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Development of a Multi-Objective Ship Operations Optimization Decision Support System

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Abstract

Optimizing ship operations in the maritime industry is crucial for enhancing efficiency and sustainability. With the increasing emphasis on reducing carbon emissions and fuel consumption, innovative solutions are needed to address these challenges. The multi-objective ship operations optimization decision support system (MSODSS) aims to improve the efficiency and sustainability of ship operations by integrating advanced simulation-based optimization algorithms and considering inputs such as power sources, equipment health, route, navigation, and weather data. This paper presents the development of an MSODSS prototype based on the FlexSim simulation system. The MSODSS system architecture, data sources, and simulation model are discussed, and a case study for comparing ship operations in different weather conditions is used to demonstrate the system's functionalities. Preliminary results indicate that a significant increase in fuel consumption and carbon emissions may occur with even modest increases in ship speed.

Keywords
Multi-objective optimization, Simulation-based optimization, Ship operations, Decision support system, Carbon emission reduction, FlexSim model.

1. Introduction

The maritime industry plays a crucial role in global trade and transportation, with ships being the primary mode of transporting goods globally. However, the industry faces significant challenges in optimizing ship operations to enhance efficiency, reduce costs, and minimize environmental impact. Traditional methods of ship operations often fall short in addressing these challenges due to their limited ability to handle multiple objectives simultaneously. This has led to a growing interest in developing advanced decision support systems that can optimize ship operations by considering multiple objectives such as fuel consumption, carbon emissions, and operational costs.

The Multi-objective Ship Operations Decision Support System (MSODSS) described in this paper aims to leverage multi-objective optimization algorithms, simulation-based optimization, and data integration techniques to provide comprehensive decision support for ship operators. By optimizing multiple objectives simultaneously, the system aims to enhance the overall efficiency and sustainability of ship operations. The development of this system will provide a robust tool for decision-makers in the maritime industry to improve operational performance and reduce environmental impact.

This paper presents the preliminary development of the MSODSS system. It discusses the system architecture, data sources, and simulation models used in the project. A case study is also presented to validate the system, demonstrating its effectiveness in evaluating and optimizing ship operations. The paper concludes with a discussion of the preliminary results, insights, and implications for the maritime industry, along with suggestions for future research directions.

2. Literature Review

With the adoption of the International Maritime Organization (IMO) Strategic Plan for 2018–2023, which includes "Integrate new and advancing technologies in the regulatory framework" as one of its pivotal Strategic Directions, and the increasing call for efficiency improvement and carbon reduction in the maritime industry, there is an increasing demand for the development of smart ship operations that make use of automation in navigation and control technology to operate shipping systems smartly, safely, and economically (Kumar 2023).

Fuel oil consumption constitutes approximately two-thirds of a vessel's voyage costs (Stopford, 2009). The fuel efficiency and reliability of modern vessels can be strongly impacted by weather. Ship motions and resistance in waves and wind influence the operation of a vessel's propulsion system. This can increase fuel consumption and reduce the attainable speed. The average reliability of container shipping lines has historically hovered around the 66% mark, implying that only two in three vessels arrive as per schedule, where timely delivery in most cases is defined as being "plus or minus 1 day" (Bhonsle 2023).

Smart ship operations take into account local data onboard the ship such as speed, power, and fuel consumption; and global data such as shipping traffic, weather conditions, and port costs to optimize goals such as economy, energy efficiency, and carbon emissions. For example, during a 90-day period, the weather forecasting service provider, StormGeo's routing software assisted the Odfjell Tankers in avoiding severe storms in the Pacific resulting in a fuel consumption reduction of 1,000 MT (3000 MT of CO2) and saving 30 sailing days (StormGeo.com 2023a).

There are also ship weather routing systems such as SIMROUTE that aim to provide a comprehensive, open, and easy tool including pre- and post-processing for ship weather routing simulations (Grifoll et al. 2022). The Mentis cloudbased analytics platform provides an Augmented Routing Optimization that integrates weather routing functionality from specialized service providers to optimize an individual ship's performance for fuel consumption, hull fouling, emissions, etc (Mentis 2023). Besides providing ship operators with weather forecasting services, StormGeo's weather routing service, "Ship Performance Analyst", will recommend a safe, time-saving, and fuel-efficient sailing route based on the weather forecast and other factors such as vessel traffic, piracy threats or local conflicts etc (StormGeo.com 2023b).

In another study by DeepSea.ai (2023), an AI-based Pythia platform was used to analyze various ship and weather parameters of Seanergy's fleet to recommend optimal routes and speed profiles for each voyage to improve fuel efficiency and reduce emissions. Pythia has enabled Seanergy's Capesize vessels to achieve a reduction of fuel consumption of up to 12%, with average fuel savings of 8%, as recorded over a series of voyages during the first four months of 2021.

