A data-driven digital twin framework to support early-stage ship design

A case study on data-driven engine configuration selection integrating operational data

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Summary

Keywords: Digital twin, data-driven design, engine configuration, bunker delivery notes, rule-based modeling

The shipping industry faces increasing pressure to reduce greenhouse gas emissions in line with international regulations set by the International Maritime Organization (IMO). Traditional ship design methods, however, rely primarily on static assumptions and generalized performance estimates, offering limited support for sustainable design decisions. At the same time, the industry is generating vast amounts of operational data that remain underutilized in early-stage design.

This thesis addresses this gap by developing a Digital Twin (DT)-aided framework for ship design, with the specific aim of integrating operational data into decision-making. The framework outlines the process of data acquisition, modeling, verification, and knowledge management, ensuring that real-world operational insights can inform and improve early design phases.

To demonstrate the framework, a case study is conducted on the optimization of engine room configurations for a bulk carrier. Engine data from industrial databases and operational profiles derived from Bunker Delivery Notes (BDN) are combined to construct a digital model of the vessel's propulsion system. A rule-based modeling approach is applied to generate feasible configurations, which are then evaluated for fuel consumption and CO_2 emissions across multiple load profiles.

The case study highlights both the potential and the limitations of DT-aided design in current practice. While the adapted framework produces a digital model rather than a fully validated digital twin, the results demonstrate that operational data can substantially improve configuration selection and support IMO decarbonization goals. The methodology also provides a scalable foundation for future research, extending towards hybrid propulsion systems, alternative fuels, and full DT integration.

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Contents

Nomenclature

Abbreviations

Abbreviation	Definition
ANN	Artificial Neural Network
AI	Artificial Intelligence
BDN	Bunker Delivery Note
CAD	Computer-aided design
CCS	Carbon Capture Storage
CII	Carbon Intensity Indicator
CO_2	Carbon Dioxide
DC	Direct Current
DCF	Direct Conversion Factor
DNN	Deep Neural Network
DT	Digital Twin
DWT	Deadweight Tonnage
ECA	Emission Control Area
EEDI	Energy Efficiency Design Index
EEXI	Energy Efficiency Existing Ship Index
EF	Emission Factor
EGR	Exhaust Gas Recirculation System
EV	Electric Vehicle
FPP	Fixed Pitch Propeller
GHG	Greenhouse Gas
HFO	Heavy Fuel Oil
ICE	Internal Combustion Engine
IMO	International Maritime Organization
ISA	International Standard Atmosphere
KPI	Key Performance Indicator
LNG	Liquefied Natural Gas
LFO	Light Fuel Oil
MDO	Marine Diesel Oil
NO_x	Nitrogen Oxides
PLM	Product Lifecycle Managment
RFID	Radio Frequency Identification Device
SCR	Selective Catalytic Reduction
SDGs	Sustainable Development Goals
SEEMP	Ship Energy Efficiency Management Plan
SFOC	Specific Fuel Oil Consumption
SO_x	Sulfur Oxides
UN	United Nations

Symbols

Symbol	Definition	Unit
a, c	Constants in CII reference function	[-]
C_F	Carbon conversion factor	[gCO_2/g fuel]

Symbol	Definition	Unit
D_{year}	Annual transport work distance	[nm]
DWT	Deadweight Tonnage	[t]
EF	Emission Factor	[tCO_2/t fuel]
MCR	Maximum Continuous Rating	[kW]
M_j	Emissions from other energy sources	[tCO_2]
P	Power (engine)	[kW]
P_{load}	Engine power at load	[kW]
$SFOC$	Specific Fuel Oil Consumption	[g/kWh]
SFC_{actual}	Load-adjusted SFOC	[g/kWh]
$SMCR$	Service Maximum Continuous Rating	[kW]
V	Velocity	[m/s]
V_{ref}	Reference speed at design load	[knots or m/s]
Δt	Time interval	[h]
η	Efficiency (thermal or system)	[-]
ρ	Density	[kg/m^3]
ζ	Reduction factor (CII context)	[-]

1 Introduction

1.1. Research Background

The European Union has set an ambitious goal to achieve climate neutrality by 2050, aiming to eliminate 100% of its carbon emissions, with an interim target of a 55% reduction by 2030 [1]. In 2018, the shipping industry was responsible for approximately 13% of all transport emissions within the EU [2]. To address this, the International Maritime Organization (IMO), the UN's specialized agency with responsibility for the safety and security of shipping and the prevention of marine and atmospheric pollution by ships, has introduced new initiatives to drive the maritime sector toward adopting sustainable practices. These measures are designed to facilitate the industry's transition to low-carbon operations, paving the way for a greener and more environmentally friendly future for the shipping sector.

The shipping industry is one of the largest consumers of fossil fuels and, consequently, a significant contributor to global air pollution. There are estimates that the shipping industry consumes approximately 330 million tons of fuel annually [3]. The most common fuel used by cargo vessels currently is Heavy fuel oil (HFO), which is obtained from the residue left after oil refining. This type of fuel contains high levels of sulfur and, during combustion, contributes directly to the emission of sulfur oxide(s) (SO_x). Burning this fuel also releases Nitrogen oxides (NO_x) emissions into the atmosphere. It is likely that the demand for marine fuel will double by 2030, further increasing air pollution [4, 5].

To mitigate the amount of harmful exhaust gas emissions, the IMO has devised rules that existing and new vessels have to adhere to. These rules intend to regulate and prevent pollution from ships [6, 7]. The first strategy, Annex VI of the MARPOL Convention (International Convention for the Prevention of Pollution from Ships), adopted in 1997, already aimed to limit air pollution from ships. This was the first step for a more comprehensive strategy of reducing emissions of the worldwide fleet (Figure 1.1).

Through the convention, a more comprehensive framework for ship design and management was established [8]. A few regulations are discussed in the framework: the Energy Efficiency Design Index (EEDI), the Energy Efficiency Existing Ship Index (EEXI), the Ship Energy Efficiency Management Plan (SEEMP), and the Carbon Intensity Indicator (CII).

They all prevent and fix some limitations to the air-polluting emissions of marine vessels. However, these regulations alone are insufficient. A fundamental shift in fuel sources and propulsion technologies is required [9].

1.1.1. Recent technological developments

Recent advances in alternative marine fuels are accelerating the shift toward greener propulsion technologies in response to international decarbonization goals. Promising candidates include methanol, biodiesel, ammonia, hydrogen, and liquified natural gas (LNG), each offering varying degrees of energy density, infrastructure readiness, and emission reduction potential [6, 10, 11]. Fuels such as biodiesel and LNG have already seen partial integration into existing ship operations, while others like ammonia and hydrogen offer zero-carbon possibilities if produced from renewable sources. Their feasibility

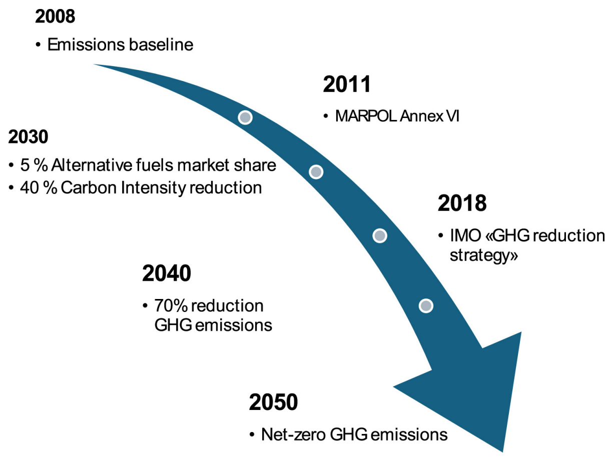

Figure 1.1: IMO initiatives for ship emissions reduction

depends not only on energy content and emissions but also on compatibility with propulsion systems.

The adoption of hybrid-electric engines for marine vessels as a propulsion and auxiliary power source is another approach to reducing harmful emissions by lowering fuel consumption. To determine the most effective way of configuring a hybrid-electric engine, the power generation and power storage systems need to be analyzed. As sustainability is the primary reason for the switch to hybrid energy sources, the literature generally focuses on batteries, supercapacitors, and flywheels as electric storage, in combination with ICEs and fuel cells as the energy converters [12, 13, 14]. The use of a multi-source energy system will also improve the possibility of optimization, further improving power generation. Already, by only including a diesel-battery hybrid propulsion system, 2-3% reduction in fuel consumption and 5-7% CO_2 and NO_x can be reached, increasing the efficiency of the system [15]. However, using alternative fuels and power sources will increase the system's costs, but the higher efficiency that is attainable should be explored to assess its potential. As sea-going vessels have to operate in changing conditions due to waves and wind constantly, the speed of the vessel and power requirements vary continually. This results in the primary propulsion system not operating at its optimum point, leading to an increase in specific fuel oil consumption (SFOC). These innovations come at a critical time, as the maritime sector must transition to greener practices of operating and producing marine vessels to reduce environmental impact.

1.1.2. Operational data

Data and its analysis have become the center of modern science and business [16]. There is an abundance of data that is produced by every industry, including the marine industry. Operational data, such as ship speed, location, and fuel consumption, is collected every minute. Along with this data, there is also the data outside of the ship, such as business data, like fees and ship demands, or production and lifetime data. The Automatic Identification System (AIS) has been in use since 2002. But besides that, with new sensor technology and the option to store so much more data, there is much more possible. This shipping information serves industry-specific purposes for a better understanding of the port and the sector itself. The increasing capacity to measure and analyze vast amounts of data helps quantify performance and cost issues in both port operations and marine vessel operations [17]. This data can be found in multiple forms, from operational data to ship databases and other voyage data. Currently, this data is primarily used for the purpose it was collected. For example, Bunker delivery notes are only used to measure the environmental impact of an individual ship. Such a variety of data shouldn't be used to serve one purpose; there is much more potential [18]. To overcome this hurdle, new research is needed on innovations related to the digitalization of the shipping industry and the utilization of the vast amount of ship data. Digitalization refers to the use of digital technologies to optimize ship design, ship operation, and business processes [19].

Measurements from on-board monitoring are widely used in performance analysis and the study of ship efficiency. New studies have also started to predict vessel propulsion power and energy consumption [20]. This type of monitoring can also be applied in the health monitoring of equipment using either vibration analysis or machine learning techniques [21, 22]. Most data-driven techniques applied are pattern recognition methodologies for classifying load profiles of electric ships [23, 24].

The transition to greener and retrofitted ships requires a gradual yet accelerated approach, supported by an efficient production and design cycle. Improving the production cycle, and thereby decarbonizing the industry, can be achieved through several methods.

With more data, more accurate decision-making can be achieved through the use of multiple methods. When discussing data, the term Industry 4.0 is often mentioned in conjunction with it. This new '4th industrial revolution' represents a shift toward more intelligent, automated, and interconnected systems driven by real-time data, artificial intelligence (AI), and the internet of things (IoT) [25, 26]. Due to the data explosion, an extensive examination of the impact on design practices is required.

1.1.3. Innovative design strategies

Traditional ship design methods rely heavily on fixed assumptions about vessel performance, fuel consumption, and operational profiles. While such approaches provide structured procedures, they often struggle to capture the variability and complexity of real-world operations. The growing availability of high-frequency operational data opens new opportunities to address this gap by informing early-stage design decisions with empirical evidence [27].

This shift is part of a broader movement toward data-driven design, in which actual operational conditions guide the evaluation of technical options and trade-offs [28]. One promising concept in this domain is the Digital Twin (DT), which establishes a dynamic connection between a physical object and its virtual counterpart. While DTs are currently most mature in the operational phase of a vessel's lifecycle—supporting tasks such as performance monitoring, predictive maintenance, and emissions tracking—the underlying principles demonstrate the potential of utilizing real-world data to enhance design robustness.

For early-stage ship design, adopting data-driven approaches inspired by DT principles could provide a structured way to link operational realities with early-stage design choices. By integrating empirical data into design frameworks, it becomes possible to move beyond static assumptions and explore solutions that are better aligned with decarbonization targets and evolving regulatory requirements. The need to connect operational insights with design practice forms the foundation of the problem addressed in this thesis.

Despite its potential, the use of operational data in data-driven ship design remains limited [29]. Further research is therefore needed to establish how such data can be systematically integrated into design methodologies before it can be applied in practice.

1.2. Problem definition

The shipping industry is a major contributor to global greenhouse gas emissions due to its reliance on fossil fuels, primarily Heavy Fuel Oil (HFO). Despite international regulations aimed at reducing emissions, the transition to sustainable propulsion technologies remains a slow process. A key challenge in this transition is the lack of an efficient framework for early-stage design using operational data, specifically in optimizing performance and emissions.

Current decision-making processes in ship design rely heavily on generalized estimations and static regulations, rather than data-driven insights tailored to the abundance of data that is slowly becoming available, like specific operational profiles.

This thesis addresses the gap between regulatory goals and practical implementation by exploring how operational data can be integrated into early-stage ship design. While operational data is increasingly available, its use in informing design decisions—such as propulsion selection and system configuration—remains underdeveloped. Bridging this gap requires methods that can translate real-world operational insights into design strategies, supporting the industry's transition toward more efficient and sustainable ships.

1.3. Research goal and objectives

This research aims to **develop a data-driven design framework that utilizes operational data to support the early-stage decision-making process in ship design.** The objectives of the thesis are as follows:

- Analyze data-driven design methods according to traditional ship design
- Determine how ship design can be improved according to IMO standards and indexes
- Develop a data-driven design framework that incorporates real-world operational data
- Use the data-driven design framework in a case study, optimizing ship performance factors
- Verify the data-driven model using operational data

1.4. Scope of the research

This thesis focuses specifically on the design of large marine bulk carriers. The product is a data-driven design framework designed to enhance early-stage design decisions. The framework will be applied to engine configuration selection, with the possibility of expanding to include additional propulsion systems that may be introduced in the future. The study will consider both conventional internal combustion engines (ICE) and possible hybrid-electric systems. It will not cover detailed hydrodynamic analyses of ship hulls or a possible real-world implementation of propulsion system retrofits. The research primarily relies on the operational and emissions data from bulk carriers, simple expandable simulation modeling of propulsion systems, and the IMO regulations.

1.5. Research questions

The main research question this thesis wishes to answer is,

> **How can operational data be integrated into a data-driven design framework to support early-stage ship design?**

To answer this central research question, the question is split up into sub-questions to answer the central question:

RQ1: What is the potential of operational data to support current design methods?

RQ2: What data-driven methods can be used to improve early-stage ship design?

RQ3: How can an organized data-driven design method be applied to early-stage ship design?

RQ4: How can the data-driven framework be applied to the early-stage design to improve fuel consumption and emissions?

RQ5: To what extent can the data-driven design approach inform early-stage ship design decisions?

1.6. Methodology

This thesis employs a quantitative, data-driven methodology to investigate how operational data can inform early-stage ship design. The study first examines the principles of traditional ship design alongside recent trends in data-driven methods, with a particular focus on integrating alternative propulsion systems and fuels.

Building on this foundation, digital twin (DT) technology is evaluated as a potential means of incorporating operational data into design practices. To support this, a dedicated DT-aided framework is developed, structured to integrate both component-level characteristics and operational datasets.

The framework is applied in a case study focused on optimizing engine configuration. Using real operational data, multiple load profiles are generated and applied to simulate alternative engine configurations. For each configuration, fuel consumption and emissions are quantified, and the results are validated against the same operational dataset. This case study demonstrates the potential of the framework to enhance decision-making in early-stage ship design.

1.7. Structure

Chapter 2 will discuss the ship design process and the research gap concerning the use of operational data in design. Following this will be a discussion on the state-of-the-art of data-driven design, followed by a review of the state-of-the-art of propulsion systems. The possible options and configurations will then be explored. Chapter 3 examines how a data-driven design approach can enhance the ship design process by utilizing operational data and establishes the requirements for implementation. In Chapter 4, a framework is established for implementing a data-driven design method that integrates operational data. In Chapter 5, the data-driven design framework is employed and applied to optimize performance in a case study of a bunker vessel engine room. Chapter 6 will present the results of the model. Chapter 7 will conclude the thesis and give answers to the research questions. Chapter 8 will discuss the results and possible improvements of the implementation and of the framework.

2

Ship design phase and ship design developments

This chapter reviews both traditional ship design methods and the current state of data-driven approaches, with a particular focus on opportunities for improving efficiency and reducing emissions. Section 2.1 introduces the conventional ship design process, while Section 2.2 discusses the potential of data-driven methods in the maritime sector. The regulatory context is outlined in Section 2.3, which surveys the requirements set by the International Maritime Organization (IMO). Section 2.4 examines optimization within traditional propulsion systems, followed by Section 2.5, which considers alternative engine topologies. Finally, Section 2.6 identifies the research gap and defines the scope of this thesis.

2.1. General ship design

Every product designed follows the same production cycle. For ship design, this is the same. According to Gale, the ship design cycle is as follows [30]:

- Conceptual design
- Preliminary design
- Contract design
- Detailed design

These design phases (Figure 2.1) are based on ship design theories from the 80s; during these phases, only new ships are considered. The coming section will discuss the different stages of the design process.

Figure 2.1: Ship design process as described by Gale [30]

2.1.1. Conceptual & preliminary design

These phases are often considered the feasibility study stage. The primary objective is to clarify the shipowner's requirements, including the vessel's expected performance and intended missions. Key factors such as cargo and passenger capacity, range, speed, and other operational requirements guide the definition of the initial design concepts [30, 31]. These initial concepts will not necessarily include the power needed for the ship to operate. After these first concepts are explored and their feasibility regarding the primary ship requirements has been studied, the design process seamlessly flows into the preliminary design phase.

The next part in basic design (which consists of the conceptual and preliminary design) happens during the preliminary design stage. The objectives during this phase are [30]:

- validate the primary ship performance and requirements,
- establish ship size and overall configuration,
- select the major ship systems,
- quantify the ship performance,
- estimate costs.

During this stage, the various ship design steps previously completed in the first phase are further elaborated upon in greater detail. The ship's main characteristics are more accurately determined and aligned with the client's requirements. The client's feedback will then refine the design and incorporate any necessary modifications and adjustments. The preliminary design has been finalized as the basis for compiling the shipbuilding contract between the client and the shipbuilder. The design must conform to regulatory standards and serve as the basis for the contract design [31].

This thesis aims to support the early-stage design phase by leveraging new advancements in the industry. With the early-stage design phase, specifically the conceptual design phase is meant. This early-stage phase is crucial in determining the ship's sizing and initial component designs, laying the groundwork for its power and emissions characteristics. This first step will guide the selection of components and the overall design in the subsequent steps.

2.1.2. Contract design

The principal objectives of the contract design are to: [30, 32]

- confirm the ship capabilities and the cost with the shipowner,
- captures all technical, commercial, and legal aspects in agreement with the shipowner,
- provides criteria for the shipowner to accept the ship.

This phase is completed with the completion of the necessary calculations and naval architectural drawings, along with the technical specifications drawings. The phase includes a detailed description of the ship's hull form through the ship line plan and an exact estimation of the power required for the specified speed based on model tests in a tow tank, as well as the theoretical or experimental analysis of the ship's behavior [31].

2.1.3. Detail design

In the final phase, the contract design is translated into a detailed design of all structural elements of the ship, along with the establishment of technical specifications for ship construction and the installation of equipment. This information is then given to the shipyard. The subsequent implementation, following the outcomes of studies by expert naval and marine engineers, depends solely on the capabilities of the shipyard's production engineers, in terms of hardware infrastructure and human resources [31].

2.1.4. From traditional design to data integration in design

This thesis aims to address the limitations of traditional design by incorporating operational data into the early-stage design phase (conceptual design). By integrating real-world performance insights at this stage, it becomes possible to estimate propulsion and emission characteristics better, thereby guiding engine room design choices with greater accuracy.

In doing so, the research aims to enhance decision-making processes in early design, resulting in ships that are both operationally efficient and environmentally sustainable. The following section will explore how data-driven design methods offer opportunities to realize this integration.

2.2. Data-driven ship design

There are multiple ways in which data can enhance the design method of ships. This section will describe the potential of operational data. With the digitalization of the industry, several data-driven methods utilizing operational data have emerged, and their respective strengths, weaknesses, and uses will be examined.

2.2.1. Requirements for Data-driven implementation

To implement a well-defined, data-driven approach, certain prerequisites should be explored. Anderson has defined them as, [33]:

- Data Collection
- Data Quality
- Data Access
- Data Analysis

For the shipping industry, this means the following [34].

Data Collection: Refers to all relevant data that can be gathered across the maritime sector, including from ship designers, suppliers, testers, operators, and ports.
Data Quality: Is related to the reliability of the data. This can be observed through various aspects, including accessibility, accuracy, coherence, completeness, consistency, and relevance. Separating the unusable data from the usable data, as well as handling missing data, is one of the key challenges for high data quality.
Data Access: Before even looking at the quality of the data, you first need to acquire it. When multiple players in the industry share their data, different entries can be connected, and the quality of the data can rise. Another important aspect is efficient access to data within an organization, enabling the data-driven design process to progress smoothly.
Data Analysis: This aspect concerns the transformation of the data. How is the data used, and how can it be used better or for another purpose? When different parts of the data are used, this may affect the quality of the data. After the data is used, it is essential to record how the data was utilized and what was achieved with it.

Once the data is approved and deemed correct against these pre-requisite criteria, it can be used to inform designers using data-driven design methods.

2.2.2. Operational Data

Data used in ship design can broadly be divided into two categories: static data and operational data. Static data refers to fixed characteristics such as ship dimensions, engine specifications, or regulatory requirements—information that remains unchanged once defined. In contrast, operational data captures the dynamic behavior of vessels in service. Enabled by advances in sensor technology and digital reporting, operational data reflects how ships are actually operated, offering detailed insights into performance, efficiency, and environmental impact.

Operational data can be classified into these four types:

- **Voyage data**: Speed, draft, route
- **Engine data**: Load, power output, fuel usage
- **Environmental conditions**: Weather, state of the sea
- **Logbook data**: Shipper’s journal

Data is being used in research across an increasing number of industries. However, the applications of operational data used in ship design are limited. This is due to limitations and challenges that come with the abundance of operational data. For specific goals, the data can be too sparse or inconsistent, which makes outcomes unreliable. All data that comes in needs to be cleaned and processed before it can be used. Standardization would be required to make real-time fleet data more easily usable.

Operational data can provide valuable insights into vessel behavior, which can be utilized for early-stage ship design. Real-world operational profiles provide actual engine loading conditions, which should help in sizing for future vessels. This should help avoid over-designing or under-designing both main and auxiliary systems. Will also support evaluating whether alternative, more sustainable fuel options or different topologies can be considered.

This study aims to address the gap in the utilization of operational data by developing a data-driven design method that supports the use of operational data and enables the analysis and storage of this data accordingly.

2.2.3. Product lifecycle management tools

The first data-driven design and production method to be discussed is Product Lifecycle Management (PLM). In PLM, data is produced continuously using modern technology (i.e., radio frequency identification (RFID) tags and smart sensors) to monitor the state of health of products [35]. Manufacturers use these types of technologies for their daily production and management. The products, vehicles, and plants are equipped with smart sensors and RFID tags, which collect massive amounts of data about themselves and their surroundings. The overall goal of PLM is to provide more product-related information and a shared platform for the creation, organization, and dissemination of product-related knowledge [36]. To assist in the analysis of quality during the conceptual design phase, Zhang et al. employed an Apriori-based data mining approach to extract knowledge from historical data [37]. For ship design, PLM is utilized in all phases of the lifecycle. The part of interest for this thesis is the design phase, where virtual models are used instead of real prototypes to generate, analyze, and verify product feasibility according to standards and requirements [38]. Most conceptual design relies on initial main component requirements and product management grounded in prior experience. However, there remains significant potential for improvement in PLM through the integration of operational data. PLM methods offer a solution for managing large amounts of data throughout the complex product lifecycle. Multiple techniques address this data, including information indexing, database management, product decomposition and analysis, and project management [34]. Generally, PLM can be divided into six elements [34, 38]:

- **Database**, indexation of data and document management
- **Modeling and simulation tools**, all software used to design and virtual prototype the vessel
- **Value Chain Processes**, the management of the lifecycle processes
- **Product Hierarchy management**, classifies the diverse ship functions, systems and components
- **Product Management**, gather all information related to all the physical components
- **Project Management**, connects all processes among the vessel lifecycle

Using these elements, data is used in the design of products. Using PLM efficiently can promise an integrated platform that merges these management aspects with virtual prototype concepts (i.e., 3D libraries, computer-aided tools, and the knowledge bank of previous designs). This way, the platform benefits from the management concepts of the PLM methodology, guiding the process from design visualization to the construction phase.

If a PLM system is implemented effectively, it should be able to manage all product data and process-related information in one system using software. This would provide all teams across an organization with access to the data, including CAD models, standards, documents, manufacturing instructions, requirements, and material needs. However, the implementation of such a broad structured system proves to be difficult as it is necessary to have well-established requirements, compatibilities, and expectations across the entire PLM system from the ship designers all the way to the shipyard [39, 34]. In the PLM industry, no software is one size fits all, capable of covering efficient data-driven design in ship design. It only covers CAD model storage and lacks integration with operational data, which is essential for modeling in data-driven design.

2.2.4. Machine learning models

With increased computing power, the applicability and simplicity of solving complex problems have heightened interest in machine learning techniques, such as Artificial Neural Networks (ANN). Here, input data and the targeted reference values are connected via patterns that can be recognized and learned from ANNs and a subset technique, Deep Neural Networks (DNN). These techniques can process new input data and forecast outcomes after being taught by known datasets. An ANN can process highly nonlinear and complicated data, even if noisy and imprecise [40, 41]. The technique lends itself to marine vessel design as traditional methods rely on statistical and empirical correlations. La Ferlita et al. have applied a DNN to predict fuel consumption for five different ship types. These results were sufficiently accurate predictions for an oil tank, a bulk carrier, and a RoRo ship [42]. In a later study, a simplified digital framework approach is used to predict a ship's fuel consumption under realistic operating conditions. The study employed a trained deep learning neural network to capture the characteristics of energy systems effectively. The biggest issue is the limited amount of measured data that is available on operating conditions. This leads to a still general approach with limited validation possibilities [40]. The data and estimations produced by these machine learning approaches may be beneficial for design, but more data is needed to reach that point.

2.2.5. Digital Twin-aided design

Digital Twin technology (DT) is quickly emerging as an efficient way of improving the production cycle [43]. DTs are a technology that has been around for many decades. A DT is a digital replica of a physical artifact that replicates the states and behaviors of the original object [44]. Although the concept was only recently popularized, it dates back to the 1970s, during NASA's Apollo program, where digital models of the spacecraft were used to simulate and monitor conditions remotely [45].

The evolution of DTs has been accelerated by advancements in sensor technology, Internet of Things (IoT), Artificial Intelligence (AI), big data, and wireless connectivity. As a result of these developments, DTs are now utilized in numerous aspects of the industry and help integrate and combine the digital and physical worlds in real-time.

There is no general DT model, as the application changes the way the DT is defined. Grieves' model (Figure 2.2) provides a widely adopted conceptual framework; the model was present in a presentation on PLM with the title 'Conceptual Ideal for PLM' [46]. It consists of three core elements: the physical object, its virtual counterpart, and the data/information connection between them [46, 47]. The last element distinguishes older models from newer ones; new information technology enables real-time data exchange between the real and virtual spaces.

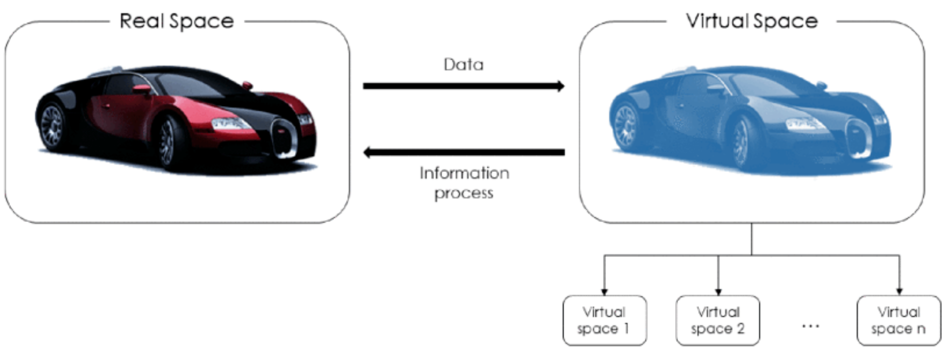

Figure 2.2: Digital Twin as defined by Grieves [47]

DTs are applied across multiple industries, including aerospace, manufacturing, and infrastructure. In aerospace, they support life-cycle management and high-fidelity simulations [48], while in structural monitoring, they integrate onboard diagnostics with fleet data [49].

Most applications can be found in the field of product design. Where, due to the introduction of data science and information technology, data can be collected during the lifetime of a product and managed using the technologies mentioned above [43, 50, 51, 52]. In the marine sector, the use of DTs remains limited, especially in commercial ship design. While offshore and defense applications are increasing [53], full integration of DTs into ship lifecycle design and operation is still in its infancy. Their potential, however, is significant. By integrating operational data with design simulations, DTs could support decarbonization, retrofitting, and performance optimization in green ship design.

2.3. IMO requirements in design

The IMO is the specialized agency responsible for the safety and security of shipping. To prevent atmospheric pollution by ships. The IMO's work supports the UN Sustainable Development Goals (SDGs). To minimize carbon emissions in international shipping, the IMO implements technical and operational energy efficiency measures [7]. The Energy Efficiency Design Index (EEDI) was first introduced in 2013 and represents the first global mandatory greenhouse gas (GHG) reduction regime for an entire international industry sector. In 2021, the IMO adopted a new set of technical and operational measures, the Energy Efficiency Existing Ship (EEXI) and the Carbon Intensity Indicator (CII). When looking at green alternatives for the gray engines being used right now, these tools can be used to compare the environmental impact on society with the benefits to society, by looking at CO_2 emissions and the transport work. These measurement tools will be discussed in the following sections.

EEDI

The EEDI aims at promoting the use of more energy-efficient equipment and engines for the design of new ships to reduce their emissions. To pass the EEDI, ships require a minimum energy efficiency level per capacity mile (transport work); the requirement differs per ship type and size segment. The general formula for calculating the EEDI is given below (Equation 2.1)

$$EEDI = \frac{\text{Designed } CO_2 \text{ emissions}}{\text{Designed Transport Work}} = \frac{\sum(P_i \cdot SFOC_i \cdot CF_i) + \sum(M_j \cdot DCF_j)}{DWT \cdot V_{ref}} \tag{2.1}$$

In this equation, P_i is the Power of the main and auxiliary engines (in kW). The $SFOC_i$ is the Specific Fuel Oil Consumption of the i-th engine (in G/kWh). The CF_i is the Carbon conversion factor for the fuel type used (in CO_2/g of fuel burned). M_j is the emissions from other energy sources, like waste heat recovery systems. The DCF_j is the Direct Conversion Factor for these additional energy sources. The DWT is the Dead Weight Tonnage of the ship (in metric tons), and the V_{ref} is the reference speed of the vessel at its design load (in knots or m/s). The model discussed in chapter 5 will explore only a hybrid engine and won't discuss other energy sources, but does, however, discuss multiple engines. So the equation that will be used in this thesis to compare emissions of different engine equipment is found below (Equation 2.2) [54].

$$EEDI_{attained} = \frac{\sum(P_i \cdot SFOC_i \cdot CF_i)}{DWT \cdot V_{ref}} \tag{2.2}$$

This EEDI should be lower than the required EEDI, which is given by the IMO.

EEXI

For the new framework that was implemented in 2023, all existing ships of 400 gross tonnage and above are required to calculate their attained EEXI. This index measures energy efficiency relative to a baseline. This attained EEXI is then compared to a required EEXI, which is based on an applicable reduction factor expressed as a percentage that is relative to the EEDI baseline. The calculated attained EEXI value must be below the required EEXI to ensure the ship meets a minimum energy standard [55]. The attained and required EEXI is calculated as follows 2.4 [56].

$$EEXI_{attained} \leq EEXI_{required} \tag{2.3}$$

$$EEXI_{attained} = EEDI = \frac{\text{Designed } CO_2 \text{ emissions}}{\text{Designed Transport Work}} = \frac{\sum(P_i \cdot SFOC_i \cdot CF_i)}{DWT \cdot V_{ref}} \tag{2.4}$$

$$EEXI_{required} = (1 - \frac{X}{100}) \cdot EEDI_{ref} \tag{2.5}$$

CII

The CII is based on the operational energy efficiency of ships. It determines the annual reduction factor required to ensure continuous improvements of a ship's operational carbon intensity. The CII is a mandatory indicator for vessels of 5,000 gross tonnage and above. The attained annual operational CII is documented and verified against the required annual operational CII (equation 2.6). Finding the attained CII is calculated by dividing the yearly CO_2 emissions, found by multiplying the fuel by the carbon conversion factor, by the Annual Transport Work that is done by the ship (equation 2.7). The CII required by the industry is calculated by multiplying the reduction factor for the required annual operational CII Z, with a reference value CII_{ref} (equation 2.8). This reference value is a general value defined in 2019 that is based on the type of ship that is examined [57].

$$CII = \frac{CII_{attained}}{CII_{required}} \tag{2.6}$$

$$CII_{attained} = \frac{\text{Annual CO}_2\text{ Emissions}}{\text{Annual Transport Work}} = \frac{\sum(FC_{i,year} \cdot CF_i)}{DWT \cdot D_{year}} \tag{2.7}$$

$$CII_{required} = \frac{(1-Z)}{100} \cdot CII_{ref} \tag{2.8}$$

$$CII_{ref} = a \cdot DWT^{-c} \tag{2.9}$$

Based on this, a CII rating is given to the ship; such a rating can be seen in Figure 2.3. The rating scale is shown as A, B, C, D, or E, ranging from superior to inferior performance levels. When a ship acquires a rating of D for three consecutive years or is rated E, it is required to develop a 'Plan of corrective actions'.

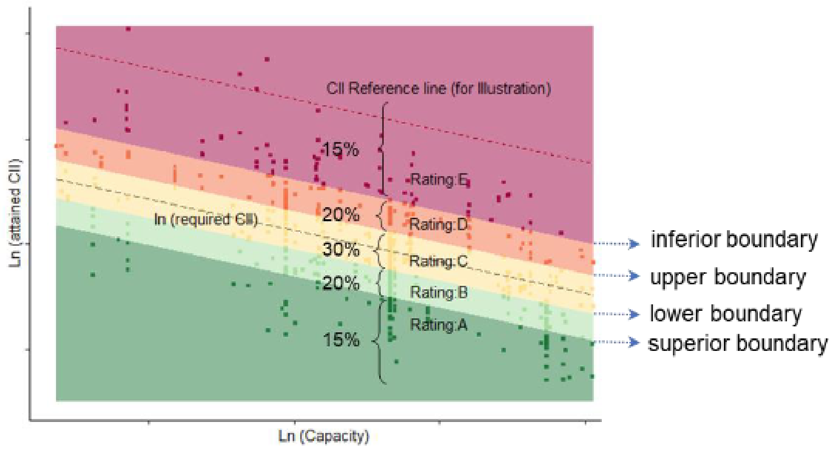

Figure 2.3: Operational energy efficiency performance rating scale [58]

2.4. Engine room design

The EEDI and EEXI are calculated using the power and efficiencies of the components in the ship. This would create the notion that there is considerable potential in optimizing every component to improve fuel consumption and reduce emissions. With this in mind, marine engineers are motivated to replace the conventional power systems with more complex power systems to adjust to the new emission legislation and to reduce operational costs. Hybridization has excellent potential with vessel types that have a variant operational profile, and that are powered by a single prime mover, most commonly an internal combustion engine (ICE) [59]. Along with the engine, there is also the fuel that can be optimized. Different fuels have differing caloric value, but also energy density. With advances in other fuels, emissions can also be lowered when looking into optimizing fuel use. This section will explore the various power system designs in marine vessels, focusing on different types of engines and fuels, and ultimately examining the powertrain configurations, referred to as topologies.

2.4.1. Traditional propulsion system opportunities

Power and propulsion are essential aspects in green shipping. The type of propulsion that is considered is linked to the kind of vessel that will be explored. In this thesis, the type of vessel that will be explored is a bulker vessel of at least 300 meters in length.

Figure 2.4 shows that in typical shipboard propulsion systems, the most significant losses in the system are thermodynamic and mechanical losses in the engine. These losses account for roughly 60% of the losses in the system. Leaving only about 40% of the engine power (the Brake Horsepower). The remaining losses are attributed to the gearbox and propeller, which account for approximately 16% of the system's losses.

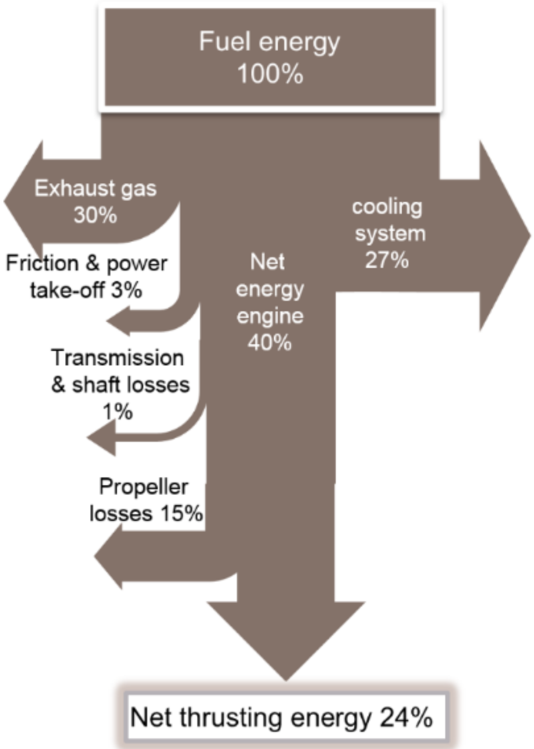

Figure 2.4: Efficiency of a typical engine

On larger vessels, the most common system is a slow-speed 2-stroke diesel engine serving as the main engine. It generally has a maximum speed of 100-130 revolutions per minute and is connected to a fixed-pitch propeller (FPP). Recent research has looked into ways to make ships' power systems greener. The following section will explore the measures that can be taken to improve this existing system.

