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HÅLLBAR SJÖFART

Increase shipping efficiency using ship data analytics and AI to assist ship operations

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Summary

Various energy efficiency measures (EEMs) have been used in the shipping market, but their potential to reduce fuel consumption and air emissions are not fully recognized partly due to uncertain ship performance models used in those EEMs. The project report investigates the feasibility of shipping EEMs that can be improved by implementing data analytics and AI through the demonstration of their integration into the IMO Just-In-Time (JIT) arrival guidance. What Big data analytics can help to improve and promote EEMs in shipping through, 1) improving ship performance models in these EEMs, 2) developing intelligent decision support for individual vessels, 3) accurate evaluation of fuel and environmental benefits from these measures, etc?

This report also investigates the requirements and willingness of different stakeholders to use data analysis for those EEMs from seafarers' perspectives to find obstacles/requirements for the implementation of these EEMs. From a social perspective, by studying the capability, willingness, and barriers to use AI to assist ship operations, this project has looked for AI integrated solutions to help smoothen implementation and utilization of the EEMs without introducing extra workload/burdens to seafarers and assist decision-making processes to reduce pressure for ship masters onboard. Through the analysis, several findings can be concluded in this report:

- empirical and theoretical ship performance models contain large uncertainties for predicting ship speed/power during seaway operations,
- purely data-driven models can give good predictions of historical ship performance if proper AI/machine learning methods are chosen to build the AI models, however large discrepancy between prediction and actual performance for future sailing is not satisfactory to ship operators.
- a ship energy system is a complex dynamic coupling system. Adding more energy efficiency devices onboard will make the system even more complex and hard to model. Some automatic/intelligent systems should be provided to make the EEMs efficiently used by crew members onboard.
- dynamic interaction of different ship energy components should be systematically considered in the development of EEMs rather than looking at increasing efficiency of a single energy components.
- current pure data-driven models may not capture the dynamic coupling of different ship energy components for EEMs. Therefore, this report recommends combining physics into data-based machine learning methods to increase modelling accuracy.
- large energy savings are demonstrated to implement JIT using AI assisted EEMs.

Sammanfattning

Olika energieffektivitetsåtgärder (EEM) har använts på sjöfartsmarknaden, men deras potential att minska bränsleförbrukningen och luftutsläppen är inte fullt erkänd, delvis på grund av osäkra fartygsprestandamodeller som används i dessa EEMs. Projektrapporten undersöker genomförbarheten av att skicka EEMs som kan förbättras genom att implementera dataanalys och AI genom demonstration av deras integration i IMO:s Just-In-Time (JIT) ankomstvägledning. Vilken Big data-analys kan hjälpa till att förbättra och främja EEM inom sjöfarten genom, 1) förbättra fartygsprestandamodeller i dessa EEMs, 2) utveckla intelligent beslutsstöd för enskilda fartyg, 3) korrekt utvärdering av bränsle- och miljöfördelar med dessa åtgärder, etc?

Denna rapport undersöker också olika intressenters krav och vilja att använda dataanalys för dessa EEM ur sjöfolks perspektiv för att hitta hinder/krav för implementeringen av dessa EEMs. Ur ett socialt perspektiv, genom att studera förmågan, viljan och hindren för att använda AI för att hjälpa fartygsoperationer, letar detta projekt efter AI-integrerade lösningar för att underlätta implementering och utnyttjande av EEM utan att införa extra arbetsbelastning/bördor för sjöfolk och hjälpa beslut - Att göra processer för att minska trycket för fartygsbefälhavare ombord. Genom analysen kan flera slutsatser dras i denna rapport:

- empiriska och teoretiska fartygsprestandamodeller innehåller stora osäkerheter för att förutsäga fartygets hastighet/styrka under sjöfart,
- rent datadrivna modeller kan ge bra förutsägelser om historiska fartygs prestanda om korrekta AI/maskininlärningsmetoder väljs för att bygga AI-modellerna, men stor skillnad mellan förutsägelse och faktisk prestanda för framtida segling är inte tillfredsställande för fartygsoperatörer.
- fartygets energisystem är ett komplext dynamiskt kopplingssystem. Att lägga till fler energieffektiva enheter ombord kommer att göra systemet ännu mer komplext och svårt att modellera. Vissa automatiska/intelligenta system bör tillhandahållas för att EEM ska kunna användas effektivt av besättningsmedlemmar ombord.
- Dynamisk interaktion mellan olika fartygsenergikomponenter bör systematiskt beaktas vid utvecklingen av EEM snarare än att titta på ökad effektivitet hos en enskild energikomponent.
- nuvarande rent datadrivna modeller kanske inte fångar den dynamiska kopplingen av olika fartygsenergikomponenter för EEM. Därför rekommenderar den här rapporten att man kombinerar fysik i databaserade maskininlärningsmetoder för att öka modelleringsnoggrannheten.
- stora energibesparingar har demonstrerats för att implementera JIT med hjälp av AI-stödda EEM.

Contents

1 Introduction

Although measures to increase energy efficiency are mandatory according to the UN organization International Maritime Organization (IMO 2019), there is still much room for improvement in reducing emissions in commercial shipping (e.g., DNV 2015; IMO 2020; Poulsen et al. 2021). This report investigates how fuel consumption and air emissions can be reduced through digitalization and Artificial Intelligence (AI) in shipping. Machine Learning (ML) technology, a core technology within AI, opens new avenues for energy savings in the shipping industry by enabling improved energy performance models that can identify more efficient ways of operating individual ships. Improved knowledge of a ship's performance at sea can help calculate potential fuel savings, suggest general measures that would decrease fuel use, and provide instructions to individual vessels based on identified correlations in existing ship data. Thus, ML can become an integrated part of energy efficiency measures (EEMs).

Previous research and commercial development have produced promising results in developing ML models that can calculate how ships perform in various conditions and provide recommendations on how to operate ships more efficiently. However, these methods still need to be improved. The models that are used to make predictions for a specific ship are usually imprecise as they use certain baselines to make these calculations (for example, assuming the ships are running with full cargo). In real-life conditions, loading, navigational, and environmental factors will differ from theoretical models and experimental settings (e.g., Tillig et al. 2017, Andersson 2018, Lang et al. 2022, etc.). By considering relevant variables that influence the ship propulsion under varying real-life conditions, the accuracy of these predictions can be improved. This can be done by adapting models to varying circumstances (e.g., the technical specificities of the ship, operation mode, and whether the ship is running fully loaded with cargo or not). This will help identify the most suitable energy efficiency measures for domains and specific ships. This knowledge will be beneficial in determining the most suitable energy efficiency measure (EEM).

Identifying the most optimal way to save fuel through digital models is not a straightforward task. The computer models used to improve efficiency will always be an extrapolation and approximation of real-life conditions. Models will need to be evaluated using the same or similar testing data used to build the model, as real-life trials are very time-consuming and would require many journeys to provide mathematically significant results on savings. It is almost impossible to determine how much savings are made when a ship uses a specific EEM. Because each journey is executed in unique weather conditions, you would not know how much fuel would have been used if the ship was operated in any other way. A crucial part of decreasing consumption is finding better ways to assess potential fuel savings of EEMs.

A key to creating digital models for improving energy efficiency in shipping is identifying strategies for arriving just in time (JIT). It's a well-known fact in the industry that a just-in-time approach would increase energy effectiveness compared to current practices of the average ship, i.e., so that the ship doesn't use excessive speed throughout the journey. Due to physical principles, more energy will be used if a ship uses excessive speed throughout the journey and waits at anchorage in the harbor area. Keeping an even speed or even better constant energy consumption and arriving just in time for off-loading and on-loading will significantly reduce fuel consumption. As DNV formulated it: "Due to the steepness of the speed-power curves of vessels, speed variability results in excess consumption compared to constant speed or better constant RPM" (DNV 2015).

Theoretically, every hour spent in the harbor could have been used to reduce the fuel consumption of the journey. DNV writes that "Our work experience with shipping companies and ports as well as AIS data analytics show that waiting times are a major issue in some ports – bearing significant improvement potential" (DNV 2015). A way of evaluating potential energy savings that will be used in this report is to see how much time ships spend at anchorage. This method can help identify where interventions can be most beneficial as digital tools for improving energy efficiency will be most useful for ships that currently operate in a sub-optimal way. The report will also investigate the different potentials for ships using speed as the control variable/target and those using engine power/RPM as the control variable. This work is important because the development, installation, and evaluation of EEMs rely on accurate modeling of a ship's energy performance when sailing, which describes a ship's power consumption in terms of navigational conditions, encountered sea weather environments, loading conditions, etc.

The efficiency of EEMs that require adaptation in navigation by the captain (and other involved actors) in terms of planning and execution of the journey depends on several social factors. Although theoretically and mathematically sound, an EEM will only be efficient if it is used as intended. Compliance with EEMs will depend on, among other things, the determination and attitudes of involved actors and the ability to overcome various organizational challenges. This pilot project takes as its point of departure that methods of reducing shipping emissions are always embedded in social practices and organizations (Viktorelius et al. 2021). Thus, fuel savings requires both technical changes and changes in organizational/ social practices. Potential energy savings are thus situated in the socio-technical system, including human organization, machinery, and the materiality of harbors and oceans. Or to speak with Palm and Thollander (2020), problems related to energy use must be tackled from a multi-disciplinary perspective (Palm and Thollander 2020). Therefore, this pilot project aims at finding feedback loops between the social and technical aspects of energy efficiency—i.e., how can knowledge of the practicalities of the social dimensions of the shipping industry provide helpful knowledge for developing technical measures, and how can technical measures be made relevant in a ship's operation?

The project studies the feasibility of shipping energy efficiency measures (EEMs) that can be significantly improved by integrating data analytics and AI into the IMO Just-In-Time (JIT) arrival guidance. The following tasks are carried out to achieve the objectives,

- Analyze the average anchor and waiting times of ships arriving at two typical ports, identify energy efficiency measures (EEMs) used in the shipping industry and investigate the feasibility of making use of those EEMs to facilitate IMO JIT arrival guidance, as well as its potential for fuel saving.
- Study the knowledge gaps on the efficiency of applying different EEMs to achieve the IMO JIT, in terms of e.g., improving ship performance models in these EMMs, providing accurate evaluation of ETA, fuel and environmental benefits of different energy metrics, etc., under the assistance of big data analytics and AI techniques.
- Based on the investigation of IMO JIT and uncertainties of EEMs implementation, investigate how AI can help us increase our understanding of coupling interaction between ship resistance, propulsion efficiency, and engine load when sailing in random sea environments for better development of EEMs and IMO JIT
- A simple demonstration (which should be extended and more thoroughly investigated if more time is allowed to give a more realistic consideration) of different assumed scenarios for voyage optimization on a ship with full-scale measurement is performed to investigate how the ship's operation related measures can be integrated into the IMO JIT, under the assistance of AI.
- Show how these EEMs are situated in the shipping industry's current organizational and technical systems and discuss how they relate to the technical solutions suggested in this report.
- Studying the capability, willingness, and barriers to using AI assist ship operations from a social perspective

Several factors that can promote or hinder the use of energy efficiency measures are explored and discussed in this report. The presenting and discussing of these factors rely on our interviews conducted for this pilot project and on previous research literature and reports.

2 Overview of ship energy efficiency measures

There is an increasing awareness in the shipping industry of the importance of reducing fuel consumption. Most importantly, it is a question of creating competitive advantages for individual shipping companies, as fuel constitutes a major part of the cost of an operation. The cost of fuel reaches somewhere between 25 and 50 percent (depending on current fuel prices, margins in operation, and other factors) of total operating costs in shipping (DNV 2015). From a study, DNV concludes that "cost impact is the key driver for energy efficiency" (DNV 2015). Shipping companies also have the drive to lessen their environmental footprint due to regulatory pressure and increasing demand from customers to minimize the quantity of carbon emission per transported item.

Regulations that affect all shipping companies are the ones decided upon by the IMO. In 2018, the IMO adopted an initial greenhouse gas (GHG) abatement strategy, aiming to lower "CO2 emissions per transport-work, as an average across international shipping, by at least 40% by 2030, pursuing efforts toward 70% by 2050 compared to 2008" (IMO, 2018). But there are also other relevant regulations for example, in a new climate plan, the European Union (EU) proposes that the scope of its Emissions Trading System (ETS) be expanded to include carbon dioxide (CO2) emissions from ships, which would be the first time this has been done. In a similar vein, Japan has informed the IMO that it would support a carbon tax that would raise more than $50 billion (B) per year [2], marking a significant step forward by the world's second-largest shipowner nation in addressing emissions from maritime transport.

But despite obvious benefits associated with fuel savings, "many shipping companies struggle with implementation" (DNV 2015) of energy efficiency measures.

Besides saving costs for individual business companies, reducing fuel consumption in shipping is crucial for combating anthropogenic climate change. Maritime transportation is associated with much lower emission of greenhouse gases per weight unit of cargo than air freight and road transportation. In fact, "shipping is the most energy-efficient way of transporting bulk freights" (Jafarzadeh & Bouwer Utne 2013). However, given the large quantities of goods transported by sea, maritime transportation still contributes to global emissions and anthropogenic global warming. Depending on the source, the shipping industry contributes between 2% (Rehmatulla et al. 2017) and 3.1% (Turan 2015) to anthropogenic CO_2 emissions globally. Within the EU, shipping answers to 4% of the emission of greenhouse gases. According to the Fourth IMO GHG study (IMO 2020), GHG emissions from shipping have increased by 9.6% from 2012 to 2018. It has been argued that these emissions globally "are likely to represent around 17% of CO_2 emissions under the business-as-usual scenario by 2050" (Rehmatulla et al. 2017).

2.1 Overview of implementing ship energy efficiency measures

There are many ways to reduce emissions in maritime transportation while transporting the same amount of goods over the same distance. The consumption of energy can be reduced through the technical development of machinery and equipment. The engines, propellers, and the construction of the hull of newly built vessels can be improved from previously built ships. In Fig. 2-1 this step is represented by the first circle. This step is concerned with the hardware of the ship and having the ships fitted with more energy-efficient engines and other less polluting equipment. In line with directions from IMO, the design energy efficiency is measured through an Energy Efficiency Design Index (EEDI) referring to the amount of CO_2 emitted by the ship per capacity mile (tonne-mile) (Fig. 2-1). IMO's goal is to continuously lower the "required EEDI value for the ships so future ships are even more energy efficient" (Jassal 2018). The EEDI was made mandatory for new ships in July 2011 (IMO 2019).

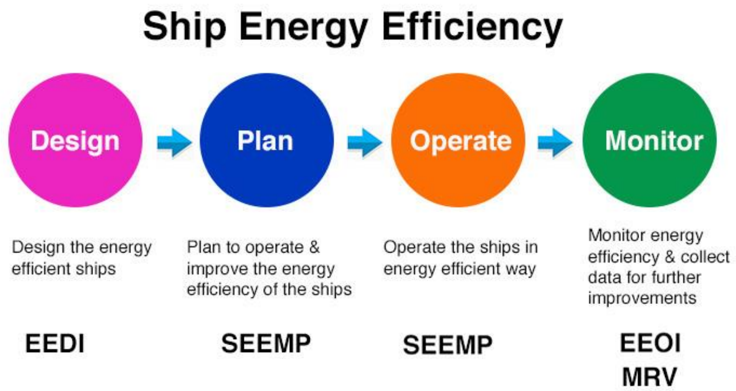


Figure 2-1: Steps of energy efficiency implementation

But energy efficiency is not only related to the physical equipment but also to how the equipment of the vessel is used. Fuel consumption can also be reduced by planning and executing voyages differently (e.g., Eide et al. 2009; IMO 2020; Viktorelius et al. 2022). For example, by running fully loaded with cargo and reducing the speed (as energy consumption per nautical mile will increase at high speed). It might also be more beneficial to take a longer route in good weather conditions compared to a shorter route in bad weather conditions. If there are variations in weather throughout the journey, it is likely more efficient from a fuel consumption perspective to slow down in bad weather conditions and speed up in good weather conditions. Improving energy efficiency through planning and execution is illustrated by the second two circles in Fig.2-1. These steps are regulated through the IMO by a demand for vessels to have a Ship Energy Efficiency Management Plan (SEEMP). In short, SEEMP is the plan of all practices that can be performed to achieve better energy efficiency (IMO 2019). "The SEEMP urges the ship owner and operator at each stage of the plan to consider new technologies and practices when seeking to optimize the performance of a ship." (IMO 2019) The demand for a Ship Energy Efficiency Management Plan (SEEMP) came into force in 2013 (DNV 2015).

