, with final decisions on the compulsory adoption of such factors yet to be made. Chapter 2 details the discussions on the weather correction factors more thoroughly.

Apart from the short-term measures, the IMO introduced medium- and long-term measures during MEPC 76. The basket of medium-term measures first consists of an economic element, namely Market-Based Measures (MBMs), which are environmental policies relying on the 'polluter-pays' principle. These measures can take various forms, such as carbon taxes, Emissions Trading Scheme (ETS), or offsetting mechanisms. Additionally, a technical component involves the establishment of goal-based fuel standards to reduce the GHG intensity of marine fuels. Among other potential mid-term GHG reduction measures are better data utilization through the IMO DCS mechanism for informed policymaking, as well as the development of life-cycle assessment guidelines to steer the adoption of zero or near-zero GHG emission fuels and

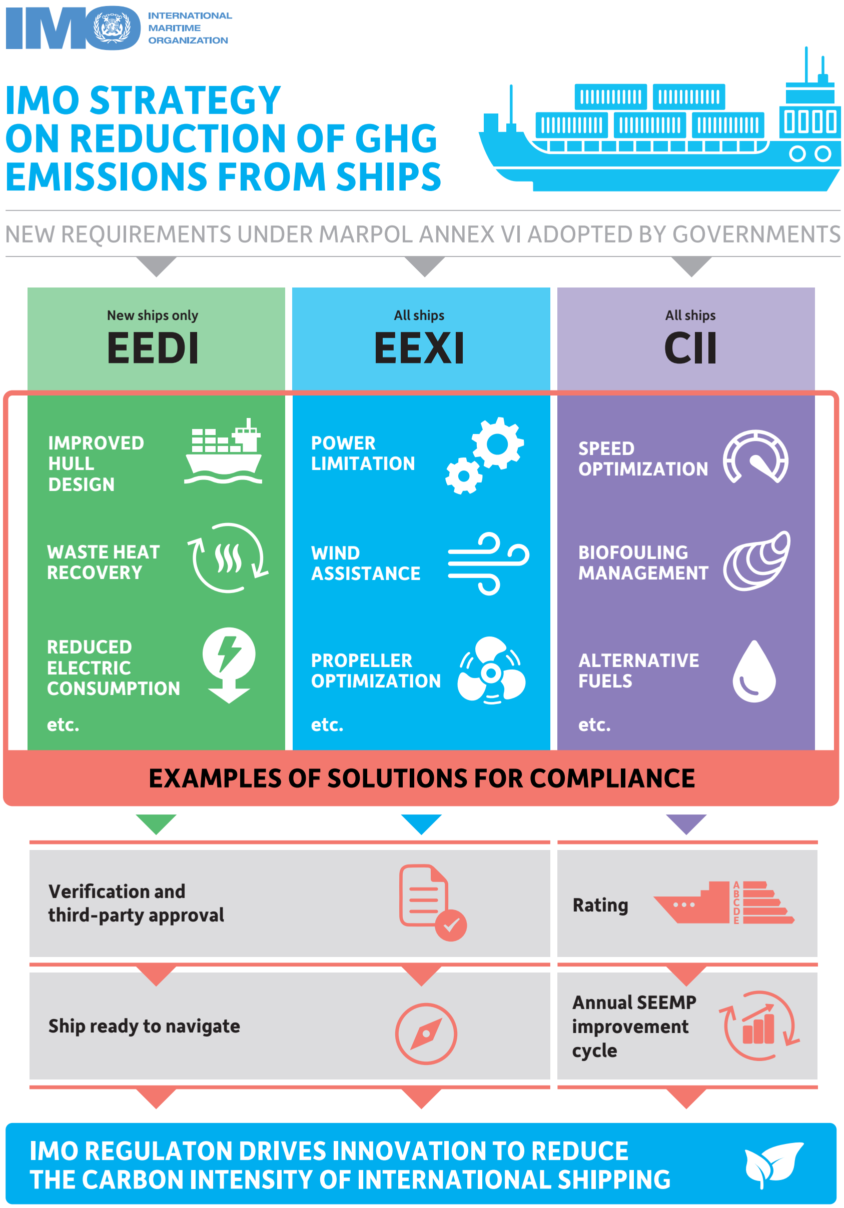

Figure 1.5: Overview of IMO energy efficiency and carbon intensity requirements. Source: IMO (2023b)

energy sources.

Despite a more ambitious 2023 IMO GHG revised strategy, it remains uncertain whether the IMO targets will be sufficient to align with the Paris Agreement's goal of limiting global warming to below 1.5°C with a 50% likelihood. According to Bullock et al. (2021), achieving this objective would demand a 34% reduction of absolute GHG emissions from the 2008 level by 2030. Although the target of achieving net-zero emissions by 2050 has been established, the rate of decarbonization is a critical factor in ensuring compatibility with the global carbon budget (Bullock et al., 2021).

Furthermore, Bach and Hansen (2023) highlights the IMO's lack of comprehensive policy for the decarbonization of the shipping industry and identifies three challenges in implementing stricter regulations: 1. insufficient capacity to regulate multiple emerging fuels and technologies after decades of handling only one fuel type; 2. uncertainty surrounding the IMO's regulatory mandate, historically focused solely on technical aspects; 3. a lack of political consensus during negotiations. Additionally, Cariou and Randrianarisoa (2023) observes a lack of diversity in stakeholder participation (among member states, inter-governmental and non-governmental organizations).

Baumann (2023) observed an increased attendance by delegations at the MEPC compared to the general attendance at IMO meetings. This suggests a growing interest in environmental matters, particularly GHG-related issues. The four main contributors to MEPC submissions are Japan, Norway, the United States, and Germany, and some countries have emerged more recently in the discussions (Denmark, the Netherlands, China, Marshall Islands) (Baumann, 2023; Cariou and Randrianarisoa, 2023). Cariou and Randrianarisoa (2023) found that around 52% of the submissions originate from Europe. This emphasizes a strong commitment and capacity from certain countries to make significant contributions, aligning with the emergence of regional policies in these regions.

Regional regulatory frameworks have emerged in the past decade to address the challenges encountered by the IMO in advancing decarbonization regulations. The European Union (EU) developed a set of policies to regulate ships' emissions and pursue a decarbonization strategy. Preceding the IMO DCS, the EU Monitoring Reporting and Verification (MRV), adopted in 2015, is a mechanism for collecting and analyzing data on fuel consumption and emissions from ships traveling to, from, or within the EU (EU, 2015). Although the European scheme provides more transparency than the IMO's, it can introduce regional biases that reduce 'the practical values of the published metrics' (Panagakos et al., 2019). In fact, Panagakos et al. (2019) discovered that the same ships emitted 38.4% more per transport work outside the EU, most likely driven by a better capacity utilization within the EU. Additionally, the EU included maritime transportation in its EU ETS in 2023 (EU, 2023a). However, Lagouvardou and Psaraftis (2022) highlighted the risk of leakage and transshipment to non-EU ports, potentially leading to increased GHG emissions. Nevertheless, while expressing some reservations about the scheme, Cariou et al. (2021) demonstrated that the inclusion of maritime shipping in the EU ETS has a substantial impact and provides incentives for industry players to transition toward less carbon-intensive fuels and technologies.

Concerning the adoption of zero and near-zero GHG fuels, the EU introduced its FuelEU Maritime initiative, scheduled to become effective in 2025, as part of the broader *Fit for 55* package (i.e., EU legislation with proposals to reduce GHG emissions by at least 55% by 2030). The objective is to gradually reduce the GHG intensity of maritime fuels, adopting a life-cycle perspective (EU, 2023b). Malmborg (2023) recognized this as a significant policy change, emphasizing the EU's role in advancing shipping decarbonization. Both Cariou et al. (2021) and Malmborg (2023) acknowledged the EU's capacity to drive policy initiatives and pave the way for other regulations. While the IMO regulations remain central in maritime governance, van Leeuwen (2015) identified the instrumental role of regionalization in maritime governance. Regional initiatives increase the effectiveness of maritime governance, particularly in implementing stricter regulations and enforcement. These regional efforts complement the IMO's regulations and are further expanded by private industry-led initiatives, which are discussed in the following section.

1.1.4 Private frameworks for reduction of carbon emissions

Private non-regulatory frameworks have emerged since the 2000s to address environmental concerns that regulatory frameworks have not yet covered. These private initiatives and frameworks, in conjunction with regional initiatives, seek to tackle sustainability challenges and promote collaboration among stakeholders in the shipping industry. Chapter 5 provides an in-depth exploration of various existing frameworks, outlining their characteristics, advantages, and limitations. The chapter focuses on the case of Clean Cargo, a collaborative partnership between ocean container carriers, freight forwarders, and cargo owners supporting the decarbonization of containerized ocean cargo transportation. This section introduces the motivations for private initiatives, with an update on new schemes that emerged in the past years. Gritsenko (2017) and Malmborg (2023) emphasize the necessity for multiple initiatives to experiment across different scales, address market and regulatory shortcomings, in order to facilitate technological investments, support information-based MBMs, and increase awareness among end-consumers.

In recent years, new voluntary initiatives have emerged. In 2019, the Poseidon Principles established a 'framework for assessing and disclosing the climate alignment of ship finance portfolios,' with four leading principles (assessment of climate alignment, accountability, enforcement, and transparency) (Poseidon Principles, 2023). The chosen metric for evaluating ship carbon intensity within the Poseidon Principles is the AER (Poseidon Principles, 2023). Another notable initiative, the Sea Cargo Charter initiative, launched in 2020, is a 'global framework for measuring and reporting how ship charterers' activities align with society's goals' for bulk carriers and tankers (i.e., chemical, liquefied gas, and oil tankers) (Sea Cargo Charter, 2023). In 2022, 33 charterers disclosed their climate alignment, with 14 of them aligning with the IMO's initial strategy. The Sea Cargo Charter initiative is built on the same four principles as the Poseidon Principles (Sea Cargo Charter, 2023). We can also cite the Maritime Singapore Green Initiative among regional initiatives, encompassing four voluntary green programs related to ships, ports, energy, technology, and awareness (Dong et al., 2022). Further initiatives are presented in Chapter 5.2.1.

These voluntary initiatives and frameworks are crucial in filling the gap of comprehensive public regulatory frameworks in the shipping sector (Yliskylä-Peuralahti and Gritsenko, 2014). Furthermore, Gritsenko (2017) argued that initiatives like Clean Cargo have paved the way for increased access to performance data, consequently enhancing the democratic quality of governance within the shipping industry. These initiatives have generated new processes, fostered stakeholder collaborations, and assigned new responsibilities to ship managers and operators (Gritsenko, 2017). Similarly, Zhang et al. (2023) recognized supply chain governance as a driving force for more binding policy.

Moreover, Parviainen et al. (2018) drew similar conclusions regarding the potential of multi-stakeholder pressure to promote environmental and social responsibility within the shipping industry, addressing previously unattended issues like the safety and rights of seafarers. However, Gibson et al. (2019) argued that, while these initiatives typically exceed regulatory frameworks, the certification thresholds are generally set at low ambition levels. Malmborg (2023) also emphasized that, without policy intervention, significant uptake of alternative fuels is unlikely and will remain the domain of pioneering organizations.

Voluntary frameworks often reflect collective intentions in the value chain, providing three main advantages: they offer informative, integrative, and discursive benefits (Gritsenko and Roe, 2019). Alger et al. (2021) cautioned that industry leaders raising the environmental performance bar may create challenges for smaller companies to keep pace in an industry characterized by centralization and low-profit margins, arguing that 'sustainability has become, in part, a competitive tool for some corporate players to make the industry even less democratic.'

During the 2010s, private voluntary initiatives received significant attention, advocating for greater transparency in performance data and more rigorous environmental standards. The introduction of mechanisms like the IMO DCS and the EU MRV may fulfill some of their initial purposes. Nevertheless, initiatives like Clean Cargo (now under the management of the Smart Freight Center) continue to engage 85% of carriers (in terms of capacity) (Smart Freight Centre, 2023). This section highlighted the advantages of adopting a multi-approach with both public and private frameworks, as they complement regulatory structures.

1.2 Research objectives

Decarbonizing international shipping is currently a hot topic. Working towards more efficient ships and operations is critical in this journey. Monitoring ships' carbon emissions and energy efficiency is imperative to achieve this objective. Therefore, this thesis primarily focuses on energy efficiency indicators, exploring different frameworks and strategies to enhance them and effectively address current and future challenges.

The context of this thesis draws on a prior research project aiming notably at evaluating the effectiveness of performance indices in aligning with their respective policy goals. As outlined in Panagakos et al. (2019), the project assessed various energy efficiency indicators for sister ships. Unfortunately, none of these indicators were deemed robust enough to provide reliable information on the fuel efficiency of ships. Furthermore, the results revealed the substantial influence of weather conditions on these indicators. Therefore, Panagakos et al. (2019) suggested establishing standard CO_2-test cycles per ship type to assess the ship's performance. These findings led to the Normalized Indicator for Carbon Emissions of ships (NICE) project, supported by the Danish Maritime fund. This thesis was carried out within the framework of this project, which aimed to contribute to the policy debate on greening international shipping by developing a carbon intensity indicator that combines both technical and operational aspects of the energy efficiency of a ship.

The following research question frames the focus of this thesis:

> ***Main Research Question*:**
>
> How can we monitor and assess ships' carbon emissions and energy efficiency, grasping its technical and operational aspects, to support shipping decarbonization?

As introduced in Section 1.1, many approaches for evaluating ships' energy efficiency exist through public and private frameworks. Challenges emerge when considering and using these energy efficiency indicators for benchmarking, mainly due to the various factors affecting energy efficiency. To deal with these specific challenges, the thesis further addresses three sub-questions, covered in different chapters:

> ***Sub-Research Question 1 (Chapter 2)*:**
>
> How can the influence of weather on fuel consumption be quantified, and what is the extent of weather's impact on energy efficiency indicators?

> ***Sub-Research Question 2 (Chapters 3 and 4)*:**
>
> How can standard operational cycles be defined for different ship sizes, and how effective are these cycles for assessing and benchmarking ships' energy efficiency?

> ***Sub-Research Question 3 (Chapter 5)*:**
>
> How can the effectiveness of voluntary frameworks in promoting shipping decarbonization be enhanced?

The research conducted during this PhD thesis aimed to contribute to the global sustainability agenda, as outlined in the UN's 2030 Agenda and the SDGs. Its primary objective is to contribute to the policy initiatives to decarbonize the shipping industry. Therefore, it directly supports *SDG 13 Climate action*, incorporating climate-related measures into policies (target 13.2). Additionally, the research contributes to the advancement of energy efficiency assessments, including the weather influence, and promotes the call for increased transparency in reporting, e.g., through voluntary frameworks. As such, the research addresses *SDG 12 Responsible consumption and production*, particularly emphasizing target 12.6 'encourage companies, especially large and transnational companies, to adopt sustainable practices and to integrate sustainability information into their reporting cycle.' Finally, the need for more comprehensive regulations by the IMO and the complementary approaches of voluntary and regulatory frameworks align with *SDG 17 Partnerships for the goals*. This resonates especially with target 17.14, 'enhance policy coherence for sustainable development,' and target 17.17, 'encourage and promote effective public, public-private and civil society partnerships, building on the experience and resourcing strategies of partnerships.'

1.3 Thesis outline and scientific contributions

The remainder of this thesis consists of four scientific papers dedicated to the previously presented objectives. This section provides an overview of the thesis's structure, including the content of individual chapters and their interconnections. Additionally, it outlines the scientific contributions and dissemination opportunities, including journal articles, conference proceedings, and presentations. Chapters 2 to 5 are identical to the journal articles published or submitted, with minor editorial modifications regarding section, figure, and table numbering and formatting. Note that the chapters are organized based on the different aspects of the thesis and were written chronologically as follows: paper 4 (chapter 5), paper 2 (chapter 3), paper 1 (chapter 2) and finally, paper 3 (chapter 4).

Chapter 2: Quantifying the impact of weather on ship fuel efficiency

In Chapter 2, we investigate the impact of weather conditions at sea on ships' fuel consumption and energy efficiency. At sea, ships encounter various levels of wind and waves, leading to added resistance and increased fuel consumption, significantly affecting energy efficiency indicators. This impact on indicators must be quantified to use them as benchmarking tools since weather conditions are external factors beyond the operator's control. This chapter presents models to estimate the impact of weather components on fuel consumption and develops correction factors to nullify the weather effect on energy efficiency indicators.

We present various models utilizing model-based machine-learning techniques. These models are trained and tested using noon reports from two sister container ships spanning two years. The reported weather effects include wind, waves, and swells, which originated from hindcasted data provided alongside the noon reports. The examined model types are linear regressions (with and without consideration of the weather component directions), polynomial regressions (with and without weather directions), generalized additive models (with and without weather directions), and a customized model based on ship propulsion principles.

The evaluation of models' performances indicates that the customized model exhibits the lowest performance, while the remaining models display similar performances. Given its good performance and interpretability, we choose the polynomial model for further investigation to assess the quantification of weather-related fuel consumption. We also compare it to the customized model for validation purposes. The assessment of the weather's impact on fuel consumption reveals an average impact ranging from 7% to 9%, with variations from 2% to 20% across different sea states. Specific to each sea state, these quantifications enable estimating weather correction factors, similar to the concept of f_w in the context of EEDI. Further analysis is necessary to generalize these findings to other ship sizes and types.

This research shows the capacity of model-based machine-learning techniques to estimate the impact of weather on fuel consumption and calculate relevant weather correction factors. We introduce a novel perspective on weather correction factors, emphasizing the significance of customizing these factors for specific sea states. We outline the importance of incorporating these correction factors when using energy efficiency indicators as benchmarks.

The work of **Chapter 2** has been disseminated as follows:

- A journal paper co-authored with Lukas Wallner, George Panagakos, and Michael Bruhn Barfod submitted to *Ocean Engineering*
- A presentation by Amandine Godet at the *PostGradMarTec2021* online conference, in November 2021
- A poster presentation by Amandine Godet at the *Transportation Research Arena 2022* conference, held in November 2022 in Lisboa, Portugal
- A presentation by Amandine Godet to the Advisory board of the NICE project, in October 2021
- A seminar presentation by Amandine Godet, held in June 2021 at the Technical University of Denmark in Kgs. Lyngby, Denmark

Chapter 3: Operational cycles for maritime transportation: A benchmarking tool for ship energy efficiency

Chapter 3 introduces the innovative concept of operational cycles for maritime transportation, inspired by the automotive industry. It addresses the complexity of benchmarking energy efficiency in ships due to the different factors affecting the efficiency. This chapter defines the concept of maritime operational cycles, develops a methodology and applies it to a fleet of container ships, evaluates the accuracy and effectiveness of these cycles, and discusses potential directions for further development.

Unlike the automotive industry, which has used driving cycles to assess vehicle emissions for decades, maritime operational cycles have received limited attention in prior studies. Drawing inspiration from the World harmonized Light vehicles Test Cycles (WLTC), we propose a methodology for developing maritime operational cycles based on real-world data from container ships.

We develop operational cycles for container ships in eight size groups using operational data (noon reports) collected from a company's global fleet. These cycles describe the ship's main engine power over time, categorized into low, medium, and high power segments. We suggest several alternatives for building these cycles, either based on a target duration or a fixed number of legs (voyages between two ports). Moreover, we address specific challenges inherent to different size groups and present alternative solutions for creating satisfactory operational cycles.

We then evaluate the accuracy of these cycles in modeling fleet emissions and their effectiveness in reducing the variability of energy efficiency indicators, assessed through the Annual Efficiency Ratio (AER) for sea passages. Successfully getting accurate and effective cycles, we validate the concept of maritime operational cycles to reduce operational indicator variability. Given the concept's potential, we propose various directions for refinement.

The work of **Chapter 3** has been disseminated as follows:

- A journal paper co-authored with Jacob Normann Nurup, Jonas Thoustrup Saber, George Panagakos, and Michael Bruhn Barfod, published in *Transportation Research Part D: Transport and Environment* in July 2023
- A presentation by Amandine Godet at the *World Maritime Technology Conference*, held in April 2022 in Copenhagen, Denmark
- A presentation by Amandine Godet to the Advisory board of the NICE project, in February 2023

Chapter 4: Operational cycles for maritime transportation: Consolidated methodology and assessments

In Chapter 4, we continue exploring the concept of operational cycles for maritime transportation. Building on the findings from Chapter 3, we extend the methodology for developing and assessing the cycles.

The extended methodology provides more comprehensive cycles, considering all types of emissions (main engine, auxiliary engines, and boilers) and all voyage stages (sea passages, berthing times, arrivals to and departures from ports). We also compare two types of cycles: the first type is based on a combination of ship speed and draft, while the other relies on main engine (ME) power. We introduce new data sources with more recent and comprehensive data that allows the estimation of all voyage stages. In addition to estimating the AER, we enhance the methodology to assess the EEOI, which requires estimating the cargo on board based on the ship's draft.

An assessment comparing speed and draft-based cycles with those introduced in Chapter 3 reveals that the former are more accurate but less efficient. While speed and draft-based cycles offer comprehensiveness and the capability to estimate the EEOI, ME power-based cycles seek more simplicity, require less data, and are more readily applicable. Nonetheless, both approaches confirm the validity of the operational cycle concept in maritime transportation. They demonstrate satisfactory accuracy in modeling fleet emissions and effectively reduce the variability of energy efficiency indicators, making the cycles suitable for benchmarking purposes.

We explore the policy implications of maritime operational cycles, particularly their potential to broaden the scope of the EEDI, enhancing the assessment of design energy efficiency. The additional methods and assessments, extending the ones from Chapter 3, improve the comprehensiveness of operational cycles. Further work on the subject may include establishing cycles on more granular data, exploring different ship types, and handling the weather impact more precisely.

The work of **Chapter 4** has been disseminated as follows:

- A journal paper co-authored with George Panagakos, Michael Bruhn Barfod, and Elizabeth Lindstad, submitted to the special issue 'The changing maritime transport and its effects on carbon emissions' of the journal *Transportation Research Part D: Transport and Environment*

Chapter 5: Voluntary reporting in decarbonizing container shipping: the Clean Cargo case

Chapter 5 uses the Clean Cargo case to explore voluntary reporting frameworks within the shipping industry. While most of this thesis centers around regulatory frameworks established by the IMO, this chapter focuses on complementary approaches for achieving decarbonization in shipping through voluntary reporting. The chapter aims to identify stakeholders' expectations and motivations for voluntary disclosure of environmental information and discuss governance challenges within these initiatives. After presenting several voluntary initiatives and schemes, we focus on Clean Cargo, a partnership between container carriers, freight forwarders, and cargo owners, working together to monitor and mitigate GHG emissions from container shipping. Their annual disclosure of carriers' GHG emissions performance data is designed to improve transparency and facilitate informed decision-making.

Given the evolving regulations and the increasing pressure from stakeholders for more ambitious emission reduction targets, members of Clean Cargo recognized the need to adapt their annual reporting framework. Building on these discussions, we designed a questionnaire to gather insights from the initiative members and to identify the underlying needs and aspirations regarding a new reporting scheme. This questionnaire's design, distribution, and analysis were conducted in collaboration with the Clean Cargo Secretariat at the time of the study in 2020. The questionnaire responses were complemented by interviews with carriers, freight forwarders, and cargo owners, which provided further context and elucidated trends.

While the questionnaire, like the current reporting framework, covered a wide range of environmental impacts, most participants ranked GHG emissions as their predominant concern. Shippers and freight forwarders expressed a strong demand for more standardized and granular data, especially data on GHG emissions per shipment. These emissions fall within the Scope 3 (indirect emissions that occur in a company's upstream and downstream activities) of shippers and freight forwarders despite most of them not having specific maritime emission targets. However, more granular data would necessitate additional reporting efforts from carriers. Besides, decarbonization strategies, e.g., the uptake of alternative fuels, underscore the need for a new adapted framework.

With the regulatory framework moving forward, Chapter 5 discusses the role voluntary initiatives such as Clean Cargo can play and how the interests of carriers, freight forwarders, and cargo owners are evolving. While all stakeholders emphasize the need for voluntary initiatives, the reporting framework must evolve and balance the wishes of shippers and freight forwarders and carriers' willingness to disclose their performance data. We also reflect on how such a voluntary framework can complement and accelerate the industry changes needed to meet the IMO reduction targets.

The work of **Chapter 5** has been disseminated as follows:

- A journal paper co-authored with George Panagakos and Michael Bruhn Barfod, published in *Sustainability* in July 2021
- An online presentation by Amandine Godet to Clean Cargo members in June 2020

1.4 Conclusions and perspectives

This PhD thesis focuses on monitoring carbon emissions in the shipping industry. Given the climate crisis and the pressing need to decarbonize maritime transportation, this research deals with the assessment techniques for quantifying ships' carbon emissions and energy efficiency. It encompasses both international regulatory frameworks and voluntary initiatives. The research approach is interdisciplinary, combining machine learning, data-driven assessment methodologies, and techniques from the social sciences.

This thesis explores various methods for monitoring and evaluating carbon emissions within international shipping, specifically focusing on container ships. The primary goal is to assess energy efficiency indicators, considering both their technical and operational aspects. Ultimately, this thesis aims to establish a solid foundation for a benchmarking framework designed to evaluate ships' efficiency in the context of decarbonization.

The first aspect of the thesis investigates how weather conditions influence fuel consumption and energy efficiency. Chapter 2 details the significance of addressing the weather's impact for developing indicators capable of benchmarking ships navigating various sea conditions. The research employs model-based machine learning techniques to comprehensively study the complexity and interdependencies of operational factors and weather conditions that impact fuel consumption.

The analysis of noon reports from two sister container ships reveals that polynomial regressions exhibited satisfactory modeling performance and interpretive capabilities. Additionally, a customized model based on the principles of ship propulsion is proposed, although it demonstrates comparatively less effectiveness. In response to sub-research question 1, Chapter 2 concludes that model-based machine learning techniques represent a suitable approach for estimating the influence of weather and sea conditions on fuel consumption. However, having access to more detailed data could enhance the thoroughness and precision of this estimation.

As for the second facet of the first sub-research question, Chapter 2 explores the calculation of distinct weather correction factors for various sea states. This aspect highlights the importance of assessing the impact of weather across a wider range of sea conditions, as opposed to solely relying on the standard established by the IMO, which is limited to Beaufort 6 conditions. The chapter's findings underscore the significance of this broader assessment, with an estimated impact ranging from 2 to 20% across different sea states, encompassing calm seas to strong breezes.

The second aspect of the thesis deals with the development and assessment of standard operational cycles for maritime transportation, as a benchmarking tool for ship energy efficiency. The cycles aim to reduce the variability of energy efficiency indicators. Drawing inspiration from the driving cycles in the automotive industry, a data-driven approach is introduced for developing these operational cycles, with a seven-step procedure and related assessment methods. Chapters 3 and 4 present the work on operational cycles, addressing the sub-research question 2.

To elaborate further, Chapter 3 initiates the development of the methodology and validates the conceptual framework. These cycles serve the core objective of reducing the inherent variability observed in energy efficiency indicators, making them suitable for benchmarking purposes. The initial set of cycles is categorized based on various main engine power levels within eight distinct size groups. The cycles effectively model the main engine emissions of the entire fleet. Furthermore, the estimation of a modified AER, which considers only main engine emissions at sea, showcases the cycles' effectiveness in reducing the indicator's variability. This success validates the concept of maritime operational cycles.

Building upon the promising outcomes of Chapter 3, Chapter 4 introduces a consolidated methodology for developing and assessing operational cycles. The use of more comprehensive and recent data offers the possibility to estimate more voyage stages and include all associated emissions (main engine, auxiliary engines, and boiler emissions). Furthermore, cycles based on a new combination of speed and draft extend the assessment possibilities to the EEOI. These newly developed cycles, based on real-world data, encapsulate a variety of weather conditions, smoothing the external influence of weather. However, a precise assessment of the weather impact would require additional data. With the development of new cycles, the overall results remain conclusive regarding their accuracy and effectiveness, including the new assessment using EEOI. The findings further enhance the comprehensiveness of the operational cycles concept. The use of operational cycles to assess the energy efficiency of ships holds significant promise in addressing the shortcomings of existing indicators, effectively addressing sub-research question 2.

This thesis's third and final aspect explores an alternative approach to monitoring carbon emissions, namely, voluntary frameworks. Chapter 5 presents the case of Clean Cargo and its reporting framework. By examining the role of such a voluntary initiative as a complementary framework to regulatory ones, the Clean Cargo case allows for a direct examination of stakeholders' needs. Through a questionnaire supplemented by interviews, different stakeholders (carriers, freight forwarders, and shippers) express their motivations for participating in a voluntary initiative and their anticipated needs for an improved voluntary framework in light of upcoming regulations from both the EU and IMO. While the study encompasses all environmental aspects covered by the Clean Cargo framework, the primary concern of initiative members revolves around climate impact and GHG emissions, as the issue is central to most customers. The research also indicates that voluntary frameworks have the potential to accelerate the decarbonization of the shipping industry by establishing more stringent standards accepted by stakeholders. This addresses the third sub-research question. Furthermore, considering that this work was conducted in 2020, it is expected that stakeholders' ambitions have grown over the past three years.

To summarize, this thesis analyzed carbon emissions and energy efficiency frameworks within the maritime industry's decarbonization strategy and policy. It revealed inherent shortcomings within these frameworks, particularly regarding the influence of weather conditions and the variability of indicators, making them unfit for benchmarking purposes. The thesis responded to these challenges by proposing methodologies and pathways to enhance the robustness of ship efficiency assessments. The following key findings and recommendations emerged from the research conducted in this thesis:

- The weather impact on ships' fuel consumption prevents a real assessment of accurate ships' efficiency. The introduction of multiple weather correction factors for energy efficiency indicators presents a novel approach compared to the IMO's current method.

  - On the technical side, having EEDI requirements for different sea conditions would improve the reliability and efficiency of this indicator.
  - On the operational side, tailored weather correction for ships sailing in different regions when assessing the CII would result in fairer and more coherent comparisons of operational efficiency.

- The use of operational cycles can capture technical and operational aspects of a ship's energy efficiency.

  - Modifying the EEDI to include a broader set of typical operational conditions could improve the assessment of the design efficiency moving beyond calm sea, design speed, and fully loaded conditions. This approach would encourage ship designs that prioritize energy efficiency under real sea conditions, ultimately enhancing the performance of ships in practical scenarios.
  - Operational cycles would complement the IMO regulatory framework by providing comprehensive coverage of emissions per transport work. They supplement Market-Based Measures, which aim to regulate market distortions, and the GHG Fuel Standard, which encourages less carbonized fuels. Energy-efficient ships remain es-

sential even with zero-carbon alternative fuels due to expected fuel scarcity and high prices.

- While the IMO regulatory framework remains central to the shipping decarbonization strategy, regional regulatory frameworks and private initiatives have demonstrated their ability to improve industry practices and ease regulatory changes. Encouraging the emergence of these new industry standards requires mitigating risks of over-complexity and redundancy regarding regulatory frameworks.

These recommendations aim to advance the decarbonization efforts within the shipping industry and promote more sustainable and efficient practices. The thesis lays the groundwork for further research on energy efficiency indicators and assessments in the maritime industry, including:

- Developing models to estimate the weather impact on a broader range of ships, with their associated weather correction factors.
- Expanding the concept of operational cycles to encompass other ship types, such as bulk carriers or tankers and continuing to refine the concept with more comprehensive data from the global fleet.
- Formulating additional policy recommendations for integrating operational cycles and weather correction factors within the regulatory framework, particularly concerning EEDI and CII.

Generally, the thesis contributes to improving carbon emissions assessment in the maritime industry by presenting a series of recommendations designed to facilitate ship benchmarking. These suggestions are intended to enrich the ongoing dialogues within the IMO and complement the existing regulatory frameworks. More specifically, the modified EEDI proposed by the thesis needs to be viewed in conjunction with the CII, and the expected mid-term measures (GFS and MBM) to streamline and simplify the regulatory environment as much as possible.

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2 Quantifying the impact of weather on ship fuel efficiency (Paper 1)

Amandine Godet[a], Lukas Jonathan Michael Wallner[a], George Panagakos[a], Michael Bruhn Barfod[a]

[a] Department of Technology, Management and Economics, Technical University of Denmark, Akademivej 358, 2800 Kongens Lyngby, Denmark

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Abstract The International Maritime Organization employs technical and operational indicators to assess ship energy efficiency. Weather conditions significantly impact ship fuel consumption during voyages, necessitating the integration of this influence into energy efficiency calculations. This paper aims to design models to estimate the impact of weather components on fuel consumption and develop a correction factor to nullify the effect of weather on the fuel consumption of container ships for different sea states. The paper analyzes noon reports and hindcasted weather data from two sister container ships using model-based machine learning. It quantifies weather-induced fuel consumption across various sea states, ranging from 2% to 20%, with an average of 7-9%. Correction factors specific to each sea state are derived, and different approaches for their integration into energy efficiency indicators are proposed. This study pioneers tailored weather correction factors for energy efficiency metrics tied to specific sea states, emphasizing the need for standardized weather impact assessments. Future work will extend this approach to various ship sizes and types and evaluate policy implications for energy efficiency measures.

Keywords: *Ship efficiency; Fuel consumption; Weather; EEDI; Correction factor; Policy-making*

2.1 Introduction

The shipping industry is crucial in transporting goods worldwide and is responsible for 2.89% of greenhouse gas (GHG) emissions (Faber et al., 2020). In 2023, the International Maritime Organization (IMO) revised its *Initial Strategy to Reduce GHG emissions* (IMO, 2018) to increase the levels of ambitions to reach net zero GHG emissions by or around 2050 (IMO, 2023). Accompanying these targets, IMO adopted short-term measures (mid- and long-term ones are presently under discussion), based on indicators assessing the energy efficiency of ships. In this context, we can distinguish between technical indicators, such as the Energy Efficiency Design Index (EEDI), which regulates newly-built ship design's energy efficiency since 2013 (IMO, 2011), and operational indicators, such as the Carbon Intensity Indicator (CII), assessing the annual energy efficiency of ship operations since 2023 (IMO, 2021a). Several factors affect the operational efficiency of ships, e.g., speed, draft, trim, weather, and fouling, some of which lie beyond the operator's control.

Weather is the most uncontrollable of these factors calling for special treatment when it comes to operational and technical indicators to be used for benchmarking purposes (Panagakos et al., 2019). Given that EEDI is calculated under conditions of calm weather and design speed, the IMO introduced a weather correction factor f_w to account for different weather conditions (IMO, 2012). Two ways of calculating f_w exist: expressed as the ratio of speeds in weather conditions corresponding to Beaufort (BF) 6 and in calm water under constant power, or as a function of capacity using reference lines (IMO, 2012). Polakis et al. (2019) highlight that f_w typically spans between 0.8 and 0.95 for slow-speed ships (bulk carriers, tankers), which indicates the existence of substantial disparities in design efficiency expressed by the normal EEDI. f_w is not mandatory and is limited because it reflects a specific sea state irrespective of the conditions prevailing in the areas where the ship is expected to sail (IMO, 2009). Bøckmann and Steen (2016) show that the value of EEDI corrected for weather depends slightly on the calculation method. Therefore, the procedure suggested by IMO (2012) and ISO (2015b) needs clarification before implementation in a harmonized way (Bøckmann and Steen, 2016). For example, Lindstad et al. (2019) suggest adjustments to EEDI calculation during sea trial tests, including upward adjustments to real sea conditions coupled with downward adjustments to calm water conditions, and Tu et al. (2018)

propose a modified admiralty coefficient for estimating power curves in EEDI calculations.

Correcting energy efficiency indicators for weather conditions requires a reliable quantification of the weather's impact on energy efficiency and, by extension, fuel consumption. In the last decade, machine learning methods have been extensively applied to predict fuel consumption under various operational conditions. See, for example Bal Beşikçi et al. (2016), Gkerekos et al. (2019), Adland et al. (2020), Uyanık et al. (2020), Berthelsen and Nielsen (2021), Vorkapić et al. (2021), Yuksel et al. (2023). However, although algorithms predicting fuel consumption are becoming more and more accurate, few studies estimate the relative impacts of operational factors on fuel consumption. Prpić-Oršić and Faltinsen (2012) simulate the speed loss and CO_2 emissions for different wave heights and headings of the container ship hull S-175. For the same design, Kim et al. (2017) predict speed loss and sea margin for BF 6 for different speeds (same heading). Meng et al. (2016) quantify the contributions of lousy weather to fuel consumption for four container ships and different wave directions. Bialystocki and Konovessis (2016) study the effect of different sea states on the fuel consumption of a car carrier, based on noon reports. Finally, Bilgili (2023) determines the weights of external conditions (e.g., wave height, wave direction, wind speed, and direction) using an artificial neural network.

While the IMO has been discussing weather correction factors for over a decade, limited research exists on the correction factors and indicators suitable for benchmarking the energy efficiency of ships. A large share of the research articles that look at the impact of operational conditions on added resistance, fuel consumption, or power, focus on prediction and only a little on estimating the detailed effect of the different parameters. Among the second category, some focus solely on wind (e.g., Bialystocki and Konovessis (2016)) or waves (e.g., Prpić-Oršić and Faltinsen (2012)), and few use actual data (e.g., Bilgili (2023)).

This paper aims to:

1. design models to estimate the impact of weather components on fuel consumption
2. develop a correction factor to nullify the impact of weather on the fuel

consumption of container ships for different sea states

Our analysis relies on model-based machine learning, from linear regressions to a customized model using naval architecture knowledge. The models are applied to the noon reports of two sister container ships. Performance comparison among the models enables the selection of the best ones and the corresponding estimation of the impact of weather components. Finally, weather correction factors are developed and discussed in relation to their policy implications.

2.2 Data and variables

The analysis relies on noon reports, daily reports from a ship crew, and hindcasted weather data. The data set was provided by a globally leading container ship operator, hereafter referred to as the "shipping company". The noon reports of two sister container ships for 2018 and 2019 are provided. Table 2.1 details the ship particulars. Figure 2.1 illustrates the routes undertaken by the two ships.

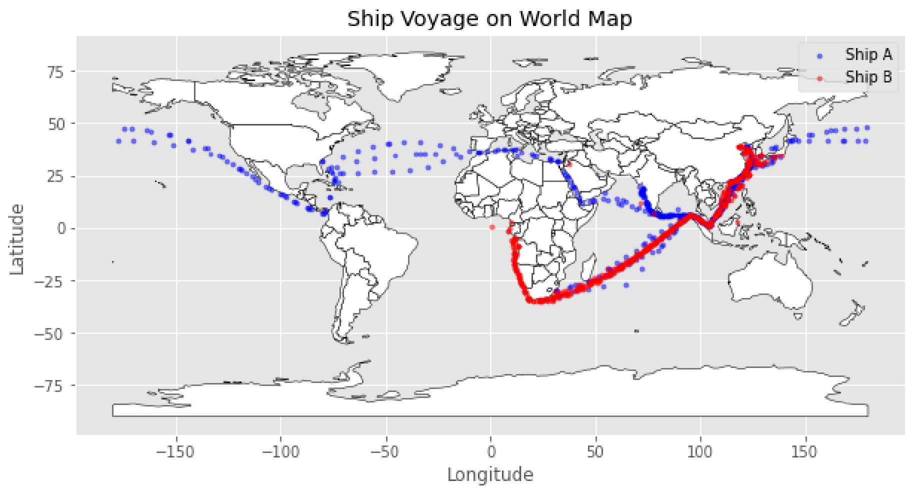

Figure 2.1: Ships voyages

Table 2.1: Ship particulars

Capacity	8,112 TEU
Deadweight at scantling draft	114,210 tons
Displacement at design draft	119,567 m^3
Length between perpendiculars	318 m
Breadth	43.2 m
Design draft	13 m
Main engine maximum continuous rating	61,776 kW

2.2.1 Variable selection

The inputs for the models, further described in Section 2.3, are:

- Operational variables: speed through water, average draft
- Ship-specific variables: efficiency coefficients, resistance coefficients
- Weather variables: wave height and direction, swell height and direction, wind speed and direction

The prediction variable of all models is the ship's fuel consumption. The selection and description of the independent variables (predictors) are presented below.

Speed is available as speed through water and speed over ground in the original data set. As ocean and tidal currents influence the speed over ground (Perera and Mo, 2018), the analysis considers speed through water for the speed variable. The average draft is the mean of the fore and aft drafts.

Ship-specific variables complement the ship particulars by accounting for different efficiency coefficients (e.g., hull and engine efficiencies) and resistance coefficients, as further detailed in Section 2.3 and shown in Table 2.3. These variables are obtained from the company's ship class model tests.

The weather effect covers the influence of waves, swells, and wind. Waves, also called wind waves, are distinguished from swells. Wind waves are "formed due to the direct action of local winds," while swells are "wind waves that have traveled out of the generating area" (Toffoli and Bitner-Gregersen, 2017). Swells typically have longer periods and smaller heights than wind waves

(Toffoli and Bitner-Gregersen, 2017). Both height and direction (relative to the ship's bow) are considered for wind waves and swells. Considering the wind, the relative (also referred to as 'apparent') speed and direction are available in the data set. The true wind speed is calculated in Section 2.2.2. Note that the impact of wind on fuel consumption depends on the loaded containers on board and is complex to estimate (see, e.g., Andersen (2013)). In the absence of data on the configuration of containers on deck, this aspect is not considered in the analysis.

Other variables influence fuel consumption, such as trim, hull and propeller fouling, water depth, water salinity, and water temperature. These variables are also excluded from the analysis and left for future work.

2.2.2 Data preparation

The data set provided by the shipping company contains all noon reports generated for two sister container ships during 2018 and 2019. We filter the data to keep only noon reports where the ship is sailing in the open sea, called 'sea reports,' thus excluding port stays, anchorage, and canal passages. Reports with missing data for the selected variables and data with physically unrealistic values (speed over 30 knots, ship sailing at zero main engine power) are excluded. Table 2.2 summarizes the number of reports used in the analysis before and after filtering.

Table 2.2: Number of reports

	Original number of reports	Number of sea reports	Number of reports after filtering	Time period
Ship A	744	574	555	24 months
Ship B	663	527	494	24 months
Total	1407	1101	1049	

The fuel consumption figures of the noon reports indicate consumption over the report duration. Separate figures for all different fuel qualities are provided, i.e., low- and high-sulfur heavy fuel oil and low- and high-sulfur fuel oil. The aggregate fuel consumption is calculated as the equivalent of high-sulfur heavy fuel oil, weighting the different fuels by their lower calorific values. Note that the data reflects fuels used before the 1st January 2020, when the IMO rule limiting the sulfur content of marine fuels came into force (IMO, 2019).

The true wind speed $V_{Wind,True}$ is calculated based on the ship's speed V and the relative wind speed $V_{Wind,Relative}$ and its direction α, according to Equation 2.1:

$$V_{Wind,True} = \sqrt{V^2 + V^2_{Wind,Relative} - (2 \cdot V \cdot V_{Wind,Relative} \cdot \cos\alpha)} \tag{2.1}$$

The wave, swell, and wind directions are reported on a 0º to 360º scale relative to the ship's heading. Assuming that the ships' reactions to weather conditions are symmetrical (as in Taskar et al. (2021)), the scale is adjusted to 0º to 180º. Furthermore, for each weather condition, dummy variables are created for each direction as follows: 0º to 60º for the bow, 60º to 120º for the beam, and 120º to 180º for the stern. This categorization follows Bialystocki and Konovessis (2016), who stated that the impact of the wind on a ship's hull is similar within the ranges 0º to 60º, 60º to 120º, and 120º to 180º. Lastly, wind speed values identify the sea state in which the ship sails. Sea states spread from 0 (calm) to 12 (hurricane), following the Beaufort (BF) Scale, as defined in ISO (2015a).

2.2.2.1 Data exploration

Figure 2.2 shows histograms of speed, draft, and fuel consumption. In relation to weather variables, Figure 2.3 presents the histograms of wave height/direction, and Figure 2.4 of swell height/direction. The mean wave height is 0.9 m, and the mean swell height is 1.5 m. In respectively 44% and 40% of the data points, the wave, and swell directions are on the bow. This high proportion of waves and swells coming on the bow is due to the method used by the company averaging hindcasted weather observations (every four hours) to noon report level (24 hours). Indeed, for each weather observation, the wave/swell/wind energy is calculated; the wave/swell/wind direction of the observation with the maximum energy component is then used for the entire noon report.

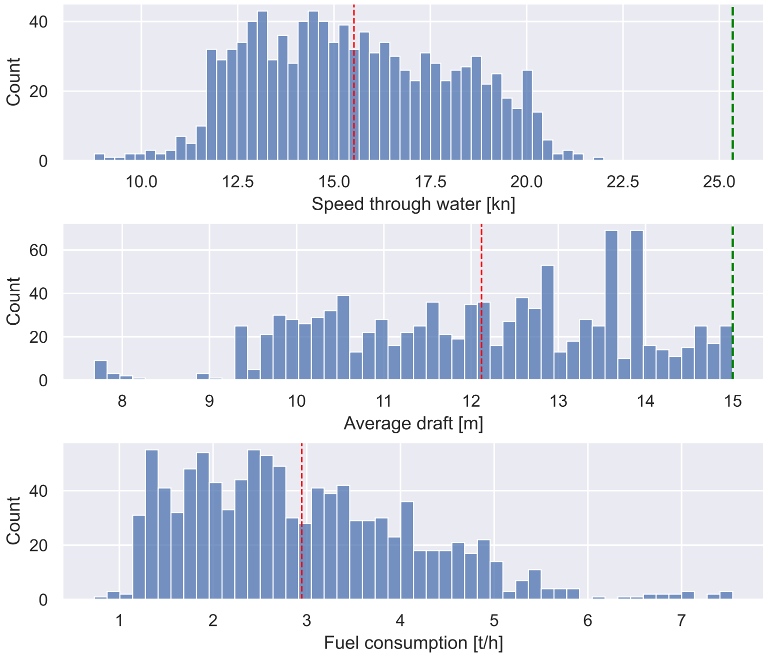

Figure 2.2: Histograms for speed, draft, and fuel consumption. The red dashed lines represent the mean value, and the green dashed lines represent the design speed and the scantling draft.

Figures 2.5 and 2.6 show the histograms of relative wind speed/direction, and true wind speed/direction, respectively. The mean apparent wind speed is 9.7 m/s. The mean true wind speed is 5.8 m/s, corresponding to BF 4[1]. Figure 2.7 shows the distribution of the sea states according to the Beaufort scale, as calculated based on the true wind speed.

Table 2.3 summarizes the variables used in the models, further described in Section 2.3, along with the ship-specific coefficients. Figure 2.8 shows the Pearson correlation matrix of the different variables. As expected, the ship's speed is the most correlated with the ship's fuel consumption (0.84), followed by the relative wind speed (0.39). The relative wave direction shows a correlation of 0.54 with the relative wind direction, which is expected as the wind forms waves, and a correlation of 0.52 with the relative swell direction.

[1]The average of BF 4 differs from the average sea state presented in Table 2.3, as the latter is calculated based on the discrete sea state figures.

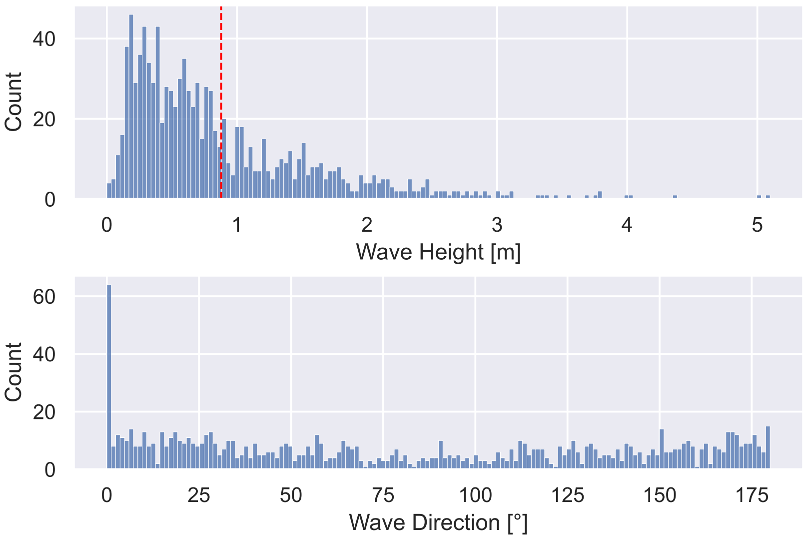

Figure 2.3: Histograms for wave height and relative wave direction to the ship's bow. The red dashed line represents the mean value.

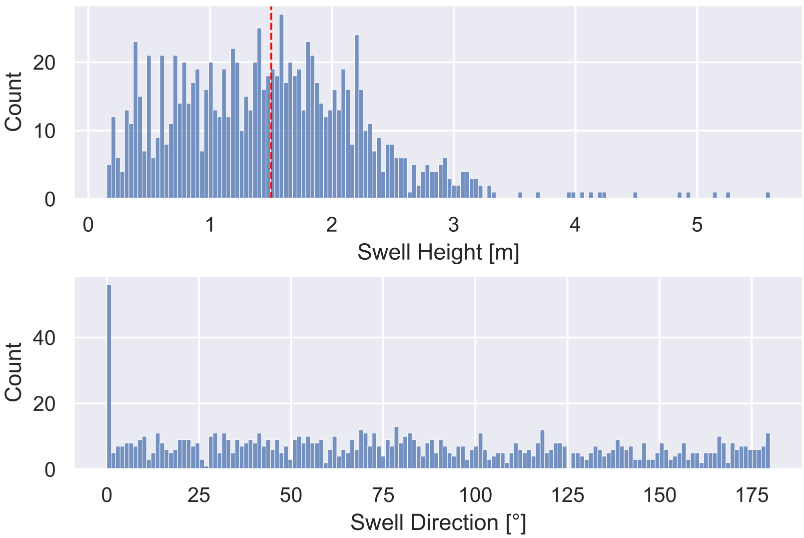

Figure 2.4: Histograms for swell height and relative swell direction to the ship's bow. The red dashed line represents the mean value.