While weather-aware ship routing can help to achieve significant economic and practical value in ship operating costs, reliability, and safety, most of the traditional algorithms can only solve a single-objective optimization, such as the minimum voyage time or minimum fuel consumption. It is very difficult to deal with optimization problems that consider multiple objectives that can sometimes be conflicting such as minimizing the voyage time and minimizing the voyage risk.

Existing work on ship operations optimization focused on achieving efficiency, safety and economy. In Li et al (2017), the multi-objective evolutionary algorithm NSGA-II is applied to solve a multi-objective ship weather routing problem that considers voyage time and voyage risk. Fuel consumption is not directly considered but is related to the minimum voyage time, which may not reflect the actual situation. In Yang et al. (2022), an improved multi-objective ant colony (IMACO) algorithm that considers ship navigation risk and fuel consumption cost under complex sea conditions is used to generate different route planning grid maps according to the differences in navigation strategies of different shipping companies.

While these works used multi-objective optimization to obtain Pareto-optimal routing solutions in terms of voyage time/fuel consumption and navigation risk, they were carried out using a static model of a ship that uses a single fuel source, and do not consider other operational issues such as hull and engine degradation, equipment efficiency, and alternative energy and propulsion sources such as solar and wind.

The Maritime and Port Authority (MPA) of Singapore has released a call for Expression of Interest (EOI) for the design and development of electric harbour craft in July 2023 (MPA 2023). The multi-objective optimization engine to be developed in MSODSS will complement the effort of the EOI as it allows the evaluation of trade-offs between conflicting objectives in the operations of electric harbour craft such as the following:

- **Energy Efficiency vs. Speed**: While all-electric ships do not consume fuel, they still need to optimize energy efficiency to maximize the range of the ship. Balancing energy efficiency with speed is important, as higher speeds can drain the onboard batteries more quickly, reducing the ship's operating range.

- **Time Efficiency vs. Battery Management**: All-electric ships need to carefully manage their battery usage to ensure they have sufficient power throughout the voyage. Balancing time efficiency with battery management can be challenging, as faster speeds or shorter routes may require higher power consumption and drain the batteries more rapidly.

- **Renewable Energy Availability vs. Route Optimization**: All-electric ships rely on renewable energy sources, such as solar or wind, to charge their batteries. However, the availability of renewable energy can vary depending on the ship's location and weather conditions. Optimizing the route while considering the availability of renewable energy sources can be a conflicting objective.

- **Safety vs. Efficiency**: Safety considerations, such as avoiding storms or hazardous areas, remain important for all-electric ships. While optimizing for efficiency, there may be a conflict with safety objectives, as taking a more direct or faster route may involve navigating through potentially dangerous conditions.

- **Environmental Impact vs. Route Optimization**: All-electric ships are chosen for their reduced environmental impact compared to conventional vessels. Balancing the environmental benefits with route optimization can be challenging, as the most efficient route may not always be the most environmentally friendly, especially if it involves passing through sensitive ecosystems or protected areas.
- **Charging Infrastructure vs. Route Optimization**: All-electric ships rely on charging infrastructure to recharge their batteries. Optimizing the route while considering the availability of charging stations and the time required for charging can be conflicting objectives. Deviating from the optimal route to reach charging stations may impact efficiency and voyage planning.

The above list of conflicting objectives in all-electric harbour craft operations highlights the complexity of optimizing the routing for all-electric ships. Balancing energy efficiency, time efficiency, safety, environmental impact, and infrastructure considerations is crucial to ensure the successful and sustainable operation of these vessels.

3. System Architecture

Figure 1 shows the components of the MSODSS. The MSODSS takes in input from simulated ship data as well as live ship data. The types of simulated and live ship inputs include data from the power and propulsion models, the Equipment Health Monitoring model, navigation data, route data, and weather data.