The fourth step in Figure 2-1 is about monitoring energy use and collecting data for future improvements. This is a voluntary measure but recommended by the

IMO. Energy Efficiency Operational Indicator (EEOI) is a monitoring tool that is suggested by the IMO and is measured in the amount of CO_2 emitted by the ship per ton-mile of work (Jassal 2018). The EEOI (how efficiently the ship is operated) is not to be confused with the EEDI (how energy efficient the ship is built). “EEOI enables operators to measure the fuel efficiency of a ship in operation and to gauge the effect of any changes in operation, e.g., improved voyage planning or more frequent propeller cleaning, or introduction of technical measures such as waste heat recovery systems or a new propeller” (IMO 2019). This data collection opens new avenues for using digital measures to decrease the use of fuel in shipping. The availability of historical data on ship performance can help facilitate improvement in future operations. Because interpretation and understanding of the data pose many demands to ship operators and crew, the large dataset collected does not automatically lead to optimal energy use in shipping (Viktorelius and Lundh 2019), or “Having set up an IT system providing all relevant reports in perfect granularity and frequency does not necessarily mean that performance is managed” (DNV 2015).

2.2 EEMs in assisting ship operations

So, what energy efficiency measures exist, and which ones are preferred by shipping companies and crew? There is no agreed-upon list of available energy efficiency measures (EEMs) in shipping, and in the available categorizations, there are many overlaps, i.e., a particular measure might tick several of the boxes in the various categorizations. Figure 2-2 displays some examples of measures that could fit into the SEEMP plan. ABS energy outlook (ABS 2020) has identified several measures (EEMs) that could be used to reach the goals set by the IMO, including fuel-efficient operations, weather routing, draft and trim optimization, propeller and hull cleaning, speed optimization, and timely maintenance. These are the most common measures that are implemented in today’s shipping market.

In the same fashion as ABS (Fig. 2-2), DNV has comprised a list of common EEMs and inquired into their frequency of use (DNV 2015). Slow steaming is understood to be the measure that saves the most energy. “Asked about the major contributors to energy savings in 2014, “slow steaming” outpaced all other measures by far”. Followed by hull and propeller cleaning, voyage planning optimization, performance monitoring and reporting, hull coating, advanced weather routing, propulsion retrofitting, trim & draft optimization, and then Awareness and/ or incentives.

IMO understands the EEDI to be the “most important technical measure and aims at promoting the use of more energy efficient (less polluting) equipment and engines” (IMO 2019). Measures that relate to the planning and execution of journeys are much harder to implement and require changes in established practices (while a generally improved energy efficiency of the ship keeps on operating the ship as has always been done. AS the DNV report state:

"operational measures appear less tangible than technical measures" (DNV 2015). Few continuously work with and update their SEEMP (DNV 2015), as discussed in the introduction, it is not necessarily saving energy to comply with the IMO regulations when it comes to the planning and execution of a voyage (ibid). As DNV states, "Only a minority of shipping companies have achieved their targets entirely or at least largely. Many others have chosen the compliance driven approach and realized hardly any savings" (DNV 2015). Only complying with regulation does not offer any king's road to energy savings.

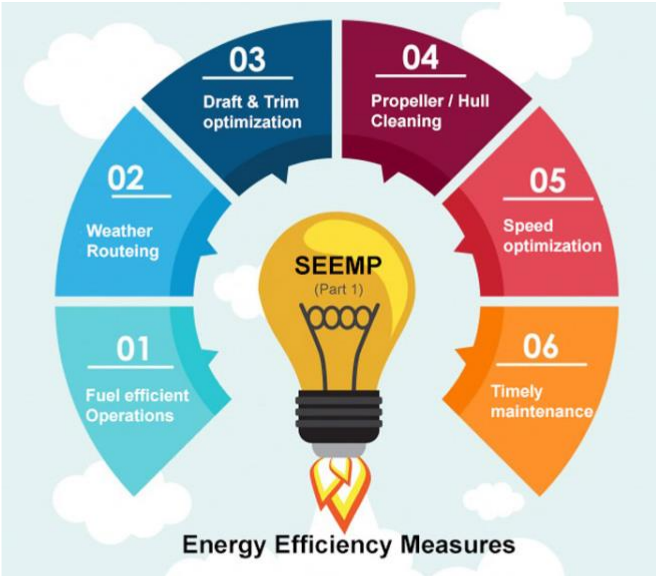


Figure 2-1: Example of Energy Efficiency Measures that can fit into the SEEMP framework.

2.3 Incentives and challenges of implementing EEMs in shipping

As shown by DNV (2015), ship operators do not choose only one but use several energy efficiency measures. According to the comprehensive shipping energy management study by DNV (2015), the selection of measures is mainly "driven by financial considerations (payback period 80%, vessel age 70%, investment 66% and ongoing costs of a measure 34%). But nearly half of the participants names 'availability of information' as a driver for the selection of measures, which indicates further improvement potential at relatively low effort." "For 29% of respondents, "tracking savings through performance management systems" is viewed as a key enabler, too".

The adaptation of EEMs is dependent on technological factors. As Armstrong & Banks write: "Whilst various technological and operation improvements are known and available, with many being demonstrated to be cost effective and with savings reported in the industry, their take up in the world fleet remains low" (Armstrong & Banks 2015). Technical reports such as the *Energy management study* by DNV (2015), the *Just in Time Arrival Guide* by IMO (2020), and the *Zero Carbon*

Outlook by ABS (2022) identify social factors that limit shipping companies' work towards improved energy efficiency.

Through a poll distributed to actors within the shipping industry, DNV identified; i) "lack of financial resources", ii) lack of expertise among staff, iii) resistance to change by crew/office staff as the most important, and iv) lack of time for implementation, as the most important blocking mechanisms towards implementing energy saving measures. The complete list from DNV (2015) is presented in Figure 2-3.

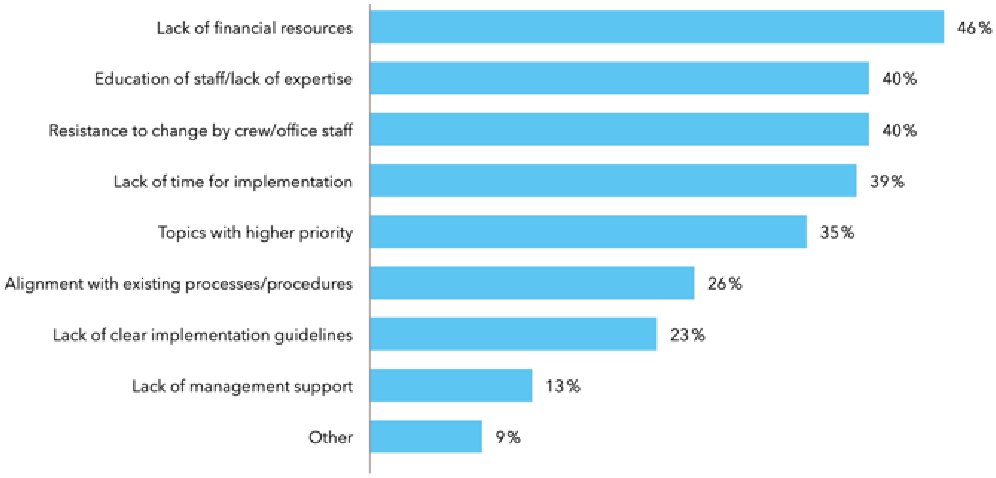


Figure 2-2: Challenges for implementing energy efficiency measures identified in DNV (2015).

The socio-technical research on maritime energy efficiency focuses less on such individual factors but demonstrates how the implementation of energy efficiency measures is situated in the broader socio-technical system of shipping. This research demonstrates through empirical examples how various actors have different sometimes mutually exclusive goals (Armstrongs & Banks 2015). Various "cultures, and concerns, grounded in their different roles and responsibilities" (Viktorelius et al. 2022). Overlapping responsibilities or gaps in responsibility, difficulties in establishing joint goals and shared visions (Borg & von Knorring 2019). Problems in communication and cooperation between actors have also been identified as crucial barriers to energy-efficient voyage execution (Poulsen & Sornn-Friese 2015), i.e., a lack of communication and correct information made it difficult to establish the communication and trust that was necessary to facilitate energy efficiency measures.

Another blocking mechanism towards increased energy efficiency identified in previous research is that responsibilities are divided between many subsectors of the organization so that no one can be held responsible or accountable for implementing any measure (Johnson et al. 2014). The fact that some energy efficiency measures require collaborations not only within one organization (such as a shipping company) but between several organizations (for example the JIT arrivals) makes the implementation even more difficult (Johnson & Styhre 2015).

2.4 Trend of utilizing AI/ML and EEMs for IMO JIT

Given the acknowledged difficulties in improving the energy efficiency of the planning and execution of voyages, much scholarly work has been done to determine the best way to plan and operate ships. Machine learning (ML) techniques and Artificial Intelligence (AI) come with great possibilities to develop more accurate ship performance models and more reliable EEMs to reduce GHG emissions. Academics and industry actors work to devise the best ways to operate a ship using weather forecasts and ship data to predict the ship's performance during various conditions. For EEMs used for ship voyage planning and operations, a key component is a ship’s sailing speeds along voyages, and it is strongly related to the arrival time. To facilitate a ship’s JIT guidance, those operation EEMs should implement reliable models that can predict a ship’s accurate arrival time under various operational and environmental conditions. This report will focus on the impact of uncertain (arrival time) prediction models on the energy efficiency of JIT operations, especially, how the AI/ML techniques can help to improve the efficiency of those EEMs to facilitate JIT guidance.

The results of this report are based on an interdisciplinary approach, identifying potential savings and optimization of energy efficiency from both a social perspective and a technical perspective. The social obstacles to energy efficiency are identified through a literature review as well as through interviews with captains, shipping companies, and charter departments. Interviews were conducted with individual captains and charter departments in three shipping companies. This data collection is not designed to provide a full mapping of how social dimensions and organization of the shipping industry hinder/facilitate increased energy efficiency or, for that matter, estimate how much each of these factors hinders measures to increase energy efficiency. Rather the study aims at identifying relevant areas that can create bottlenecks in reducing emissions from the shipping industry. These social perspectives are used to inform the technical inquiry of this pilot study and discuss in what circumstances certain methods are suitable. The social perspective will also be used to critically discuss and contextualize the relevance of the project's technical findings.

Also, these digital tools and predictions are situated in the above-mentioned difficulties in implementing EEMs, which will be discussed in more detail in Section 7.

3 Potentials of EEMs related to IMO JIT

There is a gap in the research of the impact of vessel sailing delays and, on their arrival, ahead of schedule. It is apparent that port congestion is one of the causes of vessel delays. Official reports agree with this reason. That, however, is not the only reason for vessel delays as rough weather, labor shortages and customs’ delays also contribute to vessel delay. The consequences of vessel delays can be categorized into several levels, from an increase in operational costs, to further delays in the supply chain. The impact of port and canal congestion or long waiting time at port can be categorized as the following items,

- Extra costs for port services.
- Charterers need to pay extra (demurrage).
- Shipping companies may lose new contracts due to ship unavailability.
- Customers experience an increase in the costs of goods and services.
- Escalating environmental impact.
- Hull fouling
- Extra CO_2 emissions

However, from shipping energy efficiency perspectives, longer waiting times at ports mean larger potential of fuel saving by implementing different EEMs related to IMO Just-In-Time (JIT) arrival strategies. Before presenting the statistics of ship waiting times at ports, several terminologies will be given below for the completeness of the report.

3.1 Terminologies to describe Port and Canal Congestion

Vessels are handled in a First Come First Served (FCFS) queue. If a ship arrives too late or too early, it must wait in queue until a new place is available in the quay for berthing.

- **Port Congestion:** A situation where several ships are waiting outside a port unable to load/unload freight. Associated with waiting vessels. Causes:
  - Mismatch between port capacity and port demand.
  - Low infrastructure.
  - Miscellaneous.
- A **quay** is a place by the water where boats stop to load and unload cargo. The time a ship stays at the quay can be denoted as: **Processing time, Handling time, Duration of operation.**

Some other terms and definitions related to port operations:

- **Berth Time**: How long a ship stays docked.
- **Laytime**: The set time for a ship to load and unload without extra costs.
- **Demurrage**: Extra time a ship stays docked beyond the set time, usually with extra charges.
- **Detention**: Extra time a ship stays in the port area, but not necessarily docked.
- **Turnaround Time**: Total time from when a ship enters to when it leaves the port.
- **Call Size, Workload**: The number/volume of cargo the port must handle.

Definitions associated with waiting vessels:

- **Anchored, Anchoring, Moored, Waiting, Non-Sailing** (Franzkeit, et al. 2020)

- **Offshore waiting** (Akakura 2023)
- **Vessels at anchor**

These are associated with speeds (in general) <1 knots, other thresholds can be found in the literature. Because of quay restrictions, a ship waiting for berthing waits in the anchoring area outside of the port. The **Waiting Time** is defined as the difference between the time of arrival and the time the ship gets to dock (enters the quay area):

$$t_{wait} = t_{arrival} - t_{docking}$$

Some other definitions: **Waiting times** are defined as the period between "Arrival to port limits", that is, when the ship enters the anchorage zone.

An alternative definition of waiting time is the time the ship spends in the anchoring area moving at a very low speed:

$$t_{wait} = t_{anchoring} \mid V_{ship} \ll 1\ knots\ \&\ r_{anchoring} \leq small$$

In the case of canal congestion ships wait in queue until they can cross the channel. Canals have physical limitations on how many ships can transit. An excessive influx produces a bottleneck effect. Canal congestion was brought to public attention after the Ever Given incident in 2021.

3.2 Statistics on waiting/anchor time at ports from official reports

Ports authorities rarely share data about how many ships are anchored or their waiting times for loading/unloading. Therefore, most information on this topic is usually sourced from official reports and academic studies. In the following subsections, the statics of waiting/anchor time at different ports are summarized based on official reports from the United Nations Conference on Trade and Development (UNCTAD), International Monetary Fund (IMF) and World Bank. The statistics are expected to give us some qualitative overview of how much the IMO JIT can help to reduce shipping emissions. Some assumed scenarios by implementing voyage optimization for JIT are presented in Section 6 to provide quantitative estimations of emission reductions for JIT related EEMs.

3.2.1 Statistics from UNCTAD reports

The United Nations Conference on Trade and Development (UNCTAD) annual "Review of Maritime Transport" (RMT) sets out port performance indicators to gauge port efficiency. The concepts of Port Congestion and Ship Waiting times gained prominence after the 2016 UNCTAD report. Their importance was further highlighted during the COVID-19 pandemic, which brought these issues to the forefront in the annual reports. The waiting times at ports of US and China as two examples are extracted and presented in Table 1. The 2016 RMT report indicated that the global average ship waiting time at ports was 4.53 days in 2014 and 3.46 days in 2015. This report did not differentiate between loading and discharging or by cargo type. From 2017 to 2020, the RMT reports did not offer this data. However, the 2022 RMT report introduced a breakdown by cargo type. This report revealed that, between 2018 and 2021, the average waiting time in US ports was 101 hours for loading and 49 hours for discharging dry bulk carriers. For tankers, the times were 54 hours for loading and 69 hours for discharging. The 2023 RMT report, which analyzed data from January to May 2022, showed a slight improvement for US ports. Dry bulk carriers had waiting times of 88 hours for loading and 30 hours for discharging. Tankers waited 39.3 hours for loading and 30.7 hours for discharging.