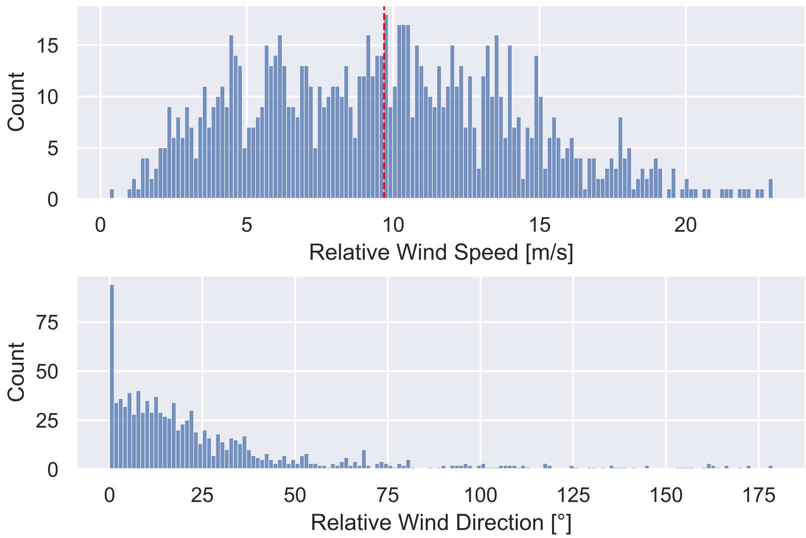

Figure 2.5: Histograms for relative wind speed and relative wind direction to the ship's bow. The red dashed line represents the mean value.

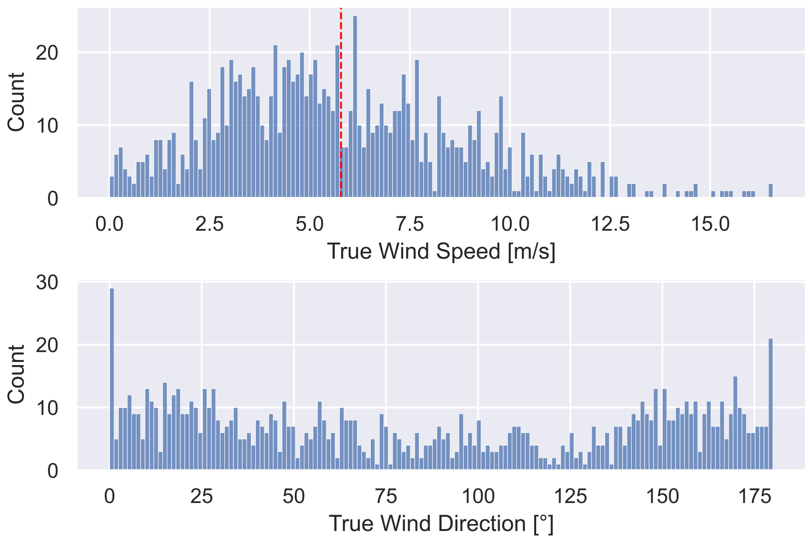

Figure 2.6: Histograms for true wind speed and true wind direction. The red dashed line represents the mean value.

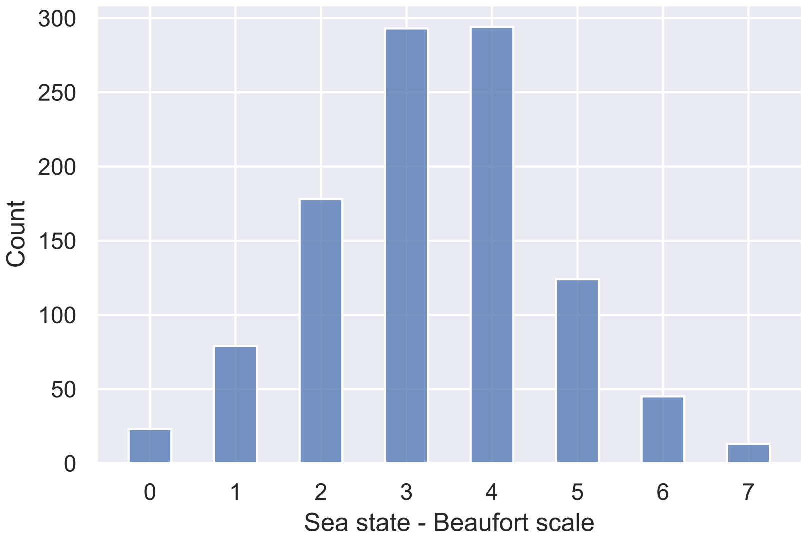

Figure 2.7: Histogram of the sea state, according to the Beaufort scale.

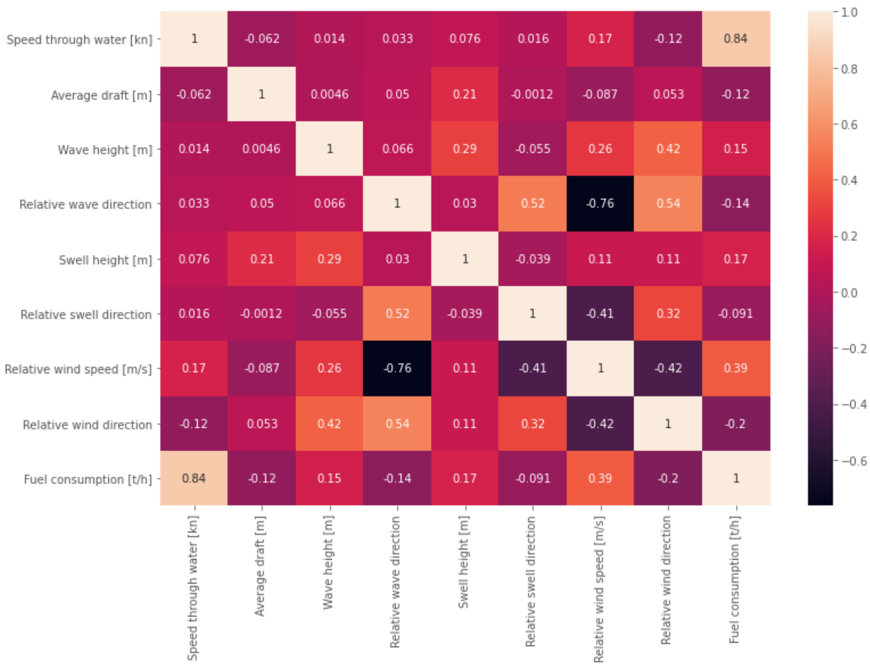

Figure 2.8: Correlation matrix of the variables

Table 2.3: Summary of variables

Variable	Unit	Data source	Mean value	Range value
Output variable				
Hourly fuel consumption	ton/h	Noon report	2.9	[0.7, 7.5]
Operational variables				
Speed through water	kn	Noon report	15.5	[8.8, 22.0]
Average draft	m	Noon report	12.1	[7.7, 15.0]
Weather variables				
Wave height	m	Hindcast weather	0.9	[0.0, 5.1]
Relative wave direction	^{o}	Hindcast weather		[0, 180]
Swell height	m	Hindcast weather	1.5	[0.2, 5.6]
Relative swell direction	^{o}	Hindcast weather		[0, 180]
Relative wind speed	m/s	Hindcast weather	9.7	[0.3, 23.0]
Relative wind direction	^{o}	Hindcast weather		[0, 180]
True wind speed	m/s	Calculation	5.8	[0.0, 16.6]
True wind direction	^{o}	Calculation		[0, 180]
Sea state (on Beaufort scale)	/	Calculation	3	[0, 7]
Dummy variables for weather				
Wave on the bow	/	Based on direction		{0, 1}
Wave on the beam	/	Based on direction		{0, 1}
Wave on the stern	/	Based on direction		{0, 1}
Swell on the bow	/	Based on direction		{0, 1}
Swell on the beam	/	Based on direction		{0, 1}
Swell on the stern	/	Based on direction		{0, 1}
Wind on the bow	/	Based on direction		{0, 1}
Wind on the beam	/	Based on direction		{0, 1}
Wind on the stern	/	Based on direction		{0, 1}
Ship specific coefficients				
Aerodynamic resistance coefficient C_{Air}	/	Ship model tests	-0.6	[-0.8, 0.9]
Total resistance coefficient C_T	/	Ship model tests	2.1	
Hull efficiency η_H	/	Ship model tests	1.15	
Rotative efficiency η_R	/	Ship model tests	0.99	
Open-water efficiency η_O	/	Ship model tests	0.67	
Shaft efficiency η_S	/	Ship model tests	0.77	

2.3 Modelling approach

2.3.1 Selected principles of marine engineering

According to MAN Energy Solutions (2018), the fuel power P_{fuel}, needed to propel the ship, depends on the total ship resistance R_T, the ship speed V, and several efficiency coefficients (hull efficiency η_H, rotative efficiency η_R, open water efficiency η_O, shaft efficiency η_S, gearbox efficiency η_{GB}, engine efficiency η_E), as illustrated in Figure 2.9.

$$P_{fuel} = \frac{R_T \cdot V}{\eta_H \cdot \eta_R \cdot \eta_O \cdot \eta_S \cdot \eta_{GB} \cdot \eta_E} \tag{2.2}$$

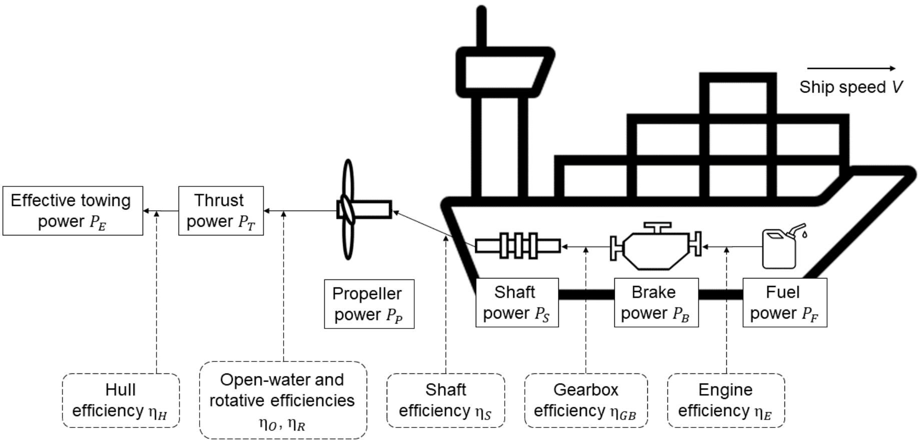

Figure 2.9: A ship's propulsion system. Own representation based on MAN Energy Solutions (2018) and Shi et al. (2010).

The total resistance R_T is the sum of the calm-water resistance and the added resistance due to weather conditions. The calm-water resistance is composed of the frictional resistance (friction between the hull and the water), the air resistance (from the ship's superstructure and hull above water resistance to the air), and the residual resistance (MAN Energy Solutions, 2018). The residual resistance accounts for additional effects, omitted here as their description and calculation are complex and left to specialized literature. Consequently, the total resistance R_T becomes the sum of frictional resistance $R_{Friction}$, the air resistance R_{Air}, the added resistance caused by wind R_{Wind}, and the added resistance caused by waves and swells R_{Waves}. Therefore, the fuel consumption consists of the fuel consumption in calm water and the added fuel consumption due to weather conditions. The former mainly depends on the ship's speed and draft, while the latter depends on wind, waves, and swells.

Equation 2.3 shows the formula for the frictional resistance:

$$R_{CalmWater} = \frac{1}{2} \cdot C_T \cdot \rho_{water} \cdot S \cdot V^2 \tag{2.3}$$

where C_T is the total resistance coefficient, ρ_{water} the mass density of water, S the wetted surface area of the ship, and V the ship's speed.

Equation 2.4 expresses the air resistance (MAN Energy Solutions, 2018):

$$R_{Air} = \frac{1}{2} \cdot C_{air} \cdot \rho_{air} \cdot A_F \cdot V^2 \tag{2.4}$$

where C_{air} is the aerodynamic resistance coefficient, ρ_{air} the mass density of air, A_F the frontal area of the ship above the waterline, and V the ship's speed.

Regarding the added resistance due to weather conditions, Equation 2.5 expresses the wind resistance, similarly to Equation 2.4, except that the wind speed V_{Wind} replaces the ship's speed V and the aerodynamic resistance coefficient C_{air} and the area of the ship above the water line A_{air} changes according to the wind direction α (MAN Energy Solutions, 2018):

$$R_{Wind} = \frac{1}{2} \cdot C_{air}(\alpha) \cdot \rho_{air} \cdot A_{air}(\alpha) \cdot V_{Wind}^2 \tag{2.5}$$

Following IMO (2021b), Equation 2.6 expresses the added resistance in irregular short-crested waves, and for wave directions from 0 to 30 ° relative to the ship's heading:

$$R_{Waves} = 1336 \cdot (5.3 + V) \cdot \left(\frac{B \cdot d}{L_{pp}} \right)^{0.75} \cdot h_S^2 \tag{2.6}$$

where B is the breadth of ship, L_{pp} the length between perpendiculars, d the draft at the specified condition of loading, h_S the significant wave height, and V the ship speed. Note, however, that this method only works for irregular short-crested waves and does not apply to swells. Taskar and Andersen (2021) mention several methods that apply to various wavelengths, like the DTU method, the STAwave2 method, or the NTUA method, which require the calculation of the wave spectrum. Due to the practical incompatibility of these methods' complexity with the capabilities of the software package for probabilistic programming used in the modeling process, the waves and swells resistance is not analyzed further.

2.3.2 Models

Due to the additive nature of the resistances on a ship, models assuming that the response variable combines the explanatory variables are suitable here. Known models of this group are the Linear Regression Models, the Polynomial Regression Models, and the Generalized Additive Models (James et al., 2023). The modeling process combines statistical learning with domain knowledge, as in Coraddu et al. (2018) and Berthelsen and Nielsen (2021). Model-based machine learning, also called probabilistic machine learning, allows for such a process, as it enables the creation of customized models individually designed for each particular use case (Bishop, 2013). The following subsections describe the different models used for the analysis.

2.3.2.1 Linear model

First, we use a linear regression model, where the weather parameters (wind, wave, and swell) appear without their directions. Knowing that the relation between some variables, e.g., between fuel consumption and ship or wind speeds, is not linear, we use this model as our baseline for assessing the performance of the other models. The linear model is adapted to the prior knowledge mainly by constraining the parameter distributions. For most parameters in all the models (except stated otherwise), the standard deviation σ is initialized with the default value of one since no prior information indicated something different. For the linear model without direction, prior knowledge leads to the following distributions:

- The fuel consumption y is assumed to be zero if all explanatory variables are zero, i.e., the ship is not in operation. Thus, the intercept β_0 is an unconstrained normal distribution with a mean of zero. It also means, in practice, that the error term ϵ is merging with the coefficient β_0 to build the intercept of the fitted model $\hat{\beta}_0$.
- Since the fuel consumption y can never be negative, it is modeled using a truncated normal distribution with a lower bound of zero. The prior distribution for the standard deviation σ is chosen as a standard half-normal distribution, accounting for the non-negativity of σ.
- The ship's speed is expected to have a very strong positive relation with fuel consumption since an increase in speed is, in most cases, a direct

result of an increase in engine power. Thus, the coefficient β_{Speed} is modeled using a truncated normal distribution with a lower bound (a) of 0.

- Since an increase in wave and swell heights increases the fuel consumption, their coefficients ($\beta_{Waves}, \beta_{Swell}$) are also modeled using a truncated normal distribution with a lower bound of zero.
- While wind on the stern can decrease the fuel consumption (Perera and Mo, 2018), most data points reflect headwind. Therefore, the coefficient β_{Wind} is expected to be positive and modeled as a truncated normal distribution with a lower bound of 0.
- The wetted surface area increases with larger draft, resulting in higher calm-water resistance and fuel consumption. Therefore, the respective coefficient β_{draft} is modeled analogously to the others.

The model summarizes as follows:

$$
\begin{gathered}
\beta_0 \sim \mathcal{N}(0,1) \\
\beta_{Speed}, \beta_{Draft}, \beta_{Wind}, \beta_{Wave}, \beta_{Swell} \sim \mathcal{N}(0,1,a=0) \\
\mu = \beta_0 + \beta_{Speed} \cdot X_{Speed} + \beta_{Draft} \cdot X_{Draft} \\
+\beta_{Wind} \cdot X_{Wind} + \beta_{Waves} \cdot X_{Waves} + \beta_{Swell} \cdot X_{Swell} \\
\sigma \sim \mathcal{N}(0,1,a=0) \\
y \sim \mathcal{N}(\mu,\sigma,a=0)
\end{gathered}
$$

We then build upon the previous model and add directions to the weather parameters. The impact of cross-wind, cross-waves, and cross-swell is complex to quantify (see, e.g., Majidian and Azarsina (2019), and Park et al. (2019)). Therefore, the coefficients $\beta_{WindBeam}$, $\beta_{WavesBeam}$, and $\beta_{SwellBeam}$ are modeled using an unbounded normal distribution. The negative relation between wind, waves, and swell on the stern and fuel consumption, as described by Perera and Mo (2018), is reflected by the coefficients $\beta_{WindStern}$, $\beta_{WavesStern}$, and $\beta_{SwellStern}$, modeled by a truncated normal distribution with an upper bound (b) of zero. The specifications of the probabilistic model are:

$$\beta_0, \beta_{WindBeam}, \beta_{WavesBeam}, \beta_{SwellBeam} \sim \mathcal{N}(0,1)$$
$$\beta_{Speed}, \beta_{Draft}, \beta_{WindBow}, \beta_{WavesBow}, \beta_{SwellBow} \sim \mathcal{N}(0,1,a=0)$$
$$\beta_{WindStern}, \beta_{WavesStern}, \beta_{SwellStern} \sim \mathcal{N}(0,1,b=0)$$
$$\mu = \beta_0 + \beta_{Speed} \cdot X_{Speed} + \beta_{Draft} \cdot X_{Draft}$$
$$+\beta_{WindBow} \cdot X_{WindBow} + \beta_{WindBeam} \cdot X_{WindBeam} + \beta_{WindStern} \cdot X_{WindStern}$$
$$+\beta_{WavesBow} \cdot X_{WavesBow} + \beta_{WavesBeam} \cdot X_{WavesBeam} + \beta_{WavesStern} \cdot X_{WavesStern}$$
$$+\beta_{SwellBow} \cdot X_{SwellBow} + \beta_{SwellBeam} \cdot X_{SwellBeam} + \beta_{SwellStern} \cdot X_{SwellStern}$$
$$\sigma \sim \mathcal{N}(0,1,a=0)$$
$$y \sim \mathcal{N}(\mu,\sigma,a=0)$$

2.3.2.2 *Polynomial regression*

According to James et al. (2023), a polynomial model expands upon the linear model by including polynomials of the explanatory variables, which enables fitting a non-linear curve to the data. The polynomial regression model allows the use of more prior knowledge concerning the non-linear relations between fuel consumption and the explanatory variables. The relation between fuel consumption and speed is cubic, according to Section 2.3.1. Equations 2.5 and 2.6 show a squared relation between the wind speed, the wave height, and swell height with the fuel consumption. Since the exact exponents of the variables are known, modeling the complete polynomial would only add complexity. Instead, the model only includes the identified exponents. The model, without directions, is then:

$$\beta_0 \sim \mathcal{N}(0,1)$$
$$\beta_{Speed}, \beta_{Draft}, \beta_{Wind}, \beta_{Wave}, \beta_{Swell} \sim \mathcal{N}(0,1,a=0)$$
$$\mu = \beta_0 + \beta_{Speed} \cdot X^3_{Speed} + \beta_{Draft} \cdot X_{Draft}$$
$$+\beta_{Wind} \cdot X^2_{Wind} + \beta_{Waves} \cdot X^2_{Waves} + \beta_{Swell} \cdot X^2_{Swell}$$
$$\sigma \sim \mathcal{N}(0,1,a=0)$$
$$y \sim \mathcal{N}(\mu,\sigma,a=0)$$

The polynomial regression model with directions is also investigated, using the same distributions as for the linear model. The only difference lies in the μ term, as follows:

$$\begin{gathered}\mu = \beta_0 + \beta_{Speed} \cdot X^3_{Speed} + \beta_{Draft} \cdot X_{Draft} \\ + \beta_{WindBow} \cdot X^2_{WindBow} + \beta_{WindBeam} \cdot X^2_{WindBeam} + \beta_{WindStern} \cdot X^2_{WindStern} \\ + \beta_{WavesBow} \cdot X^2_{WaveBows} + \beta_{WavesBeam} \cdot X^2_{WavesBeam} + \beta_{WavesStern} \cdot X^2_{WavesStern} \\ + \beta_{SwellBow} \cdot X^2_{SwellBow} + \beta_{SwellBeam} \cdot X^2_{SwellBeam} + \beta_{SwellStern} \cdot X^2_{SwellStern}\end{gathered}$$

2.3.2.3 Generalized additive model

A generalized additive model (GAM) expands upon the linear model by substituting the terms $\beta_i \cdot X_i$ with a function $f_i(X_i)$, fitted to distinct sections i of the variable space (James et al., 2023). These independent polynomial functions, called splines, can produce a very flexible fit (James et al., 2023). The points on which the space is split into sections are called knots. To fit splines to the data, matrices B containing several basis functions are created for each variable and then weighted using a set of coefficients w_i. The spline for each variable is then the weighted linear combination of these basis functions, as in $f(X) = \sum_i w_i \cdot B_i$.

For this GAM, cubic splines are chosen as they are the lowest-degree splines that can generate adequate curves for most situations (Martin et al., 2021). The prior distributions over the coefficients w_i are modeled as normal distributions since no prior knowledge indicates a different underlying distribution. The associated standard deviations are modeled as standard half-normal distributions.

Following Martin et al. (2021), the knots are spaced according to data quantiles and not linearly so that sections with more data points can be modeled flexibly. The number of knots for each variable is chosen after evaluating 2, 4, 6, 8, 10, and 12 knots using leave-one-out cross-validation (Vehtari et al., 2015). Figure 2.10 shows the resulting sections for each variable.

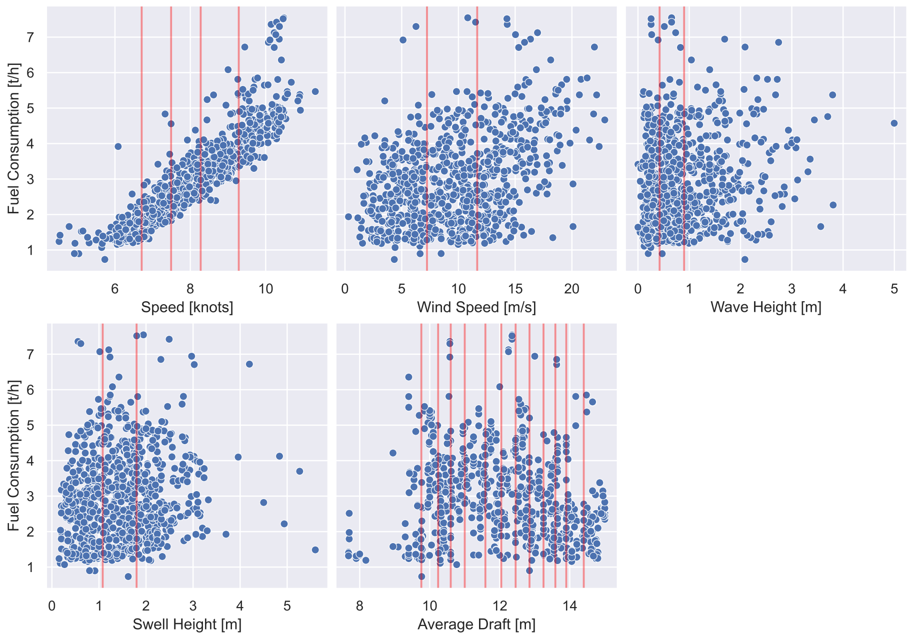

Figure 2.10: Subdivision of the variable spaces - GAM without directions

The model specification is:

$$
\begin{gathered}
\beta_0 \sim \mathcal{N}(0,1) \\
\tau_{Speed} \sim \mathcal{N}(0,1,a=0) \\
\ldots \\
\tau_{Swell} \sim \mathcal{N}(0,1,a=0) \\
w_{Speed} \sim \mathcal{N}(0,\tau_{Speed}) \\
\ldots \\
w_{Swell} \sim \mathcal{N}(0,\tau_{Swell}) \\
\mu = \beta_0 + w_{Speed} \cdot B_{Speed} + w_{Draft} \cdot B_{Draft} \\
+ w_{Wind} \cdot B_{Wind} + w_{Waves} \cdot B_{Waves} + w_{Swell} \cdot B_{Swell} \\
\sigma \sim \mathcal{N}(0,1,a=0) \\
y \sim \mathcal{N}(\mu,\sigma,a=0)
\end{gathered}
$$

A GAM is also made with weather directions, using the same principles. Figure 2.11 shows the splines for this model.

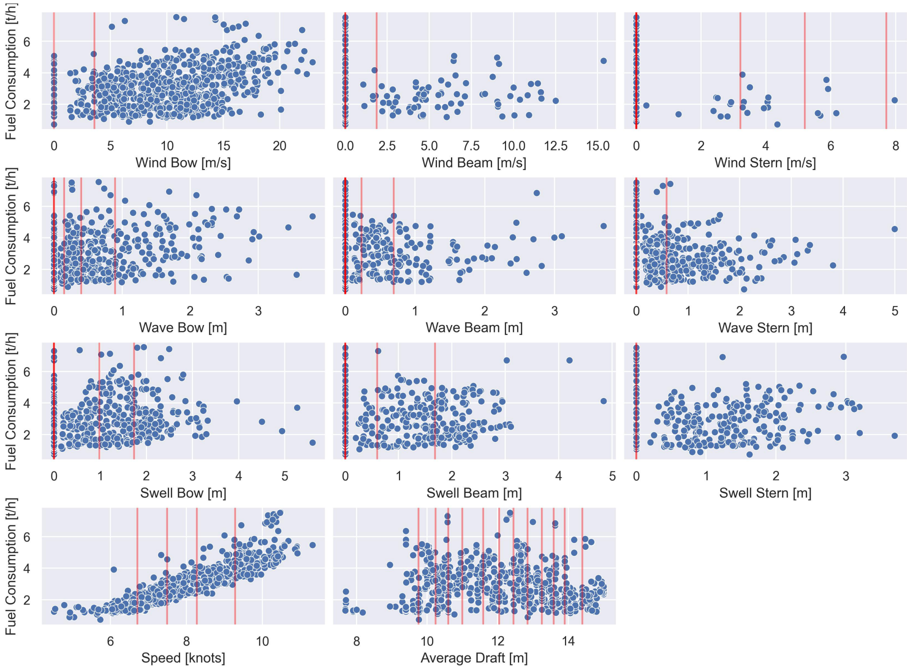

Figure 2.11: Subdivision of the variable spaces - GAM with directions

2.3.2.4 *Custom model considering the principles of naval architecture*

Lastly, a custom model directly reflects the dependencies of a ship's fuel resistance based on naval architecture principles.

The resistances are modeled as normal distributions, where the means are obtained from the respective formulas of Section 2.3.1. The relative wind speed is used for calculating R_{Wind} since the coefficient C_{air} is based on the relative wind direction. Therefore, R_{Wind} consists of the wind and the air resistance.

$$R_{CalmWater} \sim \mathcal{N}(\frac{1}{2} \cdot C_T \cdot \rho_{water} \cdot S \cdot X^2_{Speed}, 1)$$
$$R_{Air} \sim \mathcal{N}(\frac{1}{2} \cdot C_{air} \cdot \rho_{air} \cdot A_F \cdot X^2_{Speed}, 1)$$
$$R_{Wind} \sim \mathcal{N}(\frac{1}{2} \cdot C_{air}(\epsilon) \cdot \rho_{air} \cdot A_F \cdot X^2_{Wind}, 1)$$
$$R_{WavesBow} \sim \mathcal{N}(1336 \cdot (5.3 + X_{Speed}) \cdot \left(\frac{B \cdot d}{L_{pp}}\right)^{0.75} \cdot X^2_{WavesBow}, 1)$$

Calculating wave resistance from directions other than head wave and the swell resistance would require formulas too complex for the software package. Therefore, the fuel consumption of these variables is approximated analogously to the linear and polynomial models.

$$\beta_{WavesBeam}, \beta_{SwellBeam} \sim \mathcal{N}(0,1)$$
$$\beta_{WavesStern}, \beta_{SwellStern} \sim \mathcal{N}(0,1, b=0)$$
$$\beta_{SwellBow} \sim \mathcal{N}(0,1, a=0)$$

The power required by the resistances is calculated using a modified Equation 2.2, where the engine efficiency is omitted, to determine the brake power rather than the fuel power. This allows the fuel consumption to be calculated based on brake-specific fuel consumption.

$$P_{CalmWater} = \frac{R_{CalmWater} \cdot X_{Speed}}{\eta_{overall}}$$
$$P_{Air} = \frac{R_{Air} \cdot X_{Speed}}{\eta_{overall}}$$
$$P_{Wind} = \frac{R_{Wind} \cdot X_{Speed}}{\eta_{overall}}$$
$$P_{WavesBow} = \frac{R_{WavesBow} \cdot X_{Speed}}{\eta_{overall}}$$

The company provides the formula for fuel oil consumption as a function of power requirements, indicated as $f_{foc}()$. The formula is based on the polynomial relation between power and fuel consumption, derived from ship tests. Note that the wind resistance R_{Wind} is calculated based on the wind speed relative to the ship and therefore includes the true wind resistance and the air resistance. As such, and to isolate the fuel consumption solely caused by the wind, the fuel consumption attributed to air resistance is deducted from the overall wind-related fuel consumption.

$$
\begin{gathered}
foc_{CalmWater} = f_{foc}(P_{CalmWater}) \\
foc_{Air} = f_{foc}(P_{Air}) \\
foc_{Wind} = f_{foc}(P_{Wind}) - foc_{Air} \\
foc_{WavesBow} = f_{foc}(P_{WavesBow}) \\
foc_{Wave} = foc_{WavesBow} + \beta_{WavesBeam} \cdot X^2_{WavesBeam} + \beta_{WavesStern} \cdot X^2_{WavesStern} \\
foc_{Swell} = \beta_{SwellBow} \cdot X^2_{SwellBow} + \beta_{SwellBeam} \cdot X^2_{SwellBeam} \\
+ \beta_{SwellStern} \cdot X^2_{SwellStern}
\end{gathered}
$$

The wetted surface area S entering the previously mentioned resistance distributions is calculated based on Mumford's formula (MAN Energy Solutions, 2018):

$$
S = 1.025 \cdot L_{pp} \cdot (C_B \cdot B + 1.7 \cdot T) \tag{2.7}
$$

where L_{pp} is the length between perpendiculars, C_B the block coefficient, B the ship's breadth, and T the draft. The remaining specifications of the probabilistic model are given below, where A_F is the frontal area of the ship above the waterline, $A_{F_{dry}}$ the total frontal area of the ship, T the average draft and B the breadth of the ship.

$$
\begin{gathered}
\beta_0 \sim \mathcal{N}(0,1) \\
A_F = A_{F_{dry}} - T \cdot B \\
\mu = \beta_0 + foc_{CalmWater} + foc_{Air} + foc_{Wind} + foc_{Wave} + foc_{Swell} \\
\sigma \sim \mathcal{N}(0,1,a=0) \\
y \sim \mathcal{N}(\mu,\sigma,a=0)
\end{gathered}
$$

2.3.3 Model implementation

The probabilistic programming software package PyMC by Salvatier et al. (2016) is used and implemented in Python 3.8.5. The basis functions for the GAM are created using design matrices from the python package patsy (Smith, 2023).

The original data set is divided into a training and a test data set, with the training set containing 80% of the original data. In PyMC, explanatory variables declared as "MutableData" can be replaced with the test data after training, which enables the user to make predictions for the test data using the model trained on the training data (The PyMC Development Team, 2023). From these predictions, metrics assessing the performance of the models are calculated using the scikit-learn library (Pedregosa et al., 2011). The ArviZ library complements the previous library by providing a Pareto-smoothed importance sampling leave-one-out cross-validation method, introduced in Section 2.3.4 (Kumar et al., 2019).

2.3.4 Model evaluation

This section evaluates the predictive performance of the different models to determine the most appropriate one. Three evaluation metrics are chosen: the coefficient of determination (R^2 score), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The R^2 score describes the share of the total variance explained by the model and measures a model's overall fit to the data. The MAE represents the mean of the errors, i.e., the differences between the observed and predicted values for all data points. The MAPE calculates the error divided by the actual target variable, averaged over all data points, which puts the expected deviation from the actual fuel consumption into the perspective of the overall fuel consumption. Table 2.4 shows the obtained performance metrics for all the models, together with their expected log pointwise predictive density (elpd), introduced in the next paragraph.

Table 2.4: Out-of-sample performance comparison between the models

Model	R2-Score	MAE	MAPE	elpd
GAM - No Direction				-437
GAM - Direction				-463
Polynomial - Direction	0.865	0.307 t/h	10.2%	-510
Linear - Direction	0.875	0.290 t/h	10.5%	-534
Polynomial - No Direction	0.838	0.347 t/h	11.4%	-614
Linear - No Direction	0.835	0.357 t/h	12.5%	-639
Custom model	0.706	0.515 t/h	17.7%	-769

These metrics are not calculated for the GAMs, as a different software library is used for the basis functions of the splines. Therefore the approach for calculating metrics based on the test data using variables of the type "MutableData" cannot be applied. However, the Pareto-smoothed importance sampling leave-one-out cross-validation method, provided by the Arviz library (Kumar et al., 2019), estimates the expected log pointwise predictive density (elpd) for the test data. This metric allows the comparison of all models. The higher the elpd value, the better the models' ability to predict the test data. Figure 2.12 displays the elpd-comparison for the models, with the standard error of the elpd as horizontal lines, and the elpd difference indicates the difference from the top-ranked model, here the GAM without direction. The GAMs provide the best fit, closely followed by the polynomial and the linear models considering the weather directions. The model based on the principles of naval architecture exhibits a noticeably inferior performance compared to the other models.

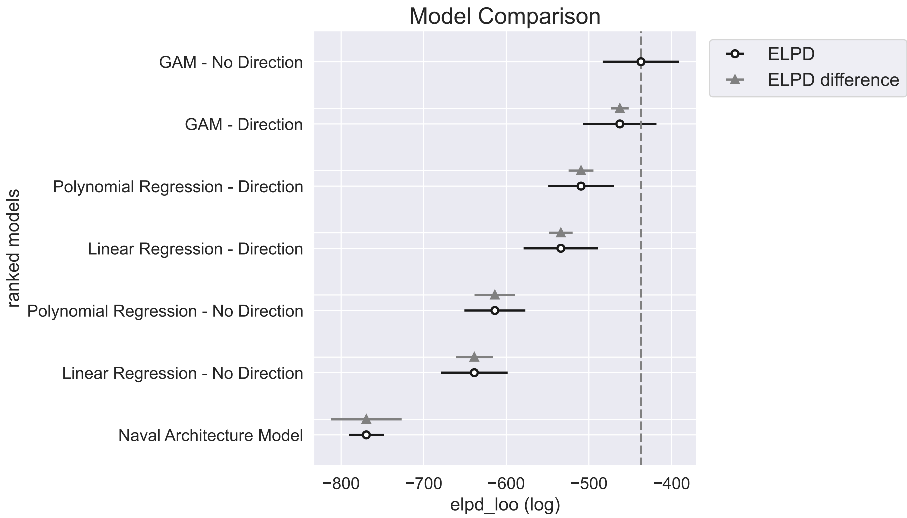

Figure 2.12: Pareto-smoothed importance sampling LOO cross-validation results

Figure 2.13 shows a graphical representation of the models' data fit, only for the models with directions. The blue and orange lines represent the predicted fuel consumption distributions and their average. The polynomial and the GAM predict the underlying distribution well. The linear model fits the actual distribution well, apart from the range from one to two tons per hour. The

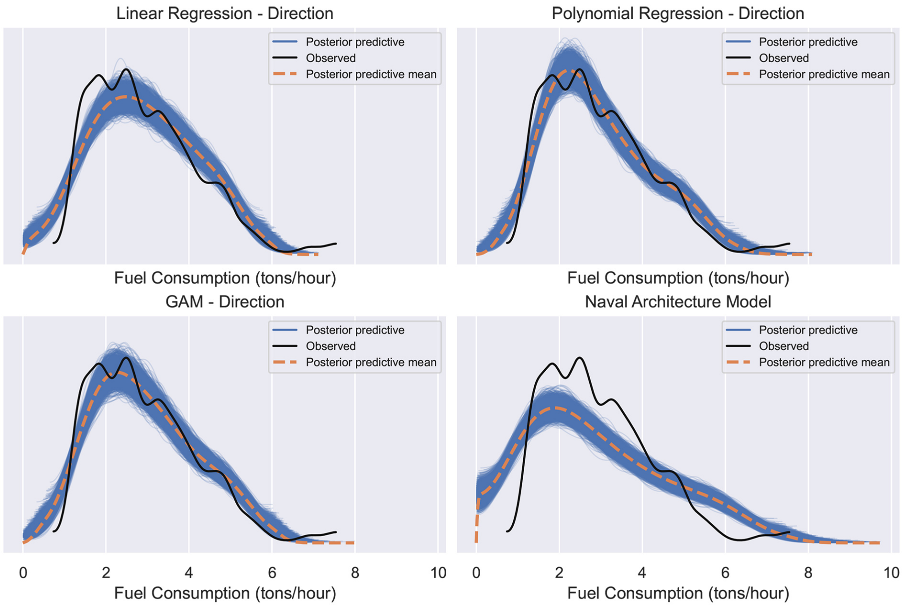

Figure 2.13: Posterior predictive distribution

model based on the principles of naval architecture predicts many data points in the range from zero to one ton per hour, whereas such instances are scarce in reality. Similarly, the model tends to overestimate predictions for higher consumption rates. As a result, the fuel consumption from approximately one to four tons per hour is significantly less often predicted, although most of the actual data points are within that range. Figure 2.14 highlights this issue where the model's predicted and actual fuel consumption values are plotted against each other and compared with the polynomial model for reference. The figure indicates that the naval architecture model underestimates the fuel consumption where the actual values are up to three tons per hour and overestimates the consumption where the actual values are above three tons per hour.

Based on these results, the GAM demonstrates superior predictive performance. However, the lack of available test data performance metrics for these models reduces the intuitiveness of the prediction interpretation. Moreover, the model's interpretability is more complex due to the creation and fitting of splines compared to polynomial models. Consequently, the polynomial

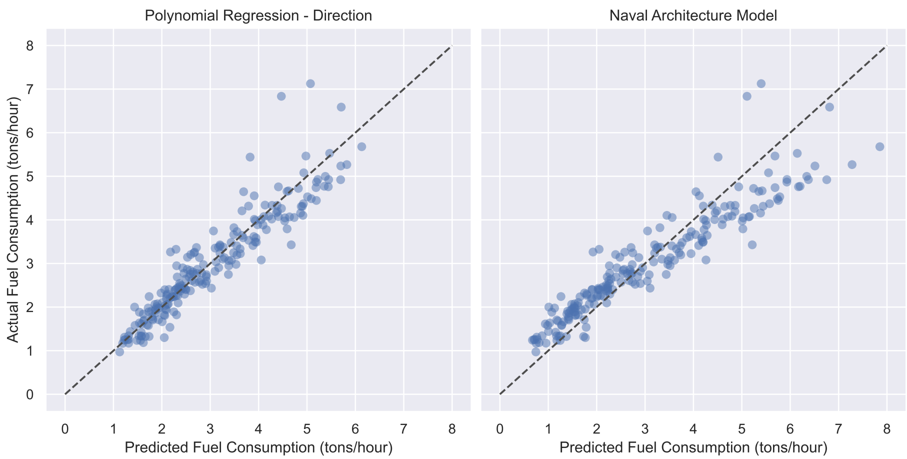

Figure 2.14: Posterior predictive fit

model, which incorporates the weather directions and performs similarly well, is preferred for further analysis. Given the research objective, which aims to gather comprehensive insights into the influence of weather conditions, the model that considers the directions is preferred over the one that does not. Despite its comparatively poor performance, the naval architecture model is still included in the following analysis to examine potential outcome variations attributed to the knowledge-based formulas.

2.4 Results and Discussion

This section presents the results, quantifying the weather impact on ship fuel consumption. It further develops weather correction factors and includes a discussion on the methodology and the limitations of the present work.

2.4.1 Results

To evaluate the impact of weather on fuel consumption, the fuel consumption attributed to weather is divided by the total fuel consumption minus the coefficient $\hat{\beta}_0$. Indeed, the intercept β_0 does not represent the influence of weather or calm-water conditions. Considering that β_0 should be zero (i.e., no fuel consumption if the ship is not in operation), we assume that the fitted value for $\hat{\beta}_0$ solely consists of the error term ϵ. Therefore, the value of $\hat{\beta}_0$ can be subtracted from the total fuel consumption (y_{Total}) without losing information regarding the impact of weather. Equation 2.8 expresses the share of fuel consumption attributed to weather:

$$\text{Share of fuel consumption due to weather} = \frac{y_{Weather}}{y_{Total} - \hat{\beta}_0} \tag{2.8}$$

where $y_{Weather}$ is the fuel consumption attributed to weather, y_{Total} the total fuel consumption and $\hat{\beta}_0$ the fitted intercept term.

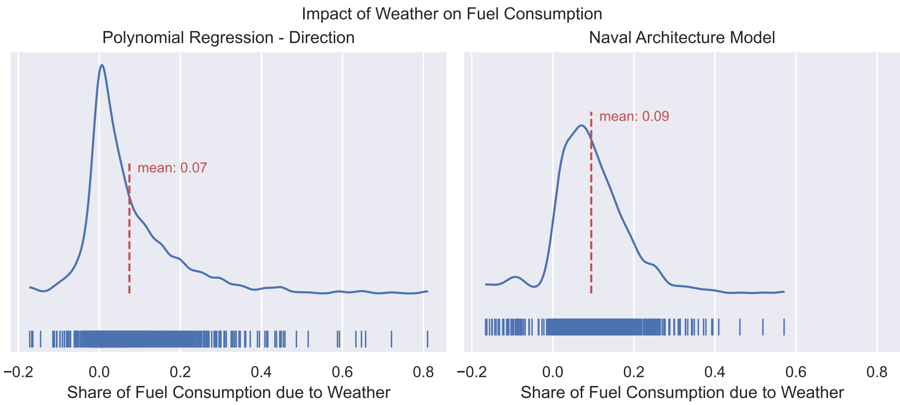

Figure 2.15: Distribution of the impact of weather as a share of the total fuel consumption. The vertical blue lines indicate the individual observations and the dotted red line is the mean value.

Figure 2.15 shows the result of the share of fuel consumption due to weather for the polynomial regression model with weather direction and the naval architecture model. The polynomial model reports a mean of 7% of the fuel consumption attributed to weather, while this is raised to 9% for the naval architecture model. Figures 2.16 to 2.18 show the impact of each weather variable (wind, wave, and swell) on the total fuel consumption, differentiated depending on the relative direction.

Figure 2.16 shows that, on average, 3% to 2% of the fuel consumption can be attributed to the wind impact for the polynomial and the naval architecture models. In headwind (42.3% of the observations), the share increases to 8%

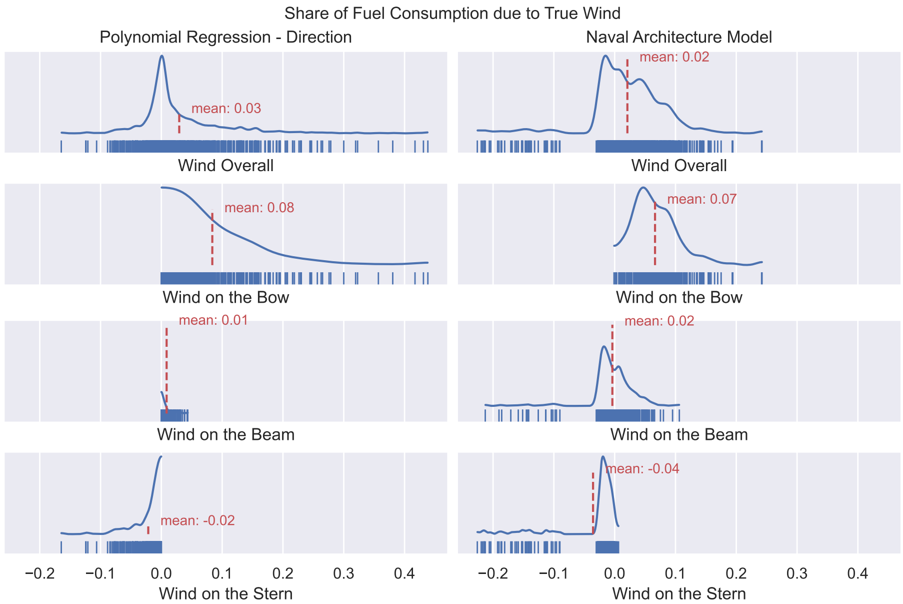

Figure 2.16: Distribution of the impact of wind on fuel consumption, depending on the direction

and 7%, respectively, while it decreases to -2% and -4% for the wind on the stern (34.6% of the observations). Wind on the beam (23.1% of the observations) shows intermediate values, with 1% and 2%, respectively.

Figure 2.17 presents the results regarding waves. According to the polynomial and naval architecture models, the average share of fuel consumption attributed to waves is 2% and 5%. In head waves (45.3% of the observations), it is 3% and 6%, and 3% and 1% for waves on the beam (21.7%). Finally, the share of fuel consumption attributed to waves on the stern (33.0% of the observations) is negligible for both models.

The overall average share of fuel consumption due to swells is 3% according to the polynomial model (2% for the naval architecture model), as shown in Figure 2.18. The swell on the bow (41.6% of the observations) accounts to 5% (4%). Swells on the beam (31.8% of the observations) have a share of 3% (2%), while the share for the swells on the stern (26.6% of the observations) falls to 0% (-1%).

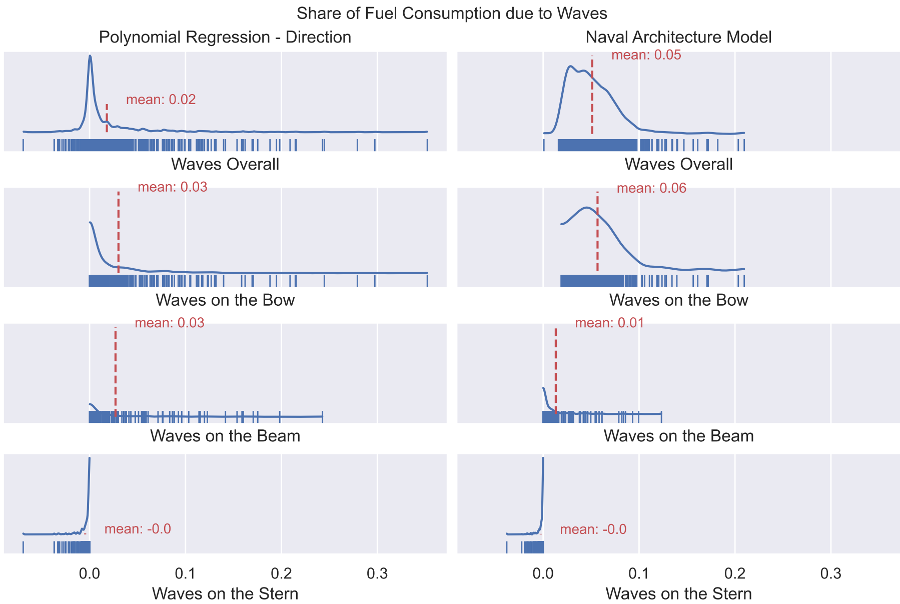

Figure 2.17: Distribution of the impact of waves on fuel consumption, depending on the direction

The naval architecture model over-predicts fuel consumption at the lower and higher ranges and underestimates the intermediate figures. Therefore, the polynomial model is more accurate and is used to examine the influence of weather on fuel consumption for the different sea states. Figure 2.19 shows the weather impact for different sea conditions according to the polynomial model. The numbers in parentheses indicate the wind speeds related to the respective sea state.

2.4.2 Weather correction factor

This section explains the logic behind the different weather correction factors and provides some figures based on the results from Section 2.4.1. These correction factors follow the same principle as the EEDI weather correction factor f_w, meaning that the factors are meant for the EEDI denominator and with a value between zero and one (one being calm-sea conditions). Note that the weather correction factors decrease as the weather conditions get harsher.