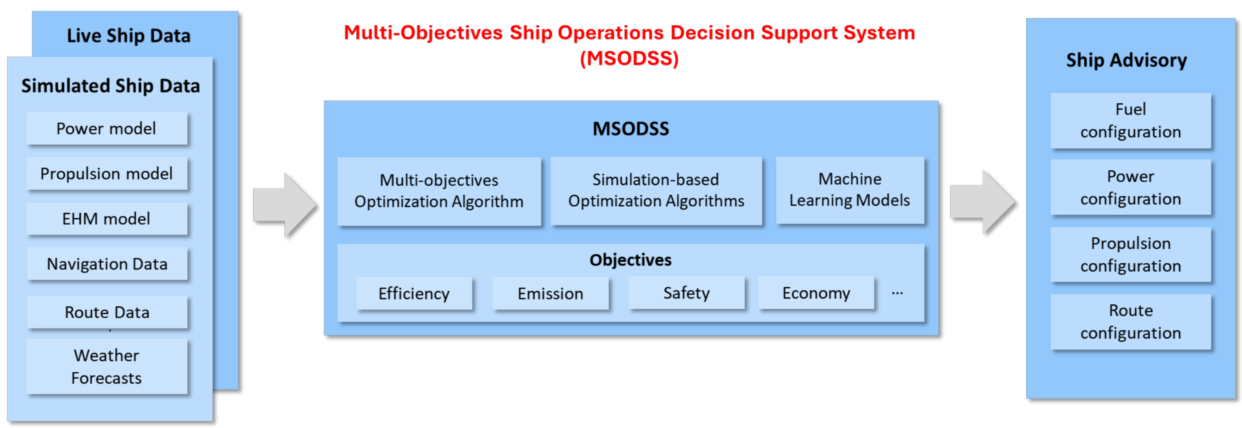

Figure 1. Multi-Objective Ship Operations Decision Support System (MSODSS)

In MSODSS, we will evaluate different optimization algorithms to make use of the input data to generate the output ship advisory to recommend the optimal fuel, power, propulsion, and route configurations the ship should adjust dynamically.

We will use several data sources as follows.

1. A power and propulsion model will be used to predict the fuel consumption and efficiency of the engine under different power sources such as hydrogen, fuel-cells, solar, and wind.
2. An equipment health monitoring (EHM) model will be used to predict the serviceability of the different equipment onboard the vessel.
3. Route data will include the source and destination of the ship, and waypoints (if any) the ship must pass through. It can also include positions of shore charging stations and floating charging stations.
4. Navigation data will include information such as the bathymetry (water depths), coastlines, obstructions, beacons, etc. It can also include data on the vessel traffic volume as well as any piracy threats.
5. Weather data will include information such as the state of the ocean and the atmosphere, such as the ocean currents, wave heights, wind speed, temperature, precipitation, air pressure and visibility. Commercial weather data providers are available for clients to access weather forecast data. For example, Spire (www.spire.com) has a constellation of 100 low-earth satellites that collect weather data for training its proprietary weather forecasting model and offers model access and services through a set of APIs. Open-Metro (www.open-metro.com) is another company that provides an open-source weather API with free access for non-commercial use.

The optimization algorithms to be studied in this project can include multi-objective optimization algorithms such as the popular Nondominated Sorting Genetic Algorithm (NSGA-2) (Deb et al. 2002), NSGA-3 (Deb and Jain 2014), and multi-objective Ant-Colony optimization (Yang et al. 2022). However, existing algorithms cannot be readily used (effectively) for our research task. We will work on detailed research tasks such as chromosome representation of the input and fitness functions in MSODSS. It is possible that evolutionary algorithms (e.g., the ones mentioned above) alone are not effective enough, and we also plan to investigate the hybrid solutions with both evolutionary algorithms and machine learning, e.g., machine learning-based operator selection and parameter optimization.

To evaluate the complex interactions between the different parameters, it is necessary to construct simulation models that consider the interactions of these input data and carry out simulation-based optimization to evaluate the efficacy of different combinations of ship advisory recommendations. The simulation models can be developed using MATLAB (Pennino et al. 2020) or a general-purpose discrete event simulator such as FlexSim (www.flexsim.com). The necessary APIs and GUIs will be developed based on common programming languages like Python to facilitate coordination among team members and potential future end users.

As simulation-based optimizations are time-consuming to execute, we can use data from past simulations and actual ship data from our industry partners to train machine-learning models that can act as surrogates and take in the input data to generate the recommended ship advisory without running any simulations. A surrogate shall approximate the original system accurately and the accuracy depends on several factors such as data and machine learning algorithms. We plan to utilize limited data available in the beginning stage to train a less accurate surrogate and keep improving the surrogate with more new data collected.

4. System Development

Figure 2 shows a prototype MSODSS system that we have developed using the FlexSim simulation system. It currently supports the simulation of ship operations for different types of ships (Non-Green ship, Green ship, Hybrid-Electric ship, and Full-Electric ship) around Singapore waters. Note that these ships are modelled using the vessel particulars of a 5000 twenty-foot equivalent unit (TEU) container ship described in Ridwan et al (2023). A Non-Green ship has marine diesel oil (MDO) engines, with fuel derived from diesel, while a Green ship uses dual-fuel engines with a 95-5 Ammonia-MDO ratio. Hybrid-Electric ship combines MDO and/or Ammonia with battery to power the ship. Marine vessels frequently use MDO engines due to their broad availability and affordability. MDO engines offer adaptability, dependable performance, and the capacity to manage a range of load circumstances. A promising alternative fuel is ammonia, which has low carbon and sulphur content within its chemical structure. Ammonia has also been used by internal combustion engines and fuel cells in the past as fuel. Due to its special characteristics, ammonia has drawn interest as a potential fuel for engines. It can lessen greenhouse gas emissions and slow down climate change.