Table 1: US and China Average Waiting time of dry-bulk and tankers at ports (UNCTAD)

Report Year	Analysis Period	Cargo Type	Waiting time to load (hours)		Waiting time to discharge (hours)	
			US	China	US	China
2021	2018 - 2021	Dry Bulk	101	66	49	56
		Tankers	54	45	69	77
2022	Jan-May 2022	Dry Bulk	88	78.8	30	38.9
		Tankers	39.3	39.7	30.7	54.4
2023	Jan-Apr 2023	Dry Bulk	91.1	61.5	41.6	39
		Tankers	49.1	37.9	56.2	56.3

In contrast, the 2022 RMT report showed that in Chinese ports, dry bulk carriers waited 66 hours to load and 56 hours to discharge. Tankers had waiting times of 45 hours for loading and 77 hours for discharging. The 2023 RMT report indicated that these times changed to 78.8 hours and 38.9 hours for loading and discharging dry bulk carriers, respectively, and 39.7 hours for loading and 54.4 hours for discharging tankers. The reported waiting times include transit times and the time in anchorage, and it could be used to optimize the speed of vessels following the IMO JIT proposal. Furthermore, the 2023 RMT report provided a monthly breakdown of waiting times from 2016 to 2023. This data highlighted a notable disparity between developing and developed countries. A rising trend in waiting times was observed over this period.

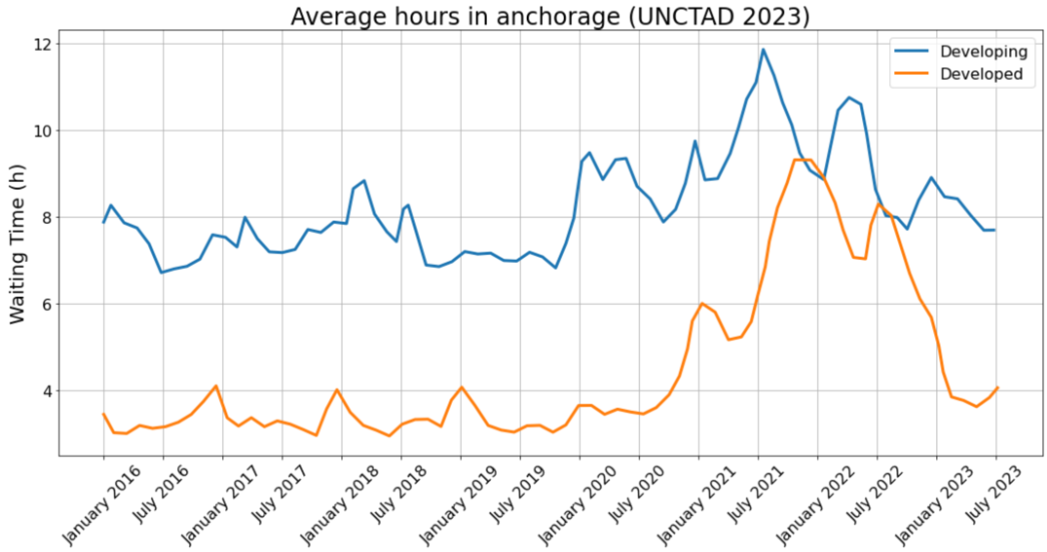


Figure 3-1. Average waiting time ships between 2016 and 2023 clustered by country development status. Source: Clarksons Research retrieved from UNCTAD.

The average waiting time in anchorage is presented in Figure 3-1 by country development status. Developed countries presented lower waiting times in ports, most likely due to better infrastructure and better handling capabilities compared to developing countries. Despite that it can be noted that under high congestion the waiting times can be similar in both cases. The congestion seems to return to normal after the second half of 2022 with respect to the pre-pandemic levels.

3.2.2 Statistics from International Monetary Fund (IMF) reports

Before the onset of the COVID-19 pandemic, a container ship typically took between 6 to 6.5 days to complete its journey in the North Atlantic trades. However, post-pandemic conditions have seen a surge in these travel times by about 25%, pushing the average duration to between 8 and 9 days. The report by Komaromi, Cerdeiro, and Liu (2022) highlights a significant increase in port delays, with average delay deviations, respect to pre-pandemic conditions, exceeding 1.5 days by December 2021. This assessment was made possible using AIS data, which tracks whether ships are anchored or moored in proximity to ports.

It is important to note that a significant portion of this increase (66%), is due to ships being anchored for extended periods as they await permission to enter ports. Figure 3-2 shows the deviations in waiting times for ships compared to a pre-pandemic baseline. Like the statistics in Figure 3-1, the data shows a growing trend in waiting times during the year 2021. The reasons of said sudden increase in waiting times was the stricter regulations in place to slow the spread of the pandemic.

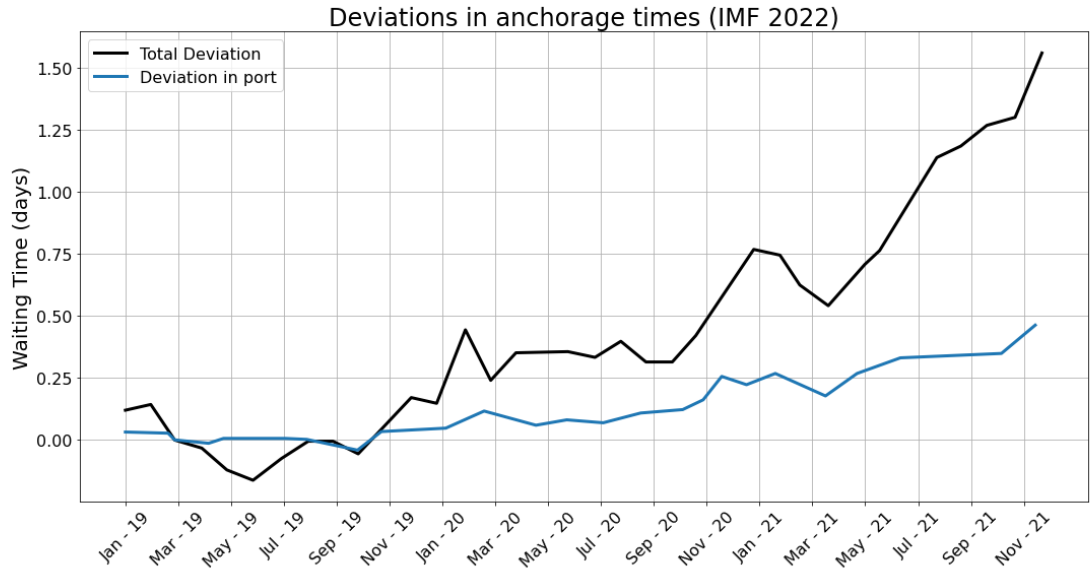


Figure 3-2: Deviation in anchorage times respect to pre-pandemic times. (Source: Komaromi, Cerdeiro and Liu 2022. IMF Reports)

3.2.3 Statistics from World Bank reports

The World Bank releases an annual report titled "The Container Port Performance Index" (abbreviated as CPPI). This report is dedicated to evaluating the efficiency of ports within the broader supply chain. It's important to note that inefficiencies or delays at ports can have a ripple effect, leading to subsequent delays for scheduled liner ships. To gauge port efficiency, the CPPI analyzed AIS data. This data pinpoints the locations of ships in proximity to ports staying in or close to anchorage areas. The report further delves into the relative time consumption at ports, breaking it down based on different ship sizes.

Their reports for 2021 and 2021 show that, in average, only 60% of the time a ship spend in port is used for port operations and 30% of the time is consumed from port arrival to anchoring until berth allocation (arrival time) as can be observed in Figure 3-3 and Figure 3-4. The report suggests that the average port call worldwide in 2021 was 36.3 hours and it increased to 36.8 hours in 2022. The average arrival time is presented in Figure 3-5. The data is taken from the moment the ship enters the anchoring area until berth. It shows a growing trend in the reported period.

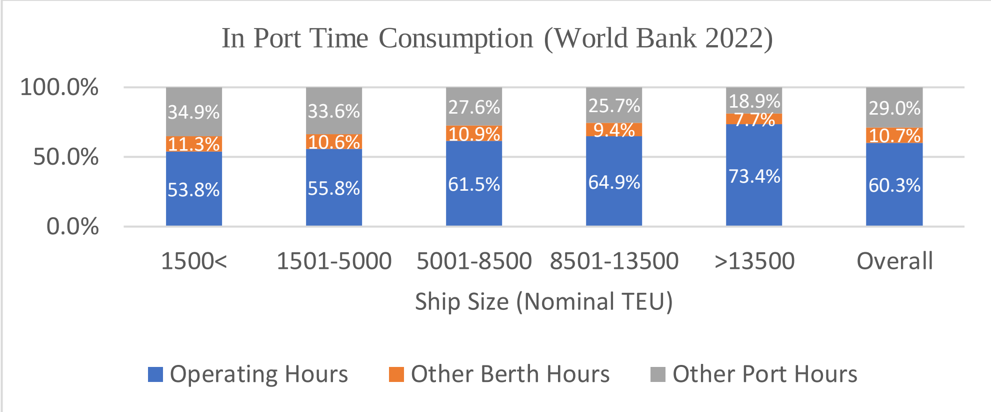


Figure 3-3: Port Time Consumption in 2021 (Source: Word Bank 2021)

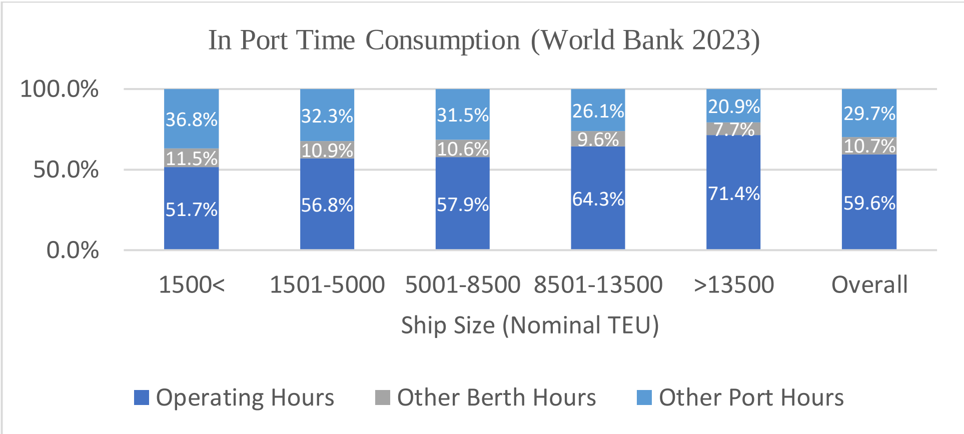


Figure 3-4: Port Time Consumption in 2022 (Source: Word Bank 2022)

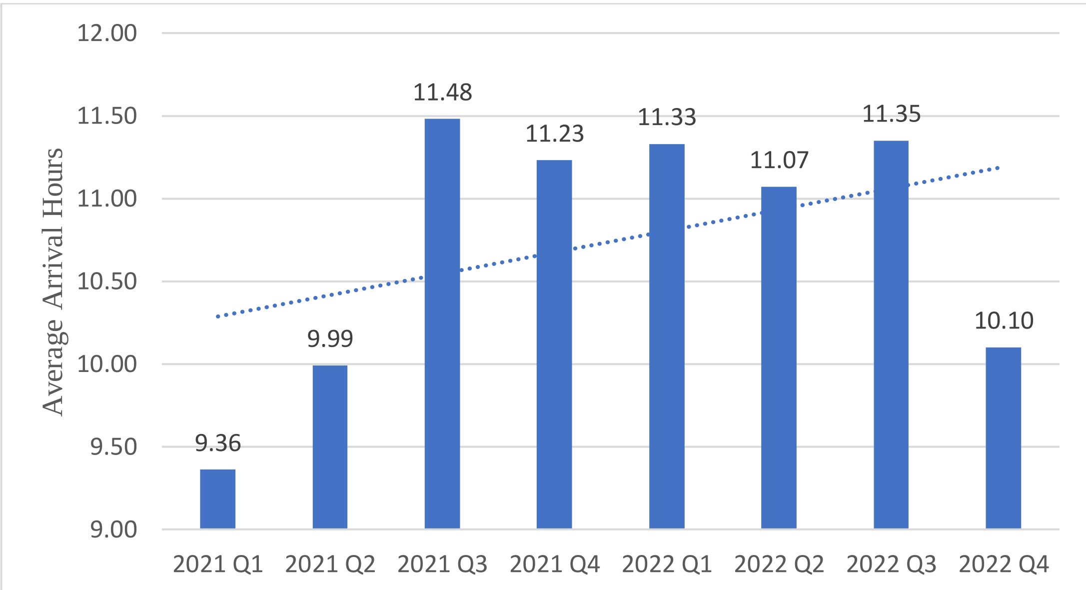


Figure 3-5: Average arrival time during 2021 and 2022 (Source: Word Bank 2022)

3.2.4 Report for the Port of Gothenburg

The 2021 BRAVE ECO report (Benchmark for Reduction of Anchoring Vessels' Emissions – Enabling Change of Operation) studies the significance of the "Just in Time" (JIT) shipping. The JIT shipping method emphasizes the timely arrival of vessels, ensuring that they dock only when they can be immediately serviced. This minimizes idle time at ports, which in turn reduces unnecessary emissions from ships waiting at anchor. In BRAVE ECO the Port of Gothenburg is brought as a case study and statistics during the years 2010 and the period 2014 to 2020 is presented. Conversely to the previously shown institutional reports, the presented data does not account for individual waiting times but for the total waiting time across all vessels. The total waiting time of all ships and minimum waiting time per ship at the Port of Gothenburg port are presented in Figure 3-6 and Figure 3-7, respectively.

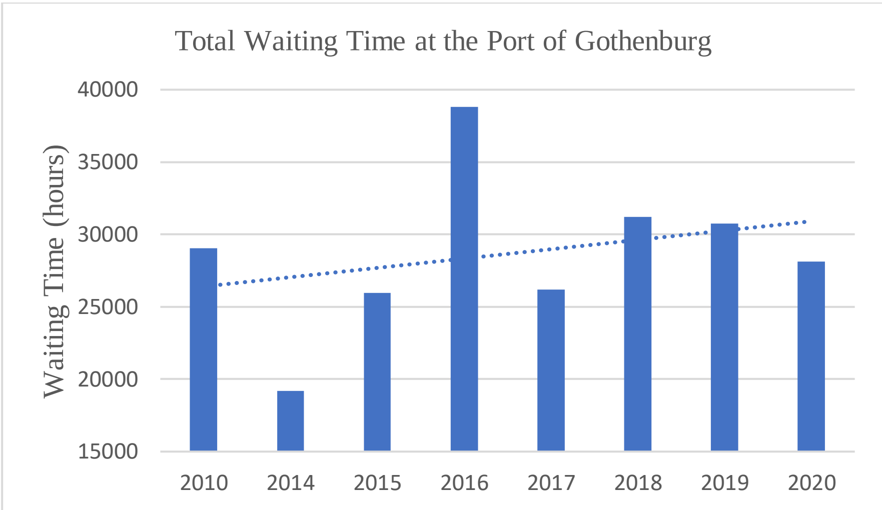


Figure 3-6: Total Waiting time at Port of Gothenburg between 2010 and 2020 (BRAVE ECO 2021).