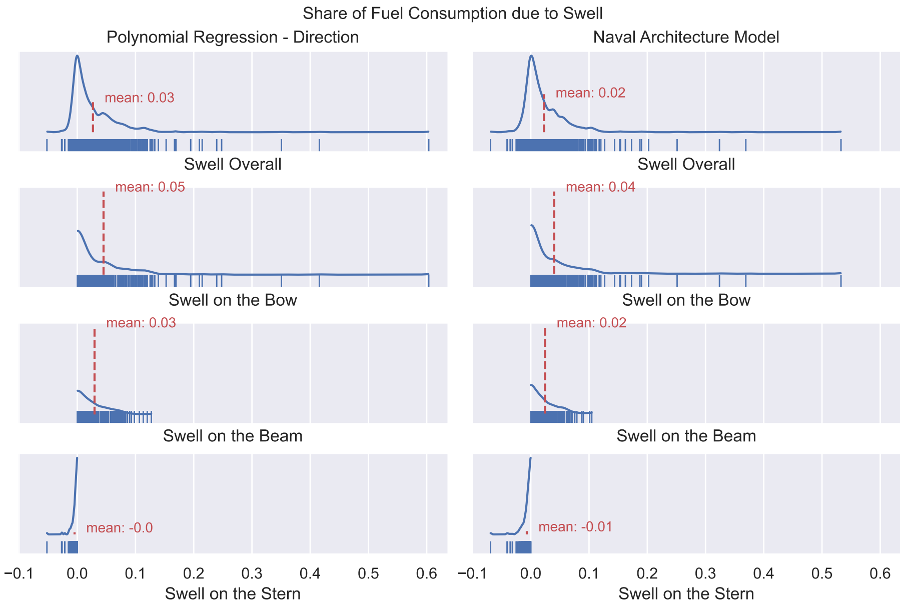

Figure 2.18: Distribution of the impact of swells on fuel consumption, depending on the direction

The correction factor for each sea state is obtained by dividing the fuel consumption in calm water by the fuel consumption in the corresponding sea condition. Simple transformations lead to Equation 2.9, expressing the correction factor as a function of Share of $y_{Weather}$, which is defined as the weather-related fuel consumption as a share of the total fuel consumption, and results directly from the analysis of the previous section.

$$\text{Weather correction factor} = 1 - \text{Share of } y_{Weather} \tag{2.9}$$

Due to the higher accuracy of the polynomial model, we calculate the correction factors based on the results of this model. Table 2.5 provides the sea state-specific correction factors and compares them with the mean of the sample voyages and the IMO weather correction factor f_w. The calculation of f_w, based on the reference line for container ship, results from Equation 2.10

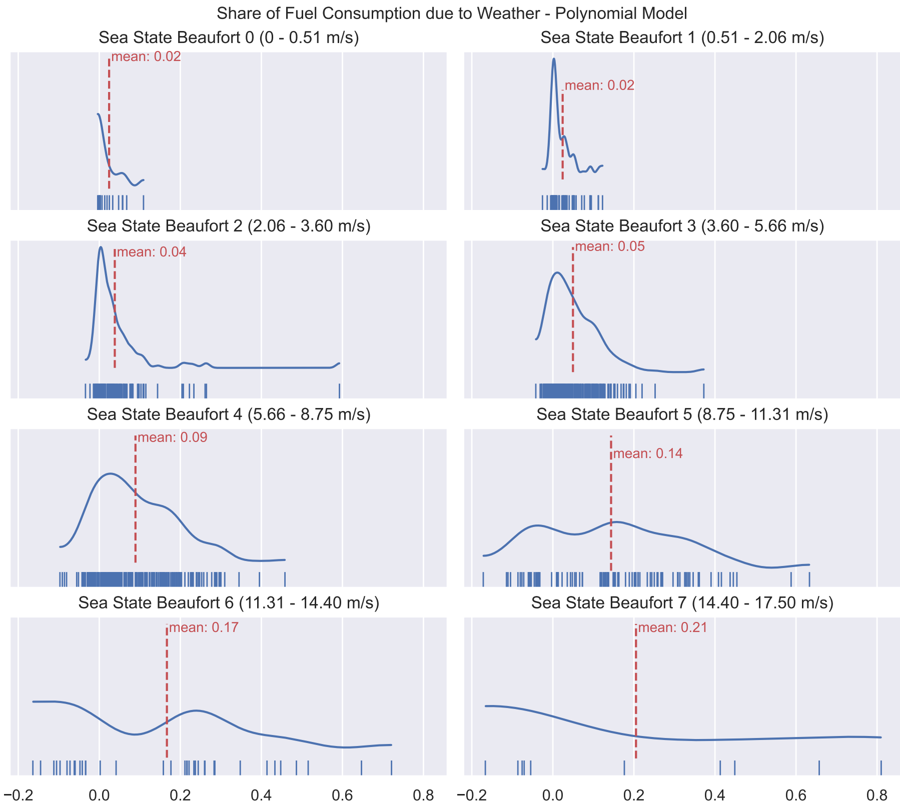

Figure 2.19: Weather impact by sea state

based on IMO (2012):

$$f_w = 0.0208 \cdot \ln(\text{Capacity}) + 0.633 \tag{2.10}$$

According to Table 2.5, the influence of weather conditions is minimal for BF 0 to BF 3. However, it notably increases with each subsequent step from BF 4 to BF 7. This aligns with the model following a quadratic function for the weather variables. The weather correction factor decreases correspondingly. Surprisingly, the weather impact in BF 0 is reported to be slightly greater than in BF 1. This finding contradicts the assumption that as weather conditions become more adverse, the weather's influence on fuel consumption increases. However, considering the acknowledged model inaccuracy, the difference of

Table 2.5: Correction factor for different sea states

Sea state	Correction factor	Weather impact
Beaufort 0	0.9755	2.45%
Beaufort 1	0.9758	2.42%
Beaufort 2	0.9617	3.83%
Beaufort 3	0.9505	4.95%
Beaufort 4	0.9110	8.90%
Beaufort 5	0.8570	14.30%
Beaufort 6	0.8338	16.62%
Beaufort 7	0.7955	20.45%
Sample voyages	0.9258	7.42%
f_w from IMO	0.8752	12.48%

0.03 percentage points is negligible. Therefore, the impact of weather conditions can be considered the same for these two sea states.

2.4.3 Discussion

This section compares the present results with existing literature, discusses the policy implications of weather correction factors, and finally presents the limitations of the paper.

2.4.3.1 *Comparison with existing literature*

As described in Section 2.1, only a few studies have been concerned with estimating the impact of weather variables on fuel consumption. Among them, Meng et al. (2016) estimate the contribution of bad weather (defined as bow/beam waves of 2.5 m or higher) on the fuel consumption of four container ships. When considering all directions, they find that bad weather contributes between 4 and 10% of fuel consumption, depending on the ship. These numbers rise to 6-20% when excluding wind and waves from the stern (Meng et al., 2016). Their definition of bad weather can correspond to BF 5 or higher (ISO, 2015a), which would result in estimations similar to our analysis.

Studies using Computational Fluid Dynamics (CFD) tend to estimate higher numbers for the weather effect on fuel consumption than the present paper. For example, Islam and Guedes Soares (2022) study a KRISO container ship and find that the required propulsion power for BF 3 is 42% above the estimated one for calm sea. The CFD analysis of an S175 container ship by Kim et al. (2017) results in a sea margin between 17% at 23 knots and 34% at 16 knots, for BF 6 with head wind and waves. It is worth mentioning that the relatively fewer observations with BF 6 or higher in our data set (refer to Figure 2.7) challenges the reliability of our estimates for these sea states.

2.4.3.2 Policy implications of weather correction factors

The developed weather correction factors based on operational data are compared to IMO's technical correction factor f_w. The results from Table 2.5 indicate a significant difference in the weather impact for BF numbers greater than three. Therefore, choosing the representative sea state for a correction factor is key. E.g., BF 6, adopted by IMO as a reference, is not the most encountered sea state in our case. This is also not the case in Bialystocki and Konovessis (2016) where the most common condition is BF 5. However, it should be noted that the factors developed in this paper only result from data stemming from two sister container ships. Thus, further analysis is required to generalize the findings to other ship types and sizes.

Different approaches can develop the current work further. From a technical point of view and considering weather correction factors for EEDI, a set of correction factors for different sea states could improve the reliability of this energy efficiency indicator. Different EEDI requirements could become mandatory for various weather conditions, as suggested by Bøckmann and Steen (2016).

From an operational perspective, the weather correction factor, corresponding to the most encountered sea state, could be used to correct operational indicators, such as CII, to nullify the impact of weather on energy efficiency and thereby achieve a fairer comparison. Alternatively, the weather correction factor could be estimated as a weighted average across the sea states faced rather than selecting the most frequent one. Weather correction factors can also be combined with other approaches to operational indicators, such as operational cycles (Godet et al., 2023) or real-time monitoring of energy efficiency

(Chi et al., 2018).

2.4.3.3 Limitations

There are several limitations of this work that need to be mentioned. First, the data frequency makes the weather analysis rather coarse, while noon reports are often challenged for their uncertainties, see, e.g., Aldous et al. (2013). The uncertainties of hindcast weather data must also be considered. See, e.g., Vettor and Guedes Soares (2022).

Second, as explained in Section 2.2.1, other operational factors that influence fuel consumption are excluded from our analysis. For example, the influence of trim varies with the draft and the ship's speed. Using CFD, Islam and Guedes Soares (2019) find a difference between 0 and 4% in calm-water resistance when changing the draft and trim angle. For hull fouling, Adland et al. (2018) indicate a 9% savings in fuel consumption by hull cleaning. However, as our data only covers two years, analyzing the effect of dry-docking or other maintenance operations is impossible. Moreover, the water depth is essential to monitor for inland and shallow water transport. Our study, however, assumes that the ships sail in the open deep sea.

Third, regarding the models, linear regressions assume the independence of variables. However, as shown in Figure 2.8, wave height/direction are, to some extent, correlated with wind speed/direction. Besides, the ship's speed cannot be considered independent, as a ship would sail slower in harsh weather conditions (Psaraftis and Lagouvardou, 2023).

2.5 Conclusion

International shipping contributes significantly to GHG emissions, burning fossil fuels to transport goods. The IMO regulations intend to reduce these emissions by setting standards for energy efficiency, which rely on technical (EEDI) and operational (CII) indicators. Ships' fuel consumption, directly related to energy efficiency, depends on many operating factors, including weather conditions, which are uncontrollable by the operators. To have comparable indicators across different ships, the impact of weather needs to be isolated. This paper aimed to estimate the weather impact on fuel consumption and develop correction factors nullifying this impact. Based on the analysis of noon reports of two sister container ships, key conclusions can be summarized as follows:

- Linear and polynomial regression models and a custom model based on naval architecture principles were developed using model-based machine learning. While the models showed similar results, the polynomial model significantly outperformed the naval architecture model.
- The models showed a 7 to 9% average impact of weather on fuel consumption. These numbers result from two-year data, with most data points resulting from moderate sea conditions (sea states 3 and 4 on the Beaufort scale). The weather impact spans from 2.4% for Beaufort 0 to 20.4% for Beaufort 7. No observations were reported above Beaufort 7, noting that the reported weather conditions are averaged over the report duration (about 24 hours).
- Weather correction factors were calculated for the different sea conditions and compared with the IMO weather correction factor f_w. The average correction factor during the sample voyages is 0.9258, higher than the 0.8752 figure of IMO's f_w. The resulting factors span from 0.9758 for Beaufort 1 to 0.7955 for Beaufort 7.

This paper aimed to bring a new perspective on energy efficiency indicators by considering weather correction factors differentiated for specific sea states. The need for normalizing the impact of weather on these indicators is emphasized if the latter are to be used as benchmarks. Further studies will extend this work to different ship sizes and evaluate the policy implications on EEDI and CII.

Nomenclature – Chapter 2

A_F	Frontal area of the ship above the waterline
B	Ship breadth
B_i	Basis function for the section i
C_T	Total resistance coefficient
C_{air}	Aerodynamic resistance coefficient
L_{pp}	Length between perpendiculars
P_{fuel}	Fuel power
R_T	Total ship resistance
R_{Air}	Air resistance
$R_{Friction}$	Frictional resistance
R_{Waves}	Added resistance due to waves
R_{Wind}	Added resistance due to wind
S	Ship wetted surface area
V	Ship speed
$V_{Wind,Relative}$	Relative wind speed (or apparent wind speed)
$V_{Wind,True}$	True wind speed
V_{Wind}	Wind speed
α	Relative wind direction (relative to the ship bow)
β_0	Intercept
β_x	Prior distributions of the variables, $x \in \{\text{Speed}, \text{Draft}, \text{Wind}, \text{Waves}, \text{Swell}\}$
ϵ	Error term
η_E	Engine efficiency
η_H	Hull efficiency
η_O	Open water efficiency
η_R	Rotative efficiency
η_S	Shaft efficiency
η_{GB}	Gearbox efficiency
$\mathcal{N}$	Normal distribution
μ	Mean
ρ_{air}	Mass density of air
ρ_{water}	Mass density of water
σ	Standard deviation
a	Lower bound of the normal distribution

b	Upper bound of the normal distribution
d	Draft
f_w	Weather correction factor developed by the IMO
f_{foc}	Function giving the specific fuel consumption
h_S	Significant wave height
i	Section in the GAM
w_i	Weight coefficient for the section i
y	Fuel consumption
y_{Total}	Total fuel consumption
$y_{Weather}$	Fuel consumption attributed to weather

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3 Operational cycles for maritime transportation: A benchmarking tool for ship energy efficiency (Paper 2)

Amandine Godet[a], Jacob Normann Nurup[a], Jonas Thoustrup Saber[a], George Panagakos[a], Michael Bruhn Barfod[a]

[a] Department of Technology, Management and Economics, Technical University of Denmark, 2800 Kongens Lyngby, Denmark

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Abstract Benchmarking the energy efficiency of ships is not a straightforward task, mainly due to the diversity of operations. Although driving cycles have been used for decades in evaluating the performance of road vehicles, these do not exist in formal policy-making for maritime transport. This work builds on a previously proposed methodology. It uses noon reports of 327 vessels for 2019 to construct operational cycles for seven size classes of container ships using the main engine power as the main parameter. Concerning the main engine emissions, the resulting cycles reduce variation in the carbon intensity indicator values by more than 30% while maintaining an average accuracy of 97.7% in absolute emissions. These figures show that the concept can improve operational carbon intensity indicators in terms of robustness and their technical counterparts in optimizing ship design. The paper also proposes further work required for benchmarking applications in policy-making.

Keywords: *Operational cycles; International shipping; Decarbonization; Carbon intensity indicators; Maritime policy*

3.1 Introduction

Shipping is generally the most climate-friendly mode of freight transport, in terms of carbon intensity (gCO_2/ton*km) (Buhaug et al., 2009). However, the vast volume of international maritime trade, which reached the record-breaking level of almost 59 trillion ton-miles in 2021 (UNCTAD, 2022), results in a substantial carbon footprint. According to the 4^{th} International Maritime Organization (IMO) greenhouse gas (GHG) Study, the GHG emissions - including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) - of the entire shipping sector (international, domestic and fishing) reached 1,076 million tonnes of CO_{2_e} in 2018, representing 2.89% of global anthropogenic emissions (Faber et al., 2020). Alarmingly, the same study projects emissions to increase from about 90% of the 2008 level in 2018 to 90-130% of 2008 emissions by 2050.

Reports such as those of the IMO (Faber et al., 2020) or the Intergovernmental Panel on Climate Change (IPCC) (Jaramillo et al., 2022) strengthen the pressure on global regulators to reduce the carbon emissions of international shipping. Setting proper standards, then, becomes a priority. The sector's regulatory framework is built around technical and operational carbon intensity indicators that suffer specific drawbacks. The automotive industry is explored as a source of inspiration for addressing these drawbacks. The 'driving cycle' feature of the car assessment methodology is worth investigating.

The objectives of the present article will be derived later in this section after discussing the problems of the existing indicators used in shipping and the previous experiences with the 'driving cycle' concept. This discussion takes the place of the usual literature search.

3.1.1 The global regulatory framework

The emissions of international shipping (and aviation, for this matter) are excluded from the national obligations of the United Nations Framework Convention on Climate Change (UNFCCC) framework as a consequence of the international 'location' of the released emissions (Bows-Larkin, 2015). For the same reason, these two sectors are excluded from the 2015 Paris Agreement on

Climate Change, which deals primarily with national commitments relating to domestic emissions and removals. Instead, the Kyoto Protocol delegated the global regulatory role for reducing GHG emissions from international shipping to the IMO (UN, 1997). In September 1997, IMO's Marine Environment Protection Committee (MEPC) was invited to consider CO_2 reduction strategies and, in December 2003, the IMO Assembly 'urged MEPC to identify and develop the mechanism(s) needed to achieve the limitation or reduction of GHG emissions from international shipping' (IMO, 2023).

The most significant elements of the IMO's work undertaken during the last 20 years to address GHG emissions from ships (seen from the perspective of this article) are briefly presented below:

3.1.1.1 EEDI and SEEMP (EEOI)

In July 2011, resolution MEPC.203(62) introduced a package of technical and operational energy efficiency requirements applicable to ships of 400 gross tonnage (GT) and above (IMO, 2011). The technical requirements concern the Energy Efficiency Design Index (EEDI), which measures the energy efficiency level of the maximum transport work of a ship sailing in ideal conditions (fully laden, design speed, calm sea, no wind). EEDI is expressed in CO_2 emissions per ton-mile. The attained EEDI values of all newly built vessels from 2013 onwards have to be lower than specific values depending on ship type, size, and year built. These standard values become progressively stricter and are set so that ships constructed in 2025 will be at least 30% more energy efficient than those constructed in 2014.

On the operational front, all existing ships must adopt a Ship Energy Efficiency Management Plan (SEEMP) for monitoring performance improvements against business-as-usual operations. The Energy Efficiency Operational Index (EEOI), defined as a measure of CO_2 emissions per unit of actual work undertaken by the ship, also expressed in CO_2 emissions per ton-mile, was a suggested tool for SEEMP implementation, but only voluntarily and solely for monitoring the performance of individual ships.

3.1.1.2 Data Collection System (DCS)

In October 2016 and as part of a three-step approach consisting of: (1) collecting data on ships' fuel oil consumption, (2) analyzing this data, and (3) deciding on possible measures to enhance ships' energy efficiency, resolution MEPC.278(70) introduced the requirement for ships of 5,000 GT and above to record and report their fuel oil consumption (IMO, 2016). As of 1 Jan. 2019, ships need to collect data on each type of fuel oil they consume, as well as on distance traveled and hours underway (to be used together with the deadweight (DWT) and the gross tonnage (GT) of the ship as proxies for transport work). The aggregated annual data are reported to the flag State and, after approval, are transferred to the relevant IMO database. The reported data do not support EEOI, as the figure of actual cargo carried is missing. The Annual Efficiency Ratio (AER) and Cargo-distance (cgDIST) metrics are supported instead, where the actual cargo of the EEOI denominator is replaced by the DWT and GT of the ship, respectively.

It is worth noting that IMO's DCS is the global equivalent of the EU's Monitoring Reporting and Verification (MRV) requirement, which was introduced one year earlier (EU, 2015). This EU directive obliges companies to monitor, report and verify the fuel consumption and GHG emissions of their ships on voyages to, from, and within EU ports. Unlike IMO, the corresponding annual indicators, including EEOI, are published by the European Commission to incentivize emission reductions by providing energy efficiency information to the relevant stakeholders (Panagakos et al., 2019).

3.1.1.3 Initial IMO Strategy on reduction of GHG emissions from ships

In April 2018, resolution MEPC.304(72) adopted the Initial IMO Strategy on reduction of GHG emissions from ships, setting out the organization's vision for international shipping and defining its future targets (IMO, 2018). These targets include strengthening the EEDI requirements for new vessels, reducing carbon intensity (CO_2 emissions per transport work) by at least 40% by 2030, pursuing efforts toward 70% by 2050, compared to 2008, and reducing the total annual GHG emissions by at least 50% by 2050 compared to 2008. Furthermore, the strategy identified possible short-, mid-, and long-term measures to be agreed upon before 2023, during 2023-2030, and beyond 2030 respectively.

The revision of the initial strategy started in November 2021 while recognizing the need to strengthen the initial ambitions (IMO, 2021b). The revised strategy is presently being negotiated; a decision is expected during MEPC 80 scheduled for July 2023.

3.1.1.4 *Short-term measures (strengthened EEDI, EEXI, and CII)*

Strengthening the EEDI requirements was an explicit target of the initial IMO strategy. In this respect, resolution MEPC.324(75) agreed in November 2020 to bring forward the entry into effect of EEDI Phase 3 by three years (from 2025 to 2022) for several ship types and to increase the reduction rate of Phase 3 for container ships (IMO, 2020). For example, new container ships of 200,000 DWT and above had to meet a 50% reduction already in 2022 (instead of 30% starting from 2025).

Furthermore, in June 2021, resolution MEPC.328(76) introduced a package of short-term GHG reduction measures containing a technical Energy Efficiency eXisting ship Index (EEXI) and an operational Carbon Intensity Indicator (CII) through an enhanced SEEMP, all supported by a series of seven technical guidelines (IMO, 2021a). EEXI is the equivalent of EEDI for existing ships. The EEXI standards depend on ship type and size and are expressed as reduction requirements in relation to the EEDI reference line. All existing ships of 400 GT and above have to meet these standards once in a lifetime by the first periodical survey in 2023 at the latest.

The simplest compliance option available to existing ships is the Engine Power Limitation (EPL), a mechanism imposing a limit to the maximum main engine power, resulting in lower operational speeds and fuel consumption (Schroer et al., 2022). In addition, the SEEMP of ships of 5,000 GT and above is strengthened by introducing mandatory annual reductions concerning the CII, which for the time being is the AER/cgDIST metrics of IMO's DCS. For 2023-2026, the required CII is reduced by 2% per year, while the reduction requirement for subsequent years is to be agreed upon later. A rating mechanism using a labeled scale from A to E has been set up to benchmark the annual performance of a ship. A rating of C or better does not require corrective actions. However, ships rated D for three consecutive years, or E must include a verified correction plan into their SEEMP.

3.1.1.5 *Future actions*

In addition to the revised IMO strategy on reduction of GHG emissions previously mentioned, current MEPC work focuses on the mid-term measures that include a market-based measure (in the form of a fuel/emission levy or a cap-and-trade mechanism) and a technical measure (in the form of carbon intensity restrictions of the energy consumed onboard). It is worth mentioning that the EU policy-making is more advanced than its global counterpart is (Scott et al., 2017). Starting from 2024, shipping will be included in the EU Emissions Trading Scheme (ETS), while the FuelEU Maritime Initiative imposes carbon intensity limits on the energy consumed as of 2025, both measures adopted in the frame of the EU 'Fit for 55' package (European Council, 2023).

3.1.2 Problem definition

The description of the previous section demonstrates that the entire regulatory framework of IMO is structured around two families of carbon intensity indicators, the technical (EEDI and EEXI) and operational (CII, AER, cgDIST and EEOI) ones. Both categories face criticism concerning their benchmarking role.

Most of the concerns relate to the operational indicators. Even formal documents, such as IMO (2019) submitted by Japan and Norway, argue that the operational energy efficiency of a ship depends on various factors, including: (1) technical factors (within the scope of EEDI); (2) business-related factors that are partially controllable by the operator/charterer (such as cargo volume and speed); and (3) external uncontrollable factors (including weather condition, sea condition, market demand, etc.). Poulsen et al. (2022) go one step further and split the 'business-related factors' of IMO (2019) into 'commercial' (relating to the matching of cargoes and ships, routes, and speed choices) and 'nautical' (trim/ballast optimization, optimized auto-pilot usage, weather routing, etc.) aspects of energy efficiency. They conclude that 'indices that aggregate the commercial, nautical, and weather/sea aspects of energy efficiency into one metric fail to provide valid measures of energy efficiency in ship operations' and state that both AER and EEOI suffer from this short-coming.

Panagakos et al. (2019) analyze 1,675 voyages undertaken by 1,041 dry bulk carriers in 2018 and estimate the values of four operational indicators including AER and EEOI. They conclude that none of the examined indicators is suitable for benchmarking purposes, as the range of variation is too wide to convey any meaningful message regarding energy efficiency. The AER values of an 80,000 DWT-ton bulker in the sample vary between 1.5 to 8.2 gCO_2/tm (=1:5.5) against a range of 2.6 and 14.1 gCO_2/tm (=1:5.4) for the EEOI. They further find that the variation width among four sister Handymaxes amounts to 27.9% and 22.3% around the mean AER and EEOI values, respectively.

More recently, Ghaforian Masodzadeh et al. (2022) provide a detailed list of operational parameters that affect the carbon intensity indicators (AER and EEOI), including the loading factor, fuel quality, navigation circumstances, weather condition, contractual obligations and sailing speed, and hull roughness due to the ship's age. They conclude that these uncertainties can account for more than 50% of the indicators' value, raising serious concerns about their benchmarking potential. From a different perspective, Wang et al. (2021) prove that by intentionally increasing the ballasted/laden distances, ships can reduce their AER/EEOI values respectively and suggest the development of more elaborate CII formulations.

Technical indicators also receive criticism. Polakis et al. (2019) argue that the required EEDI standards can be easily met by simply reducing the design speed without reducing the ship's resistance or increasing its efficiency. Speed reduction may raise safety concerns due to possible underpowering (necessitating the introduction of minimum power requirements). They also argue that the regressions that resulted in the EEDI reference lines were influenced much more by a large number of smaller ships at the expense of the fewer very large ones, leading to a subsequent correction for the EEDI requirements of dry bulk carriers with a DWT above 279,000 tons. However, their loudest criticism is that EEDI (therefore, also EEXI) constitutes 'a snapshot of ship's performance at a rarely used draft (maximum) and in ideal sea conditions (no wind and no waves).' As a result, ships with better attained EEDI values in calm seas can be outperformed by lower-EEDI ships in real sea conditions.

Lindstad et al. (2019) build on this argument, stating that the existing EEDI estimation procedure excessively rewards full-bodied ’bulky’ hulls, which perform well in calm water conditions, despite the calm sea being the exception at sea. They use model results to compare two alternative hull forms of a 63,000 DWT Supramax bulk carrier (a ’traditional’ vs. a ’slender’ one). They find that under a Beaufort wind scale of 6 (3-meter significant head waves), the latter design outperforms the former despite having a higher EEDI value in calm seas. They further conclude that excessive reliance on meeting EEDI requirements might lead to short-term solutions, such as special coatings or restricting speeds, rather than improving hull designs. They propose adjusting the testing cycle requirements to include a threshold for wave performance.

Although the combination of technical (EEDI/EEXI) and operational (CII/AER/EEOI) restrictions will result in lower CO_2 emissions (Schroer et al., 2022), the drawbacks previously mentioned indicate that the resulting emission reduction will not be optimal in terms of cost-effectiveness (for example, due to sub-optimal ship designs based on the existing EEDI). Furthermore, the nature of the drawbacks is such that they do not cancel each other out when the two indicator families are combined. In other words, the variability of AER/EEOI cannot make up for EEDI’s restrictive perspective.

3.1.3 Previous experiences with driving/operational cycles

Most experiences with driving cycles originate from the automotive sector. The maritime literature contains only a few references to road transport. Arguing against the idea of using operational indicators to benchmark ship performance, Polakis et al. (2019) explain that a car is rated by design on its performance against predetermined conditions and cycles, not by how efficiently a driver runs it. Similarly, Lindstad et al. (2019) state that the lesson learned from the automotive industry is that ’testing methods must reflect realistic operating conditions to deliver the desired emission reductions.’ Ghaforian Masodzadeh et al. (2022) also seek inspiration in the road transport sector, noting that the lack of standards (similar to EURO 6 for road transport) in ship operation is ’undeniable’ and rewards inefficient ships. Godet et al. (2022) provides an overview of the methods and uses of the ’driving cycles’ in road transport and suggests an initial procedure for developing similar cycles in maritime transport. The present article builds on the work by Godet et al. (2022) and summarizes its main findings in this section.

3.1.3.1 The driving cycles of the automotive industry

As a regulatory tool, the driving cycle is a standardized set of operating conditions against which a car's performance is assessed. As such, the cycles must be 'representative of real-world vehicle operation in terms of emissions and energy consumption' (EU, 2018). Having harmonized cycles is of significant interest for regulating authorities as it allows for more efficient development of and adaption to technical progress and knowledge sharing (Riemersma, 2015). The interest in driving cycles started in the 1970s, with various cycles adopted worldwide. Since then, the industry and academia have proposed several adjustments and refinements. The EU, the United States (US), and Japan were the front-runners in developing such cycles.

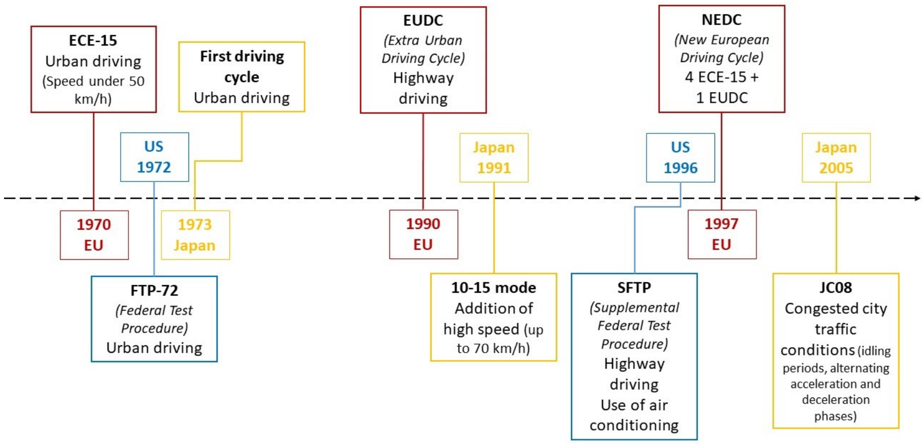
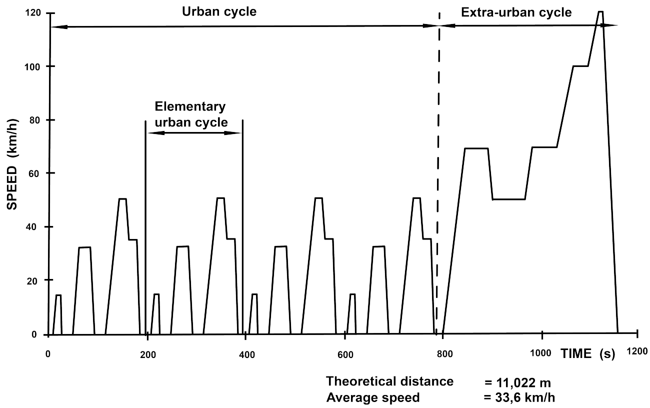
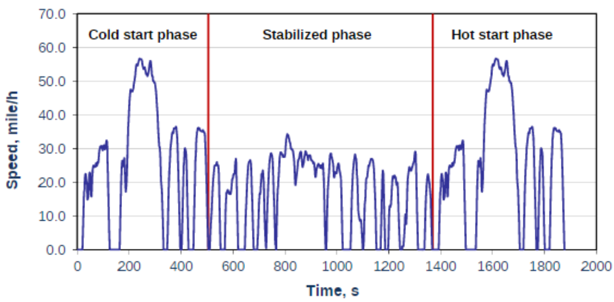


Figure 3.1: Timeline of selected development steps of the driving cycles for Light duty Vehicles (LDV) in the EU, the US, and Japan (based on Gieseke and Gerbrandy (2017); MLIT (2005); Tutuianu et al. (2015); U.S. Environmental Protection Agency (2021))

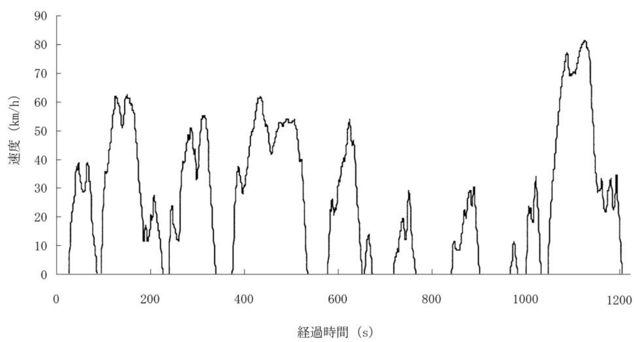
Figure 3.1 shows a snapshot of the development steps for the driving cycles in the EU, the US, and Japan. The first driving cycles in the 1970s focused only on urban driving. The inclusion of high speeds came later in the 1990s. Figure 3.2 shows one typical cycle from each region.



(a) The New European Driving Cycle (NEDC) combines urban and extra-urban driving cycles (UNECE, 2013)



(b) Federal Test Procedure (FTP) FTP-75, which differentiates from the FTP-72 by the addition of a hot phase (U.S. Environmental Protection Agency, 2020)



(c) Japanese Cycles JC08 (JC08). The X-axis is time (s), and Y-axis is speed (km/h) (MLIT, 2005)

Figure 3.2: Three regional driving cycles

Responding to the industrial and regulatory desire to have a unified cycle worldwide, the United Nations Economic Commission for Europe (UNECE) developed the World harmonized Light vehicles Test Cycles (WLTC). They consist of different cycles for vehicles with various Power-to-Mass Ratio (PMR). In 2017, the EU adopted WLTC to assess the emissions and fuel consumption of Light duty Vehicles (LDV), replacing NEDC as the European standard (EU, 2018).

To certify the CO_2 emissions of Heavy-Duty Vehicles (HDV), the European Commission developed an alternative methodology named Vehicle Energy Consumption Calculation Tool (VECTO), also using the driving cycle principle (Zacharof and Fontaras, 2016). CO_2 emissions are calculated through simulation over predetermined cycles, supported by specific test procedures for the main fuel efficiency components (engine, transmission, torque components, axle, air drag, and tires), and standardized pre-processing tools to account for auxiliaries such as cooling fans, steering pumps, the electrical system, pneumatic systems, and the air-conditioning systems.

Although broadly adopted, the automotive driving cycles have attracted criticism because of certain limitations. While NEDC is simple and easily repeatable, it fails to reflect real-world emissions (Gieseke and Gerbrandy, 2017; Pelkmans and Debal, 2006; Tsiakmakis et al., 2017). Using portable emissions measurement systems, Degraeuwe and Weiss (2017) measured actual on-road NO_X emissions exceeding those measured on the NEDC by 206%. FTP does not reflect all driving conditions, and JC08 only covers congested urban traffic.

Pettersson et al. (2018) identify limitations due to oversimplifying the actual driving behavior through merely targeting speed while omitting the effects of diverse operations and the impact of external parameters, such as road and traffic conditions. To address these limitations, Pettersson et al. (2019) introduce the term operational cycles for HDVs, which add the following parameters to the driving cycle definition: vehicle's mission (transportation of goods or passengers), traffic (influence of other vehicles and traffic lights), road conditions (road physical properties), and weather. Nevertheless, Chindamo and Gadola (2018) argue that the WLTC estimates are the closest ones to real-world emissions and suggest higher acceleration and deceleration values for more accurate driving cycles.

3.1.3.2 The WLTC procedure

Despite its persisting limitations, WLTC inspires this paper due to its international dimension and use of actual data, which emerges as a suitable quality for reproduction in the maritime sector. It aims at reflecting the average real-world vehicle operation. According to Riemersma (2015), the procedure associated with its development requires a method for determining emissions and energy consumption levels in a 'repeatable, reproducible, cost-effective and practicable' manner.

Actual data, including driving behavior data (speed and acceleration profiles) and traffic statistics for various road types (rural, urban, motorway) and driving conditions (peak, off-peak, weekend), were collected from Europe, India, Japan, Korea, and the US to construct WLTC. Analyzing the most important parameters revealed that regional activity data is essential to derive driving behaviors and their distributions. In addition, regional weighting factors are necessary to account for the variety of driving behaviors across geographical areas (Tutuianu et al., 2015).

441 vehicles across five regions (Europe, India, Japan, Korea, and the US) used onboard data acquisition systems to collect traffic data, including speed, acceleration, and engine rotational speed at a frequency of at least 1 Hz. While Japan, Korea, and India collected data from hired vehicles operating on a predefined route, Europe used data from vehicles where the drivers were not instructed to follow a specific route. A combination of both methods was used in the US, where 'an instrumented vehicle [...was] following a target vehicle in the traffic stream and attempting to mimic its behavior' (Tutuianu et al., 2015). The complementary methods filter out the 'most extreme driving behaviors' (Tutuianu et al., 2015).

Databases were created for idling periods (when the vehicle operates at less than 5 km/h) and short trips (between two idling periods, comprising acceleration, deceleration, and cruise phases) to represent various road types (urban, rural, and motorway) in each region. Filters on phase duration and acceleration range improved the statistical representation and laboratory tests feasibility, including the cycle's maximum duration of 1,800 seconds (Tutuianu et al., 2015).

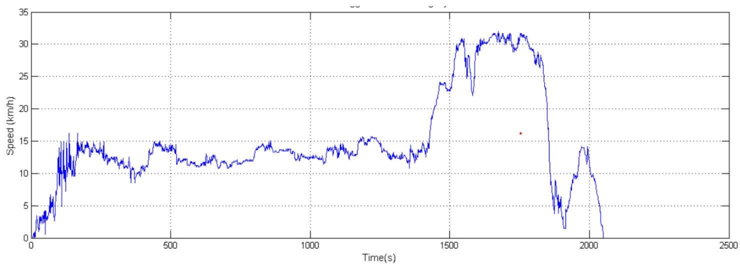
Countries have different speed limits for the same road categories, making speed classes more relevant for a globally standardized cycle. Consequently, the low, medium, high, and extra-high speed categories replaced the urban, rural, and motorway ones to represent the speed and acceleration distributions. The selection of short trips to be included in the cycle is based on a chi-square (χ^2) test, measuring the discrepancy level of the samples (Corder and Foreman, 2011; Tutuianu et al., 2015). Laboratories from the five regions tested the initial cycle (combination of short trips with the smallest χ^2) and investigated the cycles' driveability and repeatability.

3.1.3.3 Experiences from the maritime sector

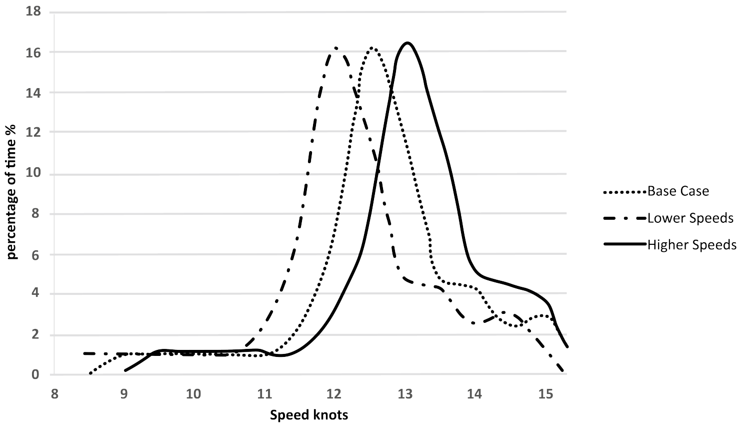
Although no studies were found in the maritime literature under 'operational cycle', the authors identified four applications of principles conforming to an operational cycle. Norbakyah et al. (2015) studied plug-in hybrid electric recreational boats sailing on a Malaysian river, where speed-time data was obtained for a specific route using a GPS. An operational profile was defined by selecting the voyage closest to the mean values for acceleration, deceleration, and cruise phases, as shown in Figure 3.3a. The authors also applied the same methodology to two other Malaysian rivers (Atiq et al., 2015; Norbakyah et al., 2015; Salisa et al., 2015).

Trivyza et al. (2016) identified four operation modes (ballast, laden, port loading, and port unloading) for an Aframax tanker sailing between the Persian Gulf and North America. Using actual voyage data, the authors defined three-speed distribution profiles (as a share over a trip duration, with a base case, lower and higher speed cases) for ballast and laden voyages, shown in Figure 3.3b.

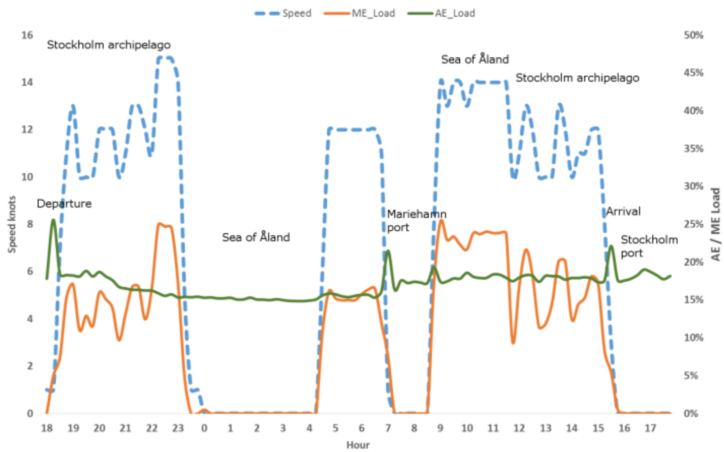
Baldi et al. (2018) studied a cruise ship operating daily in the Baltic Sea. The analysis, which included frequent monitoring data of the engines (60-second intervals), showed that the ship was seagoing for 59%, maneuvering for 7%, and berthed in port for 34% of the time. Based on these observations, the authors developed an operational profile to maximize energy efficiency and reduce fuel consumption, as shown in Figure 3.3c.



(a) Specific Malaysian river profile (Norbakyah et al., 2015)

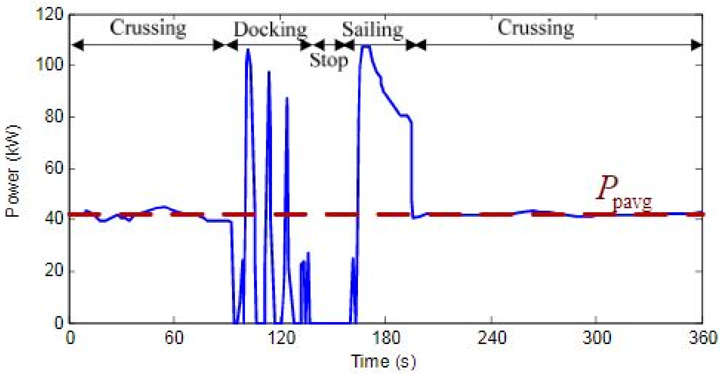


(b) Different speed profiles (Trivyza et al., 2016)



(c) Operational profile of a cruise ship (Baldi et al., 2018)

Figure 3.3: Examples of cycles in the maritime industry



(d) Typical driving cycle of an all-electric boat (Han et al., 2014)

Figure 3.3: Examples of cycles in the maritime industry

Finally, Figure 3.3d shows the '*typical power driving cycle of the boat propulsion motor for docking and sailing*' of an all-electric boat (Han et al., 2014). The cycle models the fuel cell/battery hybrid energy system and assesses its performance.

Furthermore, the cycle concept is used by the NOx Technical Code, which controls emissions from marine diesel engines. To do so, it uses test cycles to verify engine compliance (IMO, 2008). These test cycles consist of four-to-five engine loads and associated speeds and use weighting factors for the different loads. However, these test cycles are theoretical (100% of the nominal speed, and 100%, 75%, 50%, and 25% of engine load for an example test cycle) and cannot be considered as 'operational cycles', as they only account for a limited number of specific engine speed/load combinations out of the entire range of operational conditions.

3.1.4 Objectives and contribution

This article investigates the possibility of transferring the 'driving cycle' concept as a regulatory tool of the automotive industry to the shipping sector. The cycle-based maritime applications mentioned above do not relate to the possible regulatory uses of such a concept. Neither any other document suggests cycle-based policy-making in shipping to the best of the authors' knowledge. A possible explanation is that ships are built in small batches of identical units, reducing the scale economies achieved through car-type testing. In this regard, HDVs is the automotive industry segment that comes closer to shipping operations, as the VECTO methodology also applies mission-based benchmarking cycles. Similarly, different cycles for various segments (e.g., container ships) and group sizes are needed to reflect the difference in ship operations while avoiding overspecialization that could damage the benchmarking cause. In any event, the paper addresses a gap in the literature; in this sense, it is an innovative work.

The paper addresses four objectives:

1. Define the concept of maritime 'operational cycles',
2. Develop operational cycles based on a fleet of 327 container ships and test the relevant procedure proposed by Godet et al. (2022),
3. Analyze the accuracy and effectiveness of the cycles, and
4. Discuss further work to improve the cycles and their suitability as a benchmarking tool.

A note on terminology is in order here. In the automotive world, the widely-used term '*driving cycle*' is defined as a standardized set of operating conditions against which a vehicle's performance is assessed. Only Pettersson et al. (2019) use the term '*operational cycle*' (in connection to HDVs) to denote a broader cycle that adds external factors (mission, traffic, road conditions, and weather) to the usual speed/acceleration parameters of the driving cycle. In the maritime context, no distinction can be made content-wise, as the concept has not been defined yet. However, the broader '*operational cycle*' appears to express the diversity of shipping operations better than its narrower counterpart does. As such, the term '*operational cycle*' is used in this paper. The maritime '*operational cycle*' is envisioned as a standardized set of operating conditions to test a ship's performance and should not be confused with a '*life-cycle*' approach, which assesses environmental impacts over an asset's entire life from cradle to grave.

Due to its innovativeness, this paper is the first approach to standardized maritime operational cycles and does not aspire to answer all possible questions. Its main ambition is to initiate the relevant dialogue for policy regulation. Its expected contribution concerns defining the concept and improving the proposed methodology for developing the cycles. Once defined, the cycles can be used to improve the effectiveness of the carbon intensity indicators, such as EEDI and EEXI, the content of which can be enriched by accounting for a ship's behavior in realistic conditions, in the same way the VECTO methodology of HDVs involves simulation based on driving cycles. Furthermore, the cycles are expected to increase the robustness of the operational indicators, such as AER, EEOI, and CII, improving their effectiveness in benchmarking.

The paper is structured as follows: Section 3.2 describes the sample data and procedure for constructing the maritime operational cycles. Section 3.3 presents the resulting cycles and their assessment through existing operational indicators of energy efficiency. Section 3.4 discusses the present work's prospects and limitations and suggests further research directions. Section 3.5 concludes.

3.2 Development of the operational cycles: data and procedure

The development of the maritime operational cycles is data-driven. Therefore, this section combines the description of the procedure with that of the available data. Figure 3.4 presents the cycle developing procedure as suggested by Godet et al. (2022). The following subsections explain each step of the procedure. The performance optimization and finalization steps are described in Section 3.3, with the analysis results.

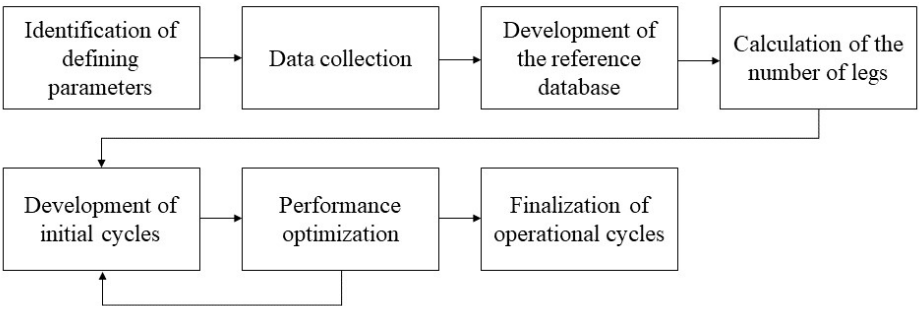


Figure 3.4: Procedure to develop maritime operational cycles (Godet et al., 2022)

3.2.1 Identification of defining parameters

The first step of the development process is to select the main parameters on which the cycles are built. The WLTC approach uses speed and acceleration as the most representative driving cycle determinants. The database, described in the next subsection, provides information on the average speed during each noon report. However, the low frequency of the noon reports (roughly about every 24 hours) does not allow a meaningful acceleration estimation. This subsection discusses the selection of defining parameters for the cycles.

Bialystocki and Konovessis (2016) show that speed is the most significant parameter determining both the main engine (ME) power and fuel consumption, and consequently ME emissions. Schroer et al. (2022) confirm the tight interdependence between speed and ME power on some of the ships included in the database of the present article. Işkl et al. (2020) find that the three main determinants of a ship's fuel consumption are speed, the ME rotational speed, and draft. ME power is the common denominator of all these determinants, accounting for 80-90% of a ship's fuel consumption and emissions (Faber et al., 2020).

To keep this first attempt of cycle development as simple as possible, the authors chose to define the operational cycles on ME power, the single parameter that reflects both the speed and draft of a ship. In the case of two main engines, the ME power parameter is the sum of the power generated by the two engines. A maritime '*operational cycle*' is thus defined as a standardized set of ME power, against which a ship's carbon emissions are assessed.

3.2.2 Data collection

3.2.2.1 Sample fleet

As suggested in Section 3.1.4, different operational cycles need to be developed for each size range of the container ship segment, which constitutes the object of this study. IMO has defined a bin classification for container ship sizes (Faber et al., 2020). The entire fleet of a globally leading container ship operator comprises the study sample. It consists of 327 ships (after excluding

16 ships due to incomplete or non-applicable data). Table 3.1 shows the bin classification and the number of sample ships in each bin class. Table 3.1 also includes the corresponding components of the world fleet for 2018 for comparison purposes (Faber et al., 2020). The sample ships cover seven bin classes (no ships are in the first and last classes). Their share of the world fleet ranges from 1% (bin class 2) to 39% (bin class 8). With 50 vessels, the sample of bin class 5, used throughout this paper as the presentation case, represents a 9% share of the world fleet. Therefore, operational cycles are developed for bin classes 2 to 8. Each bin class is treated separately from the others.