Component improvements

Component improvement can increase fuel and emission efficiency; propeller design can already contribute to about 4-5% improvement in a vessel's energy consumption [60, 61]. Hydrodynamics improvements, including bow design, stern bulbs, stern flaps, and slender hulls that reduce wave resistance, have been shown to lead to a reduction of fuel consumption by 5-20% [62]. Optimizing the transmission system, the plant design, and reducing weight can also lead to an additional fuel reduction of between 1-5% [61, 62, 63].

Emission efficiency systems

Introducing emissions efficiency systems can also improve the traditional diesel engine. These systems are included in the context of turbochargers and exhaust gas recirculation systems (EGR). Using a turbocharger helps slow-speed two-stroke diesel engines be among the most efficient thermal power plants, with thermal efficiencies approaching or exceeding 50% [64]. The turbocharger allows an increase of engine power density through the downsizing concept, further reducing fuel consumption [65]. The creation of a simulation of a turbocharger is essential for any engine model to be able to provide accurate predictions and predict how to increase performance and emissions [64]. Especially for slow-speed 2-stroke diesel engines, since the turbocharger has a crucial role in the gas exchange. The development of such a model also paves the way for the development of transient air-to-fuel ratio control and exhaust gas recirculation [66]. Exhaust gas recirculation (EGR) is another strategy that improves emissions figures in marine diesel engines. Such an EGR system cuts down the amount of air intended for fuel combustion, and consequently cuts down the amount of exhaust gases, which return to the engine cylinder. With an EGR system, NO_x emissions drop by 37.9-53.5% depending on the engine operating mode and degree of EGR [67].

Control systems

Another way to improve diesel engine efficiency is through the use of control systems. The paper by Sinha proposes a mathematical model of a marine diesel engine speed control system. These kinds of systems are still in their preliminary investigation phase, but do look promising, and their results are consistent [66, 68].

Fuel

Alternative fuels can significantly improve the emissions performance of traditional marine diesel engines. The introduction of biodiesel has been shown to reduce nitrogen oxide (NO_x) emissions by up to 24.3%, according to multiple sources [69, 70, 71]. Dual-fuel systems, particularly those using liquefied natural gas (LNG), have the potential to lower CO_2 emissions by 25–30%. Additionally, NO_x emissions can be reduced by up to 85% due to lower peak combustion temperatures in these systems [12].

2.4.2. Fuel options in the context of emissions reduction

The transition to low-carbon shipping depends heavily on the fuels that can realistically replace or supplement traditional marine fuels. While many fuel candidates are being explored, they can broadly be categorized into three types based on their production method and climate impact: blue fuels, biofuels, and electrofuels. Each of these offers distinct advantages and limitations from an energy, infrastructure, and emissions perspective [72]. This section will discuss each of them.

Blue Fuels

Blue fuels are derived from fossil sources such as natural gas but incorporate carbon capture and storage (CCS) to reduce net emissions. An example is blue hydrogen produced via steam methane reforming with CO_2 capture. While not fully renewable, blue fuels are seen as bridge solutions due to their relatively established supply chains and the possibility of integrating with existing infrastructure. Their well-to-tank emission factors are lower than conventional marine fuel oil, but they still depend on effective CCS and methane leakage management [73].

Liquefied Natural Gas (LNG)

LNG is currently one of the most widely adopted alternative fuels in the maritime sector and is considered a transitional or “blue” fuel. It consists primarily of methane and is stored at around –162°C to reduce its volume. Compared to heavy fuel oil (HFO), LNG combustion produces significantly lower emissions of sulfur oxides (SO_x), nitrogen oxides (NO_x), and particulate matter. CO_2 emissions are also reduced by roughly 20–30%, depending on engine type and operational conditions [74].

LNG can be used in dual-fuel or gas-only engines and is supported by a growing global bunkering infrastructure. However, methane slip, which is the unburned release of methane, another potent GHG, remains a significant concern, especially for older or less-optimized engine technologies [75]. Methane has a global warming potential over 80 times that of CO_2 over a 20-year horizon, which can undermine the climate benefits of LNG if not adequately controlled [76].

Despite this drawback, LNG remains one of the most feasible near-term options for reducing emissions in deep-sea shipping. Its maturity, availability, and regulatory compatibility make it a central component in many fleet upgrade strategies, as seen in the case study of this study.

Biofuels

Biofuels are derived from biomass sources and include options like biodiesel, bio-methanol, and bio-LNG. They are often drop-in compatible with existing engines, making them attractive for short-term implementation. In modeling scenarios, biofuels could reduce lifecycle emissions significantly, especially when blended with fossil fuels like VLSFO. However, concerns around sustainable feedstocks, land use, and indirect emissions remain barriers to large-scale adoption. In the context of this study, biofuel blending is considered a discussion point for future optimization strategies.

Biodiesel

Biodiesel is derived from plant oils via the transesterification process [77, 78]. It shares many characteristics with fossil diesel, including viscosity and density, though its calorific value is approximately 12% lower [69]. The sulfur content of biodiesel is also very low, around $\sim$0.01 wt% [79]. It can be used directly in compression-ignition engines or blended with fossil diesel, offering flexibility in implementation [80, 81].

Studies show biodiesel can significantly reduce carbon monoxide (up to 41%) and unburned hydrocarbons, especially at lower engine speeds [82, 83, 84]. However, it may increase NO_x emissions by 10–45%, depending on engine tuning and operating conditions [69, 85, 86]. These trade-offs highlight the need for emissions treatment systems or blending strategies in marine applications [87, 88, 89].

Other obstacles include fuel stability, feedstock availability, high production costs, engine compatibility, and the lack of standardized marine-grade biodiesel specifications.

Bio-methanol

Bio-methanol is produced from biomass sources such as forestry residues, black liquor, or biogas through gasification and synthesis. It is chemically identical to fossil methanol, but as it is produced in a carbon-neutral way, it offers reduced lifecycle emissions, with the potential to be used in existing methanol-compatible engines. Bio-methanol is considered a drop-in fuel for dual-fuel or methanol-specific engine systems and benefits from being miscible in water. It is also easier to handle compared to LNG or ammonia, as it is liquid at room temperature [90].

However, its environmental impact depends on the sustainability of the biomass feedstock and the production method used. While bio-methanol has a lower volumetric energy density than diesel, it is more energy-dense than ammonia and easier to store, as shown in Figure 2.5. Its main barriers to adoption are production scale, supply chain maturity, and cost.

Electrofuels: Long-Term Renewable Solutions

Electrofuels, or e-fuels, are produced using renewable electricity and non-fossil carbon or nitrogen sources. These include e-ammonia, e-methanol, and synthetic methane (SNG). Their appeal lies in zero-carbon production pathways; however, their current limitations include low energy efficiency, high costs, and limited availability. For long-term decarbonization, electrofuels are likely essential, but for this model, they are not yet included in operational simulations due to their early stage of deployment.

e-Ammonia

Ammonia is an already commercially available fuel that has been numerously mentioned as a candidate to fulfill global decarbonisation strategies [91, 92]. Ammonia can be produced in multiple ways. Blue Ammonia is produced with natural gas, which would not make the fuel carbon neutral. New developments offer the option for ammonia to be created using electrolysis powered by renewable energy, making it a green e-ammonia —a zero-carbon fuel. This zero-carbon alternative would push the industry quicker than the blue ammonia variant [72].

As shown in Figure 2.5, the volumetric energy density of liquid ammonia is significantly lower than diesel—by a factor of approximately 2.85, which has implications for fuel storage and range [93].

One of the primary technical hurdles is ammonia's poor ignitability due to its low volatility and high ignition energy requirements [94]. This limits its standalone application in marine engines and makes fuel blending a more viable short-term strategy [95]. Studies have explored blends of ammonia with fuels such as gasoline, ethanol, or hydrogen to improve combustion properties. For instance, ammonia-hydrogen blends (5-20% hydrogen by volume) have shown promise in enhancing thermal efficiency, but the ammonia blends also increase NO_x emissions [96, 97, 98].

These emission trade-offs suggest that ammonia-fueled engines may require additional aftertreatment technologies, such as selective catalytic reduction (SCR), to meet regulatory standards. Another challenge lies in unburned ammonia slip, which can occur due to incomplete combustion [99, 100, 101].

Despite these limitations, developments in 2-stroke marine engine technology are steadily advancing toward the commercial use of ammonia as a marine fuel. Its zero-carbon potential makes it a strong long-term candidate, provided the technical challenges around combustion and emissions can be addressed.

e-Methanol
E-methanol is synthesized using green hydrogen and captured carbon dioxide, making it a carbon-neutral electrofuel when produced with renewable electricity [72]. Like bio-methanol, it is compatible with existing methanol engines and offers a pathway for decarbonization without requiring completely new propulsion systems. Its handling characteristics and infrastructure requirements are the same as those for bio-methanol, which are less demanding compared to fuels like hydrogen or ammonia.

The main limitations of e-methanol are its low energy efficiency (due to the production method requiring electricity) and high production cost. Nonetheless, it is considered one of the more promising long-term options for long voyage shipping if scalable, green CO_2 and hydrogen sources become widely available.

Hydrogen
Hydrogen is a prominent zero-carbon fuel candidate due to its clean combustion profile and potential for complete decarbonization when produced via electrolysis using renewable energy. However, it presents several challenges that currently limit its applicability for large-scale marine propulsion. Hydrogen has a low volumetric energy density (even when compressed or liquefied), resulting in significant storage requirements, as shown in Figure 2.5.

Although hydrogen is volatile and highly flammable, these properties lead to operational safety concerns, such as flashback and pre-ignition. Additionally, high-pressure or cryogenic storage systems introduce complexity, cost, and space constraints on board ships. While hydrogen can be used directly in internal combustion engines or in fuel cells, both pathways are still in early development for seagoing vessels.

Given these limitations, hydrogen is not considered in the present simulations. Nonetheless, it remains a controversial fuel with considerable potential for long-term decarbonization strategies, especially as infrastructure and safety systems continue to mature.

Fuels used in this study

This thesis primarily simulates configurations using fuel oil and LNG, as they represent the most common and technically mature options in current shipping practice, and consequently also have the most data available. Each engine in the simulation is linked to a specific fuel type and corresponding CO_2 emission factor. While the model does not simulate direct fuel switching, modifying emission factors enables comparative assessments across different fuel types. In this way, future scenarios—such as biofuel blending can be explored through sensitivity analysis or discussed qualitatively in the discussion section. As shown in Figure 2.5, ammonia and other zero-carbon fuels have significantly lower energy densities than fossil fuels, which impacts fuel storage and engine performance. Table 2.1 summarizes the main takeaways discussed in this section, highlighting the energy density, technological readiness, and whether they are included in the case study.

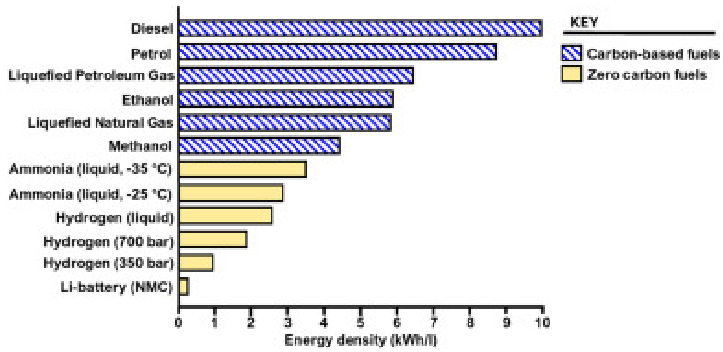

Figure 2.5: Volumetric energy density of selected fuels relevant to marine applications [4, 93].

Table 2.1: Comparison of alternative fuel types relevant to ship design

Fuel Type	Category	Energy Density	Tech Readiness	Modeled in Case Study
HFO	Fossil (baseline)	High	Fully deployed	Yes
LNG	Blue	High	Mature	Yes
Biodiesel	Bio	Medium	Medium–High	No (for now)
Bio-methanol	Bio	Medium	Medium	No
Ammonia	Electro / Blue	Low	Experimental	No
E-methanol	Electro	Medium	Low	No
Hydrogen	Electro / Blue	Very Low	Low	No

2.4.3. Alternative Propulsion options

This thesis will consider alternative engines that are already being used in large vessels or are compatible for use in larger vessels. This subsection will be split up into three categories:

- Conventional Propulsion systems
- Emerging and alternative engine technology
- Renewable systems

Conventional Propulsion systems

The engines that have conventionally been used have been mentioned a few times in this chapter already. The high-efficiency, fossil-fuel-using Diesel two-stroke engine is the most used engine for large seagoing vessels. And the latter introduced a more environmentally friendly dual-fuel engine.

Diesel two-stroke engine

The diesel 2-stroke engine is the most widely used in large ocean-going vessels. The engine is highly efficient compared to even other types of heat engines, and it burns a wide variety of hydrocarbon fuels, which are easily obtainable. HFO, intermediate fuel oil, and marine diesel oil are the most common hydrocarbon fuels. There are three types of diesel engines, namely the slow, medium, and high-speed diesel engines. As the medium and high-speed diesel engines are commonly used in smaller vessels, these will not be considered for the configuration. The slow-speed diesel engine (60–300 RPM) is widely used in large ocean-going vessels due to its ability to drive the propeller shaft without reduction gearing directly. Operating in the optimal 200–300 RPM range, these engines also enable higher propeller efficiency. Figure 2.6 shows the topology of such a slow rpm diesel two-stroke engine, where the engine is directly connected to the shaft.

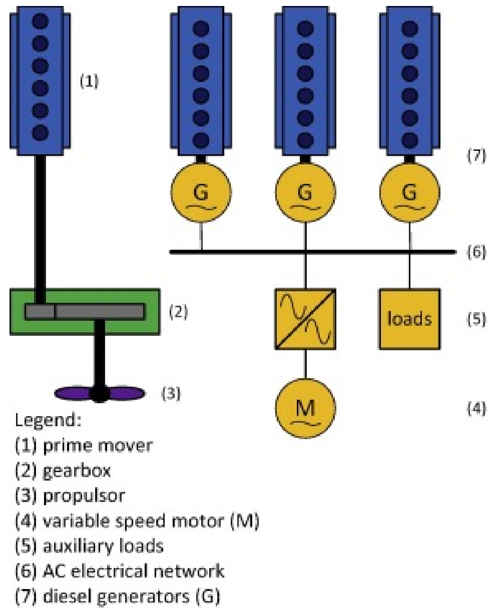

Figure 2.6: Typical mechanical propulsion system [102]

Section 2.5 will go into more detail on the different engine topologies that are used for marine vessels. These engines exhibit high thermal efficiency (up to 50%) and are capable of delivering power outputs exceeding 70,000 kW, making them ideal for deep-sea faring and high-demand shipping. However, their environmental footprint is the biggest concern, particularly concerning NO_x and SO_x emissions when operating on HFO. Although emission control technologies such as exhaust gas scrubbers and selective catalytic reduction (SCR) systems are increasingly adopted, the shift to lower-carbon or zero-carbon fuels poses technical challenges. In this study, diesel two-stroke engines serve as the baseline configuration, against which alternative engines are assessed in terms of fuel consumption, emissions, and operational adaptability.

Dual Fuel Engine
In 1995, Wärtsilä introduced the first dual-fuel engine, with its first marine application following in 2003 [103]. As such, its use is relatively recent in maritime contexts. Dual fuel engines allow vessels to operate on either LNG or conventional hydrocarbon fuels such as LFO, HFO, and even liquid biofuels. Operating on LNG drastically reduces CO_2, NO_x, SO_x, and particulate matter emissions [104]. The degree of reduction depends on the secondary fuel used, but LNG operation typically results in a 15–20% decrease in GHG emissions. Additionally, LNG is an established marine fuel with a growing global infrastructure, mature regulatory frameworks, and widespread availability.

A key advantage of dual-fuel engines is their ability to switch seamlessly between fuel types without loss of speed or power. This enables easier compliance with emission control area (ECA) regulations and allows ship operators to adapt fuel use based on cost and availability.

However, these systems come with engineering and operational challenges. They require advanced control units, double-walled fuel lines, and cryogenic storage, which increases both complexity and capital costs. Methane slip—unburned methane released during LNG operation—remains a significant concern for total GHG performance.

In the context of this thesis, dual-fuel engines are particularly relevant due to their being relatively new technology in large vessel applications and their data availability due to their use in recent years. Their compatibility with LNG, an increasingly available low-carbon fuel, aligns well with the decarbonization goals set by the IMO. The ability to operate in both gas and diesel modes introduces operational flexibility, which is advantageous when evaluating different engine configurations under varying voyage conditions.

Overview of propulsion technologies

Some engines should be considered or at least mentioned when discussing advancements in sustainable propulsion systems for big vessels. Such as the gas turbine engine, fuel cells, and nuclear energy.

Gas Turbine engine

Gas turbines have seen limited application in commercial shipping, though they are well-established in naval vessels, fast ferries, and LNG carriers. Their high power-to-weight ratio and compactness make them ideal for maritime applications and high-speed ferries, but less so for cargo vessels with steady-state power demands. Their ability to start quickly and operate flexibly across power ranges makes them attractive for specific vessel types requiring rapid maneuvering or reduced mechanical complexity.

Despite these benefits, gas turbines are less efficient at part load and generally have higher fuel consumption compared to slow-speed diesel engines, particularly under typical merchant vessel operating profiles. They also require higher-grade fuels, contributing to elevated operational costs.

The data sets used in this study include gas turbine information and fuel consumption. Due to their nature, the Specified Fuel Consumption is relatively high, signaling that they will mostly not be considered for configurations. They do, however, remain a candidate for hybrid systems or as supplementary propulsion in specialized applications. Future work may explore their role in DT frameworks where other types of vessels are examined and compact high-power engines become more attractive.

Fuel cell propulsion

Fuel cells have emerged as a promising zero-emission propulsion option in the maritime sector, particularly for short-sea shipping and auxiliary power applications. They convert chemical energy directly into electrical energy, typically using hydrogen or ammonia as fuel, and produce only water and heat as by-products when using pure hydrogen. In addition to zero or low greenhouse gas emissions, fuel cells offer several operational advantages:

- Noise and vibration reductions
- Reduced infra-red signatures
- Reduced maintenance
- Modular and flexible design
- Improved part load efficiency
- Water generation

Among the various types, Solid Oxide Fuel Cells (SOFCs) show strong potential for marine applications due to their high efficiency and fuel flexibility [105]. However, challenges remain in scaling the technology for high-power, long-duration use. These include system durability, hydrogen infrastructure, and integration with existing propulsion systems.

In the context of this thesis, fuel cell systems are acknowledged as a long-term alternative but are not modeled due to limited large-scale deployment and insufficient operational data in current vessel configurations.

Nuclear power propulsion

Nuclear propulsion is primarily used in military and specialized high-power vessels such as aircraft carriers, submarines, and a few civilian icebreakers. It operates by using nuclear reactors to generate heat, which then drives steam turbines for propulsion and electricity generation.

While nuclear power offers virtually unlimited range and zero operational emissions, its application in commercial shipping is limited due to high regulatory, safety, and public acceptance challenges—additionally, cost, crew training, and nuclear waste handling present significant barriers to widespread adoption.

Given these constraints and the lack of commercial deployment, nuclear propulsion is not included in the modeling scope of this study. While not modeled, nuclear propulsion is included here for completeness as a theoretical zero-emission option for high-endurance operations.

Renewable-assisted propulsion

Renewable-assisted propulsion refers to technologies that utilize naturally occurring forms of energy, such as wind and solar, to reduce reliance on fossil fuels and hopefully improve vessel efficiency. While not primary propulsion methods for most commercial ships, these technologies are increasingly considered as auxiliary systems to reduce emissions and fuel consumption, especially in long-haul or retrofitted vessels.

Wind Propulsion

Wind propulsion is one of the oldest forms of marine propulsion and has recently experienced renewed interest due to environmental pressures. Modern implementations include rotor sails (Flettner rotors), rigid sails, kites, and suction wings, which can help reduce engine load and fuel consumption. They are especially suitable for retrofitting on large cargo vessels where available deck space allows for installation without significant design changes. A study by Hermans explores the potential of wind-assisted propulsion systems for reducing emissions in commercial fleets through retrofit strategies [106].

Solar propulsion

Solar-assisted propulsion involves using photovoltaic (PV) panels to generate electricity onboard, which can be used to support auxiliary systems or, in limited cases, propulsion [107]. While power output remains relatively low, especially for large vessels, solar panels can contribute to hybrid systems or support electric drive systems in small craft. Though not yet widely adopted in commercial shipping, solar energy remains a promising supplementary energy source and is included here due to its potential in future low-emission vessel designs.

In summary, while a range of propulsion technologies is emerging, only those with sufficient data and applicability to large vessel types are considered for modeling in this study. The following section discusses how these technologies map onto feasible powertrain topologies.

2.5. Hybrid engine design

To create a model of a hybrid powertrain, the definition of a hybrid engine and its requirements have to be explored. To model hybrid powertrains in this study, a hybrid system is defined as a propulsion or auxiliary configuration that combines multiple types of energy sources, such as ICEs, batteries, or fuel cells. This includes configurations where ICEs provide direct mechanical power or generate electricity for propulsion. The feasibility of these systems depends on the integration of their power management and control, as well as their ability to meet operational demands. This thesis models only hybrid systems for which sufficient data exists—primarily diesel and dual-fuel configurations.

A key modeling question is how hybrid systems can and have effectively replaced traditional single-engine configurations, particularly in delivering sufficient and stable propulsion power. As section 2.4.3 mentioned, the conventional engine topology does not include a secondary power supply that drives the propeller. The diesel engine is isolated to power the propeller (Figure 2.6).

2.5.1. Typical hybrid engine

When looking at possible hybrid engine topologies, some have already been established by Geertsma. To understand how these topologies differ and what they mean for the engine configuration selection, a simple, typical hybrid configuration is shown in Figure 2.7.

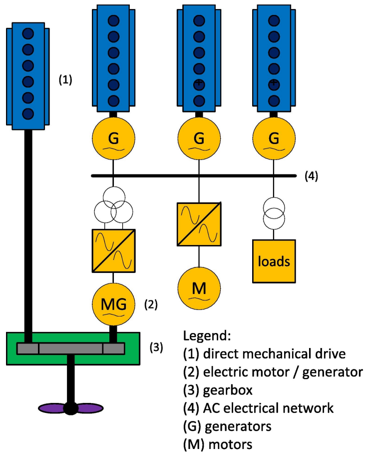

Figure 2.7: Typical hybrid propulsion system [102]

In this setup, the main propulsion is provided by a large diesel engine directly connected to the shaft, while auxiliary engines (via converters) can contribute additional power. This also allows for some generating capacity, either through the electric generator or the generator sets, which provides operational flexibility. This topology benefits from a combination of electrical and mechanical propulsion. The primary benefit of this system lies in combining mechanical propulsion with electrical support for varying loads, though the system lacks integration of alternative or renewable energy sources. The generating capacity of the propeller is also a significant benefit. Typically, however, a large diesel engine is still required to drive the entire propulsion system.

2.5.2. Electrical propulsion with hybrid power supply

This topology combines conventional combustion engines (e.g., diesel or gas turbines) with energy storage systems such as batteries or supercapacitors to power an electric drive. As shown in Figure 2.8, the combined sources generate electricity used for propulsion and auxiliary systems.

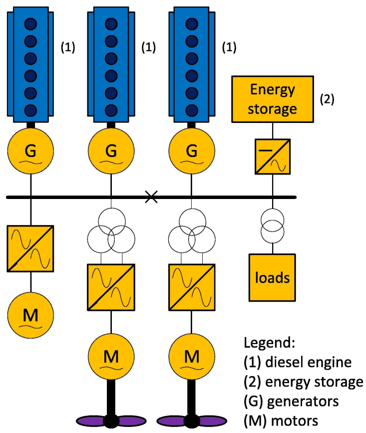

Figure 2.8: Electrical propulsion with hybrid power supply [102]

In this topology, power is generated evenly by multiple energy sources that generate the electricity, which drives the propellers. Most applications of this type of topology are in tugs and ferries [108]. While promising, especially for short-sea shipping and ferries, this topology is not included in the simulation of the current study due to limited operational data on energy storage systems and their energy sharing behavior.

2.5.3. Hybrid propulsion with hybrid power supply

Combining these systems is the hybrid propulsion with hybrid power supply topology (Figure 2.9.

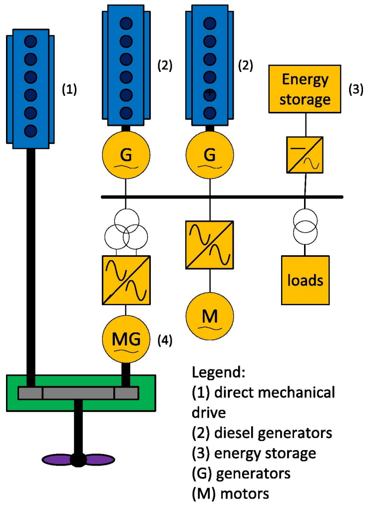

Figure 2.9: Typical Hybrid propulsion system with hybrid power supply [102]

This propulsion system is currently used in tugs and yachts, such as the Savannah, built in Aalsmeer. [109].

While this setup allows for maximum flexibility and redundancy by combining mechanical drives, electric motors, and diverse energy sources, it also introduces significant complexity in terms of control systems, power management, and integration. Applications have been limited to smaller vessels like tugs and yachts due to these challenges. In the context of DT-aided design, such systems would benefit from real-time optimization and predictive maintenance strategies, but are not modeled in this thesis due to insufficient performance and integration data for large vessels.

2.5.4. Electrical propulsion with DC hybrid power supply

Another topology is also using fully electrical propulsion, but with a DC power supply (Figure 2.10). All generator sets are converted to DC power to power both the auxiliaries and the propeller.

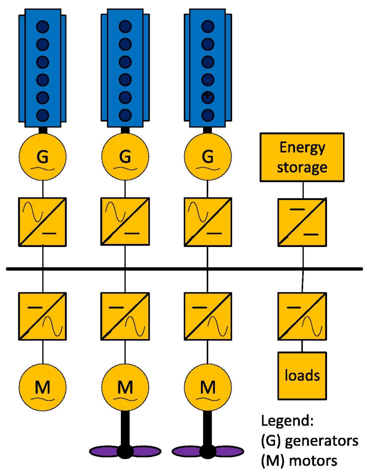

Figure 2.10: Typical Electrical propulsion system with DC hybrid power supply [102]

This DC-based topology enhances efficiency by minimizing energy losses during the conversion process. It simplifies integration with renewable energy systems and energy storage devices (e.g., batteries and fuel cells), which naturally operate on DC. It is particularly suited for vessels with fluctuating load profiles, such as cruise ships and offshore support vessels. However, the complexity of onboard energy management systems and the current scarcity of operational data for DC distribution networks limit their inclusion in the present simulation model.

2.6. Engine room optimization and gap in research

While hybrid propulsion systems can encompass a wide array of possible configurations, including fully electric, fuel cell-based, and DC-powered systems, this thesis focuses solely on systems that are both technologically mature and data-accessible. The data-driven design approach presented in this study is explicitly applied to configurations involving diesel and dual-fuel internal combustion engines in the case study, which can be arranged in hybrid topologies where auxiliary engines contribute to propulsion or onboard energy supply. This focus reflects current industry trends in large vessel design, ensuring realistic modeling grounded in operational data.

Most studies in this domain focus on modeling specific engines rather than comparing and optimizing different engine configurations for design. There is limited research on integrating Data-driven design into early-phase powertrain design, particularly for selecting hybrid configurations that reduce emissions and improve lifecycle performance.

Fully electric and alternative systems remain outside the scope due to limited implementation and scarce operational data. By centering the study on hybrid ICE-based propulsion, the framework remains robust, practical, and directly applicable to contemporary ship design challenges. The goal is that future research can extend the model capabilities by using this framework as their baseline as data availability and technology maturity increase.

2.6.1. Scope and modeling focus

This review has examined the progression from traditional ship design methods to emerging data-driven approaches, highlighting both the opportunities and limitations of digital technologies. Conventional frameworks remain valuable for structuring design work, but they rely heavily on generalized assumptions made early in the process. In contrast, operational data offers a means to capture the complexity of real-world vessel behavior, enabling design decisions that are both more efficient and more aligned with regulatory and environmental demands.

Despite the promise of data-driven methods, applications in early-stage ship design remain scarce. Most research and industry practice have focused either on operational optimization or on high-level regulatory compliance, leaving a gap in how operational data can systematically inform component-level design choices—particularly in the engine room. This gap is critical, as propulsion and auxiliary systems are major drivers of both fuel consumption and emissions.

The scope of this thesis is therefore to develop and test a data-driven framework for early-stage design decision-making using operational data as a basis for modeling and optimization. The framework aims to demonstrate how such data can be structured, analyzed, and integrated into a digital model that supports early-stage decision-making. The next chapter introduces the modeling approach and details how operational data and performance metrics are integrated within the proposed data-driven method.

3 Data-driven approach

The growing availability of operational data in the maritime industry presents a valuable opportunity to enhance early-stage ship design. As discussed in the previous chapter, traditional methods often rely on assumptions that may not fully capture the complexity of real-world vessel performance. To address this gap, various data-driven approaches have emerged, including simulation-based optimization, machine learning, and statistical modeling. However, these methods differ in their ability to support the continuous integration of operational feedback and system-level understanding.

After evaluating these alternatives, this thesis adopts the Digital Twin (DT) approach as the most suitable framework for supporting data-informed design decisions. The core strength of Digital Twins lies in their ability to synchronize real-time or historical operational data with virtual models, allowing for more adaptive and context-aware design decisions. In contrast to one-off simulations or black-box models, DTs provide a dynamic representation of the physical system throughout its lifecycle—making them especially well-suited for optimizing engine configurations under realistic operational conditions.

The remainder of this chapter explores the background, capabilities, and applications of Digital Twins, particularly in the context of engine room and powertrain optimization. Section 3.1 introduces the concept and historical development of DTs. This is followed by an examination of the role of operational data in enabling DT models, and finally, a review of existing DT-aided design applications in the maritime sector and related industries.

3.1. Digital twins in design and production

The term Digital twin, given by Grieves, was described initially as 'a digital informational construct about a physical system, created as an entity on its own and linked with the physical system in question' [47, 110]. A DT is, in its origin, something that mirrors a product. This was shown by Grieves in the Figure 2.2.

Digital twins in production offer numerous advantages that can enhance the entire design process, boosting competitiveness, productivity, and efficiency. Toa et al. investigated the different application methods and frameworks of digital twin-driven product design, manufacturing, and service in their 2018 paper. Most applications of DTs were found in the design of a product, before the product is sold to a customer. A product's quality is improved through multiple iterations while data is gathered, before it is put on the market [43]. The paper also suggests that, as of right now, the abundance of data that is generated by the different phases of a product's lifecycle is not efficiently used, and a lot of resources are wasted. To solve this problem, DT technology has potential due to its characteristics of high synchronization and fidelity, as well as convergence between the physical and virtual products [18].

DTs have been implemented using multiple concepts and solutions across various industries. Before diving into these, a more general understanding can be gained from the different levels of integration of DTs. The gradation of data integration can be split up into three subcategories. These subcategories

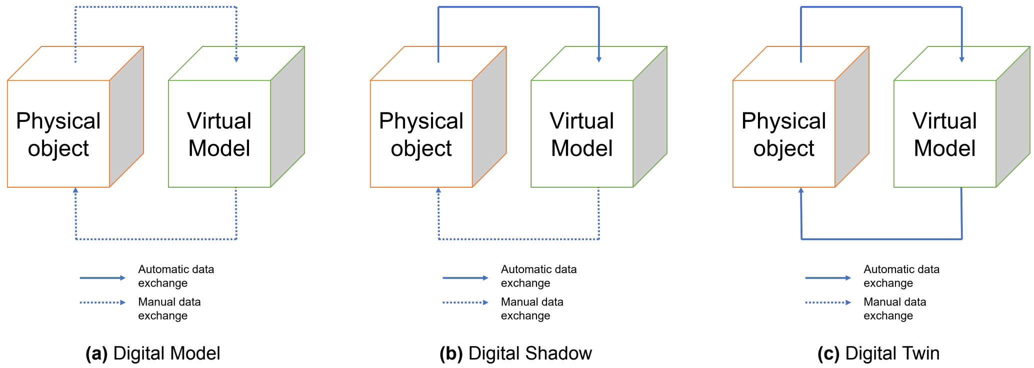

Figure 3.1: Integration level of data exchange

contain the Digital model, Digital shadow, and Digital twin [110]. A description of the characteristics is given in the sections below; their difference has been depicted in Figure 3.1 [111, 112, 113, 114].

Digital Model

The differentiation between the subcategories is the difference in the way the automatic exchange of data is integrated. For a digital model, automatic exchange of data is not integrated, neither from the physical object to the virtual model nor from the digital model to the physical object. Such a model can be a mathematical model, simulation model, or vice versa of a physical object, but without any automatic exchange of data. A digital model is a comprehensive description of a physical object. In a digital model, a transformation of the state of the physical object will not result in an automatic change in the virtual model.

Digital Shadow

The difference between a digital model and a digital shadow is the way data flows from the physical object to the virtual model. For a digital shadow, this is done automatically. It does, however, still not have an automatic data flow in the other direction. A transformation of the state in the physical object will affect the state of the virtual model, but not the other way around. A depiction of a digital shadow can be seen in Figure 3.1

Digital Twin

The final evolution is the step toward the digital twin. In this stadium, there is an automated flow of data from the physical object to the virtual model and vice versa. As described by Grieves' DT model, a digital twin serves, in some applications, as a controller of the physical object. As described in Grieves' model, other virtual, digital, or physical objects may also influence the state of the Digital Twin or its underlying virtual model. In a digital twin, a transformation in the state of the physical object will affect the state of the virtual model, and vice versa.

3.2. DT-aided Design

DT technology has been widely used for design in multiple different industries, as was mentioned in chapter 2.2. Multiple advancements have been made in the shipping industry using life-cycle data, mainly in the Product life-cycle management sector. However, the use of operational data is still in its infancy. Primarily due to the lack of data or the lack of shared data. This section will explore the usage of operational data in DT-aided design, both in shipping and in related industries.

3.2.1. Ship design

DT technology in ship design has seen only a limited number of applications since the boom in information technology. The different types of data have slowly been expanding and growing.

A paper by Maura et al. examined the use and the grade of implementation of DTs in the maritime industry. The division of the use in the ship's phase can be seen in Figure 3.2.

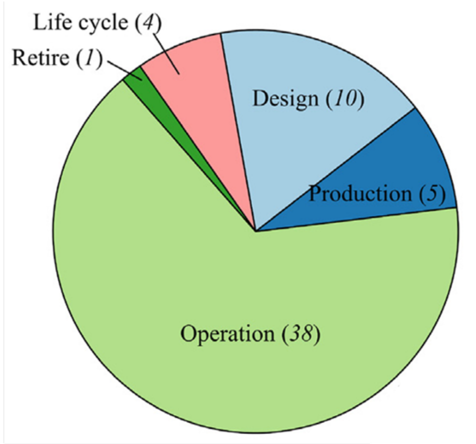

Figure 3.2: Division of filtered papers on Digital Twins of the phase [29]

Of the 10 papers found in design, only three concepts, concerning general descriptions, definitions, and capabilities of DTs, were in ship design. Not a single framework of how a DT could be implemented in ship design is produced according to this study [29].

In the paper by Semeraro et al., the main features of Digital Twins are explored; here, most applications for maritime and shipping are used as support for design. Most time and money are invested into the preparation of analytical models for simulations. The DTs allow visualization of all the key components, perform analyses and calculations, and improve the control of the effects of the operations on the ship's structural and functional components [115, 116].

Sapkota proposes a framework for benchmarking validation data and metrics during model validation in different domains. This data involves operational data and other validating data from physical assets that would require operational validation. The approach focuses on addressing the problem of parameter uncertainty of a predictive model. The goal is to enable the online availability of operational data from the physical asset required for operational validation in Digital Twins. The approach is not associated with the design of the whole ship, but the design of single subsystems, in this case, structural components [29, 117].

Other papers addressing the design phase primarily focus on CAD modeling and ship design. While the term 'Digital Twin' is frequently used in this context, the mere adoption of a virtual 3D CAD environment during the advanced and detailed design stages does not fully align with the core principles of the Digital Twin concept [118, 119]. As there is no direct communication with a hypothetical physical space.

A paper by Nikolopoulus and Boulougouris from 2020 explores an example of a holistic design optimization approach [31] for a merchant vessel to potentially use design points that are derived from onboard measurements on existing ships. The approach is a novel data-driven design method that utilizes DT principles to optimize ship design [120]. This approach was proposed earlier by Papanikolaou and focuses on the way ship design can be approached, considering the entire vessel as an integrated system. The subsystems and components vary for a cargo ship from cargo storage and handling to the energy/power generation and ship propulsion to accommodation of crew/passengers to the navigation of the vessel [121].