Although the report does not include the number of ships, a quick estimation can be made of the severity of the waiting. According to the Port of Gothenburg official report, the port handles approximately 110 ship calls a week. It is equivalent to 5,720 ships/year. A quick estimation of the average waiting at port for an individual ship is given by:

$$t_{ship} = \frac{t_{year}}{\#ships_{year}}$$

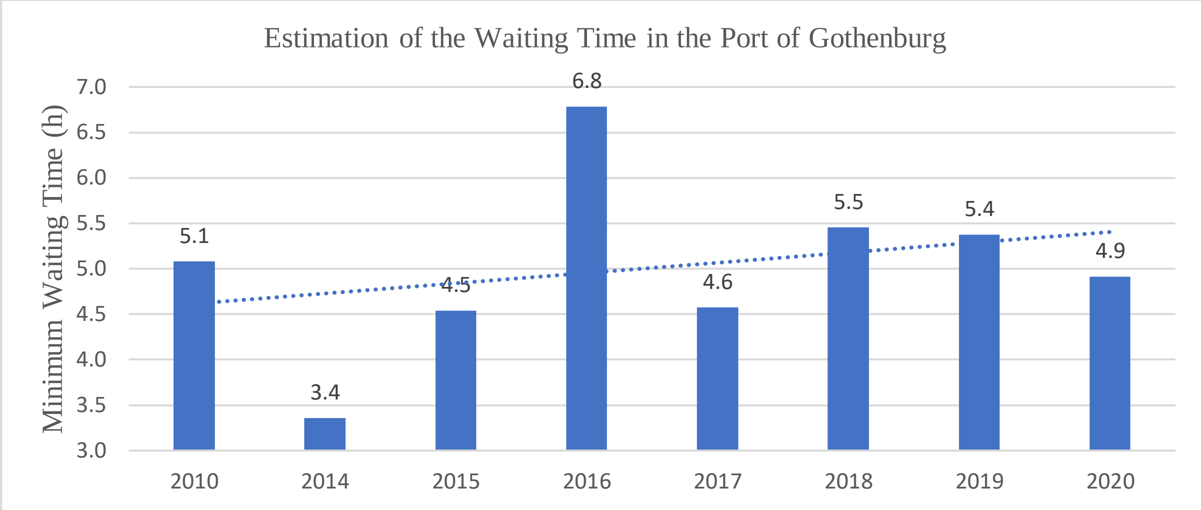


Figure 3-7. Minimum Waiting time per ship at Port of Gothenburg 2010-2020. (BRAVE ECO 2021).

Table 2. Lighthouse report on port congestion of Gothenburg during 2019. (BRAVE ECO 2021).

Ship Type	**Time [h]**		**Number of times at anchor**		**Times per anchor occasion**	
	Port Call	In transfer	Port Call	In transfer	Port Call	In transfer
Product Tanker	24455	19124	766	879	32	22
Crude Oil Ship	3004		42		72	
Bunkering Ship	13317	5434	1384	915	10	6
Container Ship	1201	347	56	44	21	8
Vehicle Carrier	288	93	4	3	72	31
General Cargo	2334	5646	245	853	10	7
Other	174	807	15	161	12	5
Bulk	77	4318	12	465	6	9
Total (hours)	**44850**	**35770**	**2524**	**3320**	**18**	**11**

In addition, the report provides data on the total time various ship categories spent anchored outside the Port of Gothenburg in 2019. The data was derived from AIS records. The results are listed in Table 2. The provided information gives insight into the cumulative time ships spent in anchorage during port calls in 2019 at the Port of Gothenburg. Specifically, ships spent a total of 35,770 hours anchored. The 35,770 hours represent the combined total of all ships' anchorage times. This could mean a few ships spent a long time at anchor, or many ships spent shorter periods anchored. Without the number of ships or individual anchorage durations, we can't determine the average time a ship spends at anchor. However, high cumulative anchorage times indicate inefficiencies or congestion at the port, leading to longer wait times for ships.

3.3 Statistics on waiting/anchor time from research papers

Research by **Akakura (2023)** highlights the increased offshore waiting times at global container terminals due to the COVID-19 pandemic's impact on port services. Utilizing historical AIS data, the study reveals that many ships experienced extended delays to access port services. The study also shows that some ships would rather opt to wait outside designated anchorage areas or choose to drift instead of waiting in the designated anchorage area. Despite the evident challenges, port authorities rarely disclose related statistics. The study emphasizes the need for improved port efficiency and scheduling to mitigate these delays and their broader implications on trade and the environment. The result is presented in Figure 3-8.

The research presents discrepancies with respect to the official reports regarding the waiting times. Nonetheless, the trend presented in the figure corresponds to the trends presented by UNCTAD and the IMF (Figure 3-1 and Figure 3-2) but differs in magnitude. The data provided by Akakura (2023) suggests that the phenomenon is still relevant in 2023.

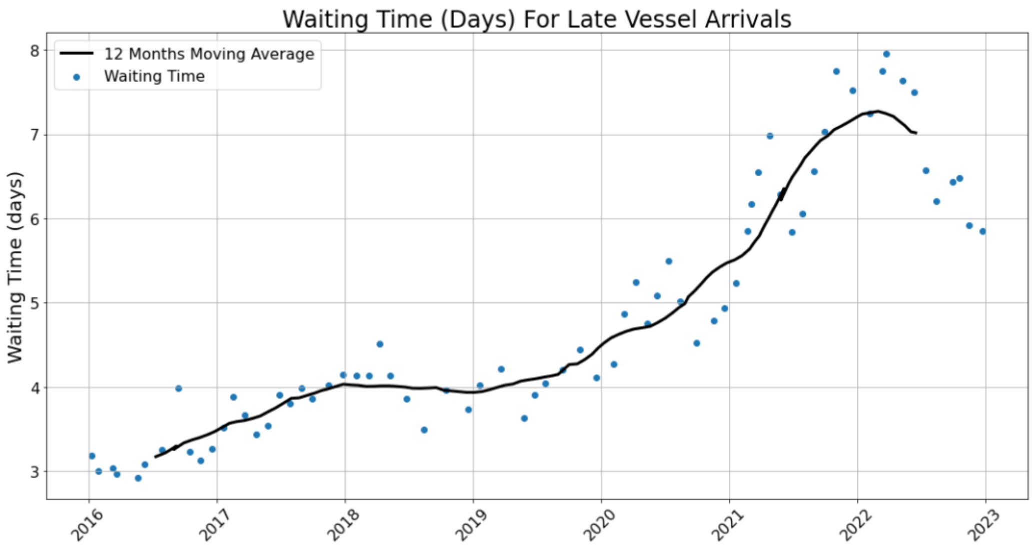


Figure 3-8: Average delays to planned arrival time of destination ports (Akakura 2023).

Other research activities are reported in **Vukić and Lai (2022)**, which provides an in-depth examination of the San Pedro Bay ports in the US, specifically the Port of Los Angeles (LA) and the Port of Long Beach (LB). The results are extracted and presented in Figure 3-9. Together, these ports account for 40% of the US's seaborne container imports. However, increased demand for port services has led to significant congestion, with ship queues reaching 100 and wait times extending up to 23 days. By January 2022, a record 105 ships were anchored. Prolonged anchoring not only disrupts the supply chain but also results in increased fuel consumption and CO_2 emissions. Although the data reflects the case study of San Pedro Bay during the pandemic it is still relevant to bring into consideration as stricter environmental regulations, accidents, adverse weather conditions, and other unforeseen events can exacerbate port congestion.

Figure 3-9. Number of ships waiting at anchor at Port of Los Angeles (Vukić and Lai 2022).

From the research reported by Franzkeit et al. (2020), the Automatic Identification System (AIS) is used to understand and track vessel movements. Specifically, it examines the waiting times for vessels near the port of Rotterdam. The research brings different definitions of waiting times detection using AIS data. It specifies that some vessels may not opt for anchoring but instead on steaming at very slow speeds (<3 knots) around the anchoring area. Their research suggests that dry cargo has significantly shorter waiting times compared to tankers. Figure 3-10 shows the average waiting time in Rotterdam port between 2016 and 2018. It is evident that the waiting times during October-December 2016 and June-August 2017 show a significant increase with respect to the rest of the study period showing signs of port congestion. The increase may be due to the increased demand for port services during the period.

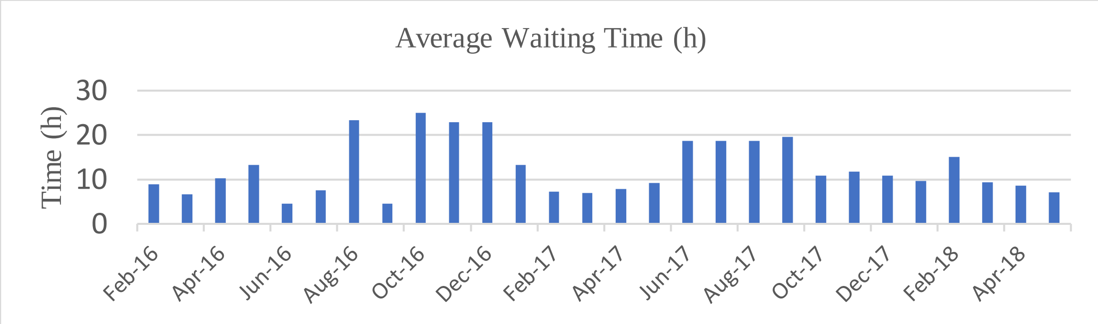


Figure 3-10. Average Waiting time at Port of Rotterdam (Franzkeit et al. 2020).

3.4 Conclusion remarks and potential EEMs for JIT operation.

Port congestion poses significant challenges, but port authorities often lack transparency regarding relevant statistics. Access to such data is crucial for enhancing port operations and developing strategies like "Just in Time" (JIT) shipping, as suggested by the IMO, to reduce idle times at ports. One notable issue is the consistent increase in ship waiting times at ports, with a particular spike post-COVID-19. This problem affects both developed and developing countries and remains relevant as we return to normalcy. Prolonged waiting times have a ripple effect throughout the supply chain, disrupting downstream activities and potentially causing shortages and increased costs for consumers. Furthermore, extended waiting times contribute to unnecessary emissions, stemming from ships anchoring or drifting while waiting and the missed emission reduction opportunities through speed optimization. Discrepancies between official reports from financial and research institutions like UNCTAD, the World Bank, and the IMF, and independent research in journal articles using AIS data highlight a knowledge gap that requires closure. In consequence, research in this area should include the analysis of historical AIS data near ports to validate congestion numbers and assess the actual economic and environmental impacts of ships waiting offshore.

Several shipping EEMs (energy efficiency measures) can be used to implement IMO Just-In-Time strategy to allow for accurate expected of arrival. All of them require reliable ship energy performance models to accurately estimate a ship's speed in terms of setting engine power under different ocean environmental conditions. Those EEMs are briefly described as follows:

Speed optimization: Speed optimization plays a key role in guaranteeing an accurate Estimated Time of Arrival (ETA) for voyages, considering the dynamics of weather forecasting, fuel efficiency, and navigational strategies. By adjusting a ship's speed in response to changing weather conditions, vessels can either avoid areas with unfavored weather, such as storms or rough seas, which could slow the ship down and even cause danger and damage or take advantage of favorable conditions like the calm sea and tailwind. This approach helps in maintaining a steady pace toward the destination, reducing the likelihood of unexpected delays.

ETA performance monitoring: ETA performance monitoring indicates tracking and evaluating the performance of the ship to reach the destination. This usually involves the following aspects, such as real-time monitoring of the operation, data analysis, ETA predictions, and improvements in adhering to the required ETA. Real-time data from onboard monitoring systems is crucial for updating route plans and ETA predictions. The integration of such data into voyage optimization/speed optimization systems allows for more responsive and informed decision-making. ETA performance monitoring is crucial in the shipping industry, since it can impact operational costs, operation management, and overall shipping efficiency. By closely monitoring and analyzing ETA performance, shipping companies can identify the potential for improvement, enhance their shipping operation's reliability, and make more informed and adaptive operational decisions.

Voyage optimization: Voyage optimization is the key factor in improving and ensuring accurate ETA for voyages. It involves comprehensive approaches to planning and executing voyages, considering various factors such as weather conditions, sea states, fuel efficiency, and vessel performance. The route optimization can find and provide the ship with optimized routes with respect to different objectives, such as operation safety, efficiency, and accurate ETA. Specifically, when it integrates with other components, for example, weather forecast, real-time monitoring, and predictive analytics, the voyage optimization could constantly update the plan, adjust, and respond to the dynamic changes to ensure the shipping is on schedule, and the operation is on track with minimum cost.

Trim/engine/CPP optimization: Trim, engine, and Controllable Pitch Propeller (CPP) optimization are crucial concepts in maritime navigation and can significantly contribute to achieving an accurate Estimated Time of Arrival (ETA). Trim optimization involves adjusting the distribution of cargo and ballast on a vessel, to achieve optimal balance and buoyancy. It can minimize resistance through water, therefore reducing the total fuel consumption. This optimal trim position depends on the load of the vessel, water depth, and sea states. By reducing the resistance and optimizing the hydrodynamic efficiency, ships can maintain the required speeds or achieve the same speed using less fuel, directly influencing the accuracy of ETA.

Engine optimization is about balancing and arranging the ship's main and auxiliary engines in the most efficient way. This involves tuning engine settings to adapt to the current conditions, such as sea state, load, and vessel speed. Proper engine arrangement can ensure that the vessel operates within the optimal power range, reducing fuel consumption and the wear and tear of the engine. This optimization is crucial since it directly correlates with the ability to maintain or adjust speed, following the voyage/speed optimization, to meet the scheduled ETA.

CPP optimization refers to adjusting the pitch of the propeller blades in a controllable pitch propeller system. Unlike fixed-pitch propellers, CPPs control the angle of the blade during operation, providing greater efficiency for the ship's propulsion. This flexibility is beneficial in varying sea conditions or when maneuvering in ports. By adjusting the pitch, the ship can maintain optimal propulsion efficiency, adhering to the schedule and achieving accurate ETA. Together, these optimizations form an integrated approach to efficient maritime navigation. They ensure the vessel not only travels at optimal speeds and follows the defined routes, but also reduces fuel and operational costs. Moreover, they ensure that ships can adhere to their scheduled ETAs, even when confronting changing sea conditions and operational demands.

4 Challenges to achieve JIT operations

To help ships have an accurate JIT operation, the models used to predict the JIT usually include various uncertainties. Below we will list some examples to show the difference/uncertainty between today's models and real measurements, as well as possibilities for improvement.

4.1 Weather forecasts

In maritime applications, voyage planning heavily relies on weather forecasts, therefore the accuracy of the weather forecast has a great impact on the planning result. The safety and efficiency of the voyage depend on the capability of the weather model in prediction and speed to respond to dynamic changes. However, weather forecasting is a comprehensive process and includes lots of uncertainty, especially for long-term predictions. Its uncertainty is due to the limitations of weather prediction models, the varying spatial and temporal resolution of weather data, and the unpredictable and dynamic changing nature of the environment. These uncertainties in weather forecasts consequently impact the ETA predictions.

Concerning safety and efficiency, ships need to adjust voyages according to the updated weather forecasts. This continuous adjustment makes it difficult to predict ETAs accurately. Furthermore, the complexity can also increase with the length of the voyage, since longer routes can have a higher probability of encountering unexpected weather changes. Weather changes can lead to deviations from the pre-planned voyages, speed adjustments, and in extreme cases, re-plan to avoid harsh weather. All these situations can significantly change arrival times. Traditional route optimization methods, especially early-stage methods, focused on achieving the shortest time or distance sailing, and usually neglecting the uncertainties in weather data. Currently, many state-of-the-art approaches (Yuan et al, 2022; Vettor et al. 2020) address these uncertainties by employing advanced weather models with different strategies.