Table 3.1: Bin classification according to the IMO and number of sample ships in each bin class

Bin class	Capacity [TEU]	Sample fleet (2019)	World fleet (2018)	Percentage of world fleet
1	0 - 999	0	1,027	0 %
2	1,000 - 1,999	17	1,271	1.3 %
3	2,000 - 2,999	32	668	4.8 %
4	3,000 - 4,999	90	815	11.0 %
5	5,000 - 7,999	50	561	8.9 %
6	8,000 - 11,999	80	623	12.8 %
7	12,000 - 14,499	19	227	8.4 %
8	14,500 - 19,999	39	101	38.6 %
9	20,000+	0	44	0 %
Total		327	5,337	6.1 %

Source: Fourth IMO GHG Study 2020 (Faber et al., 2020)

3.2.2.2 *Data*

The study's data source is the noon reports of all sample ships for 2019. To continuously monitor ship performance, the crew produces noon reports daily covering a wide range of operational data (about 130 variables). They include information on the position of the ship, its speed, loading condition, draft, power, and operating hours of all fuel consumers onboard (main engine (ME), auxiliary engine (AE)[1], boilers), the corresponding fuel consumption by fuel type, etc. The reported data comprise either an average value over the 24-hour report period (e.g., ME power, measured onboard by a torsion meter)

[1] If ME or AE are followed by a number, it indicates a specific engine onboard.

or a snapshot of a parameter at the time of submission (e.g., ship position). For this study, the 2019 data set was preferred over the more recent 2020 and 2021 ones to avoid the significant distortions in maritime traffic induced by the pandemic crisis. Table 3.2 shows a selection of noon report information of relevance to the definition of the operational cycles. Numbers are fictitious.

Table 3.2: Sample data - Noon reports

Vessel	Reporting time	Report type	Report period *[Hours]*	Origin port
Ship A	03-01-2019 18:00	Port report	30	Port X
Ship A	04-01-2019 15:00	Sea report	21	Port X
Ship A	05-01-2019 15:00	Sea report	24	Port X
Ship A	06-01-2019 15:00	Sea report	24	Port X
Ship A	07-01-2019 15:00	Sea report	24	Port X
Ship A	09-01-2019 06:00	Port report	39	Port Y

Destination port	Sea Distance *[Nm]*	Speed *[Kn]*	Fore draft *[m]*	Aft draft *[m]*
Port Y	0	0	12.8	13.2
Port Y	351	17.8	14.2	12.5
Port Y	408	16.9	14.1	12.6
Port Y	402	16.7	14.0	12.8
Port Y	410	17.1	13.4	13.5
Port Z	0	0	12.5	12.5

ME1 Power *[kW]*	ME1 RPM *[rpm]*	ME Consumption *[tons of HsHFO]*	ME Emissions *[tons]*	AE1 Power *[kW]*
0	79.6	7.4	23.4	3,795
18,540	68.3	72.5	229.9	22,950
18,250	68.5	87.2	276.1	5,770
19,380	68.2	91.3	288.3	0
19,470	68.0	91.5	289.1	0
0	71.2	5.5	15.4	4,660

AE Consumption *[tons of HsHFO]*	Boiler Consumption *[tons of HsHFO]*	Cargo on board *[tons]*	Ballast water *[tons]*
8.8	2.68	71,480	0
5.8	0	71,480	15,560
6.7	0	71,480	15,560
6.9	0	71,480	15,561
6.8	0	71,480	11,702
12.1	2.24	48,920	0

Noon reports distinguish between those concerning cruising at deep sea (sea reports) and those involving a port call (port reports). Other report types, such as canal passage and anchorage reports, are excluded from this analysis.

In addition to covering the approaches to/from a port, port reports describe short coastal journeys between ports, which are usually too short for the ship to maintain a steady state for several hours. Including the phases of deceleration, berthing, acceleration, and (sometimes) sailing at reduced speeds in coastal areas in a single port report does not allow the estimation of operational characteristics (speed, engine power, fuel consumption, etc.) for each of these constituent phases. As such, port reports only entered the analysis for the idling periods at berth. Therefore, the resulting cycles reflect only the cruising stages of sailing. It is estimated that the excluded reports from sailing in coastal areas range between 8% and 17% of the total number of noon reports for each size bin examined here. The importance of this limitation makes this particular aspect an area for further research.

Additional filters were applied to the original noon reports to:

- remove duplicated reports (5,115 reports),
- remove reports on anchorage and channel passage (2,418 reports),
- remove ships with unspecified characteristics (e.g., tonnage) (this applies to 12 ships, 2,922 reports),
- exclude reports with a zero ME power at sea (3,066 reports),
- exclude reports with speeds over ground below or equal to 0 or above 30 knots (19 reports),
- exclude reports with average draft below 4.4 m or above 20 m (44 reports),
- remove ships with only port reports (this applies to four ships, 215 reports).

Due to this initial filtering, the original 118,505 noon reports from 343 ships were reduced to a database of 80,453 sea reports from 327 ships and 24,253 port reports.

The analysis is conducted using the programming language Python version 3.8.5, the packages *pandas* and *numpy* for the data handling and calculations, and the package *matplotlib* for the figures.

3.2.3 Development of the reference database

3.2.3.1 *Leg database*

As with the WLTC, the maritime operational cycles consist of a succession of sailing and idling intervals, selected respectively from the 'leg[2]' and 'idling' databases. Note that a pair of such databases are developed separately for each bin class. The leg database of a bin class contains all legs sailed by the ships of this bin class during 2019, and the same applies to the idling database. Each leg in a bin class receives a unique leg number to distinguish it from other legs in the same class.

Given that the sailing between two consecutive ports denoted as a *leg* can take several days (reported through an equal number of sea reports), the leg duration is calculated as the sum of the duration of all constituent sea reports. The average of a parameter (e.g., ME power) over a leg is taken as the weighted average of the corresponding sea report values using the duration of each report as the applicable weight.

An important feature of WLTC is the division of the main parameter into categories (low, medium, high, and extra-high speeds), ensuring that observations from all categories participate in the final cycle. Similarly, the ME power of the maritime application is divided into three categories: low, medium, and high ME power. To do so, the total number of legs of each bin class is divided into three equally sized groups (in case the division does not result in an integer number, the high-power category can end up having one or two leg(s) more than those of the other categories). For example, if the total number of legs in a bin class is 320, categories 1 and 2 (low and medium ME power, respectively) will have 106 legs each, while category 3 (high ME power) will contain the remaining 108 legs. Note that the boundaries between categories (range of ME power values) differ among bin classes as they depend on the engine size and the distribution of the leg ME power within each bin class.

The arithmetic mean and standard deviation of the leg ME power are calculated for each category, based on which legs with a power outside the plus/mi-

[2]In the context of this paper, the term *leg* denotes the journey between two consecutive ports. In contrast, the term *voyage* is reserved for the journey between the origin and destination ports, which might include several intermediary port calls.

nus two standard deviation interval are excluded from the analysis as outliers. The adjusted mean ME power is then calculated for the leg database of each category, followed by the absolute value of the difference between the power of each leg and the corresponding category mean.

3.2.3.2 *Idling database*

The duration of a ship's stay in port is the central concern of the idling database, which is constructed similarly to the leg database. The categories used for the analysis remain the same as those of the leg database (low, medium, and high ME power). The observations now consist of the berthing duration at the destination port of each leg in the respective category. The following filters have been applied in addition to those listed in Section 3.2.2.2:

- remove port reports with zero berthing duration,
- remove port reports with a berthing duration longer than the targeted duration for each category (see Section 3.2.4),
- remove port reports with a non-zero ME power at berth.

Once again, the adjusted mean idling duration is calculated for each category after excluding legs with an idling duration outside the plus/minus two standard deviation interval. The absolute difference of each idling period in the category from the adjusted mean is also calculated for further use.

3.2.4 Calculation of the number of legs

WLTC's length is 1,800 seconds divided among four-speed categories: Low=589s, Medium=433s, High=455s, and Extra-high=323s. In the maritime application, a leg duration can be several days long. To standardize the cycle's length, the authors started with a 30-day duration for each of the three ME power categories, leading to an overall cycle of 90 days for each bin class. The choice of 30 days allows several legs to enter the definition of the cycle part of each category. Equation 3.1 calculates the number of legs $N_c \in \mathbb{N}$ to be included in category c to reach the 30-day duration:

$$N_c = \left\lfloor \frac{|td_c - \overline{i_c}|}{\overline{i_c} + \overline{t_c}} \right\rfloor \tag{3.1}$$

where td_c is the targeted duration for the category c (30 days), $\overline{i_c}$ is the adjusted mean idling period in category c, and $\overline{t_c}$ is the adjusted mean leg duration in the category c. For example, if $td_c = 30$ days, $\overline{i_c} = 1$ day and $\overline{t_c} = 5$ days, then $N_c = \lfloor 29/6 \rfloor = 4$. Therefore, the part of the cycle for category c will comprise four legs.

The N_c legs with the lowest differences in ME power from the adjusted mean among the candidate legs are selected to represent the category c in the cycle. Similarly, this category's cycle selects the N_c idling periods closest to the adjusted mean value. Note that the last of these N_c idling periods aims at dividing a category from the next. Given that the entire cycle starts and ends with a leg, the idling periods of the last category (high ME power) only contain $N_c - 1$ idling periods.

3.2.5 Development of initial cycles

Once the legs and idling periods relative to each category have been selected, they are combined to form an initial cycle, as described in this subsection.

3.2.5.1 Time adjustment

It is improbable that the total duration of a category's selected set of legs and idling periods perfectly matches the target duration (30 days). An adjustment is therefore needed to ensure that each category is given equal weight in forming a cycle. The differential Δt_c between the target total duration td_c of category c and the selected set of legs and idling periods duration is:

$$\Delta t_c = td_c - \left(\sum_{l \in S_{l_c}} t_{l_c} + \sum_{i \in S_{i_c}} t_{i_c}\right) \tag{3.2}$$

where S_{l_c} are the selected legs, t_{l_c} the duration of leg l in category c, S_{i_c} the selected idling periods of category c and t_{i_c} the duration of idling period i in category c. For example, if the target duration is 30 days, and four legs (4.8, 5.3, 4.5, and 6.1 days) and four idling periods (1.3, 0.6, 1.4, and 1.4 days) are selected, the differential $\Delta t_c = 30 - (4.8 + 5.3 + 4.5 + 6.1 + 1.3 + 0.6 + 1.4 + 1.4) = 4.6$ days.

The adjusted duration for each selected leg t'_{l_c} then becomes:

$$t'_{l_c} = t_{l_c} \cdot \left(1 + \frac{\Delta t_c}{\sum_{l \in S_{l_c}} t_{l_c} + \sum_{i \in S_{i_c}} t_{i_c}}\right) \tag{3.3}$$

And the same adjustment factor also applies to the duration of the idling periods, where t'_{i_c} is the adjusted idling period i in category c.

3.2.5.2 *Initial cycles*

The following procedure combines the selected legs and idling periods into an operational cycle for a bin class:

- Sort the selected legs based on their category and leg number.
- Sort the selected idling periods based on their category and their difference from the mean.
- Create a sequence of legs in the sorted order divided from each other by an idling period in the sorted order.

In the resulting cycle, the legs/idling periods of the low ME power category are followed by those of the medium- and high-power categories, respectively. Once the cycle is defined, the noon reports corresponding to the selected legs are used to calculate the desired variables (e.g., fuel consumption and emissions) over the entire cycle.

The proposed methodology ensures that the total duration of the cycle is 90 days (30 days for each category). To create a common basis for comparing cycles of varying duration (refer to Section 3.3.3), it was decided to downscale cycles into their 72-hour equivalent. Thus for the 90-day cycle described above, a 30:1 ratio is applied to all time-dependent variables. Note that the 72-hour duration is arbitrary and was selected as a convenient scale for depicting the

ME power profiles of the leg segments and idling periods. It only affects the absolute volume of emissions generated during the cycle without influencing the comparisons across ships or periods of the same ship.

3.3 Results

3.3.1 The cycles

The methodology described in Section 3.2 is applied to the data sample covering 80,453 sea reports from 327 container ships for 2019. Figure 3.5 depicts the 72-hour equivalent of the 90-day cycle for bin class 5, representing medium-sized ships in the range 5,000-7,999 TEUs.

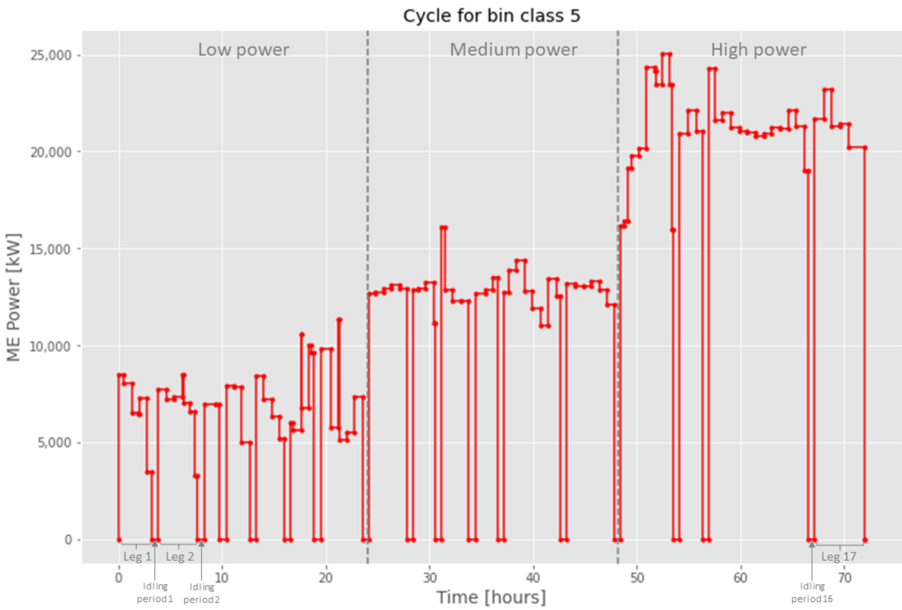


Figure 3.5: 90-day cycle for bin class 5 (transformed into a 72-hour duration)

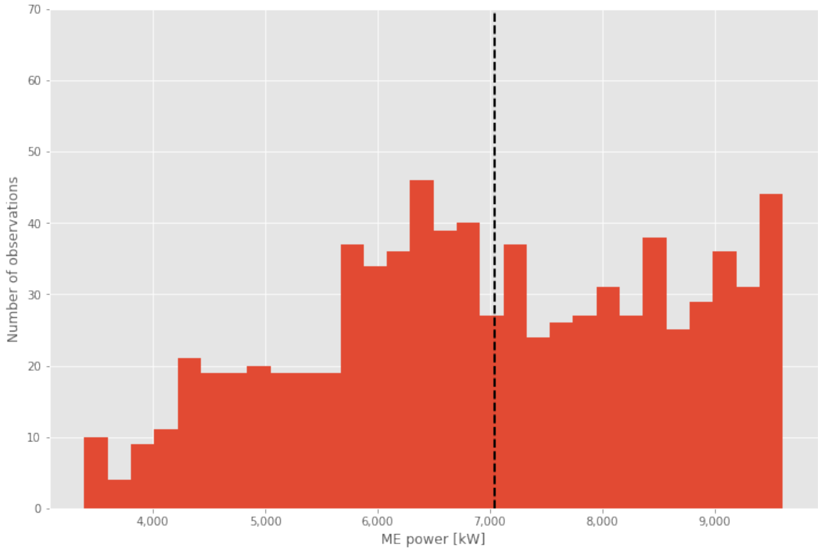
The cycle consists of 17 legs, divided by 16 idling periods. The seven first legs and idling periods comprise the low ME power category, followed by six leg/idling-period pairs for the medium power category and a four-leg/three-idling-period combination for the high-power one. Each leg consists of several segments corresponding to individual sea reports. As an example, the first leg contains six segments (34 minutes of a ME power of 8,521 kW; 44 minutes of 8,050 kW; 39 minutes of 6,519 kW; 4 minutes of 6,472 kW; 46 minutes of 7,284 kW; and 26 minutes of 3,508 kW).

Note that some legs contain considerable spikes or drops. See, for example, the short (4 min.) segment of a ME power of 11,360 kW in the last leg of the low-power category, which is much higher than the mean value of the relevant leg (6,695 kW) and the entire category (7,173 kW). This is because the selection of legs is based on the mean ME power of the leg, which is calculated over all constituent segments. Another filter was introduced to avoid highly variable legs with steep peaks/drops in ME power. The filter excludes legs containing segments with a ME power higher or lower than one standard deviation (as calculated in Section 3.2.3.1) of the mean value. The filter was applied to all bin classes, except bin class 5, for which no improvement in the coefficient of variation was identified (refer to the next section). The resulting cycles for all bin classes, after the adjustments of Sections 3.3.2 and 3.3.3, are presented in Appendix 3.A.

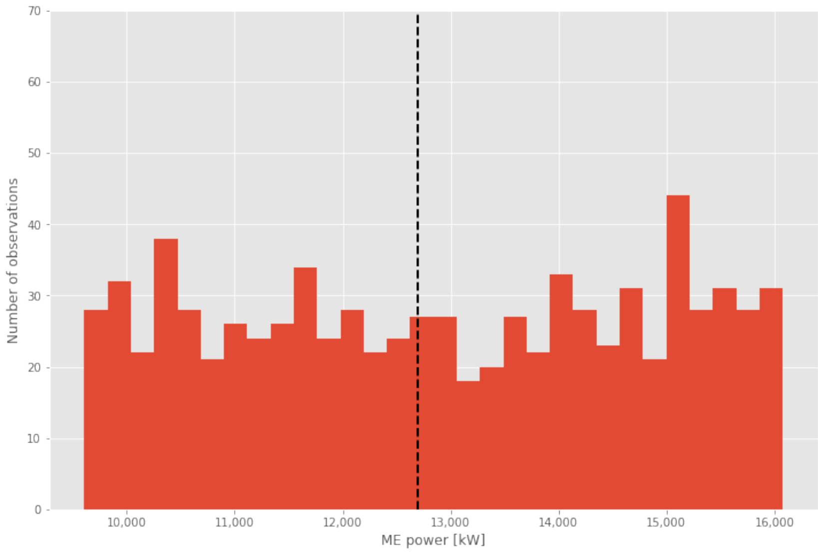
Table 3.3: Characteristics of the 90-day cycle for bin class 5

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	90 days	72 hours	90 days	72 hours	90 days	72 hours
All legs [number]	806		830		795	
Min ME power [kW] - leg level		3,391		9,607		16,164
Max ME power [kW] - leg level		9,606		16,077		41,408
Mean ME power [kW] - leg level		6,984		12,891		22,091
Std ME power [kW] - leg level		1,599		1,923		4,892
Min duration [hours] - leg level	04h 00m	08m	04h 00m	08m	07h 17m	14m
Max duration [hours] - leg level	24d 05h 06m	19h 22m	28d 06h 00m	22h 36m	25d 07h 23m	20h 14m
Mean duration [hours] - leg level	03d 03h 36m	02h 31m	04d 00h 16m	03h 12m	05d 10h 28m	04h 20m
Std duration [hours] - leg level	02d 08h 14m	01h 52m	03d 19h 55m	03h 04m	03d 21h 36m	03h 07m
Selected legs [number]	7		6		4	
Min ME power [kW] - segment level		3,301		11,048		16,002
Max ME power [kW] - segment level		11,360		16,100		25,052
Mean ME power [kW] - segment level		7,173		12,915		21,149
Std ME power [kW] - segment level		1,821		904		2,158
Min duration [hours] - segment level	01h 00m	02m	06h 00m	12m	03h 36m	07m
Max duration [hours] - segment level	01d 08h 42m	01h 05m	01d 06h 23m	01h 00m	01d 03h 00m	54m
Mean duration [hours] - segment level	18h 08m	36m	21h 25m	42m	20h 19m	40m
Std duration [hours] - segment level	08h 25m	16m	05h 20m	10m	06h 45m	13m
All idling periods [number]	138		150		138	
Min duration [hours] - leg level	02h 28m	04m	02h 47m	05m	02h 25m	04m
Max duration [hours] - leg level	03d 03h 23m	02h 30m	02d 12h 00m	02h 00m	01d 19h 00m	01h 26m
Mean duration [hours] - leg level	19h 57m	39m	18h 59m	37m	20h 30m	41m
Std duration [hours] - leg level	12h 31m	25m	08h 39m	17m	08h 17m	16m
Selected idling periods [number]	7		6		3	
Min duration [hours] - leg level	19h 11m	38m	18h 38m	37m	20h 26m	40m
Max duration [hours] - leg level	21h 06m	42m	19h 22m	38m	20h 30m	41m
Mean duration [hours] - leg level	20h 16m	40m	18h 52m	37m	20h 28m	40m
Std duration [hours] - leg level	36m	01m	14m	00m	01m	00m

Table 3.3 presents the descriptive statistics of the 90-day cycle, supported by Figure 3.6 that shows the histograms of the leg-ME-power and the idling-period-duration observations for the three categories of bin class 5. The information of Table 3.3 relates to leg and segment features after the exclusion of outliers. The increasing average duration of the legs with the ME-power categories indicates the association of larger ME powers with longer journeys. This increased duration explains the unequal number of legs in the three categories. Besides, the idling period database contains a much lower number of entries than the leg database due to the additional filters imposed on this database, especially the requirement of zero ME power at berth. The consistent average duration of berthing between 19 and 20.5 hours across categories, which in Table 3.3 appears before the time adjustment of Section 3.2.5.1, is noteworthy. Appendix 3.B provides the same information for all bin classes.

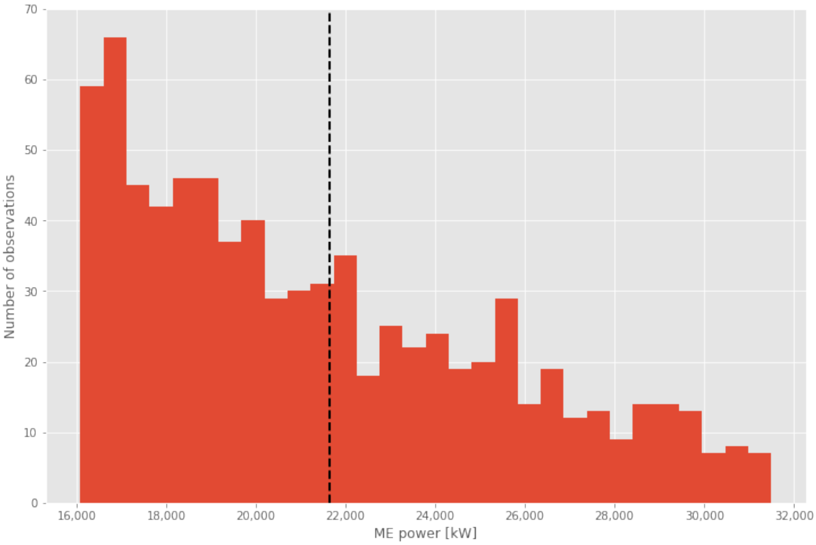


(a) ME power - Category 1

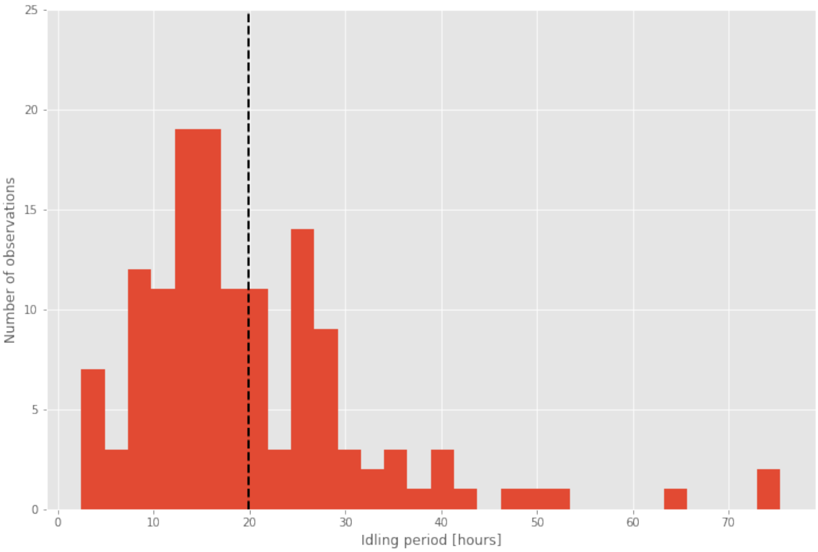


(b) ME power - Category 2

Figure 3.6: Histograms of ME power and idling period duration for all legs and idling periods of bin class 5. The dashed black line represents the mean value. The x-axis of Figures (a) to (c) presents the ME power in kW, and of Figures (d) to (f) the idling period duration in hours. The y-axis is the number of observations.

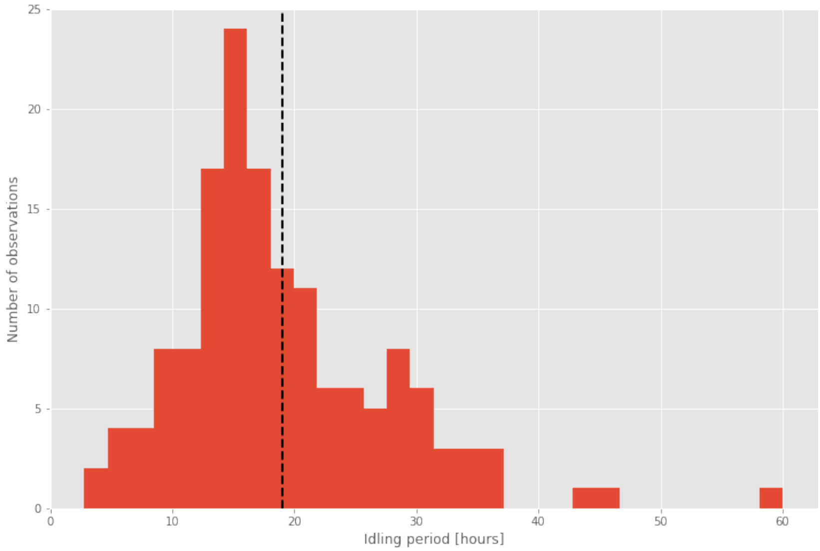


(c) ME power - Category 3

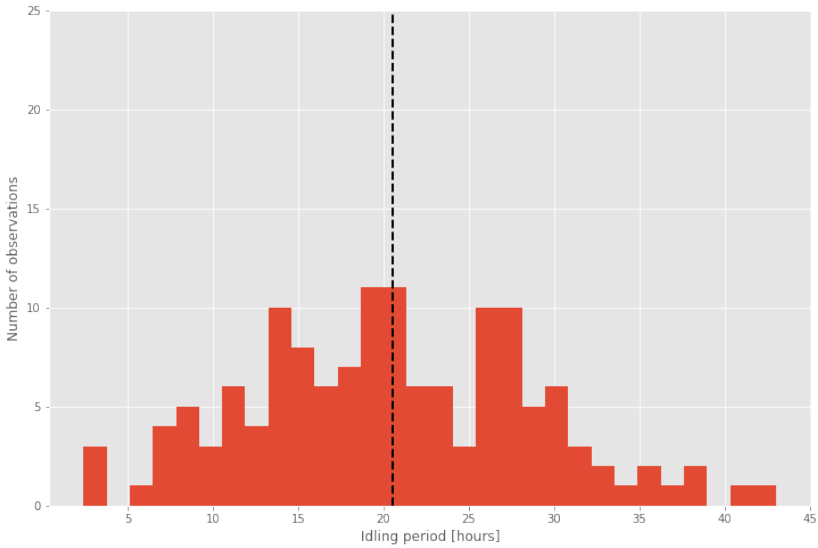


(d) Idl. period duration - Category 1

Figure 3.6: Histograms of ME power and idling period duration for all legs and idling periods of bin class 5. The dashed black line represents the mean value. The x-axis of Figures (a) to (c) presents the ME power in kW, and of Figures (d) to (f) the idling period duration in hours. The y-axis is the number of observations.



(e) Idl. period duration - Category 2



(f) Idl. period duration - Category 3

Figure 3.6: Histograms of ME power and idling period duration for all legs and idling periods of bin class 5. The dashed black line represents the mean value. The x-axis of Figures (a) to (c) presents the ME power in kW, and of Figures (d) to (f) the idling period duration in hours. The y-axis is the number of observations.

3.3.2 Assessment of the cycles

To use the cycles as a benchmarking tool for decarbonizing the maritime industry, it is necessary to assess their accuracy in estimating CO_2 emissions and effectiveness in reducing the dispersion of carbon intensity values due to operational versatility. Table 3.4 presents the hourly ME emissions of the specific legs comprising the cycles. For example, the 8.52 t/h figure of Table 3.4 for bin class 5 results by dividing the sum of ME emissions of all segments comprising the 17 legs of this cycle, as shown in Figure 3.5, by the sum of the corresponding segment duration. These figures are compared to the actual emissions of the entire sample fleet in the respective bin class. These observed emissions, expressed in tons_{CO_2}/hour per ship, are derived from the fuel consumed reported in the noon reports, the corresponding emission factor, and the duration of the relevant reporting periods.

The deviation between the cycle-based and actual emissions is expressed as a percentage of the actual ones. The arithmetic mean of the absolute values of these deviations amounts to 9.2%. Despite dropping to 6.2% when considering the number of ships in each bin class, there is room for improvement. Particularly the smallest and largest size bins of the sample exhibit deviations of 35.3% and 10.7%, respectively, requiring a different treatment (see Section 3.3.3).

Table 3.4: Comparison of the 90-day cycles to the actual ME emissions (2019) in terms of accuracy, in tons of CO_{2_e} per hour per ship

	Actual emissions, 2019	**90-day cycles**	
Bin class	*t/h*	*t/h*	%
2	3.14	2.03	-35.3
3	4.27	4.28	0.2
4	6.22	6.00	-3.6
5	9.22	8.52	-7.6
6	10.69	10.99	2.8
7	12.37	12.91	4.3
8	15.26	13.62	-10.7
Absolute average			**9.2**
Absolute average weighted by number of ships			**6.2**

The carbon intensity indicator used for assessing the effectiveness of the cycles is the AER. For container ships, the IMO defines the AER as follows:

$$AER = \frac{\sum_l \sum_f FC_{f,l} \cdot C_{F_f}}{DWT \cdot \sum_l D_l} \tag{3.4}$$

where l is the leg, $FC_{f,l}$ is the mass of fuel type f consumed over leg l (in tons), C_{F_f} the factor used for converting the fuel consumed to CO_2 emissions (in grams of CO_2 per ton of fuel consumed), D_l the distance sailed (in nautical miles), and DWT the deadweight of the ship (in tons). The formal definition of the indicator includes the emissions from all fuel consumers on board (main engines, auxiliary engines, and boilers) both at sea and in port throughout a calendar year. However, for this paper, the indicator considers only the fuel consumed by the main engines at sea and is referred to as AER_{sea}.

To assess the effectiveness of the cycles, one needs to compare the cycle-based AER_{sea} values to the actual ones for all sample ships in each bin class. The hypothesis is that the variation among the cycle-based AER_{sea} values in a bin class is substantially lower than the observed one among the actual AER_{sea} values. If this is true, the usefulness of the operating cycles concept can be validated for two reasons. Firstly, if applied to operational indicators such as AER or EEOI, the cycles will make them much more robust and suitable for benchmarking. Secondly, if applied to technical indicators such as EEDI and EEXI, the cycles will enrich these indicators' content improving their role in optimizing ship design.

The actual AER_{sea} is directly calculated from the noon reports through Equation (3.4). However, the cycle-based AER_{sea} is less straightforward, as each selected leg of a cycle has only been performed by a specific vessel in the corresponding class. The performance of all other ships on the same leg has to be estimated based on available data. The direct information derived from the cycle consists of the ME power of each selected leg segment and the corresponding duration. Given that the data source directly provides deadweight figures, the missing parameters of Equation (3.4) are the nominator's ME emissions and the denominator's distance sailed. Their estimation is explained in the following paragraph.

Theoretically, the ME power P_r can predict the ME emissions E_r of a ship during report period r using the following equation:

$$E_r = P_r \cdot t_r \cdot \frac{C_{F_r}}{\eta_r \cdot LCV_r} \tag{3.5}$$

where t_r is the duration of report r, C_{F_r} the carbon emission factor of the fuel mix used during report r, η_r the thermal efficiency of the ship engine for the fuel mix of period r, and LCV_r the low calorific value of the period's fuel mix. To avoid complications stemming from the fuel mix and its effect on the thermal efficiency of the main engine(s), it was decided to follow a statistical approach expressing the ME emissions $E_{s,r}$ of ship s during report period r as a linear function of the corresponding energy consumed, which is defined by the product of ME power $P_{s,r}$ and the duration of the report $t_{s,r}$:

$$E_{s,r} = \alpha_s + \beta_s \cdot P_{s,r} \cdot t_{s,r} \tag{3.6}$$

where α_s and β_s are constant ship-specific coefficients, which depend on the fuel mix and the engine's thermal efficiency. As an example, Figure 3.7 relates to a specific ship of bin class 5 and is indicative of the predictive power of Equation (3.6). The same coefficients are calculated for all sample ships with a similar level of accuracy. The emissions of leg l, comprising the nominator of Equation (3.4), are then calculated as the sum of $E_{s,r}$ over all constituent segments (reporting periods) r.

The missing distance of Equation (3.4) can be obtained through the available duration of each segment of a cycle leg if the corresponding speed is estimated. The speed-power relationship of each sample ship is then needed (Adland et al., 2020; Berthelsen and Nielsen, 2021). The use of a logarithm transformation accounts for the non-linearity of this relationship:

$$ln(P_{s,r}) = ln(A_s) + B_s \cdot ln(V_{s,r}) + \epsilon \tag{3.7}$$

where $P_{s,r}$ and $V_{s,r}$ are respectively the ME power and the speed of ship s for report r, A_s and B_s constant coefficients for ship s, and ϵ is a residual perturbation, such that $E(\epsilon) = 0$ and $V(\epsilon) = \sigma^2$. The A_s and B_s coefficients are determined using the ordinary least-squares method. Figure 3.8 shows the speed-power relationship for the ship in bin class 5 with the highest R^2. For the AER_{sea} calculation, the ships with an R^2 of less than 0.8 for the speed-power relationship are excluded. While the threshold of 0.8 is arbitrary, having

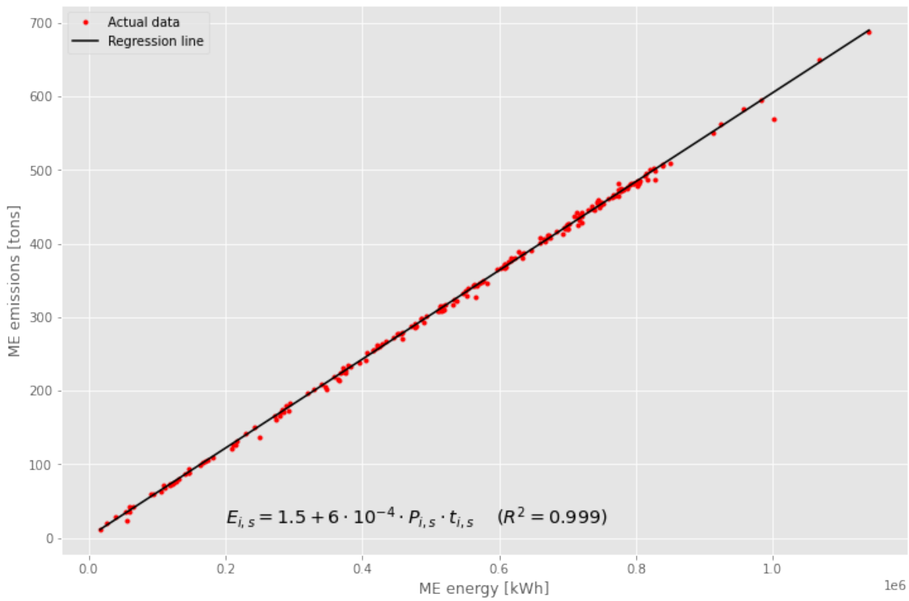


Figure 3.7: ME emissions as a function of ME energy for a sample ship of bin class 5.

sufficient regression results are necessary for the coherency of the AER_{sea} calculation. Table 3.5 presents the number of ships with an R^2 >0.8 for each bin class (refer to Section 3.3.3 for the definition of bin classes 8.1 and 8.2).

Table 3.5: Number of ships selected for the prediction of AER_{sea}, based on the value of the R^2 for the speed-power relationship

	Bin 2	**Bin 3**	**Bin 4**	**Bin 5**	**Bin 6**	**Bin 7**	**Bin 8**	**Bin 8.1**	**Bin 8.2**
Ships with an R^2 >0.8	3	17	55	40	54	15	31	6	25
All ships	17	32	90	50	80	19	39	8	31
Percentage of selected ships	18%	53%	61%	80%	68%	79%	79%	75%	81%

The predicted distance is then calculated by:

$$D_r = \left(\frac{P_r}{A_s}\right)^{\frac{1}{B_s}} \cdot t'_r \tag{3.8}$$

where D_r is the predicted distance of segment covered by noon report r, P_r the ME power in segment r, and t'_r the corresponding adjusted duration. The D_l

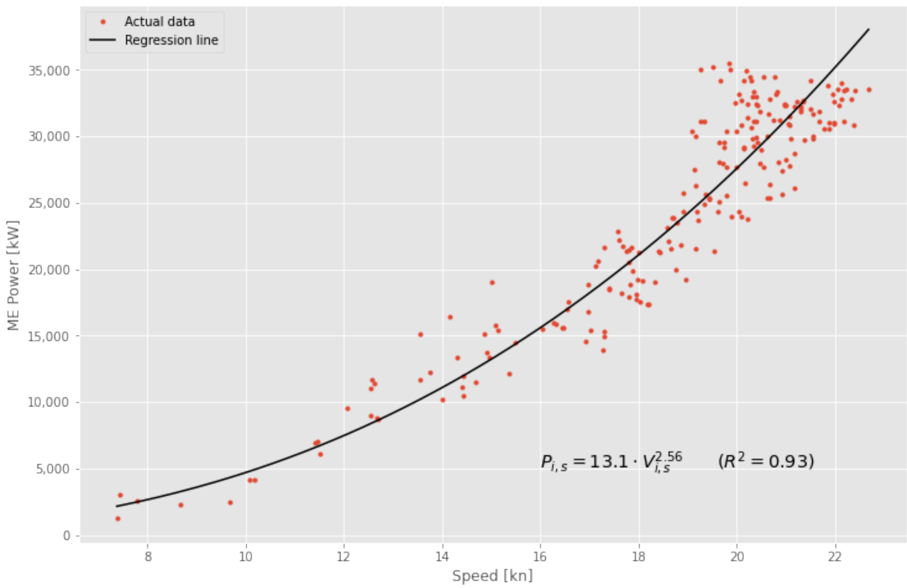


Figure 3.8: Illustration of the speed-power relationship for the ship with the best R^2 in bin class 5.

of leg l is the sum of all constituent segment distances D_r. The cycled-based AER_{sea} is then calculated through Equation 3.4.

Table 3.6 compares the cycle-based AER_{sea} with the actual one for all bin classes. The cycle leads consistently to lower AER_{sea}, probably because, due to the U-shaped curve of the specific fuel consumption when plotted against ME power, the exclusion of extreme sailing conditions in terms of the ME power results in artificially higher engine efficiencies. Nevertheless, the difference is only 5.9% in terms of weighted average, while it remains below the 10% mark for all bin classes, except bin class 2, for which the accuracy is problematic.

Nevertheless, what is more important is that the coefficient of variation, defined as the ratio of standard deviation to the mean value, drops substantially for most bin classes, indicating the positive effect of the cycles in reducing fluctuations in the values of carbon intensity indicators due to operational conditions. The exceptions are bin class 2, for which the reduction is only 1.5%, and bin class 8, which exhibits an increase in the coefficient of variation. Both these bin classes require a different treatment (refer to Section 3.3.3).

Table 3.6: Comparison between 90-day-cycle-based and actual AER_{sea} [gCO2/(t.nm)]

	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8	Average	Weighted average
Mean actual AER_{sea}	9.17	8.85	6.81	6.67	5.84	4.29	4.35		
Mean cycle-based AER_{sea}	7.60	8.50	6.58	6.28	5.45	4.15	4.02		
Difference in mean [%]	*-17.1*	*-4.0*	*-3.4*	*-5.9*	*-6.7*	*-3.1*	*-7.6*	*-6.8*	*-5.9*
SD of actual AER_{sea}	1.49	1.51	1.25	1.06	0.73	0.65	0.28		
SD of cycle-based AER_{sea}	11.21	0.74	1.05	0.83	0.39	0.49	0.38		
CV of actual AER_{sea}	0.163	0.170	0.183	0.159	0.125	0.152	0.065	0.145	0.147
CV of cycle-based AER_{sea}	0.160	0.087	0.159	0.132	0.071	0.119	0.093	0.117	0.116
Difference in CV [%]	*-1.5*	*-48.8*	*-13.2*	*-16.6*	*-42.9*	*-21.7*	*43.2*	*-19.1*	*-20.8*

*The figures include only the ships for which the speed-power relationship coefficient β has a R^2 of more than 0.8. The weighted average is weighted by the number of ships in each bin class. SD is the standard deviation and CV is the coefficient of variation.

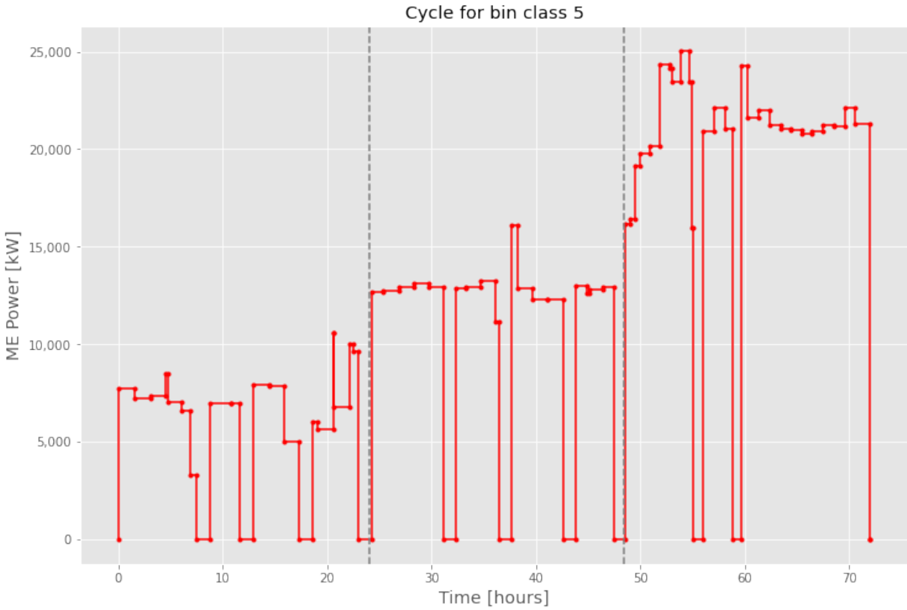
3.3.3 Alternative cycle generation mechanisms and final cycle configuration

One of the several arbitrary features of the proposed methodology is the decision to form cycles of a fixed 90-day duration. To address this issue, it was decided to investigate possible alternative mechanisms in two directions:

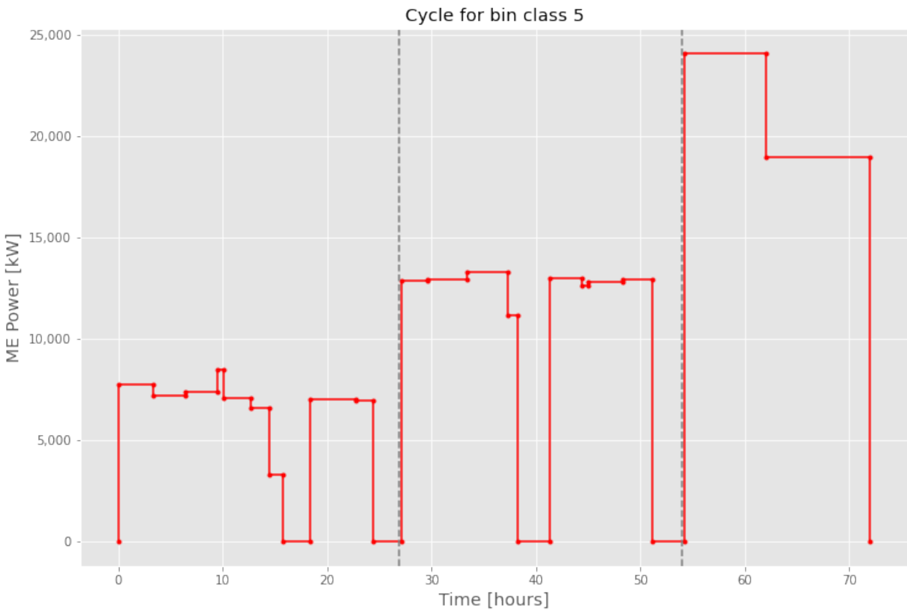
- Cycles of fixed duration (other than 90-days long)
- Cycles of a fixed number of legs in each category

Concerning fixed duration, two additional time lengths are tested, those of 60- and 30-day long cycles. No changes in the methodology are required for this test, as the td_c parameter of Equation (3.1) needs to be set to 20 and 10 days, respectively.

About the second direction and given the average leg duration in the three categories (refer to Table 3.3), the options of two and three legs per category were tested. Therefore, td_c is not required anymore as N_c now becomes a direct input parameter. The N_c legs with the lowest absolute difference from the mean value of ME power among the candidate legs are selected to represent the category c in the cycle. The idling periods follow the same procedure. The cycle's duration now depends on the lengths of the constituent legs and is proportionally converted to the 72-hour target for uniformity. Figure 3.9 shows the resulting cycles for bin class 5.

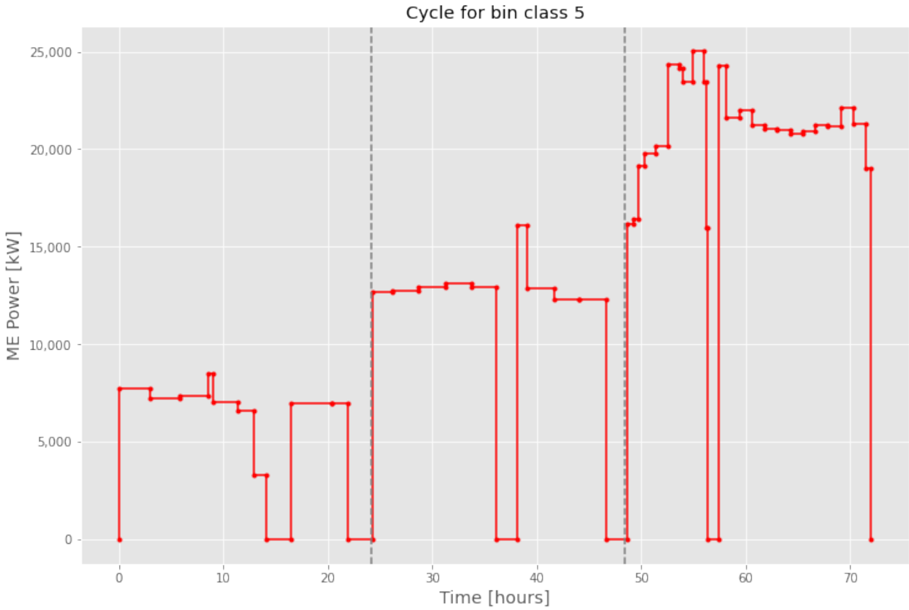


(a) Cycle - 60 days for bin class 5

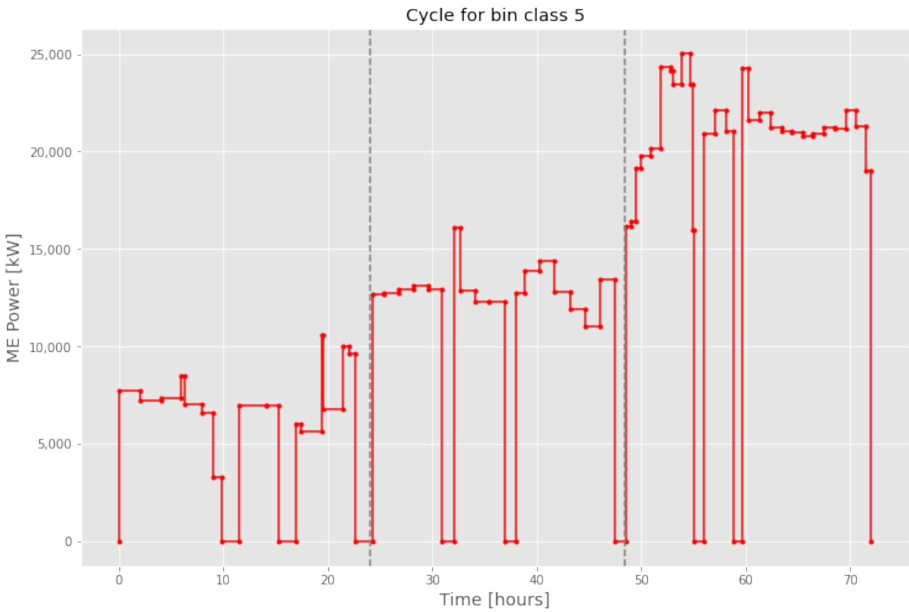


(b) Cycle - 30 days for bin class 5

Figure 3.9: Alternative cycles for bin class 5 (transformed into a 72-hour duration)



(c) Cycle - 2 legs for bin class 5



(d) Cycle - 3 legs for bin class 5

Figure 3.9: Alternative cycles for bin class 5 (transformed into a 72-hour duration)

Modifying the procedure followed for constructing the cycles can help improve the results. For instance, the problem with bin class 2, identified in Section 3.3.2, is that the mean values of the ME power categories get trapped in areas of repeated legs of the same (or similar) ship(s), rendering the selected legs poor representatives of the entire class. Increasing the number of ME power categories from three to five and setting three legs per category without applying any filter solved the problem. By doing so, the legs with high power are better represented in the cycle, as illustrated in Figure 3.10, and the cycle reflects better the actual emissions data of the bin class 2. The deviation now is only 3.0% in absolute values. After this adjustment, the cycle of bin class 2 is not a 90-day cycle anymore.