There is limited research on embedding vessel operation simulation into the early design process, despite its significant potential. Tillig et al. propose a generic energy system model capable of predicting a ship's energy consumption under various operational conditions. However, the model does not account for variations in the vessel's engine characteristic limits [122]. The paper by Sandvik et al. in 2018 proposed a quasi-static discrete-event simulation model that replicates and assesses the voyage of a cargo vessel. It uses a prescribed route based on real-time data and a constant speed assumption. The goal was to compare and evaluate the results in relation to performance monitoring system measurements [123]. The interesting novelty of the newer research is that the methodologies of the simulation-driven research have the goals of deriving the key design attributes after the simulation is done, instead of using prescribed loading conditions and operating speeds [120, 124].

This research aims to leverage operational data to account for the real-world conditions under which ships operate—conditions that are often volatile and uncertain. By incorporating this data into the assessment of engine room configurations, the goal is to ensure that design decisions lead to robust solutions. These solutions should maintain strong performance across a wide range of operating environments throughout the vessel's entire life cycle.

3.2.2. Modeling Approaches from Related Industries

As research in DTs advances across multiple industries, various modeling approaches and data frameworks have emerged. These implementations, while industry-specific, offer valuable insights for structuring potential DT systems and frameworks in the maritime sector. This section highlights relevant case studies from industries such as automotive and consumer products, where real-time data, system interdependencies, and simulation-driven design have already been successfully applied. By examining these precedents, key building blocks can be identified to inform the development of a DT-aided design approach for ship engine room configurations.

DT-aided design is actively explored across many industries. Traditional design methods alone are often inadequate for supporting emerging data-driven approaches [125]. Insights from these industries can inform how operational data can be leveraged within the shipping sector. The automotive industry has been the focus of significant research on DT technology. With the rise of electric and autonomous vehicles, the concept of the digital twin is gaining traction in automotive applications. While electric vehicles (EVs) lend themselves well to visual representation, the real challenge lies in managing the complex interdependencies between their many subsystems [126]. For a digital twin of an EV to be effective, its surrounding environment must also be dynamically modeled, including all parameters that influence performance. Thanks to extensive real-time sensor feedback, EVs are well-suited for digital twin replication.

When breaking down the essential aspects of a DT for EVs, there are six significant aspects. The project data, construction data, sensor data, as-built data, data insight, and artificial intelligence [126]. The model is first founded on the existing project data to create data-driven simulations of the physical entity. To expand the simulations to a functional DT, construction data and as-built data are incorporated through horizontal and vertical integration topologies. These 3 data aspects form the contemporary framework of the DT. To include the real-time data that will enable a vital data stream for a proper DT, sensory elements are added that attain an abundance of raw data. Here, big data comes into play to extract the pertinent data insights that the system can use for feedback to the DT. In this concept, AI or deep learning is used to provide insight into the system's performance or to inform future decision-making based on the physical model's use. These interconnected data aspects form the foundation of the DT framework, as illustrated in Figure 3.3.

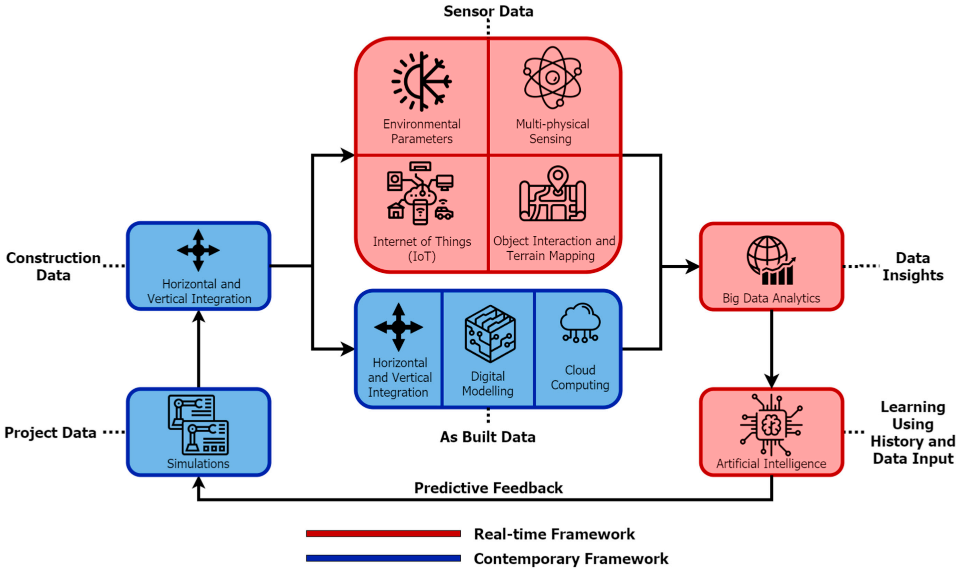

Figure 3.3: Digital Twin conceptual overview for electric vehicles [126].

Tao et al. present a case study where traditional bike design is redefined [125]. In conventional bike design, the methods are primarily based on designers' knowledge and experience. When breaking down a DT of a bicycle, there are three parts: The virtual bicycle in the virtual space, the real bicycle in the physical space, and the interactive data between virtual and real bicycles, which is, for instance, the speed, acceleration, wheel pressure, user comments, relevant environment data, etc. This data establishes a virtual model within the virtual space, a mapping and reflection of the physical object. In this setup, the virtual space continuously collects, analyzes, and accumulates data from the physical space, which can then be used to inform the design or redesign of next-generation bicycles. This process is illustrated in Figure 3.4.

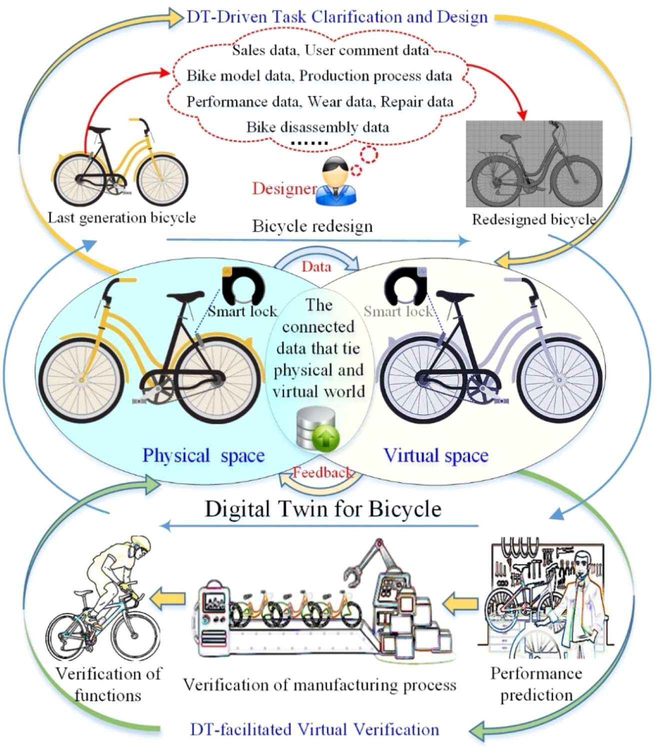

Figure 3.4: DT-driven bicycle design process [125].

Designers obtain all their data from the DT, which will be used to design the newer generation. At the underside of the figure, three steps are included: the performance prediction, the verification of the manufacturing process, and the verification of functions. Performance prediction is self-explanatory: through simulation and data-driven mapping, structural fractures can be reduced, assuming the simulations are sufficiently accurate. Verification is performed using real-world data from the customer, enabling the identification of design issues early on. Verification can also be achieved by integrating various environmental data and applying functions under different circumstances. Brake distance, tyre wear, etc., are tested under different weather conditions through the digital model. This approach illustrates how even relatively simple physical systems can benefit from digital twin modeling. By creating a continuous loop between physical measurements and virtual simulations, designers can iterate more quickly and with greater confidence. These principles are equally relevant for complex systems, such as ship engine rooms. During the virtual verification process, problems are identified, and the design is refined through iterations. This conceptual DT framework is adaptable across industries and can support businesses in developing DT-aided design strategies tailored to their products. Reducing costs and increasing efficiency, security, and satisfaction [125].

These examples illustrate how other industries have integrated physical systems with virtual models to facilitate continuous feedback, simulation, and design improvement. Common elements such as sensor-based data acquisition, real-time feedback loops, environment-aware modeling, and iterative validation provide a strong foundation for developing a similar approach in ship design. In the context of this research, these case studies serve as conceptual references from which a DT-aided framework for robust, operationally-informed ship design can be constructed.

3.3. Goal of DT-aided design process

Building on the modeling principles from other industries, this section defines the specific goals and structure of the DT-aided design process as applied to engine room configurations in green marine vessels.

The objective of a DT is context-dependent and shaped by the system or process it supports. The aim of a DT is context-dependent and shaped by the system or process it supports. In this case, the goal is to improve the component design process—particularly engine selection and configuration—through better integration of operational data and predictive modeling. Ultimately, this should support the adoption of more energy-efficient technologies and the reduction of greenhouse gas emissions.

At the core of the DT-aided design process is the creation of a virtual model that simulates fuel consumption under realistic operating conditions. Fuel consumption serves as a proxy for emissions and efficiency, making it a critical performance metric for green ship design [127].

These models are built on two key data sources: real-world operational data and engine-specific characteristics. Together, they form the foundation of the virtual space, where various configurations can be tested and optimized before real-world deployment. A comprehensive framework illustrating this process will be introduced in the next chapter (in section 4.5).

A successful DT-aided design depends not only on the modeling approach, but also on the quality and quantity of the input data. Therefore, the design method must include a structured way to assess data reliability, model feasibility, and integration between the virtual and physical domains [128, 106].

This thesis aims to address this gap by proposing a Digital Twin-aided design framework that integrates the use of operational data. The following chapter presents this framework and its constituent blocks, detailing how operational data, component modeling, and optimization logic can be combined to support low-emission, data-informed early-stage ship component design.

4

DT-aided design framework

This chapter will use the theory and applications that were explored in chapter 3 to build the framework for an application using operational data in ship design.
First, the operational data will be examined and assessed. After which, the data should be processed to serve the needs of the proposed model.
Next, the modeling approach will be explained, along with how the operational data will be utilized within this approach. Different optimization strategies will be explored and examined for the chosen approach.
After this, the data management system required for a DT-aided design model is explained. Then the verification & validation process will be examined. Afterwards, the total framework of the DT-aided design method will be described, and with it, the interaction between physical and virtual space.

4.1. Operational Data

As was briefly introduced in section 2.2.2, data can come in many forms. For a marine ship, especially, a vast amount of information is collected. With such large volumes, it becomes easy to lose sight of the various data types and the specific roles they can play in supporting design, operation, and decision-making. This data is required to establish the DT-aided design method. In section 2.2, some prerequisites of the collection and processing of data were listed; this section will go over these steps in the context of operational data used for the DT-aided ship framework, improving performance indexes. The four requirements are:

- Data collection
- Data quality
- Data access
- Data analysis

This section will first go over the data collection/acquisition and the quality of that data. The section will then discuss how the data is accessed and what the analysis should look like.

4.1.1. Data Collection and Quality

Quality data collection is a fundamental part of DT-aided design. The ability to transfer data between the physical and virtual spaces is what defines the process as DT-aided in the first place.

Traditionally, ship performance data was gathered through noon reports, submitted daily by the captain or chief officer. These reports included key operational details such as the vessel's position, speed, fuel consumption, and weather conditions over the last 24 hours. While initially intended for compliance and operational monitoring, they also supported fuel optimization efforts [129].

Since 2016, the IMO's Data Collection System (DCS) has made data reporting mandatory, requiring ships to log fuel oil consumption to support future greenhouse gas (GHG) reduction measures. From

2019 onward, vessels over 5,000 gross tonnage are required to report fuel consumption of all fuels used. The data is also used to compute the performance indexes discussed in Section 2.3.

Modern vessels are equipped with a range of onboard sensors that continuously collect operational data. A key example is the Automatic Identification System (AIS), which provides information such as [130]:

- Vessel Type [-]
- Beam [m]
- Speed [knots]
- Longitude and Latitude [degrees]

With advances in IoT and smart sensors, data is now collected more frequently, transmitted wirelessly, and processed automatically. In a case study by Coraddu et al., data such as propeller speed, fuel consumption, and fuel properties were collected in abundance every 15 seconds and averaged into 15-minute intervals by a data handler for analysis [131].

Leveraging systems like the DCS is promising for DT applications, as they provide a standardized and continuous source of operational data over the vessel's lifetime. This aligns with a key DT requirement: the automatic, ongoing exchange of data between the physical and digital environments.

However, the reliability of this data depends heavily on the accuracy of onboard equipment. While some data types—such as ship speed from AIS—have been reliably collected and can be cross-verified, others like speed through water (LOG speed) can be inaccurate due to hull effects and environmental conditions [131].

The effectiveness of any DT-based model relies on the quality of its input data. Challenges such as noise, missing values, and inconsistent formats can affect model performance [34]. Therefore, automated data validation and fault detection systems are critical for ensuring reliable digital twin operation [132, 133].

4.1.2. Data Access and Analysis

Before data collection begins, it is essential to define both the source and the method of acquisition. Equally important is understanding how data from different sources will be integrated, as this significantly affects the success of any data-driven approach. Establishing systems such as databases of prior models, methodologies, and project records can significantly enhance the implementation of a DT, particularly if they are accessible for future use and shared across stakeholders.

Efficient access to this information is critical for supporting iterative and collaborative development. Ideally, relevant data should be available to all actors involved—from designers and engineers to ship operators and customers. However, access may be restricted by legal considerations, proprietary ownership, and risk management policies [34].

Despite the growing importance of digital infrastructure in DT applications, challenges remain. High-performance data systems often require significant investment in hardware and integration, and with the rise of cloud-based solutions, security concerns are becoming increasingly central [134].

Once data is collected and its quality verified, it can be analyzed for specific purposes. While datasets may support multiple use cases, quickly extracting the relevant information for a particular analysis or design task is key to an efficient DT workflow. For example, a reported figure of 2,500 project hours is only meaningful when compared to similar projects. If previous designs required fewer hours, this could indicate opportunities for efficiency gains or reveal hidden trade-offs, such as the need for more time in the construction phase due to earlier design shortcuts [34].

It's crucial to interpret such metrics carefully and record how the data was used, what insights were gained, and what outcomes were achieved. This process supports long-term learning and can be institutionalized through centralized knowledge repositories or digital project archives.

A key component of this workflow is data pre-processing. This step involves cleaning, filtering, reducing, and transforming raw data—whether sourced from the physical space or virtual simulated models—into

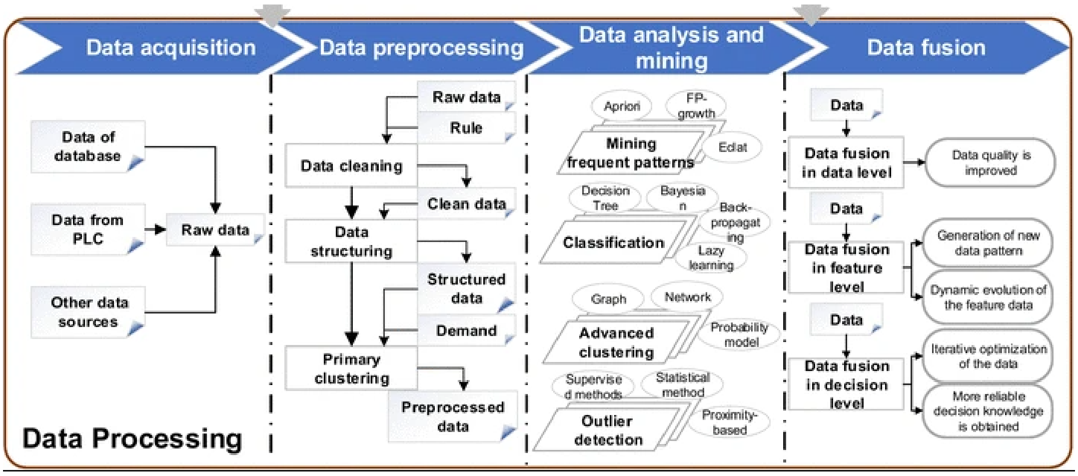

Figure 4.1: Data Processing method as proposed by Zheng et al. [137]

structured formats suitable for analysis [135, 136]. The level of detail and techniques used can vary depending on the application; however, a consistent, well-defined pre-processing framework is essential for developing a DT. A study by Zheng et al. proposes a four-stage data processing architecture for digital twins, visualized in Figure 4.1 [137]. It consists of:

- **Data acquisition** – collecting real-time data from various sources such as programmable logic controllers (PLCs),
- **Data pre-processing** – rule-based cleaning, data structuring, and primary clustering to reduce noise and improve consistency [138],
- **Data analysis and mining** – using techniques like pattern recognition, classification, clustering, and outlier detection,
- **Data fusion** – combining processed datasets to enhance overall quality and reliability.

This layered approach not only improves data quality but also supports real-time DT integration by enabling consistent, synchronized information flow between the physical and virtual environments.

4.2. Modeling approach

The modeling approach in a DT-aided design method can vary widely depending on the application. The intended purpose of the digital twin or digital model strongly influences the choice of modeling strategy. At this stage, the focus is on determining how the acquired and analyzed data will be applied within the model. Once the data has been processed through the chosen model, the corresponding virtual representation is theoretically created within the virtual space. According to a literature review by Tao et al., the most common modeling approaches in DTs include geometric models, physics-based models, behavioral models, and rule-based models [139]. This section briefly discusses each of these modeling types.

4.2.1. Geometric model construction

In geometric model construction, the geometry of the object is modeled; it covers the shape, size, internal structure, spatial position, and attitude, and assembly interfaces are modeled. For this type of modeling, model fidelity and the potential for simplification are crucial. A geometric model is not only for shaping, but also for structural integrity and data accuracy, which support the analysis of motion, design optimization, virtual interaction, and so on. Because of the detail in modeling, the true-to-life modeling possibility is crucial [139].

This type of modeling is mainly used for structural analysis. Simplification is of high importance to create a fast geometric model transfer, loading, and browsing. This uses less data and can still make a good, true-to-life model of the physical object. In a study by Zhang et al., geometric modeling was employed to indicate tool wear in an online monitoring tool, simulating the high-fidelity, real-time behavior of the tool [140]. The most important aspect of this type of modeling is that it creates a realistic visual representation of the physical entity, which can be monitored in real-time. It can be used as a data-driven tool to estimate responses to real-world simulated actions. It leaves room for the possibility of simplification while still keeping a high-fidelity model, as was shown by Li and Nan, who proposed a generic model simplification of a mesh structure [141].

4.2.2. Physical model approach

Physical model construction primarily focuses on quality control and the analysis and prediction of physical properties. This type of modeling can be split up into static and dynamic model construction.

These static models include quantitative modeling of physical properties, states, and behaviors. These models are based solely on the characteristics of physical entities, without considering the interactions between different physical analysis methods. However, contemporary engineering challenges increasingly require models that account for such interactions and incorporate diverse analytical approaches. In static models, this is still possible using multi-physics coupling analysis. With this, a more accurate and realistic simulation can be done. In a floating wind turbine example, this would be done through structural mechanics, aerodynamics, and the sensor readings of the power output, pitch, rotor speed, etc. The DT would run these models in parallel to simulate real-world operations [142].

In a dynamic, variable physical model, multiple nodes must be created and computed to determine the physical state distribution across the entire system. This approach is essential in scenarios such as modeling thermal conduction in mechanical components [139]. A finite element model used for real-time wear prediction is an example of this type of model, enabling dynamic assessments of an object's performance over time.

4.2.3. Behavior model approach

A behavior model should represent the sequential, concurrent, linked, periodic, and random behaviors of a physical object. If the model is created accurately, it should be able to determine the motion and the control of the DT model. Due to uncertainties of physical objects in the real world, these types of models tend to be inconsistent as a result.

If the input data contains a high number of anomalies, this will directly impact the accuracy of the behavioral model. It can also result in a consistently deviating DT model when compared to the physical object. For this reason, the data should be thoroughly analyzed and cleaned to remove any abnormal data from the dataset. A study by Boulfani et al. created such a behavioral model. It improved it significantly by extracting and analyzing the abnormal temperature variations from the physical generator, and with it removing the anomalous behavior of the DT model of the generator [143].

Iteratively adjusting the algorithm parameters of a behavior model to identify the optimal value of each parameter in relation to the operational data can also enhance model accuracy. But before this iterative tuning becomes possible, the designer must have a deep insight into the behavior of the physical object and the meaning of the parameters that tune it. This is not always possible.

4.2.4. Rule-based model approach

In a rule-based model approach, the physical entity is created via implicit knowledge of the patterns in its behavior. In rule-based model construction, there are two primary ways of model construction: through data mining and analysis of the life cycle data, and a formal representation of experience and knowledge.

A rule-based model tries to estimate the whole life-cycle of a product/physical object as the upper limit. For this reason, a good data processing procedure is required to map the entire life cycle of the object.

Its limitations are that it cannot learn from new data yet, so a complete encompassing model needs to be created beforehand. The system needs to have well-understood behavior. Through data mining, advancements in information processing, knowledge measurement, and graphical mapping enable the leveraging of more complex experiences and knowledge in rule-based modeling. Over time, this approach may evolve into dynamic knowledge domains that will allow DT models to understand and adapt to these rules [139].

4.3. Model Verification & validation

To reach the correct and desired results and to meet a certain amount of consistency in those results, model verification is required. This ensures that the virtual space mirrors the physical space. The goal of model verifications is to evaluate whether the output of both the digital model and the digital twin is consistent under the same conditions. The verification process should ensure that the model is implemented correctly and is working as intended.

Model verification should review all relevant information related to the DT implementation to determine how the model's credibility can be further enhanced. Every time the model is improved or changed, the verification should be done again, making the design and verification of the model an iterative process.

One way to verify a design is by examining historical designs or similar applications, and comparing their approaches to see if they are in a similar vein as the potential application. Another approach is to examine the application from multiple angles to verify the assumptions made beforehand and to determine what would change if these assumptions weren't made.

During the validation process, instead of the question, 'Is the model right?' The question becomes, 'Is it the right model?' During validation, the model is checked to see whether it reflects reality well enough to be trusted for decisions and predictions. This process looks at the output with more detail than the verification process, beyond just the consistency of the production. Validation focuses on the evaluation of whether the desired output is produced according to the initial expectations and objectives. The validation step can be done using real-world data to assess whether the objective is reached and the output is realistic. A case study can also be conducted to verify and validate the model. The output of the model is then compared to the pre-defined objectives to ensure they meet the intended goals [117]. The steps of validation and verification lead to the actual creation of the physical space, so this element is of high importance. This step should ensure that the DT implementation provides accurate insights into the design process and should inform decision-making.

4.4. Data management

To complete the loop of the DT-aided design process—or any other DT implementation—information from the physical system must flow back into the data acquisition phase of the virtual space. The data generated from both the physical and virtual environments must be managed. This can be achieved through a knowledge bank that is indexed correctly, allowing the data to be easily accessible and utilized. Through this, certain authorities, designers, and other stakeholders may face limitations in accessibility. A well-managed DT model should be able to provide extra functionality, reliability, efficiency, maintainability, usability, and portability of the technologies and tools produced by the DT. It will also facilitate the utilization of the data and empirical knowledge that is gathered during the creation of the DT [139].

4.5. DT-aided design framework

Now that the background for the creation of a functional DT-aided design framework has been established, the framework can be created. The framework is built based on the established framework that was described in section 3.2.2. The steps for the creation of a DT-aided design process, as explained in this chapter, are:

1. Establish DT-aided design goal
2. Data collection, assessing, and processing
3. Determine the modeling approach
4. Optimize key parameters according to the modeling approach
5. Verify and validate the model
6. Knowledge management and virtual-physical integration

The framework that is produced can be seen in 4.2. In the framework, four different types of blocks are described. They are:

- Virtual modeling

- Physical space
- Data Sources
- Feedback

Each of these colors represents a phase in the creation of the digital twin. The next chapter will apply this framework to a case study, where engine configurations are optimized based on fuel consumption performance using the operational data of a bulker vessel. A new framework will be presented that utilizes the framework in Figure 4.2 to establish the steps that are taken in the context of the case study.

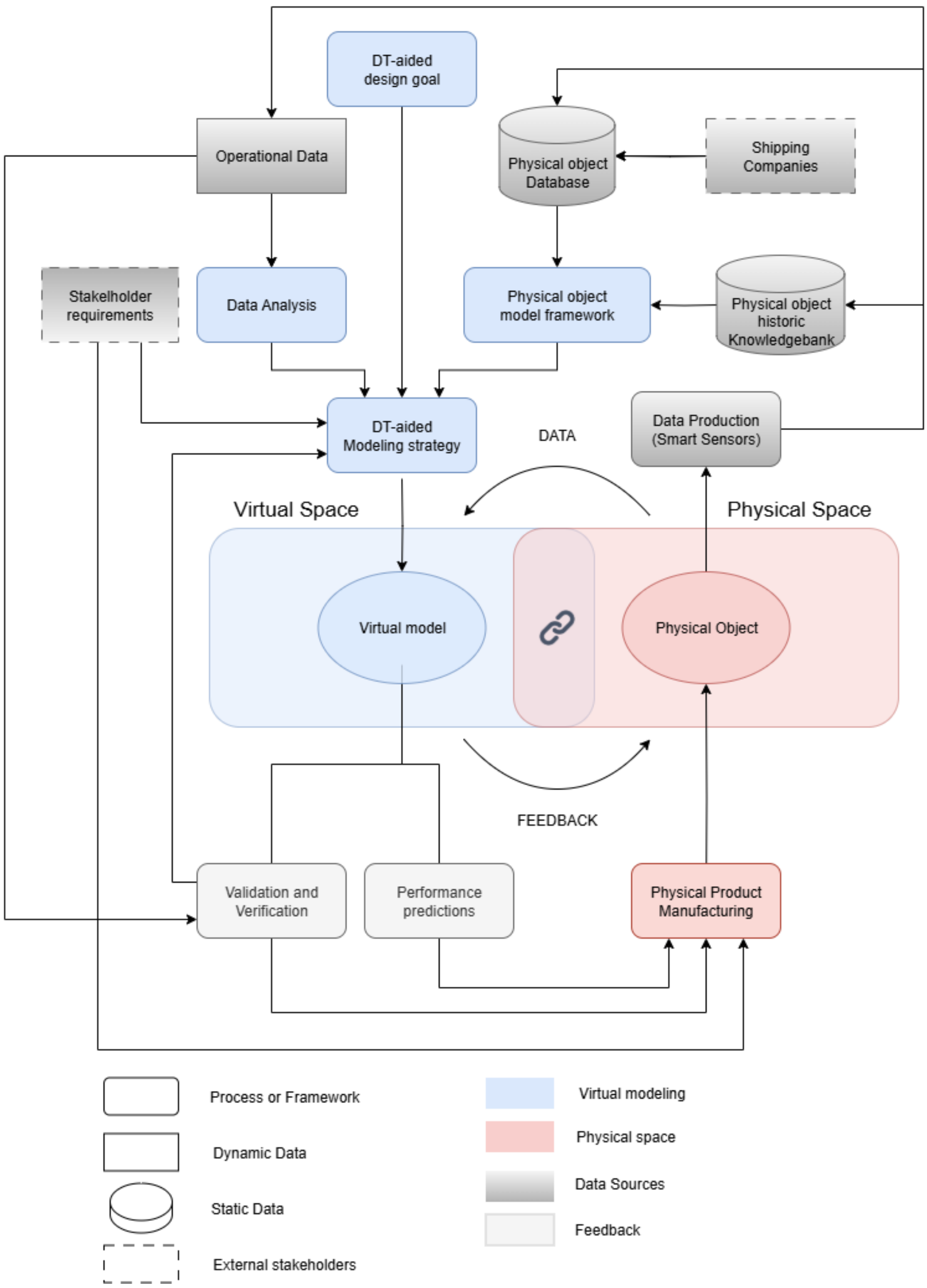

Figure 4.2: Proposed DT-aided design framework for ship design

5 Digital Twin Modeling

This chapter applies the proposed DT-aided design framework to a case study focused on engine configuration for low-emission ship design. The first section outlines the overall structure of the framework, defining its scope and relevance to the modeling approach. The remainder of the chapter illustrates how each step of the framework contributes to a structured, data-driven design process for an engine room.

Figure 4.2 serves as the conceptual backbone for this modeling effort. It connects the physical and virtual spaces through operational data, modeling tools, and verification steps, guiding the integration of real-world constraints with simulation-based design decisions.

5.1. The Case-study

To evaluate and verify the proposed framework, it is applied to a case study focused on engine room design. The objective is to optimize engine selection for a seagoing vessel to support the International Maritime Organization's (IMO) decarbonization targets. Specifically, the case study aims to identify engine configurations that minimize fuel consumption and CO_2 emissions by utilizing operational data.

5.1.1. DT-Framework application

The generic DT-aided design framework is adapted for this case study to reflect its specific design goal: reducing emissions and fuel consumption. Figure 5.1 highlights the adjustments made with respect to the original framework.

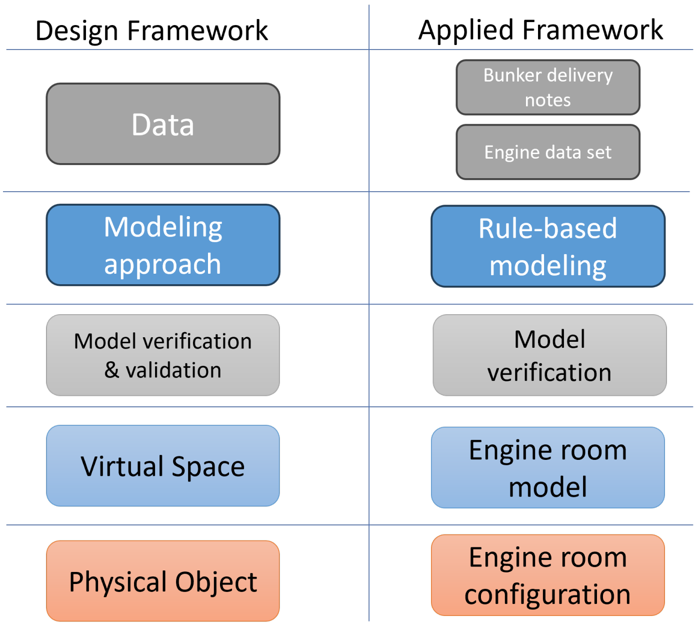

Figure 5.1: Changes in the DT-aided framework

The key changes in the application are as follows:

- **Data sources** are specified and will use Bunker Delivery Notes (BDN) and an engine data described in Section 5.3.
- **Modeling approach** is specified to be a rule-based modeling strategy that will be examined in section 5.4. The emission and fuel consumption models are described in Section 5.5.
- **Model verification and validation** is changed by excluding the validation step, as it requires experimental or cross-model comparison beyond the scope of this thesis. Verification remains and is explained in Section 5.6.
- **Virtual Space** becomes an engine room model.
- **Physical Object** becomes the physical engine room configuration.

Because no feedback is provided to the physical system, data flows only from the physical to the virtual. Following Kritzinger's definitions [110], the outcome is therefore a *Digital Model*, as seen in Figure 3.1. All these changes are applied in the framework shown in Figure 5.2.

In using the framework in this case study, the following steps that were proposed in Section 4.5 were taken and are repeated below but for this specific approach:

1. Establish DT-aided design goal
2. Data collection and processing
3. Selection of the modeling approach
4. Optimization of engine configurations
5. Model verification and sensitivity
6. Knowledge management and virtual-physical integration

The adapted framework provides a structured path for applying operational data to engine room configuration. By organizing the case study into clear phases—from goal definition to optimization and verification—it ensures that the design process remains both systematic and transparent. At the same time, the reliance on available datasets (BDN records and engine specifications) reflects the practical limitations of data in early-stage ship design. Together, this approach highlights both the opportunities and the constraints of the data-driven methods. Each step in the approach will include the blocks in the framework that are relevant to that step.

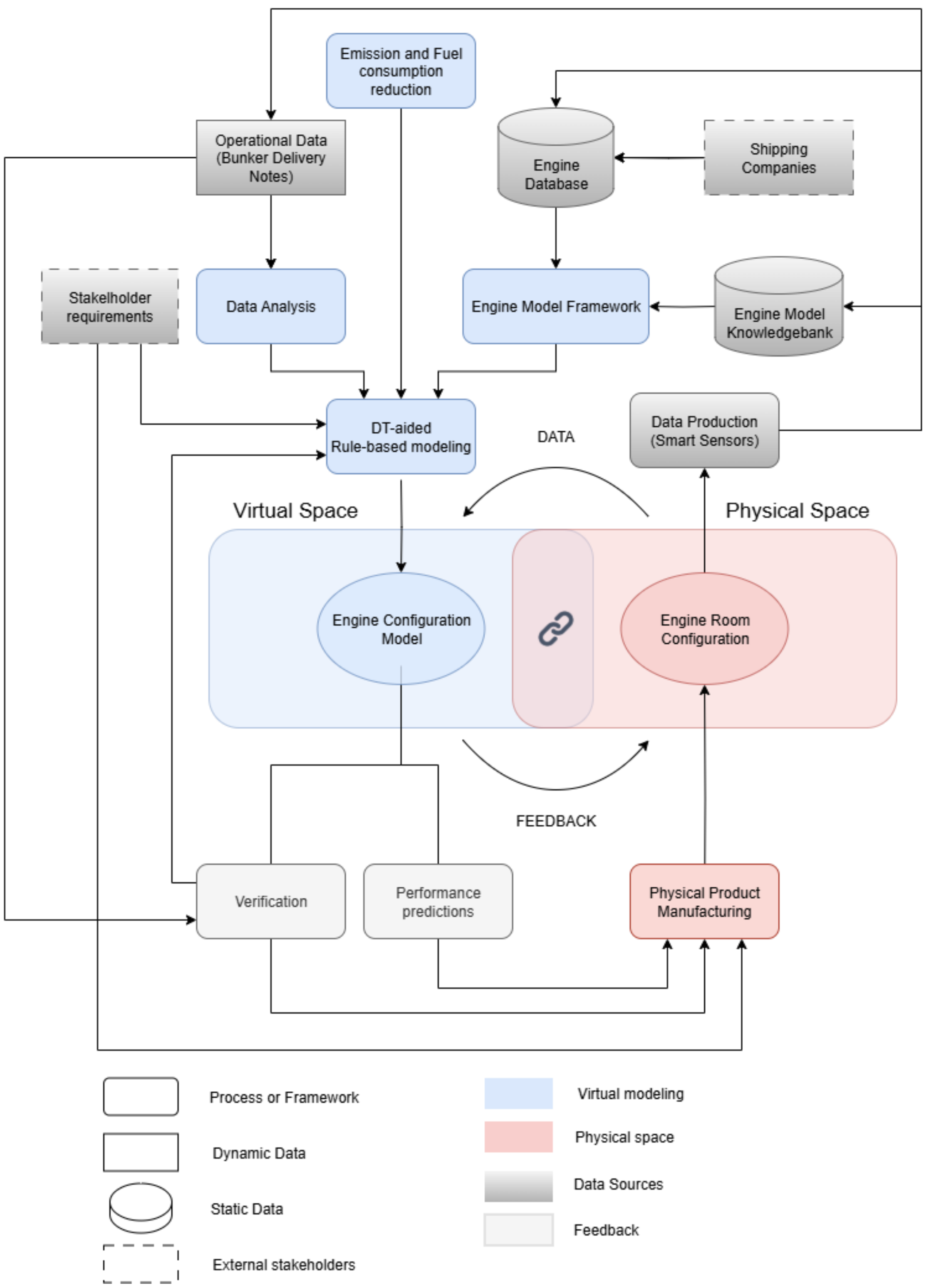

Figure 5.2: DT-aided design methodology for engine room selection application

5.2. DT-aided design goal

Block: **Emission and Fuel consumption reduction**

The goal of this case study is to apply the DT-aided framework to support the configuration and selection of ship engines in a way that enables more sustainable vessel design. By modeling and comparing different engine setups under realistic operational profiles, the framework aims to improve design robustness and support emissions reduction targets. The case study utilizes operational data generated by a large bunker vessel, the type of vessel being examined. The data will be further explored in section 5.3.

To achieve a robust model that supports emission reduction, the virtual space must simulate the performance of various internal combustion engine (ICE) configurations—primarily diesel and dual-fuel types—based on the completeness of available data. While this limits the fuel and engine diversity explored, the framework remains flexible and scalable for future data expansion.

In the following sections, each part of the DT-aided design framework presented in the last section (Figure 5.2) is translated into a modeling task, supporting a structured and repeatable workflow for early-stage engine room design.

5.3. Data Collection and Processing

Blocks: **Shipping Companies, Engine Model Knowledgebank, Engine Database, Operational Data, Data Analysis**

The first step in the DT-aided design process is the acquisition and processing of data. For the improvement of the design and choice of the ship engine, ship engine data is required, and ship operation data is needed. The gathering and processing of this data will be achieved through the method of Zheng et al., which was discussed in section 4.1 in Figure 4.1. Because the case study uses both ship engine data and operational data, the section will be split into a ship engine data subsection and an operational data subsection.

5.3.1. Engine data

One of the essential building blocks for this model is data on different ships and the engines they use. While many engine manufacturers publish information on their products, no comprehensive database covering all manufacturers exists. Instead, this information is compiled and made available through external organizations that provide dedicated shipping and engine datasets.

Data acquisition

To acquire the data of different engines that are used to generate the different engine configurations, the database of Clarksons Research is used [144]. This database contains data and insights on all aspects of shipping and trade. The database contains a comprehensive overview of different ships and the engines being used in these ships. Varying in size and power.