The forecast model indicates the weather models that can provide short-term or medium-term predictions, to assist the operation and planning. And generally, it can be developed by numerical approaches or using AI/machine learning algorithms. The hindcast approach is a validation and test method for the forecast models, that entails running the weather model with previously observed data in a past time, to test the outcome and the accuracy of the forecast weather models.

Numerical weather models being used widely now, for example, are those provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), and the National Oceanic and Atmospheric Administration (NOAA). They use equations to simulate the atmospheric processes and predict future changes. They are deterministic approaches assisted with ensemble techniques, and ensemble forecasting enables multiple models to run with different initial conditions, therefore providing a wide range of possible results, to compensate for the uncertainties. Thus, these models have high requirements on prior knowledge of the related physical processes with great complexity. They can predict short-term changes with high accuracy, but as time increases, the deviation will grow significantly. Besides, small differences in initial conditions can lead to significant changes in results for long-term prediction.

AI and machine learning technologies can also be employed for weather predictions. They analyze the observation data to identify and establish the relationship between key factors, and generally can achieve great accuracy in interpolation when the resolution of data is not high enough. Since they are driven by the measurement datasets, AI models can potentially reduce uncertainties by learning from historical and real-time dataset and keep updating the model to provide more accurate predictions, responding to the dynamic change in the external environment. The limitation therefore lies in the data quality and quantity, in order to acquire well-trained models.

In conclusion, the uncertainty in weather forecasting shows a great challenge for voyage planning, especially to achieve accurate ETA predictions. The integration of probabilistic and ensemble forecasting models, as well as advanced AI/ML models with real-time data, into voyage optimization methods can provide a significant advancement in addressing the challenge. However, the unpredictability of weather and the complex considerations including various factors, such as safety, fuel efficiency, and operational constraints, continue to make accurate ETA predictions a challenging endeavor.

4.2 Ship performance models

Fuel consumption in a seaway is dependent on many parameters, such as marine engine operating parameters, propeller efficiency, and ship resistance (Carlton, 2012). Ship propulsion power is generally connected to the sailing speed and the encountered sea environments. The relationship between ship power/fuel consumption and ship speed is illustrated in Figure 4-1.

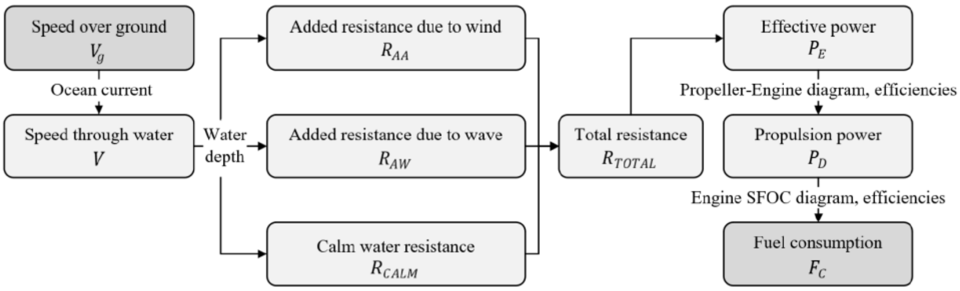


Figure 4-1: Typical workflow for the conventional estimation of the speed to propulsion power/fuel consumption of a ship.

In the workflow, the first step is acquiring ship resistance at different sailing speeds. The engine configuration, propeller efficiencies and fuel-related factors of a ship will be used to compute the propulsion power and fuel consumption for sailing under different operational and environmental conditions. Various methods have been developed for ship performance modeling, mainly relying on a set of ship parameters. These methods can be categorized into empirical or semi-empirical formulations, computational fluid dynamics (CFD), and model tests (Aertssen, 1966; Journee, 1976; Faltinsen et al., 1980; Townsin and Kwon, 1982; Guang, 1987; Kwon, 2008; Prpic-Orsic and Faltinsen, 2012; Chuang and Steen, 2012, 2013; Kim et al., 2017). However, those traditional methods have different drawbacks. The CFD methods require high computation resources, while the model tests are typically time-consuming and expensive. Although the empirical or semi-empirical methods can provide accurate expected mean values since the parameters are (in principle) obtained by regression, they may lead to significant scattering among different ship types. Especially with the installation of fuel-saving devices, e.g., wave foils, Flettner rotor, and ship retrofitting, the changes in ship resistance and related energy efficiency also cause significant differences between individual ships. Moreover, it is challenging to model the complex and massive environmental conditions randomly encountered during actual ship navigation.

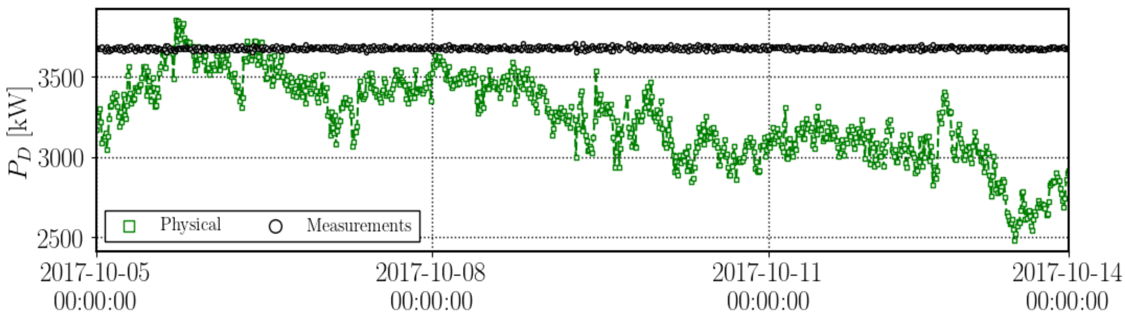


Figure 4-2: The propulsion power comparison between state-of-art physical model and full-scale measurement for one chemical tank sailing voyage.

A comparison between the predicted propulsion power of a chemical tanker based on the current ITTC guideline methods and its actual measured values is presented in Figure 4-2. The vessel adopted a constant power strategy during its voyages, and there's a significant underestimating discrepancy between the predictions of the physical performance model and the actual measurements. The uncertainties associated with traditional physical models are also increasingly being reported within the maritime industry. Dalheim and Steen (2020) evaluated one year of onboard monitoring data and reported that the added resistance from full-scale measurements was significantly larger than the conventional frequency-domain CFD calculations. Vitali et al. (2020) analyzed the speed loss of container ships integrated with weather data and found some discrepancies compared with existing empirical methods. And a significant difference between the linear superposition principal calculation and the ship's full-scale measurements has been investigated by Lang and Mao (2020, 2021).

4.3 Coupling of hull-propulsion-engine

Specific Fuel Oil Consumption (SFOC) is a critical metric in the maritime industry, used to represent the efficiency of a marine engine. It represents the amount of fuel consumed by the engine relative to its power output over a certain period. Essentially, it measures how much fuel is needed to produce a specific amount of power, therefore it is a key indicator of marine engine efficiency. Lower SFOC indicates a more fuel-efficient engine that generates more power with less fuel, leading to reduced operating costs and lower emissions. Conversely, higher SFOC values indicate less efficient fuel usage, which translates to higher costs and increased emissions.

Several factors can influence an engine's SFOC, including the engine type and design, its operating conditions, and maintenance practices. For a specific marine diesel engine, its SFOC is significantly affected by the engine operation/setting parameters and its interactions with ship resistance/propulsion systems. Moreover, the actual operating conditions often differ from the ideal or test conditions under which the theoretical SFOC is determined. Factors such as load variations, sea state, hull condition (like fouling), and ambient temperature can all influence the actual engine performance.

In the voyage optimization system, a ship performance model is an essential component, since the optimization requires the evaluation of the associated sailing cost for decision-making, to suggest a feasible voyage with the optimized cost. For energy-efficient sailings, the voyage optimization system needs the ship performance model to estimate the corresponding fuel consumption of each feasible route, based on the sailing and environmental conditions. Thus, the accuracy and the robust assessment of the ship performance model would have a great influence on the voyage optimization result. For the performance model, SFOC is one of the significant elements that the estimation of fuel consumption is dependent on. If the value of SFOC fails to reflect the real value in the actual operation, the decisions provided by the voyage optimization can also lead to great deviations. It not only causes sub-optimal voyage planning concerning optimization objectives, such as consuming more fuel, but also can make the ship not capable of following the scheduled ETA, since the planned power/fuel is based on an inaccurate estimation. Moreover, when ships are sailing in a dynamic marine environment, the variation of ship resistance and propulsion efficiency can lead to continuous adjustment of marine engine settings to keep ships' pre-defined navigation patterns. The combination of dynamic sailing marine environments and engine setting variations may cause actual engine SFOC to differ significantly from the provided SFOC curve. These differences could also lead to deviations in sailings, which may continuously accumulate as the voyage proceeds.

For the hull-propulsion-engine coupling, if only to consider the single resistance or power in the voyage optimization, the result will be quite different from considering also SFOC for fuel optimization. The same might also stand if voyage optimization only uses resistance instead of power. Then the coupling between resistance and propeller, i.e., the propulsion efficiency is neglected and not considered in the voyage optimization. Especially, the comparison of voyage optimization between using power and fuel can be quite inspiring.

In this report, different ship/engine operation parameters that affect the SFOC of the marine diesel engine are evaluated and compared with conventionally used SFOC curves, based on the full-scale measurement of two types of ships with controlled pitch propellers. Especially, how the operation of CPPs affects SFOC is studied. The most relevant parameters that affect the efficiency of marine engine operations SFOC are identified and used to establish data-driven SFOC models by different machine learning techniques. The impact of more accurate SFOC machine learning models in comparison with empirical SFOC curves on a ship's fuel consumption is briefly studied by demonstrating their application to evaluate a ship's energy performance along several typical voyages. Methods and potentials for optimization of marine engine settings in terms of fuel savings are briefly discussed for further investigations.

5 Feasibility of AI/ML to implementing JIT

5.1 Data-driven VPP models

Driven by today's digital transformation in shipping, large amounts of ship operation data are collected via sensors and data acquisition systems for in-service monitoring (Dalheim and Steen, 2020). There is a trend to apply data-driven methods to significantly improve vessel prediction program (VPP) capabilities and related energy efficiency measures.

Petersen et al. (2012) compared artificial neural networks (ANNs) and Gaussian processes (GP) for a domestic ferry's fuel consumption and ship speed prediction by using a two-month dataset (254 trips). Tree-based supervised machine learning algorithms and rigid/lasso regression methods were also applied for the ferry dataset by Soner et al. (2018, 2019) and Bassam et al. (2022). Mao et al. (2016) applied a 2nd-order autoregression model to establish the relationship between ship speed and engine RPM and extracted sea environments from a container ship's one-year measurements. Gan et al. (2017) constructed a multilayer perceptron network for the long-term speed prediction of inland ships using AIS data. Brandsaeter and Vanem (2018) adapted and validated different regression models to predict a ship's speed based on the shaft thrust, draft, trim and related 6 DOFs motions. Coraddu et al. (2019) proposed a deep learning model to estimate the speed loss of two Handymax chemical/product tankers based on two-year onboard measurements, with main engine fuel consumption, auxiliary engine power, shaft power, ship draft, and MetOcean data as input features. Berthelsen and Nielsen (2021) investigated the ship speed-power relationship based on a combined econometric and naval architectural data-driven model fed with operational data from more than 50,000 noon reports. Different machine learning methods have been recently used based on simulated or full-scale measurements (Abebe et al., 2020; Milakovic et al., 2020; Tarelko and Rudzki, 2020; Moreira et al., 2021; Yuan et al., 2021; Gupta et al., 2022; Lang et al., 2022).

The predicted speed over ground of a chemical tanker based on the conventional machine learning method is presented in Figure 5-1. For the voyage illustrated in the upper figure, prior to 2018-07-04, the machine learning model's prediction deviates from the full-scale measurement by approximately one knot. For the remainder of this voyage, the predicted values closely match the actual measurements. In contrast, for the voyage depicted in the lower figure, the vessel encountered untrained sea conditions in the latter part. As the machine learning model had not been trained on such data, its predictive capability was compromised. This underscores a limitation of traditional machine learning methods: they tend to perform suboptimal and can produce unreasonable results when faced with unseen scenarios.

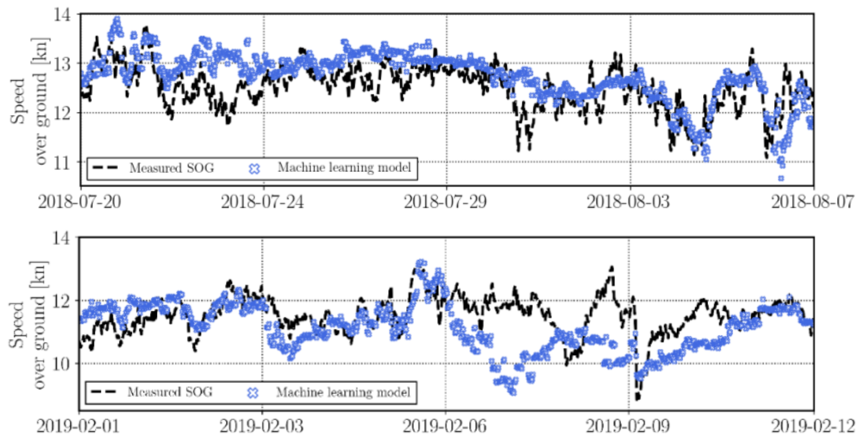


Figure 5-1: The speed over ground comparison between machine learning model prediction and full-scale measurement for two chemical tank sailing voyages.

5.2 Grey-box models

Models based on first principles or semi-empirical methods are named as white-box models (WBMs). The accuracy of WBMs depends on the assumption and simplification made in the physical modeling process. The data-driven regression/machine learning models belong to black-box models (BBMs), using experimental or full-scale sailing data. BBMs do not require prior knowledge, but they do need a large number of ship performance data. The interpretability and extrapolation of BBMs are poor, which could lead to significant wrong results for unseen scenarios. A third model category, i.e., grey-box models (GBMs), is classified by Haranen et al. (2016). GBMs are developed by combining physical principles from WBMs, and big ship data inferences from BBMs. The GBMs can be built by using much less data than BBMs, and provide higher accuracy than WBMs. Furthermore, GBMs have good model interpretability and extrapolation capability, and can avoid unreasonable results for unseen scenarios. Table 3 summarizes the advantage/disadvantage of the WBMs, BBMs, and GBMs.

Table 3: Summary advantage/disadvantage of WBMs, BBMs and GBMs.

Type	Description	Advantage	Disadvantage
WBMs	Based on prior knowledge and physical principles	Don't need historical data, and can extrapolate beyond the given data range with good interpretability	Require lots of prior knowledge, and the accuracy depends on assumptions and uncertainties implicit in the model
BBMs	Established using experimental or full-scale sailing data and is purely data-driven	Don't require prior knowledge, and more accurate than WBMs	Require large number of full-scale measurements, the model interpretability and extrapolation are poor, and may result in unseasonable results for unseen data

GBMs	Developed based on physical properties underlying WBMs, and knowledge from operational data in BBMs	Less full-scale data required than BBMs, higher accuracy than WBMs, with good model interpretability and extrapolation capability, can avoid unreasonable results for unseen data

Current research activities to build models for ship speed prediction focus on either BBMs based on ship data, or WBMs based on ship principles. There is an emergent trend towards hybrid approaches that synergistically combine physics with machine learning paradigms for more accurate ship speed estimation, harnessing the inherent interpretability of physical models. Recently, Lang et al. (2024) proposes a novel physics-informed machine learning method to build grey-box model (GBM) predicting ship speed for ocean crossing ships. In this method, the expected ship speed in calm water is first modeled by the physics-informed neural networks (PINNs) based on speed-power model tests. Then a machine learning algorithm is integrated to estimate ship speed reduction under actual weather conditions. The architecture of the approach is depicted in Figure 5-2, where the white-box model is PINNs model, and the black-box model is machine learning model.