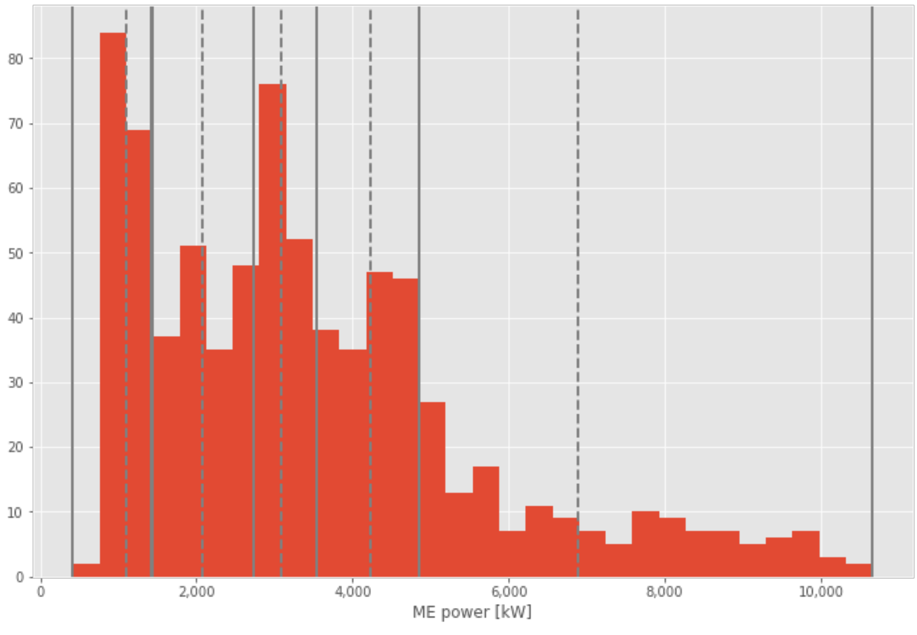


Figure 3.10: ME power distribution for bin class 2, showing the five categories of the modified cycle. The plain lines delimit the categories, and the dashed lines indicate the mean value within each category.

The problem with bin class 8 relates to the fact that this is the widest class, ranging from 14,500 to 19,999 TEUs (see Table 3.1). Furthermore, the sample, consisting of 39 ships in total, contains eight ships (of about 17,000 TEUs) with distinctively different behavior from the others, deteriorating the effectiveness of any single cycle. Therefore, it was decided to split this class into two sub-classes (bins 8.1 and 8.2) with an intermediate boundary of 17,999 TEUs. For bin class 8.1, a five-category scheme with three legs per category was selected (as with bin class 2). Bin class 8.2 kept the 30-day cycle.

Table 3.7: Comparison of different cycle schemes in terms of accuracy, in tons of CO_2 per hour per ship.

Bin class	**Sample fleet 2019**	**3 categories 90 days**		**3 categories 60 days**		**3 categories 30 days**		**3 categories 3 legs**		**3 categories 2 legs**		**5 categories 3 legs**		**Selected cycles**	
	t/h	*t/h*	*%*	*t/h*	*%*	*t/h*	*%*	*t/h*	*%*	*t/h*	*%*	*t/h*	*%*	*t/h*	*%*
2	3.14	2.03	-35.3	1.99	-36.6	2.02	-35.8	1.97	-37.2	1.86	-40.5	**3.05**	**-3.0**	3.05	-3.0
3	4.27	**4.28**	**0.2**	3.86	-9.6	4.20	-1.7	4.28	0.2	4.15	-2.7	3.43	-19.8	4.28	0.2
4	6.22	5.99	-3.6	**6.00**	**-3.5**	4.79	-23.0	6.97	12.0	7.14	14.8	6.33	1.7	6.00	-3.5
5	9.22	8.52	-7.6	**9.28**	**0.7**	6.69	-27.5	9.51	3.1	9.96	8.0	8.35	-9.5	9.28	0.7
6	10.69	**10.99**	**2.8**	8.30	-22.4	9.87	-7.7	12.60	17.9	11.68	9.2	10.68	-0.1	10.99	2.8
7	12.37	12.91	4.3	**12.78**	**3.3**	11.92	-3.6	13.34	7.8	12.90	4.3	11.40	-7.9	12.78	3.3
8	*15.26*	*13.62*	*-10.7*	*13.67*	*-10.5*	*12.45*	*-18.4*	*14.19*	*-7.0*	*13.28*	*-2.9*				
8.1	14.06	10.72	-23.7	10.55	-24.9	9.00	-35.9	11.00	-21.8	10.64	-24.3	**14.11**	**0.4**	14.11	0.4
8.2	15.61	13.31	-14.8	12.35	-20.9	**15.31**	**-1.9**	13.11	-16.0	13.12	-15.9	14.56	-6.7	15.31	-1.9
Absolute average			**11.5**		**15.2**		**17.1**		**14.5**		**15.0**		**6.1**		**2.0**
Absolute average weighted by ship			**6.9**		**12.2**		**15.7**		**12.6**		**12.3**		**5.1**		**2.3**

*The weighted averages exclude bin class 8, only kept for comparison.

Table 3.7 compares the accuracy of the different cycle schemes in expressing the emissions of the sample fleet. On average, the 90-day cycle, the longest one, represents actual emissions better than the other fixed-duration schemes. The differences between 2- and 3-leg cycles are small to be decisive. The most accurate scheme among all alternative ones for each bin class is selected as the suggested cycle. As shown in Table 3.7, the adjustments for bin classes 2 and 8 reduce the modified cycles' overall deviation to 2.0% of the actual emissions. The adjustments also reduce the average weighted by the number of ships in each bin class to 2.3%, compared to 6.2% previously. Appendix 3.A shows the selected cycles for all bin classes. Figure 3.11 plots the modified cycle-based AER_{sea} against DWT for all sample ships. This curve fits better than the actual AER_{sea} one. It is worth noting that these curves cannot be directly compared with reference lines from the CII regulation. Indeed, the CII reference lines include all emissions while the regression curves of Figure 3.11 pertain only to the ME emissions and only while sailing at sea (excluding port approaches and short coastal legs).

Table 3.8 shows the performance of the suggested set of cycles in reducing the variation of AER_{sea}. Bin class 8 appears in the table just for comparison purposes. Compared to Table 3.6, the selected modified cycles improve

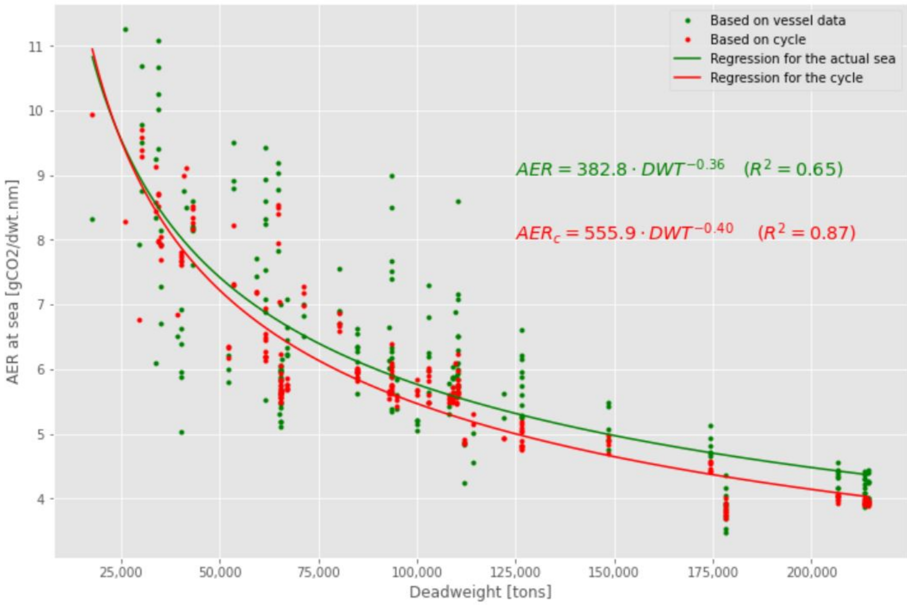


Figure 3.11: AER values for different ship sizes. Comparison of AER at sea values and the predictions of AER values based on the cycle for each ship in the data.

both AER_{sea} accuracy and the effectiveness in reducing variation. Indeed, the weighted average of the coefficient of variation improves by ten points, from a reduction of 20.8% to 30.9%. Bin class 8, now divided into two sub-classes, achieves a decrease of the coefficient of variation for both bins 8.1 and 8.2 by 57.3% and 69.2%, respectively.

Table 3.8: Comparison between selected cycle-based and actual AER_{sea} [gCO2/(t.nm)]

	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8	Bin 8.1	Bin 8.2	Average	Weighted average
Mean actual AER_{sea}	9.17	8.85	6.81	6.67	5.84	4.29	*4.35*	4.82	4.24		
Mean cycle-based AER_{sea}	8.33	8.50	6.59	6.30	5.45	4.16	*4.02*	4.50	3.96		
Difference in mean [%]	*-9.1*	*-4.0*	*-3.2*	*-5.6*	*-6.7*	*-2.9*	*-7.6*	*-6.6*	*-6.6*	*-5.6*	*-5.2*
SD of actual AER_{sea}	1.49	1.51	1.25	1.06	0.73	0.65	*0.28*	0.16	0.17		
SD of cycle-based AER_{sea}	1.30	0.74	1.05	0.83	0.39	0.49	*0.38*	0.07	0.05		
CV of actual AER_{sea}	0.163	0.170	0.183	0.159	0.125	0.152	*0.065*	0.034	0.040	0.128	0.144
CV of cycle-based AER_{sea}	0.156	0.087	0.159	0.132	0.071	0.119	*0.093*	0.014	0.012	0.094	0.107
Difference in CV [%]	*-4.1*	*-48.8*	*-13.2*	*-16.6*	*-42.9*	*-21.6*	*43.2*	*-57.3*	*-69.2*	*-34.2*	*-30.9*

*The figures include only the ships for which the speed-power relationship coefficient β has a R^2 of more than 0.8. The weighted average is weighted by the number of ships in each bin class. The averages exclude bin 8 (but include 8.1 and 8.2). SD is the standard deviation and CV is the coefficient of variation.

3.3.4 Comparison with 2018 and 2020 data

A final investigation concerns the performance of the cycles in different years. Company data were made available for the period 2018-2020. Table 3.9 compares the hourly emissions of the cycles, as they have been derived based on 2019 data, to the actual fleet emissions for 2018 and 2020. As expected, the deviations increase when moving away from the base year. However, the weighted average figures of these deviations remain below 6%. Table 3.10 presents the AER_{sea} values for 2018 and 2020 alongside the coefficient of variation. The AER_{sea} accuracy remains acceptable, with less than 7% for the weighted average. In terms of effectiveness in reducing variation, despite the slight increases in bins 2 (2018) and 4 (2020), the overall weighted decrease is 26.6% and 21.7% for the 2018 and 2020 fleets, respectively.

Table 3.9: Performance of the selected cycles in terms of ME emissions compared to 2019, 2018, and 2020 data, in tons of CO_2 per hour per ship

	Selected cycles	**Sample fleet 2018**		**Sample fleet 2019**		**Sample fleet 2020**	
Bin class	*t/h*	*t/h*	%	*t/h*	%	*t/h*	%
2	3.05	2.86	6.7	3.14	-3.0	2.84	7.3
3	4.28	4.50	-4.9	4.27	0.2	4.01	6.7
4	6.00	6.28	-4.4	6.22	-3.6	6.28	-4.5
5	9.28	9.12	1.8	9.22	-7.6	8.61	7.8
6	10.99	11.63	-5.5	10.69	2.8	11.44	-3.9
7	12.78	13.73	-6.9	12.37	4.3	13.36	-4.4
8.1	14.11	15.71	-10.1	14.06	0.4	16.17	-12.7
8.2	15.31	16.86	-9.2	15.61	-1.9	16.40	-6.7
Absolute average			**6.2**		**2.0**		**6.7**
Absolute average weighted by ship			**5.2**		**2.3**		**5.6**

3.3.5 Validation and verification of the operational cycles

The validation of the proposed operational cycles has been a guiding principle throughout the development process described above. Two criteria have been used for validating the performance of the cycles: (i) the accuracy in modeling ME emissions during sea legs, and (ii) the effectiveness of the cycles in reducing the observed variation in the values of operational energy efficiency indicators, such as the AER. The tons of CO_2 emissions per hour of ME

Table 3.10: Comparison between cycle-based and actual AER_{sea} [gCO2/(t.nm)] for 2018 and 2020 data

	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8.1	Bin 8.2	Average	Weighted average
Mean actual AER_{sea} 2018	9.04	9.11	7.00	6.42	6.09	4.69	5.07	4.38		
Mean actual AER_{sea} 2020	10.20	8.26	7.16	6.62	6.02	4.67	5.23	4.46		
Mean cycle-based AER_{sea} 2018	7.99	8.62	6.76	6.23	5.47	4.27	4.45	3.93		
Mean cycle-based AER_{sea} 2020	8.67	8.33	6.89	6.45	5.41	4.25	4.53	4.05		
Difference in mean [%] 2018	*-11.7*	*-5.3*	*-3.4*	*-2.9*	*-10.1*	*-9.0*	*12.1*	*10.3*	*-8.1*	*-6.7*
Difference in mean [%] 2020	*-14.9*	*0.9*	*-3.8*	*-2.6*	*-10.2*	*-9.1*	*-13.3*	*-9.1*	*-7.8*	*-6.2*
SD of actual AER_{sea} 2018	1.09	1.36	1.43	1.02	0.64	0.66	0.13	0.16		
SD of actual AER_{sea} 2020	2.25	1.50	1.36	1.05	0.57	0.51	0.10	0.22		
SD of cycle-based AER_{sea} 2018	1.00	0.83	1.21	0.87	0.33	0.50	0.08	0.5		
SD of cycle-based AER_{sea} 2020	0.94	0.59	1.32	0.88	0.39	0.46	0.06	0.08		
CV of actual AER_{sea} 2018	0.120	0.149	0.204	0.159	0.105	0.140	0.025	0.037	0.117	0.140
CV of actual AER_{sea} 2020	0.221	0.181	0.189	0.158	0.095	0.109	0.019	0.050	0.128	0.146
CV of cycle-based AER_{sea} 2018	0.125	0.097	0.179	0.139	0.060	0.118	0.018	0.013	0.093	0.110
CV of cycle-based AER_{sea} 2020	0.109	0.071	0.192	0.137	0.073	0.108	0.014	0.019	0.090	0.117
Difference in CV [%] 2018	*3.8*	*-35.0*	*-12.3*	*-12.2*	*-43.2*	*-15.8*	*-30.1*	*-64.2*	*-26.1*	*-26.6*
Difference in CV [%] 2020	*-50.8*	*-61.0*	*1.3*	*-13.5*	*-23.3*	*-1.0*	*-29.0*	*-61.5*	*-29.8*	*-21.7*

*The figures include only the ships for which the speed-power relationship coefficient β has a R^2 of more than 0.8. The weighted average is weighted by the number of ships in each bin class. SD is the standard deviation and CV is the coefficient of variation.

operation and the coefficient of variation have been defined as the metrics used for assessing the performance of the cycles against these two criteria respectively. The final configuration of the proposed cycles, as described in Section 3.3.3, reflects the adjustments made on the initial cycles to optimize accuracy in line with the validation mechanism. Furthermore, the assessment of the cycle performance for 2018 and 2020, two years different than the one used for developing the concept (2019), is an additional facet of the validation process. Overall, the proposed cycles reflect a rigorous validation process, which is necessary for introducing a scheme that can have important policy-making repercussions.

Verification is an equally important procedure for a concept that plays a central role in a highly influential benchmarking scheme. The raw data cannot be revealed due to confidentiality restrictions. However, every effort has been made to report all assumptions made in the development process. The equations and computational procedures used were tested, compared with real-world data, and examined carefully by all co-authors to ensure proper implementation. Nevertheless, it is certain that an innovative concept such as the proposed cycles will only be debated by the policy-makers if the analysis is performed by certified institutions, such as the various classification societies. These institutions are not only aware of the relevant scientific literature but have also access to the necessary data, which can extend beyond the boundaries of the company that supported this particular research.

3.4 Discussion

The development of standardized operational cycles for assessing ship energy efficiency is a novel idea greatly inspired by the automotive industry. Despite the amount of work performed, this paper is introductory in many aspects, aiming at initiating a dialogue within the research community on this topic. Several limitations need to be addressed in terms of both the methodology applied and the required data input.

The main methodological concern relates to the authors' decision to base the cycles' construction solely on the ME power of the ship. Ship fuel consumption can undoubtedly be modeled in different ways. Speed and draft, for example, are two decisive parameters that could replace the ME power or be used in conjunction with it. The use of speed and draft would have enabled assessing the effectiveness of the cycle through EEOI, which is a much richer carbon intensity indicator than AER.

Another important methodological issue concerns the decision to base the selection of the legs on the mean value of each category (low-, medium-, and high-ME power). As shown with bin classes 2 and 8, this path can lead to serious representation problems. The statistically correct method is through the use of the χ^2 test. However, the volume of the processed data made this approach infeasible for the available resources.

Similar concerns can be raised in relation to the stratification of the fleet in size bins, the segregation of the main parameter(s) in categories, the duration of the cycles, the number of legs in a cycle, and the applicable filters in developing the leg and idling-period databases. Although much work has been performed in these directions, a more detailed optimization procedure could be pursued.

Concerning data requirements, the frequency of observations is a significant determinant of the quality of the cycles. The noon reports used in this work are a low-frequency data source, lacking the detail needed to capture variations of the main parameter(s) (e.g., ME power) within the report's duration. Moreover, noon reports are prone to human error (Aldous et al., 2013, 2015). More frequent data, such as those derived from the Automatic Identification System (AIS) and continuous onboard monitoring systems, would enable a more accurate definition of the cycles.

Another limitation is the exclusion of short trips from the proposed operational cycles due to data unavailability. These short trips represent 11.2% of the noon reports and 23.5% of the total duration of the reports, including time at ports. Table 3.11 shows the percentage of short trips excluded for each bin class. Small-sized ships are particularly affected, as they usually operate within shorter distances. Short trips are imperative for functional operational cycles, particularly for the smaller bin classes.

Table 3.11: Percentage of short trips for each bin class

Bin class	2	3	4	5	6	7	8	All fleet
Percentage of reports for short trips (%)	16.7	16.9	11.9	11.8	9.2	8.2	8.4	11.2
Percentage of duration for short trips (%)	30.3	28.9	23.5	22.5	19.9	24.7	23.9	23.5

In terms of coverage, the authors were privileged to have access to a sample amounting to 6.1% of the world container fleet. However, the segments of very small (under 1,000 TEU) and large (over 20,000 TEU) ships are still missing. Besides, the resulting cycles reflect the operational arrangements of a single owner/operator. For this particular exercise, the cooperation of as many actors as possible is needed.

This paper excludes the emissions generated by onboard fuel consumers other than the main engine(s), i.e., the auxiliary engines and the boilers. If the cycles are to be used for benchmarking purposes, they must also incorporate these dimensions. Particularly the carriage of refrigerated containers is an operational parameter with essential repercussions on the value of CII, as recently acknowledged by the CII correction factor for reefers adopted during the MEPC 78 meeting (IMO, 2022).

Furthermore, a critical external factor in terms of a ship's energy efficiency is weather (Kim and Roh, 2020; Kwon, 2008; Medina et al., 2020; Taskar and

Andersen, 2020; Vettor et al., 2015). Its effect on a ship's performance is complex and depends on factors, such as the wind speed and direction, the wave distribution, the current, the sea depth, etc. (Adland et al., 2020; Berthelsen and Nielsen, 2021; Bialystocki and Konovessis, 2016; Degiuli et al., 2019; Panagakos et al., 2019). Due to lack of data, this aspect has been left outside the scope of this paper. However, the weather effect must be considered as part of the operational cycles or as a separate correction factor.

All limitations mentioned constitute directions for further work on the subject. The WLTC standard for road transport highlighted four requirements to obtain working driving cycles: repeatability, reproducibility, cost-efficiency, and practicability (Tutuianu et al., 2015). The maritime industry also needs to address these issues to construct cycles suitable for regulatory purposes. Measurement systems, assessment, and validation are critical elements for further development. The involvement of international policy-making institutions, both regional and global, might be necessary for this type of work.

Once successful, coverage can be expanded to include other ship types, such as bulk carriers and tankers, which, together with container ships, are the three segments responsible for most maritime transport emissions (Faber et al., 2020). Different cycles would need to be developed for the different shipping segments, due to their diverse nature of operations. These differentiated cycles for shipping segments mirror the use of various cycles based on the mission of HDVs. Similar to the different cycles for each bin class of container ships, cycles for different group sizes of other ship segments will be needed, while at the same time, an effort should be made to keep their number reasonable ensuring the effectiveness of this benchmarking mechanism.

3.5 Conclusion

The shipping industry faces significant challenges in achieving the IMO decarbonization goals. While much research is devoted to new technologies and alternative fuels, this study focuses on tools for assessing ships' carbon efficiency and tracking progress toward lowering carbon emissions. The main contribution of this paper is the development and application of operational cycles for maritime transportation. The use of driving cycles in the automotive industry, implemented for decades, has inspired the work.

The analysis relies on a fleet of 327 ships, amounting to 6.1% of the world container ship fleet, divided into seven bin classes. The main engine(s) power constitutes the main parameter for constructing operational cycles for each one of these bin classes. The resulting cycles exhibit a satisfactory accuracy (97.7% on average) in representing the actual emissions for the base year of analysis (2019), as shown in Table 3.7. Their accuracy remains high (above 94% on average) for 2018 and 2020 (refer to Table 3.9). More importantly, they have proved effective in reducing variation in the AER values (above 30% on average, as per Table 3.8), thus validating the concept's usefulness in improving the indicators used today for regulatory purposes.

The applied methodology, as proposed by Godet et al. (2022), proved useful from a broad perspective outlining the necessary steps and their sequence. However, the initial results had to undergo significant modifications to address limitations in terms of both methodological aspects and data availability. In this respect, several new paths have been tested successfully. The results of this paper lay the foundations for extensive further work on the subject, involving ship owners/operators as well as regional and global regulatory bodies. Several directions for further research are provided.

Nomenclature – Chapter 3

AER_{sea} Annual Efficiency Ratio, considering only the fuel consumed by the main engines at sea

A_s Ship-specific constant

B_s Ship-specific constant

C_{F_f} Carbon intensity of fuel f [tons of CO_2 / tons of fuel]

DWT Deadweight of the ship [tons]

D_l Distance sailed during leg l

FC_f Mass of fuel type f consumed [tons]

LCV_r Low calorific value of the fuel mix used during the noon report r

N_c Number of legs in the category c

P_r Average Main Engine Power for noon report r [kW]

S_{i_c} Selected idling periods for the category c

S_{l_c} Selected legs for the category c

Δt_c Differential between the target duration for the category c and the selected set of legs and idling periods duration

α_s Ship-specific constant

β_s Ship-specific constant

ϵ Residual perturbation

η_r Thermal efficiency of the ship engine for the fuel mix consumed during noon report r

$\overline{i_c}$ Adjusted mean idling period in category c

$\overline{t_c}$ Adjusted mean leg duration in the category c

c Category in the cycle

f Fuel type

i Idling period

l Leg

r Noon report r

s Ship

t'_{l_c} Adjusted duration of leg l in category c

t_r Noon report duration

t_{i_c} Duration of idling period i in category c

t_{l_c} Duration of leg l in category c

td_c Targeted duration for the category c

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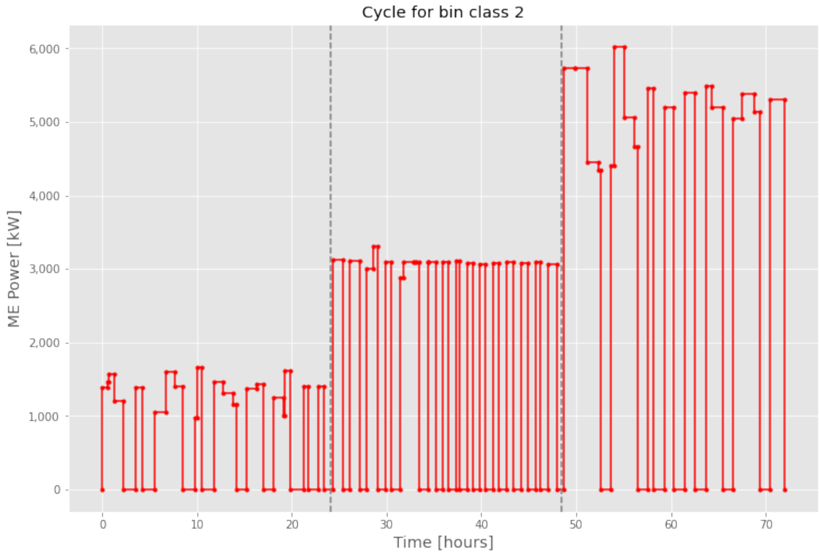
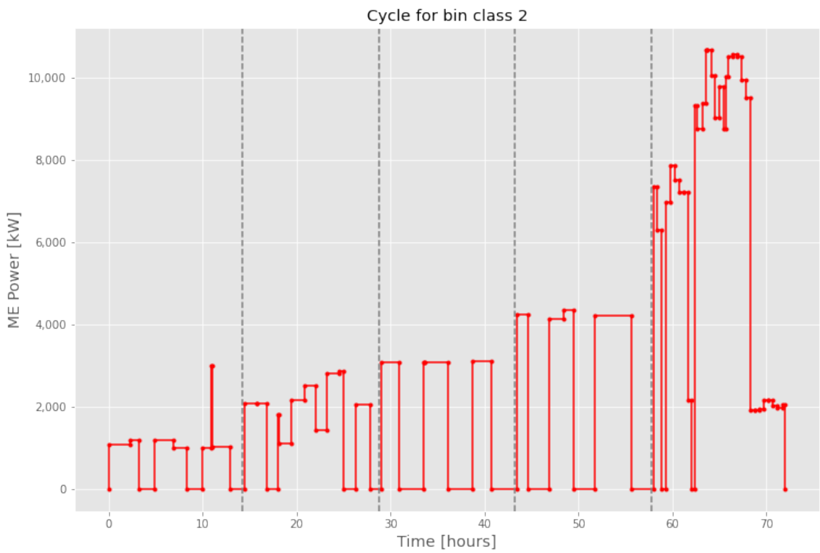
Appendix 3.A Cycles

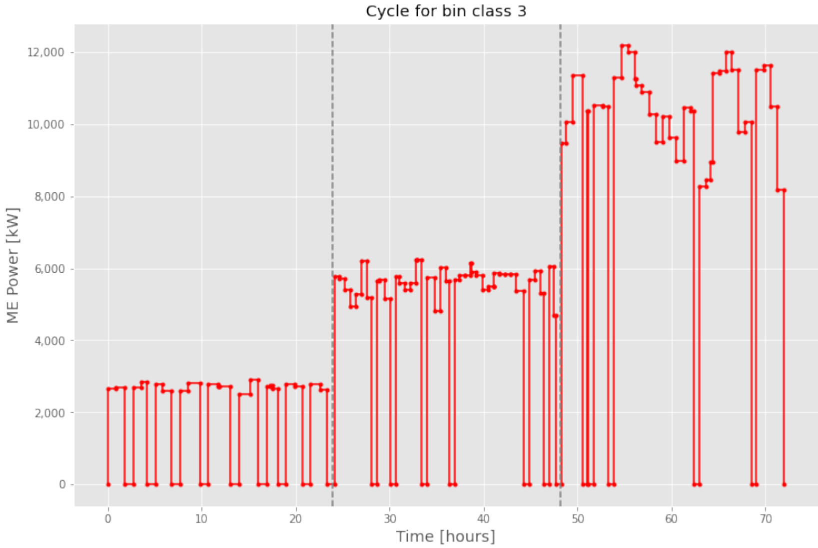


(a) Bin class 2 - 90-day cycle

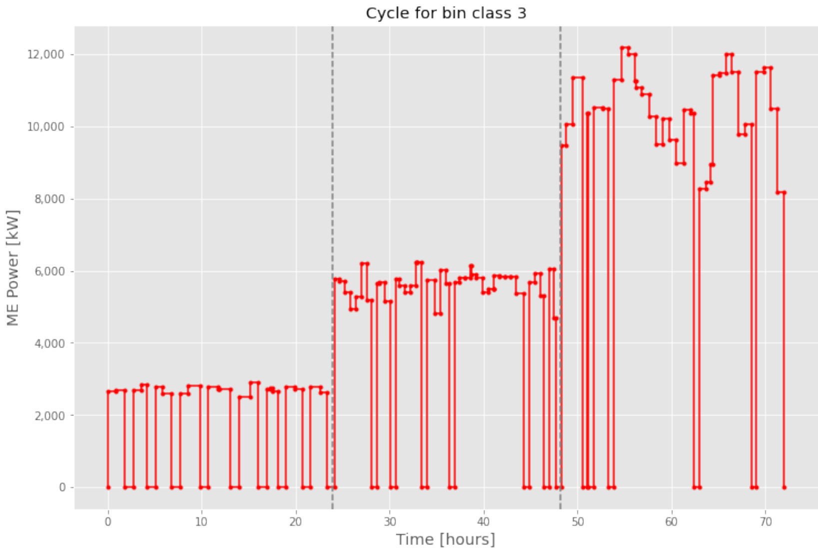


(b) Bin class 2 - Selected cycle (5 categories, 3 legs)

Figure 3.12: Operational cycles for bin class 2

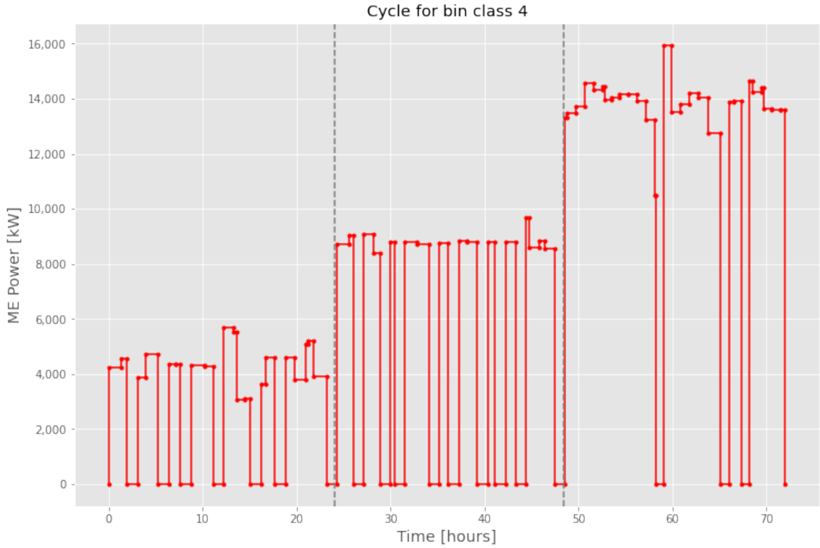


(a) Bin class 3 - 90-day cycle

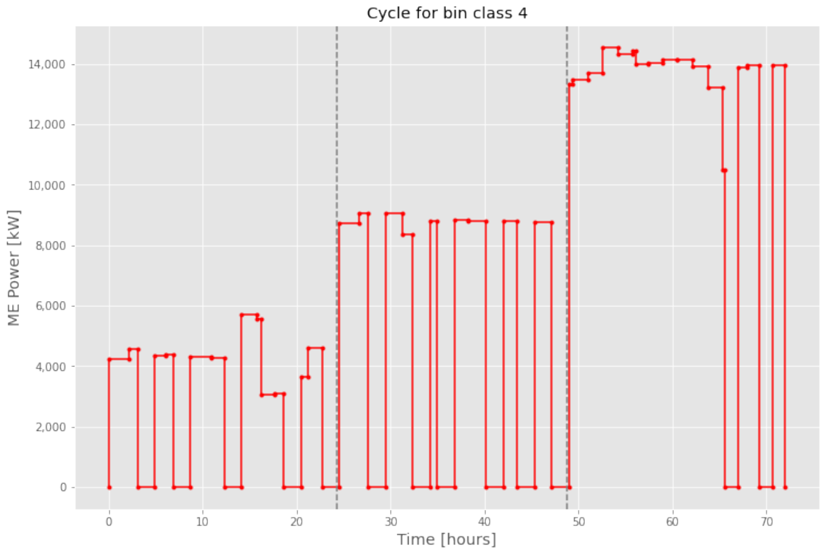


(b) Bin class 3 - Selected cycle

Figure 3.13: Operational cycles for bin class 3

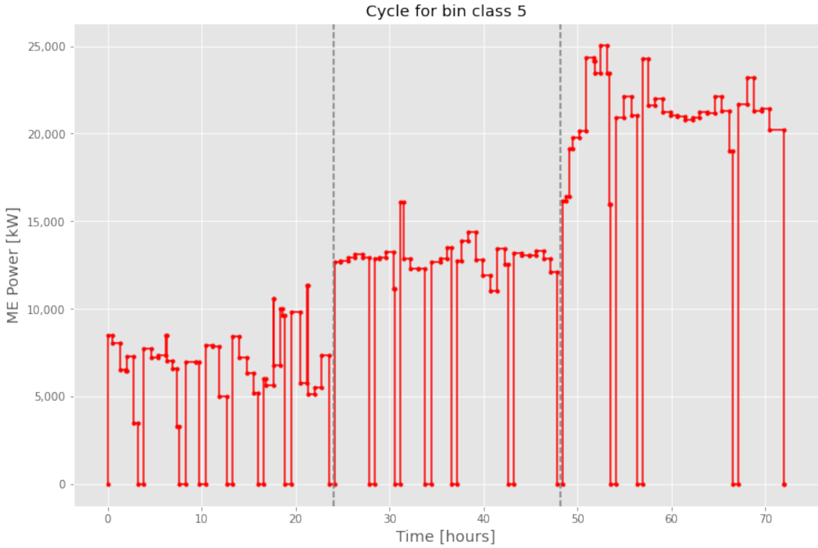


(a) Bin class 4 - 90-day cycle

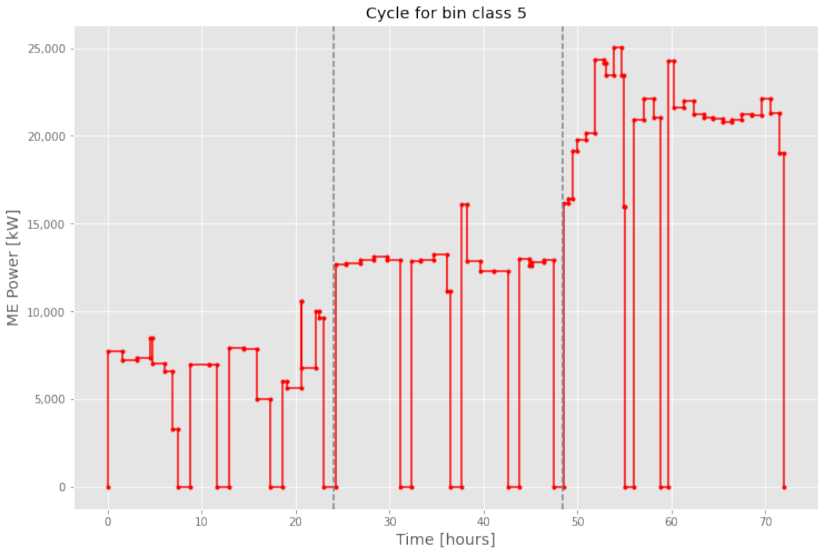


(b) Bin class 4 - Selected cycle

Figure 3.14: Operational cycles for bin class 4

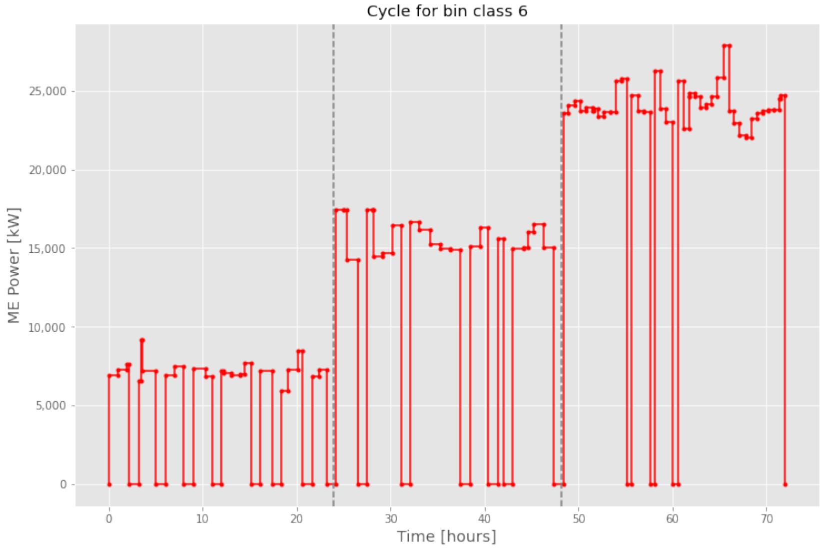


(a) Bin class 5 - 90-day cycle

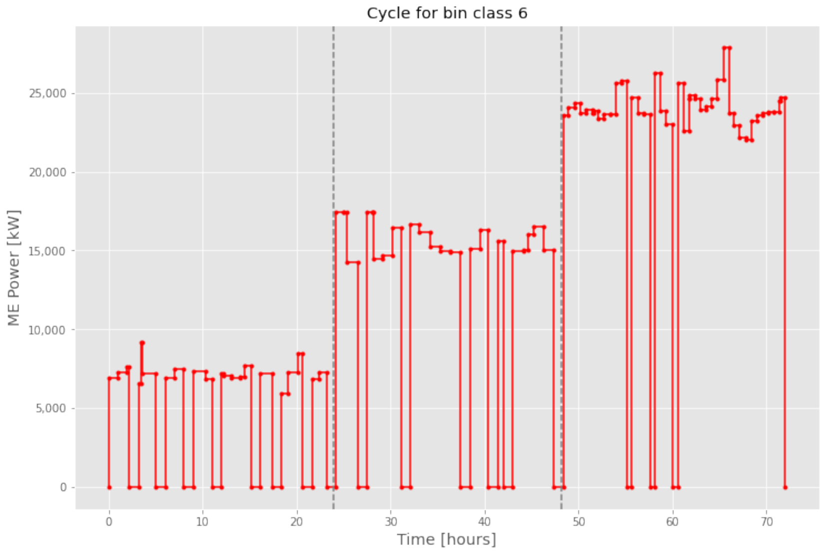


(b) Bin class 5 - Selected cycle

Figure 3.15: Operational cycles for bin class 5

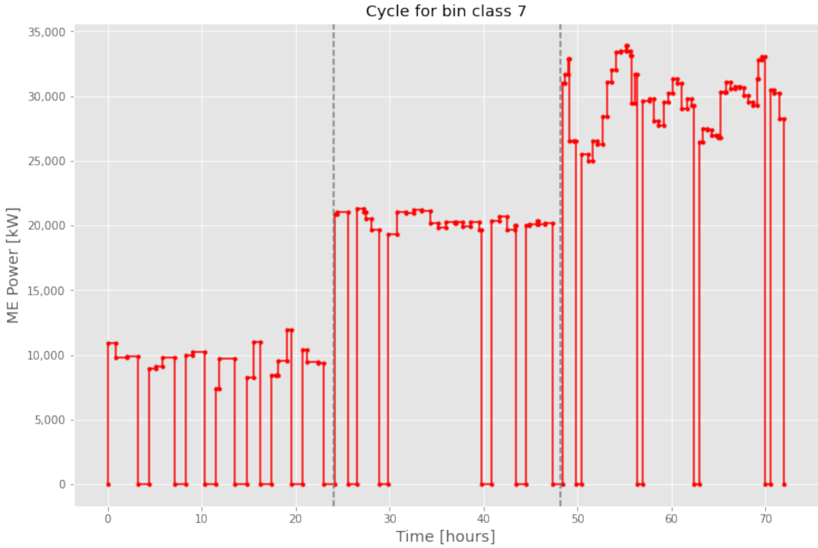


(a) Bin class 6 - 90-day cycle

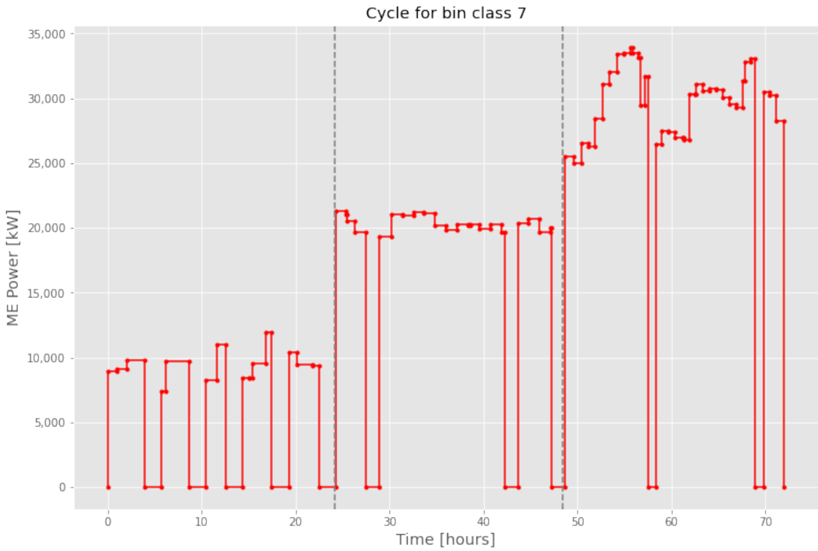


(b) Bin class 6 - Selected cycle

Figure 3.16: Operational cycles for bin class 6



(a) Bin class 7 - 90-day cycle



(b) Bin class 7 - Selected cycle

Figure 3.17: Operational cycles for bin class 7

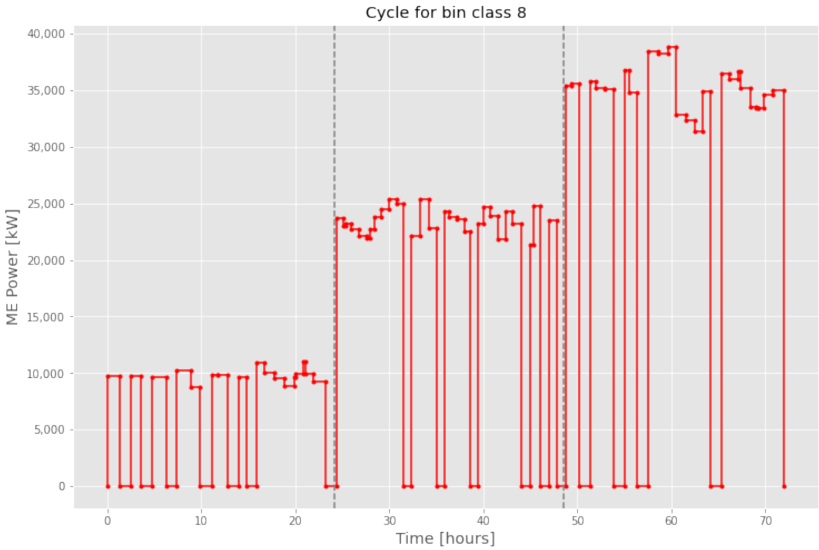
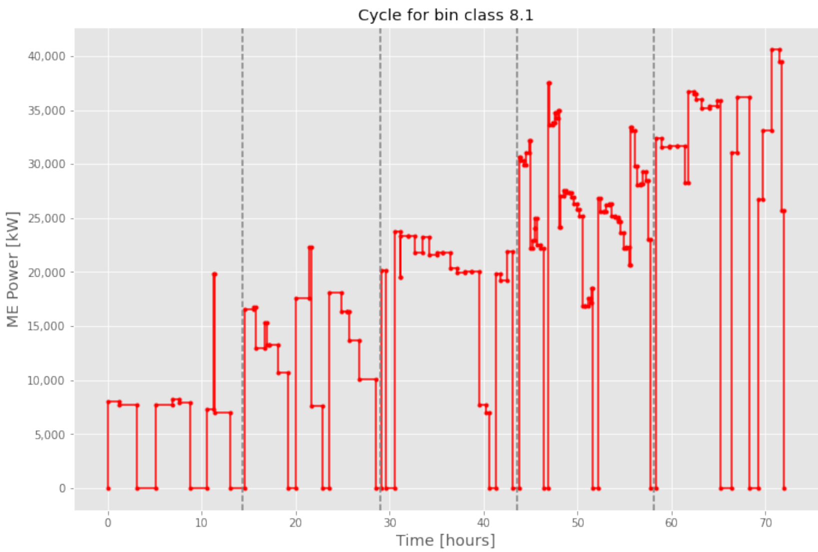
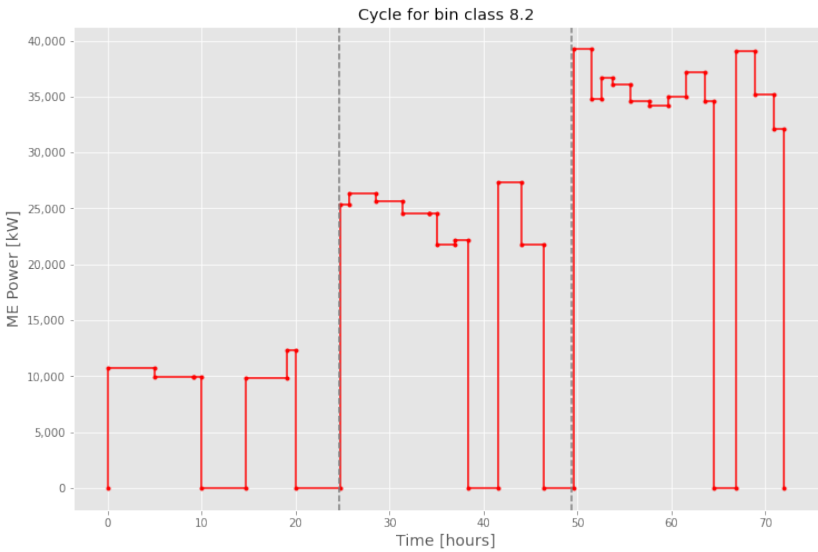


Figure 3.18: Operational cycles for bin class 8



(a) Bin class 8.1 - Selected cycle



(b) Bin class 8.2 - Selected cycle

Figure 3.19: Operational cycles for bin classes 8.1 and 8.2

Appendix 3.B Characteristics of the cycles

Table 3.12: Characteristics of the selected cycle for bin class 2

	Category 1 Very low ME power		Category 2 Low ME power		Category 3 Medium ME power		Category 4 High ME power		Category 5 Very high ME power	
	60 days	72 hours	60 days	72 hours	60 days	72 hours	60 days	72 hours		
All legs [number]	152		154		154		154		152	
Min ME power [kW] - leg level		795		1,435		2,736		3,542		4,846
Max ME power [kW] - leg level		1,424		2,725		3,535		4,845		10,177
Mean ME power [kW] - leg level		1,109		2,069		3,090		4,225		6,796
Std ME power [kW] - leg level		148		377		233		373		1,574
Min duration [hours] - leg level	07h 35m	23m	12h 00m	36m	08h 05m	24m	02h 47m	08m	01h 00m	03m
Max duration [hours] - leg level	09d 02h 30m	11h 06m	08d 12h 00m	10h 22m	11d 11h 30m	14h 00m	11d 14h 00m	14h 08m	22d 15h 42m	27h 38m
Mean duration [hours] - leg level	02d 01h 02m	02h 29m	02d 06h 37m	02h 46m	01d 12h 43m	01h 52m	01d 12h 42m	01h 52m	06d 19h 17m	08h 18m
Std duration [hours] - leg level	01d 01h 17m	01h 17m	01d 10h 40m	01h 45m	01d 11h 21m	01h 47m	01d 15h 49m	02h 01m	07d 13h 39m	09h 14m
Selected legs [number]	3		3		3		3		3	
Min ME power [kW] - segment level		999		1,101		3,091		4,129		3,417
Max ME power [kW] - segment level		3,005		2,860		3,095		4,355		10,680
Mean ME power [kW] - segment level		1,357		2,084		3,093		4,236		6 ,977
Std ME power [kW] - segment level		732		555		2		93		3,417
Min duration [hours] - segment level	02h 00m	06m	03h 00m	09m	01h 00m	03m	09h 00m	27m	04h 00m	12m
Max duration [hours] - segment level	01d 07h 00m	01h 34m	01d 05h 00m	01h 28m	18h 11m	55m	01d 10h 42m	01h 45m	01d 02h 48m	01h 21m
Mean duration [hours] - segment level	18h 09m	55m	20h 38m	01h 03m	12h 18m	37m	17h 00m	51m	21h 08m	01h 04m
Std duration [hours] - segment level	09h 12m	28m	07h 32m	22m	06h 39m	20m	10h 22m	31m	05h 10m	15m
All idling periods [number]	54		72		39		64		58	
Min duration [hours] - leg level	03h 24m	10m	04h 30m	13m	05h 05m	15m	04h 54m	14m	03h 21m	10m
Max duration [hours] - leg level	04d 01h 47m	04h 58m	06d 00h 24m	07h 20m	01d 23h 58m	02h 26m	02d 12h 12m	03h 03m	02d 14h 46m	03h 11m
Mean duration [hours] - leg level	21h 50m	01h 06m	01d 00h 29m	01h 14m	19h 32m	59m	19h 34m	59m	22h 39m	01h 09m
Std duration [hours] - leg level	20h 51m	01h 03m	01d 00h 40m	01h 15m	11h 11m	34m	12h 18m	37m	14h 37m	44m
Selected idling periods [number]	3		3		3		3		2	
Min duration [hours] - leg level	21h 06m	01h 04m	22h 41m	01h 09m	19h 18m	58m	19h 39m	01h 00m	22h 06m	01h 07m
Max duration [hours] - leg level	22h 00m	01h 07m	23h 41m	01h 12m	19h 53m	01h 00m	20h 00m	01h 01m	22h 36m	01h 08m
Mean duration [hours] - leg level	21h 24m	01h 05m	23h 14m	01h 10m	19h 32m	59m	19h 51m	01h 00m	22h 21m	01h 08m
Std duration [hours] - leg level	25m	01m	24m	01m	15m	00m	08m	00m	15m	00m