The data is acquired from two different data sets, ship data and engine data. The data is combined into a single, larger dataset to gather as much information as possible per engine. The ship data contains information on both the auxiliary engines and the main engine. The data gathered from the main engine from this set is the following:

- Ship type
- DWT
- Power Type
- Main Engine Model
- Main Engine Fuel Type
- Main Engine Number
- Engine Derived Total Main Engine Mechanical kW
- Main Engine SFOC g/kWh

This data is not always complete and must be processed to achieve a high enough quality for use. It will also be filled out with data from the engine data set, which contains some extra info on the main engines of ships. This data is the following:

- Main Engine Model
- Main Engine Model kW Total max Value
- Main Engine Model SFOC (g/kWh)
- Main Engine Fuel Type
- Main Engine Model IMO NOx Tier Rating

The required information for auxiliary engines is similar, but it is available only through the ship dataset. This includes:

- Ship Type
- Main Engine Power Type
- Auxiliary Engine Model
- Auxiliary Engine i Fuel Type
- Auxiliary Engine i SFOC g/kWh
- Auxiliary Engine i (mkW)

Since most vessels are equipped with multiple auxiliary engines, each engine entry is indexed (i) to distinguish between them. Including all auxiliary engines is essential to capture the full operational redundancy and power availability of a vessel, ensuring that the dataset accurately reflects realistic engine room configurations.

Data pre-processing
The raw data that is gathered here contains several flaws that would not give satisfactory results. After the data pre-processing steps, combining the engine data set and ship data set to acquire the total main engine data set, the gathered data will have the following form:

Engine Model	Ship Type	Power Type	Fuel Types	Number of Engines	Power Generated (kW)	SFOC (g/kWh)	NOx Tier Rating
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

The auxiliary data gathered from the ship data set has a similar shape and is of the following form:

Engine Model	Power Type	Fuel Types	Number of Engines	Power Generated (kW)	SFOC (g/kWh)
⋮	⋮	⋮	⋮	⋮	⋮

The auxiliary engine dataset contains slightly less information than the main engine dataset. This is likely because most ships are equipped with multiple auxiliary engines, making it more challenging for data collection organizations to track and record each engine individually. One crucial type of data that is listed but is empty in a lot of the entries is the 'SFOC (g/kWh)'. This is a critical piece of information that when missing, the entire engine entry will have to be removed, for the auxiliary engines some of this data is imputed

The data pre-processing steps taken to obtain these final datasets include data cleaning, data restructuring, and handling missing data.

Data cleaning: As was mentioned, the different data sets were combined from the two sets to include all other types of engines. After this step, some main and auxiliary engines were listed multiple times, due to multiple ships using the same engines. These entries are taken out, and the ones with the most complete data are kept. In some cases, important data that cannot be imputed is missing, such as the power of the engine; these entries are also removed. When fuels are used that do not fit the specific engine type dataset, they are also removed.

How the data changes quantitatively for both the main and auxiliary dataset will be explained in Section 6.1. The steps for cleaning the main engine dataset were as follows

- Split engine model
- Remove when data is missing
- Merge data
- Duplicate removal
- Fuel Filter
- SFOC cleaning

The steps for the auxiliary dataset were marginally different. These steps are listed below:

- Split engine model

- Remove missing data
- Duplicate removal

Data restructuring: Following this, the auxiliary engine summary data was restructured, as they included all engines as a group entry, so all auxiliary engines were considered and listed individually. Then, the total power of the engines is divided by the number of engines; this was done for both the main engine and the auxiliary engines. The rule that was followed for both types of engines can be seen in Equations 5.1a and 5.1b:

$$P_{i,ME} = \frac{P_{total,ME}}{n_{ME}} \tag{5.1a}$$

$$P_{i,AE} = \frac{P_{total,AE}}{n_{AE}} \tag{5.1b}$$

Handling missing data: The auxiliary engine data initially missed a lot of SFOC data, which is essential for the emission calculation. For 80% of engines not being taken into account, data is imputed in three different ways to make the database more complete. These three strategies are:

- **Engine model-based**, this strategy uses the median SFOC from comparable engine models
- **Power-based regression**, which estimates SFOC based on power within fuel types
- Using **Industry standards**, which applies conservative typical values as a fallback if the first two strategies do not give satisfactory results

The first strategy yields little bonus data; the algorithm searches for models with the same name and assigns the same SFOC to those entries. These data entries have mostly been filtered out by this step, as there is no use for double engine entries. This strategy serves more of a validation check.
The second strategy uses linear regression to fit the power to the SFOC per fuel type using Equation 5.2:

$$\text{SFOC} = \beta_0 + \beta_1 \cdot P_E + \varepsilon \tag{5.2}$$

Where β_0 is the intercept (baseline SFOC), β_1 is the slope (how SFOC changes with power), P$_E$ equals the power of the auxiliary engine, and ε is the error term. The power is related to the SFOC (bigger engines often have lower SFOC and vice versa). The regression model is trained where:

$$x = P_E$$
$$y = SFOC$$

Then, the SFOC value is predicted based on the power value for entries where the SFOC is missing. This is done for each fuel, only if there are at least five values to create the estimation.
The final imputation strategy utilizes the industry standard to fill in 'obvious' SFOC if the linear regression did not yet fill them in. This strategy is only used for diesel oil engines, so if the fuel includes HFO, MDO, MGO, or Diesel. The SFOC is filled in based on the size of the engine, categorized from small to large:

- Small: <1000 kW
- Medium: 1000 - 3000 kW
- Large: >3000 kW

With the SFOC being filled in for the fuels in the following way (As using this final strategy is an estimation, the values are taken conservatively).

- HFO : Small = 225, Medium = 215, Large = 205
- MDO/MGO/Diesel: Small = 200 - 205, Medium = 195 - 200, Large = 190 - 195

The linear regression is done before the industry standard because the engines that are taken into account are from ships with similar power profiles and length, thus with comparable power to the SFOC range.
The data is validated to exclude unrealistic values, lower than 150 g/kWh and higher than 300 g/kWh.

Data analysis and mining A significant portion of data analysis occurs during the modeling phase, where pre-processed data is used to evaluate system behavior. More advanced data mining techniques—such as clustering, outlier detection, and classification—offer further potential for pattern discovery and deeper insights. However, the application of these methods lies beyond the scope of this case study.

5.3.2. Operational data used in case study

This case study utilizes operational data to simulate actual shipping operations, supporting decision-makers in early-stage design. The data will be explored and processed in this section.

Data acquisition
The operational data is gathered from Bunker Delivery Notes (BDN). This dataset comprises 129,174 data points collected over five distinct periods between January 7, 2022, and September 30, 2023. The data has been collected at 5-minute intervals, encompassing 107 different data types. The source of the data is the European Horizon project, aiming to create Digital Twins for green shipping [145]. The data is gathered through a multitude of sensors that give direction, speed, engine use, and fuel efficiency.

Data pre-processing
The data contains an abundance of different types of data that need to be processed for the specific application. For this case study, the data that needs to be retrieved from the dataset are:

- Time
- Main engine power
- Auxiliary engine power
- Location
- Speed

By gathering this data, a model can be created that predicts fuel consumption (and thus emission output) for different power profiles. To collect these data entries, some of the raw data have to be restructured.

Time

The time is taken directly from the TimeStamp entry. The time is registered in intervals of 5 minutes. The dataset records voyages of approximately 3 months. The model uses periods of about 1-2 weeks of this period to simulate specific moments of the voyage, including: Constant load at sea, in-port movement, and special operations.

Main engine power

The most important piece of data that is provided by the dataset is the shaft power. As a bulk carrier commonly does not have a gearbox, the shaft power is taken directly as the brake power required by the engine. This is given by the equation 5.4.

$$P_s = \eta_{GB} \cdot P_B \tag{5.4}$$

To calculate the fuel consumption of the ship, typically the engine load (in %) is used. This case study is no different; the shaft power will be divided by the specified continuous mechanical propulsion power of the engine used in the data (equation 5.5). When configuring the engine design, the engine load % would change per configuration.

$$load\% = \frac{SMCR}{P_B} \tag{5.5}$$

Auxiliary engine power

To find the Auxiliary engine power, the 'diesel generator power total' is used. This variable includes the total power required by the auxiliary engines.

Location

The vessel's location is obtained by converting the recorded degrees, minutes, and lateral indicators into decimal degree coordinates, enabling accurate mapping of the ship's trajectory. This positional data serves two primary purposes. First, it supports the identification of distinct operational phases (e.g., port stays, voyages, or loitering), which form the basis for constructing representative load profiles used in the engine simulations. Second, in combination with time data, it allows the calculation of the total distance sailed, which is required for the Carbon Intensity Indicator (CII) assessment.

Speed

Speed is included as one of the entries in the raw dataset and is recorded as speed through water. This occasionally results in negative values, particularly when the vessel is stationary in port and water continues to move past the hull. While this could be corrected, speed in this case is primarily used to distinguish between operational profiles and is therefore not directly used in the modeling process.

Data analysis and mining

As the data is gathered from 5 separate voyages, it is of value to see which voyages contain the most accurate and defined operation profiles. This is done by plotting the voyages on an Open Street Map and looking for distinct load profiles. The power data should then show differences in value during hotel load and port operation. The data can be utilized for a multitude of applications when further mined and analyzed. Finding outliers in the speed, for instance, would improve the data and make it more accurate. In this case study, the power data is the most important and should be correct, and this data does not show any outliers.

5.4. Modeling approach and assumptions

Blocks: **Engine Model Framework, Stakeholder requirements, DT-aided Rule-based modeling**

To determine the appropriate modeling approach, the objective of the DT-aided design process must be clearly defined—specifically, the type of ship and the system being modeled. From this, a suitable fuel consumption model can be developed, which in this case will follow a rule-based modeling approach. This block can be found in the virtual modeling space.

5.4.1. Rule-Based modeling approach

The rule-based modeling approach is chosen because it offers a controllable method for constructing and evaluating engine room configurations. In the early stages of ship design, where full-scale simulations and data-driven optimization may not yet be feasible or available, rule-based systems allow a structured way of applying domain-specific knowledge.

In this context, rules serve as encoded logic that governs the behavior of the configuration process. These rules define acceptable engine types, fuel constraints, redundancy requirements, and power balance conditions. For instance, a rule may ensure that the total auxiliary power must exceed a minimum threshold based on operational peak load, or that no more than two distinct fuel types are used in a given setup. These constraints are critical for ensuring that resulting configurations are not only efficient but also practical and aligned with real-world design standards.

The rule-based approach is also modular and easily adaptable. As new technologies (e.g., hybrid-electric systems, fuel cells) become more prominent, additional rules can be incorporated without having to redesign the entire modeling framework. This makes the method future-proof and scalable.

Moreover, it aligns well with a DT-aided design process, where the configuration system reflects a set of "virtual design constraints" that can evolve as new operational insights are gathered. Instead of relying purely on black-box optimization or exhaustive brute-force search, rule-based modeling provides a tractable, interpretable, and engineering-aligned strategy for narrowing down feasible and environmentally friendly propulsion configurations.

The engine and operational data feed the Rule-based modeling approach block, which incorporates different modeling frameworks (the fuel consumption model and engine configuration rules), as well as stakeholder requirements. First, the reference vessel will be discussed. Then the stakeholder requirement block will be explained, and afterwards the data and rules of the rule-based model will be explored.

5.4.2. Case Study Vessel

The configurations will be selected and modeled for a ship of about 300 meters in length overall (LOA). This is because the data from the BDN corresponds to that of a bigger bulk carrier. The ship utilizes a two-stroke diesel engine; some extra relevant characteristics are listed in Table 5.1.

Ship/engine Characteristic	**Value**
DWT [mt]	209,472
LOA [m]	300
Main Engine Power Type	Diesel 2-stroke
Specified Continuous Mechanical Propulsion [kW]	15,131
Maximum Continuous Rating [kW]	21,840
Main engine SFOC [g/kWh]	168
Auxiliary Power	3x Aux Diesel Gen.
Auxiliary power generated (per unit) [kW]	4,110

Table 5.1: Characteristics of 300 meter Bulker

To ensure relevance to larger vessels, engine data is filtered by selecting ships with a LOA of at least 100 meters. This approach captures a range of engines suitable for large ship applications, while still including smaller engines that may offer promising alternative configurations. The resulting dataset provides a comprehensive list of potential engine candidates. From this list, possible engine combinations are identified and evaluated as viable replacements for the reference vessel described in Table 5.1.

5.4.3. Stakeholder requirements

One of the blocks going into the rule-based model is the stakeholder requirements. This block is from outside stakeholders who order the type of ship they want to design or specify the performance characteristics the vessel must have. These extra 'rules' also add to the rule-based model. In this case study, the stakeholder requirements are simulated by the request to generate an optimized engine room for a bulk carrier.

5.4.4. Configuration rules

This section describes the modeling rules and constraints used to generate propulsion configurations. The configuration logic consists of three key parts: main engine selection, auxiliary engine combination strategy, and fuel constraints.

Main Engine selection

The ship is assumed to operate with a mechanical propulsion system, where the main engine directly drives the propeller. In the case of hybrid configurations, auxiliary engines may support or partially drive the propulsion shaft, depending on the topology selected (see Section 2.5).

Each candidate's main engine is sourced from the engine dataset and filtered based on:

- Available model and fuel type
- Available Specific Fuel Oil Consumption (SFOC) data

Main engines are categorized by their `Power Type` (e.g., *diesel 2-stroke*, *dual-fuel*, *gas turbine*, or *diesel 4-stroke*), as labeled in the dataset. Each category is sorted based on an efficiency score defined as:

$$\text{Efficiency Score} = \frac{P_{\text{MCR}}}{\text{SFOC}} \tag{5.6}$$

where P_{MCR} is the maximum continuous rating of the engine.

For each category, a limited number of top-performing engines are selected. The selected engine must have a suitable SMCR (Service MCR), defined as:

$$0.5 \cdot P_{\text{required}} \leq P_{\text{SMCR}} \leq 2 \cdot P_{\text{required}} \tag{5.7}$$

This ensures the selected main engine provides sufficient but not excessive power compared to the total propulsion requirement; the range of engines that can be chosen in this way is still quite broad. This will ensure that multiple types of main engines are considered, even if, in a hybrid topology, the auxiliary engine can also provide extra power to the shaft.

Auxiliary Engines selection

A single auxiliary engine should at least be able to generate the at-sea constant auxiliary power that is required. The general fluctuation of auxiliary load in the data is between 400 kW and peaks of up to 1000 kW.

For ships with a total propulsion power of 10,000 kW or higher, the minimal power of the auxiliary engine (P_{AE}) is defined as follows:

$$P_{AE,min} = \left(0.025 \times \left(\sum_{i=1}^{n_{ME}} MCR_{ME(i)} + \frac{\sum_{i=1}^{n_{PTI}} P_{PTI(i)}}{0.75}\right)\right) + 250 \tag{5.8}$$

To attain redundancy, some extra power will be required by the auxiliary engines beyond just the constant power that needs to be provided. To achieve this redundancy, the choice is made that the total auxiliary power should be greater than the peak auxiliary load by multiplying it by a safety factor (SF) of at least 1.15:

$$\sum_{i=1}^{n} P_{\text{aux},i} \geq P_{\text{aux, peak}} \cdot SF \tag{5.9}$$

To ensure redundancy and operational flexibility, auxiliary engine power per unit is limited to a maximum of 30% of the main engine's MCR. This is aligned with industry practices and ensures compliance with redundancy requirements, which are also typically observed in larger cargo vessels.

$$P_{AE,max} = 30\% \cdot P_{\text{MCR}} \tag{5.10}$$

Auxiliary combinations are generated using four strategic rules:

1. **Single Engine:** A high-power auxiliary engine that alone meets the power requirement
2. **Twin Identical:** Two identical engines offering redundancy
3. **Twin Diverse:** Two different engines to explore fuel diversity
4. **Triple Redundant:** Three engines with different ratings but limited to two fuel types

Only engines that have valid entries for model, SFOC, power, and fuel type are considered. Each combination includes metadata such as total power, fuel types used, and the number of engines.

Fuel Constraints and Configuration filtering

Configurations are constrained to use no more than two different fuel types across both main and auxiliary engines:

$$\text{Fuel Types Used} \leq 2 \tag{5.11}$$

This ensures realistic fuel storage logistics for vessels. Configurations that exceed this threshold are discarded.

Finally, the total installed power must be within a 20% deviation of the required design power, to ensure not too many configurations are created:

$$|P_{\text{total}} - P_{\text{required}}| \leq 0.2 \cdot P_{\text{required}} \tag{5.12}$$

Configuration creation
Each configuration includes:

- Main engine type, model, fuel, power, and SFOC
- A list of auxiliary engines with type, model, power, SFOC, and fuel
- Auxiliary selection strategy
- Total installed power
- Fuel diversity and count

These configurations are stored as dictionaries and later converted into tabular format (see Section **??**) for analysis and emissions simulation.

5.4.5. Power allocation of Hybrid configuration

To further improve the optimization capabilities of the model, a hybrid configuration model is implemented. In this setup, auxiliary engines are not only used to cover hotel loads but can also contribute propulsion power, supplementing or partially replacing the load on the main engine when this results in improved efficiency, as is the case for a hybrid topology (section 2.5).

The hybrid mode is modeled using a power distribution optimization algorithm that allocates required propulsion and auxiliary power between the main engines and auxiliary engines at each timestep. The optimization seeks to minimize total fuel consumption based on load-dependent SFOC curves of the engines. This reflects the way engine efficiency varies significantly with load, and suboptimal loading can lead to disproportionately higher emissions.

The strategy works in the following way:

1. Total power demand is calculated as the sum of the shaft power and auxiliary power required
2. Different power splits are performed between the main and auxiliary engine (in 10% increments)
3. When a feasible distribution is found, the corresponding fuel consumption is calculated with the load-adjusted SFOC calculator.
4. The distribution that minimizes fuel consumption is selected

This method enables the simulation of scenarios where the main engine is lightly loaded, allowing auxiliary engines to run at a more optimal load and provide additional propulsion power. Using this system does require some extra processing time or computational power. With this added feature, a conventional system can be compared to a hybrid system. In the model and the results, this hybrid functionality will be referred to as using hybrid mode. Either on or off:

- **Hybrid Mode: *ON*** - Hybrid functionality is active, the ideal power distribution between main and auxiliary engine is calculated and used.
- **Hybrid Mode: *OFF*** - Hybrid functionality is inactive, and the main engine only powers the propeller.

5.5. Emissions & Fuel Consumption Modeling

Block:**DT-aided Rule-based modeling**

This section explains how fuel consumption and CO_2 emissions are estimated for each configuration. The approach combines operational load profiles with engine-specific efficiency characteristics and emission factors to simulate engine performance. This enables a realistic, data-driven ranking of configurations based on their environmental performance. The configurations will be ranked and assessed according to a few key performance indicators (KPIs) that will be discussed in this section. They are the:

- **Total CO_2 emissions**
- **Total Fuel consumption**
- **Emission Intensity**
- **CII index**

First, the logic for calculating emissions will be explained.

5.5.1. Engine Load and SFC modeling

Accurately estimating emissions requires modeling how engine efficiency varies under different operational conditions. The key factor in this is the Specific Fuel Oil Consumption (SFOC), which depends on the engine load. Most engines are rated at a base SFOC value at optimal load conditions (typically 75–85% load), but this value changes significantly at lower or fluctuating loads.

Jalkenen et al. have studied the specific fuel oil consumption (SFOC) of marine diesel engines and, via a regression analysis of comprehensive SFOC measurements from Wärtsilä, derived a second-degree polynomial equation 5.13 for the relative SFOC [146].

$$SFC_{\text{rel}} = 0.455 \cdot L^2 - 0.71 \cdot L + 1.28 \tag{5.13}$$

Where $L \in [0, 1]$ is the engine load expressed as a fraction of the engine's SMCR (Service Maximum Continuous Rating). The actual SFOC is then computed as:

$$SFC_{\text{actual}} = SFC_{\text{base}} \cdot SFC_{\text{rel}} \tag{5.14}$$

This load-dependent SFC is calculated at each 5-minute interval of the ship's operation using historical load profile data, for both main and auxiliary engines. These values are then used to estimate instantaneous fuel consumption and emissions. The polynomial can be seen in Figure 5.3.

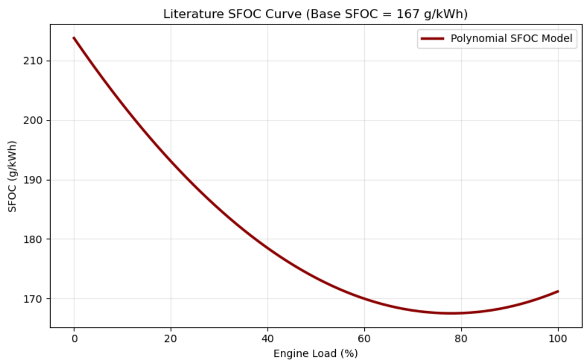

Figure 5.3: SFOC polynomial gathered from Jalkenen [146].

5.5.2. Emission estimation

Emission factors

To estimate CO_2 emissions from fuel consumption, standard emission factors are used. Each fuel type has an associated emission factor EF expressed in tonnes of CO_2 per tonne of fuel. These values are sourced from literature and public databases such as the IMO's GHG studies and EMEP/EEA emissions inventory [147].

- Marine Diesel Oil (MDO): 3.206 tCO_2/t fuel
- Heavy Fuel Oil (HFO): 3.114 tCO_2/t fuel

- LNG: 2.750 tCO_2/t fuel
- Biofuel: 3.2 tCO_2/t fuel

When systems use both LNG and a heavy fuel, in a dual-fuel engine, for instance, the emission factors are averaged.

Emissions calculation logic

Fuel consumption is calculated for each interval Δt based on the following formula:

$$\text{Fuel}_{\Delta t} = \frac{P_{\text{load}} \cdot SFC_{\text{actual}} \cdot \text{Losses}}{10^6} \cdot \Delta t \tag{5.15}$$

Where:

- P_{load} is engine power at load [kW]
- SFC_{actual} is load-adjusted SFOC [g/kWh]
- Losses include mechanical, thermal, and auxiliary system factors (typically 38–40% total system efficiency)
- Δt is the time interval in hours (e.g., 5 min = 1/12 h)

Total CO_2 emissions are computed as:

$$\text{Emissions}_{\text{CO2}} = \text{Fuel}_{\text{total}} \cdot EF \tag{5.16}$$

Emissions are tracked separately for main and auxiliary engines, and by fuel type in the case of dual-fuel or hybrid configurations.

5.5.3. Emissions Intensity and Performance Metrics

In addition to total CO_2 output, the model calculates emissions intensity to allow fair comparison across configurations. This is defined as:

$$\text{Emissions Intensity} = \frac{\text{Total CO2 Emissions} \cdot 10^6}{\text{Total Energy Output (kWh)}} \quad [\text{g } \text{CO}_2/\text{kWh}] \tag{5.17}$$

This intensity metric is used as one of the main criteria for ranking and selecting the optimal configurations. While not identical, it is conceptually similar to the IMO's Carbon Intensity Indicator (CII), as both express emissions relative to transport performance. The difference is that this thesis applies a simplified energy-based measure (g CO_2/kWh), whereas the IMO's CII is defined in terms of g CO_2/dwt·nm. Nonetheless, both indicators provide a way to benchmark environmental performance beyond absolute emission totals.

5.5.4. Carbon Index Indicator (CII)

The CII calculation was also implemented in the model to evaluate engine room configurations against the IMO's Carbon Intensity Indicator (CII) framework, as described in section 2.3. The CII calculator follows IMO's MEPC.354(78) and MEPC.355(78), which incorporates vessel-specific baseline coefficients for various ship types. First, the reference CII value is calculated for the vessel based on its deadweight tonnage (DWT) and the ship type, using the reference function. Then the CII is computed using total CO_2, DWT, and distance sailed based on the BDN. This produces a value in grams of CO_2 per tonne nautical mile.

Then, a rating from A to E is assigned by comparing the actual ship value to the reference CII, applying the reduction factor that responds to the IMO's performance category, and the 2025 reduction is taken. The CII rating chart is also visualized, plotting the A-E rating boundaries and the reference line. This allows the configuration to be positioned against the regulatory thresholds.

5.6. Model Verification and sensitivity analysis

(Blocks:**Verification**)

Verification of the model was carried out both during the data analysis phase and after calculating emissions. This process involved systematically checking that all loaded operational data and computed outputs fell within realistic operational margins, based on known vessel performance ranges and engine manufacturer specifications. Any anomalies, such as unrealistically high power loads or negative consumption values, were inspected and corrected before further analysis. This ensured that subsequent results were more credible and valid.

In addition to verification, a sensitivity analysis was included to assess the influence of key input parameters (e.g., SFOC, emission factors, and auxiliary load) on the model's outcomes. This ensures that the robustness of the results can be evaluated, highlighting which assumptions have the most significant impact on emissions performance. The results of this analysis are presented in Chapter 6.5.

The sensitivity analysis of this model was performed using both one-at-a-time (OAT) and Monte Carlo sampling to assess the impact of key input parameters, such as SFOC, emission factors, and auxiliary load, on total CO_2 emissions. The correlation and variation in outputs were used to identify the most influential parameters. This analysis can be found in section 6.5.

5.7. Knowledge Management and DT-feedback

(Blocks: **Manufacturing, Physical space, Engine Model Knowledgebank, Engine Database, Operational Data**)

Knowledge management and the DT-feedback to the physical entity are out of the scope of this thesis. It is an important aspect to consider when the model is expanded for industry purposes. In this case study, all results are locally stored in Excel sheets. Future applications should utilize a databank and inform existing databases as the framework suggests. The feedback blocks in the framework serve this purpose. How the knowledge management and DT-feedback can be further expanded will be discussed in 8.

6

Results and Analysis

This chapter presents the results of applying the DT-aided design framework to reduce fuel consumption and emissions of a bulk carrier by implementing the rule-based model created in chapter 5. Due to the complexity of operational conditions, data limitations, and model sensitivity, results vary depending on engine types, fuel assumptions, and optimization parameters.

The analysis begins with an examination of the data and its potential impact on the results. Afterwards, the outputs of different engine configurations are compared, followed by emission estimates and performance trade-offs. Where possible, sensitivity to data uncertainty or modeling choices is discussed. The goal is not to identify a single "optimal" configuration, but to explore how the framework supports informed decision-making through data-driven simulation.

6.1. Engine Dataset Overview

To acquire the data used in the model, several data processing steps were taken. First, the main engine data processing steps are shown, then the auxiliary engine data steps are shown. The steps taken and the data point modifications are shown for the main engine in Table 6.1.

	Data intergration	Data processing					
Engine Type	LOA >50m	Split Engine Model	Remove missing data	Merge data	Duplicate removal	Fuel Filter	SFOC cleaning
Diesel 2-Stroke	14,158	14,159 (+1)	14,157 (-2)	14,157 (0)	597 (-13,560)	538 (-59)	463 (-75)
Diesel 4-Stoke	166	178 (+12)	178 (0)	178 (0)	66 (-112)	60 (-6)	27 (-33)
Dual-Fuel	259	430 (+171)	429 (-1)	429 (0)	21 (-408)	21 (0)	13 (-8)
Gas Turbine	16	16 (0)	13 (-3)	13	5 (-8)	5 (0)	4 (-1)
Steam Turbine	264	264 (0)	222 (-42)	222 (0)	17 (-205)	17 (0)	0 (-17)
Nuclear	10	10 (0)	5 (-5)	5 (0)	3 (-2)	3 (0)	0 (-3)
Total	14,885	15,069 (+1.24%)	15,004 (-0.43%)	15,004 (0)	707 (-95.29%)	642 (-9.19%)	507 (-21.03%)

Table 6.1: Data pre-processing of main engine dataset

The auxiliary dataset was also filtered and processed. Fewer steps were taken in this process as the data set was less broad. The data processing for the auxiliary engines can be seen in Table 6.2.

	Data integration	Data processing		
Engine Type	Aux. Engine dataset	Split Engine Model	Remove missing data	Duplicate removal
Diesel 2-Stroke	13,272	18,428 (+5,156)	14,736 (-3,692)	355 (-14,381)
Diesel 4-Stoke	181	264 (+83)	121 (-143)	35 (-86)
Dual-Fuel	298	590 (+292)	290 (-300)	0 (-290)
Gas Turbine	11	70 (+59)	42 (-28)	15 (-27)
Steam Turbine	323	742 (+419)	294 (-448)	5 (-289)
Nuclear	2	4 (+2)	0 (-4)	0 (0)
Total	14,087	20,098 (+42.67%)	15,483 (+22.96%)	410 (-97.35%)

Table 6.2: Data pre-processing of auxiliary engine dataset

The final processed datasets used in this case study contain 507 main engines and 410 auxiliary engines.

The amount of data that is available for each type of engine is divided. As the number of diesel engines in bigger transport vessels is significantly more than that of newer, potentially greener but smaller engines, they have an abundance of information on them. The final different types of engines for which there is information are also shown in the Figure 6.1.

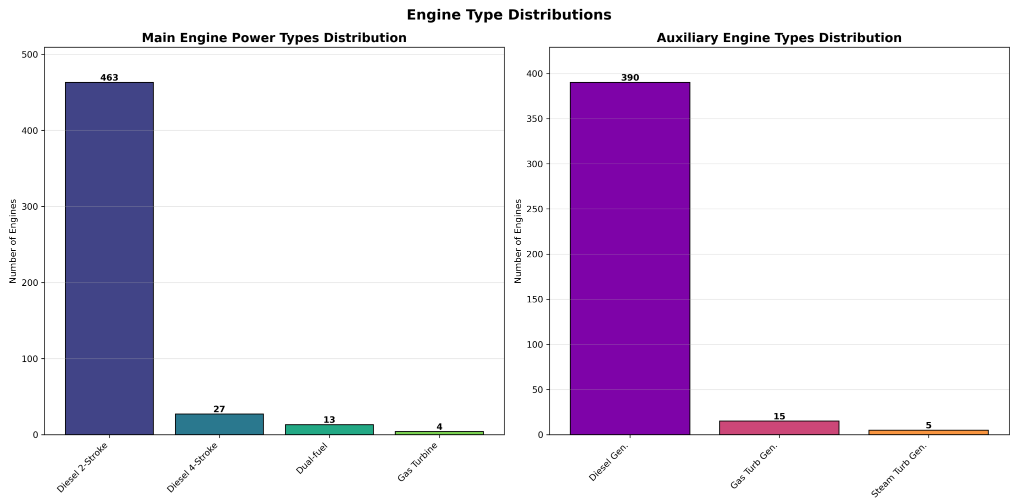

Figure 6.1: Distribution of engines in the main and auxiliary engine dataset

As was predicted, the number of diesel 2-stroke engines and diesel generators far exceeds the number of other engines.

As with the engines, there is also data on the types of fuel used, both in the main and the auxiliary engines. This distribution is shown in Figure 6.2. The fuel correlates to the engine type used, and the main type of fuel used is indeed the type of fuel oil that is used by diesel engines/generators.

An important variable for the fuel consumption model used in this case study is the Specified Fuel Consumption (SFC) of each engine. This SFC value is used to calculate how much fuel is consumed by the engine. The companies often provide this value, but it is also imputed by the model, as discussed in 5.3.1. Figure 6.3 shows the distribution of the SFC of the main and auxiliary engines. In line with industry norms, larger main engines typically achieve lower SFC values than smaller auxiliary engines, due to their higher thermal efficiency and optimized operation at sustained loads. Next to this figure is the distribution of the power range of both the main and auxiliary engines, where indeed it is clear that there are more powerful main engines than auxiliary engines (Figure 6.4).

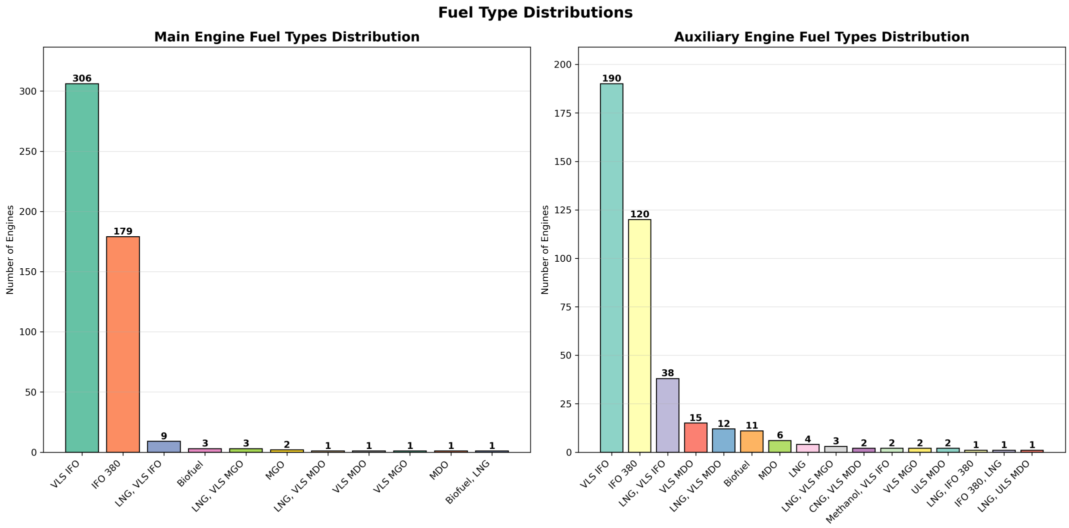

Figure 6.2: Distribution of fuels used in the main and auxiliary engine dataset.

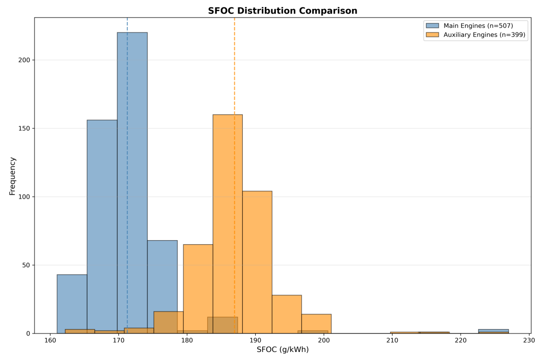

Figure 6.3: Distribution of the SFC of the main and auxiliary engines dataset.

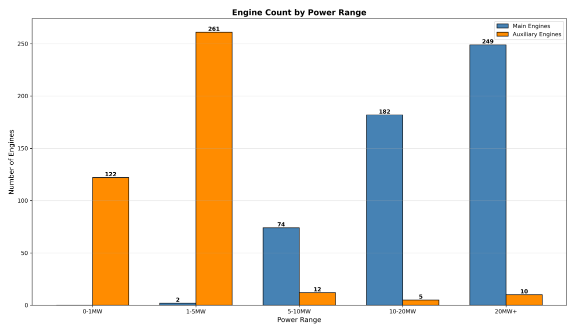

Figure 6.4: Distribution of power ranges main and auxiliary engines

To get some extra insights into what types of ships these engines are gathered from, the distribution of vessels is given in Figure 6.5. This distribution suggests what types of ships would be easier to simulate or configure based on the data set. The most common ship listed in this engine set, or the ship type that has the most data on it, is cellular container vessels. The operational data studied and used in this case study are of a bulker vessel, which is the second most common ship type.

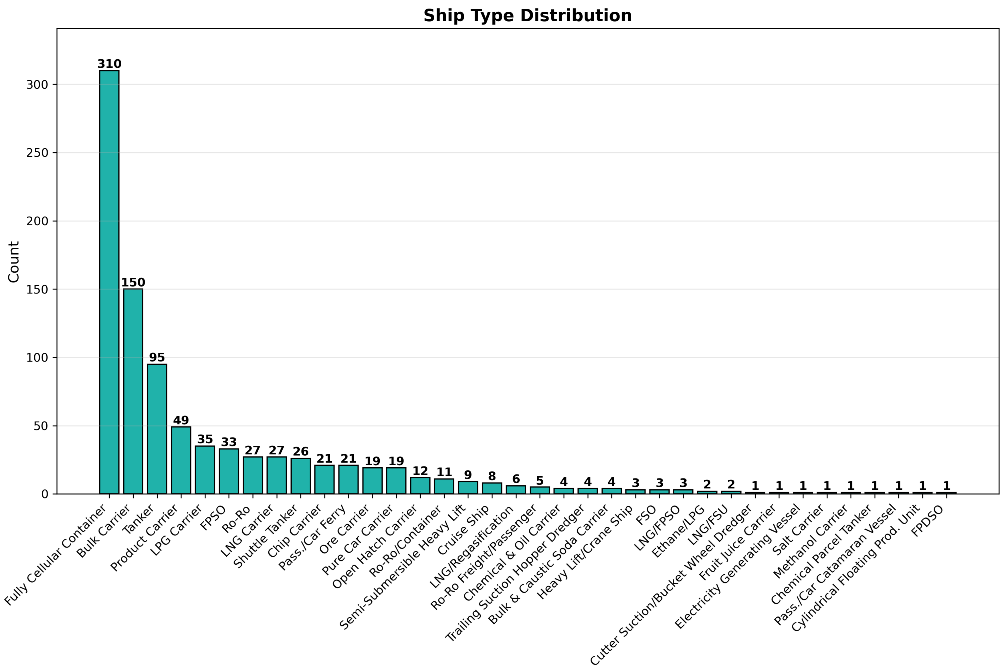

Figure 6.5: Distribution of ship types in the engine dataset.

Figure 6.6 shows the relation between the different fuels and their respective SFOC vs the power the engine using it produces. A clear relation can be seen that the lower SFOC engines mostly use the heavier fuels. But the fuels with a lower emission factor can be found at a higher SFOC. Lower SFOC engines (165 g/kWh) typically use HFO, whereas higher SFOC engines (260-280 g/kWh) use lower carbon fuels such as methanol. For auxiliary engines, this distribution is a little more spread out.