Subsequently, the same two voyages delineated in Figure 5-1 are employed as case studies to juxtapose the conventional machine learning model with the established grey-box model as presented in Figure 5-3. It is evident that the grey-box model consistently outperforms in predictive capability across both voyages. Notably, when confronted with limited training data—as seen in the latter part of the depicted voyage in 2019 - the grey-box model, considering physical principles, yields predictions that are both plausible and closely aligned with the measured values.

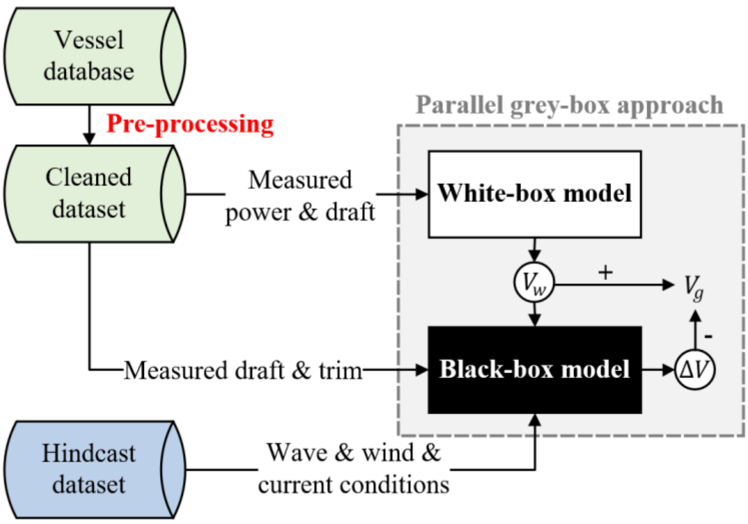


Figure 5-2: The parallel grey-box modeling procedure for ship speed prediction.

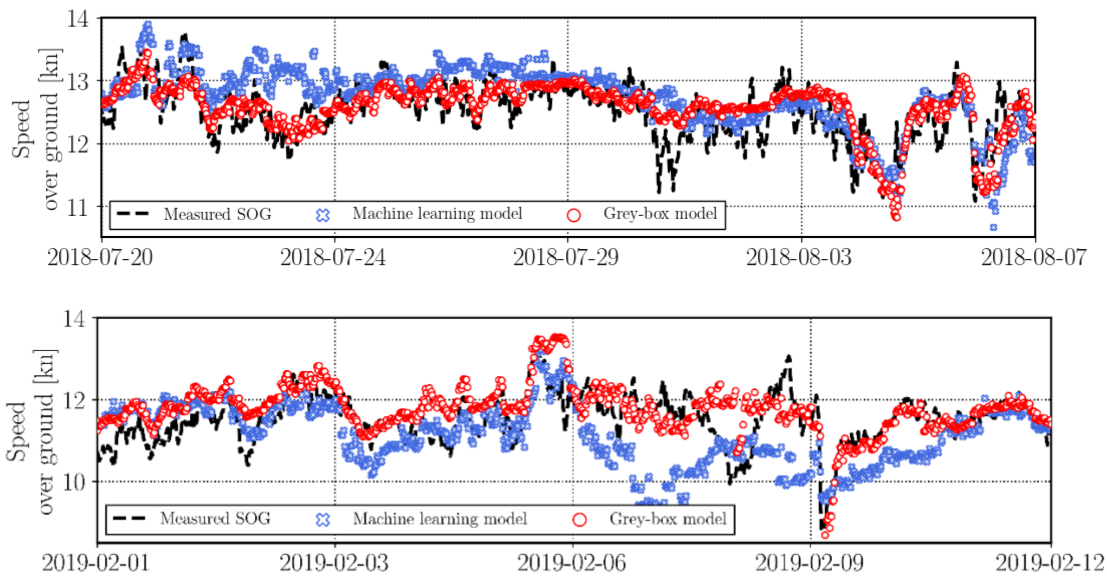


Figure 5-3: The speed over ground prediction comparison between machine learning model and grey-box model for two chemical tank sailing voyages.

5.3 JIT feasibility from today's models

In this section, a comparative analysis is conducted between traditional machine learning algorithms and the grey-box model, evaluating their efficacy in achieving Just-In-Time (JIT) operations when predictions are initiated from 72 to 12 hours ahead of arrival. Fourteen voyages of chemical tankers are employed as case studies.

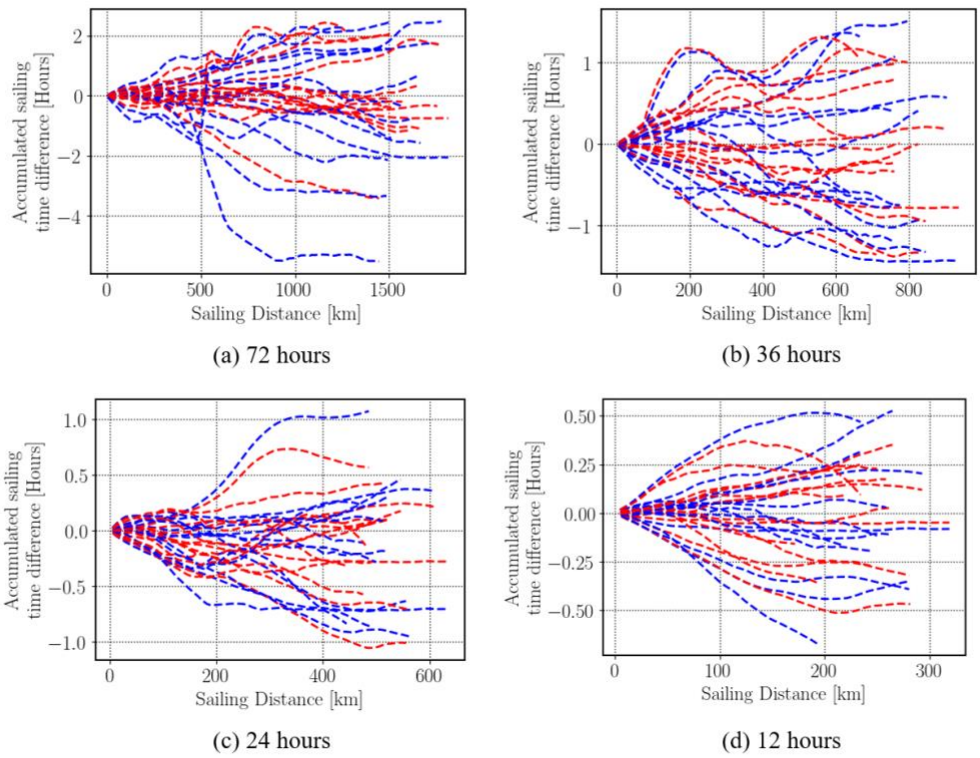


Figure 5-4: The accumulated error in sailing time of the machine learning model (in blue) and grey-box model (in red), for time ahead of arrival (a) 72 hours, (b) 36 hours, (c) 24 hours and (d) 12 hours.

In the associated Figure 5-4, the x-axis represents the varying distances traveled over time, while the y-axis delineates the cumulative navigational time errors. As inferred from the figure, for predictions initiated 72 hours ahead of a JIT requirement, the machine learning model can accrue an error close to 6 hours, whereas the grey-box model restricts its maximal error to approximately 50% of that, around 3 hours. However, for predictions 36 and 24 hours ahead, both models effectively reduce the error margin to approximately 1 hour. When forecasting the port arrival time 12 hours in advance, the discrepancy narrows further to about half an hour. Consequently, in practical navigation scenarios, employing AI/ML techniques to enhance JIT operations can offer precise estimations, particularly when predictions begin a day and a half prior to the expected port arrival.

6 JIT analysis from AI-assist voyage optimization

To demonstrate the benefits of AI techniques integrated voyage optimization for assisting the IMO JIT EEM in terms of fuel saving, this section first presents results of voyage optimizations using various ship performance modelling techniques of cost functions in the optimization process, in comparison with optimization using AI/ML built ship performance/cost models. The objective of voyage optimization is set as the minimum fuel consumption along a voyage, and meanwhile, the ETA of voyage planning is set the same as the selected case study voyages. In total, five modelling approaches to build the cost function are investigated. The results indicate the importance of accurate performance/cost models for reliable voyage optimization by using AI/ML-techniques in the modelling process. Then, the AI/ML performance models are used to study the benefits of using the AI-assist voyage optimization for the IMO JIT implementation in terms of different JIT scenarios.

6.1 Ship performance modelling for cost functions

In the voyage planning/optimization process, the cost function, which describes a ship's speed and energy consumption under various environmental conditions, is needed to search for optimal sailing waypoints with specific speeds. A typical framework to establish the ship performance model, i.e., relationship between speed and fuel/power, is illustrated in Figure 6-1.

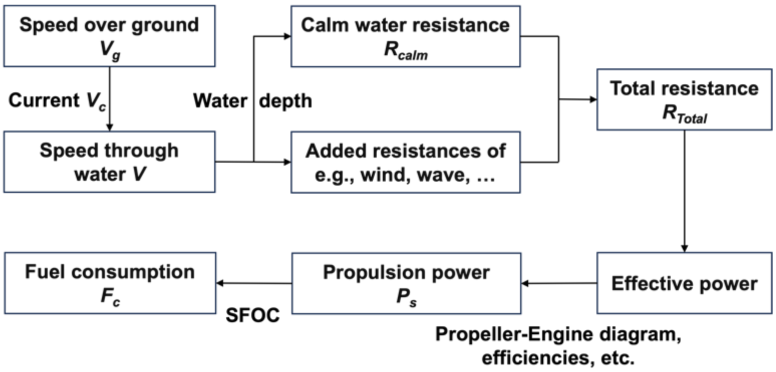


Figure 6-1. Ship energy consumption estimation process

For a given ship speed V (speed through water), a ship's total resistance of the ship R_{Total} is normally estimated by summing calm water resistance R_{Calm}, and added resistances of wind R_{Wind}, wave R_{Wave}, current R_c, and shallow water R_s, i.e.,

$$R_{Total} = R_{Calm} + R_{Wind} + R_{Wave} + R_c + R_s.$$

The thrust forces from the engine and propellers counteract the total resistance R_{Total} to push the ship forward. Therefore, the shaft power P_s that the engine needs to produce can be estimated by,

$$P_s = R_{Total} \times V/\eta$$

where η is the efficiency coefficient including the hull efficiency, propeller open water efficiency, and engine shaft efficiency. Finally, the relationship between engine power and fuel consumption is as follows:

$$\text{Fuel} = P_s \times \text{SFOC}.$$

It should be noted that for ship voyage optimization systems, different cost functions have been used to search for energy efficiency shipping routes. Due to large uncertainties/discrepancies of SFOC between measured and provided by theoretical models/manufacturers as shown in Figure 6-2, the easily accessible power consumptions are also used as cost for such a voyage optimization. The power consumption model is also the performance models that shipping companies can get from towing tank tests during their design stage. More practically, the fuel consumption along a voyage is used for the optimization purpose. In addition, different modelling techniques have been used in the shipping market to build models for the cost of power and fuel consumption. Table 4 summarizes different cost models which are used in this report to investigate the sensitivity of voyage optimization EEM on the modelling techniques of ship performance/cost functions.

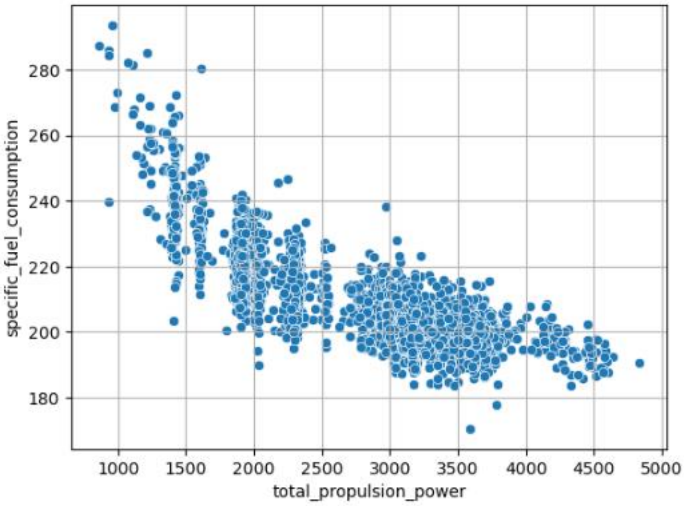


Figure 6-2. Results of voyage optimization with five different ship performance models

Table 4: Different performance models used for the cost functions

Cost models in optimization	Speed-Power	SFOC
Empirical Power	Empirical	-
ML Power	ML	-
Empirical Fuel	Empirical	Empirical
ML Power + SFOC	ML	Empirical
ML Fuel	ML	ML

6.1.1 Cost models of power consumptions

There are two models of power consumption in this study, i.e., the empirical model and machine learning data-driven model to estimate the power consumption at various operational and environmental conditions. In the "***Empirical Power***" model, all the resistance components and propulsion efficiency related parameters in Section 6.1 are estimated by empirical formulas as in Tillig et al. (2017). When a ship's performance monitoring data is available, the "**ML Power**" model could be established and used for her voyage optimization system. In this case, the relationship between speed and power is established by a Machine learning method. In this study, the XGBoost (Extreme Gradient Boosting), an advanced and efficient implementation of gradient boosting, is employed as the ML technique to develop the speed-power model, and the cost function utilizes the XGBoost model to obtain the evaluation of engine shaft power as an ML approach.

6.1.2 Cost models of fuel consumptions

Three models of fuel consumption are investigated in this study. In the "**Empirical Fuel**" model, the same empirical formulas as in the "**Empirical Power**" model are used to estimate the relationship between speed and power. To estimate the fuel consumption for a specific power, the so-called Specific Fuel Oil Consumption (SFOC) is needed. For the "**Empirical Fuel**" model, the SFOC is coming from engine manufacturers, and it follows a standardized curve as in Figure 6-3. If the speed-power relationship is modelled by the machine learning method and the SFOC is coming from the engine manufacturers, it is named as "**ML Power + SFOC**" model. Finally, if the machine learning method, i.e., XGBoost method in this study, is used to establish the direct relationship between speed and fuel consumption, this model is called the "ML Fuel" model as in Table 4. But it should be noted that in this model, the fuel only refers to the marine engine fuel consumption related to propulsion.

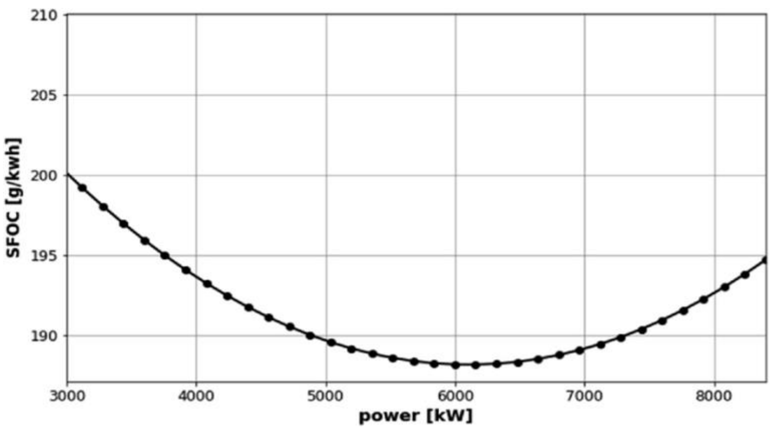


Figure 6-3. SFOC for the case study ship used in this report.

For the fuel performance model, SFOC is one of the essential. If the SFOC model fails to reflect a ship's actual operational performance, the voyage optimization may lead to great deviations. It not only causes sub-optimal voyage optimization such as consuming more fuel than expected, but also can make the ship not capable of following the scheduled ETA, since the planned power/fuel is based on an inaccurate estimation. So, in the following study we would like to investigate the impact of different cost functions on the ship voyage optimization results. The selection of those five different cost function models may be due to

1) confidence of the accuracy of various models, such as the empirical speed to power models are normally more reliable if the variation of SFOC as in Figure 6-2 is not considered; and

2) available resources to build such cost function models, such as most ships do not have performance monitoring data to build the Machine learning models.