Table 3.13: Characteristics of the selected cycle for bin class 3

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	90 days	**72 hours**	**90 days**	**72 hours**	**90 days**	**72 hours**
All legs [number]	234		167		248	
Min ME power [kW] - leg level		1,467		3,883		7,503
Max ME power [kW] - leg level		3,820		7,492		15,160
Mean ME power [kW] - leg level		2,722		5,592		10,470
Std ME power [kW] - leg level		487		1,058		2,286
Min duration [hours] - leg level	08h 30m	17m	05h 00m	10m	04h 00m	08m
Max duration [hours] - leg level	08d 18h 45m	07h 04m	12d 13h 18m	10h 06m	12d 04h 00m	09h 48m
Mean duration [hours] - leg level	02d 04h 49m	01h 46m	02d 19h 37m	02h 16m	03d 20h 49m	03h 07m
Std duration [hours] - leg level	01d 06h 50m	01h 02m	02d 02h 07m	01h 40m	03d 00h 13m	02h 25m
Selected legs [number]	9		7		6	
Min ME power [kW] - segment level		2,510		4,682		8,180
Max ME power [kW] - segment level		2,897		6,230		12,200
Mean ME power [kW] - segment level		2,174		5,637		10,442
Std ME power [kW] - segment level		92		366		1,107
Min duration [hours] - segment level	04h 00m	08m	02h 00m	04m	04h 00m	08m
Max duration [hours] - segment level	01d 08h 00m	01h 04m	01d 12h 00m	01h 12m	01d 08h 00m	01h 04m
Mean duration [hours] - segment level	20h 05m	40m	20h 59m	42m	21h 27m	43m
Std duration [hours] - segment level	07h 26m	14m	06h 42m	13m	06h 29m	13m
All idling periods [number]	202		194		176	
Min duration [hours] - leg level	00h 41m	01m	02h 30m	05m	00h 42m	01m
Max duration [hours] - leg level	04d 12h 36m	03h 38m	02d 22h 12m	02h 21m	02d 10h 19m	01h 57m
Mean duration [hours] - leg level	22h 35m	45m	01d 00h 48m	49m	17h 51m	35m
Std duration [hours] - leg level	16h 28m	33m	16h 41m	33m	11h 44m	23m
Selected idling periods [number]	9		7		5	
Min duration [hours] - leg level	21h 41m	43m	01d 00h 02m	48m	17h 24m	35m
Max duration [hours] - leg level	23h 11m	46m	01d 02h 06m	52m	18h 23m	37m
Mean duration [hours] - leg level	22h 21m	45m	01d 00h 57m	50m	17h 55m	36m
Std duration [hours] - leg level	32m	01m	39m	01m	21m	00m

Table 3.14: Characteristics of the selected cycle for bin class 4

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	60 days	72 hours	60 days	72 hours	60 days	72 hours
All legs [number]	653		513		596	
Min ME power [kW] - leg level		1,780		7,118		10,522
Max ME power [kW] - leg level		7,109		10,505		21,810
Mean ME power [kW] - leg level		4,322		8,796		13,941
Std ME power [kW] - leg level		1,415		928		2,723
Min duration [hours] - leg level	04h 00m	12m	04h 00m	12m	04h 00m	12m
Max duration [hours] - leg level	18d 23h 41m	23h 14m	16d 01h 00m	19h 38m	19d 23h 53m	24h 28m
Mean duration [hours] - leg level	02d 18h 46m	03h 24m	01d 22h 04m	02h 20m	04d 22h 12m	06h 01m
Std duration [hours] - leg level	02d 09h 36m	02h 56m	01d 15h 46m	02h 01m	04d 08h 16m	05h 19m
Selected legs [number]	5		6		3	
Min ME power [kW] - segment level		3,070		8,374		10,500
Max ME power [kW] - segment level		5,693		9,074		14,559
Mean ME power [kW] - segment level		4,316		8,805		13,722
Std ME power [kW] - segment level		799		203		935
Min duration [hours] - segment level	06h 00m	18m	09h 00m	27m	02h 30m	07m
Max duration [hours] - segment level	01d 05h 00m	01h 28m	01d 04h 23m	01h 26m	01d 00h 00m	01h 13m
Mean duration [hours] - segment level	16h 34m	50m	18h 54m	57m	18h 22m	56m
Std duration [hours] - segment level	06h 57m	21m	05h 56m	18m	07h 13m	22m
All idling periods [number]	369		251		272	
Min duration [hours] - leg level	01h 11m	03m	02h 23m	07m	03h 47m	11m
Max duration [hours] - leg level	03d 10h 16m	04h 11m	03d 00h 43m	03h 42m	03d 19h 58m	04h 41m
Mean duration [hours] - leg level	23h 29m	01h 11m	01d 00h 49m	01h 15m	21h 19m	01h 05m
Std duration [hours] - leg level	19h 05m	58m	17h 22m	53m	16h 23m	50m
Selected idling periods [number]	5		6		2	
Min duration [hours] - leg level	23h 06m	01h 10m	01d 00h 12m	01h 14m	21h 15m	01h 05m
Max duration [hours] - leg level	23h 36m	01h 12m	01d 01h 11m	01h 17m	21h 19m	01h 05m
Mean duration [hours] - leg level	23h 25m	01h 11m	01d 00h 47m	01h 15m	21h 17m	01h 05m
Std duration [hours] - leg level	10m	00m	24m	01m	01m	00m

Table 3.15: Characteristics of the selected cycle for bin class 6

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	90 days	72 hours	90 days	72 hours	90 days	72 hours
All legs [number]	528		226		378	
Min ME power [kW] - leg level		3,473		11,634		19,536
Max ME power [kW] - leg level		11,544		19,534		32,961
Mean ME power [kW] - leg level		7,145		15,600		24,131
Std ME power [kW] - leg level		1,944		2,307		3,430
Min duration [hours] - leg level	04h 00m	08m	10h 18m	20m	06h 00m	12m
Max duration [hours] - leg level	16d 09h 41m	13h 13m	25d 05h 00m	20h 19m	23d 21h 00m	19h 14m
Mean duration [hours] - leg level	02d 09h 20m	01h 55m	03d 14h 27m	02h 54m	05d 03h 08m	04h 08m
Std duration [hours] - leg level	01d 15h 59m	01h 20m	04d 06h 04m	03h 25m	05d 00h 17m	04h 02m
Selected legs [number]	8		6		4	
Min ME power [kW] - segment level		5,900		14,230		22,017
Max ME power [kW] - segment level		9,201		17,460		27,900
Mean ME power [kW] - segment level		7,244		15,809		24,139
Std ME power [kW] - segment level		664		1,057		1,134
Min duration [hours] - segment level	02h 00m	04m	02h 00m	04m	04h 00m	08m
Max duration [hours] - segment level	01d 11h 30m	01h 11m	01d 02h 00m	52m	01d 06h 00m	01h 00m
Mean duration [hours] - segment level	18h 53m	38m	18h 35m	37m	22h 01m	44m
Std duration [hours] - segment level	08h 48m	17m	06h 27m	13m	05h 26m	10m
All idling periods [number]	258		228		271	
Min duration [hours] - leg level	02h 39m	05m	04h 05m	08m	02h 11m	04m
Max duration [hours] - leg level	05d 15h 57m	04h 33m	02d 11h 50m	02h 00m	02d 06h 23m	01h 49m
Mean duration [hours] - leg level	01d 00h 17m	48m	21h 43m	43m	21h 46m	43m
Std duration [hours] - leg level	17h 28m	35m	10h 03m	20m	10h 16m	20m
Selected idling periods [number]	8		6		3	
Min duration [hours] - leg level	23h 53m	48m	21h 18m	42m	21h 27m	43m
Max duration [hours] - leg level	01d 00h 39m	49m	21h 57m	44m	21h 55m	44m
Mean duration [hours] - leg level	01d 00h 09m	48m	21h 36m	43m	21h 43m	43m
Std duration [hours] - leg level	13m	00m	13m	00m	11m	00m

Table 3.16: Characteristics of the selected cycle for bin class 7

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	60 days	72 hours	60 days	72 hours	60 days	72 hours
All legs [number]	159		74		108	
Min ME power [kW] - leg level		3,834		16,441		24,720
Max ME power [kW] - leg level		16,305		24,664		39,401
Mean ME power [kW] - leg level		9,637		20,569		29,401
Std ME power [kW] - leg level		3,433		2,467		3,572
Min duration [hours] - leg level	04h 00m	12m	19h 53m	08m	07h 54m	24m
Max duration [hours] - leg level	12d 12h 12m	15h 12m	17d 02h 14m	20h 47m	15d 03h 29m	18h 25m
Mean duration [hours] - leg level	02d 17h 32m	03h 19m	04d 01h 50m	04h 57m	04d 06h 04m	05h 10m
Std duration [hours] - leg level	02d 01h 59m	02h 31m	03d 12h 52m	04h 18m	03d 08h 36m	04h 05m
Selected legs [number]	5		3		3	
Min ME power [kW] - segment level		7,419		19,353		24,996
Max ME power [kW] - segment level		11,909		21,292		33,940
Mean ME power [kW] - segment level		9,414		20,348		29,827
Std ME power [kW] - segment level		1,161		578		2,562
Min duration [hours] - segment level	04h 00m	12m	04h 00m	12m	04h 00m	12m
Max duration [hours] - segment level	01d 09h 00m	01h 40m	01d 02h 41m	01h 21m	01d 08h 00m	01h 37m
Mean duration [hours] - segment level	14h 45m	44m	20h 02m	01h 01m	19h 58m	01h 00m
Std duration [hours] - segment level	07h 40m	23m	07h 35m	23m	06h 48m	20m
All idling periods [number]	82		86		76	
Min duration [hours] - leg level	02h 47m	08m	06h 27m	19m	27m	01m
Max duration [hours] - leg level	02d 15h 31m	03h 13m	06d 12h 20m	07h 55m	02d 22h 36m	03h 34m
Mean duration [hours] - leg level	01d 00h 29m	01h 14m	01d 05h 35m	01h 29m	01d 06h 37m	01h 33m
Std duration [hours] - leg level	10h 23m	31m	20h 42m	01h 02m	13h 27m	40m
Selected idling periods [number]	5		3		2	
Min duration [hours] - leg level	01d 00h 00m	01h 13m	01d 04h 20m	01h 26m	01d 06h 26m	01h 32m
Max duration [hours] - leg level	01d 00h 41m	01h 15m	01d 05h 33m	01h 29m	01d 06h 51m	01h 33m
Mean duration [hours] - leg level	01d 00h 22m	01h 14m	01d 04h 46m	01h 27m	01d 06h 38m	01h 33m
Std duration [hours] - leg level	13m	00m	33m	01m	12m	00m

Table 3.17: Characteristics of the selected cycle for bin class 8.1

	Category 1 Very low ME power		Category 2 Low ME power		Category 3 Medium ME power		Category 4 High ME power		Category 5 Very high ME power	
	104 days	72 hours	104 days	72 hours	104 days	72 hours	104 days	72 hours	104 days	72 hours
All legs [number]	53		55		55		55		55	
Min ME power [kW] - leg level		5,860		9,995		17,767		23,641		29,508
Max ME power [kW] - leg level		9,995		17,763		23,609		29,454		41,711
Mean ME power [kW] - leg level		7,846		13,846		20,336		26,405		33,935
Std ME power [kW] - leg level		1,149		2,589		1,760		1,773		3,313
Min duration [hours] - leg level	21h 00m	36m	01d 06h 00m	52m	15h 00m	26m	01d 07h 00m	53m	01d 08h 00m	55m
Max duration [hours] - leg level	09d 18h 59m	06h 48m	12d 15h 00m	08h 46m	18d 17h 00m	12h 59m	19d 07h 00m	13h 24m	18d 18h 00m	13h 01m
Mean duration [hours] - leg level	02d 18h 26m	01h 55m	03d 13h 53m	02h 29m	07d 15h 35m	05h 18m	09d 08h 38m	06h 30m	07d 18h 51m	05h 24m
Std duration [hours] - leg level	01d 08h 59m	57m	01d 19h 35m	01h 15m	05d 12h 48m	03h 50m	05d 06h 01m	03h 38m	05d 14h 55m	03h 54m
Selected legs [number]	3		3		3		3		3	
Min ME power [kW] - segment level		6,962		7,600		7,004		16,850		25,680
Max ME power [kW] - segment level		19,850		22,290		23,698		37,540		40,640
Mean ME power [kW] - segment level		9,197		14,725		19,805		26,522		33,562
Std ME power [kW] - segment level		4,323		3,655		4,612		4,930		4,069
Min duration [hours] - segment level	01h 34m	02m	03h 00m	05m	03h 00m	05m	05h 00m	08m	05h 00m	08m
Max duration [hours] - segment level	22h 00m	38m	01d 09h 00m	57m	01d 00h 00m	41m	01d 07h 00m	53m	01d 11h 00m	01h 00m
Mean duration [hours] - segment level	13h 44m	23m	15h 37m	27m	20h 11m	35m	20h 36m	35m	18h 21m	31m
Std duration [hours] - segment level	06h 35m	11m	08h 56m	15m	05h 56m	10m	06h 00m	10m	07h 25m	12m
All idling periods [number]	9		5		10		4		7	
Min duration [hours] - leg level	11h 41m	20m	12h 39m	21m	08h 01m	13m	20h 18m	35m	01d 01h 03m	43m
Max duration [hours] - leg level	01d 15h 14m	01h 08m	01d 05h 00m	50m	01d 12h 39m	01h 03m	01d 21h 15m	01h 18m	02d 16h 40m	01h 52m
Mean duration [hours] - leg level	23h 31m	40m	19h 45m	34m	01d 01h 25m	44m	01d 12h 47m	01h 03m	01d 08h 45m	56m
Std duration [hours] - leg level	09h 49m	17m	07h 07m	12m	08h 46m	15m	10h 09m	17m	13h 10m	22m
Selected idling periods [number]	3		3		3		3		2	
Min duration [hours] - leg level	18h 26m	32m	12h 39m	21m	20h 18m	35m	01d 12h 28m	01h 03m	01d 04h 15m	49m
Max duration [hours] - leg level	23h 44m	41m	16h 07m	27m	01d 02h 45m	46m	01d 21h 15m	01h 18m	01d 07h 23m	54m
Mean duration [hours] - leg level	21h 15m	36m	14h 02m	24m	23h 18m	40m	01d 18h 16m	01h 13m	01d 05h 49m	51m
Std duration [hours] - leg level	02h 10m	03m	01h 29m	02m	02h 38m	04m	04h 06m	07m	01h 34m	02m

Table 3.18: Characteristics of the selected cycle for bin class 8.2

	Category 1 Low ME power		Category 2 Medium ME power		Category 3 High ME power	
	30 days	72 hours	30 days	72 hours	30 days	72 hours
All legs [number]	233		886		92	
Min ME power [kW] - leg level		3,096		19,625		30,442
Max ME power [kW] - leg level		19,501		30,232		44,577
Mean ME power [kW] - leg level		10,284		24,715		35,967
Std ME power [kW] - leg level		4,258		2,719		3,770
Min duration [hours] - leg level	02h 00m	12m	14h 30m	01h 29m	11h 00m	01h 08m
Max duration [hours] - leg level	08d 09h 30m	20h 48m	05d 21h 00m	14h 33m	09d 20h 00m	24h 22m
Mean duration [hours] - leg level	02d 07h 43m	05h 45m	02d 13h 57m	06h 23m	02d 21h 38m	07h 11m
Std duration [hours] - leg level	01d 07h 20m	03h 14m	01d 06h 28m	03h 08m	01d 17h 23m	04h 16m
Selected legs [number]	2		2		2	
Min ME power [kW] - segment level		9,847		21,717		32,107
Max ME power [kW] - segment level		12,350		27,372		39,287
Mean ME power [kW] - segment level		10,554		24,379		35,724
Std ME power [kW] - segment level		1,061		2,075		2,064
Min duration [hours] - segment level	05h 00m	30m	07h 00m	43m	12h 00m	01h 14m
Max duration [hours] - segment level	01d 04h 48m	02h 58m	01d 00h 00m	02h 28m	01d 00h 00m	02h 28m
Mean duration [hours] - segment level	17h 45m	01h 50m	17h 23m	01h 47m	20h 19m	02h 06m
Std duration [hours] - segment level	10h 08m	01h 02m	06h 26m	39m	05h 13m	32m
All idling periods [number]	68		83		68	
Min duration [hours] - leg level	11h 00m	01h 08m	11h 54m	01h 13m	07h 00m	43m
Max duration [hours] - leg level	04d 06h 33m	10h 35m	02d 03h 12m	05h 17m	02d 08h 00m	05h 47m
Mean duration [hours] - leg level	01d 04h 01m	02h 53m	01d 03h 17m	02h 49m	01d 05h 04m	03h 00m
Std duration [hours] - leg level	15h 40m	01h 37m	07h 56m	49m	09h 35m	59m
Selected idling periods [number]	2		2		1	
Min duration [hours] - leg level	01d 03h 22m	02h 49m	01d 03h 17m	02h 49m	01d 05h 03m	03h 00m
Max duration [hours] - leg level	01d 03h 37m	02h 51m	01d 03h 30m	02h 50m	01d 05h 03m	03h 00m
Mean duration [hours] - leg level	01d 03h 30m	02h 50m	01d 03h 23m	02h 49m	01d 05h 03m	03h 00m
Std duration [hours] - leg level	07m	00m	06m	00m		

4 Operational cycles for maritime transportation: Consolidated methodology and assessments (Paper 3)

Amandine Godet[a], George Panagakos[a], Michael Bruhn Barfod[a], Elizabeth Lindstad[b]

[a] Department of Technology, Management and Economics, Technical University of Denmark, 2800 Kongens Lyngby, Denmark
[b] Sintef Ocean, Trondheim, Norway

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Abstract Operational cycles for maritime transportation is a new concept to improve the assessment of ships' energy efficiency and offer benchmarking options among similar ship types and sizes. This work extends previous work to consolidate the methodology, bring more comprehensiveness, and provide a more holistic assessment of these operational cycles. The cycles are designed from noon reports from a fleet of around 300 container ships divided into eight size groups. The comparison between cycles derived from speed and draft with those based on main engine power identifies that the cycles based on speed and draft are more accurate and allow for estimating the Energy Efficiency Operational Index but require more data. The main-engine-power cycles are more effective in benchmarking through the Annual Efficiency Ratio. These cycles reduce the inherent variability of the carbon intensity indicator and present good opportunities as a benchmarking tool for strengthening the regulatory framework of international shipping.

Keywords: *Operational cycles; international shipping; decarbonization; carbon intensity indicators; maritime policy; EEOI*

4.1 Introduction

Shipping is essential for global trade, transporting around 80% of the total Global trade measured in freight volumes (UNCTAD, 2022). Currently, with shipping relying nearly fully on fossil fuels, its impact on climate is critical, representing 2.89% of the anthropogenic greenhouse gas (GHG) emissions (Faber et al., 2020). To reduce this impact and enhance green shipping, the International Maritime Organization (IMO) launched its initial strategy on reduction of GHG from ships in 2018 (IMO, 2018). Criticized for its insufficient ambitions, the IMO revised the strategy in 2023 and raised the levels of ambitions to: 1. improve the energy efficiency for new ships, 2. reduce the carbon intensity by at least 40% by 2030 compared to 2008 levels, 3. increase the uptake of zero or near-zero GHG emission technologies and energy sources, and 4. reach net zero GHG emissions from international shipping by or around 2050 (IMO, 2023a). This strategy relies on short–, medium– and long-term measures to be implemented by the relevant stakeholders (e.g., ship owners, ship operators, customers) to achieve these goals. The measure of the progress in improving carbon efficiency and reducing GHG emissions is essential in the process, for which several indicators currently exist in the policy-making context.

Two distinct groups of energy efficiency indicators exist in the IMO framework: technical indicators, namely the Energy Efficiency Design Index (EEDI) and the Energy Efficiency eXisting ship Index (EEXI), and operational indicators, namely the Energy Efficiency Operational Index (EEOI) and the Annual Efficiency Ratio (AER). The EEDI regulation sets energy efficiency requirements for all new ships built since 2013 (Polakis et al., 2019), while the EEXI required for all existing ships of 400 gross tonnage and above, a defined level of efficiency to comply once in 2023 (IMO, 2022b). On the operational side, a Ship Energy Efficiency Management Plan (SEEMP) is mandatory for all ships since 2013 to monitor ship performance (IMO, 2011). The Energy Efficiency Operational Index (EEOI) measures the ship's carbon efficiency, defined by the CO_2 emissions over the transport work (mass of cargo transported over a given distance), and is a voluntary indicator within the SEEMP. As part of the short-term package, the Carbon Intensity Indicator (CII) strengthens the SEEMP by introducing mandatory annual efficiency reductions (2% per year between 2023 and 2026), measured by the AER (IMO, 2022a). Similarly to

EEOI, the AER measures the ship's carbon efficiency, simplified by taking the deadweight as a proxy of the transport work. Two distinct groups of energy efficiency indicators exist in the IMO framework: technical indicators, namely the Energy Efficiency Design Index (EEDI) and the Energy Efficiency eXisting ship Index (EEXI), and operational indicators, namely the Ship Energy Efficiency Management Plan (SEEMP) and the Carbon Intensity Indicator (CII). The EEDI regulation sets energy efficiency requirements for all new ships built since 2013 (Polakis et al., 2019), while the EEXI requires all existing ships of 400+ gross tonnage to comply once in 2023 to a defined level of efficiency (IMO, 2022b). On the operational side, a SEEMP is mandatory for all ships since 2013 to monitor ship performance (IMO, 2011). The Energy Efficiency Operational Index (EEOI) measures the ship's carbon efficiency, defined by the CO_2 emissions over the transport work (mass of cargo transported over a given distance), and is a voluntary indicator within the SEEMP. As part of the short-term package, the CII strengthens the SEEMP by introducing mandatory annual efficiency reductions (2% per year between 2023 and 2026), measured by the Annual Efficiency Ratio (AER) (IMO, 2022a). Similarly to EEOI, the AER measures the ship's carbon efficiency, simplified by taking the deadweight miles as a proxy of the transport work.

While these measures and indicators present promising and necessary outcomes, they reveal flaws to be addressed. For instance, Hoegh-Guldberg et al. (2019) emphasized the importance of redesigning EEDI to prevent ships from being optimized solely for testing purposes. Panagakos et al. (2019) compared operational indicators and showed the incapacity of these indicators for benchmarking purposes. Section 4.2 further reviews the literature on ships' energy efficiency measures and indicators.

Due to the need for better benchmarking measures for ships' energy efficiency, Godet et al. (2023) proposed the concept of operational cycles for maritime transportation, inspired by the driving cycles from the automotive industry. The authors developed a methodology for building operational cycles, defined as "a standardized set of main engine power, against which a ship's carbon emissions are assessed," and assessed it based on operational data of 327 container ships. Results showed that such cycles can accurately represent the fleet's emissions and reduce variability in AER within similar group sizes.

As a first approach to the concept of operational cycles for maritime transportation, Godet et al. (2023) indicated several limitations to be addressed by future work. First, only sea passages and berth times are included, which leaves out the arrivals to and departures from the ports and short trips between nearby ports. These voyages are estimated to be more than 10% of the reports and 20% of the reported time (Godet et al., 2023). Second, the choice of basing the cycles solely on main engine power is questioned, suggesting using speed and draft. It would allow for the measure of EEOI, using the draft to estimate the cargo on board. Third, only the main engine emissions are assessed, while the auxiliary engine and boiler emissions can represent on average 15% and 2% respectively of a container ship's emissions (Faber et al., 2020). Fourth, a systematic procedure to define the best cycles is lacking, which would improve the assessment of these cycles. Besides, the quality of the noon report data, the partial coverage of the world fleet in the sample data, the role of refrigerated containers, and the weather impact on efficiency are raised as limitations that need to be improved in future work.

To address these first four main limitations, this paper explores methods for strengthening the robustness of the operational cycle concept as developed by Godet et al. (2023). The following contributions aim to enhance the robustness of the operational cycle concept as a benchmarking tool for international shipping: compare various cycles based on different parameters (main engine power, speed, and draft), include all types of emissions (main engine, auxiliary engines, boilers), assess all voyages (by introducing the approaches and departures from the ports in the cycles), and evaluate two operational indicators (AER and EEOI).

The rest of the paper is structured as follows: Section 4.2 reviews the literature on energy efficiency indicators and operational cycles in maritime transportation; Section 4.3 presents the improvements of the methodology for the development of the cycles, for their assessment, and the data used; Section 4.4 elaborates on the results; Section 4.5 reflects on the methodology presented in the paper, its limitations and pathways for future work; Section 4.6 ends the article with concluding remarks.

4.2 Literature review

The present paper relies on two research areas: energy efficiency indicators for ships and operational cycles for maritime transportation. The driving cycles from the automotive industry inspired the operational cycles, and a detailed literature review on the matter, as well as the link towards the maritime sector, can be found in Godet et al. (2023, 2022). This section only focuses on energy efficiency indicators and the operational cycles for maritime transportation.

4.2.1 Energy efficiency indicators

As mentioned in the introduction, indicators used to measure the energy efficiency of ships can be divided into technical and operational indicators, whether they are looking at design characteristics or actual performances. These approaches are complementary. The technical indicator assesses the theoretical performance of the hull design and the engine, among other technical measures. At the same time, the operational one captures the performance in operations, which depends on the business activity and external factors. The following two subsections focus on these two types of indicators.

4.2.1.1 Technical indicators

In the policy framework of IMO, two technical indicators exist: EEDI and EEXI. Since its enactment in 2013, the required EEDI becomes more stringent for every phase defined by the IMO: phase 0 happened between 2013 and 2014 (for 3,392 ships built in that period, including 373 container ships), phase 1 occurred between 2015 and 2019, requiring a 10% reduction compared to the reference lines, i.e., phase 0 for 3,669 ships, including 511 container ships, phase 2 happened between 2020 and 2022 for some ship types, and continues until 2024 for other ship types and requires 20% reduction compared to phase 0 for 118 ships, including two container ships as of February 2022 (IMO, 2022c).

Studies have continuously evaluated the robustness of the EEDI and its potential to reduce CO_2 emissions from ships. Bøckmann and Steen (2016) focused on the correction factors (e.g., weather correction factor f_w, power correction factor f_j) and their impact on the EEDI values. They concluded that applying the guidelines for the correction factor on their case ship reduces its EEDI value by 22%, which results in being 14% lower than the reference line. Regarding the weather correction factor, they found slightly different results depending on the method used, arguing the need for more information from the theoretical procedure to calculate the added resistance in waves (Bøckmann and Steen, 2016). Lindstad et al. (2019) added that the test conditions for EEDI should be adjusted from "calm water conditions only" to "real sea conditions" to be more representative of the actual conditions during the tests. They concluded that the emissions could increase if such an adjustment is not made (Lindstad et al., 2019). This was also highlighted in the World Resources Institute report *"the Ocean as a solution to Climate Change"* (Hoegh-Guldberg et al., 2019).

On the potential for EEDI to reduce GHG emissions from shipping, Comer and Sathiamoorthy (2022) looked at the EEDI future requirements and how to promote lower GHG emissions from ships. Based on models for large container ships and cruise ships, they recommended shifting the EEDI regulation from tank-to-wheel (TTW) CO_2 to TTW CO_2e20 (20-year global warming potential for GHG and black carbon emissions), to avoid the use of liquefied natural gas (LNG) in high-methane-slip engines, which would be counterproductive for the decarbonization of the sector (Comer and Sathiamoorthy, 2022). Lindstad and Bø (2018) found out that the reduction in the EEDI values is generally larger than the GHG reduction. Three main reasons explain this difference: 1. ships sail at lower power compared to EEDI level (75% of Maximum Continuous Rate (MCR)), 2. ships encounter wind and waves at sea compared to the calm-water baseline of the EEDI, 3. only CO_2 is accounted for. They added that policies need to promote the best solutions in terms of reduction of GHG emissions (in the case of Aframax tankers: slender hull form with best LNG technology and a hybrid power setup). Otherwise, the higher costs of these solutions would prevent their adoption (Lindstad and Bø, 2018).

Weaknesses of EEDI are the following according to Polakis et al. (2019): 1. only reducing the design speed can be enough to comply (e.g., no need for more efficient design), 2. which leads to safety concerns looking at potential underpowering, 3. the reference lines are 'oversimplified' making it more appropriate for smaller ships compared to the larger ones, 4. the attained EEDI weather (attained EEDI corrected for the weather effect with the correction factor f_w) provides a 'truer picture of efficiency.' Vasilikis et al. (2023) raised the limitations of EEDI and EEOI in not 'providing sufficient insight into the operation of multifunction vessels with diverse operational profiles'. Vladimir et al. (2018) studied more thoroughly the effect of ship size on EEDI requirements for large container ships. They recommended consistently updating the EEDI reference lines as the new ships entering the market are, on average, larger than previously. Besides, they extended the EEDI reference lines to an EEDI reference surface, taking into account both the deadweight of ships and the speed as independent variables, to capture different operational conditions (Vladimir et al., 2018).

Regarding the EEXI, Rutherford et al. (2020) assessed the potential CO_2 reductions under the EEXI, which is evaluated between 0.7% and 1.3% from the 2030 fleet. This small reduction is explained by the slow steaming and the engines that are already operated between 38% and 50% of their Maximum Continuous Rate (MCR) as of 2019. Therefore, the authors suggested calculating EEXI including a sea margin and evaluating the EEXI at 87% of limited MCR to avoid a rebound effect with higher speeds when the market allows it (Rutherford et al., 2020). Bayraktar and Yuksel (2023); Schroer et al. (2022) identified the Engine Power Limitation (EPL) as the prominent solution to comply with both the EEXI and the CII. Schroer et al. (2022) also showed that pre-EEDI ships, with over-sized main engines, are not as penalized as the most recent ships because they already operate at low engine loads, and an engine power limitation won't affect much the operations (in terms of sailing time).

4.2.1.2 *Operational indicators*

Operational indicators aim to measure the operational efficiency of ships at sea. Figure 4.1 highlights the factors influencing operational efficiency, which can be divided into technical aspects, business activity, and external factors (IMO, 2019). Ghaforian Masodzadeh et al. (2022) listed the operational parameters influencing the operational efficiency, which includes 'loading factor, fuel quality, navigation circumstances, weather conditions, contractual obligations and sailing speed, hull roughness, and inclusion or exclusion of ballast legs in calculations.' Sou et al. (2022) looked at energy efficiency trends at a global level and identified the driving factors of carbon intensity indicators as 'seaborne trade, energy intensity, carbon intensity of fuel used and vessel capacity utilization.' They observed that the EEOI and AER have decreased worldwide since 2008, mainly due to improvements in the energy intensity (Sou et al., 2022).

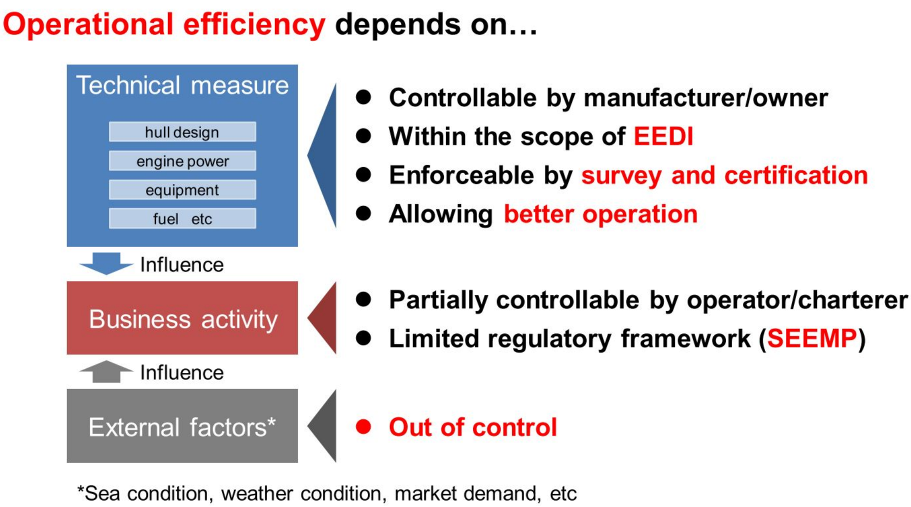


Figure 4.1: Factors affecting operational efficiency of ships. Source: IMO (2019)

Regarding the external factors, Polakis et al. (2019) argued that operational indicators (e.g., EEOI) are not effective in reflecting the ship's operational efficiency due to the effect of bad weather, the ballast voyages, and the inaccuracy of some data. These operational indicators are thoroughly studied by Panagakos et al. (2019), who reached similar conclusions. For instance, they found that the EEOI values of a sample bulk carrier can vary between 2.6 and 14.1 gCO_2/tm annually. This range is too wide to reach meaningful conclusions on the ship's energy efficiency. The variation of EEOI among sister ships is also reported to be above 20%, making a benchmarking attempt across ships inaccurate (Panagakos et al., 2019).

Psaraftis (2021) acknowledged the volatility of AER and EEOI, making the CII performance of a ship uncertain from one year to another. Using seven examples, Wang et al. (2021) showed some paradoxes of the CII and how it can result in some cases in an augmentation of the CO_2 emissions. Kim et al. (2023) studied the CII requirements, using the European Union (EU) Monitoring Reporting and Verification (MRV) data, and assessed the implications of having the AER (which used the deadweight as a proxy for the cargo carried) as the efficiency indicator versus the EEOI. They concluded that using the AER would lead to significantly inaccurate estimations of the energy efficiency of international shipping.

Some studies focused on specific ship types and the issues of operational indicators for these ships. For example, Prill et al. (2020) raised the issue regarding the EEOI calculation for specialized ships (e.g., research and training vessel) and suggested a method to determine EEOI based on the importance of different exploitation states (e.g., implementation of the maritime practice, and conducting scientific research). Cruise ships also reveal difficulties in assessing their CII and Braidotti et al. (2023) enhanced the reduced time at sea for cruise ships compared to other types of ships and proposed a correction to remove the time-dependency of CII.

The CII introduction led to several studies on ways to comply with this new regulation. For example, Yuan et al. (2023) proposed an optimization method for ship fleets to comply with CII regulation. They show that, for the sample ships, an average speed reduction of 7% is necessary and that ships have different inherent emission reduction capacities based on their routes (Yuan et al., 2023). Rauca and Batrinca (2023) looked at the impact of CII regulation on ship's operations and concluded that, for container ships, a solution to reduce CII is to minimize the waiting time at anchorage, allowing for lower speeds at sea. Based on the study of six container ships, Schroer et al. (2022) concluded that the CII regulation is costly for ship owners and operators to invest in compliance options, and if the payback period exceeds the remaining lifetime of the ship, scrapping could become the only option.

4.2.2 Operational cycles in maritime transportation

Extensive research on driving cycles in the automotive industry has been ongoing since the 1970s. On the contrary, the shipping industry has not explored this concept thoroughly, except for a few instances where operational profiles have been derived for individual ships (Atiq et al., 2015; Baldi et al., 2018; Esmailian and Steen, 2022; Khac et al., 2020; Trivyza et al., 2016). However, none of these studies used the operational profiles of multiple ships for benchmarking purposes. For example, Esmailian and Steen (2022) used the power profile of a ship obtained from in-service data to propose an approach for optimal design at sea. Vasilikis et al. (2023) compared actual fuel consumption to theoretical calculations based on the design's operational profile, which was defined according to the speed through water.

Both technical and operational energy efficiency indicators present some drawbacks, suggesting that the GHG emission reduction would be lower than attended. Even though driving cycles (e.g., World harmonized Light vehicles Test Cycles (WLTC)) still fail to accurately represent the real-world emissions (Chindamo and Gadola, 2018; Pettersson et al., 2019), the concept applied to maritime transportation appears promising to reduce the variability of operational indicators, which is raised as an issue in Section 4.2.1.2. This work fills the gap for using operational cycles for ships by extending the work done by Godet et al. (2023) and addressing some of its limitations.

4.3 Methodology

The methodology used to develop and assess operational cycles for ships has been presented and tested in Godet et al. (2023), inspired by the WLTC from the automotive industry. This section presents the additions and changes from the previous work regarding the cycle developments, the indicator assessments, and the data used.

4.3.1 Methodology developments

Building on the methodology developed by Godet et al. (2023), this paper addresses some of its main limitations. They can be divided into two groups: the methodologies to develop the cycles, detailed in Section 4.3.1.1, and the assessment of the energy efficiency using the cycles (including the choice of efficiency indicator), further explained in Section 4.3.1.2.

4.3.1.1 Cycles

Godet et al. (2023) proposed a seven-step procedure to develop maritime operational cycles based on real-world data. Figure 4.2 summarizes the methodology for developing the operational cycles and highlights the changes from the previous work. This section presents step-by-step the methodology and the new propositions.

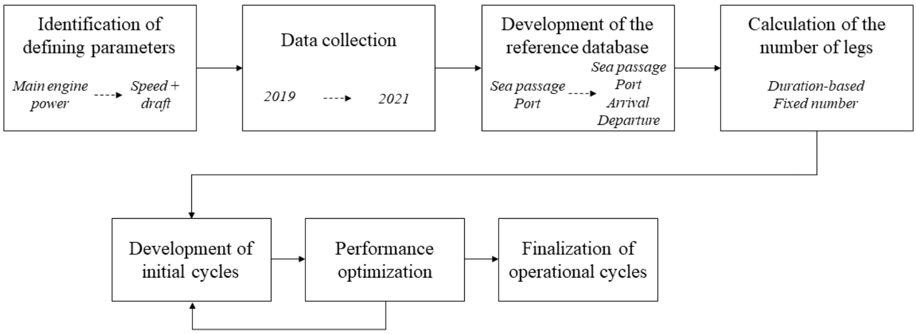


Figure 4.2: Updated procedure to develop maritime operational cycles. The plain text describes the seven steps, while the italic text highlights the different updates. Source: authors' adaptation from Godet et al. (2023).

For the *identification of defining parameters*, Godet et al. (2023) used the main engine (ME) power as the main parameter to define the cycles, because the authors wanted to keep the cycles simple and the ME power reflects both the speed and draft of the ship. To explore other strategies, cycles based on speed and draft are developed and compared to the ones based solely on ME power. Having sets of speed and draft better reflects operational and market conditions (how fast the ship sails, how much it is loaded) and represents the transport work (cargo transported over a given distance). Note that the draft describes the ship's average fore and aft drafts. Besides, having the draft in the cycle allows us to estimate the cargo on board, which is useful for EEOI estimation (see further Section 4.3.1.2).

The second step is the *data collection*, as the cycles are based on real-world data. The primary data source is the noon reports of a shipping company's global container ship fleet. While the numbers for 2019 were used in Godet et al. (2023), this paper adds the analysis of the 2021 figures, as it offers more details on the different voyage stages (sea passages, arrivals to port, alongside periods, departures from port). The ships are divided into group sizes, which are further presented with the data used in Section 4.3.2, and the next step of the procedure gives more details on the voyage stages.

The *development of the reference database* divides the data into different voyage stages and operational categories of equal number of observations (e.g., speed categories). To represent a full voyage, the cycles need to reflect the different voyage stages, which are:

- Departure: between the time when the ship leaves the berth and the start of sea passage (one noon report, usually a couple of hours)
- Leg: between the start and the end of sea passage (from one to 49 consecutive noon reports depending on the length of the leg)
- Arrival: between the end of sea passage and when the ship is at berth (one noon report, from a couple of hours to a couple of days)
- Idling: when the ship is at berth (one noon report, from a few hours to a few days)

Note that canal passages and anchorage periods are excluded from the analysis due to limited data to draw typical patterns (further discussed in Section 4.5). Each voyage stage is treated separately, and all reports from the same stage are combined into a specific database. These reports include the parameters of interest (e.g., speed and draft, or ME power), as well as the reporting period, fuel consumption, and all variables included in the noon report (see more on the data structure in Section 4.3.2). Within these separate databases, categories of reports are created based on a defined parameter (e.g., ME power, speed) to capture various operational conditions to be included in the cycles (e.g., low–, medium–, and high–speed if three categories are defined based on the parameter 'speed'). Even if the cycles combine two parameters (e.g., speed and draft), the categories only rely on one parameter (e.g., speed), to avoid having too many categories. Within each category and for each voyage stage, the mean value and standard deviation of the important parameter(s) are calculated, and the reports or legs (combinations of reports at sea) over plus/minus two standard deviations are excluded from the database as outliers.

Following these reference databases, the *calculation of the number of legs* defines how many groups of departure/leg/arrival/idling constitute the cycle. There are two alternative ways to define this number:

- Set a specific number of departures/legs/arrivals/idling for each category.
- Set a specific duration for each category and calculate how many departures/legs/arrivals/idling are needed to fill this duration based on the average time of the departures/legs/arrivals/idling in the category.

The number of legs needed N_c for the category c is the same for the number of departure and arrival reports. There are $N_c - 1$ idling periods (a cycle starts by departing from the port and finishes when the ship is back in port after a few voyages). The N_c departures/legs/arrivals/idling closer to the mean of the category for the parameter are selected for the cycles. When two defining parameters are used, a normalized score is given for each parameter based on the difference from the category's mean, and the reports with the best-added scores are chosen.

The *development of initial cycles* is the step when all the selected departures/legs/arrivals/idling periods (from the previous step) are combined into one cycle, according to the methodology presented in Godet et al. (2023). Each category is adjusted time-wise to ensure the same duration in each. For a baseline, the initial cycles are defined with three categories, 90-day duration and no particular filtering on the legs (apart from the outlier filter of two standard deviations).

The *performance optimization* aims to find the best cycles possible and move from the initial solution presented in the previous paragraph. Three elements are being tuned:

- The duration of the cycles (resulting in a variable number of legs per category) or the number of legs per category (a fixed number for all categories)
- The number of categories
- The filtering approach applied to the leg databases. The legs are combinations of several noon reports, and three approaches are tested to find representative legs:
  - No additional filter
  - Additional filter to remove legs with high report variability

($1std_{reports}$): the filter removes legs with one or more reports exceeding more or less than one category's standard deviation
- Additional filter to remove legs with one more/less standard deviation compared to the other legs ($1std_{general}$)

All these elements can be combined, and a comparison of all these tests is performed. Table 4.1 summarizes all the test choices (which are systematically combined) to find the best cycles. Note that, for the duration-based cycles, three categories are kept for all tests, as having more would significantly reduce the number of possible legs, exceeding the cycle's period. For example, 60 days, divided into five categories, would result in 12 days for each category, less than some leg lengths, especially for bigger ships.

Table 4.1: Summary of test choices

	Duration or number of legs	**Categories**	**Filters**
Duration-based	{90 days, 60 days, 30 days}	{3}	{no filter, 1std_reports, 1std_general}
Fixed number	{2 legs per category, 3 legs per category}	{3, 4, 5}	{no filter, 1std_reports, 1std_general}

Finally, the *finalization of operational cycles* is done by selecting the best cycles in terms of accuracy (of the ME emissions) and effectiveness (in reducing the variability of the operational indicators), as presented in the next section.

4.3.1.2 Indicators

The operational cycles aim to assess ships' energy efficiency and benchmark it across similar ship sizes. AER and EEOI are the two indicators used in the assessment. The AER is defined as:

$$AER = \frac{\sum_e \sum_f FC_{e,f} \cdot C_{F_f}}{DWT \cdot D} \tag{4.1}$$

where $FC_{e,f}$ is the annual mass of fuel type f (in tons) consumed for the engine e (main engine(s), auxiliary engines, boiler), C_{F_f} the factor used for converting the fuel consumed to CO_2 emissions (in grams of CO_2 per ton of fuel consumed), D the annual distance sailed (in nautical miles), and DWT the deadweight of the ship (in tons).

As mentioned in Sections 4.1 and 4.2, EEOI is another indicator measuring the operational energy efficiency of ships, being more precise on the actual transport work than AER by using the actual cargo on board in the denominator, as follows:

$$EEOI = \frac{\sum_e \sum_f FC_{e,f} \cdot C_{F_f}}{\sum_i m_{cargo_i} \cdot D_i} \tag{4.2}$$

where D_i the distance sailed during the voyage i (in nautical miles), and m_{cargo_i} the mass of cargo transported during the voyage i (in tons), for all the annual voyages.

These indicators assess the annual total emissions (from all main engine(s), auxiliary engines, and boiler) over all the ship's voyage stages. The operational cycles allow us to calculate the indicators for each ship in a normalized way to reduce the inherent variability of these indicators (see Section 4.2). Their accuracy and effectiveness assess the validity of the cycles.

The accuracy test aims to measure how accurate the cycles are in reflecting the ME emissions of the ships. For each ship's group size, the hourly average ME emissions are compared to the hourly average ME emissions from the cycles. The selection of the cycles with the best accuracy is the first step in selecting the best cycles.

The effectiveness test assesses how effective the cycles are in reducing the variability of the efficiency indicators (either AER or EEOI) within a given set of ships (same type, similar sizes). To do so, the ship's indicator (based on its reported data) is compared to the indicator calculated from the cycle. The idea for the latter is to estimate the efficiency indicator from a set of normalized operational conditions. The actual indicator and the cycle-based indicators are then compared using the coefficient of variation (CV), defined as:

$$CV = \frac{\text{Standard deviation}}{\text{Average value}} \tag{4.3}$$

for a given set of ships.

The variables (emissions, distance, cargo in case of EEOI) must be evaluated to estimate the indicators based on the cycles. A statistical approach is chosen to avoid many assumptions regarding the ship's efficiencies, fuel type, and calorific values. Table 4.2 shows all the regression lines used for each ship, depending on the voyage stage, the type of emissions, and the indicator. The coefficient of determination R^2, which depicts how much of the variation in the dependent variable is predictable from the independent variables, is chosen to assess the fit quality. The p-value using a t-test is also calculated for each regression to test if the variables are statistically significant. Results from the regression lines are shown in Section 4.4.

Regarding the ME, its emissions are derived from the power, with a linear regression that captures, for each ship, the engine and fuel efficiencies and the fuel type mainly used. The relation between power and speed/draft is based on the Admiralty coefficient: $P = C \cdot \nabla^{2/3} \cdot V^3$, where p is the shaft power [kW], C a constant, ∇ the displacement [tons] and v the ship speed [kn] (Babicz, 2015). Concerning arrivals to and departures from ports, an empirical analysis showed that equations of the type $y = a \cdot x^b$ using time as the independent variable were the most accurate. Note also that the ME is assumed not to emit anything during its port stay. The auxiliary engine (AE) emissions are taken as a function of time for all voyage stages. The boiler is assumed to run only at ports, and the emissions are taken as a function of time. The cargo on board is considered a function of the average draft.

Table 4.2: Summary of the regressions used for the cycle-based energy efficiency indicators

	Sea passage	Port stay	Arrival to port	Departure from port
Main engine(s)	$x = \alpha_{ME_s} + \beta_{ME_s} \cdot p \cdot t$ x: ME emissions (tons_{CO_2}) p: ME power (kW) t: reported time (s) α_{ME_s}, β_{ME_s}: ship-specific constants s: specific ship $p = \tau_s \cdot v^{\nu_s} \cdot T^{\phi_s}$ p: ME power (kW) v: speed (kn) T: average draft (m) τ_s, ν_s, ϕ_s: ship-specific constants s: specific ship *Note: only for speed/draft cycles.*	Not applicable	$x = \zeta_{ME_s} \cdot t^{\lambda_{ME_s}}$ x: ME emissions (tons_{CO_2}) t: reported time (s) ζ_{ME_s}, λ_{ME_s}: ship-specific constants s: specific ship	$x = \psi_{ME_s} \cdot t^{\omega_{ME_s}}$ x: ME emissions (tons_{CO_2}) t: reported time (s) ψ_{ME_s}, ω_{ME_s}: ship-specific constants s: specific ship
Auxiliary engines	$y = \alpha_{AE_s} + \beta_{AE_s} \cdot t$ y: AE emissions (tons_{CO_2}) t: reported time (s) α_{AE_s}, β_{AE_s}: ship-specific constants s: specific ship	$y = \gamma_{AE_s} + \delta_{AE_s} \cdot t$ y: AE emissions (tons_{CO_2}) t: reported time (s) γ_{AE_s}, δ_{AE_s}: ship-specific constants s: specific ship	$y = \zeta_{AE_s} + \lambda_{AE_s} \cdot t$ y: AE emissions (tons_{CO_2}) t: reported time (s) ζ_{AE_s}, λ_{AE_s}: ship-specific constants s: specific ship	$y = \psi_{AE_s} + \omega_{AE_s} \cdot t$ y: AE emissions (tons_{CO_2}) t: reported time (s) ψ_{AE_s}', ω_{AE_s}: ship-specific constants s: specific ship
Boiler	Not applicable	$z = \gamma_{BE_s} + \delta_{BE_s} \cdot t$ z: boiler emissions (tons_{CO_2}) t: reported time (s) γ_{BE_s}, δ_{BE_s}: ship-specific constants s: specific ship	Not applicable	Not applicable
Cargo on board *Note: only for EEOI*	$w = \alpha_{cargo_s} + \beta_{cargo_s} \cdot T$ w: cargo on board (tons) T: average draft (m) α_{cargo_s}, β_{cargo_s}: ship-specific constants s: specific ship	Not applicable	$w = \zeta_{cargo_s} + \lambda_{cargo_s} \cdot T$ w: cargo on board (tons) T: average draft (m) ζ_{cargo_s}, λ_{cargo_s}: ship-specific constants s: specific ship	$w = \psi_{cargo_s} + \omega_{cargo_s} \cdot T$ w: cargo on board (tons) T: average draft (m) ψ_{cargo_s}, ω_{cargo_s}: ship-specific constants s: specific ship

4.3.2 Data

The present work studies operational cycles for different sizes of container ships. As previously mentioned, the cycles result from real-world data. A case company provided the noon reports for its fleet for 2019 and 2021. 2020 is left out of the analysis due to significant disruptions resulting from the pandemic, making it unsuitable for deriving typical operational cycles. The fleet is divided into bin classes, as defined by Faber et al. (2020) and reported in Table 4.3. The fleet comprised 327 container ships in 2019 and 293 in 2021. The details for each bin class are reported in Table 4.3. Note that bin class 8 has been divided into two sub-classes by Godet et al. (2023) due to a large ship size range, and the subdivision is kept in this work.