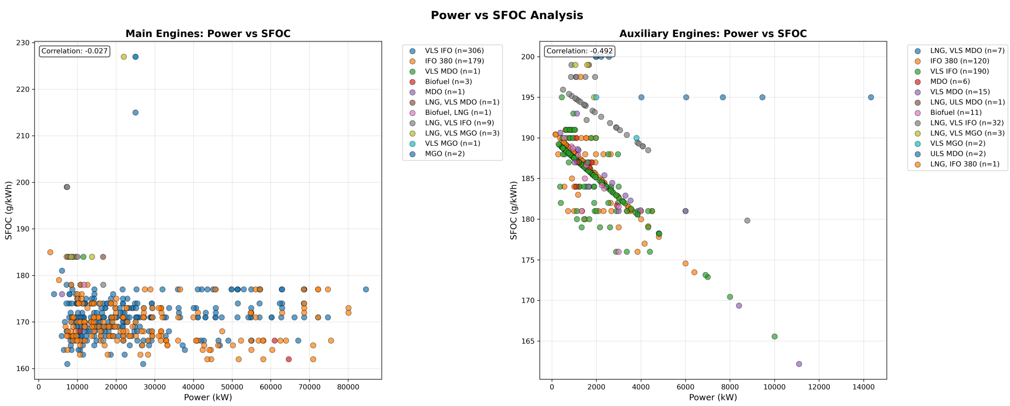

Figure 6.6: Scatter plot of different engines with their SFOC vs their power

6.1.1. Operation dataset Overview

The operation data set is gathered from Bunker Delivery Notes (BDN) and has data from 3 different periods, as was discussed in 5.3.2. For this case study, several different load profiles are used as the simulation input. These load profiles will be used to assess the engine configurations quantitatively. The load profiles include:

- 2 week voyage
- Port operation (entering, operating, and leaving)
- Loitering in port

Each of these load profiles is shown in the following figures. The data confirms the predicted results, with clear load profiles corresponding to the type of operations performed during the specific operation. A fluctuating load profile during the port operations, a steady non-fluctuating load profile during the voyage, and a more auxiliary heavy load profile during loitering. The first figure (Figure 6.7) showcases a voyage of two weeks where a steady main engine and constant fluctuating auxiliary power are required.

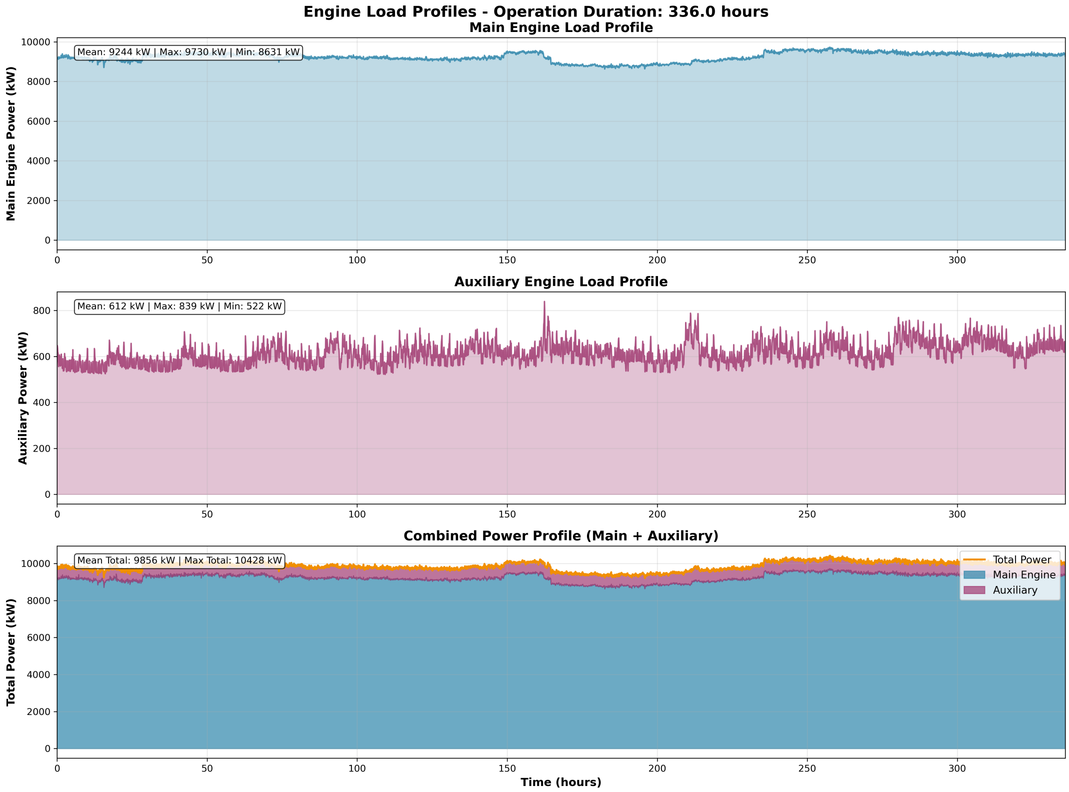

Figure 6.7: 2-week voyage load profile.

The following load profile is for port operations. Here, there is a long pause in the use of the main engine with only two small spikes, while the auxiliary engines have a constant fluctuation with some peaks during the operations, with peaks of up to 800 - 1000 kW.

Figure 6.8: Port operation load profile.

The final load profile examined is the loitering condition of the vessel. In this operating mode, the main engine remains idle, and only the auxiliary engines are engaged at low load to cover essential onboard power demand. The resulting profile is shown in Figure 6.9.

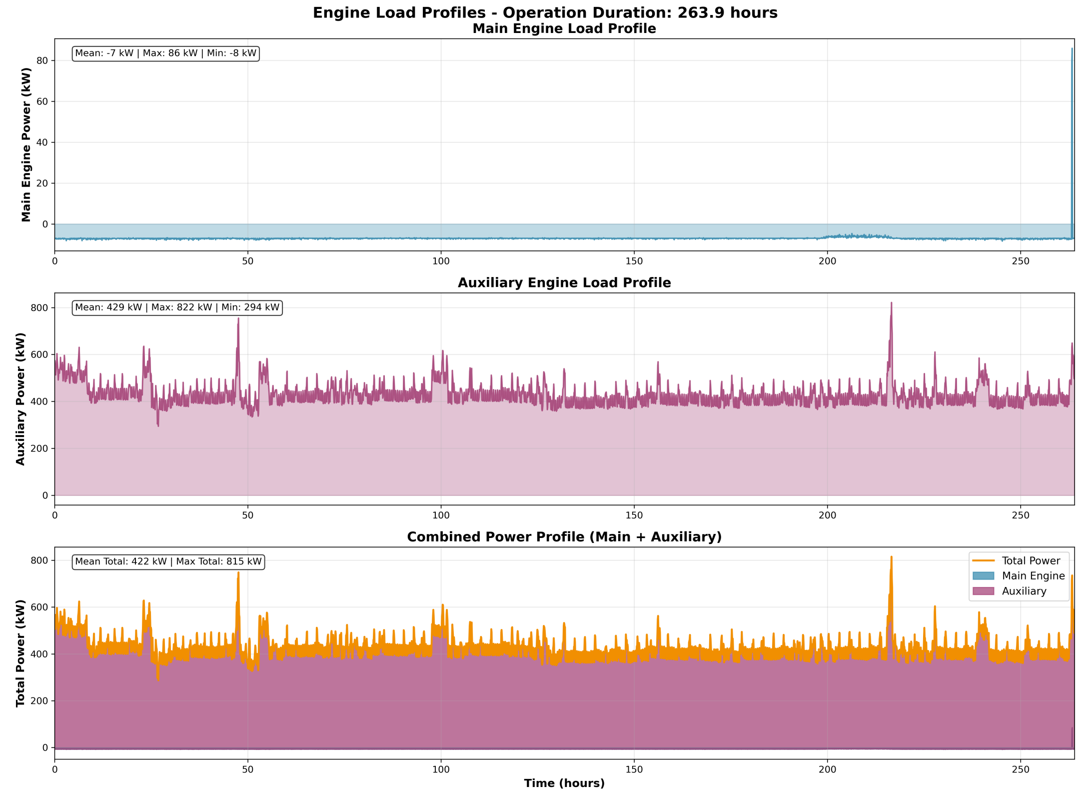

Figure 6.9: Loitering near port load profile.

6.2. Configuration modeling results

Now that the data sets have been explored and processed, a more detailed analysis of different types of configurations can be done. The goal of the case study is to see if entirely different configurations show logical changes when different load profiles are applied to them.

6.2.1. Configurations generation

The first step is to clarify how engine configurations are generated within the framework. The rules and constraints that govern engine selection and configuration building were outlined in Chapter 5.4.4. This section illustrates what such a generated configuration looks like in practice.

The algorithm begins by selecting the most efficient main engines from the filtered dataset, ensuring that different engine categories are represented (e.g., two-stroke, four-stroke, dual-fuel, and gas turbines). Once a suitable main engine is chosen, auxiliary engines are selected within the minimum and maximum power ranges defined by regulatory requirements and industry practice. These auxiliary candidates are then ranked by performance, after which viable combinations are assembled to form complete configurations. An example of such a configuration is shown in Figure 6.10. In this illustration, different engine categories are represented by color, while the auxiliary system consists of diesel generators. In the specific configuration shown, two auxiliary engines are included.

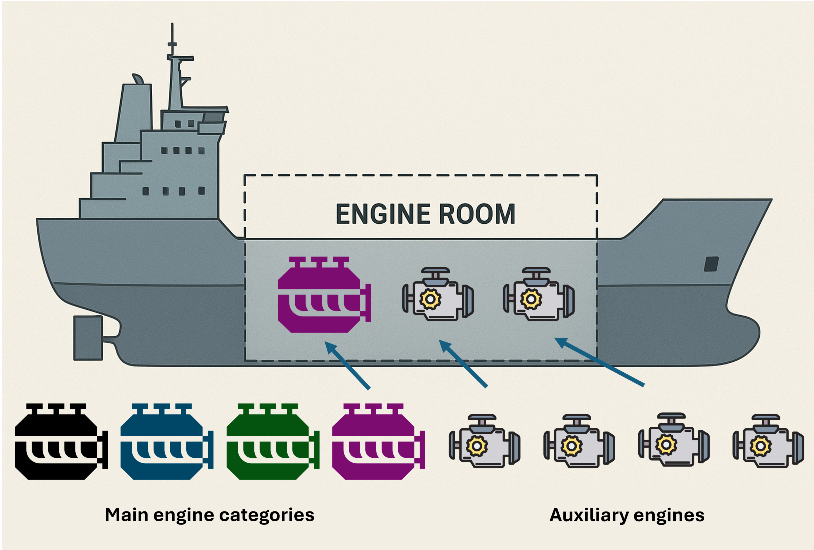

Figure 6.10: Diagram of how engines are selected from a range of different engines

In the model, such a configuration will look like the table below (Table 6.3)

Configuration No.	Main engine model	Main engine power	No. of Aux. engines	Aux. models	Aux. power	Total power
Configuration 1	7S80MC Mk3	23.478 kW	1	6H32/40	2.880 kW	26.358

Table 6.3: Example of a configuration using a diesel 2-stroke engine.

All configurations have a configuration number. This number is used in subsequent mentions of configuration to identify the type of configuration and its specific details. This also helps with finding configurations in a high number that can be generated. To have a reasonable simulation time of about 1 hour, 350 configurations are generated. They are split up into the categories as can be seen in 6.4.

Main engine type	Amount of configs
Diesel 4-Stroke	100
Diesel 2-Stroke	100
Dual-Fuel engine	100
Gas Turbine	50

Table 6.4: Configuration split

The number of configurations can be scaled up further, but the resulting improvements in emissions would be marginal. The engine dataset is filtered by SFOC to remove the highest percentile. So, since the best-performing, lowest-emitting engines are already included within the current set, adding more options would primarily introduce engines with higher SFOC values. For example, while the most efficient engines in the selection operate around 165–175 g/kWh, additional engines typically exceed 190–200 g/kWh. Including these would increase the average fuel consumption per configuration, making the relative emission reduction potential negligible compared to the already optimized set.

6.2.2. Engine Load example

Now that the method in which configurations are created has been shown, the configurations can be simulated. As mentioned in the modeling section, the load percentage is based on the load percentage of the main engine of the modeled vessel in table 5.1 and the shaft generator power of the data set. Due to the model simulating different configurations that have different control of the main engine, there is a case for using the main power of the created configuration to generate the new load percentage. When these differences are simulated over the 2-week voyage, as seen in Figure 6.7, the following load percentage differences can be seen (Figure 6.11).

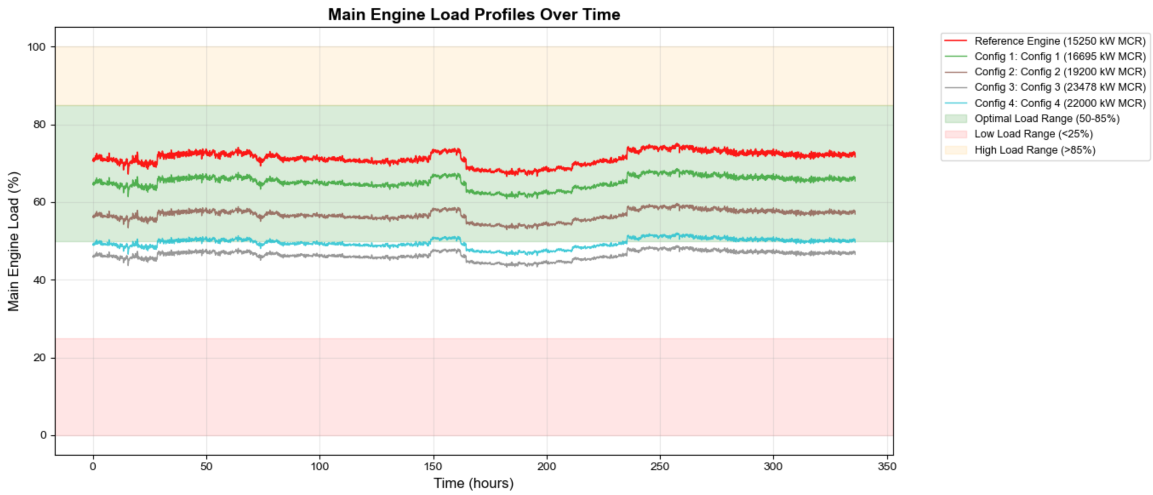

Figure 6.11: The Load % of the selected modeled after ship and the least emitting configurations analysis

In this example, the load percentage for the modeled vessel (benchmark) averages around 80%, which falls within the optimal efficiency range for most engines. Operating within this margin is associated with favorable specific fuel oil consumption (SFOC) and reduced emissions.

This highlights the importance of using actual operational load profiles when selecting or validating engine configurations. The load distribution of a vessel that has operated provides realistic conditions for assessing performance, as these will likely reflect the operational range of any proposed configuration.

It is worth noting that configurations involving larger engines might maintain similar load percentages while delivering higher absolute power output, potentially resulting in increased vessel speed. While this is outside the scope of the current model, it presents an interesting direction for future research.

The emission results and the most favorable configuration in the different load configurations will be examined in section 6.4.

The following section will go into how the use of a hybrid functionality in the model can change the way in which loads are divided over the main and auxiliary engines.

6.3. Hybrid topology results

By using the mode discussed in section 5.4.5, some different engine load choices are made. However, due to the efficiency of the main engines compared to the auxiliary engines, the hybrid mode most often chooses the full use of the main engine instead of sharing the load in all instances. For 'less efficient', mostly high-power main engines where the load profile is not always favorable, the mode is used, and the auxiliary engine takes some of the load of the main engine. When using one of the more efficient configurations, which uses a more efficient main engine that performs mainly in the optimal range, the load distribution is shown in Figure 6.12.

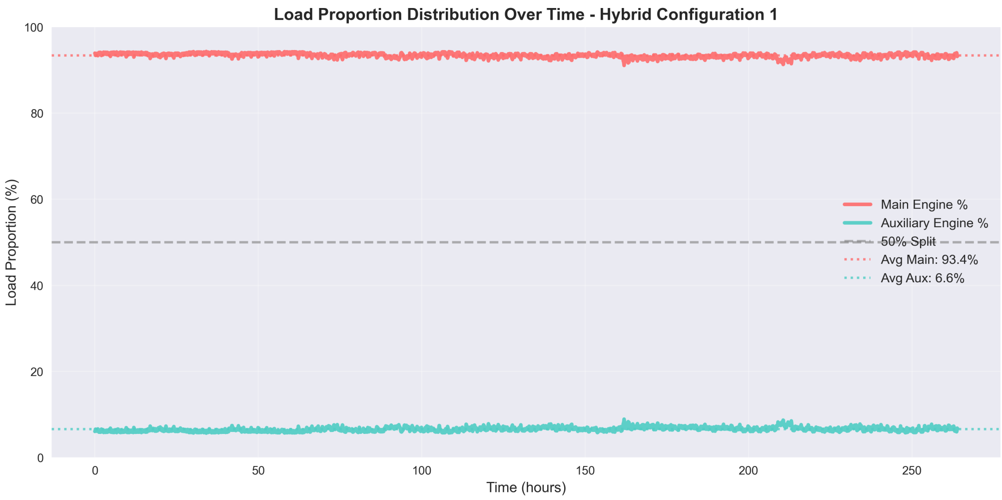

Figure 6.12: Load distribution of an efficient engine using hybrid mode.

When using the less favorable configuration, the hybrid mode activates more frequently during operation. This load distribution is shown in Figure 6.13.

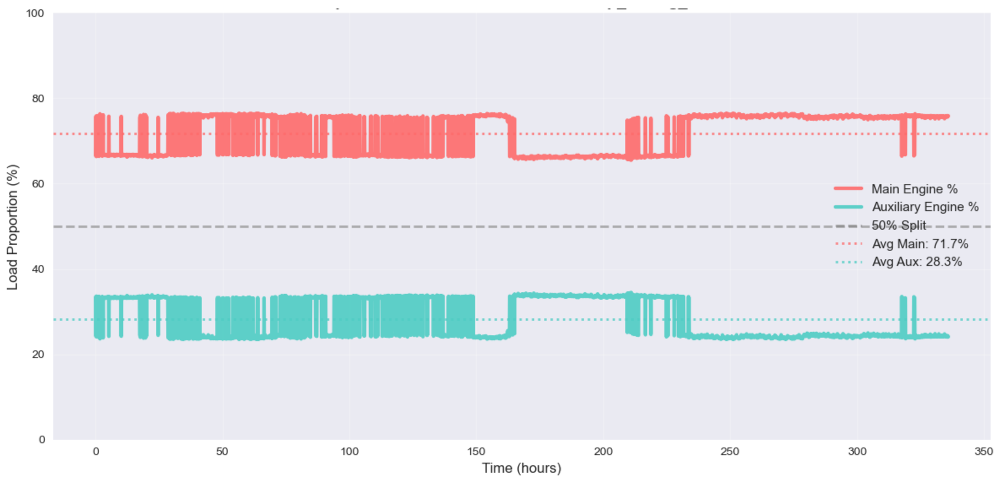

Figure 6.13: Load distribution of less efficient engine using hybrid mode.

How much fuel and emissions are saved by using this mode will be explored in the following section.

6.4. Emission and Performance evaluation

This section will first compare the different configurations and then present quantitative results that showcase how the case study examines various uses of operational data and differences in modeling.

6.4.1. Emissions Estimation

In Section 5.5, the way emissions are calculated was explained. Before calculating the emissions of different configurations, a benchmark must be established to compare the configurations. This benchmark is gathered from operational data. By interpolating the SFOC data from the BDN, an estimated polynomial can be drawn that can be used to verify the model's use of the polynomial found by Jalkenen et al. This curve can be seen in the last chapter in Figure 5.3. The polynomial produced by the data is shown in Figure 6.14.

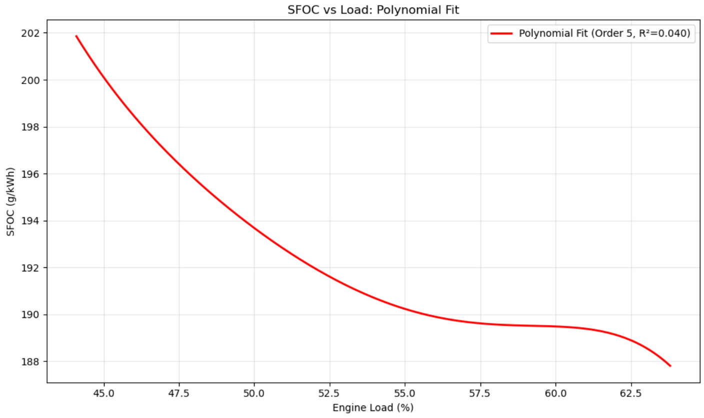

Figure 6.14: Polynomial deduced from operational data of the SFOC vs Engine Load

The curves are similar in form, but the operational data polynomial consistently yields higher SFOC values compared to the literature curve from Jalkanen et al. The difference at the minimum point is approximately 20 g/kWh (189 g/kWh compared to 167 g/kWh), indicating that the operational data predicts less efficient fuel consumption across the load range. The results in the following section will show how this difference propagates into emission estimates.

6.4.2. Emissions Results specific configurations

When comparing the simulated results with the operational data, some interesting results can be found. This section will explore the differences and similarities.

A benchmark is calculated using the polynomial as explained in the last section. This benchmark is compared to the emission calculated by the simulation; the results of the load profile of a voyage of 2 weeks can be seen in Table 6.5. The top entry is the benchmark, which is calculated using the same method as for the configurations, but with the SFOC derived from the data measured by the sensors on the vessel. During the simulation, 350 configurations are generated. The benchmark is then compared against the two best-performing configurations for each engine type, with two auxiliary engines. Here, *best-performing* refers to the configurations that result in the lowest total CO_2 emissions over the operational profile. The first table presents the differences in both fuel consumption and CO_2 emissions.

Configuration	Main Engine Type	No. of Aux. Engines	Total Fuel (tonnes)	Total CO2 (tonnes)	vs Benchmark CO2 (%)
Benchmark	Diesel 2-Stroke (Benchmark)	3	641.51	2002.79	0
Config 1	Diesel 4-Stroke	2	506.2542	1576.476	-21.29%
Config 2	Diesel 4-Stroke	2	506.9777	1578.728	-21.17%
Config 71	Dual-fuel	2	679.4693	2020.433	0.88%
Config 72	Dual-fuel	2	680.3307	2023.116	1.01%
Config 121	Diesel 2-Stroke	2	832.0442	2590.985	29.37%
Config 122	Diesel 2-Stroke	2	841.2629	2619.693	30.8022%
Config 231	Gas Turbine	2	1367.856	4380.188	109.99%
Config 232	Gas Turbine	2	1368.674	4382.737	118.83%

Table 6.5: Comparison of engine configurations with benchmark by CO\textsubscript{2} emissions and fuel consumption.

Figure 6.15 shows the table visualized using two bar charts, which show the absolute difference and the percentage difference between the best-performing configurations and the benchmark.

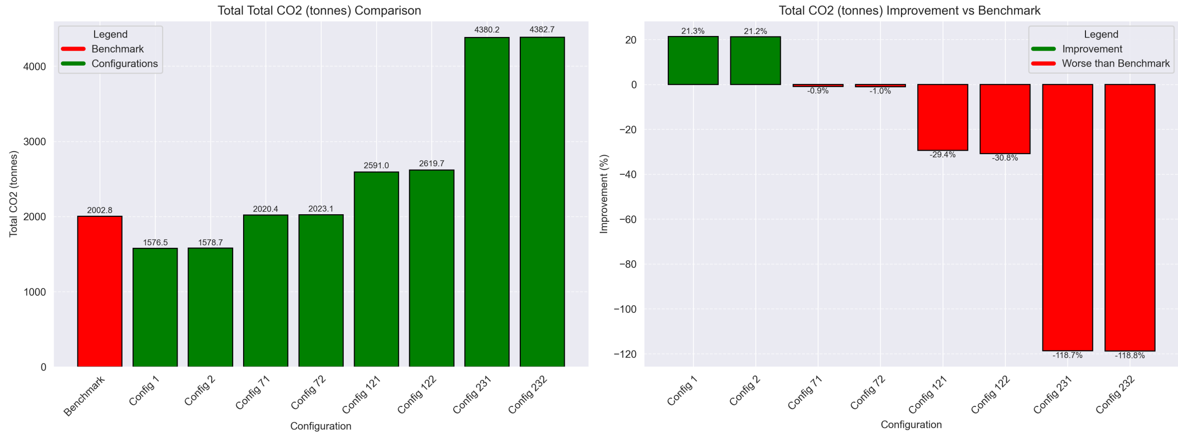

Figure 6.15: Comparison of CO_2 emissions between configurations and benchmark (left), Percentile improvement of CO_2 emissions vs Benchmark (right)

A comparison of emission intensity provides additional insight into how efficiently each engine configuration performs over a given voyage, relative to its installed capacity. This metric accounts not only for total emissions but also for the effect of engine sizing and operational loading. The results for the best-performing configurations are summarized in Table 6.6. In contrast, Figure 6.16 illustrates the percentage difference between the benchmark vessel and the alternative configurations. These differences primarily reflect variations in how efficiently engines operate under the load conditions observed in the operational profiles.

Configuration	Main Engine Type	No. of Aux. Engines	Total Fuel (tonnes)	Emissions Intensity (g CO2/kWh)	vs Benchmark Intensity (%)
Benchmark	Diesel 2-Stroke (Benchmark)	3	641.51	604.64	0
Config 1	Diesel 4-Stroke	2	506.2542	759.4543	25.60%
Config 2	Diesel 4-Stroke	2	506.9777	760.5396	25.78%
Config 71	Dual-fuel	2	679.4693	778.4957	28.7536%
Config 72	Dual-fuel	2	680.3307	779.5292	28.92%
Config 121	Diesel 2-Stroke	2	832.0442	755.2807	24.91%
Config 122	Diesel 2-Stroke	2	841.2629	756.2809	25.08%
Config 231	Gas Turbine	2	1367.856	965.9085	59.75%
Config 232	Gas Turbine	2	1368.674	966.4705	59.84%

Table 6.6: Comparison of Engine Configurations with benchmark for fuel consumption and emission intensity.

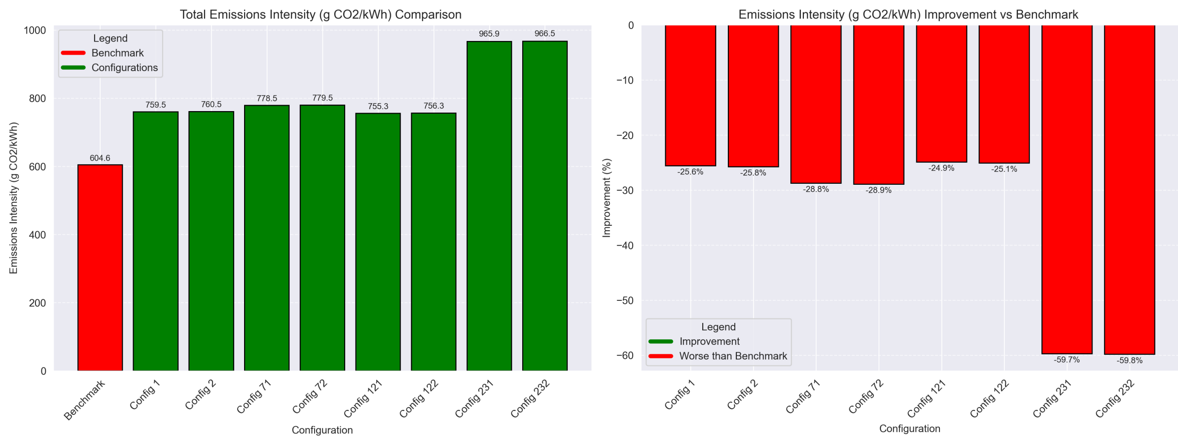

Figure 6.16: Comparison of emission Intensity between configurations and benchmark (left), Percentile improvement of emission intensity vs Benchmark (right)

6.4.3. Load profile configuration results

The previous section examined the emission outputs of the reference vessel and benchmarked them against alternative configurations. Building on this, this section evaluates how different engine room setups perform under the operational load profiles discussed in Section 6.1.1. By simulating each configuration under realistic operating conditions, including a 2-week voyage, port operations, and loitering in port, the analysis identifies which setups minimize fuel consumption and emissions most effectively. The following results present the highest-performing configurations for each load profile.

Results for a 2-week voyage load profile

The top results for the different engine types can be seen in Table 6.7. For each load profile presented in the following section, the top-performing configurations are ranked using gold, silver, and bronze to indicate the three best results. There is a clear pattern for fuel consumption and CO_2 emissions where the diesel 4-stroke engine ranks highest, followed by the dual-fuel engine and then the Diesel 2-stroke. But for the emission intensity, the diesel 2-stroke scores highest, followed by the diesel 4-stroke.

Main Engine Type	Main Engine Model	Auxiliary Engine Types	Auxiliary Engines Model	Total Power kW	Total Fuel in tonnes	Total CO2 Emissions tonnes	Emissions Intensity gCO2 / kWh
Diesel 4-Stroke	12V46	Diesel Gen.	2x 9H21/32	13,590	462.8673	1441.369	772.754
Diesel 4-Stroke	12V46	Diesel Gen.	2x 7L21/31	13,790	463.158	1,442.274	773.2393
Dual-fuel	12V51/60DF	Diesel Gen.	2x 7H25/33	1,5090	531.098	1,579.188	778.80
Dual-fuel	12V51/60DF	Diesel Gen.	2x 7L21/31	14,810	531.77	1,581.28	779.83
Diesel 2-Stroke	6S70ME-C7.1	Diesel Gen.	2x 7L27/38	20,449.55	650.40	2,025.36	755.52
Diesel 2-Stroke	6RT-flex68D	Diesel Gen.	2x 6L32/44CR	20,316.27	657.64	2,047.896	756.56
Gas Turbine	LM2500+®	Diesel Gen.	2x 7L21/31	22,790	1,069.63	3,425.23	966.44
Gas Turbine	LM2500+®	Diesel Gen.	2x 4L20	22,770	1,070.263	3,427.20	966.998

Table 6.7: Best performing configurations during a 2-week voyage

Results for port operation load profile

The top-ranked configurations for port operations are presented in Table 6.8. The results highlight that the best-performing engine type differs between the port and voyage load profiles. The difference in power demand essentially drives this variation: while the 2-week voyage requires sustained main engine operation, port operations involve long periods where only auxiliary engines are active. In this context, a smaller main engine proves sufficient for the limited propulsion required. The auxiliary engine choice also shifts to the best 4-stroke configuration. In contrast, the dual-fuel setup remains unchanged across both profiles, reflecting the efficiency of this configuration under the applied case study rules.

Main Engine Type	Main Engine Model	Auxiliary Engine Types	Auxiliary Engines Details	Total Power kW	Total Fuel in tonnes	Total CO2 Emissions tonnes	Emissions Intensity gCO2 / kWh
Diesel 4-Stroke	9L46F	Diesel Gen.	2x 8H32/40	11,846.67	72.09159	224.4932	821.8727
Diesel 4-Stroke	9L46F	Diesel Gen.	2x 9H25/33	11,880	72.48151	225.7074	826.3179
Dual-fuel	12V51/60DF	Diesel Gen.	2x 7H25/33	15,090	88.05744	267.7061	838.514
Dual-fuel	12V51/60DF	Diesel Gen.	2x 7L21/31	14,810	88.86	269.35	843.67
Diesel 2-Stroke	6RT-flex68D	Diesel Gen.	2x 6L32/44CR	20,316.27	103.55	322.444	813.503
Diesel 2-Stroke	6RT-flex68D	Steam Turb Gen.	2x 8L32/40	19,853.6	103.71	322.9478	814.77
Gas Turbine	LM2500+®	Diesel Gen.	2x 7L21/31	22,790	149.468	475.75	968.11
Gas Turbine	LM2500+®	Diesel Gen.	2x 4L20	22,770	150.09	477.76	972.21

Table 6.8: Best performing configurations during port operations

Results for the loitering in port load profile

The results for the loitering load profile are shown in Table 6.9. In this operational mode, the main engine is inactive, unlike in the previous load profiles, and therefore does not influence performance. Only the auxiliary engines contribute to fuel consumption and emissions. The table presents the eight best-performing auxiliary engine configurations, ranked according to their ability to minimize emissions and fuel consumption.

Main Engine Type	Auxiliary Engine Types	Auxiliary Engines Details	Total Power kW	Total Fuel in tonnes	Total CO2 Emissions tonnes	Emissions Intensity gCO2 / kWh
Diesel 2-Stroke	Diesel Gen.	2x 5L21/31	22,391.33	29.49964	91.86188	811.13
Diesel 2-Stroke	Diesel Gen.	2x 5L21/31 50Hz	22,391.33	30.46151	94.85713	837.5799
Diesel 2-Stroke	Diesel Gen.	2x 8L21/31	22,772.67	31.00083	96.53658	852.4093
Diesel 2-Stroke	Diesel Gen.	2x 5L27/38	22,658	31.24	97.28479	859.016
Diesel 2-Stroke	Diesel Gen.	2x 6L23/30A	22,618	31.41165	97.81587	863.71
Diesel 2-Stroke	Diesel Gen.	2x 5H17/28	22,808	31.80024	99.02594	874.3901
Diesel 2-Stroke	Diesel Gen.	2x 6N18AL-HV	22,548	31.93885	99.45759	878.2016
Diesel 2-Stroke	Diesel Gen.	2x 7L21/31	22,688	32.24252	100.4032	886.5549

Table 6.9: Best performing configurations during loitering at port

Comparison of the best configurations

The top-performing configurations for each load profile were analyzed in the previous sections. Table 6.10 compares these configurations across all load profiles, ranking them from best to worst in each scenario. Notably, the configuration using the main engine *9L46F* does not appear in the 2-week voyage results, as other engines outperformed it under that operational profile.

An important observation is that no single configuration dominates across all load profiles. Instead, three different configurations emerge as optimal depending on the operational context. This highlights the sensitivity of performance to load profile characteristics and underlines the importance of tailoring engine room design to realistic operational data. The best-performing configurations even outperform the benchmark vessel.

Main Engine Type	Main Engine Model	Auxiliary Engine Types	Auxiliary Engines Details	Total Power kW	2-week Voyage	Port Operations	Loitering in Port
Diesel 2-Stroke	Benchmark	Diesel Gen.	-	27,461	641.52	89.46	42
Diesel 4-Stroke	12V46	Diesel Gen.	2x 9H21/32	13,590	462.87	94.86	34.17
Diesel 4-Stroke	9L46F	Diesel Gen.	2x 8H32/40	11,846.67	N/A	72.09	33.05
Diesel 2-Stroke	7S80MC6.2	Diesel Gen.	2x 5L21/31	22,658	887.21	127.03	29.50

Table 6.10: Comparison of fuel consumption of best performing configurations with benchmark

6.4.4. Hybrid mode emission results

For this analysis, the most efficient configuration for each engine category is taken. The hybrid mode is turned ON and OFF for these configurations and compared. As was explained in section 6.3, the difference in fuel consumption (Figure 6.11) and in CO2 emissions (Figure 6.12) for the diesel 2-stroke, diesel 4-stroke, and the dual-fuel engine is zero. The gain using the hybrid system for the Gas Turbine is positive.

The comparison of fuel consumption can be seen in Table 6.11. By using the hybrid system, 3.1% fuel can be saved, only when using the gas turbine. The gas turbine is one of the least efficient engines; in this case, the SFOC of the gas turbine is close to or higher than that of the other engines.

Main engine type	No. of Aux. Engines	Fuel consumed Hybrid OFF	Fuel consumed Hybrid ON	Fuel consumed difference
Dual-fuel	2	737,1161	737,1161	0%
Diesel 4-Stroke	2	885,3098	885,3098	0%
Diesel 2-Stroke	1	1037,443	1037,443	0%
Gas Turbine	2	1279,558	1239,875	-3.1%

Table 6.11: Comparison of Fuel consumed between configurations when Hybrid mode is ON and OFF

The comparison in CO_2 emissions is shown in Table 6.12. When the hybrid mode is ON, 2.17% emissions can be saved. This is also only the case for the gas turbine configuration, due to the same reason as the difference in the fuel consumed.

Main engine type	No. of Aux. Engines	Total CO_2 Hybrid OFF	Total CO_2 Hybrid ON	Total CO_2 difference
Dual-fuel	2	2172,281	2172,281	0%
Diesel 4-Stroke	2	2756,855	2756,855	0%
Diesel 2-Stroke	1	3230,598	3230,598	0%
Gas Turbine	2	3796,847	3714,392	-2.17%

Table 6.12: Comparison of CO_2 production between configurations when Hybrid mode is ON and OFF

6.4.5. CII Index

Using the IMO's CII calculator, the CII of different configurations can also be estimated. The CII is calculated over an annual period of time to evaluate a ship for a whole year. Because this thesis examines shorter periods in the operational data, data from a yearly period is not used. To still use this metric, the results are scaled to the period it is measured in, instead of using annual emissions.

A configuration using a diesel 4-stroke engine and two auxiliary engines during port operations gives the CII rating shown in Figure 6.17.