6.2 Voyage optimization by different performance/cost models

A chemical tanker with full-scale measurement is used in this case study, to compare the voyage optimization results by different methods. A conventional weather routing system was installed on the ship to guide the voyage planning.

Combined with the ship master's experience, the actual sailing routes are supposed to be more efficient than ordinary voyage planning systems. To estimate power/fuel consumption, the cost functions also require encountered MetOcean environment inputs (wind, wave, and current), which are extracted from ECMWF ERA-5 (2019) dataset for wind and wave, and ocean current data is acquired from Copernicus 2019 server. And finally, the voyage optimization algorithm is chosen as the three-dimensional Dijkstra algorithm (3DDA) (Wang et al, 2019, 2021).

Two westbound voyage cases are used in this part for optimization validation, with optimized routes presented in

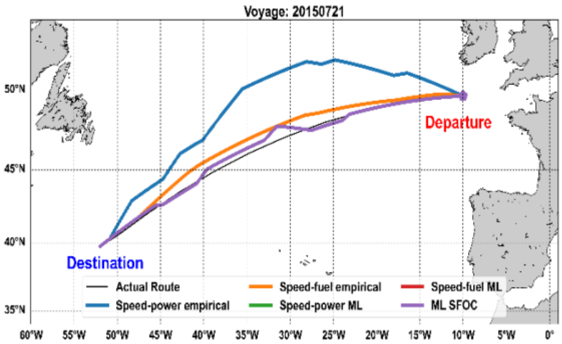


Figure 6-4. Optimized routes by different cost functions for the case study voyage 20161108 (Left), and for the case study voyage 20150721 (Right).-4. The weather changes in both two cases are not dramatic, and the highest significant wave heights is no more than 4 meters as shown in **Error! Reference source not found.**. These two cases present the normal and calm sailing status for ships operating in the North Atlantic Sea. The optimization results by changing different cost functions are listed in **Error! Reference source not found.**5, where the fuel consumption is given both in amount and the reduction percentage compared to the actual fuel cost. The actual fuel consumption is estimated by the ML ship model to provide the most accurate estimation of the actual cost.

Figure 6-4 shows that the actual routes for both cases have undergone a well-considered planning process. The routes in general do not deviate much from the shortest Great Circle route, leading to a relatively short total distance, and their encountered weather conditions are also calm. Especially for the case Voyage 20161108, the actual route adjusts its heading twice to keep sailing in very calm waves. Therefore, the actual fuel consumption for both cases is not very high. For such calm sailing cases, a fuel reduction of around 5% from voyage planning compared with the actual route can be considered significant. However, from the result shown in **Error! Reference source not found.**, the result of total fuel consumption fluctuates greatly in the amount due to the change of ship cost function models.

Table 5: Comparison of ship voyage optimization results when employing different ship performance/cost function models

Cost function models	Voyage 20161108		Voyage 20150721	
	Fuel [Ton]	Saving %	Fuel [Ton]	Saving [%]
Actual ship routes	177.9	-	178.5	-
Empirical Power	163.1	8.4	178.0	0.3
ML Power	154.6	13.1	151.4	15.2
Empirical Fuel	162.3	8.8	165.9	7.0
ML Power + SFOC	154.3	13.3	151.3	15.2
ML Fuel	161.3	9.3	161.3	9.6

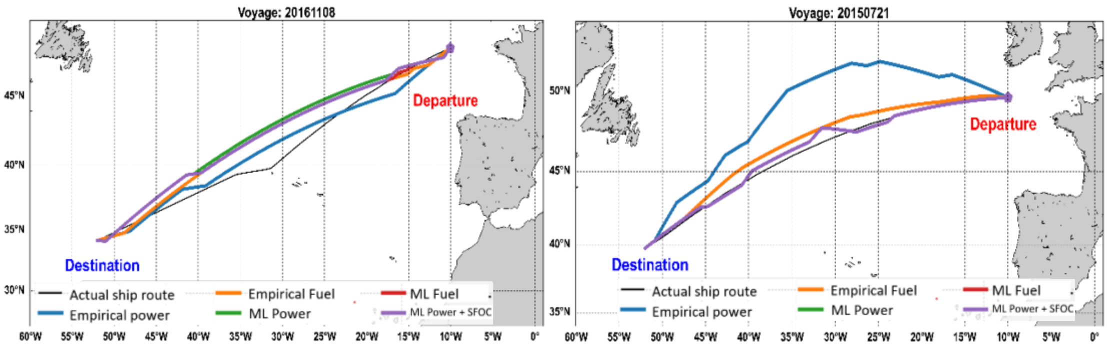


Figure 6-4. Optimized routes by different cost functions for the case study voyage 20161108 (Left), and for the case study voyage 20150721 (Right).

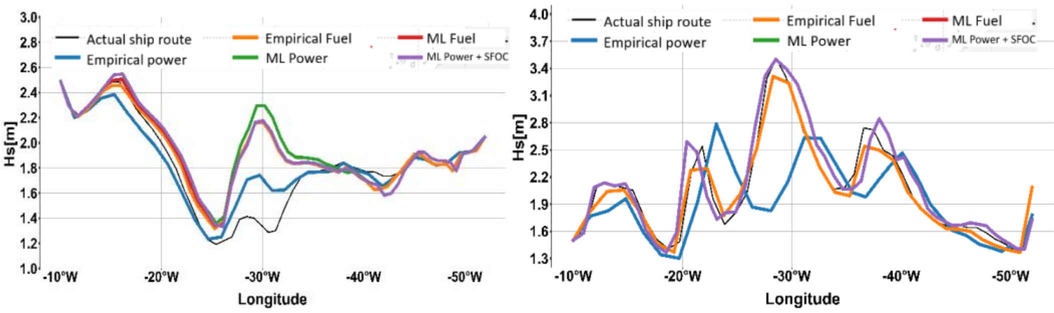


Figure 6-5. Significant wave height encountered along the optimized voyage 20161108 (Left), and along the case study voyage 20150721 (Right).

For fuel savings, the three cost functions by ML techniques, i.e., "ML Power", "ML Fuel" and "ML power + SFOC" models, all present a higher fuel saving from voyage optimizations for both two case study voyages. Specifically, for the summer Voyage 20150721 with a bit larger variation along the sailing routes, the divergences in the fuel consumption become more noticeable. Moreover, to compare the voyage optimization when different cost functions are used, i.e., power consumption or fuel consumption as the cost, the empirical models give more apparent deviations of voyage planning results in terms of both trajectories and fuel consumption for the summer Voyage 20150721. The "Empirical Power" model gives 0.3% fuel savings, while the "Empirical Fuel" model shows a result of 7.0%. The two ML ship models give close results for both cases, with around 13% and 15% saving, respectively. However, when considering the effect of SFOC, the result both changes to around 9%.

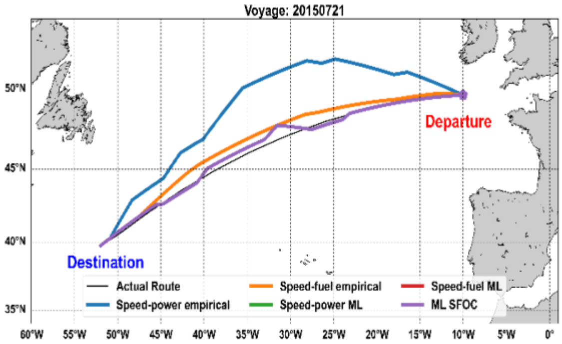
For the suggested routes shown in 

Figure 6-4. Optimized routes by different cost functions for the case study voyage 20161108 (Left), and for the case study voyage 20150721 (Right).-4, the two empirical models, i.e., "Empirical Power" and "Empirical Fuel" models, give the most diverged planning results. Especially, voyage optimizations using the "Empirical Power" model suggests a noticeable long detour, which explains its relatively high fuel cost with only 0.3% savings, while choosing fuel as energy cost can lead to 7.0%. It may be due to using the power cost as the optimization objective can neglect the effect of long-distance and only opt for the lower power, thereby leading to local optimizations. This corresponds to the encountered H_s during the voyage shown in **Error! Reference source not found.**6-5, where the cost function of "Empirical Power" model gives the optimized route with the modest waves encountered. Similar results can also be observed in the other case study Voyage 20161108. Optimization results using ML models present closer results in both two cases, with similar suggested routes, fuel savings, and encountered sea states.

6.3 Deep sea navigation with different JIT notifications

Assume the waiting time at the port is 8 hours as an example. Two scenarios of being informed in advance about the waiting time are simulated below. To achieve the objective of Just-In-Time (JIT), an update of the voyage planning can be performed to avoid the traffic congestion inside and around the port area. Meanwhile, slowing down the sailing speed also shows a reduction in fuel consumption. The two JIT scenarios are defined in Table 6, named as JIT24h and JIT48h. When the expected time of arrival without waiting, i.e., JIT arrival of this voyage, is known, the 3DDA voyage optimization algorithm is used to plan the left voyage, i.e., from the current position of this voyage to its destination.

Table 6: Different scenarios of arrival time expected and updated for JIT

Name	JIT scenarios	Description in detail
JIT24h	*Know the exact time to the destination port without waiting 24 hours ahead of arrival.*	It means that the ship's sailing time from now to the destination is extended to 32 hours. When the ship is arriving at the port, she does not need to wait for loading/unloading. The total computation time of the 3DDA voyage optimization algorithm to update the voyage

		planning of the last 32 hours sailing at the left voyage by an ordinary laptop is 24 seconds.
JIT48h	*Know the exact time to the destination port without waiting 48 hours ahead of arrival.*	It means that the ship's sailing time from now to the destination is extended to 56 hours. When the ship is arriving at the port, she does not need to wait for loading/unloading. The total computation time of the 3DDA voyage optimization algorithm to update the voyage planning of the last 56 hours sailing at the left voyage by an ordinary laptop is 174 seconds.

The optimization results of the updated voyage are presented in Figure 6-6, Figure 6-7, and Figure 6-8. The routes of the voyage are revised with slight deviations, from the preliminary planned voyage in the rest of the sailing for both scenarios, and the speeds are also slowed down accordingly to compensate for the 8 hours waiting time. The updated ship route trajectories optimized by the same 3DDA optimization algorithm are given in Figure 6-6, and the speed profiles are given in Figure 6-7, with the x-axis in longitude and time respectively.

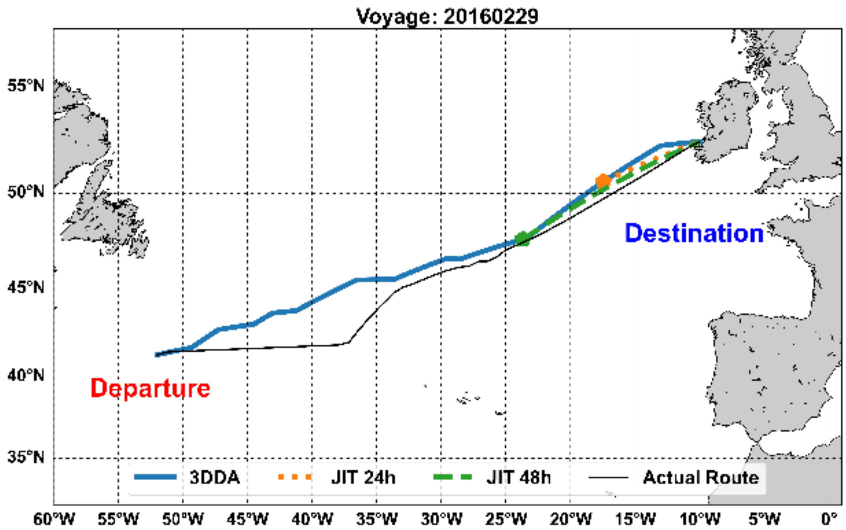
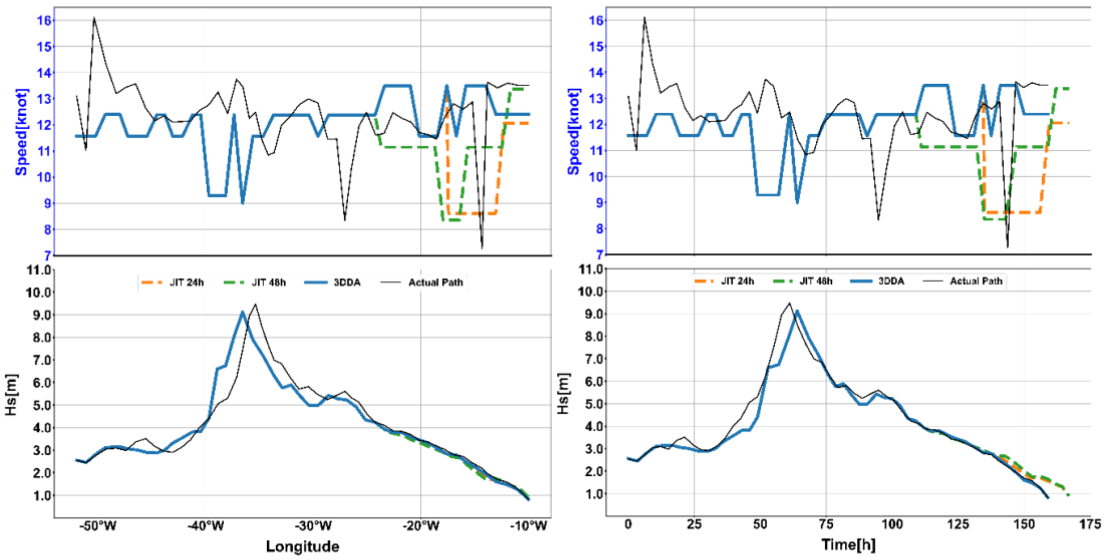


Figure 6-6. Updates of optimized ship routes based on the two listed JIT scenarios.



(a) (b)

Figure 6-7. The speed profiles and encountered significant wave height H_s of ship routes optimized by the 3DDA method in terms of Longitude (a) and time (b), respectively.

The accumulative fuel consumption along the voyage is also shown in Figure 6-4 to compare the fuel consumption. The final overall consumptions are nearly identical for both simulated scenarios, which are 142.0 tons (JIT 24) and 141.9 tons (JIT 48), respectively. However, compared with the previously planned voyage (3DDA), which consumes fuel 151.8 tons, it still shows around 5% more fuel reduction. And compared with the actual voyage which shows 171.3 tons of fuel usage, the 3DDA method shows a fuel saving of 11.4%, and JIT update contributes to around 17.1% for both scenarios. Moreover, the update of the voyage is efficient and takes only several minutes, which can be performed easily, since the left of the voyage is only in a short length of time.

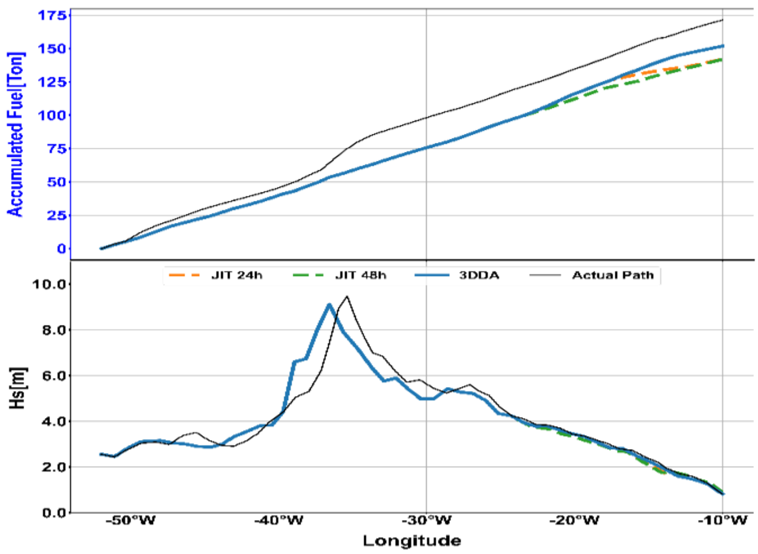


Figure 6-8. Accumulative fuel consumption optimized on different JIT scenarios.