Table 4.3: Bin classification according to the IMO and number of sample ships in each bin class

Bin class	Capacity [TEU]	World fleet (2018)	Sample fleet (2019)	Percentage of world fleet (2019)	Sample fleet (2021)	Percentage of world fleet (2021)
1	0 - 999	1,027	0	0 %	0	0 %
2	1,000 - 1,999	1,271	17	1.3 %	16	1.3 %
3	2,000 - 2,999	668	32	4.8 %	32	4.8 %
4	3,000 - 4,999	815	90	11.0 %	85	10.4 %
5	5,000 - 7,999	561	50	8.9 %	41	7.3 %
6	8,000 - 11,999	623	80	12.8 %	68	10.9 %
7	12,000 - 14,499	227	19	8.4 %	19	8.4 %
8	14,500 - 19,999	101	39	38.6 %	32	31.7 %
8.1	14,500 - 17,999		8		8	
8.2	18,000 - 19,999		31		24	
9	20,000+	44	0	0 %	0	0 %
Total		327	5,337	6.1 %	293	5.5 %

Sample fleet represents the number of ships after filtering. Source for the world fleet: Fourth IMO GHG Study 2020 (Faber et al., 2020)

The 2021 data differs from the 2019 reporting system and offers more granularity on the reports other than sea passages. While for 2019 the period between the end of sea passage and the start of the next sea passage after a port visit was merged into a single report, it is separated into three different stages for 2021 data: arrivals (from the end of sea passage to berthing at port), idling periods, and departures (from the berthing at port to the start of sea passage). This granularity brings more insight into the different voyage stages. It allows us to include the arrivals and departures into the cycles, compensating for the 8% to 17% of reports excluded in the previous work by Godet et al. (2023).

Table 4.4: Sample data - Noon reports for the 2021 data

Vessel	Reporting time	Report type	Report period [Hours]	Origin port	Destination port
Ship X	15-01-2021 11:30	Departure	0.8	Port X	Port Y
Ship X	15-01-2021 15:30	Sea	4	Port X	Port Y
Ship X	15-01-2021 21:00	Sea	5.5	Port X	Port Y
Ship X	16-01-2021 17:42	Arrival	20.7	Port X	Port Y
Ship X	17-01-2021 13:06	Alongside	19.4	Port X	Port Y
Ship X	17-01-2021 18:30	Departure	5.4	Port Y	Port Z

Distance [Nm]	Speed [Kn]	Fore draft [m]	Aft draft [m]	Ballast water [tons]	Cargo on board [tons]
4	5	6.4	6.3	/	6,742
43	10.7	6.4	6.3	610	6,742
54	9.8	6.4	6.3	610	6,742
129	6.2	6.5	6.5	/	6,742
0	0	/	/	/	6,742
76	14.0	4.4	6.2	/	2,468

ME Power [kW]	ME Consumption [tons of Very low sulfur]	AE Consumption [tons of Very low sulfur]	Boiler Consumption [tons of Very low sulfur]
1,215	0.1	0.1	0
3,011	2.3	0.4	0
2,925	3.1	0.6	0
1,427	9.2	2.3	0
0	0	1.9	0.4
2,543	4.3	0.6	0

Noon reports are made by the crew every day, with over 130 variables reported. Table 4.4 shows a sample of the noon report data, with all variables used further in the analysis. As noon reports may contain some errors and to ensure coherent data and analysis, the noon reports were filtered as follows:

- Remove duplicated reports (5,115 reports for 2019, 24 for 2021)
- Exclude all canal passages and anchorage (2,418 reports for 2019, 4,655 for 2021)
- Remove ships with no characteristics (e.g., deadweight, capacity) specified (2,922 reports for 12 ships for 2019, 903 reports for five ships for 2021)
- Exclude reports with null ME power at sea (3,066 reports for 2019, 1,938 for 2021)
- Exclude reports with null speed for sea passage or above 30 knots for all voyage stages (19 reports for 2019, 719 for 2021)
- Exclude reports with average draft below 4.4 m for sea passages or above 20 m for all voyage stages (44 reports for 2019, 49 for 2021)
- Remove ships with no sea passages reported (215 reports for four ships for 2019, 930 reports for two ships for 2021)
- Exclude reports with null report period (0 reports for 2019, 387 reports

for 2021)

The following filters have been added for the 2021 data, due to the new data structure and the need to have precise data for the estimation of EEOI:

- Exclude reports with a null average draft for arrival and departure stages (23 reports for 2021)
- Exclude reports with negative or zero containers on board reported (2,322 reports for 2021)
- Exclude reports with the sum of ballast water and cargo on board greater than the deadweight (6,207 reports for 2021)
- Exclude reports for arrivals and departures if the speed is higher than 20 knots (36 reports for arrivals and 344 reports for departures for 2021)
- The last two filters are further explained in Section 4.4 but are mentioned here for the list's comprehensiveness:
  - Exclude ships with EEOI over 75 for bin 2 (two ships, 627 reports for 2021) and over 35 for bin 3 (four ships, 1,797 reports for 2021)
  - Remove sister ships with a deadweight of 40,100 tons in bin 4 (five ships, 1,973 reports for 2021)

The data analysis was conducted using *Python 3.8.5*, and the data structure was handled with the package *pandas 1.4.3*.

4.4 Results

This section presents our results. First, cycles are developed based on the combination of speed and draft for 2019 data and are directly compared to the ones from Godet et al. (2023). Second, complete cycles (with all emissions and voyage stages) are proposed, using 2021 data, with an assessment of the EEOI.

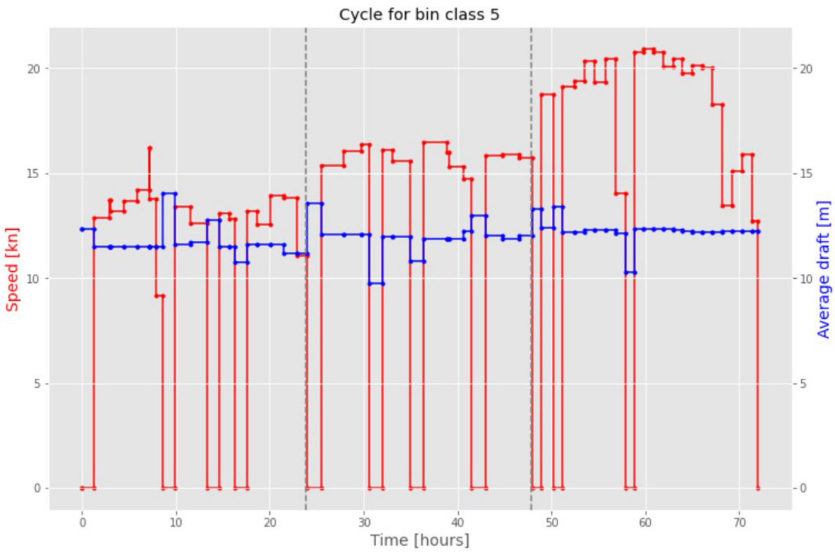
4.4.1 From main engine power to combined speed and draft

As mentioned in Section 4.3, a new way of developing the cycles is to use speed and draft as the defining parameters. In this subsection, this new method is compared with the one presented in (Godet et al., 2023) which used ME power for defining the cycles and was based on 2019 data. Following the systematic tests shown in Table 4.1, the best cycles based on speed and draft are chosen. Table 4.5 presents the cycle combinations selected for each bin class for the combined speed and draft. Figure 4.3 shows an example cycle for bin 5 compared to the ME power-based cycle. A different visualization is also proposed: Figures 4.3c and 4.3d present the cycles with no time adjustment and the legs sorted with ascendant values. Such a visualization helps to capture the profile over time. The successive changes of speed or ME power from Figures 4.3a and 4.3b are not crucial, as acceleration and deceleration phases are not as important as in the automotive industry, due to a preference to sail steadily at sea.

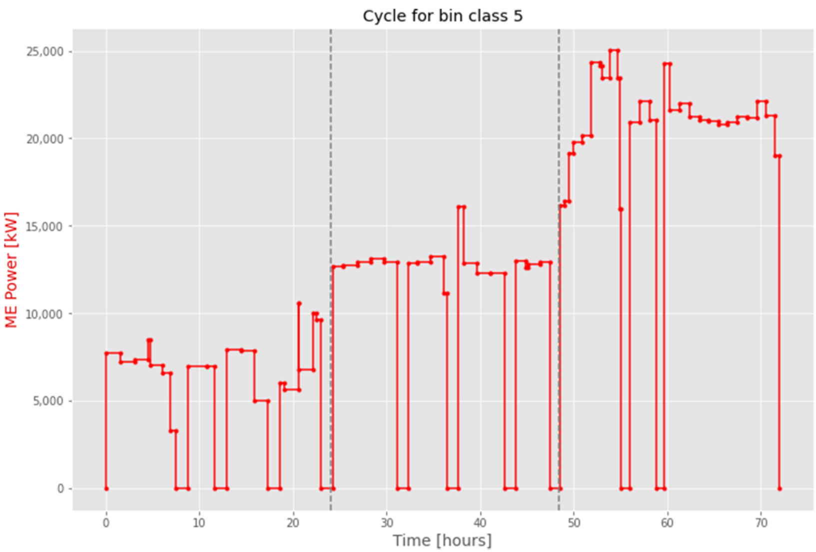
Table 4.5: Comparison of the ME power-based cycles and the combined speed and draft-based cycles, in terms of accuracy in modeling the actual ME emissions (2019), in tons of CO_{2_e} per hour per ship

	Sample fleet	ME power cycles		Speed and draft cycles		
Bin class	*t/h*	*t/h*	%	*t/h*	%	Selected combination
2	3.14	3.05	-3.0%	2.51	-20.0%	2 legs, 5 categories, no filter
3	4.27	4.28	0.2%	4.25	-0.4%	60 days, 3 categories, $1std_{reports}$
4	6.22	6.00	-3.5%	6.22	0.1%	3 legs, 3 categories, $1std_{general}$
5	9.22	9.28	0.7%	9.22	0.0 %	60 days, 3 categories, no filter
6	10.69	10.99	2.8%	10.79	0.9%	2 legs, 4 categories, no filter
7	12.37	12.78	3.3%	12.47	0.8%	3 legs, 3 categories, no filter
8.1	14.06	14.11	0.4%	14.14	0.6%	2 legs, 5 categories, no filter
8.2	15.61	15.31	-1.9%	15.52	-0.6%	3 legs, 4 categories, no filter
Absolute average			**2.0%**		**2.9%**	
Absolute average weighted by ship			**2.3%**		**1.4%**	

The combined speed and draft cycles are compared to the cycles based only on ME power in terms of accuracy in modeling the ME emissions, as displayed in Table 4.5. These cycles are problematic for bin class 2, which shows a very low accuracy (-20%). Apart from bin class 2, the combined speed and draft cycles allow to obtain better accuracy on average (2.9% on average compared to 2.0% in Godet et al. (2023), and 1.3% compared to 2.3% in terms of weighted average based on the number of ships in each bin class).

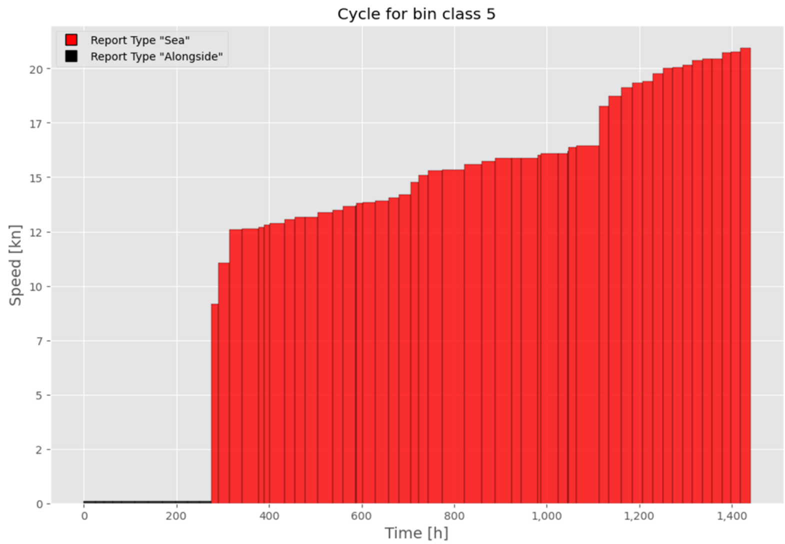


(a) Selected combined speed and draft-based cycle for bin class 5

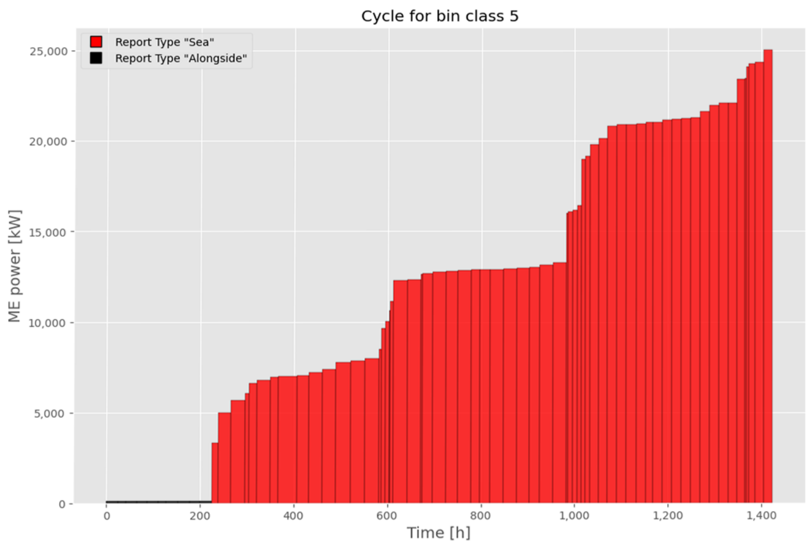


(b) Selected ME power-based cycle for bin class 5. Source: Godet et al. (2023).

Figure 4.3: Comparison of cycles for bin class 5 for 2019



(c) Selected combined speed and draft-based cycle for bin class 5, as a distribution over time



(d) Selected ME power-based cycle for bin class 5, as a distribution over time

Figure 4.3: Comparison of cycles for bin class 5 for 2019

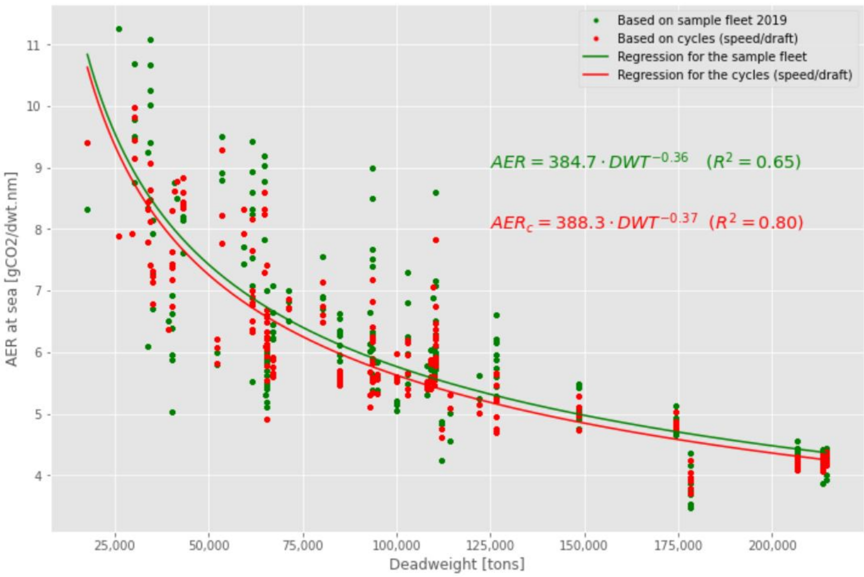
To continue the comparison of the two types of cycles, the effectiveness is assessed based on the AER for the ME emissions during the sea passages, referred to as AER_{sea}. The calculation of the AER_{sea} based on the cycles requires the ship-specific coefficients for the relation between ME power and ME emissions, and the ones between speed and draft and ME power, as reported in Table 4.2. While the coefficient of determination R^2 is close to one for the former, the average R^2 for the latter in each bin class spans from 0.60 for bin 2 to 0.86 for bin 8.2, with an average across bin classes of 0.79. Table 4.6 shows the results using the same ships analyzed from the ME power cycles by Godet et al. (2023).

Table 4.6: Comparison between ME power based-cycle, combined speed and draft based-cycle, and actual AER_{sea} [gCO2/(t.nm)]

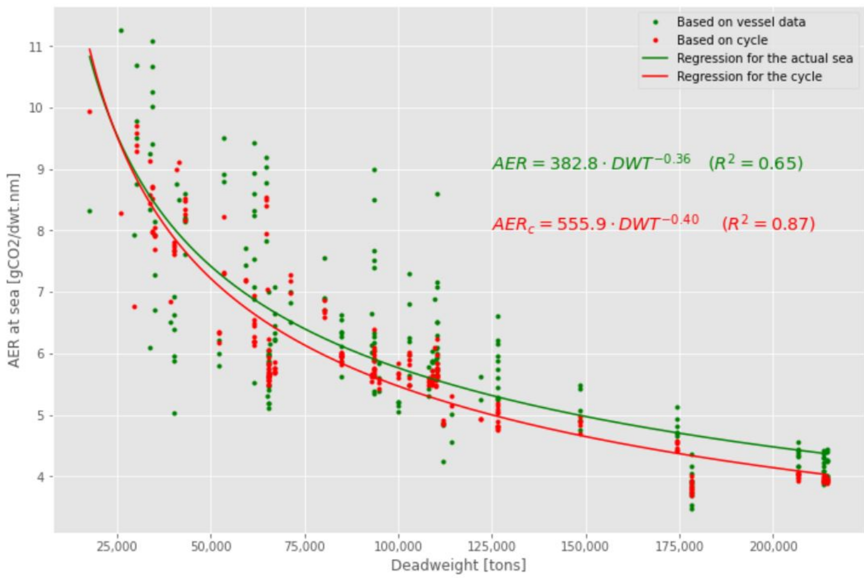
	Bin 2	**Bin 3**	**Bin 4**	**Bin 5**	**Bin 6**	**Bin 7**	**Bin 8.1**	**Bin 8.2**	**Absolute average**	**Absolute average weighted by ship**
Number of ships with an R^2 >0.8 (% of total ships)	3 (18%)	17 (53%)	55 (61%)	40 (80%)	54 (68%)	15 (79%)	6 (75%)	25 (81%)	Total:	215 (72%)
Mean value of actual AER_{sea}	9.17	8.85	6.81	6.67	5.84	4.29	4.82	4.24		
Mean value of ME power based-cycle AER_{sea}	8.33	8.50	6.59	6.30	5.45	4.16	4.50	3.96		
Difference in mean for ME power based-cycle [%]	*-9.1*	*-4.0*	*-3.2*	*-5.6*	*-6.7*	*-2.9*	*-6.6*	*-6.6*	*5.6*	*5.2*
Mean value of speed/draft based-cycle AER_{sea}	8.34	8.33	6.89	6.16	5.57	4.31	4.84	4.21		
Difference in mean for speed/draft based-cycle [%]	*-9.0*	*-5.8*	*1.2*	*-7.7*	*-4.6*	*0.7*	*0.4*	*-0.7*	*3.8*	*3.6*
Standard deviation of actual AER_{sea}	1.49	1.51	1.25	1.06	0.73	0.65	0.16	0.17		
Standard deviation of ME power based-cycle AER_{sea}	1.30	0.74	1.05	0.83	0.39	0.49	0.07	0.05		
Standard deviation of speed/draft based-cycle AER_{sea}	0.68	1.07	1.05	0.85	0.56	0.55	0.08	0.09		
CV of actual AER_{sea}	0.163	0.170	0.183	0.159	0.125	0.152	0.034	0.040	0.128	0.144
CV of ME power based-cycle AER_{sea}	0.156	0.087	0.159	0.132	0.071	0.119	0.014	0.012	0.094	0.107
Difference in CV for ME power based-cycle [%]	*-4.1*	*-48.8*	*-13.2*	*-16.6*	*-42.9*	*-21.6*	*-57.3*	*-69.2*	*-34.2*	*-30.9*
CV of speed/draft based-cycle AER_{sea}	0.081	0.129	0.152	0.137	0.100	0.126	0.017	0.021	0.098	0.119
Difference in CV for speed/draft based-cycle [%]	*-49.8*	*-24.0*	*-16.8*	*-13.4*	*-20.1*	*-16.8*	*-48.9*	*-48.9*	*-25.4*	*-19.3*

*The figures include only the ships for which the speed-power relation coefficient β has a R^2 of more than 0.8, for comparison with Godet et al. (2023). The weighted average is weighted by the number of ships in each bin class.

As shown in Table 4.6 and Figure 4.4, the combined speed and draft cycles for 2019 are more accurate than the ME power ones for 2019, regarding the assessment of the AER_{sea} (the accuracy in assessing AER_{sea} changes from 5.2% as the absolute weighted average to 3.6% using these new cycles). However, the combined speed and draft cycles are less effective in reducing the variability of the indicator, with a coefficient of variation of -19.3% weighted by the number of ships in each bin class, compared to -30.9% for the ME power based-cycles. Figures 4.4a and 4.4b illustrate the same observation, with the two fitting curves being most similar for the combined speed and draft based-cycles, but with a lower R^2 (0.80 compared to 0.87 for the ME power based-cycles). Therefore, based on this test, the speed/draft cycles are observed to be more accurate but less effective than the ME power-based cycles.



(a) Combined speed and draft-based cycles



(b) Selected ME power-based cycles. Source: Godet et al. (2023).

Figure 4.4: Comparison of AER_{sea} with cycle-based values for the two methods (ME power and speed/draft) for 2019

4.4.2 Inclusion of all emissions for all the voyage stages

As mentioned in Section 4.3.2, the 2021 data structure of the noon reports allows us to get more insights into the arrivals and departures stages. As such, the calculations for the 'full' AER and EEOI are possible. The number of legs/arrivals/departures N_c is defined by the best cycles found for the accuracy of ME emissions at sea. Indeed, Table 4.7 shows that ME emissions at sea account for the greatest share (from 60 to 78% of the total emissions depending on the bin class), and, therefore, must be optimized first. As presented in Section 4.3.1.1, the number of legs/arrivals/departures in each category, N_c, is the same. As such, optimizing the accuracy of the ME emissions at sea defines the number of legs N_c and the number of categories c as well. There is little room for maximizing the arrivals and departures after that. Table 4.7 also highlights that the share of AE emissions and the share from the voyage stages other than sea passages are more important for smaller ships. In contrast, the emissions are driven mainly by ME emissions at sea (more than 75%) for the four largest bin classes.

Combined speed and draft-based cycles are developed and assessed using the EEOI. Figure 4.5 shows an example for bin class 5 for these combined speed and draft cycles and their counterpart from ME power. Note that the draft is not reported for port stays and is therefore shown as zero on the cycle. Table 4.8 shows the results for the accuracy of ME emissions at sea and during arrivals to and departures from ports. The averages show better accuracy for the ME power-based-cycles, mainly due to bin classes 2 and 8.2, for which the accuracy is lower (-6.0% and -5.3%, respectively). However, the accuracy is much better for the arrivals to and departures from ports using the combined speed and draft cycles than the ME power cycles. The quality of the ME power reporting during these voyage stages could explain this poor performance.

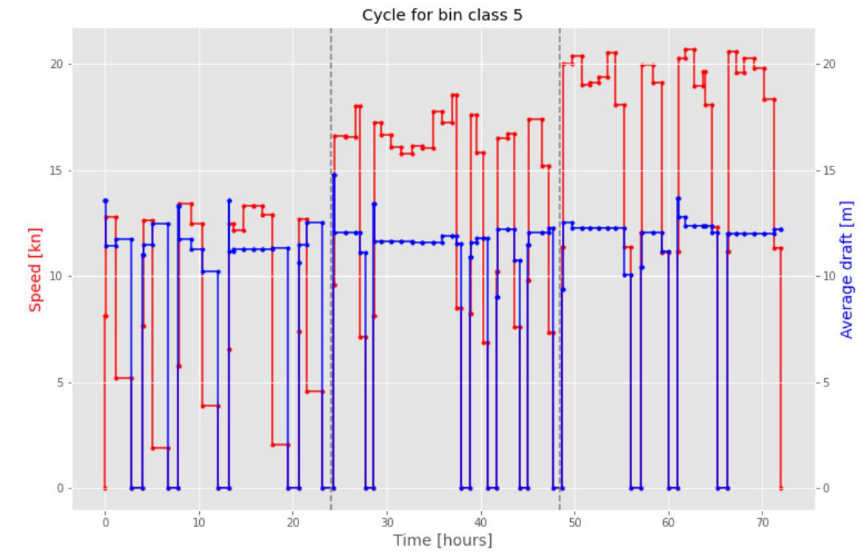
To go from the cycles to the EEOI estimate, the regressions presented in Table 4.2 must be fitted for all ships. Table 4.9 presents the average results for the bin classes for each regression. It shows fairly good results for the ME emissions at sea, and the estimation of ME power on the basis of speed and draft ($R^2 = 0.8$ on average), which is the most critical due to the predominant share of ME emissions at sea. The R^2 average for the AE emissions at sea is low mainly due to the larger bin classes, especially bin 8.2, for which the

Table 4.7: Percentage of total emissions for the sample fleet for all voyage stages and types of emissions

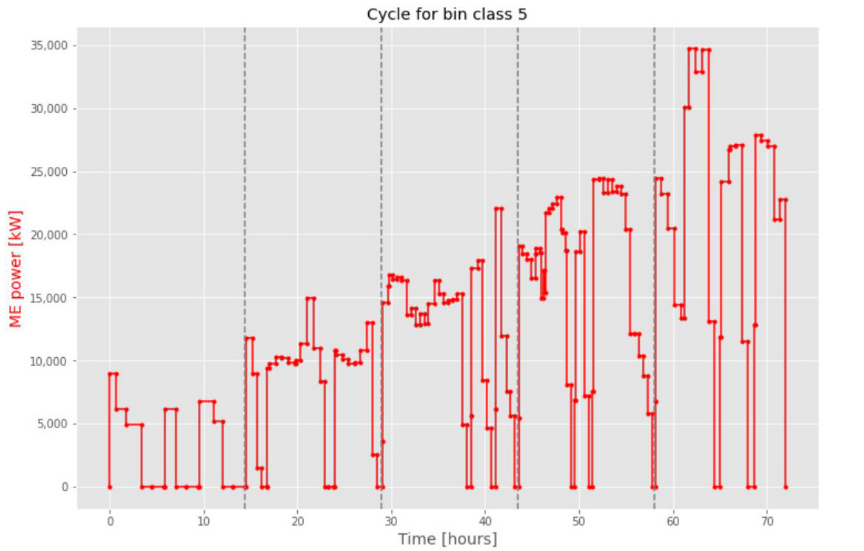
		Total	Sea	Port	Arrival	Departure
Bin 2	ME emissions [%]	**78.5**	65.2	0.0	10.8	2.5
	AE emissions [%]	**18.1**	9.7	3.0	4.8	0.6
	Boiler emissions [%]	**3.4**	0.2	1.6	1.5	0.1
Bin 3	ME emissions [%]	**76.2**	60.6	0.0	12.3	3.3
	AE emissions [%]	**20.6**	9.7	4.3	5.6	1.0
	Boiler emissions [%]	**3.2**	0.1	1.7	1.2	0.1
Bin 4	ME emissions [%]	**80.0**	70.4	0.1	7.6	1.9
	AE emissions [%]	**17.9**	10.4	3.2	3.7	0.6
	Boiler emissions [%]	**2.1**	0.1	1.1	0.8	0.1
Bin 5	ME emissions [%]	**80.2**	70.7	0.0	7.5	1.9
	AE emissions [%]	**17.9**	10.6	3.1	3.7	0.6
	Boiler emissions [%]	**1.9**	0.1	1.0	0.7	0.1
Bin 6	ME emissions [%]	**83.6**	76.4	0.0	5.5	1.7
	AE emissions [%]	**14.9**	8.8	2.4	3.2	0.5
	Boiler emissions [%]	**1.6**	0.1	0.7	0.7	0.1
Bin 7	ME emissions [%]	**86.3**	77.8	0.0	6.4	2.1
	AE emissions [%]	**12.5**	6.4	2.8	2.7	0.5
	Boiler emissions [%]	**1.2**	0.0	0.8	0.4	0.0
Bin 8.1	ME emissions [%]	**82.6**	75.1	0.0	4.7	2.8
	AE emissions [%]	**15.2**	7.5	3.8	3.2	0.7
	Boiler emissions [%]	**2.2**	0.1	1.3	0.7	0.1
Bin 8.2	ME emissions [%]	**88.5**	77.5	0.0	7.4	3.6
	AE emissions [%]	**9.3**	3.0	3.0	2.6	0.7
	Boiler emissions [%]	**2.3**	0.3	1.3	0.6	0.1

Table 4.8: Comparison of the ME power-based cycles and the combined speed and draft-based cycles in terms of accuracy in modeling the actual ME emissions for different voyage stages (2021) in tons of CO2e per hour per ship

	Sea passages					**Arrivals**					**Departures**				
	Sample fleet	**Speed/draft cycles**		**ME power cycles**		**Sample fleet**	**Speed/draft cycles**		**ME power cycles**		**Sample fleet**	**Speed/draft cycles**		**ME power cycles**	
	t/h	*t/h*	%	*t/h*	%	*t/h*	*t/h*	%	*t/h*	%	*t/h*	*t/h*	%	*t/h*	%
Bin 2	3.18	2.99	-6.0	3.19	0.12	0.76	0.72	-5.7	1.19	55.7	1.75	1.74	-0.2	1.58	-9.7
Bin 3	4.17	4.17	-0.1	4.19	0.5	1.23	1.44	16.9	1.37	10.9	2.30	2.15	-6.3	5.57	142.3
Bin 4	6.69	6.70	0.3	6.60	-1.3	1.74	1.62	-6.5	2.76	58.7	3.06	3.27	6.9	4.13	35.2
Bin 5	9.62	9.64	0.2	9.64	0.23	2.36	1.77	-24.8	4.51	91.4	4.16	5.03	21.0	4.55	9.4
Bin 6	11.79	11.83	0.3	11.87	0.7	1.99	3.02	51.9	7.64	283.3	5.39	5.48	1.6	5.89	9.2
Bin 7	13.86	13.91	0.4	13.99	0.9	2.53	3.50	38.4	2.30	-9.3	5.57	7.79	39.9	8.18	46.8
Bin 8.1	15.68	15.57	-0.7	15.60	-0.6	2.26	2.32	2.8	4.31	91.2	7.30	10.39	42.3	10.03	37.4
Bin 8.2	15.75	14.91	-5.3	15.73	-0.1	3.85	4.15	5.6	7.34	90.6	8.51	9.08	6.6	9.24	8.5
Absolute average			**1.7**		**0.6**			**19.4**		**86.4**			**15.6**		**37.3**
Absolute average weighted by ship			**1.0**		**0.7**			**23.3**		**113.0**			**10.5**		**33.1**

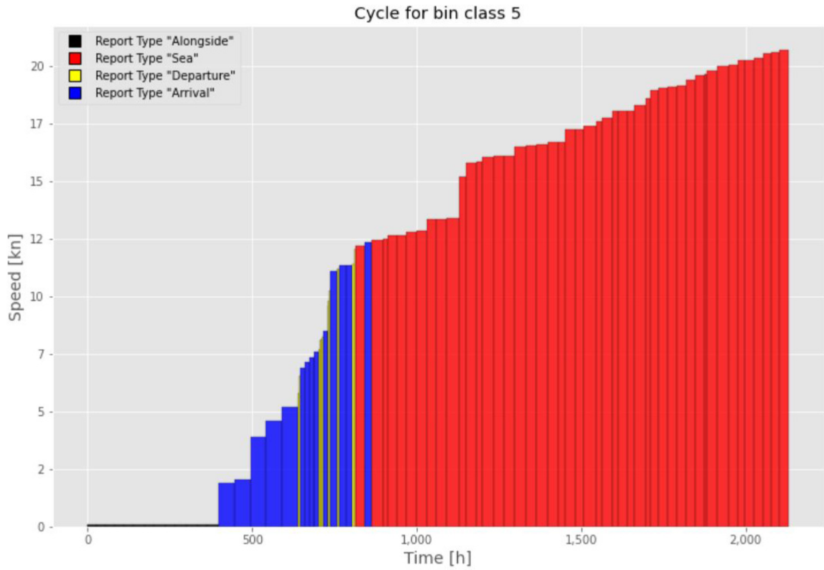


(a) Selected combined speed and draft-based cycle for bin class 5

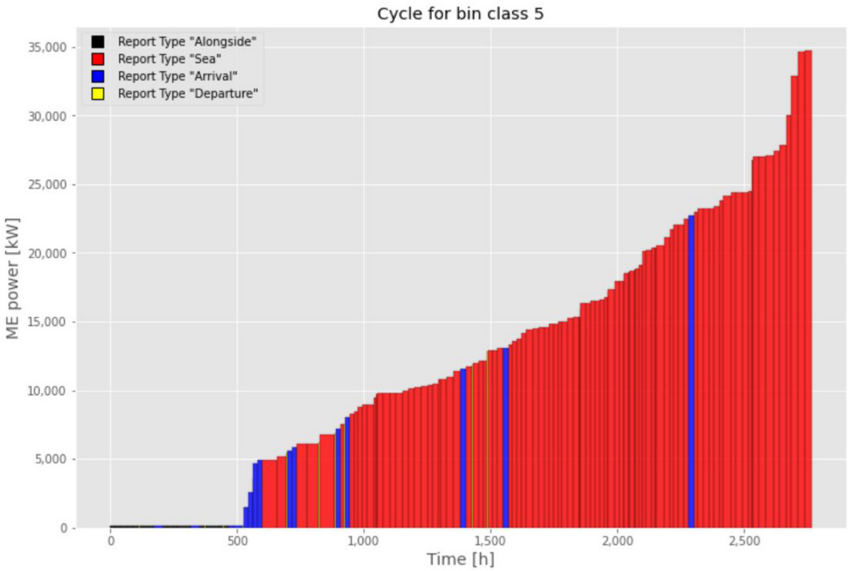


(b) Selected ME power-based cycle for bin class 5.

Figure 4.5: Comparison of cycles for bin class 5 for 2021



(c) Selected combined speed and draft-based cycle for bin class 5, as a distribution over time



(d) Selected ME power-based cycle for bin class 5, as a distribution over time

Figure 4.5: Comparison of cycles for bin class 5 for 2021

performance is problematic. These large ships are generally equipped with shaft generators and motors and can be equipped with waste heat recovery systems, which skew the results. While these tendencies can also be found for the AE emissions during port stays, the results are more consistent for the arrivals to and departures from ports. The low regression performance for the ME emissions during arrivals to ports is also worth noticing. It mirrors the poor accuracy from the cycles shown in Table 4.8, which may conclude that either the quality of data is not good enough for this stage to capture typical operations or that the operations are so diverse when it comes to this voyage stage, that typical operations cannot be accurately derived.

Table 4.9: R^2 average values for all the regressions required to calculate the EEOI from the cycles

	Sea passage				**Port**		**Arrivals**			**Departures**		
	ME emissions	ME power	AE emissions	Cargo	AE emissions	Boiler emissions	ME emissions	AE emissions	Cargo	ME emissions	AE emissions	Cargo
Bin 2	1.00	0.77	0.72	0.79	0.89	0.70	0.36	0.93	0.81	0.76	0.82	0.80
Bin 3	1.00	0.85	0.72	0.74	0.83	0.82	0.35	0.91	0.71	0.64	0.87	0.73
Bin 4	0.99	0.76	0.56	0.81	0.73	0.79	0.47	0.88	0.77	0.62	0.87	0.78
Bin 5	1.00	0.82	0.62	0.75	0.76	0.78	0.44	0.86	0.78	0.69	0.91	0.80
Bin 6	1.00	0.83	0.49	0.69	0.64	0.67	0.34	0.88	0.76	0.63	0.84	0.75
Bin 7	1.00	0.86	0.43	0.68	0.38	0.74	0.36	0.82	0.69	0.68	0.85	0.67
Bin 8.1	1.00	0.84	0.43	0.73	0.53	0.74	0.40	0.91	0.68	0.58	0.86	0.71
Bin 8.2	1.00	0.87	0.06	0.28	0.54	0.74	0.35	0.78	0.65	0.68	0.67	0.63
Average (for all ships)	1.00	0.81	0.52	0.71	0.68	0.75	0.40	0.87	0.75	0.65	0.85	0.75

Looking now at the effectiveness of the cycles to reduce the variability of EEOI, Table 4.10 shows the numbers for the coefficient of variation for each bin class, similarly to Table 4.6. It shows that the cycles can reduce the variability for all bin classes, from 16 to 71%, except for bin class 8.2, where there is a slight increase (1.8%). This can be explained by the limited regression performance presented in Table 4.9. Note that, similarly to the analysis for 2019 data reported in Section 4.4.1, the numbers presented in Table 4.10 exclude ships with a R^2 for the speed/draft vs ME power relation lower than 0.8, as well as ships for which the p-value for one of the regression lines was higher than 0.05 (taken as the threshold for being not statistically significant). The comparison with the ME power cycles is impossible here, as the cargo cannot be predicted without the draft. Estimates of average EEOI figures for 2018 are given as a comparison from the 4^{th} IMO GHG study (Faber et al., 2020).

A few notes regarding the exclusion/filtering from Section 4.3.2 are in order. First, ships with an EEOI of more than 75 $\text{tons}_{CO_2}/(\text{t} \cdot \text{nm})$ in bin two and of more than 35 $\text{tons}_{CO_2}/(\text{t} \cdot \text{nm})$ in bin three have been excluded from the analysis, considered as outliers within their bin classes. Besides, ships with a

Table 4.10: Effectiveness of the combined speed and draft cycles for assessing EEOI [tCO2/t.nm] (2021). Source for the IMO numbers: Faber et al. (2020)

	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8.1	Bin 8.2	Absolute average	Absolute average weighted by ship
Number of ships	8	22	41	29	48	16	7	20		
Mean value of EEOI	31.47	24.51	19.71	15.18	14.07	10.94	10.79	7.23		
Mean value of cycle-based EEOI	31.01	20.56	19.58	13.68	12.36	8.57	8.76	6.65		
Difference in mean value [%]	*-1.5*	*-16.1*	*-0.7*	*-9.9*	*-12.2*	*-21.7*	*-18.8*	*-7.9*		
(Comparison with IMO mean figures)	(26.9)	(19.9)	(17.1)	(16.3)	(13.4)	(10.8)	(8.1)	(8.1)		
Standard deviation of EEOI	7.35	3.71	4.34	2.47	3.18	3.91	0.69	0.38		
Standard deviation of cycle-based EEOI	6.03	2.16	3.22	1.19	1.90	0.88	0.40	0.35		
CV of EEOI	0.234	0.151	0.220	0.162	0.226	0.357	0.064	0.052	0.183	0.194
CV of cycle-based EEOI	0.194	0.105	0.164	0.087	0.153	0.102	0.045	0.053	0.113	0.123
Difference in CV [%]	*-16.8*	*-30.5*	*-25.4*	*-46.3*	*-32.1*	*-71.4*	*-28.8*	*1.8*	*-38.4*	*-36.5*

deadweight of 40,100 tons have been excluded from bin 4. Indeed, these sister ships, built between 2018 and 2019, typically sail with an average draft lower than the average for the bin class (9.2 m compared to 11.3 m for the bin class). As such, using the typical draft from the cycles to predict their cargo on board would result in a mass of cargo way above what would typically be transported, skewing too much the cycle based-EEOI. Therefore, they are excluded and cannot be considered ships with 'typical' operations within their bin class.

4.5 Discussion

This paper presented extensions of the work on operational cycles for maritime transportation initiated by Godet et al. (2023). Two approaches were compared: cycles based only on ME power and cycles based on a combination of speed and draft. Both of these approaches were validated, and the former showed better effectiveness while the latter reflected better accuracy. Therefore, if sufficient data is available, it is possible to use the combined speed/draft cycles, which are slightly more precise. Otherwise, the ME power-based cycles would be preferred to keep it simple for real-life applications, requiring less data. The remainder of this section presents the policy implications of these cycles and the limitations identified in this work.

4.5.1 Policy implications

Lindstad and Bø (2018) highlighted three main reasons why the EEDI does not reduce GHG emissions to the same extent, which could be addressed with the cycles. The first reason is the lower power of ships at sea compared to EEDI level. The cycles include a range of power levels, representing what the ships experience at sea. This power range also addresses the concern of Polakis et al. (2019) on reducing the design speed as the way to comply.

The second reason raised by Lindstad and Bø (2018) is the weather conditions not being calm water in real situations. While an improvement in the weather handling is possible (see Section 4.5.2), the estimates based on the cycles rely on real data that embed weather effects. As the fleet is sailing globally and the data used was for an entire year, it is assumed to reflect actual weather conditions at sea.

The third reason is the limit of having only CO_2 emissions accounted for, instead of GHG emissions. While the main difference between fuel oil (both heavy and very low sulfur) and marine gas oil would arise from the amount of black carbon (Comer and Osipova, 2021), this becomes essential when considering other fuels, such as LNG. TheGHG Fuel Standard (GFS), currently under discussion at IMO, adopts a life-cycle perspective to prevent transferring the emissions to other sectors and incrementally reduces the GHG intensity of the fuels (IMO, 2023b). The proposed operational cycles can easily be adapted to reflect GHG rather than CO_2 emissions.

As such, the present paper reinforces the conclusion of Godet et al. (2023). The cycles could enhance EEDI and address some of its limitations presented in Section 4.2.1.1. Operational cycles enable assessing a ship's energy efficiency on a more comprehensive EEDI, including various operational conditions. In conjunction with CII, GHG Fuel Standard (GFS), and the market-based measures currently under discussion at IMO, the proposed modified EEDI can enhance the effectiveness of the regulatory framework for decarbonizing international shipping.

4.5.2 Limitations

The work in operational cycles for maritime transportation is still recent, and additional work needs to be done to perfect the concept. For instance, as highlighted in Godet et al. (2023), the operational cycles presented here reflect only the operations of one company fleet. They would require data inputs from the world fleet to end up in a widely applicable policy. It is only applicable for container ships, divided into typical group sizes, and similar analyses are required for other ship types (e.g., bulk carriers, tankers). The data quality from the noon reports is also an issue, and the approach could be supplemented with a continuous onboard data collection system or Automatic Identification System (AIS) data.

More specifically, regarding the new cycles presented in the paper, the combined speed and draft cycles help calculate the EEOI and effectively reduce its variability among similar-sized groups of ships. Nevertheless, as shown in Table 4.9, the error in estimating the cargo based on the draft is not negligible (e.g., average R^2 of 0.71 at sea), and can be pretty significant in the calculation of EEOI. In comparison, the estimation of the emissions is a combination of several estimates, and, apart from the ME emissions at sea, is less dependent on only one regression curve. The draft of a ship depends not only on the cargo onboard but also on the ballast water to optimize the ship's performance. No improvement was found when attempting to combine the cargo on board and the ballast water statistically; more work is needed.

The weather, mentioned in Section 4.2, as an external factor affecting the energy efficiency of the ships is indirectly handled here. The cycles use real-world data, and, as such, the weather effect is embedded in this data. Because we used different legs and voyage stages, with data from different ships at different time points, it is roughly assumed that the weather effect thus captured in the cycles represents, on average, the conditions of the ships at sea. Indeed, more work is required to capture and separate the weather effect, which would allow cycles to include different sea states.

As mentioned in Section 4.4, bin 8.2 presents weaknesses regarding several regressions and the effectiveness in estimating the EEOI, probably due to its higher implementation of different efficient technologies (shaft generator, motor, waste heat recovery system). Specific work needs to address these new types of ships to succeed in the benchmarking goal for these cycles. Moreover, there is a need to account for ships transporting a lot of reefers on some trade lines.

Finally, the canal passages and anchorage periods are excluded from the analysis due to a lack of typical patterns. Nevertheless, these voyage stages can be significant depending on the conditions at port or issues with the canal passages (e.g., when the Suez Canal was obstructed in 2021 or when the number of Panama Canal passages was reduced due to drought in summer 2023). These voyage stages represent 0.8% of the ME emissions, 2.5% of the AE emissions, and 4.3% of the Boiler emissions, i.e., 1.1% of the total emissions for the entire fleet in 2021.

4.6 Conclusion

GHG emissions from international shipping must decrease to slow climate change and other environmental consequences in the coming years. Gains in energy efficiency and shift to less carbon-intensive fuels are part of the IMO strategy to reduce ships emissions (IMO, 2023a). Energy efficiency indicators play a crucial role in how the emissions from ships are assessed. The current paper explores the existing indicators and, building on the work by Godet et al. (2023), extends the concept of operational cycles for maritime transportation. The main contributions are the development of cycles based on the combination of speed and draft, the inclusion of all emissions (main engine, auxiliary engines, boiler), and all voyage stages (sea passages, port stays, arrivals to and departures from ports), allowing for a comparison to reference numbers. A methodology to systematically choose the best-performing cycles has also been developed.

Cycles based on speed and draft were compared with the ones based on ME power. The cycles based on speed and draft showed, on average, a better accuracy in modeling the emissions for the fleet, while the cycles based on ME power were more effective in reducing the variability among ships of similar sizes. Having cycles based on speed and draft also allowed us to estimate an EEOI for many ships, and it proved efficient in reducing the variability within bin classes. The extensions made from the work by Godet et al. (2023) improve the comprehensiveness of the concept of operational cycles in maritime transportation. Further work on the subject includes collecting more granular data for the cycles, maybe handling the weather effect more comprehensively, and extending the concept to other ship types.

Nomenclature – Chapter 4

AER_{sea} Annual Efficiency Ratio, considering only the fuel consumed by the main engines at sea [tons of CO_2/t.nm]

C_{F_f} Carbon intensity of fuel f [tons of CO_2 / tons of fuel]

D_i Distance sailed during the voyage i [nm]

$FC_{e,f}$ Mass of fuel type f consumed [tons]

N_c Number of legs in the category c

T Average draft [m]

α_{type_s} Ship-specific constant with $type \in \{ME, AE, cargo\}$

β_{type_s} Ship-specific constant with $type \in \{ME, AE, cargo\}$

δ_{type_s} Ship-specific constant with $type \in \{AE, BE\}$

γ_{type_s} Ship-specific constant with $type \in \{AE, BE\}$

λ_{type_s} Ship-specific constant with $type \in \{ME, AE, cargo\}$

ν_s Ship-specific constant

ω_{type_s} Ship-specific constant with $type \in \{ME, AE, cargo\}$

ϕ_s Ship-specific constant

ψ_{type_s} Ship-specific constant with $type \in \{ME, AE, cargo\}$

τ_s Ship-specific constant

ζ_{type_s} Ship-specific constant with $type \in \{ME, AE, BE, cargo\}$

c Category in the cycle

e Engine type

f Fuel type

m_{cargo_i} Cargo onboard during the voyage i [tons]

p Main engine power [kw]

s Ship

t Reported time [h]

v Ship speed [kn]

x Main engine emissions [tons of CO_2]

y Auxiliary engines emissions [tons of CO_2]

z Boiler emissions [tons of CO_2]

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5 Voluntary reporting in decarbonizing container shipping: the Clean Cargo case (Paper 4)

Amandine Godet[a], George Panagakos[a], Michael Bruhn Barfod[a]

[a] Department of Technology, Management and Economics, Technical University of Denmark, 2800 Kongens Lyngby, Denmark

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Abstract Led by the UN's International Maritime Organization (IMO) and the EU, the shipping industry struggles to reduce its greenhouse gas (GHG) emissions to align with the Paris Agreement. Clean Cargo, the leading voluntary buyer–supplier forum for sustainability in the cargo shipping industry, developed some years ago a methodology to calculate and report the GHG emissions from containerships. The recently introduced carbon emission requirements by the IMO and EU have reinforced the members' interest in a new Clean Cargo reporting mechanism that enables more effective and efficient monitoring of the decarbonization progress. A better understanding of the user needs accompanied by due consideration of the regulatory environment and the technological advances are key to building this new framework. This paper builds on the case of the Clean Cargo initiative to (1) identify the stakeholders' expectations and motivations for voluntary disclosure of environmental information, and (2) discuss the governance challenges of voluntary initiatives. A questionnaire was designed and deployed to investigate the current uses of Clean Cargo data and the information sharing among different stakeholders. Voluntary schemes can speed up the decarbonization process by proposing standards accepted by all actors of the global value chain. Clean Cargo members envision reporting on absolute GHG emissions per shipment as the way forward.