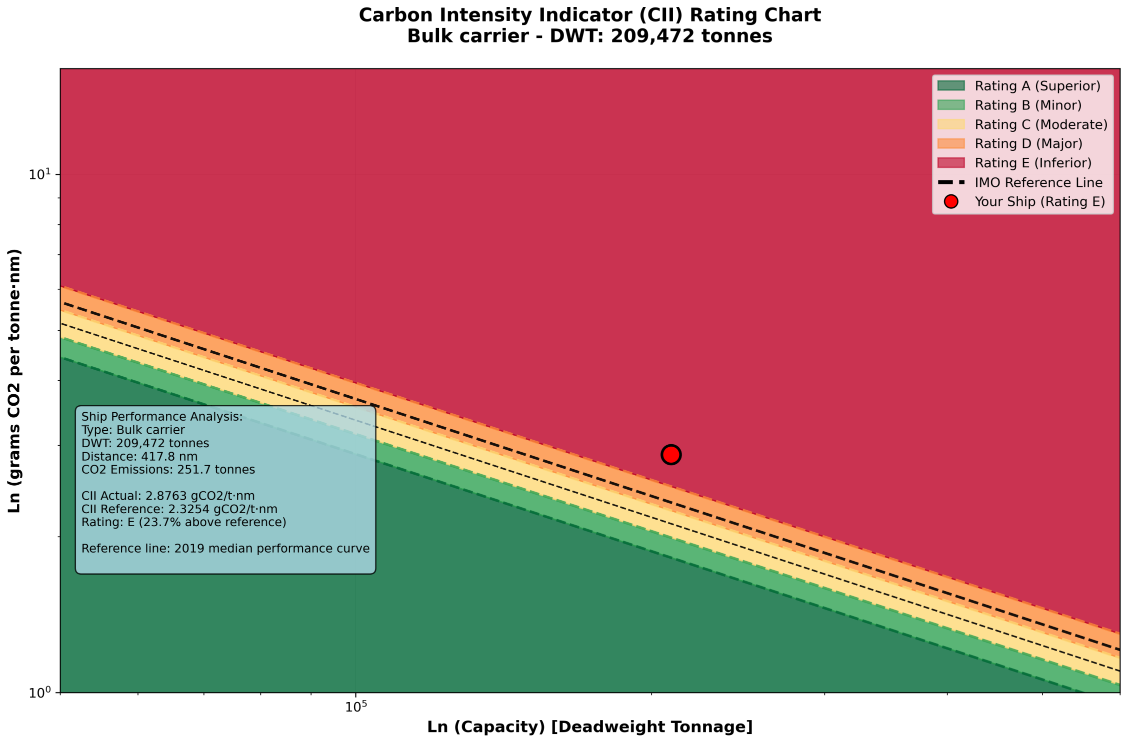

Figure 6.17: CII rating of a specific configuration

The rating of this specific configuration results in an E rating. This can be due to the high emission factor or some inefficiencies of the load profile being operated by a relatively big engine.

To test how sensitive the CII rating is to different operating conditions, the three profiles were simulated using the three best-performing configurations. The results are shown in Table 6.13. The configuration using *9L46F* does not give any results for the 2-week voyage, as was the case in the comparison between configurations (Table 6.10). For port operations and the two-week voyage, the ratings fall within a realistic and expected range. However, the loitering case shows a rating that is about ten times worse. This can be explained by how the CII is calculated: it is designed to reflect performance over a whole year of operations, not short outlier periods. Loitering is therefore not representative of the vessel's typical operational profile. Another possible reason could be the accuracy of the dataset itself, as the limited scope and sensor precision may have influenced the outcome. With a larger or more accurate dataset, this discrepancy would likely be reduced.

	Main Engine	Aux Engines	Total Emissions (tonnes)	CII Actual	CII Reference	CII Rating	vs Reference (%)
2-Week voyage	12V46	2x 9H21/32	1844.23	2.83927	2.32539	E	22.10%
	9L46F	2x 8H32/40	N/A	2.427049	2.32539	N/A	N/A
	7S80MC6.2	2x 5L21/31	3533.67	5.440236	2.32539	E	133.90%
Port Operations	12V46	2x 9H21/32	251.74	2.876299	2.32539	E	23.70%
	9L46F	2x 8H32/40	224.49	2.565006	2.32539	E	10.30%
	7S80MC6.2	2x 5L21/31	395.57	4.519735	2.32539	E	94.40%
Loiter	12V46	2x 9H21/32	106.42	27.38339	2.32539	E	1077.60%
	9L46F	2x 8H32/40	102.93	26.48542	2.32539	E	1039.00%
	7S80MC6.2	2x 5L21/31	91.86	23.63785	2.32539	E	916.50%

Table 6.13: CII rating of the three best performing configurations for each load profile

To better reflect how the IMO's CII is typically applied on an annual basis, the three configurations were also simulated over 3 months instead of just the shorter load profiles. This provides a more accurate representation of their long-term performance. The results are shown in Table 6.14 and Figure 6.18. Interestingly, the configuration that performed best under port operations now receives a **D rating**, while the other two still fall into the **E category**.

Main Engine	Aux Engines	Total Emissions (tonnes)	CII Actual	CII Reference	CII Rating	vs Reference (%)
12V46	2x 9H21/32	7166.74	2.74866	2.325390	E	+18.2%
9L46F	2x 8H32/40	6177.05	2.36909	2.325390	D	+1.9%
7S80MC6.2	2x 5L21/31	13255.71	5.08397	2.325390	E	+118.6%

Table 6.14: CII rating of the three best performing configurations in the three load operations.

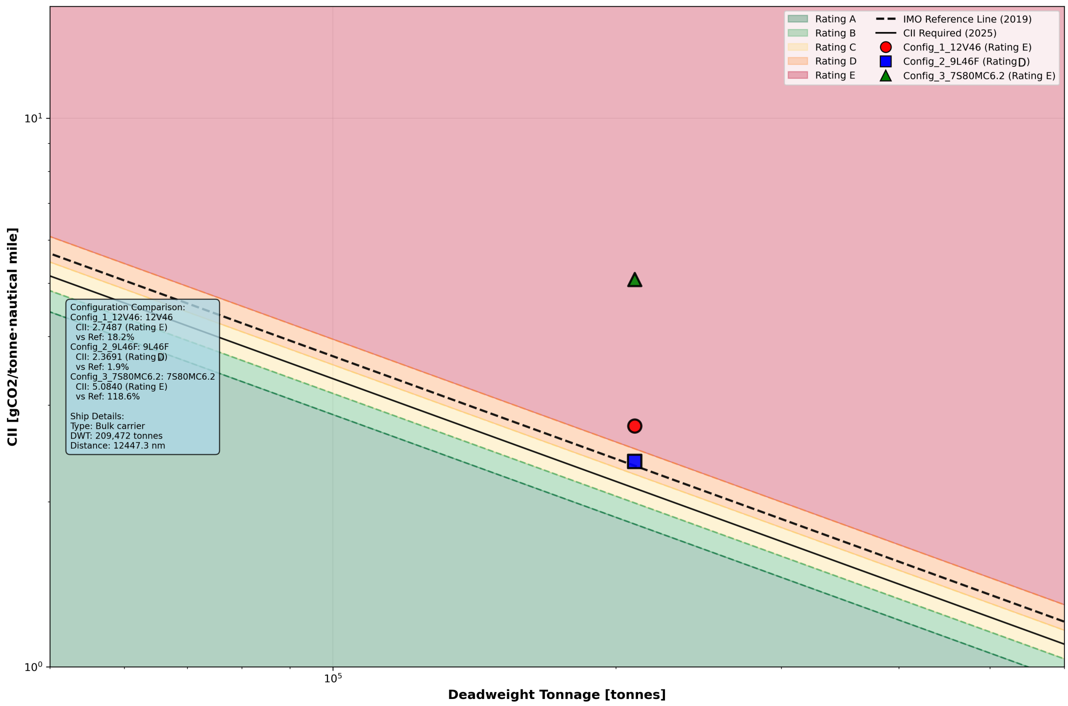

Figure 6.18: CII analysis of the three best performing configurations in each load profile during 3 months of operations

The differences between results highlight one of the key limitations of applying CII ratings to short-term load profiles: results can shift significantly depending on the time horizon used. A more extended dataset smooths out outliers from specific operations, making the ratings more realistic and aligned with how the IMO intends the metric to be applied.

6.5. Sensitivity Analysis

To understand how different parameters influence the overall emission output in the engine room model, a local sensitivity analysis was performed. This analysis explores how changes in key variables such as specific fuel oil consumption (SFOC), engine load profiles, emission factors, and auxiliary power affect the total estimated CO_2 emissions.

6.5.1. Methodology

Four parameters were varied independently using both One-At-a-Time (OAT) and Monte Carlo (MC) methods:

- **Emission factor multiplier**: accounts for uncertainty in fuel-specific CO_2 conversion factors.
- **SFOC multiplier**: simulates deviations from rated SFOC due to varying operating conditions.
- **Load multiplier**: scales the load profile, simulating under/overestimation of power demand.
- **Auxiliary power multiplier**: adjusts the base auxiliary power to account for system variance or unknown loads.

Each parameter was sampled from a uniform distribution within plausible bounds (e.g., ±15% for SFOC and load). A total of 1,000 emission simulations were performed, and outputs were aggregated.

6.5.2. Results and Observations

Figure 6.19 summarizes the overall distribution of total emissions, correlation relationships between parameters, and the cumulative emissions curve.

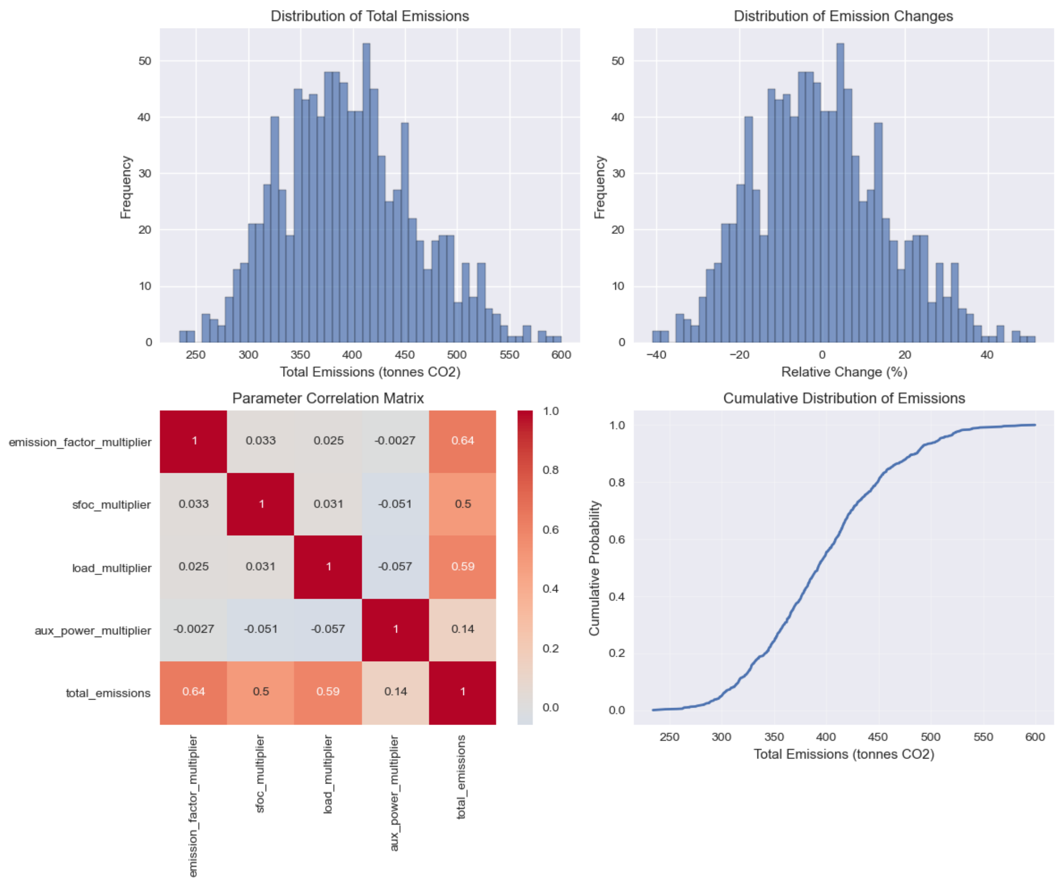

Figure 6.19: Overview of sensitivity results including emissions distributions, correlation matrix, and cumulative emissions probability.

Emission Distribution. The histogram shows a relatively normal distribution centered around 400 tonnes CO_2, suggesting most configurations are stable and fall within a predictable range. The relative change histogram indicates that model uncertainty introduces a ±20% range around the mean, but most results remain clustered.

Parameter Influence. The correlation matrix reveals that the emission factor multiplier (**0.64**), SFOC multiplier (**0.50**), and load multiplier (**0.59**) have the highest influence on total emissions. The auxiliary power multiplier has a relatively minor correlation of **0.14**, confirming it has less impact on total emissions for the scenarios tested.

Cumulative Probability. The cumulative distribution function (CDF) further supports that over 90% of the simulated emissions lie between 300 and 500 tonnes, reinforcing model robustness.

6.5.3. Detailed Parameter Sensitivities

Figure 6.20 highlights OAT results for each parameter and the associated change in emissions.

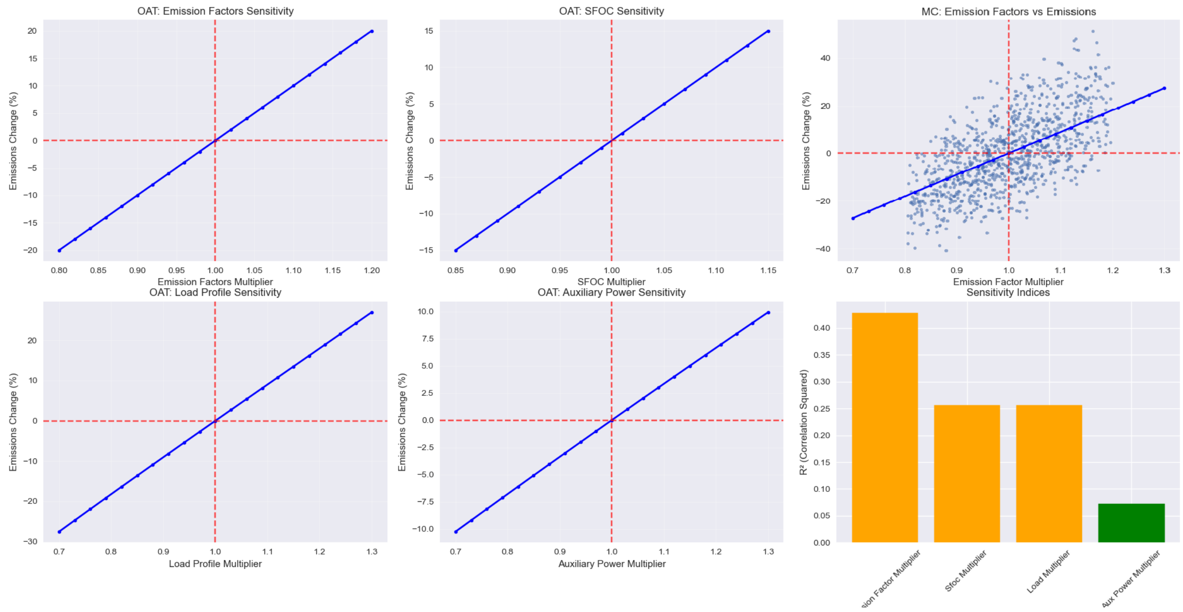

Figure 6.20: One-at-a-time (OAT) sensitivity plots and Monte Carlo scatter for key parameters. Bottom right: Sensitivity indices (R^2) based on correlation squared.

Emission Factors

This parameter exhibits the strongest linear relationship with emissions. A 20% increase in the emission factor results in an approximate 20% increase in total emissions, confirming a proportional relationship.

SFOC and Load

Both show substantial, nearly linear impacts on emission changes. A ±15% change in SFOC or engine load results in a comparable ±15% swing in emissions. This emphasizes the importance of accurate operational data and engine performance modeling.

Auxiliary Power

The effect of the auxiliary power multiplier is relatively small—only producing about a ±6% change when varied ±30%. This is consistent with expectations since auxiliary power accounts for a smaller portion of total fuel consumption.

Sensitivity Indices

The bar chart shows R^2 values indicating relative importance:

- Emission factor multiplier: **±0.40**
- Load multiplier: **0.25**
- SFOC multiplier: **0.25**
- Auxiliary power multiplier: **±0.07**

6.5.4. Discussion and Implications

The sensitivity analysis demonstrates that:

1. Fuel choice (emission factor) is the most critical factor influencing total CO_2 emissions.
2. Operational behavior—reflected through SFOC and load profile assumptions—also plays a significant role.
3. Auxiliary engine behavior has a relatively minor influence unless operating in full-electric or hoteling-dominated scenarios.

This highlights where to focus data gathering and refinement efforts in future implementations. Improving the fidelity of emission factor databases and operational load profiles will yield the most significant gains in model accuracy. Additionally, for design optimization, fuel switching remains the most effective lever for emissions reduction.

Future work could explore global sensitivity methods (e.g., Sobol analysis) to validate these findings under broader uncertainty distributions further.

6.6. Conclusion on case study

The case study demonstrated how the proposed DT-aided framework can be applied to optimize engine room configurations using operational data. Each step of the framework was tested in practice, showing both its strengths and its limitations.

First, the **design goal** of reducing emissions and fuel consumption was successfully implemented: the model consistently identified configurations with lower fuel consumption and CO_2 output compared to the benchmark vessel. Secondly, the **data collection and processing** proved feasible, although incomplete datasets required pre-processing and imputation. Despite some data loss, the available operational and engine data were sufficient to produce meaningful simulations.

The chosen **rule-based modeling approach** yielded realistic results that aligned closely with benchmark operational data, showing that even with simplified assumptions, operational insights can guide early-stage design choices. The **sensitivity analysis** further highlighted the critical influence of emission factors and SFOC on the overall outcome, underscoring where design decisions or regulatory changes would have the most impact.

Overall, the case study shows that the data-driven framework can inform early-stage ship design decisions by quantifying the trade-offs between different engine configurations and operational profiles. While the model does not yet constitute a complete digital twin, it demonstrates the potential of DT-aided design as a decision-support tool, offering more transparency than traditional methods.

7 Conclusion

This thesis aimed to develop a data-driven design framework that integrates operational data into the early-stage ship design process, with a focus on reducing emissions and fuel consumption. With the use of a Digital twin (DT)-aided, rule-based modeling approach as the modeling strategy, the framework enables designers to evaluate multiple propulsion and auxiliary configurations under realistic load conditions, quantifying emissions, fuel consumption, and performance trade-offs. This work addresses the gap in integrating operational data into early-stage design, enabling more accurate, efficient, and environmentally aligned decision-making.

7.1. Conclusions on research questions

To answer the main research question of this thesis, the following sub-questions were addressed:

RQ1: What is the potential of operational data to support current design methods?

Traditional ship design relies on sequential, assumption-heavy methodologies. While these approaches provide structure, they often overlook variability in real operating conditions, resulting in inefficiencies in fuel consumption and equipment sizing. Operational data offers the potential to inform design decisions based on actual vessel usage patterns, thereby reducing uncertainty and enhancing lifecycle performance.

Operational data also supports a realistic evaluation of topology and fuel choices, providing a data foundation for regulatory and lifecycle metrics (CII/EEXI). In short, operational data augments each design phase with evidence-based inputs and validation checks, improving both decision quality and the likelihood that a design will meet in-service performance targets.

RQ2: What data-driven methods can be used to improve early-stage ship design?

In this thesis, a range of data-driven approaches were examined, including statistical modeling, AI-based prediction, and physics-based simulation. Among these, DT technology emerged as the most promising due to its ability to combine data-driven modeling with continuous data integration. DTs enable the virtual testing of configurations under operationally realistic conditions, supporting iterative improvement during the design process. Another aspect that makes DT the most promising is its expandability and modularity.

RQ3: How can an organized data-driven design method be applied to early-stage ship design?

This thesis has established that the use of DT technology is not widespread in design, particularly when integrating operational data. Some DT-aided design approaches have been proposed, but rarely applied as was studied in Section 3.2.1. To fill this knowledge gap, it was established that a framework was required to implement operational data in the use of DT-aided design.

This thesis addressed this gap by proposing a Digital Twin-aided design framework that integrates the use of operational data. The framework includes constituent blocks that detail how operational data, performance and component modeling, and optimization logic can be combined to support low-emission, data-informed early-stage ship component design.

RQ4: How can the data-driven framework be applied to the early-stage design to improve fuel consumption and emissions?

In this research, the framework is applied to assess fuel consumption and emissions by modeling engine configurations and simulating realistic load profiles, incorporating SFOC–load relationships.

The applied framework yielded an operational data-informed, rule-based modeling strategy that optimized engine configuration selection, thereby minimizing fuel consumption and emissions. This modeling strategy creates the virtual engine configuration that runs the simulation.

Verification is performed by comparing the results to a benchmark generated from real operational data. Like this, emissions and fuel consumption are realistically modeled for each configuration. These optimized engine configuration results should inform early-stage decision-makers on which physical engine configurations should be considered.

RQ5: To what extent can the data-driven design approach inform early-stage ship design decisions?

This research demonstrates that a data-driven framework can offer meaningful guidance in early-stage ship design by enabling the quantitative evaluation of alternative configurations under realistic operating conditions. In the case study, engine configurations were assessed not only on fuel consumption and emissions but also against regulatory metrics such as the CII. Configurations tailored to specific load profiles with redundancy-aware auxiliary sizing consistently outperformed the benchmark in absolute terms, though their emission intensity remained higher. The addition of hybrid load distribution further demonstrated how rule-based, data-informed logic can capture operational complexity and improve efficiency.

Overall, the framework demonstrates that operational data can make early-stage decisions more robust by demonstrating that optimization strategies may achieve gains in absolute performance but still fall short on regulatory metrics. It also reduces the risk of over- or under-dimensioning engines by grounding assumptions in real operational profiles. However, the reliability of such insights depends on data availability, accuracy, and validation against existing ship models. With these conditions met, a data-driven design approach can substantially enhance decision-making in the conceptual stages, providing designers with additional insight into which systems are promising and which should be avoided.

7.2. Conclusion on main question

The main research question to be answered was:

> **How can operational data be integrated into a data-driven design framework to support early-stage ship design?**

Operational data can be effectively integrated into a data-driven design method. This thesis proposed a modular, DT-aided design framework that can be applied in the early design stage of marine vessels. In a case study, the framework is used to create context-aware optimization of engine room configurations. By embedding real load profiles from IMO's Bunker Delivery Notes into the configuration logic, it was demonstrated that the applied framework can produce realistic performance forecasts, select engine configurations that can be utilized and verified by operational data, and align environmental performance with decarbonization targets.

In conclusion, operational data can effectively inform early-stage ship design when structured within a data-driven framework. A DT-aided approach enables design goals—such as minimizing emissions and fuel consumption—to be directly encoded into the modeling process. The resulting digital representation of the physical system bridges the gap between design intent and operational reality, while laying the foundation for future extensions into complete DT ecosystems and lifecycle-wide optimization.

8
Discussion

In this chapter, the contributions of this research, the methodology, limitations, and recommendations are discussed. First, the scientific contributions to the industry are presented. Then the scientific method is evaluated. Thereafter, the data sources are discussed and evaluated. Then, the modeling strategy and the model are evaluated together with their limitations. Next, the requirements for transforming a digital model into a digital twin will be explored. And finally, the possibilities for further research will be examined.

8.1. Scientific Contributions

8.1.1. Operational data integration in DT-aided design framework

This thesis demonstrates the potential of integrating operational data into the early-stage design phase through the creation of a Digital Twin (DT)-aided framework. Rather than relying solely on design assumptions or aggregated metrics, this method uses time-series data to simulate engine loads, fuel consumption, and emissions for thousands of configurations.

The creation of this framework is informed by applications of operational data in other industries and in later phases of the product lifecycle. By studying these existing approaches, the most essential goals and building blocks for early-stage ship design were identified. To demonstrate its functionality, the framework was applied in a case study on engine configuration. This application highlights the framework's potential to support data-driven decision-making in early-stage design.

However, this does not imply that the framework can be universally applied to all ship components without modification. Further research is needed to adapt the building blocks—or introduce additional ones—for broader use. In this case study, a rule-based modeling approach was selected, guided by external factors such as the engine model characteristics, stakeholder requirements, design goals, available data, and the verification process. In practice, data analysis consists of multiple smaller processes that interact with the model. In more complex implementations, several physical-object models (e.g., emissions models, wave–ship interaction models) can feed into the framework simultaneously.

While the present application consolidates all required functionalities within the existing blocks, a more comprehensive version of the framework should integrate additional models and feedback loops, making it capable of addressing the full range of complexities in ship design.

Currently, the DT-aided design framework enables an iterative, data-informed process for selecting configurations. By linking engine and fuel type databases with operational load profiles, the framework bridges the gap between theoretical design and actual operational behavior. Although the DT in this thesis is not yet bi-directional or real-time, it showcases how digital models informed by real data can significantly elevate traditional ship design.

The implementation applies voyage-based emission calculations, where emissions are quantified over the duration of a single voyage. In contrast, most indices of the IMO evaluate vessels based on yearly emission figures, which provide a valuable overview of overall performance across a variety of operational profiles. While this annual perspective is beneficial for benchmarking, it does not reveal which specific operations or voyage types contribute most to total emissions. For design purposes, however, such a detailed view is crucial. By analyzing emissions at the level of distinct operations or voyage segments, such as port operations, long voyages, and loitering, designers can identify where a vessel performs most efficiently and where targeted improvements are possible. This operational perspective also benefits ship operators by highlighting high-emission scenarios and informing strategies for more sustainable operations. During research, it was found that the CII would require a different scaling to be used for shorter load profiles, as the rating scale is currently based on yearly emissions.

8.1.2. Environmental and Operational Implications

The emissions analysis revealed that even among engines of the same type, operational emissions vary considerably depending on fuel type, load efficiency, and auxiliary engine sizing. Using Dual-fuel engines as the main engine showed potential in reducing emissions under realistic load conditions, especially when auxiliary engines were sized and selected based on actual load distributions. Another reason for dual-fuel engines to perform well, even with high power, is that Dual-fuel engines utilize a different type of fuel, producing fewer emissions. This was also an outcome of the sensitivity analysis, where the emission factor had the most impact on the results.

Furthermore, the choice of fuel type has a significant impact on emissions. Switching to low-carbon or green fuels can substantially reduce overall emissions, as lowering the emission factor generally results in an almost proportional decrease in output. However, when assessing fuels, it is essential to consider the whole lifecycle perspective—whether on a well-to-tank or well-to-wake basis. This approach accounts not only for combustion emissions but also for those generated during fuel production, processing, and distribution, thereby providing a more accurate measure of the fuel's total environmental impact.

The study also imposed constraints such as limiting fuel type diversity (max two) and maximum auxiliary engine power, reflecting practical operational limitations and vessel design norms. These constraints can contribute to producing feasible, not just theoretical, configurations.

The inclusion of the International Maritime Organization's (IMO) indexes to see, based on the industry standard, how well a vessel or configuration would perform, also elevates the speed at which a model like this could be implemented in the ship design process.

8.1.3. Contributions to ship design

This DT-aided approach introduces a significant enhancement to the current ship design process by embedding real-world operational variability into early-stage ship design decision-making. The rule-based model's scalable structure enables it to be applied across various vessel types, allowing for comparative analyses of design options based on actual load profiles rather than generic operational assumptions.

In practice, this means designers can avoid over-dimensioning systems, reduce excess fuel consumption, and align designs more closely with both operational and environmental goals. While the present study focused on emissions and fuel use, the same methodology could be extended to include CAPEX/OPEX considerations, enabling cost-performance optimization in parallel with reducing environmental impact.

8.2. Data source analysis

During the case study, a variety of data sources are used. The engine data was gathered from Clarkson's dataset, a fleet dataset that collects information from shipping companies and makes it available for research. Clarkson's provides as much information as it can gather per vessel, so not all vessels have the same amount of information. Virtually identical sister vessels do not always share the same information when used by different shipping companies, and one vessel sometimes has more information than the other. During analysis, this is filled out to make sure identical ships have the same power output. Some of the engine data, however, is still missing after being filled out from either similar engines or similar-sized vessels. Due to this fact, the method includes an imputation step where the fuel consumption of the engines is calculated based on their size. Even if an engine is identified as the most efficient and installed, its actual fuel consumption will inevitably deviate from the predicted values, introducing inaccuracies into the system.

The operational data is a single type of data set gathered from the bunker delivery notes (BDN). This data is not fully available for all parties to use and is also limited to a single type of data. If inaccuracies are found in the data, this will bleed into the system, and the results will also be inaccurate. To prevent this, the data must be verified or the model must be validated against other data or models. The sensor data acquired from the BDN is as accurate as the sensors are. In the model, the sensor accuracy is unknown, which can lead to potential inaccuracies in the data.

8.3. Case study modeling strategy evaluation

The modeling strategy chosen in the case study is rule-based modeling. There are a few shortcomings with the use of this modeling strategy. For the intended purpose of proving the framework, the strategy was able to mimic the workings of an ICE engine sufficiently. It could utilize the set rules to find adequate configurations that optimize fuel consumption and emissions.

Rule-based modeling does have its limitations, however. The biggest issue in the context of DT-aided design is that it cannot yet adapt to new data. It is a static model that is not yet capable of learning from new information or new outcomes. It would require manual changes to improve. Flexibility has to be inflexibly modeled to deal with dynamic conditions. This would require excellent knowledge of the physical object to model it as accurately as possible in the first instance. Just as with the data, rule-based modeling has difficulty dealing with bias. If present, they will be inherent to their programming, resulting in unfair or inaccurate assessments.

8.3.1. Model implementation limitations

Due to the inherent complexity of ship systems, the model has certain limitations in its current form. The case study is intended primarily as a proof of concept to evaluate the DT-aided framework, rather than an entirely accurate representation of reality. Achieving a perfect digital mirror of the physical system is not yet feasible; therefore, several assumptions were required to make the modeling process manageable and the results interpretable. This model utilizes engine-specific fuel consumption to generate a fuel consumption model, enabling the calculation of fuel consumption and emissions. This limits the realistic features of engine characteristics, such as possible shutdowns, faults, and irregularities in fuel consumption. The model aligns reasonably well with theoretical expectations, as the overall shape of the SFOC curve derived from the BDN data closely matches the reference curve reported by Jalkanen [146]. However, the operational data indicate consistently higher SFOC values, with a minimum of around 188–189 g/kWh compared to the 167 g/kWh reported in literature, reflecting more conservative (i.e., less efficient) performance estimates under real-world conditions.

Research on engine-related digital twins has so far focused primarily on fault prediction, real-time monitoring, and component-level simulation [148, 149].

Another limitation is the static nature of the CO_2 emission factors. This approach enables a straightforward comparison between configurations; however, it fails to capture the variability of real-world operating environments. In practice, CO_2 emission factors vary depending on factors such as engine load, ambient temperature, maintenance condition, and fuel quality [60].

By using static values, the model assumes constant operating conditions over time, which limits the ability to simulate the environmental impacts of the configurations under changing scenarios. Although the operator attempts to operate the vessel in the most optimal state for most of the time, during specific port operations, this optimal load cannot be maintained at all times.

8.3.2. CII assessment

One of the key evaluation metrics applied in this study was the IMO Carbon Intensity Indicator (CII). This index is widely used in the maritime industry to assess the operational efficiency of vessels and to identify ships that require corrective action or reevaluation. The CII is highly sensitive to changes in key parameters such as distance travelled and fuel consumption; therefore, the accuracy of the input data is critical to the reliability of the resulting score. In practice, these inputs may be affected by sensor inaccuracies, reporting errors, or incomplete datasets, which can introduce uncertainty into the assessment.

In this study, CII calculations were based on data from smaller periods of time instead of a single operational year. While this provides an initial indication of configuration feasibility, it limits the ability to validate results across varying operational conditions and periods. Nonetheless, the use of the CII within the framework demonstrated that the modeled configurations are not only feasible but also aligned with an established industry benchmark, even though they were rated in the E category. With access to a larger and more diverse dataset, future work could enhance the robustness of the CII-based evaluation, enabling more accurate predictions of long-term performance.

8.4. Digital Twin potential

The implementation presented here does not constitute a fully realized Digital Twin. Instead, it represents an early-stage design tool inspired by DT concepts, without the continuous, two-way data synchronization between the physical and virtual object that defines a true DT [47].

Realizing a full Digital Twin for early-stage ship design will require advancements beyond the current state of this work, including greater computational resources, more detailed physical modeling of engine systems, and significantly expanded data acquisition and data management capabilities. To date, the most mature DT implementations in the maritime sector have been deployed in the operational phase of a vessel's life cycle, where abundant real-time data streams are available and can be used to optimize ongoing performance and maintenance strategies [150].

Within this framework, an attempt was made to create a circle that transitions from virtual to physical, in the form of feedback and data. While the data stream is established through sensors feeding into a databank that can be accessed at any point, the reverse, from the virtual model back to the physical system, is currently still limited. In this study, the feedback loop is implemented manually by designers and early-stage decision-makers, rather than through automated control or real-time synchronization. The adaptation to a complete real-time DT framework will therefore require not only enhanced computational infrastructure and a better interconnected system between data sources, but also automated mechanisms for translating simulation insights directly into actionable design or model synchronization. Such capabilities would enable a self-updating, continuously learning model, fulfilling the defining characteristic of a Digital Twin and moving beyond a decision-support tool toward an integrated design ecosystem.

In the case study, the framework was applied to an engine configuration application. In the application, however, not all blocks were fully utilized. As was discussed in the scope (Section 5.7) The physical integration was missing, but the direct sensor data capture was also not fully realized. That is as far as the case study could reach. The feedback from the verification phase would also further improve the design choices.

8.5. Future Developments and Research

The current framework supports diesel, dual-fuel, and gas turbine configurations but does not yet implement hybrid-electric systems or energy storage solutions. Incorporating these — especially for peak shaving and part-load optimization — would expand the model's relevance to emerging hybrid designs.

In this model, the costs of fuels or expenses in general are not taken into account. Future work could incorporate route-specific emissions regulations, ECA zones, or economic indicators such as fuel price or carbon taxes.

Additionally, spatial considerations have not yet been integrated. Future developments could include optimizing physical engine room layouts and spatial allocation for fuel storage, taking into account both operational safety requirements and fuel capacity needs. Incorporating these constraints would enable the generation of more realistic and practically implementable configurations, aligning the model's outputs more closely with actual ship design processes.

In addition to fuel modeling, the way in which configurations are created is now based on the model vessel. When more operational data becomes available, it would be a good strategy to use power envelopes of more extended periods of time to decide the engine power requirement. If a specific ship type undergoes specific loads more often than others, this can be analyzed when data is available. This would improve the selection of engine power requirements.

The dual-fuel engine in this study was modeled as a regular engine, where the emission factors of LNG and the heavier fuel were averaged. For a more accurate representation, fuel switching should be implemented. Another factor that will need to be taken into account is the fuel availability constraints at various ports. This is also the case for a multitude of other topologies.

Retrofitting existing vessels to improve efficiency or meet new regulatory standards is a complex and costly process, which must be factored into future applications of this framework. Previous studies have quantified the capital expenditures associated with retrofitting, along with operational implications such as downtime and integration challenges [151]. Incorporating such cost and feasibility assessments into the Digital Twin-aided design process using operational data would enable more involvement in the challenges the industry is facing, making the framework more relevant and actionable for industry stakeholders considering both new builds and upgrades to existing fleets.

A significant gap in many data-driven design applications is the absence of a historic, standardized databank of vessel operational and design data. Such a databank should capture all relevant research, modeling, and real-world performance information for each physical asset throughout its lifecycle. The management of this data is essential and should ideally be openly available. Some common maritime data standards have already been introduced (such as the ISO 19848 for shipboard data), but managing this data is still a critical gap. Through this data management, more advanced data mining and information processing become possible. This information can be leveraged for more advanced modeling strategies, including rule-based modeling. Over time, this approach may evolve into dynamic knowledge domains that enable DT models to understand and adapt these rules.

References

[1] European Commission. *Reducing emissions from the shipping sector - European Commission*. 2023. URL: https://climate.ec.europa.eu/eu-action/transport/reducing-emissions-shipping-sector_en.

[2] Waterborne. “Stategic Research and Innovation Agenda for the Partnership on Zero-Emission Waterborne Transport”. In: (June 2021). URL: https://www.waterborne.eu/images/210601_SRIA_Zero_Emission_Waterborne_Transport_1.2_final_web_low.pdf.

[3] Michael D. Kass et al. “Understanding the Opportunities of Biofuels for Marine Shipping”. In: (Dec. 2018). DOI: 10.2172/1490575. URL: https://www.osti.gov/biblio/1490575.

[4] Meng-Choung Chiong et al. “Challenges and opportunities of marine propulsion with alternative fuels”. In: *Renewable and Sustainable Energy Reviews* 149 (2021), p. 111397. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.111397. URL: https://www.sciencedirect.com/science/article/pii/S1364032121006821.

[5] Sulaman Muhammad and Xingle Long. “China’s seaborne oil import and shipping emissions: The prospect of belt and road initiative”. In: *Marine Pollution Bulletin* 158 (2020), p. 111422. ISSN: 0025-326X. DOI: https://doi.org/10.1016/j.marpolbul.2020.111422. URL: https://www.sciencedirect.com/science/article/pii/S0025326X20305403.

[6] Omer Berkehan Inal, Jean-Frédéric Charpentier, and Cengiz Deniz. “Hybrid power and propulsion systems for ships: Current status and future challenges”. In: *Renewable and Sustainable Energy Reviews* 156 (2022), p. 111965. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.111965. URL: https://www.sciencedirect.com/science/article/pii/S1364032121012302.

[7] 2023. URL: https://www.imo.org/en/OurWork/Environment/Pages/Improving%20the%20energy%20efficiency%20of%20ships.aspx.

[8] Giorgio Zamboni et al. “Comparative analysis among different alternative fuels for ship propulsion in a well-to-wake perspective”. In: *Heliyon* 10 (4 2024), e26016. ISSN: 2405-8440. DOI: https://doi.org/10.1016/j.heliyon.2024.e26016. URL: https://www.sciencedirect.com/science/article/pii/S2405844024020474.