7 Situating fuel savings in the social practices of the shipping industry

This section of the report situates energy efficiency measures in the social practices of shipping and is based on both interviews conducted as a part of this study and a literature review.[1] The presentation is intended to give a perspective on the importance of considering social factors when designing digital measures for energy efficiency and to support the technical inquiries of this report. When it comes to energy efficiency, this section mainly concerns the planning and operation phase of energy efficiency measures (Figure 2-1). The general purpose of this section is to inform the discussion on the technical aspects of this report—i.e., what are important social dimensions to consider when designing digital EEMs for improved propulsion in terms of energy consumption.

Fuel saving is a high priority in all interviews we have conducted, both because of high associated costs and an increasing demand from their customers to track emissions (this was especially prominent in the RoRo sector). This finding is aligned with a general understanding of the field. DNV writes that: “Most respondents name several reasons as to why energy efficiency is important to them, nobody feels unaffected. More than 80% of nomination fuel costs are the key driver for efficiency, followed by environmental footprint with 58%” (DNV 2015). But when it comes to how energy savings that are related to the planning and execution of voyages should be afforded, stakeholders have many uncertainties and conflicting views on how this should be done. When saving energy seems to be such an important target for the involved actors, one must ask the question of why the current practices are not optimal from an energy-saving perspective. The following part of this section discusses important factors that will affect the applicability of specific EEMs and identify differences in various segments of the shipping industry and among actors.

7.1 The current ship operation

The first finding is that the potential for fuel savings depends on current shipping industry practices, i.e., how the ships are operated today. Given the basic physical principles of water and wind resistance, large savings can generally be made by reducing the speed of the ship. As such a slower crossing from point A to B is generally more energy efficient (down to a certain speed). Slowing down the speed is not always a viable option, as swift deliveries often are a competitive advantage when cargo transportation is ordered. However, as shown by the presentation

[1] A complement to conducted interviews is a reading of the previous research and reports. For example, the DNV report (2015) gives a good overview of how shipping companies view and works toward increased energy efficiency, what measures are preferred and who is understood to be responsible. align with general points prevalent in interviews etc.

below, many ships have long waiting times in the harbors waiting for their designated slot to offload their cargo. Understanding the general pattern of ship movement and waiting times makes it possible to estimate potential fuel savings in the shipping industry. By identifying differences between ships in terms of various variables (cargo, shipping segment, flag) it is possible to identify where interventions would be more beneficial, i.e., EEMs to facilitate Just-In-Time arrival will be more beneficial among ships and shipping segments with long waiting times and poor ship management today.

To understand why ships aren't operated in an optimal way when it comes to energy efficiency, one must also understand why the ships are operated in the present way as in Table 7. The reasons for this are manyfold. Early arrivals can be explained by captains not wanting to be late for their assigned offloading time slot. As conveyed to us in the interviews, being slightly late on arrival can lead to much larger delays because their offloading has been down prioritized, and they might need to wait in line to use the lock (applicable in some harbors). Delays also want to be avoided because they lead to additional work for the captains in communicating with the harbor and the shipping companies' land office. Delays can sometimes also be associated with additional costs for shipping companies, in terms of fines or the customer canceling the contract. Given the uncertainties of weather conditions, captains tend to use unnecessary high speed throughout the journey, which consequently consumes too much energy. Certain types of cargo/transportation are more sensitive to delays than others. As will be discussed in the next section, this matter is also related to how contracts and charter party agreements are written.

Table 7: Overview of factors influencing the possibility of increasing energy efficiency in shipping within a particular shipping company. Inductively constructed table from information collected in the literature review and in the interviews.

How the ships are operated today	Current compliance with JIT
	Current technology used
	Target variable used in operations
	Information
The possibility to change practices	Organization
	Regulations and party agreements
	Attitudes, habits, and cultural practices
	Investment costs
The want and incentives to change practices	Determination
	Knowledge
	Incentives and rewards
	Conflicting incentives

Potential energy savings for some EEMs are also dependent on the currently used technology and the target variable for the operation i.e., if the captains can set the exact SOG (Sped Over Ground) or constant fuel consumption for the vessel, or if they operate with a leaver producing a certain engine power. These factors influence the captains' ability to navigate energy efficiently, and the potential fuel savings. When it comes to digital EEMs some of them require pitched propellers or the ability to drive the ship at a constant fuel consumption or a constant RPM. If the captain cannot make these settings, some EEMs will not work. The effectiveness of EEMs might also depend on several other ship variables. The effectiveness and willingness to try a digital tool for providing recommendations are also dependent on the control/ target variables currently used.

A related concern is the availability of information. This is a technical matter, but also a managerial matter. Ship data is stored and logged both digitally and manually and organizational decisions need to be made on how this data should be collected, stored, and utilized. As Poulsen & Johnson (2016) have argued, many shipping companies do not have accumulated real-time data on the energy performance of their vessels. Availability of information is crucial for many digital EEMs, data need to be sufficiently accurate, in a resolution that is sufficient (data points per minute) and stored and made available. If this information is unavailable, it will make the applicability of certain digital tools impossible. Previous literature has argued that "Just presenting fuel statistics to crews is not enough since the complexity of the data does not allow unambiguous causal inferences and clear implications for actions" (Viktorelius et al. 2022). This is of course true but the information needs to be available to data scientists and engineers who design digital tools.

7.2 The possibility of changing practices

In assessing potential fuel savings in the shipping industry, one must further consider that the operation of any ship is situated in the larger organization of shipping. A captain has a relatively large degree of autonomy (or at least responsibility) during a journey. However, how a captain navigates is strongly influenced by his general instructions for his job and the instructions he receives from the land office and the harbor. If captains get the order to change destination harbor or speed up during the journey, they will do this if they can do it without jeopardizing safety on board. The decisions of the captain and the instruction the captain gets from land are situated in a larger socio-technical structure. It is influenced by demands from customers, regulations, habits, and wider technical and organizational structures. Involved actors include, but are not limited to: "individual ship officers (navigators, engineers, etc.) to shipyards, shipowners, operators, charterers, cargo owners, ports, and traffic management services" (Viktorelius et al. 2022).

This larger structure of stakeholders with various objectives, values, and institutional culture (c.f., Larsson & Bengtsson 2022; Larsson & Sjölander-Lindqvist 2022) means that changes in practices cannot be made by one actor. For example, a just-in-time approach is not relevant if a harbor does not have the capacity to organize this for the arriving ships. "The work to improve ship energy efficiency cannot be reduced to the accomplishment of a single decision-maker but depends on the active engagement and collaboration among several distributed professional groups and actors" (Viktorelius et al. 2022). The multitude of actors can create "gaps in responsibilities between the stakeholders, mutually exclusive goals, and focus areas as well as differing conceptions of performance monitoring" (Viktorelius et al. 2022). Or as DNV writes: "The responsibility for energy management appears unclear in many shipping companies. Not even a third of all companies have a dedicated energy manager or team. Most companies have assigned the task to 'everybody', which often actually means 'nobody'" (DNV 2015).

Concrete examples of this can be when there is a lack of communication between stakeholders so that ships do not know that their planned offloading slot has been moved forward. Sometimes these matters can be solved with equipment and routines for communications, i.e., making information available throughout actors. Sometimes these issues cannot be resolved only through communication. For example, does a harbor have the capacity to deal with just-in-time arrival/ late arrivals to facilitate fuel savings. As DNV write: "In a perfect world each hour spent there could be transposed to slower average sailing speed with corresponding bunker savings. In practice some of this potential can be realized by better communication between, ship, operations department, and port in combination with just-in-time procedures." (DNV 2015). Because of this, several measures to save fuel must involve coordinated actions of several stakeholders within the own organization and beyond.

Furthermore, a factor that is addressed both by stakeholders in our interviews and in the literature is how regulations, and especially charter party agreements, can make EEMs more difficult or impossible to implement without changing these. Such agreements can result in a captain being unable to execute a recommendation from a digital system in terms of setting a particular speed or energy consumption setting. As IMO concludes, the possibility for a master or onshore Marine Team to change speed to arrive JIT "usually depends on the charter party terms" (IMO 2020, 2021). The extent to which this affects various operators will vary with different supply chains and contracts. For example, IMO (2020) recognizes that "there are fewer contractual barriers" in the container segment compared to tramp service. Finally, although many measures for improving energy efficiency afford savings in the long run, the cost of investments might discourage shipping companies from making investments. When asked about the most important consideration for energy efficiency measures, 80 % replied that the payback period is the most important concern (DNV 2015).

7.3 The want and incentives to change practices

While all interviewed actors express an interest in reducing emissions, engagement in this issue is not equally distributed among actors. As discussed above, all actors claim to be committed to fuel savings, but the commitment and determination to this differ among different individuals and actors across the shipping industry. While everyone we interviewed expressed concern for fuel consumption this was not the primary concern for everyone. The charter department's highest priority was always keeping their ships in business rather than saving fuel. Captains' highest priority was the safety of the ship and crew and delivering their goods as per the agreement. To facilitate the implementation of an energy efficiency measure that includes changing the way a journey is planned and executed, commitment among actors is required. Although many such EEMs within the SEEMP paradigm are executed at a local level, changes generally need to be addressed top-down to engage all relevant actors. As written in DNV (2015) "Topics can get burned in the organization, if not planned and executed well. Most shipping companies deal well with technical challenges but struggle on the people's side. This is a severe challenge, as about half of the achievable energy savings are related to ship and shore staff's behavior."

A crucial aspect of determination and engagement among actors is knowledge. While captains and other actors, of course, are very knowledgeable in their field, there is still a lack of knowledge on issues related to energy efficiency. As DNV write: "Interestingly many respondents seem to underestimate the share of fuel costs in total shipping costs. Just 30% assume the share to be 25% or more" (DNV 2015). The interviews we have conducted for this report reveal conflicting views on the most energy-efficient way to operate a vessel and show doubt when given information on the technical measures. This point is connected to the availability of information, but the information need not just be available but also possible to understand and to act upon by the involved actors. "Just presenting fuel statistics to crews is not enough since the complexity of the data does not allow unambiguous causal inferences and clear implications for actions" (Viktorelius et al. 2022, 394). This does not necessarily mean that the information needs to be interpretable by each involved actor but that the know-how is integrated into the larger socio-technical system, for some actors' clear instructions on how to act on specific data will suffice. Information is also often difficult to interpret and act upon to operate a vessel more efficiently. For example, the data processing provided by ML algorithms taking ship and weather data into consideration is impossible for any human to process and act upon. The problem is, therefore, not only what Armstrong and Banks propose: "with minimal staff onboard it could be a far stretch to expect integration of information and analysis provided by different systems." (2015)

Also, attitudes, habits, and cultural practices among staff can make the implementation of EEM more difficult. DNV write: “But still shipping companies struggle with implementation due to resistance to change among ship and shore staff, partially lacking skills and absence of a performance management culture.” (DNV 2015) Although knowledge and awareness among actors are important, general measures aimed at reducing emissions through raising awareness and fostering a culture of responsibility seem to have a limited import on climate reduction. The conclusion of the interviews we have been making is that there need to be clear incentives and rewards for fuel saving among involved actors. Talking about a study by Rasmussen et al. (2018) Viktorelius et al. write, “fuel was paid by the charterer and not the shipping company, seafarers were not encouraged to save fuel, which could even lead to a penalty if the specified ship speed was not maintained. The type of charter and the company's priorities thus influenced the seafarers' attitudes and the use of the fuel consumption indicators.” (Viktorelius et al. 2022) This is one example of when incentives and rewards are not structured in a way that promotes fuel savings. It is also common with conflicting goals and incentives both from inside and outside the organization where it is difficult for involved actors to prioritize between these goals. There are also conflicting goals within the debate on fuel savings and environmental issues—some regulations require lowering the emission of sulfur, others require lower emissions of carbon, and within the organization, a reduction of costs might be the most relevant. Depending on how these are prioritized, measures such as scrubbers, low sulfur fuel, or different fuels might be a higher priority.

8 Conclusions

One would think that general cost savings would be a strong incentive for companies to reduce fuel consumption. As DNV concluded, for an operator, 5% savings in a 40% cost position equate to two percentage points EBITA (Earnings Before Interest, Taxes, and Amortization). The operators struggle with implementation, which is a human aspect. (DNV 2015).

According to IMO (2020), both operational and technical measures are required to increase energy efficiency. When it comes to reducing and eventually discontinuing the GHG in shipping, changes in fuel will also be required. But also in this situation, energy efficiency in terms of operational and technological perspectives will be a relevant competitive advantage. It will require collaboration between stakeholders in the maritime industry (IMO 2020).

However, few studies have examined the interdependence of practices and technologies underlying organizational cognitive systems and change. The identified research gap calls for more longitudinal process-based case studies investigating the design, implementation, and use of information technologies supporting organizational planning and decision-making required for improving energy efficiency (Viktorelius et al. 2022). In addition, shipping companies struggle with the implementation of measures and acknowledge the need to address the human factor (DNV 2015). Pathways that involve changes to multiple technologies, infrastructures, organizations, and institutions are often explored slowly (Viktorelius 2022).

Communication could be listed as an additional energy efficiency measure (EEM). But when we talk about communication in this regard, we do not just refer to correspondence and exchange information or trying to reach a common understanding between different shipping stakeholders in particular ship operation situations. As an EEM, the communication can be served as a systematic way of collecting, distributing, corresponding and reflection of all ship operation related information (requirements, constraints, objectives, planning, available sources, and navigation conditions, etc.) among different stakeholders, which should help reach common understanding and continuous updating of operation goals/conditions, in terms of ship operation objectives of fuel saving and emission reduction.

By analyzing the actual benefits of using big data analytics and AI in a ship's energy efficiency measures (EEMs), this project is expected to help further reduce fuel consumption/ emissions by promoting the upgrading and utilization of AI-integrated shipping EEMs, to assist decision-making processes in reducing pressure for ship masters onboard. To know whether EEMs are suitable for a specific shipping company/ ship, it's necessary to identify how it operates, the technical details of ships, as well as willingness to adapt. Based on different reports of ship waiting time in ports, more than 5 hours of waiting time on average are expected even for the Port of Gothenburg. In large ports such as in the US or China, the waiting time can be of days. The long waiting time also means a large potential of fuel saving when implementing EEMs for the IMO Just-In-Time arrival strategy. It is also concluded that more advanced ship performance models, such as combining physical model and data-driven methods, are extremely important to develop reliable EEMs for JIT strategy. Taking the voyage optimization as an EEM to facilitate the JIT arrival for example, more than 10% fuel saving can be expected if the expected time of arrival is known 24 hours ahead of the arrival.

There are major differences across actions. According to DNV, in their daily advisory practice, they see shipping companies that have realized savings of 10 to 15% and more, while others have achieved hardly anything. All have SEEMPs in place and all are compliant. But some do significantly better than others (DNV 2015). At the 72nd session of the MEPC, the initial IMO strategy was agreed upon with a vision to, e.g., reduce at least 40% of the average carbon intensity by 2030. Having set up an IT system providing all relevant reports in perfect granularity and frequency does not necessarily mean that performance is managed. Living a performance management "culture", regularly challenging, and supporting subordinates to improve efficiency, is as challenging as the implementation of data collection, processing, and report generation. (DNV

2015). The human element in energy management should be treated as equally important as technology (Kitada and Ölçer 2015).

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