Keywords: *shipping; container ship; carbon emissions; reporting framework; buyer–supplier forum; private standard; rating scheme*

5.1 Introduction

According to the Fourth greenhouse gas (GHG) study of the International Maritime Organization (IMO) (Faber et al., 2020), the maritime industry generated 2.89% of the global anthropogenic CO_2 emissions in 2018. Although this proportion has been relatively stable over the last decade, the CO_2 emissions from international shipping have increased by more than 5% since 2012. To align with the Paris Agreement targets, the IMO launched in 2018 its 'Initial IMO strategy on reduction of GHG emissions from ships'. The strategy sets the ambition of reducing total annual GHG emissions of international shipping by at least 50% by 2050 compared to 2008. It also stipulates a reduction of carbon intensity, defined as CO_2 emissions per transport work, by at least 40% by 2030 (and towards 70% by 2050) compared to 2008 levels (IMO, 2018). Given that the transport demand is expected to increase by 4.5% annually (UNCTAD, 2019), these targets become even more ambitious, requiring significant and immediate mitigation measures.

At a global level, the first regulatory measures on shipping emissions were introduced by IMO in 2011 with the adoption of the Energy Efficiency Design Index (EEDI) and the Ship Energy Efficiency Management Plan (SEEMP) (IMO, 2011). In addition, as of 2019, ships have to report their fuel consumption and distance traveled under the IMO Data Collection System (DCS) (IMO, 2016). At a regional level, since 2018, ships traveling from, to, and within EU ports have been required to report their fuel consumption, CO_2 emissions, and transport work under the European Union (EU) Monitoring Reporting and Verification (MRV) regulation (EU, 2015). While the EU MRV regulation is a bit older and more comprehensive than IMO DCS, its regional nature unavoidably limits the achievable coverage. However, both IMO DCS and EU MRV schemes are very recent and the retrospective analysis of their impact is not sufficiently studied yet (Panagakos et al., 2019).

Container ships alongside bulk carriers and oil tankers constitute the three largest emitters within the maritime sector, both globally (Faber et al., 2020) and regionally (EU MRV, 2020) (refer to Figure 5.1). Among these segments, container shipping happens to be the closest one to the end users as it mainly carries consumable goods in break bulk form. As such, it is more susceptible to pressures for better environmental performance coming from cargo owners. The continuously increasing concern of cargo owners can be an important potential driver for environmental upgrading in maritime transport and, more specifically, in the container ship operations (Kopela, 2017; Linder, 2018; Lister, 2015; Poulsen et al., 2016).

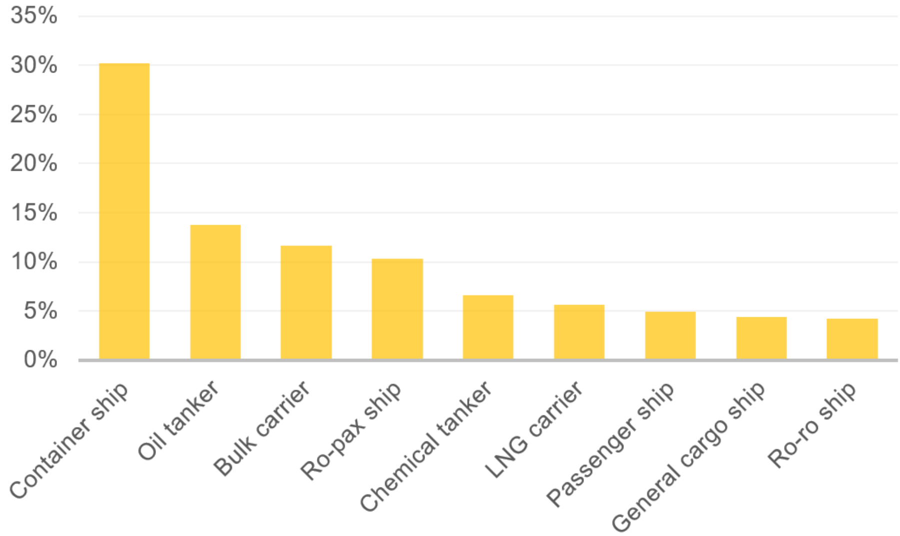

Figure 5.1: Share of different ship types in total CO_2 emissions reported under EU MRV for 2019. Source: 2019 CO_2 Emission Report (EU MRV, 2020).

Several private initiatives have emerged over the years to address sustainability issues in shipping, motivated by a need for more transparency and the corresponding exchange of information between different stakeholders. Section 5.2.1 presents a number of such initiatives. Among them, the present article focuses on Clean Cargo, previously known as the Clean Cargo Working Group (CCWG). It is a business-to-business leadership initiative dedicated to promoting responsible shipping and reducing the environmental impact of global freight transport. It was launched in the early 2000s by BSR, an organization of sustainable business experts that works with its global network of leading companies to build a just and sustainable world. Clean Cargo involves more than 80 major cargo carriers, shippers, and freight forwarders, and represents about 80% of world container cargo capacity (BSR, 2020b). In the 2010s, Clean Cargo established, among others, a standard for the calculation of CO_2 emissions generated by ocean container transportation, based on operational data reported by carriers. Shippers and freight forwarders use the calculated emissions to assess the footprint of their sea freight as part of their procurement decisions.

With the recent introduction of the above-mentioned emission reporting schemes of IMO and the EU, the initial aim of some private initiatives concerning the disclosure of environmental information becomes redundant. Should private initiatives wish to maintain their role of pulling shipping companies towards decarbonization and laying the foundations for future regulations in this direction, they need to evolve with the industry and the regulatory framework and move the decarbonization frontier forward to include new grounds.

Against this background, members of Clean Cargo expressed an interest in defining a new emission reporting framework to be applied in the next decade. To address this need, a dual objective has been set for the present paper: (i) identify the stakeholder expectations and motivations for voluntary disclosure of environmental information, and (ii) discuss the governance challenges of voluntary initiatives.

More specifically, the paper summarizes the results of a questionnaire-based study that was undertaken to map the expectations and needs of the different stakeholders, as well as their willingness to contribute and share information, supporting the definition of the Clean Cargo future reporting framework. Furthermore, the findings of the survey contribute to the ongoing dialogue on the transformational power of information with aspects such as the use of information in transport procurement negotiations, and the capacity of the relevant stakeholders (carriers, shippers, and freight forwarders) to promote the reduction of carbon emissions in this segment of maritime transport. External parameters, such as international regulation and market-based measures, are integrated into the analysis for this purpose. While several articles have focused on the advantages and weaknesses of private governance initiatives in international shipping Gibson et al. (2019); Lister et al. (2015); Poulsen et al. (2018); Scott et al. (2017), the present work investigates the operational and technical aspects of the Clean Cargo initiative, alongside its governance features in view of the above-mentioned external pressures.

Section 5.2 describes the concept of private initiatives, the common characteristics of initiatives similar to Clean Cargo, and their potential for environmental upgrading together with their limitations. Following this broad review, the Clean Cargo current reporting framework is explained in more detail. Section 5.3 highlights the context and methodology adopted for this study, and Section 5.4 presents the results of the questionnaire. Section 5.5 discusses the main findings of this work, while Section 5.6 concludes the article.

5.2 Reporting Frameworks

5.2.1 Literature Search

A great number of private initiatives have emerged since the late 1990s, with a noticeable acceleration in the past decade, to meet the environmental challenges of shipping and fill the gap created by the lack of regulation. Named 'private standards' by Scott et al. (2017), these initiatives can be of a different nature (Gibson et al., 2019). This paper focuses on the 'independent performance indicators' category in the taxonomy of Gibson et al. (2019), also defined as 'ship rating schemes' by Scott et al. (2017) or 'eco-rating schemes' by Poulsen et al. (2018). Their aim is to provide an indication of the environmental performance of ships, independently of any regulatory organization or state actor.

Gibson et al. (2019) distinguish 12 initiatives in the category 'performance indicators' with a public level of transparency, out of the 85 initiatives identified in the literature (Gibson et al., 2019). Scott et al. (2017) highlighted six prominent examples of ship rating schemes, and Poulsen et al. (2018) based their analysis on six eco-rating schemes, listed on the Sustainable Shipping Initiative (SSI) website (Sustainable Shipping Initiative, 2020). Table 5.1 summarizes the characteristics of five ship rating initiatives, which are the most frequently cited by the industry (Poulsen et al., 2018) and in the literature (BSR, 2015; Clean Shipping Index, 2020; Environmental Ship Index, 2020; Gibson et al., 2019; Green Award, 2020; Lister, 2015; Lister et al., 2015; Parviainen et al., 2018; Poulsen et al., 2018; RightShip, 2020; Scott et al., 2017).

Table 5.1: Most frequently cited ship rating schemes governing CO_2 emissions.

Scheme	Scope	Stakeholders	Outputs	Transparency	Data reliability
Clean Cargo (CCWG)	Container ships only CO_2, SO_X, NO_X, Environmental Management System (EMS), transparency	Cargo owners/ shippers, freight-forwarders, ship owners/carriers	Trade lane emissions factors Carrier scores based on fleet emissions (between 0 and 100)	Benchmark available for members (under confidentiality agreement) Public report with industry average	Carriers report data Third-party verification
Clean shipping Index CSI	All segments CO_2, NO_X, SO_X, particulate matter (PM), use of chemicals, waste and water management	Cargo owners, ports, freight-forwarders, authorities, providers of clean technology	Ship labelled between 1 and 5 Carrier's score based on the fleet	Environmental performance of vessels available for members (under confidentiality agreement)	Carriers report data Third-party verification
Environmental Ship Index (ESI)	All segments NO_X, SO_X, fuel efficiency improvements aiming at lower CO_2 and PM emissions	Mainly ports, ship owners	Score between 0 and 100 for each vessel	Scores available to members (under confidentiality agreement)	Carriers self declaration No systematic third-party verification
Green Award	All segments, inland and sea shipping Quality and safety standards, environmental performance	Ports, ship managers, charterers, maritime service providers, authorities	Different certification criteria for different vessel types	List of certified ships publicly available	Office and onboard audits, ship survey
RightShip (Existing Vessel Design Index (EVDI))	All segments CO_2, safety	Cargo owners, shipowners, financial institutions, ports	Score between A and G based on normal peer distribution	Scores publicly available	Mix of ship-sourced data and review of certificates

Private stakeholders have been motivated to join these initiatives for three main reasons: social pressures with the goal of establishing a public green image that offers competitive advantages, regulatory pressures concerning both existing and possible future regulations, and financial motivations through the identification of efficiency gains (Linder, 2018; Parviainen et al., 2018). It has been found that the interest in private standards can even be increased by unsuccessful discussions on new regulations (Scott et al., 2017). The potential and limitations of these initiatives are analyzed below. The subject is approached through five common perspectives: scope, stakeholder engagement, level of ambition, transparency, methodology, and data reliability.

The sustainability issues concerning international shipping are broad and challenging. While the initiatives that constitute the focal point of this paper mostly relate to fuel consumption and air emissions, some also include emissions to water (Gibson et al., 2019; Poulsen et al., 2018). Some schemes specialize in a specific shipping segment, as is the case with Clean Cargo, which basically concerns the container industry, while others cover the entire commercial fleet, always with a global ambition and a benchmarking perspective. The scopes of the standards cited in Table 5.1 overlap due to the objectives and interests of the different stakeholders who are, thus, partly forced to choose among the available schemes. In this respect, the lack of universality of the schemes reduces their potential for environmental benefits (Poulsen et al., 2018). On the other hand, the development of Corporate Social Responsibility (CSR) practices within the shipping industry can both boost participation in such private standards as part of the company CSR strategy and simultaneously compete with them by creating or suggesting new norms and standards (Parviainen et al., 2018).

A key determinant of the success of the private initiatives is “their ability to persuade an adequate number of target actors to make use of the standard” (Scott et al., 2017). Clean Cargo is the most successful one in this sense, as it covers more than 80% of global ocean container capacity by deadweight (Poulsen et al., 2018; Scott et al., 2017). In addition, major cargo owners, who constitute key stakeholders in the shipping industry, participate actively in the group, thus contributing critically to the scheme’s environmental effectiveness (Poulsen et al., 2018). Such wide acceptance leads to the institutionalization of private standards, which are then observed as becoming ‘obligatory’ without being ‘legally binding’, solely as a result of the industry’s self-regulatory mechanisms and peer pressure (Yliskylä-Peuralahti and Gritsenko, 2014). Nonetheless, most of these standards are developed by and for the industry, which results in neglecting important stakeholders, such as financial actors and NGOs. This omission is likely to reduce their legitimacy, and, consequently, their environmental effectiveness (Poulsen et al., 2018; Scott et al., 2017). For example, Wuisan et al. (2012) emphasized the limited participation of cargo owners in the Clean Shipping Project (CSP), formed mostly by Swedish companies with limited purchasing power. Other factors weakening the entrenched capability of private initiatives include that the standards require time and financial investments from the different stakeholders, as well as that both engagement in the schemes and willingness to invest in sustainable shipping can be tied to economic results (Wuisan et al., 2012).

Another much-criticized element in the literature is the limited level of ambition of the rating schemes. While Wuisan et al. (2012) stressed the greater ambition potential and faster implementation of private standards compared to international regulation, Scott et al. (2017) argued that in order to avoid discouraging information sharing and participation, the schemes set no absolute criteria. Instead, the schemes evaluate performance against industry averages, making the higher-rated levels easier to reach. A gain in the energy efficiency of ships, correlated with money savings, is often sought, and this does not prevent the rise of absolute emissions due to transport demand growth (Scott et al., 2017). Even if several rating schemes are considered to go 'beyond regulatory requirements', Gibson et al. (2019) note that they are unlikely to produce a reduction of emissions below the levels set by IMO. As the main reference point for international shipping, IMO standards and methods are usually integrated into the private standards (Wuisan et al., 2012). Besides, scoring mechanisms are often based on vessel design characteristics rather than operational criteria, which does not provide the necessary economic incentives for companies to perform better (Gibson et al., 2019). Furthermore, no compliance mechanism exists to impose the use of the data produced by the scheme or guide stakeholders in this direction (Wuisan et al., 2012). Finally, certain environmental issues of shipping are neglected by these schemes, such as accidental challenges (invasive species, oil spills, etc.) and end-of-life problems (recycling) (Poulsen et al., 2018).

While there is no doubt that private schemes make information available (Scott et al., 2017; Wuisan et al., 2012), limitations in terms of transparency are pointed out in the literature. For instance, when a vessel benchmarking is available, this is often reserved to the members of the initiative under certain restrictions (membership fee, confidentiality agreement, etc.) (Poulsen et al., 2018; Scott et al., 2017). The lack of transparency raises two main issues. Firstly, it is not possible to compare the schemes and how a ship or a company is performing within the different schemes. Secondly, the assessment of the environmental improvements driven by these initiatives is complicated and poorly communicated publicly in terms of concrete examples and quantitative evidence (Gibson et al., 2019; Poulsen et al., 2018; Scott et al., 2017). Limited transparency also characterizes the use of information by the different stakeholders (Wuisan et al., 2012).

Lastly, the methodology followed by the rating schemes is another subject of criticism despite the general acknowledgment that the schemes have the potential for improving the internal mechanisms of a company for measuring and mitigating CO_2 emissions (Scott et al., 2017). For instance, the schemes often cover different environmental features (CO_2 emissions, air pollutants, discharge to water, etc.) that are combined through weighting factors, which not only vary greatly across schemes but are assigned on the basis of very limited documentation (Gibson et al., 2019). The data reliability and quality are also questioned: companies often report directly to the schemes, and in the absence of any independent verification, the credibility of the outcomes is jeopardized (Poulsen et al., 2018). Even though a number of initiatives have included third-party verification in their methodology, "established procedures for routinized, ongoing, scrutiny of the standards and their implementation," are nowhere to be seen (Scott et al., 2017).

In addition to the overlaps in scope and targets previously mentioned, changes in the regulatory framework can affect the potential of private standards with regard to environmental upgrading. The introduction of the EU MRV and IMO DCS has increased overlapping, especially in terms of accountability and, in the case of EU MRV, the public access to CO_2 reporting (Scott et al., 2017). On the other hand, new regulations can "play a role in galvanizing and shaping private standards", which can intend to fill the gaps not covered by the new laws (Scott et al., 2017). An alignment of eco-rating schemes to regulations on environmental disclosure is thus encouraged in order to gain effectiveness and avoid conflict and confusion among the different stakeholders (Lister et al., 2015; Poulsen et al., 2016; Wuisan et al., 2012). To catalyze the efforts made by the actors involved, IMO can play a critical role in orchestrating these different initiatives (Lister et al., 2015). For instance, Lister et al. (2015). suggested IMO to grant consultative status to the private standards as a way to enhance their legitimacy and allow greater alignment of the initiatives. Reciprocal benefits between private initiatives and regulatory bodies are also suggested by Gibson et al. (2019) for both the implementation of regulations and the uptake of private initiatives.

5.2.2 The Clean Cargo Initiative and Its Reporting Framework

The Clean Cargo emission reporting framework was developed in the early 2000s, and, apart from small fixes and improvements, it has not changed over the years. Based on data reported by carriers, emission factors are calculated for each carrier and each trade lane, alongside a scoring system including also other environmental attributes.

The current methodology for CO_2 emissions is defined in a document from 2015, available on the Clean Cargo website (BSR, 2015). On a yearly basis, the carriers of the group (around 20 in number) report data for each one of their vessels, both owned and chartered, operated during the year. For 2019, 17 carriers reported data on approximately 3,500 vessels, which collectively represent around 85 percent of ocean container capacity worldwide (BSR, 2020a).

For every vessel of their fleet operated for more than 90 days, carriers report the following data further analyzed under the Clean Cargo framework:

- **Vessel characteristics**: IMO number, year built, nominal capacity (TEU), vessel ownership (owned/chartered), number of reefer plugs;
- **Service characteristics**: time frame of data (days), trade lane, distance sailed (km);
- **Fuel consumed (tonnes)**: HFO, MDO/MGO, LFO, propane LPG, butane LPG, LNG, methanol, ethanol, hybrid fuels;
- **Average sulfur content by weight (%)**: HFO, MDO/MGO, LFO, hybrid fuels;
- **NO_X performance**: main and auxiliary engines NO_X performance (g/kWh) and rated engine speed (rpm);
- **Certification under ISO 14001** or other equivalent environmental man-

agement system.

In addition, an environmental performance assessment is carried out concerning the company's environmental goals and policies, performance management, and public reporting.

Based on the data collected, different outputs are produced both on a carrier- and a trade lane level. Each carrier receives a yearly scorecard, including the following elements:

- The **carrier scores** for CO_2, SO_X, NO_X, Environmental Management System (EMS) and transparency: The CO_2 and SO_X scores are calculated in relation to the Clean Cargo averages for these emissions. The NO_X emission score is calculated in relation to the IMO curve defined in the resolution MEPC.251(66) of the MARPOL protocol (IMO, 2014). The EMS score is defined as a percentage of the certified fleet. Finally, the transparency score is based on corporate-level public reporting. Note that in order to account for the energy consumed by the refrigerated containers (also called reefers), a separate score (CO_2 Reefer) is calculated for this part of energy demand, while the remaining energy consumption is reflected in the CO_2 Dry score (BSR, 2015).
- The **carrier emissions** of CO_2 Dry, CO_2 Reefer and SO_X expressed in g/TEUkm per trade lane and carrier. A trade lane describes the major route on which a vessel is deployed. There are global trade lanes, such as 'Asia to-from North Europe', and intra-regional trade lanes, such as 'Intra North Europe'.
- The **year-over-year performance** for the carrier emissions of CO_2 Dry, CO_2 Reefer and SO_X per trade lane and carrier, for tracking potential improvements from one year to the next.

5.3 Methodology

One of the objectives of this paper is to identify the needs and expectations of different stakeholders for environmental information, as well as their willingness to contribute and share information. We designed a questionnaire to interrogate directly the members of the group on the definition of Clean

Cargo's future reporting framework. The members were able to access the questionnaire for three weeks in May 2020. This section describes the objectives, content, and development process of the questionnaire.

5.3.1 Preliminary Expectations about the Future Reporting Framework

Developed in the early 2000s, the Clean Cargo reporting framework based its methodology and data collection process on member expectations. At that time, companies did not have reliable IT systems in place and data processing was costly. Clean Cargo succeeded over the years in developing comparable data and a recognized methodology across the container sector.

Since the establishment of the methodology, several improvements have been implemented. A recent example is the shift of CO_2 emissions being initially calculated on a tank-to-wheel (TTW) basis to a well-to-wheel (WTW) approach in 2020, in order to align with the Global Logistics Emissions Council (GLEC) recommendations (Greene and Lewis, 2019). At the same time, the Clean Cargo initiative scaled the emission factors from CO_2 to $CO_{2_{eq}}$, following the recommendations of the GLEC framework. The shift from CO_2 to $CO_{2_{eq}}$ ($CO_{2_{eq}}$ = 101–102% of CO_2) accounts for the emissions of other GHG (methane, nitrous oxide, sulfur hexafluoride, nitrogen fluoride, hydrofluorocarbons, perfluorocarbons) (Greene and Lewis, 2019). In summary, Clean Cargo shifted from CO_2 TTW emission factors to $CO_{2_{eq}}$ WTW emission factors in 2020, as explained in Clean Cargo annual report 2019 Global Container Shipping Trade Lane Emissions Factors (BSR, 2020a). Consequently, while the Clean Cargo methodology mentions CO_2 scores and emission factors, from this point onward, we refer to GHG scores and emission factors, to emphasize this recent shift.

With the impressive advent of digital solutions and the increased societal expectations for more transparency, members across segments have expressed their desire to further develop the existing reporting framework. In response, BSR formed the 'Future of Reporting' working group within Clean Cargo, to draw the new reporting framework with a 10-year horizon. The main objective is to obtain more accurate data in an easier manner. The potential introduction of carbon pricing measures and other new regulations are issues that also need to be considered.

5.3.2 Questionnaire

The identification of the wishes of the Clean Cargo members in relation to the future reporting framework, as well as the corresponding implications, constitute the key objective of this research work. A purposely built questionnaire was chosen as the method for capturing the diversity of opinions across members. The research questions addressed and the corresponding hypotheses are those that enter the questionnaire directly and there is no need for them to be repeated here. For the sake of completion, it is mentioned that the usual deductive (for the formulation of hypotheses) and inductive (for revising the initial theory/assumptions) theory of social research is silently applied (Bryman, 2008).

Questionnaires are a common method for collecting data from a target group, particularly in social sciences. We used a self-completion questionnaire, meaning that respondents answered the questionnaire themselves. As a method, the self-completion questionnaire offers the advantage of being quick to administer and convenient for the respondents, while it avoids biases introduced by the interviewer (Bryman, 2008). The method's weakness, namely the inability of the researcher to ensure completion of the entire questionnaire or collect additional data, was perceived by the authors as the price we had to pay in exchange for securing a sufficient sample for the analysis.

The design of the questionnaire involved close cooperation and exchange of views between the authors and the BSR staff in charge of the Clean Cargo initiative. The expertise of the BSR staff in relation to the evolution of the initiative and its framework was a key asset. With the assistance of the BSR staff, the authors refined the questionnaire to serve the research purpose and customized it to the Clean Cargo segments (carriers, shippers, and freight forwarders). In addition, we conducted a pilot run for verifying the questions involving one Clean Cargo member from each segment. These pilots provided useful comments improving the quality of the questionnaire, which reflects both the industrial practices and the Clean Cargo experiences of the members. Table 5.2 provides an overview of the questionnaire structure.

Three major challenges arose when designing the questionnaire. First, the members of Clean Cargo consist of both data providers (carriers) and users (shippers and freight forwarders). These two groups of users have different needs and use the data reporting mechanism differently, resulting in two versions of the questionnaire: one for data providers and a separate one for data users, with a small differentiation between shippers and freight forwarders. Three different versions of the questionnaire were finally produced, one for each segment, with similar questions for shippers and freight forwarders.

Table 5.2: Structure and content of the questionnaire.

Section	Subsection	Content
Clean Cargo emissions reporting – Current Clean Cargo reporting framework	Motivations to report (for carriers)	Audience of environmental performance of members Importance of the different metrics Impact of environmental performance for competitiveness
	Audience for environmental performance (for shippers and forwarders)	Audience of environmental performance of members Relative importance of maritime transport
	Reporting process (for carriers)	Resources: staff, time and IT Challenging data to collect, chartered process Reporting to other initiatives
	Shipping process and climate strategy (for shippers and forwarders)	Maritime emissions and scope 3 targets Carrier selection criteria
	Use of Clean Cargo data	Outputs used by different members Integration into their system and communication
Future of Reporting — Preliminary work	Data reporting and communication	Indicators needed to track and communicate maritime emissions Additional data points to report eventually Integration with other freight modes
	Decarbonization tracking	Use of a tool internally
Sustainability and business strategy	Regulatory framework (for shippers and forwarders)	Impact of IMO 2050 on their business risk management
	Market-based measures and carbon pricing	Internal carbon pricing mechanism Carbon offsets
	Strategies to reduce maritime emissions	Technical and operational measures

A related issue concerned the desired level of detail of the output, and, consequently, input of the system. The users of the system prefer a higher level of detail in the information produced. However, this requires a much greater effort in data collection and manipulation from the side of the data providers. A balance is, therefore, necessary to meet the information requirements at minimum cost.

Second, the design of a future reporting system has to accommodate both the present and the anticipated future needs of the users. In turn, future needs are shaped by the aspirations of the users themselves and by the requirements imposed externally, such as the regulatory environment. Thus, the questionnaire provided the respondents with the opportunity to discuss their environmental strategy and their vision for Clean Cargo, as well as the possible effects of the ever-changing regulatory framework and business environment.

Third, we kept the questionnaire reasonably short (less than 30 min to fill in), to avoid the risk of a very low response rate. This was achieved through a mix of closed- and open-ended questions, enabling respondents to describe in detail their views if they so wished. The questionnaire could be filled in anonymously, and individual answers were confidential.

Due to the relatively small size of the sample, we decided to enhance the reliability of our results by conducting interviews to validate our findings. We interviewed one shipper, one freight forwarder, and one carrier. We found a good convergence between the information collected from the questionnaire and the interviews. The following section presents the results produced by both the questionnaire and the interviews.

5.4 Results

5.4.1 The Sample

The main challenge of every survey lies in obtaining a good-sized representative sample that can provide a broad picture of the target population, in this case, the Clean Cargo membership. As of 6 May 2020, the Clean Cargo membership comprised 80 companies. Among them, our questionnaire targeted a total number of 68 companies, representing all three segments (carriers, shippers, and freight forwarders). The 12 remaining companies—car carriers, subsidiaries of carrier companies not reporting to Clean Cargo, or 'Less than Container Load' freight forwarders which have limited access to the Clean

Cargo data—do not use the reporting framework. Consequently, they were excluded from the present study.

We collected 34 responses, representing 50% of the targeted companies. Nine carriers, 13 shippers, and 12 freight forwarders answered. All answers entered the analysis, although some of them were incomplete. Table 5.3 shows the composition of complete responses by segment. The resulting sample of complete responses (19 out of 68) is more than adequate, as is the representation of the segments where complete responses correspond to 41%, 23%, and 24% of the carriers, shippers, and forwarders, respectively. Sample composition in terms of total responses is more balanced with response rates of 53%, 50%, and 48%, respectively.

Table 5.3: Number of responses to the questionnaire by segment and level of completeness.

Segment	Members	Total Responses	Complete
Carriers	17	9	7
Shippers	26	13	6
Freight forwarders	25	12	6
Total Clean Cargo	68	34	19

Table 5.4 shows the respondent profiles within their affiliated companies. Most respondents work for the Sustainability department of their organization, followed by the Logistics department in the case of shippers. However, the second most popular origin for freight forwarders is the Procurement department, indicating perhaps the prominent use of the Clean Cargo data in procuring transport services.

Table 5.4: Profiles of respondents (33 responses).

Profiles	Carriers	Shippers	Freight Forwarders	Clean Cargo Membership
Sustainability	8	6	8	**22**
Logistics	0	6	1	**7**
Procurement	0	0	2	**2**
Other	0	1	1	**2**

The following two subsections present the responses to the questionnaire. The first one concerns the current reporting mechanism and investigates the motivation of the companies for participating in the Clean Cargo scheme, the data used, and the effort required by the carriers to produce these data. The second subsection deals with future reporting needs and concentrates on requirements imposed either by emission tracking or by external forces.

5.4.2 Current Clean Cargo Reporting Framework

5.4.2.1 Reasons for Using a Private Reporting Framework

Carriers identify shippers and freight forwarders as the main audience of their emission reporting and expect them to use the reports for informing their own clientele and for selecting service providers. They also use the produced output internally to evaluate their own performance and to support their policy deliberations. About half of the responding carriers use Clean Cargo data to fulfill regulatory reporting obligations and to support rebate applications with port authorities and terminal operators. Less frequently, carriers also communicate Clean Cargo data to investors and suppliers. Most carriers (5 out of 7) perceive their environmental performance (especially in terms of GHG emission abatement) as an important contributor to their competitiveness and, thus, as a strategic objective. Consequently, Clean Cargo reporting is viewed as a useful tool.

This result is in line with the responses from the shippers and freight forwarders, who mainly use Clean Cargo data to estimate their own emissions and to reach transport procurement decisions. Internally, shippers mainly use the carriers' emissions to monitor their progress towards decarbonization, to reduce their Scope 3[1]. Freight forwarders also use Clean Cargo data to provide carbon reports to their customers, namely the shippers. The audience of the shippers' and forwarders' emission reporting is mainly internal stakeholders, end customers, and investors.

Although carriers' emissions are often stated as an input in procurement decisions, Figure 5.2 shows that environmental performance is not a priority when

[1]The GHG Protocol categorizes GHG emissions in three scopes: Scope 1 covers direct emissions from owned or controlled sources, Scope 2 covers indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company, and Scope 3 includes all other indirect emissions that occur in a company's value chain (Carbon Trust, 2020) emissions, and to help set up their own strategy (only one shipper does not report their Scope 3 emissions.

selecting carriers (the vertical scale of the graph reflects the inverted average rank of each criterion with 1 being the first priority and 8 the last one). Price remains by far the main driver for selecting the service provider. The second most important criterion is delivery time for the shippers and frequency of service for the freight forwarders. It is worth noting that freight forwarders do not often make the call themselves, as the carrier is selected directly by the shipper.

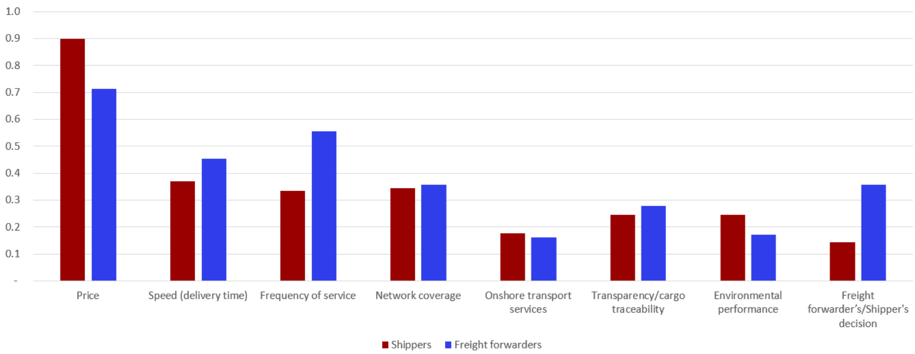

Figure 5.2: Carrier selection criteria.

5.4.2.2 Type of Data Used by Different Stakeholder Groups

The questions regarding which Clean Cargo data and outputs the different stakeholders' use were divided into two categories: the environmental attributes (GHG, SO_X, NO_X, EMS, transparency) and the outputs, which include the carrier scores, their trade lane and fleet emissions and their year-over-year performance. Regarding the first category, as shown in Figure 5.3, the most important element for all stakeholders is GHG emissions. The second most important element identified by all stakeholders is transparency, reflecting the corresponding demand of society. Carriers ranked NO_X as the least important attribute, after SO_X and EMS. It should be noted that NO_X emissions IMO (2014), and, since 2020, SO_X emissions IMO (2018) are regulated, representing a reduced strategic challenge for carriers. Similarly, the least importance was given to NO_X and SO_X emissions and EMS by shippers and freight forwarders.

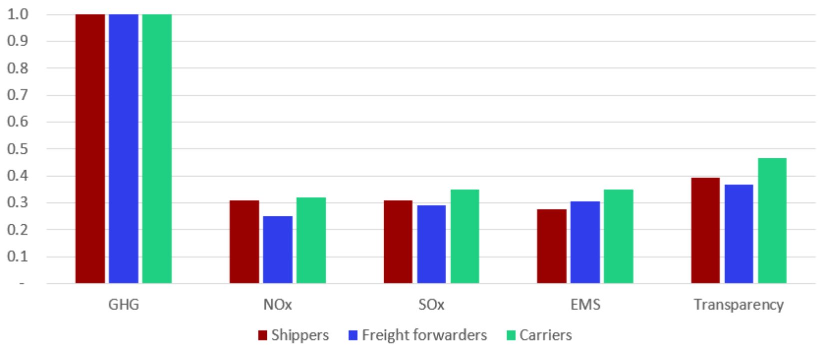

Figure 5.3: Clean Cargo environmental attributes within members' environmental strategy.

In terms of outputs, both shippers and freight forwarders consider the carrier trade lane emissions to be the most useful information (refer to Figure 5.4, where usefulness is measured on a Likert scale from 0 (never use it) to 1 (very useful)). This was expected, as most of them use Clean Cargo data to estimate their own emissions. For the same reason, both these stakeholder groups consider the year-over-year performance as the second most useful output. Shippers view the carrier fleet emissions as equally useful, ahead of carrier scores, transparency, and the environmental performance survey.

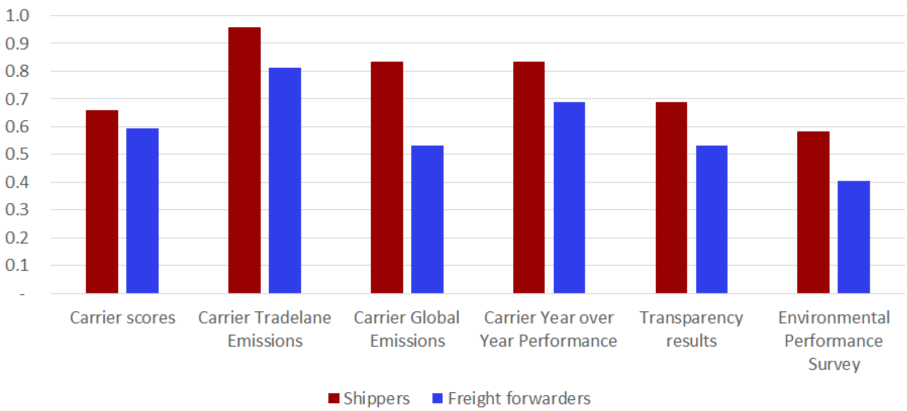

Figure 5.4: Usefulness of Clean Cargo outputs for shippers and freight forwarders.

The most useful output for the carriers is the GHG Dry emissions at both the fleet and trade lane levels, followed by GHG Reefer emissions, year-over-year performance, and SO_X emissions. More than half of the carriers use Clean Cargo scores, while none of the respondents use NO_X and EMS results.

5.4.2.3 Reporting Effort of Carriers

The data collection process can be time- and resource-consuming for both carriers and BSR staff. Nevertheless, most carriers of the sample state that their environmental reporting generally goes beyond the requirements imposed by the Clean Cargo reporting framework. This is due to internal reporting needs and requirements related to regulations and other voluntary schemes.

5.4.3 Future Reporting Framework

5.4.3.1 Emission Tracking

It is generally acknowledged that the metrics currently used for tracking emissions are insufficient to address the challenges generated by the ever-increasing societal pressure for decarbonization. However, no consensus on the metric to be used internally by the carriers emerged from the questionnaire. Most carriers agree that the actual emissions per transport work is what is mainly needed for their communication with customers (shippers and forwarders).

Indeed, in order to improve their internal reporting of maritime emissions, shippers expressed a need for GHG (CO_2 equivalent) absolute emissions on a WTW basis, more comprehensive data on trade lane and vessel level, and also information on air pollutant emissions (SO_X and NO_X). Freight forwarders expressed similar needs, with a great interest in GHG emissions by shipment ($g_{CO_2e}/t \cdot km$). Requests have also been reported for emissions per transport work ($g_{CO_2e}/TEU \cdot km$) on a per vessel, per ship type, per port pair, and on a per alliance basis.

5.4.3.2 *External Environment*

While shippers assess the impact of the maritime regulatory framework on their business as being moderate, freight forwarders state that the regulatory framework can affect their everyday business significantly. Consequently, freight forwarders follow developments in the regulatory environment closely, as opportunities for introducing new services to their clientele might emerge. Approximately half of both shippers and freight forwarders include the IMO targets in their environmental strategy. Some shippers declare having more ambitious targets at the company level than those of IMO 2050.

Figures 5.5 and 5.6 present the popularity of measures that carriers and shippers/forwarders, respectively, implement to reduce their environmental impacts (the vertical axis indicates the number of respondents who have selected each measure). Optimization of routes and port calls by the carriers, and optimization of container content by the shippers/forwarders are the most popular measures, as they also have a bearing on the financial profitability of the companies involved. More than half of the responding carriers implement slow steaming, engine downsizing, and alternative fuels, including LNG and biofuels, in relation to carbon emission reduction. Ballast water management, waste management, and ship recycling are also high on the carriers' agenda. The limited popularity of lower speeds among the shippers/forwarders in contrast to the views of the carriers is worth noting.

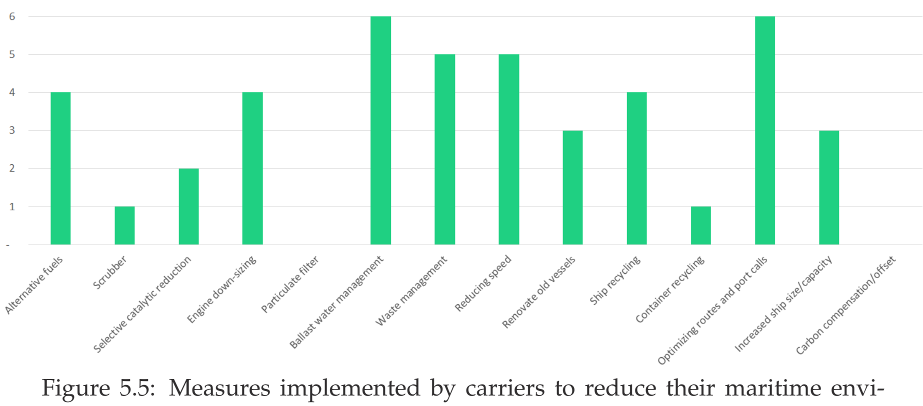

Figure 5.5: Measures implemented by carriers to reduce their maritime environmental impacts.

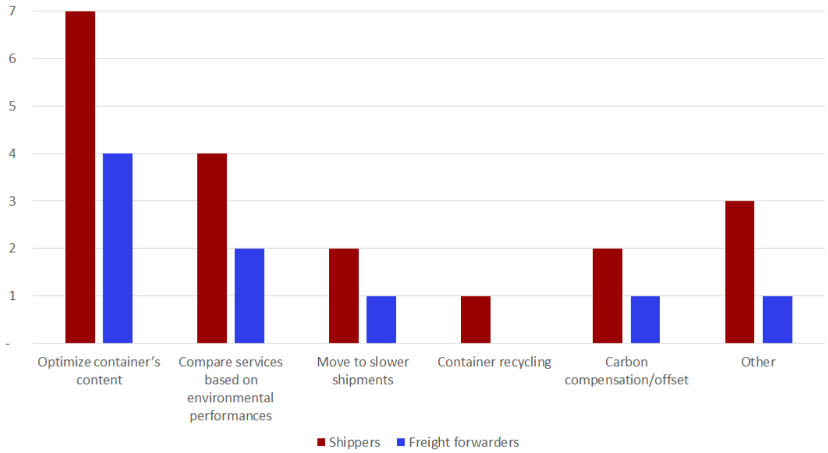

Figure 5.6: Measures implemented by shippers and freight forwarders to reduce their maritime environmental impacts.

5.5 Main Findings

The analysis of the responses received and the subsequent interviews with Clean Cargo members led to the following main findings:

- GHG emissions are at the core of the members' interests across all segments;
- Absolute GHG emissions per shipment constitutes a main request of shippers and freight forwarders;
- The way data are used by shippers and freight forwarders is not always harmonized and can lead to discrepancies;
- The reporting effort of carriers is quite substantial and needs to be considered when modifying the reporting framework;
- Several members are investing in alternative fuels to decarbonize their transport operations, posing a number of questions in relation to the Clean Cargo reporting;
- Although many shippers and freight forwarders have set Scope 3 targets, very few have a specific maritime reduction target.

5.5.1 Improving Clean Cargo Data and Its Use

GHG emissions are by far, and across all segments, the main concern of Clean Cargo members in terms of environmental impact. This aligns with the IMO 2050 targets on CO_2 emissions reduction and the need for decarbonizing the sector. Tang and Gekara analyzed the CSR report of 15 carriers and also concluded that the CO_2 emissions, along with the energy and fuel efficiency, were the top priorities for these companies (Tang and Gekara, 2020). Other environmental impacts, such as SO_X and NO_X emissions or waste, water, and chemicals management, generally garner less interest. Carriers do not use NO_X and EMS, which are also of lower priority for shippers and freight forwarders. These matters are handled more effectively by the IMO and are, thus, of a less strategic nature for the members.

Shippers, and thereby freight forwarders, often need to obtain the absolute emissions per ship to improve the granularity and accuracy of their maritime emissions reporting. Indeed, several of them would like to have the absolute emissions per shipment, expressed in $g_{CO_2e}/t \cdot km$, in order to be compatible with reporting emissions from other sources and transport modes.

Data use by shippers and freight forwarders needs to be harmonized. Weaknesses exist within the calculation of own maritime emissions by the shippers/forwarders, which uses the carriers' trade lane emissions as input. For example, the distance calculated by the users varies depending on the system used and does not always reflect the real distance sailed by carriers. A 15% distance detour factor is currently recommended by Clean Cargo to fix this problem.

Carriers spend hours collecting their vessels' data and reporting it under the Clean Cargo framework, involving several persons in their company, including crew members. Some data points are more challenging to collect, such as the sulfur content of fuels and the characteristics and operational data of the chartered vessels. These challenges need to be reconsidered in view of the recent changes in reporting requirements imposed by the regulatory framework and industry standards.

5.5.2 Driving Container Ship Decarbonization across the Membership

Several members are already investing in alternative fuels, such as LNG and biofuels. This raises questions concerning the integration of alternative fuels into Clean Cargo reporting, particularly in relation to upstream emissions and the applicability of the life cycle approach. The varying emission factors of the literature create further compatibility problems when integrated into the Clean Cargo reporting system. In fact, the matter has not been resolved scientifically and it is still being discussed at IMO.

Shippers appear as the segment that set the most ambitious decarbonization targets through their Scope 3 emissions. In fact, some shippers even consider the IMO targets to be very modest and have established their own more ambitious targets. This is not surprising since they comprise consumer-facing companies with relatively high reputation risks, while the decarbonization effort mainly has to be undertaken by a third party (carriers or ship owners). It is worth noting that the Clean Cargo initiative is dedicated to the environmental performance improvement of the marine container transport segment specifically, leaving little room for measurement, evaluation, and reporting of out-of-segment emissions.

The question that remains to be answered is whether the shippers and forwarders are in a position to incentivize the reduction of air emissions from container ships. Poulsen et al. (2021) argue that the power relations between actors in the global value chains have a decisive impact on the environmental footprint of shipping. In relation to the tanker shipping that they studied, they suggest directing attention to the powerful cargo owners. Unlike the tanker industry, however, the clientele of container shipping is much more dispersed as this part of the industry carries mainly semi-finished and finished products in break bulk form. Carriers constitute the most powerful actor here as the 10 largest companies control 84.5% of the world fleet (Alphaliner, 2020). As shown in Figure 5.2, the environmental performance of the carriers plays a rather secondary role in the procurement decisions of shippers and forwarders, which are still driven by price and reliability (Linder, 2018; Poulsen et al., 2016; Wuisan et al., 2012). The dominant role of carriers in reducing emissions is also confirmed by their active involvement in all major regulatory fora, including IMO and the EU.

Furthermore, it is worth noting that carriers already offer specialized emission calculators to their customers. Although this development addresses a real market need, the lack of standardization impedes compatibility and hinders benchmarking. A private initiative, such as Clean Cargo, can harmonize the methods deployed and allow shippers to select the most attractive service.

5.6 Discussion

5.6.1 Recommendations Based on the Main Findings

Several recommendations can be made based on the findings presented earlier. Although these recommendations are focused on the Clean Cargo framework, they can be adapted to serve other voluntary initiatives as well.

Firstly, carriers have recently started reporting fuel consumption and CO_2 emissions under the existing regulatory frameworks (EU MRV and IMO DCS). Differences exist between Clean Cargo and these schemes in terms of both aims and responsibilities. Clean Cargo aims to make GHG emissions transparent to shippers and freight forwarders. IMO DCS enables IMO to monitor progress on CO_2 savings, while EU MRV serves as the basis for the Emission Trading Scheme of the European Commission. In terms of responsibilities, the ship operator (carrier) undertakes to report for the Clean Cargo framework, while responsibility goes to the ship owner for the EU MRV and the document of compliance (DOC) holder for the IMO DCS. As such, a charter vessel owner will focus on the regulatory schemes but have no interest in private standards, while a pure operator, who does not own any vessels, concentrates on private standards and has no formal legal obligations to report emissions.

Several data items collected by these schemes are identical. An alignment of the data format required by the Clean Cargo reporting framework to IMO DCS and EU MRV could facilitate and harmonize reporting. As Poulsen et al. (2016) argue, environmental upgrading in shipping is not likely to materialize without clear and enforceable global regulation and stronger alignment between regulation and voluntary sustainability initiatives (Poulsen et al., 2016). For the metrics other than CO_2 that are less popular, new considerations should be made to investigate how members, especially shippers and freight forwarders, consider these environmental impacts in view of the regulations in force. Decisions can then be made after comparing costs with benefits.

Secondly, the absolute emissions of GHG per shipment should be examined as a new metric, in line with the requests put forward by several shippers and freight forwarders. In addition to the complications created by the nature of the cargo (volume- or weight-intensive), this would require reporting the exact weight of the cargo and working out a detailed emission allocation mechanism that takes into consideration the repositioning of containers. Such a scheme would be the equivalent of the recently published Sea Cargo Charter for the dry and liquid bulk sector (Sea Cargo Charter, 2020). Of course, such a scheme would be very demanding on the side of the carriers and the group should assess the benefits of more accurate reporting against the costs of producing these reports. In case this suggestion proves too ambitious, carriers could report emissions per voyage along with the request of some members who have already been pushing for adopting service-level reporting.

The final recommendation relates to the potential role of voluntary initiatives in driving the demand for greener services. While ambitious regulation for GHG emission abatement can take years to be negotiated and adopted, voluntary schemes such as Clean Cargo have the potential to speed up the decarbonization process by proposing standards accepted by all actors of the global value chain.

5.6.2 Limitations and Further Research

The presented work is not without limitations:

- The response rate for the questionnaire was about 50%, and some of these responses were only partially complete;
- The questionnaire was designed to raise a broad scope of issues concerning the environmental reporting of Clean Cargo, and a relatively large number of questions were asked. To reduce the time required for answering these questions, many of the questions were designed in a

multiple-choice format. Although the possibility of commenting on an answer was offered, the risk that the answers are not fully described cannot be ruled out;
- The responses received from freight forwarders were generally less elaborated than the rest, making some results difficult to interpret.

Although an effort was made to tackle these limitations by interviewing selected members following the survey, this research could benefit from having the feedback of all members, maybe in a more formalized setting. Furthermore, decisions on the metrics used by the future reporting framework can be greatly supported by assessing the benefits to be generated against the costs of production for various possible levels of detail and accuracy. The matter requires a great deal of coordination among members as it is a clear split incentive case; the party receiving the benefits (shippers/forwarders) is not the one bearing the costs (carriers).

5.7 Conclusions

The paper identifies and discusses the expectations and needs of the industrial stakeholders that participate in the Clean Cargo initiative in relation to the voluntary disclosure of environmental information. A questionnaire, supported by interviews, gathered the perspectives of Clean Cargo members on the design and integration of the future reporting framework. GHG emissions constitute the primary interest of the members, with the absolute GHG emissions per shipment being the ultimate desire of shippers and freight forwarders. Voluntary schemes such as Clean Cargo have the potential to speed up the decarbonization process by proposing standards accepted by all actors of the global value chain. Alternative fuels entering the market need to be integrated into the reporting framework, following a comprehensive analysis of their emission factors and their role in the decarbonization pathway.

The integration of these elements would greatly improve the added value of the future Clean Cargo reporting framework, particularly following the introduction of the mandatory reporting schemes of IMO and the EU. The level of ambition of this future framework depends on the balance reached between the demands of the shippers/forwarders and the required efforts by the carriers to collect and process the necessary data. In this respect, the reporting of emissions per service rather than per shipment can be a compromise worth considering. We hope that our findings and recommendations will contribute to strengthening the role of the voluntary schemes in meeting the IMO 2050 targets.

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