[9] N. Bennabi et al. “Hybrid propulsion systems for small ships: Context and challenges”. In: *2016 XXII International Conference on Electrical Machines (ICEM)*. 2016, pp. 2948–2954. DOI: 10.1109/ICELMACH.2016.7732943.

[10] Levent Bilgili. “Comparative assessment of alternative marine fuels in life cycle perspective”. In: *Renewable and Sustainable Energy Reviews* 144 (2021), p. 110985. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.110985. URL: https://www.sciencedirect.com/science/article/pii/S136403212100277X.

[11] Omer Berkehan Inal, Burak Zincir, and Cengiz Deniz. “Hydrogen and Ammonia for the Decarbonization of Shipping”. In: *Proceedings of the The 5th International Hydrogen Technologies Congress, Shanghai, China*. 2021, pp. 26–28.

[12] Chalermkiat Nuchturee, Tie Li, and Hongpu Xia. “Energy efficiency of integrated electric propulsion for ships – A review”. In: *Renewable and Sustainable Energy Reviews* 134 (2020), p. 110145. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2020.110145. URL: https://www.sciencedirect.com/science/article/pii/S1364032120304366.

[13] Armin Letafat et al. “Simultaneous energy management and optimal components sizing of a zero-emission ferry boat”. In: *Journal of Energy Storage* 28 (2020), p. 101215. ISSN: 2352-152X. DOI: https://doi.org/10.1016/j.est.2020.101215. URL: https://www.sciencedirect.com/science/article/pii/S2352152X19317177.

[14] Joeri Van Mierlo, Peter Van den Bossche, and Gaston Maggetto. "Models of energy sources for EV and HEV: fuel cells, batteries, ultracapacitors, flywheels and engine-generators". In: *Journal of Power Sources* 128 (1 2004), pp. 76–89. ISSN: 0378-7753. DOI: https://doi.org/10.1016/j.jpowsour.2003.09.048. URL: https://www.sciencedirect.com/science/article/pii/S0378775303009753.

[15] Eleftherios K Dedes, Dominic A Hudson, and Stephen R Turnock. "Assessing the potential of hybrid energy technology to reduce exhaust emissions from global shipping". In: *Energy Policy* 40 (2012). Strategic Choices for Renewable Energy Investment, pp. 204–218. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2011.09.046. URL: https://www.sciencedirect.com/science/article/pii/S030142151100735X.

[16] Seref Sagiroglu and Duygu Sinanc. "Big data: A review". In: *2013 International Conference on Collaboration Technologies and Systems (CTS)*. 2013, pp. 42–47. DOI: 10.1109/CTS.2013.6567202.

[17] César Ducruet. "Advances in Shipping Data Analysis and Modeling". In: *Tracking and Mapping Maritime Flows in the Age of Big Data, Routledge Studies in Transport Analysis* (2017).

[18] Christos et al. "Enabling Maritime Digitalization by Extreme-Scale Analytics, AI and Digital Twins: The Vesselai Architecture". In: *Intelligent Systems and Applications*. Ed. by Kohei Arai. Springer International Publishing, 2023, pp. 246–256. ISBN: 978-3-031-16075-2.

[19] Apostolos Papanikolaou et al. "Ship Design in the Era of Digital Transition: A State-of-the-Art Report". In: *International Marine Design Conference* (May 2024). DOI: 10.59490/imdc.2024.784. URL: https://proceedings.open.tudelft.nl/imdc24/article/view/784.

[20] Benjamin Pjedsted Pedersen and Jan Larsen. "Prediction of full-scale propulsion power using artificial neural networks". In: *Proceedings of the 8th international conference on computer and IT applications in the maritime industries (COMPIT'09), Budapest, Hungary May*. 2009, pp. 10–12.

[21] Robert Bond Randall. *Vibration-based condition monitoring: industrial, automotive and aerospace applications*. John Wiley & Sons, 2021.

[22] Chris Aldrich and Lidia Auret. *Unsupervised process monitoring and fault diagnosis with machine learning methods*. Vol. 16. 3. Springer, 2013.

[23] GJ Tsekouras, IK Hatzilau, and JM Prousalidis. "A new pattern recognition methodology for classification of load profiles for ships electric consumers". In: *Journal of Marine Engineering & Technology* 8.2 (2009), pp. 45–58.

[24] Anna Swider, Yi Wang, and Eilif Pedersen. "Data-Driven Vessel Operational Profile Based on t-SNE and Hierarchical Clustering". In: *OCEANS 2018 MTS/IEEE Charleston*. 2018, pp. 1–7. DOI: 10.1109/OCEANS.2018.8604502.

[25] Heiner Lasi et al. "Industry 4.0". In: *Business Information Systems Engineering* 6 (4 2014), pp. 239–242. ISSN: 1867-0202. DOI: 10.1007/s12599-014-0334-4. URL: https://doi.org/10.1007/s12599-014-0334-4.

[26] Mert Onuralp Gokalp et al. "Big Data for Industry 4.0: A Conceptual Framework". In: *2016 International Conference on Computational Science and Computational Intelligence (CSCI)*. 2016, pp. 431–434. DOI: 10.1109/CSCI.2016.0088.

[27] Juan Carlos Quiñones-Gómez, Enric Mor, and Jonathan Chacón. "Data-Driven Design in the Design Process: A Systematic Literature Review on Challenges and Opportunities". In: *International Journal of Human–Computer Interaction* 41 (4 2025), pp. 2227–2252. DOI: 10.1080/10447318.2024.2318060. URL: https://doi.org/10.1080/10447318.2024.2318060.

[28] Yong-Hong Kuo and Andrew Kusiak. "From data to big data in production research: the past and future trends". In: *International Journal of Production Research* 57 (15-16 2019), pp. 4828–4853. DOI: 10.1080/00207543.2018.1443230. URL: https://doi.org/10.1080/00207543.2018.1443230.

[29] F. Mauro and A.A. Kana. “Digital twin for ship life-cycle: A critical systematic review”. In: *Ocean Engineering* 269 (2023), p. 113479. ISSN: 0029-8018. DOI: https://doi.org/10.1016/j.oceaneng.2022.113479. URL: https://www.sciencedirect.com/science/article/pii/S0029801822027627.

[30] Peter A Gale. “The ship design process”. In: *Chapter* 5 (2003), pp. 1–5.

[31] Apostolos Papanikolaou. *Ship design: methodologies of preliminary design*. Springer, 2014.

[32] Baoyu Ni and Lingdong Zeng. “Ship Design Process”. In: *Encyclopedia of Ocean Engineering*. Ed. by Weicheng Cui, Shixiao Fu, and Zhiqiang Hu. Singapore: Springer Singapore, 2019, pp. 1–8. ISBN: 978-981-10-6963-5. DOI: 10.1007/978-981-10-6963-5_36-1. URL: https://doi.org/10.1007/978-981-10-6963-5_36-1.

[33] Carl Anderson. *Creating a data-driven organization: Practical advice from the trenches*. ” O’Reilly Media, Inc.”, 2015.

[34] Henrique Murilo Gaspar. “Data-driven ship design”. In: *COMPIT’18-17th International Conference on Computer and IT Applications in the Maritime Industries*. 2018. ISBN: 3892207070.

[35] Yingfeng Zhang et al. “A framework for Big Data driven product lifecycle management”. In: *Journal of Cleaner Production* 159 (2017), pp. 229–240. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2017.04.172. URL: https://www.sciencedirect.com/science/article/pii/S0959652617309150.

[36] Stephen G Lee et al. “Product lifecycle management in aviation maintenance, repair and overhaul”. In: *Computers in industry* 59.2-3 (2008), pp. 296–303.

[37] Zaifang Zhang, Hui Cheng, and Xuening Chu. “Aided analysis for quality function deployment with an Apriori-based data mining approach”. In: *International Journal of Computer Integrated Manufacturing* 23.7 (2010), pp. 673–686.

[38] Sthéfano L Andrade, Thiago Gabriel Monteiro, and Henrique M Gaspar. “Product Life-Cycle Management In Ship Design: From Concept To Decommission In A Virtual Environment.” In: *ECMS*. 2015, pp. 178–184.

[39] Jingran Li et al. “Big data in product lifecycle management”. In: *The International Journal of Advanced Manufacturing Technology* 81 (2015), pp. 667–684.

[40] Alessandro La Ferlita et al. “A framework of a data-driven model for ship performance”. In: *Ocean Engineering* 309 (2024), p. 118486. ISSN: 0029-8018. DOI: https://doi.org/10.1016/j.oceaneng.2024.118486. URL: https://www.sciencedirect.com/science/article/pii/S0029801824018249.

[41] Tapabrata Ray, RP Gokarn, and OP Sha. “Neural network applications in naval architecture and marine engineering”. In: *Artificial Intelligence in Engineering* 10.3 (1996), pp. 213–226.

[42] Alessandro La Ferlita et al. “A comparative study to estimate fuel consumption: a simplified physical approach against a data-driven model”. In: *Journal of Marine Science and Engineering* 11.4 (2023), p. 850.

[43] Fei Tao et al. “Digital twin-driven product design, manufacturing and service with big data”. In: *International Journal of Advanced Manufacturing Technology* 94 (9-12 Feb. 2018), pp. 3563–3576. ISSN: 14333015. DOI: 10.1007/S00170-017-0233-1/METRICS. URL: https://link.springer.com/article/10.1007/s00170-017-0233-1.

[44] Bedir Tekinerdogan. “On the Notion of Digital Twins: A Modeling Perspective”. In: *Systems* 11 (Dec. 2022), p. 15. DOI: 10.3390/systems11010015.

[45] Mengnan Liu et al. “Review of digital twin about concepts, technologies, and industrial applications”. In: *Journal of Manufacturing Systems* 58 (Jan. 2021), pp. 346–361. ISSN: 0278-6125. DOI: 10.1016/J.JMSY.2020.06.017.

[46] Michael W. Grieves. “Product lifecycle management: the new paradigm for enterprises”. In: *International Journal of Product Development* 2.1-2 (2005), pp. 71–84. ISSN: 17418178. DOI: 10.1504/ijpd.2005.006669.

[47] Michael Grieves and John Vickers. "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems". In: *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*. Ed. by Franz-Josef Kahlen, Shannon Flumerfelt, and Anabela Alves. Cham: Springer International Publishing, 2017, pp. 85–113. ISBN: 978-3-319-38756-7. DOI: 10.1007/978-3-319-38756-7_4. URL: https://doi.org/10.1007/978-3-319-38756-7_4.

[48] Jacob D Hochhalter et al. "Coupling Damage-Sensing Particles to the Digitial Twin Concept". In: *NASA Technical Reports Server* April 2014 (2014), p. 10. URL: https://ntrs.nasa.gov/search.jsp?R=20140006408.

[49] Kenneth Reifsnider and Prasun Majumdar. "Multiphysics Stimulated Simulation Digital Twin Methods for Fleet Management". In: *54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*. 2013. DOI: 10.2514/6.2013-1578. URL: https://arc.aiaa.org/doi/abs/10.2514/6.2013-1578.

[50] Lihong Jiang et al. "An IoT-Oriented data storage framework in cloud computing platform". In: *IEEE Transactions on Industrial Informatics* 10 (2 2014), pp. 1443–1451. ISSN: 15513203. DOI: 10.1109/TII.2014.2306384.

[51] Daniel E. O'Leary. "Artificial intelligence and big data". In: *IEEE Intelligent Systems* 28 (2 2013), pp. 96–99. ISSN: 15411672. DOI: 10.1109/MIS.2013.39.

[52] Matthijs Windmeijer. "Digital Twin Technology used for Control in Green Shipping, Unpublished manuscript". In: *Delft University of Technology* (2023).

[53] Vittorio Bucci et al. "Evolution in Design Methodology for Complex Electric Ships". In: *Journal of Ship Production and Design* 37 (04 Nov. 2021), pp. 215–227. ISSN: 2158-2866. DOI: 10.5957/JSPD.08190045. URL: https://doi.org/10.5957/JSPD.08190045.

[54] *2022 GUIDELINES ON THE METHOD OF CALCULATION OF THE ATTAINED ENERGY EFFICIENCY DESIGN INDEX (EEDI) FOR NEW SHIPS*. RESOLUTION MEPC.364(79). PUC$_7 60689_1 4$. International Marine Organisation. Mar. 2022.

[55] *EEXI and CII - ship carbon intensity and rating system*. Nov. 2022. URL: https://www.imo.org/en/MediaCentre/HotTopics/Pages/EEXI-CII-FAQ.aspx.

[56] *2022 GUIDELINES ON THE METHOD OF CALCULATION OF THE ATTAINED ENERGY EFFICIENCY EXISTING SHIP INDEX (EEXI)*. RESOLUTION MEPC.350(78). Annex 12. International Marine Organisation. June 2022.

[57] *2022 GUIDELINES ON OPERATIONAL CARBON INTENSITY INDICATORS AND THE CALCULATION METHODS (CII GUIDELINES, G1)*. RESOLUTION MEPC.352(78). Annex 14. International Marine Organisation. June 2022.

[58] *2022 GUIDELINES ON THE OPERATIONAL CARBON INTENSITY RATING OF SHIPS (CII RATING GUIDELINES, G4)*. RESOLUTION MEPC.354(78). Annex 16. International Marine Organisation. June 2022.

[59] Miikka Jaurola et al. "Optimising design and power management in energy-efficient marine vessel power systems: a literature review". In: *Journal of Marine Engineering Technology* 18 (2 2019), pp. 92–101. DOI: 10.1080/20464177.2018.1505584. URL: https://doi.org/10.1080/20464177.2018.1505584.

[60] Francesco Di Natale and Claudia Carotenuto. "Particulate matter in marine diesel engines exhausts: Emissions and control strategies". In: *Transportation Research Part D: Transport and Environment* 40 (2015), pp. 166–191. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2015.08.011. URL: https://www.sciencedirect.com/science/article/pii/S1361920915001169.

[61] Julio Vergara, Chris McKesson, and Magdalena Walczak. "Sustainable energy for the marine sector". In: *Energy Policy* 49 (2012). Special Section: Fuel Poverty Comes of Age: Commemorating 21 Years of Research and Policy, pp. 333–345. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2012.06.026. URL: https://www.sciencedirect.com/science/article/pii/S0301421512005368.

[62] Kjell Olav Skjølsvik et al. “Study on greenhouse gas emissions from ships”. In: *MT Rep. Mtoo A23-038. Trondheim, Norway: MARINTEK* (2000).

[63] International Council on Clean Transportation. “Reducing Greenhouse Gas Emissions from Ships – Cost Effectiveness of Available Options”. In: *White Paper. International Council on Clean Transportation, Washington, DC.* (2011).

[64] Nikolaos F Sakellaridis et al. “Development and validation of a new turbocharger simulation methodology for marine two stroke diesel engine modelling and diagnostic applications”. In: *Energy* 91 (2015), pp. 952–966. ISSN: 0360-5442. DOI: `https://doi.org/10.1016/j.energy.2015.08.049`. URL: `https://www.sciencedirect.com/science/article/pii/S036054421501124X`.

[65] Neil Watson and Marian Stefan Janota. “Turbocharging the internal combustion engine”. In: *(No Title)* (1982).

[66] Andreas Torp Karlsen. “On Modeling of a Ship Propulsion System for Control Purposes”. In: *Engineering Cybernetics* MSc (June 2012).

[67] Oleksiy Andriiovych Kuropyatnyk and Sergii Victorovych Sagin. “Exhaust gas recirculation as a major technique designed to reduce NOx emissions from marine diesel engines”. In: *NAŠE MORE: znanstveni časopis za more i pomorstvo* 66.1 (2019), pp. 1–9.

[68] Rajendra Prasad Sinha and Rajoo Balaji. “A Mathematical Model of Marine Diesel Engine Speed Control System”. In: *Journal of The Institution of Engineers (India): Series C* 99 (1 2018), pp. 63–70. ISSN: 2250-0553. DOI: `10.1007/s40032-017-0420-8`. URL: `https://doi.org/10.1007/s40032-017-0420-8`.

[69] Mohd Noor Che Wan, M M Noor, and Rosmawati Mamat. “Biodiesel as alternative fuel for marine diesel engine applications: A review”. In: *Renewable and Sustainable Energy Reviews* 94 (Nov. 2018). DOI: `10.1016/j.rser.2018.05.031`.

[70] S Kalligeros et al. “An investigation of using biodiesel/marine diesel blends on the performance of a stationary diesel engine”. In: *Biomass and Bioenergy* 24 (2 2003), pp. 141–149. ISSN: 0961-9534.

[71] A P Roskilly et al. “The performance and the gaseous emissions of two small marine craft diesel engines fuelled with biodiesel”. In: *Applied Thermal Engineering* 28 (8-9 2008), pp. 872–880. ISSN: 1359-4311.

[72] DNV. *Future Fuels*. `https://www.dnv.com/maritime/hub/decarbonize-shipping/fuels/future-fuels/`. Accessed: June 24, 2025. 2024.

[73] DNV. *Maximizing the Potential of Biofuels in Shipping*. `https://www.dnv.com/expert-story/maritime-impact/maximizing-the-potential-of-biofuels-in-shipping/`. Accessed: 2025-05-23. 2023. URL: `https://www.dnv.com/expert-story/maritime-impact/maximizing-the-potential-of-biofuels-in-shipping/`.

[74] Wärtsilä. *LNG as fuel for ships: Expert answers to 17 important questions*. Accessed: June 25, 2025. 2024. URL: `https://www.wartsila.com/insights/article/lng-fuel-for-thought-in-our-deep-dive-q-a` (visited on 06/25/2025).

[75] Sergey Ushakov, Dag Stenersen, and Per Magne Einang. “Methane slip from gas fuelled ships: a comprehensive summary based on measurement data”. In: *Journal of Marine Science and Technology* 24 (4 2019), pp. 1308–1325. ISSN: 1437-8213. DOI: `10.1007/s00773-018-00622-z`. URL: `https://doi.org/10.1007/s00773-018-00622-z`.

[76] U.S. Environmental Protection Agency. *Understanding Global Warming Potentials*. Accessed: June 25, 2025. 2024. URL: `https://www.epa.gov/ghgemissions/understanding-global-warming-potentials` (visited on 06/25/2025).

[77] A Saravanakumar, A Avinash, and R Saravanakumar. “Optimization of biodiesel production from Pungamia oil by Taguchi’s technique”. In: *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* 38.17 (2016), pp. 2524–2529.

[78] Arivalagan Pugazhendhi et al. “Optimization, kinetic and thermodynamic studies on sustainable biodiesel production from waste cooking oil: An Indian perspective”. In: *Fuel* 273 (2020), p. 117725.

[79] Meng Choung Chiong et al. “Liquid biofuels production and emissions performance in gas turbines: A review”. In: *Energy Conversion and Management* 173 (2018), pp. 640–658. ISSN: 0196-8904. DOI: https://doi.org/10.1016/j.enconman.2018.07.082. URL: https://www.sciencedirect.com/science/article/pii/S0196890418308173.

[80] Tuan Anh Hoang and Vang Van Le. “The Performance of A Diesel Engine Fueled With Diesel Oil, Biodiesel and Preheated Coconut Oil.” In: *International Journal of Renewable Energy Development* 6.1 (2017).

[81] K Nantha Gopal and R Thundil Karuppa Raj. “Effect of pongamia oil methyl ester–diesel blend on lubricating oil degradation of di compression ignition engine”. In: *Fuel* 165 (2016), pp. 105–114.

[82] IM Monirul et al. “Assessment of performance, emission and combustion characteristics of palm, jatropha and Calophyllum inophyllum biodiesel blends”. In: *Fuel* 181 (2016), pp. 985–995.

[83] V Mathan Raj et al. “Performance and emission characteristics of diesel engine fueled with mahua oil methyl ester blended diesel with methanol additives”. In: *Indian Journal of Science and Technology* 9.38 (2016).

[84] Gang Wu et al. “Emission characteristics for waste cooking oil biodiesel blend in a marine diesel propulsion engine”. In: *Pol. J. Environ. Stud* 28.3 (2019), pp. 2911–2921.

[85] Thangaraja Jeyaseelan and Pramod S Mehta. *Reducing NO in a Biodiesel Fueled Compression Ignition Engine-An Experimental Study*. Tech. rep. SAE Technical Paper, 2015.

[86] B Gokalp, E Buyukkaya, and HS Soyhan. “Performance and emissions of a diesel tractor engine fueled with marine diesel and soybean methyl ester”. In: *Biomass and bioenergy* 35.8 (2011), pp. 3575–3583.

[87] Kai Juoperi and Robert Ollus. “Alternative fuels for medium-speed diesel engines”. In: *Wärtsilä Tech. J* 1 (2008), pp. 24–28.

[88] E Jiaqiang et al. “Performance and emission evaluation of a marine diesel engine fueled by water biodiesel-diesel emulsion blends with a fuel additive of a cerium oxide nanoparticle”. In: *Energy Conversion and Management* 169 (2018), pp. 194–205.

[89] S Karthikeyan and A Prathima. “Application of cedarwood oil methyl ester with carbon nano wires in marine engine studies”. In: (2017).

[90] Argus Media. *Methanol vs Green Ammonia: The future of marine fuels*. Market Report. Brought to you ahead of the Argus Green Ammonia - Virtual Conference & Argus Methanol Forum. Argus Media, 2021. URL: https://www.argusmedia.com/green-ammonia.

[91] A Valera-Medina et al. “Ammonia for power”. In: *Progress in Energy and Combustion Science* 69 (2018), pp. 63–102. ISSN: 0360-1285. DOI: https://doi.org/10.1016/j.pecs.2018.07.001. URL: https://www.sciencedirect.com/science/article/pii/S0360128517302320.

[92] Oren Elishav et al. “Progress and prospective of nitrogen-based alternative fuels”. In: *Chemical reviews* 120 (12 2020), pp. 5352–5436. ISSN: 0009-2665.

[93] Trevor Brown and Amgad Elgowainy. “Ammonia Fuel and Energy Storage: Cracking & Fuel Cells”. In: *2018 AIChE Annual Meeting*. AIChE. 2018.

[94] HK Newhall and Ernest S Starkman. “Theoretical performance of ammonia as a gas turbine fuel”. In: *SAE Transactions* (1967), pp. 772–784.

[95] Calin Zamfirescu and IJJoPS Dincer. “Using ammonia as a sustainable fuel”. In: *Journal of Power Sources* 185.1 (2008), pp. 459–465.

[96] Shawn Grannell, C Stack, and D Gillespie. “A comparison of combustion promoters for ammonia and two ways to run engines on ammonia as the only fuel”. In: *Annual NH3 Fuel Conference*. 2010.

[97] K Boyd Fackler et al. “Experimental and numerical study of NOx formation from the lean premixed combustion of CH4 mixed with CO2 and N2”. In: (2011).

[98] JC Ganley and MS Bowery. “Engine-ready, carbon free ammonia fuel”. In: *Annual NH3 Fuel Conference*. 2010.

[99] Kyunghwa Kim et al. “A preliminary study on an alternative ship propulsion system fueled by ammonia: Environmental and economic assessments”. In: *Journal of marine science and engineering* 8.3 (2020), p. 183.

[100] Alessandro Schönborn. “Aqueous solution of ammonia as marine fuel”. In: *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment* 235 (1 July 2020). doi: 10.1177/1475090220937153, pp. 142–151. ISSN: 1475-0902. DOI: 10.1177/1475090220937153. URL: https://doi.org/10.1177/1475090220937153.

[101] Julia Hansson et al. “The potential role of ammonia as marine fuel—based on energy systems modeling and multi-criteria decision analysis”. In: *Sustainability* 12.8 (2020), p. 3265.

[102] R. D. Geertsma et al. “Design and control of hybrid power and propulsion systems for smart ships: A review of developments”. In: *Applied Energy* 194 (May 2017), pp. 30–54. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2017.02.060.

[103] Wärtsilä Corporation. *Dual-fuel engines from Wärtsilä*. Accessed: 2025-07-01. 2023. URL: https://www.wartsila.com/encyclopedia/term/dual-fuel-engines-from-wartsila.

[104] Wärtsilä Corporation. *Dual-Fuel Engines - Marine*. Product page, accessed on 2025-07-01. 2023. URL: https://www.wartsila.com/marine/products/engines-and-generating-sets/dual-fuel-engines.

[105] Xiaoyu Wang, Jianzhong Zhu, and Minfang Han. *Industrial Development Status and Prospects of the Marine Fuel Cell: A Review*. Feb. 2023. DOI: 10.3390/jmse11020238.

[106] Julien J. M. Hermans and Austin A. Kana. “Retrofit modeling for green ships”. In: *International Marine Design Conference* (May 2024). DOI: 10.59490/imdc.2024.890. URL: https://proceedings.open.tudelft.nl/imdc24/article/view/890.

[107] Tamesol. *Solar energy in maritime transport: Advantages and current uses*. Accessed: 2025-07-01. 2024. URL: https://tamesol.com/en/solar-energy-maritime/.

[108] Thorsten Völker. “Hybrid propulsion concepts on ships”. In: *Papers of 33rd International Scientific Conference” Science in Practice”*. 2015, pp. 11–16.

[109] PT van Loon and P van Zon. “From operational profile to hybrid propulsion”. In: *Proceedings of the 24th international HISWA symposium on yacht design and yacht construction, Amsterdam, The Netherlands*. 2016, pp. 14–15.

[110] Werner Kritzinger et al. “Digital Twin in manufacturing: A categorical literature review and classification”. In: *IFAC-PapersOnLine* 51.11 (2018), pp. 1016–1022. ISSN: 24058963. DOI: 10.1016/j.ifacol.2018.08.474. URL: https://doi.org/10.1016/j.ifacol.2018.08.474.

[111] Michael Grieves. *Digital Model, Digital Shadow, and Digital Twin*. 2023. URL: https://www.linkedin.com/pulse/digital-model-shadow-twin-michael-grieves/ (visited on 04/24/2024).

[112] Samad M.E. Sepasgozar. “Differentiating Digital Twin from Digital Shadow : Elucidating a Paradigm Shift to Expedite a Smart ”. In: *Buildings* 11.151 (2021).

[113] Asma Ladj et al. “A knowledge-based Digital Shadow for machining industry in a Digital Twin perspective”. In: *Journal of Manufacturing Systems* 58.PB (2021), pp. 168–179. ISSN: 02786125. DOI: 10.1016/j.jmsy.2020.07.018. URL: https://doi.org/10.1016/j.jmsy.2020.07.018.

[114] Nuwan Sri Madusanka et al. “Digital Twin in the Maritime Domain: A Review and Emerging Trends”. In: *Journal of Marine Science and Engineering* 11.5 (2023). ISSN: 20771312. DOI: 10.3390/jmse11051021.

[115] Concetta Semeraro et al. “Digital twin paradigm: A systematic literature review”. In: *Computers in Industry* 130 (2021), p. 103469. ISSN: 0166-3615. DOI: https://doi.org/10.1016/j.compind.2021.103469. URL: https://www.sciencedirect.com/science/article/pii/S0166361521000762.

[116] Vincenzo Arrichiello and Paola Gualeni. “Systems engineering and digital twin: A vision for the future of cruise ships design, production and operations”. In: *International Journal on Interactive Design and Manufacturing (IJIDeM)* 14 (2020), pp. 115–122.

[117] Madhu Sudan Sapkota et al. “An approach for adaptive model performance validation within digital twinning”. In: *International Journal of Computational Methods and Experimental Measurements* 9.3 (2021), pp. 213–225.

[118] J Munoz and A Ramirez. “Achieving the digital ship: From design to operation”. In: *RINA, Royal Institution of Naval Architects-19th International Conference on Computer Applications in Shipbuilding, ICCAS*. 2019.

[119] Rodrigo Perez Fernandez. “What the shipbuilding future holds in terms of CAD/CAM/CIM systems”. In: *SNAME International Symposium on Ship Operations, Management and Economics*. SNAME. 2021, D011S002R001.

[120] Lampros Nikolopoulos and Evangelos Boulougouris. “A novel method for the holistic, simulation driven ship design optimization under uncertainty in the big data era”. In: *Ocean Engineering* 218 (2020), p. 107634.

[121] Apostolos Papanikolaou. *A holistic approach to ship design*. Vol. 1. Springer, 2019.

[122] F Tillig et al. “A generic energy systems model for efficient ship design and operation”. In: *Proceedings of the Institution of Mechanical Engineers, Part M* 231 (2 2017), pp. 649–666. DOI: 10.1177/1475090216680672. URL: https://doi.org/10.1177/1475090216680672.

[123] Endre Sandvik et al. “Estimation of fuel consumption using discrete-event simulation—A validation study”. In: *Marine Design XIII, Volume 2*. CRC Press, 2018, pp. 953–960.

[124] L Nikolopoulos and V Boulougouris. “Applications of holistic ship theory in the optimization of bulk carrier design and operation”. In: *EUROGEN 2015 Conference, September*. 2015.

[125] Fei Tao et al. “Digital twin-driven product design framework”. In: *International Journal of Production Research* 57 (12 2019), pp. 3935–3953. DOI: 10.1080/00207543.2018.1443229. URL: https://doi.org/10.1080/00207543.2018.1443229.

[126] Ghanishtha Bhatti, Harshit Mohan, and R. Raja Singh. “Towards the future of smart electric vehicles: Digital twin technology”. In: *Renewable and Sustainable Energy Reviews* 141 (May 2021), p. 110801. ISSN: 1364-0321. DOI: 10.1016/J.RSER.2021.110801.

[127] Ailong Fan et al. “A review of ship fuel consumption models”. In: *Ocean Engineering* 264 (2022), p. 112405. ISSN: 0029-8018. DOI: https://doi.org/10.1016/j.oceaneng.2022.112405. URL: https://www.sciencedirect.com/science/article/pii/S0029801822016936.

[128] Jan-Erik Giering and Alexander Dyck. “Maritime Digital Twin architecture: A concept for holistic Digital Twin application for shipbuilding and shipping”. In: *at-Automatisierungstechnik* 69.12 (2021), pp. 1081–1095.

[129] Vibhor Gupta. *Noon Report on Ship: A Complete Guide with Examples and Data*. https://voyagex.ai/noon-report-on-ship-guide/. Accessed: 2010-09-30.

[130] Hongtao Chi et al. “A framework for real-time monitoring of energy efficiency of marine vessels”. In: *Energy* 145 (2018), pp. 246–260. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2017.12.088. URL: https://www.sciencedirect.com/science/article/pii/S036054421732131X.

[131] Andrea Coraddu et al. “Ship efficiency forecast based on sensors data collection: Improving numerical models through data analytics”. In: *OCEANS 2015 - Genova*. 2015, pp. 1–10. DOI: 10.1109/OCEANS-Genova.2015.7271412.

[132] Fabio Rodríguez et al. “Updating digital twins: Methodology for data accuracy quality control using machine learning techniques”. In: *Computers in Industry* 151 (2023), p. 103958. ISSN: 0166-3615. DOI: https://doi.org/10.1016/j.compind.2023.103958. URL: https://www.sciencedirect.com/science/article/pii/S0166361523001082.

[133] Fei Chiang and Renée J Miller. “Discovering data quality rules”. In: *Proceedings of the VLDB Endowment* 1.1 (2008), pp. 1166–1177.

[134] Aidan Fuller et al. “Digital Twin: Enabling Technologies, Challenges and Open Research”. In: *IEEE Access* 8 (2020), pp. 108952–108971. DOI: 10.1109/ACCESS.2020.2998358.

[135] Md. Shezad Dihan et al. “Digital twin: Data exploration, architecture, implementation and future”. In: *Heliyon* 10 (5 2024), e26503. ISSN: 2405-8440. DOI: https://doi.org/10.1016/j.heliyon.2024.e26503. URL: https://www.sciencedirect.com/science/article/pii/S2405844024025349.

[136] Meng Zhang et al. “Digital twin data: methods and key technologies: [version 2; peer review: 4 approved]”. In: *Digital Twin* 1.1 (2024), p. 2.

[137] Yu Zheng, Sen Yang, and Huanchong Cheng. “An application framework of digital twin and its case study”. In: *Journal of Ambient Intelligence and Humanized Computing* 10 (3 2019), pp. 1141–1153. ISSN: 1868-5145. DOI: 10.1007/s12652-018-0911-3. URL: https://doi.org/10.1007/s12652-018-0911-3.

[138] J. Zhang et al. “Big-data-driven operational analysis and decision-making methodology in intelligent workshop”. In: 22 (May 2016), pp. 1220–1228. DOI: 10.13196/j.cims.2016.05.007.

[139] Fei Tao et al. “Digital twin modeling”. In: *Journal of Manufacturing Systems* 64 (2022), pp. 372–389. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2022.06.015. URL: https://www.sciencedirect.com/science/article/pii/S0278612522001108.

[140] Xiangyu Zhang et al. “Tool wear online monitoring method based on DT and SSAE-PHMM”. In: *Journal of Computing and Information Science in Engineering* 21.3 (2021), p. 034501.

[141] Minglei Li and Liangliang Nan. “Feature-preserving 3D mesh simplification for urban buildings”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 173 (2021), pp. 135–150. ISSN: 0924-2716. DOI: https://doi.org/10.1016/j.isprsjprs.2021.01.006. URL: https://www.sciencedirect.com/science/article/pii/S092427162100006X.

[142] E Branlard et al. “A digital twin solution for floating offshore wind turbines validated using a full-scale prototype”. In: *Wind Energy Science* 9 (1 2024), pp. 1–24. DOI: 10.5194/wes-9-1-2024. URL: https://wes.copernicus.org/articles/9/1/2024/.

[143] Feriel Boulfani et al. “Anomaly detection for aircraft electrical generator using machine learning in a functional data framework”. In: *2020 Global Congress on Electrical Engineering (GC-ElecEng)*. 2020, pp. 27–32. DOI: 10.23919/GC-ElecEng48342.2020.9285984.

[144] Clarksons Research. *World Fleet Register*. https://www.clarksons.net/wfr/fleet. Accessed: 2025-01-29.

[145] European Commission. *Open collaboration and open Digital Twin infrastructure for Green Smart Shipping | DT4GS | Project | Fact sheet | HORIZON | CORDIS | European Commission*. 2022. DOI: 10.3030/101056799. URL: https://cordis.europa.eu/project/id/101056799 (visited on 02/14/2024).

[146] J. P. Jalkanen et al. “Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide”. In: *Atmospheric Chemistry and Physics* 12 (5 2012), pp. 2641–2659. ISSN: 16807316. DOI: 10.5194/acp-12-2641-2012.

[147] International Maritime Organization (IMO). *2024 Guidelines on Life Cycle GHG Intensity of Marine Fuels (2024 LCA Guidelines)*. https://www.imo.org/en/ourwork/environment/pages/lifecycle-ghg---carbon-intensity-guidelines.aspx. Resolution MEPC.391(81), adopted on 22 March 2024, MEPC 81. Mar. 2024.

[148] Iram Hernandez et al. “Thermal Performance Analysis of LOX/LCH4 Engine Feed Systems Using CFD Modeling”. In: *Fluids* 10.3 (2025), p. 62.

[149] Viet Dung Tran, Prabhakar Sharma, and Lan Huong Nguyen. “Digital twins for internal combustion engines: A brief review”. In: *Journal of Emerging Science and Engineering* 1 (1 Sept. 2023), pp. 29–35. DOI: 10.61435/jese.2023.5. URL: https://journal.cbiore.id/index.php/jese/article/view/5.

[150] Jae-Hoon Lee et al. “Real-time digital twin for ship operation in waves”. In: *Ocean Engineering* 266 (2022), p. 112867. ISSN: 0029-8018. DOI: https://doi.org/10.1016/j.oceaneng.2022.112867. URL: https://www.sciencedirect.com/science/article/pii/S0029801822021503.

[151] Jørgen Fie Padøy Mathiesen. “Retrofit solutions for energy efficiency in shipping: a study of effects, cost-efficiencies, implementation rates and barriers”. MA thesis. 2020.

A

Academic Paper

An operational data-driven digital twin framework for marine engine configuration design

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The maritime industry faces increasing pressure to cut greenhouse gas emissions, yet traditional ship design methods rely on static assumptions and rarely exploit the growing availability of operational data. This paper proposes a Digital Twin (DT)-aided design framework to integrate such data into early-stage ship design. The framework covers data acquisition, modeling, and verification, ensuring that operational insights inform decision-making. A case study on bulk carrier engine room configurations demonstrates the approach. Using industrial engine datasets and operational profiles derived from Bunker Delivery Notes, a rule-based model generates feasible configurations that are assessed for fuel consumption and CO_2 emissions. Results indicate that operational data enables insights into performance forecasts and more informed configuration selection compared to traditional methods. While the application remains a digital model rather than a full twin, the study shows the potential of DT-aided frameworks to support IMO decarbonization goals and guide future ship design.

I. Introduction

The shipping industry is a major contributor to global greenhouse gas emissions due to its dependence on fossil fuels. Meeting international decarbonization targets requires more than incremental improvements in ship efficiency: it calls for innovation in both technology and design methodology. Traditional ship design often relies on generic operational assumptions, which can lead to oversized or inefficient systems that perform poorly under real-world conditions. This creates a gap between design intent and operational reality.

With the increasing availability of operational data from ships, new opportunities arise to integrate data-driven methods into the design process. Such methods can improve early-stage decision-making by aligning design choices with realistic operating conditions, thereby reducing inefficiencies in both fuel consumption and emissions. This aligns with broader Industry 4.0 developments, where real-time data, artificial intelligence, and interconnected digital systems are transforming industrial practice [1, 2].

Digital Twin (DT) technology offers a promising foundation for this shift. DTs provide a virtual representation of a physical asset, dynamically updated with real-time data, and are increasingly applied in manufacturing and operations to improve performance and maintenance strategies [3]. In the maritime sector, DTs have primarily been implemented during the operational phase, where abundant real-time data is available. However, their application to early-stage ship design remains limited, despite the potential to bridge the gap between regulatory targets and practical implementation.

The transition to greener and retrofitted ships requires a gradual yet accelerated approach, supported by an efficient production and design cycle. Improving the production cycle, and thereby decarbonizing the industry, can be achieved through several methods.

This study addresses this gap by developing a data-driven design framework for early-stage ship design. The framework integrates operational data into a rule-based model, enabling systematic evaluation of design alternatives under realistic load conditions. To demonstrate and validate the framework, it is applied to the case of marine engine room configuration for bulk carriers. The case study illustrates how the framework can support design decisions that improve efficiency and emissions performance, while remaining extendable to other ship types and subsystems.

A. Scope of the research

The focus of this paper is the development of a design framework aided by the DT concept. This framework will be applied to a case study on bulk carrier engine configurations, serving as a proof-of-concept to illustrate the framework's capabilities. The case study currently considers conventional internal combustion and dual-fuel engines, with the potential to be expanded to hybrid-electric systems and additional ship types. Hydrodynamic design and retrofit implementation are outside of the scope of this work. The adapted framework in the case study produces a digital model rather than a fully validated digital twin, as incorporating a complete bi-directional data flow is outside the scope of this work.

The main research question this paper wishes to answer is:

> **How can operational data be integrated into a data-driven design framework to support early-stage ship design?**

B. Research approach

This study adopts a quantitative, data-driven research approach to investigate how operational data can inform early-stage ship design. The research comprises three main steps: a literature review, framework development, and a case study application.

First, the traditional ship design cycle and its limitations were reviewed, with particular attention to the underutilization of operational data in conceptual and preliminary phases. Parallel to this, the state-of-the-art in data-driven design was analyzed to establish requirements for integrating real-world operational profiles into ship design.

Second, a Digital Twin (DT)-aided design framework was developed. The framework is modular, consisting of four phases: (1) acquisition and pre-processing of data, (2) selection and creation of an appropriate modeling approach, (3) verification and validation of model outcomes, and (4) systematic data management.

Third, the framework was demonstrated in a case study of a bulk carrier engine room. Real operational data from Bunker Delivery Notes (BDN) was combined with industrial engine datasets to construct realistic load profiles. These profiles were then used to simulate main and auxiliary engine configurations, quantifying fuel consumption, CO_2 emissions, and compliance with regulatory metrics such as the Carbon Intensity Indicator (CII). Verification was performed by benchmarking results against operational data from the reference vessel.

This approach enables a structured evaluation of how operational data can bridge the gap between design assumptions and actual performance. While the case study constitutes a digital model rather than a full twin, it demonstrates the feasibility of DT-inspired methods for early-stage ship design.

II. Literature Review

A. Traditional Ship Design Methods

Every product designed follows the same production cycle. For ship design, this is the same. According to Gale, the ship design cycle is as follows [4]:

- **Conceptual design:** The primary objective is to clarify the shipowner's requirements, including the vessel's expected performance and intended missions.
- **Preliminary design:** During this stage, the various ship design steps previously completed in the first phase are further elaborated upon in greater detail. The ship's main characteristics are more accurately determined and aligned with the client's requirements.
- **Contract design:** This phase is completed with the completion of the necessary calculations and naval architectural drawings, along with the technical specifications drawings.
- **Detailed design:** The contract design is translated into a detailed design of all structural elements of the ship, along with the establishment of technical specifications for ship construction and the installation of equipment.

This paper aims to support the early-stage design, specifically the conceptual design phase. By leveraging new advancements in the maritime industry, this paper identifies potential opportunities for utilizing data, particularly operational data, in ship design. By integrating real-world performance insights at this early stage, it becomes possible to estimate propulsion and emission characteristics more accurately, thereby guiding engine room design choices with greater precision.

1. Operational data in ship design

Data used in ship design can broadly be divided into two categories: static data and operational data. Static data refers to fixed characteristics such as ship dimensions, engine specifications, or regulatory requirements—information that remains unchanged once defined. In contrast, operational data captures the dynamic behavior of vessels in service. Enabled by advances in sensor technology and digital reporting, operational data reflects how ships are actually operated, offering detailed insights into performance, efficiency, and environmental impact.

Operational data can be classified into these four types:

- **Voyage data**: Speed, draft, route
- **Engine data**: Load, power output, fuel usage
- **Environmental conditions**: Weather, state of the sea
- **Logbook data**: Shipper's journal

Data is being used in research across more and more industries; however, the applications of operational data in ship design are limited. This is due to limitations and challenges that come with the abundance of operational data. For specific goals, the data can be too sparse or inconsistent, which makes outcomes unreliable. All data that comes in needs to be cleaned and processed before it can be used. Standardization would be required to make real-time fleet data more easily usable.

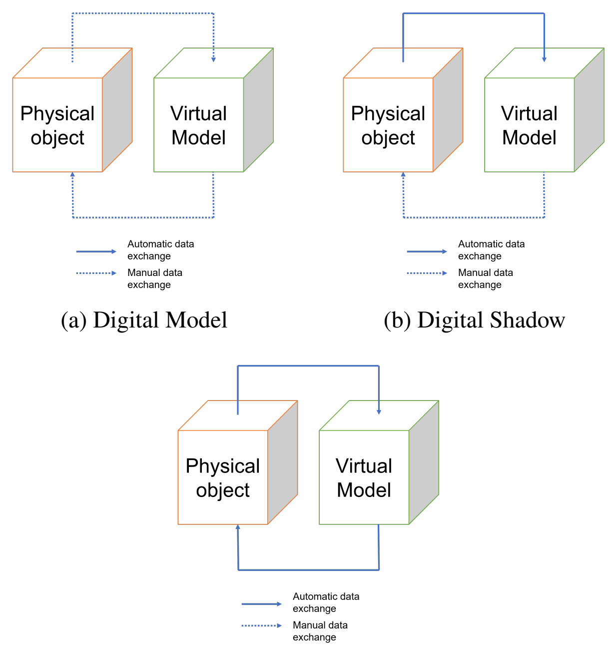
Operational data can give great insights into vessel behavior, which can be used for early-stage ship design. Real-world operational profiles provide actual engine loading conditions, which should help in sizing for future vessels. This approach helps prevent both over-dimensioning and under-dimensioning of main and auxiliary systems. It also provides a basis for evaluating different types of fuel options and different powertrain topologies.

This study aims to address the gap in the utilization of operational data in design by utilizing a data-driven method that supports the use of operational data. The data-driven design method will be discussed in the following section.

B. Data-Driven design and Digital twin-aided Approach

Industry 4.0 has brought increased attention to data-driven methods in design and production. Among these, the Digital Twin (DT) has emerged as a central concept. Grieves defines the DT as consisting of a physical object, its virtual counterpart, and the data connection between them [5, 6]. This continuous exchange of information distinguishes DTs from earlier static models.

To distinguish maturity levels of DTs, Kritzinger et al. [7] differentiate between a digital model, digital shadow, and full digital twin, depending on whether data exchange is manual, one-way, or bi-directional (Figure 1). This framework illustrates that current ship design practices rarely progress beyond digital models, leaving significant potential untapped.



(a) Digital Model (b) Digital Shadow

(c) Digital Twin

Figure 1. Integration level of data exchange

DT technology has been applied in sectors such as aerospace [8] and infrastructure monitoring [9], where it supports predictive maintenance, system optimization, and life-cycle management. In the maritime domain, applications are mostly limited to the operational phase, where real-time sensor data can optimize fleet performance and maintenance. A paper by Maura et al. examined the use and the grade of implementation of DTs in the maritime industry. The division of the use in the ship's phase can be seen in Figure 2.

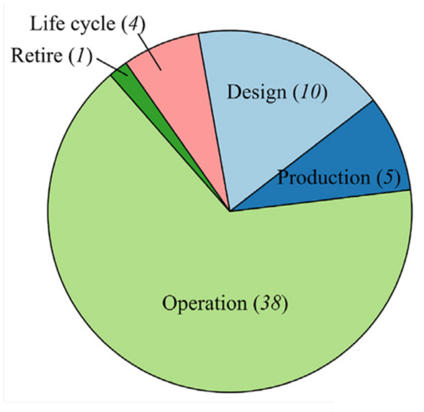


Figure 2. Division of filtered papers on Digital Twins of the phase [10]

Of the 10 papers found in design, only three concepts, concerning general descriptions, definitions, and capabilities of DTs, were in ship design. Not a single framework of how a DT could be implemented in ship design is produced according to this study [10].

C. Regulatory drivers for alternative design methods

Regulatory measures introduced by the International Maritime Organization (IMO) further highlight the need for data-informed design. Initial frameworks, such as the Energy Efficiency Design Index (EEDI) and the Energy Efficiency Existing Ship Index (EEXI), focused on technical efficiency. More recently, the Carbon Intensity Indicator (CII) evaluates ships on their operational performance, assigning annual ratings from A (superior) to E (inferior) [11]. Ships rated D for three consecutive years, or E once, must submit corrective action plans.

1. Carbon intensity indicator

The CII is calculated based on annual CO_2 emissions per transport work (Equations 1–4), linking emissions directly to ship operations. This operational focus highlights the potential for integrating real operational data into design frameworks to ensure that future vessels meet increasingly stringent targets.

The Carbon Intensity Indicator (CII) is based on the operational energy efficiency of ships. It determines the annual reduction factor required to ensure continuous improvements of a ship's operational carbon intensity. The CII is a mandatory indicator for vessels of 5,000 gross tonnage and above. The attained annual operational CII is documented and verified against the required annual operational CII (Equation 1). Finding the attained CII is calculated by dividing the yearly CO_2 emissions, found by multiplying the fuel by the carbon conversion factor, by the Annual Transport Work that is done by the ship (Equation 2). The CII required by the industry is calculated by multiplying the reduction factor for the necessary annual operational CII: Z, with a reference value CII_{ref} (equation 3). This reference value is a general value defined in 2019 that is based on the type of ship that is examined (Equation 4[12]).

$$CII = \frac{CII_{attained}}{CII_{required}} \tag{1}$$

$$\begin{aligned} CII_{attained} &= \frac{\text{Annual CO}_2\text{ Emissions}}{\text{Annual Transport Work}} \\ &= \frac{\sum(FC_{i,year} \cdot CF_i)}{DWT \cdot D_{year}} \end{aligned} \tag{2}$$

$$CII_{required} = \frac{(1-Z)}{100} \cdot CII_{ref} \tag{3}$$

$$CII_{ref} = a \cdot DWT^{-c} \tag{4}$$

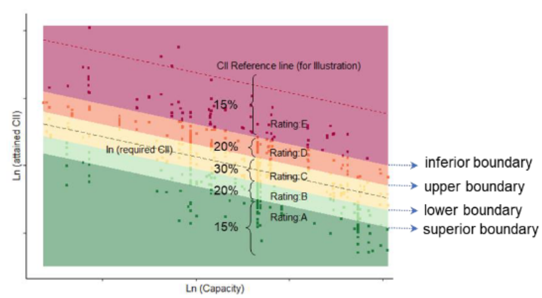


Figure 3. Operational energy efficiency performance rating scale [13]

D. Engine configuration optimization potential

Given the pressure of regulatory requirements, marine engineers are exploring both alternative fuels and hybridized propulsion systems. Hybrid-electric solutions show particular promise for ships with variable operational profiles, while dual-fuel engines allow flexibility in emissions and costs depending on fuel availability [14]. Operational data can help determine realistic engine loads, fuel switching strategies, and hybrid functionality strategies, making it central to the optimization of engine room topologies.

E. Purpose of Data-driven models

Conventional frameworks provide structured processes but fail to utilize the abundance of operational data that is now becoming available. According to the literature, a method for integrating operational data into a DT-aided design approach has not yet been established. This paper wishes to bridge that gap by proposing a DT-aided framework for early-stage ship design that can integrate operational data. The framework aims to demonstrate how such data can be structured, analyzed, and integrated into a digital model that supports early-stage decision-making.

III. DT-aided design framework

This section outlines the building blocks required for the DT-aided design framework developed in this study. The goal is to demonstrate how operational data can be systematically integrated into early-stage ship design. The section will begin with operational data and progress from the modeling approach to verification and validation, concluding with data management.

A. Operational Data

Quality data is a fundamental part of DT-aided design, as it forms the link between the physical and virtual domains. Modern vessels generate large volumes of data through reporting systems (e.g., IMO's Data Collection System, AIS) and onboard sensors, which provide continuous information on ship performance, position, and fuel use [15]. While this creates opportunities for design optimization, data reliability remains a challenge due to sensor inaccuracies, missing values, and inconsistent formats. Automated validation and fault-detection are therefore critical [16, 17].

Equally important are issues of data access and management. Effective use requires integration across sources, stakeholder access, and secure digital infrastructure, often relying on cloud-based solutions [18]. Once acquired, raw data must be pre-processed—through cleaning, filtering, and structuring—before it can support analysis and decision-making. Frameworks such as Zheng et al.'s four-stage architecture (acquisition, pre-processing, analysis, and fusion) provide structured approaches to ensure data quality and usability [19].

B. Modeling approach

The modeling approach in a DT-aided design framework depends on the application and design goals, since it determines how operational and static data are translated into the virtual space. Tao et al. identify four main categories of modeling strategies for DTs: geometric, physical, behavioral, and rule-based models [20].

- **Geometric models** focus on the physical form of the system, including structure and spatial properties. They are commonly used in structural analysis, allowing for simplified yet high-fidelity representations for visualization and monitoring [21].
- **Physical models** simulate physical properties and processes, either through static analysis (e.g., material states, multi-physics coupling) or dynamic models (e.g., thermal conduction, wear prediction) for real-time performance monitoring [22].
- **Behavioral models** represent system dynamics and control, but are highly sensitive to anomalies in input data. Accurate pre-processing and parameter tuning are essential for reliable predictions.
- **Rule-based models** encode expert knowledge and operational rules to guide configuration and lifecycle assessment. While currently limited by their static nature, they offer transparent and modular logic for early-stage design decisions.

C. Model Verification & validation

Ensuring credibility in DT-aided models requires both verification and validation. Verification focuses on whether the model has been implemented correctly and whether its assumptions and outputs remain consistent across updates. Because models evolve, verification must be repeated regularly, making it an iterative process.

Validation instead emphasizes whether the model's outputs are sufficiently realistic and reliable for their intended purpose. This typically involves comparing simulated results against real-world data, benchmarks, or case studies to confirm that the model achieves the defined objectives.

Together, these processes ensure that a DT-aided framework not only functions correctly but also provides trustworthy insights for supporting design decisions [23].

D. Data management

To complete the loop of the DT-aided design process, information from both the physical system and the virtual model must be stored and managed systematically. For ship design, this means building a structured knowledge bank of operational data, engine parameters, and modeling results, which can be reused across projects. Proper management not only improves accessibility for stakeholders but also enhances reliability, efficiency, and long-term learning within the design process [20].

E. DT-aided design goal and framework

Based on these building blocks, the DT-aided design framework follows six steps:

1) Determine the goal of the DT-aided design process
2) Process and assess collected operational data
3) Determine the modeling approach
4) Optimize key parameters according to the modeling approach
5) Verify and validate the model
6) Link the virtual and physical spaces through structured data management

The resulting framework is shown in Figure 4, where four main elements are represented: virtual modeling, physical space, data sources, and feedback. Each corresponds to a phase in the DT-aided process. The following section applies this framework to a case study, where engine configurations are optimized based on fuel consumption performance using the operational data of a bulk carrier vessel.

IV. Case Study

The goal of this case study is to apply the DT-aided framework to engine configuration design, demonstrating how operational data can support early-stage

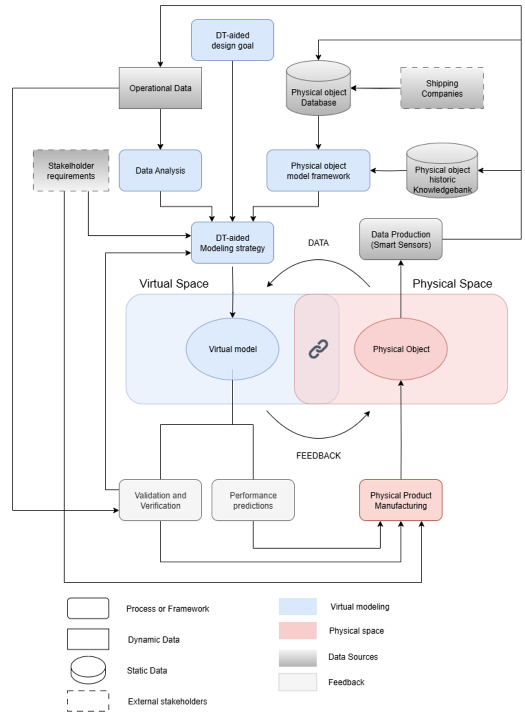


Figure 4. Proposed DT-aided design framework for ship design

decision-making in the development of more sustainable vessels. By modeling and comparing different engine setups under realistic load profiles, the framework aims to enhance design robustness and support emissions reduction targets. The case study draws on operational data from a large bulk carrier, which serves as the reference vessel.

The applied framework, shown in Figure 5, follows the same logic as the generic framework presented earlier, but adapted to the specific requirements of engine configuration modeling. A notable adjustment is the absence of a feedback-based validation loop: direct comparison with physical test data or alternative models is outside the scope of this study. As such, the case study constitutes a *Digital Model*.

A. Data Collection and Processing

Operational and engine data were gathered from industry databases and Bunker Delivery Notes (BDNs). The dataset includes main and auxiliary engine specifications, fuel types, and Specific Fuel Oil Consumption (SFOC) values. Pre-processing steps included cleaning incomplete records, harmonizing formats, and

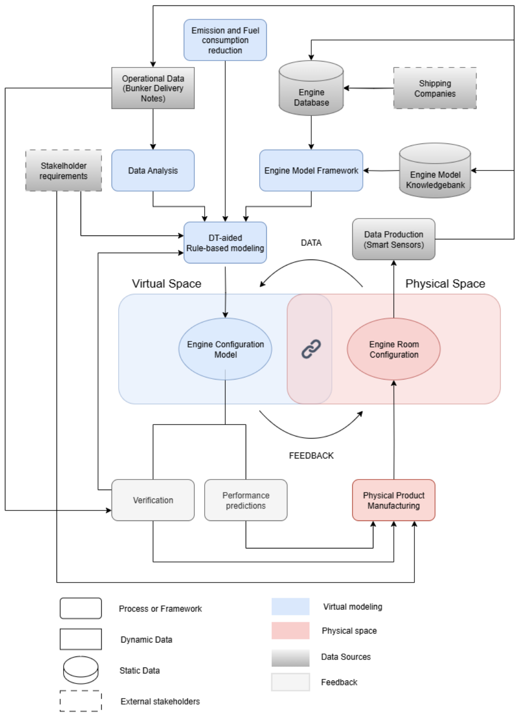


Figure 5. DT-aided design methodology of Engine Room

converting location data (degrees/minutes) into decimal coordinates for integration with voyage profiles.

B. Reference vessel

The case study vessel is a bulk carrier of approximately 300 m length overall (LOA), equipped with a two-stroke diesel main engine. The specifications of this vessel provide the baseline against which alternative configurations are assessed.

To ensure relevance to larger vessels, engine data is filtered by selecting ships with a LOA of at least 100 meters. This approach captures a range of engines suitable for large ship applications, while still including smaller engines that may offer promising alternative configurations. The resulting dataset provides a comprehensive list of potential engine candidates.

C. Modeling approach and assumptions

A rule-based modeling approach was adopted to mimic such a 300-meter bulk carrier, encoding technical constraints and industry norms. Main engines were selected first based on efficiency and feasibility, followed by auxiliary engines sized within IMO regulatory ranges. The design constraints consist of things such as:

- minimum auxiliary power thresholds based on industry standards,
- restriction to a maximum of two distinct fuel types, and
- redundancy requirements for critical power systems.

Some simplifications were made, such as excluding wave interactions and assuming steady-state engine behavior at given load levels.

D. Emissions & Fuel Consumption Modeling

Fuel consumption and CO_2 emissions were computed on a voyage basis. SFOC–load relationships were applied for each engine type, with results aggregated over simulated operational profiles. While IMO's CII typically relies on annual emissions, this study applied voyage-based calculations to identify which operations contribute most to total emissions. The configurations will be ranked and assessed according to a few key performance indicators (KPIs) listed below:

- **Total CO_2 emissions in tonnes**
- **Total Fuel consumption in tonnes**
- **Emission Intensity in g CO_2 / kWh**
- **CII index**

In addition to total CO_2 output, the model calculates emissions intensity (EI) to allow fair comparison across configurations. It is defined as:

$$\text{EI} = \frac{\text{Total CO2 Emissions} \cdot 10^6}{\text{Total Energy Output (kWh)}} \quad [\text{g CO}_2/\text{kWh}] \tag{5}$$

This intensity metric is used as one of the main criteria for ranking and selecting the optimal configurations.

1. Engine Load and SFOC modeling

To accurately model emissions, engine efficiency is modeled according to engine load. In this case study, the Specific Fuel Oil Consumption (SFOC) is dependent on engine load. Jalkenen et al. have studied the SFOC of marine diesel engines and, via a regression analysis of comprehensive SFOC measurements from Wärtsilä, derived a second-degree polynomial equation 6 for the relative SFOC [24].

$$SFC_{\text{rel}} = 0.455 \cdot L^2 - 0.71 \cdot L + 1.28 \tag{6}$$

Where $L \in [0, 1]$ is the engine load expressed as a fraction of the engine's SMCR (Service Maximum Continuous Rating). The actual SFOC is then computed as:

$$SFC_{\text{actual}} = SFC_{\text{base}} \cdot SFC_{\text{rel}} \tag{7}$$

This load-dependent SFOC is measured at each 5-minute interval of the ship's operation in the BDN data, for both main and auxiliary engines. These values are then used to estimate instantaneous fuel consumption and emissions. The polynomial can be seen in Figure 6.

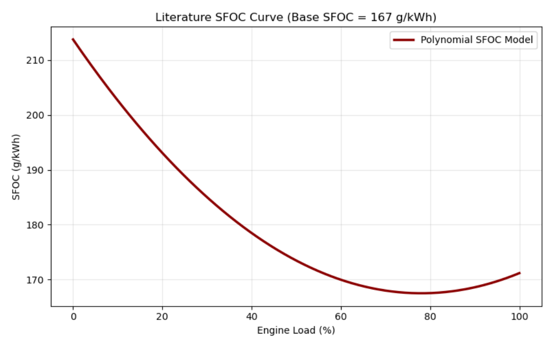


Figure 6. SFOC polynomial gathered from Jalkenen [24].

E. Load profiles

Three representative load profiles were derived from the operational dataset to capture distinct modes of vessel activity:

- **Voyage (two weeks)** – steady main engine demand with fluctuating auxiliary loads.
- **Port operations** – minimal main engine activity, highly variable auxiliary loads.
- **Loitering near port** – negligible main engine activity and light auxiliary use.

An example of one of the load profiles is provided below. The two-week voyage is shown in Figure 7. It showcases a voyage of two weeks where a steady main engine and constant fluctuating auxiliary power are required.

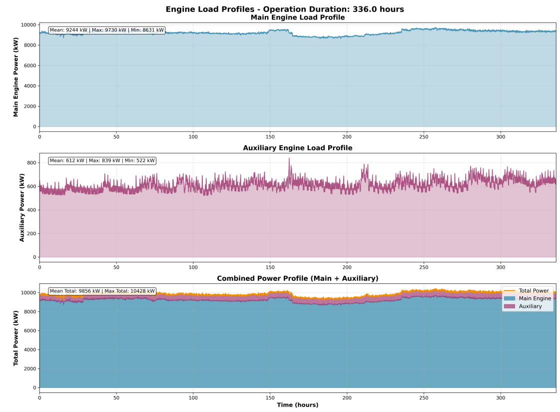


Figure 7. 2 week voyage load profile.

V. Results

This section presents the results of applying the DT-aided design framework to reduce fuel consumption and emissions by implementing the rule-based model.

A. Configuration emission comparison capabilities

When comparing the simulated results with the benchmark data, some interesting results can be found. This section will explore the differences and similarities.

A benchmark is calculated using the SFOC polynomial (Equation 6) from Section IV.D, with the engine load and SFOC data from the BDN. This benchmark is compared to the emission calculated by the simulation; the results of the load profile of a voyage of two weeks can be seen in Table 1. The top entry is the benchmark, which is the SFOC calculated in the same way as for the configurations, but using the SFOC measured by the sensors on the vessel.

Another comparison can be seen in Figure 8. In this figure, the emission intensity is compared with the benchmark. The big difference can be due to the engines not performing at exactly the engine load that they would be used to if they were operated.

Configuration	Main Engine Type	No. of Aux. Engines	Total Fuel (tonnes)	Total CO_2 (tonnes)	vs Benchmark CO_2 (%)
Benchmark	Diesel 2-Stroke (Benchmark)	3	641.51	2002.79	0
Config 1	Diesel 4-Stroke	2	506.2542	1576.476	-21.29%
Config 2	Diesel 4-Stroke	2	506.9777	1578.728	-21.17%
Config 71	Dual-fuel	2	679.4693	2020.433	0.88%
Config 72	Dual-fuel	2	680.3307	2023.116	1.01%
Config 121	Diesel 2-Stroke	2	832.0442	2590.985	29.37%
Config 122	Diesel 2-Stroke	2	841.2629	2619.693	30.8022%
Config 231	Gas Turbine	2	1367.856	4380.188	109.99%
Config 232	Gas Turbine	2	1368.674	4382.737	118.83%

Table 1. Comparison of engine configurations with benchmark by CO_2 emissions and fuel consumption.

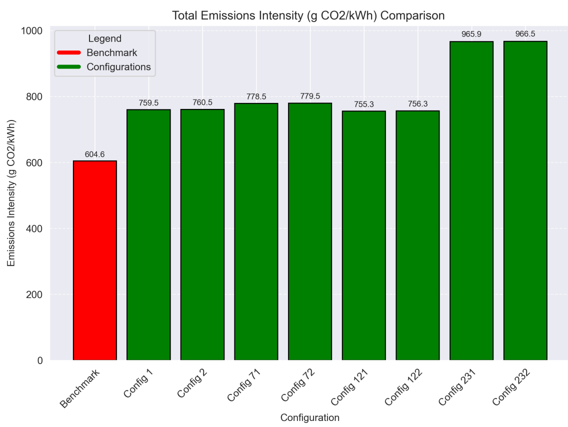


Figure 8. Emission Intensity of Benchmark and different configurations

The config numbers and what their type of configuration is can be found in table 1.

B. IMO's CII Index

Using the IMO's CII calculator, the CII of different configurations can also be estimated. In Table 2 a summary is given of the CII index ratings given to the three best performing (lowest CO_2 emissions) configurations in the different load profiles.

For port operations and the two-week voyage, the ratings fall within a realistic and expected range. However, the loitering case shows a rating that is about ten times worse. This can be explained by how the CII is calculated: it is designed to reflect performance over a whole year of operations, not short outlier periods. To better reflect how the IMO's CII is typically applied on an annual basis, the three configurations were also simulated over 3 months instead of just the shorter load profiles. This provides a more accurate representation of their long-term performance. The results are shown in Figure 9.

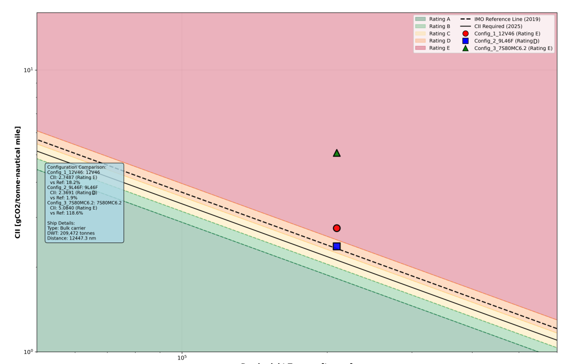


Figure 9. CII analysis of the three best performing configurations in each load profile during 3 months of operations

The differences between results highlight one of the key limitations of applying CII ratings to short-term load profiles: results can shift significantly depending on the time horizon used.

VI. Conclusion and discussion

This research set out to answer the question:

> **How can operational data be integrated into a data-driven design framework to support early-stage ship design?**

The findings show that operational data can meaningfully strengthen early-stage ship design when struc-

	Main Engine	Aux Engines	Total Emissions (tonnes)	CII Actual	CII Reference	CII Rating	vs Reference (%)
2-Week voyage	12V46	2x 9H21/32	1844.23	2.83927	2.32539	E	22.10%
	9L46F	2x 8H32/40	N/A	2.427049	2.32539	N/A	N/A
	7S80MC6.2	2x 5L21/31	3533.67	5.440236	2.32539	E	133.90%
Port Operations	12V46	2x 9H21/32	251.74	2.876299	2.32539	E	23.70%
	9L46F	2x 8H32/40	224.49	2.565006	2.32539	E	10.30%
	7S80MC6.2	2x 5L21/31	395.57	4.519735	2.32539	E	94.40%
Loiter	12V46	2x 9H21/32	106.42	27.38339	2.32539	E	1077.60%
	9L46F	2x 8H32/40	102.93	26.48542	2.32539	E	1039.00%
	7S80MC6.2	2x 5L21/31	91.86	23.63785	2.32539	E	916.50%

Table 2. CII rating of the three best performing configurations for each load profile

tured within a Digital Twin (DT)-aided framework. Traditional methods rely on generalized assumptions, often missing the variability of real operations. By contrast, embedding time-series operational data into the framework allows for the evaluation of engine configurations under realistic load profiles, capturing both absolute fuel consumption and emissions.

The framework developed in this thesis combines operational data, rule-based modeling, and verification steps into a modular process. In a case study on engine room configuration, the framework produced realistic performance forecasts and enabled the comparison of alternative configurations against both benchmarks and regulatory metrics. While the optimized configurations reduced overall fuel use and emissions in specific load profiles, they still highlighted trade-offs such as higher emission intensity under certain conditions. This demonstrates that operational data not only confirms design choices but also reveals where assumptions fall short, thereby supporting more robust and transparent decision-making.

VII. Further research and outlook

First, the framework that is applied here is a digital model. Realizing a complete DT would require bi-directional, real-time data exchange between the virtual and physical systems. This would enable the framework not only to inform early-stage design but also to update predictions as operational data evolves continuously.

Second, the case study focused on engine room configuration. Expanding the framework to include hybrid-electric systems, alternative fuels, and spatial layout considerations would broaden its applicability to holistic ship design. Integration with lifecycle perspectives—such as cost modeling, retrofitting strategies, and fuel availability in different ports—would also improve its practical relevance.

Ultimately, the scalability of the framework relies heavily on the availability and quality of the data. Wider adoption will require standardized, high-resolution datasets across the industry, along with methods for automated validation and error detection. Building such shared knowledge repositories could significantly accelerate data-driven design in the shipping industry.

Taken together, these developments suggest that DT-aided frameworks have potential. As access to operational data improves, the approach presented here could evolve into a fully integrated ecosystem, linking design intent, operational performance, and sustainability targets in a continuous loop.

References

[1] Heiner Lasi, Peter Fettke, Hans-Georg Kemper, Thomas Feld, and Michael Hoffmann. Industry 4.0. *Business Information Systems Engineering*, 6:239–242, 2014. ISSN 1867-0202. doi: 10.1007/s12599-014-0334-4. URL https://doi.org/10.1007/s12599-014-0334-4.

[2] Mert Onuralp Gokalp, Kerem Kayabay, Mehmet Ali Akyol, P. Erhan Eren, and Altan Koçyiğit. Big data for industry 4.0: A conceptual framework. In *2016 International Conference on Computational Science and Computational Intelligence (CSCI)*, pages 431–434, 2016. doi: 10.1109/CSCI.2016.0088.

[3] Fei Tao, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, and Fangyuan Sui. Digital twin-driven product design, manufacturing and service with big data. *International Journal of Advanced Manufacturing Technology*, 94:3563–3576, 2 2018. ISSN 14333015. doi: 10.1007/S00170-017-0233-1/METRICS. URL https://link.springer.com/

article/10.1007/s00170-017-0233-1.

[4] Peter A Gale. The ship design process. *Chapter*, 5: 1–5, 2003.

[5] Michael W. Grieves. Product lifecycle management: the new paradigm for enterprises. *International Journal of Product Development*, 2(1-2):71–84, 2005. ISSN 17418178. doi: 10.1504/ijpd.2005.006669.

[6] Michael Grieves and John Vickers. *Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems*. Springer International Publishing, Cham, 2017. ISBN 978-3-319-38756-7. doi: 10.1007/978-3-319-38756-7_4. URL https://doi.org/10.1007/978-3-319-38756-7_4.

[7] Werner Kritzinger, Matthias Karner, Georg Traar, Jan Henjes, and Wilfried Sihn. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11):1016–1022, 2018. ISSN 24058963. doi: 10.1016/j.ifacol.2018.08.474. URL https://doi.org/10.1016/j.ifacol.2018.08.474.

[8] Jacob D Hochhalter, William P Leser, John A Newman, Edward H Glaessgen, Stephen R Cornell, Scott A Willard, Gerd Heber, Vipul K. Gupta, Vesselin Yamakov, Stephen R Cornell, Scott A Willard, and Gerd Heber. Coupling Damage-Sensing Particles to the Digitial Twin Concept. *NASA Technical Reports Server*, (April 2014):10, 2014. URL https://ntrs.nasa.gov/search.jsp?R=20140006408.

[9] Kenneth Reifsnider and Prasun Majumdar. *Multiphysics Stimulated Simulation Digital Twin Methods for Fleet Management*. 2013. doi: 10.2514/6.2013-1578. URL https://arc.aiaa.org/doi/abs/10.2514/6.2013-1578.

[10] F. Mauro and A.A. Kana. Digital twin for ship life-cycle: A critical systematic review. *Ocean Engineering*, 269:113479, 2023. ISSN 0029-8018. doi: https://doi.org/10.1016/j.oceaneng.2022.113479. URL https://www.sciencedirect.com/science/article/pii/S0029801822027627.

[11] 2023. URL https://www.imo.org/en/OurWork/Environment/Pages/Improving%20the%20energy%20efficiency%20of%20ships.aspx.

[12] *2022 GUIDELINES ON OPERATIONAL CARBON INTENSITY INDICATORS AND THE CALCULATION METHODS (CII GUIDELINES, G1)*. International Marine Organisation, 6 2022. Annex 14.

[13] *2022 GUIDELINES ON THE OPERATIONAL CARBON INTENSITY RATING OF SHIPS (CII RATING GUIDELINES, G4)*. International Marine Organisation, 6 2022. Annex 16.

[14] Miikka Jaurola, Anders Hedin, Seppo Tikkanen, and Kalevi Huhtala. Optimising design and power management in energy-efficient marine vessel power systems: a literature review. *Journal of Marine Engineering Technology*, 18:92–101, 2019. doi: 10.1080/20464177.2018.1505584. URL https://doi.org/10.1080/20464177.2018.1505584.

[15] Hongtao Chi, Giulia Pedrielli, Szu Hui Ng, Thomas Kister, and Stéphane Bressan. A framework for real-time monitoring of energy efficiency of marine vessels. *Energy*, 145:246–260, 2018. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2017.12.088. URL https://www.sciencedirect.com/science/article/pii/S036054421732131X.

[16] Fabio Rodríguez, William D Chicaiza, Adolfo Sánchez, and Juan M Escaño. Updating digital twins: Methodology for data accuracy quality control using machine learning techniques. *Computers in Industry*, 151:103958, 2023. ISSN 0166-3615. doi: https://doi.org/10.1016/j.compind.2023.103958. URL https://www.sciencedirect.com/science/article/pii/S0166361523001082.

[17] Fei Chiang and Renée J Miller. Discovering data quality rules. *Proceedings of the VLDB Endowment*, 1(1):1166–1177, 2008.

[18] Aidan Fuller, Zhong Fan, Charles Day, and Chris Barlow. Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, 8:108952–108971, 2020. doi: 10.1109/ACCESS.2020.2998358.

[19] Yu Zheng, Sen Yang, and Huanchong Cheng. An application framework of digital twin and its case study. *Journal of Ambient Intelligence and Humanized Computing*, 10:1141–1153, 2019. ISSN 1868-5145. doi: 10.1007/s12652-018-0911-3. URL https://doi.org/10.1007/s12652-018-0911-3.

[20] Fei Tao, Bin Xiao, Qinglin Qi, Jiangfeng Cheng, and Ping Ji. Digital twin modeling. *Journal of Manufacturing Systems*, 64:372–389, 2022. ISSN 0278-6125. doi: https://doi.org/10.1016/j.jmsy.2022.06.015. URL https://www.sciencedirect.com/science/article/pii/S0278612522001108.

[21] Xiangyu Zhang, Lilan Liu, Xiang Wan, and Bowen Feng. Tool wear online monitoring method based on dt and ssae-phmm. *Journal of Computing and Information Science in Engineering*, 21(3):034501, 2021.

[22] E Branlard, J Jonkman, C Brown, and J Zhang. A digital twin solution for floating offshore wind turbines validated using a full-scale prototype. *Wind Energy Science*, 9:1–24, 2024. doi: 10.5194/wes-9-1-2024. URL https://wes.copernicus.org/articles/9/1/2024/.

[23] Madhu Sudan Sapkota, Edward Apeh, Mark Hadfield, Roya Haratian, Robert Adey, and John Baynham. An approach for adaptive model performance validation within digital twinning. *International Journal of Com-*

putational Methods and Experimental Measurements, 9(3):213–225, 2021.

[24] J. P. Jalkanen, L. Johansson, J. Kukkonen, A. Brink, J. Kalli, and T. Stipa. Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide. *Atmospheric Chemistry and Physics*, 12:2641–2659, 2012. ISSN 16807316. doi: 10.5194/acp-12-2641-2012.