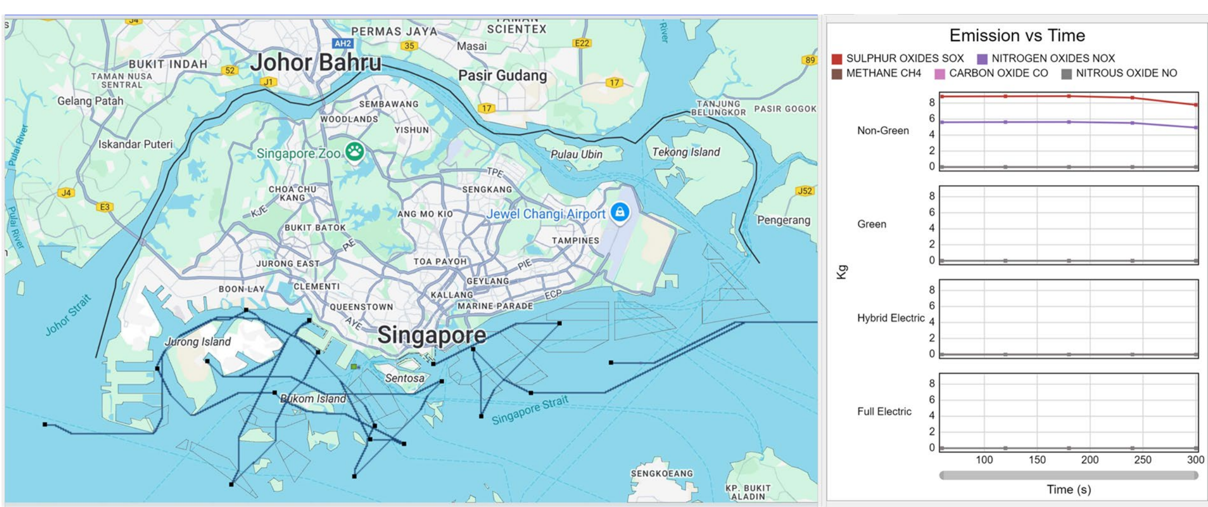

Figure 2. MSODSS Prototype of a Simulation Model for Singapore Waters, with Gas Emission Reports for Different Types of Ships

The simulation model has been developed to simulate ship operations, under the effects of wind and ocean current conditions, and compute fuel consumption and gas emissions. When a moving ship is faced with different weather conditions, the actual Speed Over Ground (SOG) of the ship will be affected during the voyage and can result in noticeable speed gain or loss. Under these varying weather conditions, the time taken for a ship to reach its destination will vary accordingly, and so will the fuel consumption and gas emissions of the ship.

The historical wind speed and direction, as well as ocean current speed and direction from online websites (e.g. http://windy.com and http://digitalport-service.mpa.gov.sg/ta/htm/tide_submenu.htm) are used to configure a series of rectangular zones representing wind and ocean currents. These zones will change the SOG of the ship moving through them. These zones can be defined with specific start times and duration to simulate the actual weather conditions of changing speed and direction of wind or ocean currents over time.

For different types of ships, the power source for the engines that drive each ship can be configured to use up to three different types of fuels. Consider a Marine Diesel Oil (MDO) engine and a dual-fuel engine with 95-5 Ammonia-MDO engine, the former is set to be 100% diesel while the latter is defined to use 95% Ammonia and 5% diesel. As for an electric ship, the fuel consumption is based on the fuel used to charge the battery pack on the ship. This combination of fuels will be used to compute the gas emissions and the total cost of fuels consumed. The gases that are considered in the model include Carbon Dioxide (CO_2), Sulphur Oxides, (SO_x), Nitrogen Oxides, (NO_x), Methane, (CH_4), Carbon Oxide, (CO) and Nitrous Oxide (N_2O). The parameters of these gases and the cost are configurable for each fuel type and are used in the gas emission derivation. The details of the calculations can be found in our previous work in Ridwan et al (2023).

The navigation path of each ship under consideration can be pre-defined based on maritime AIS data. Each path consists of a series of locations, each of which is identified with latitude and longitude information. In the model, a task sequence is created for each ship to execute the 'Move To' task for each location. The initial state of the simulation of the Singapore water can also be loaded into the model from the AIS data. This initial state includes the ship locations and its movement status in the surrounding water area. When the ship under consideration is navigating in the sea, it may interact with other ships in its neighborhood, and the ship may steer away from other ships to avoid a collision.

Faster sailing speeds require greater power to overcome air and water resistance, leading to higher fuel consumption. Usually, doubling a ship's speed requires eight times more engine power. Hence, fuel consumption is assumed to be proportional to the speed to the power of 3. For this study, we use an optimum ship speed of 20 knots to derive an approximate graph (refer to Figure 3), for our fuel computation for the ship speed change.

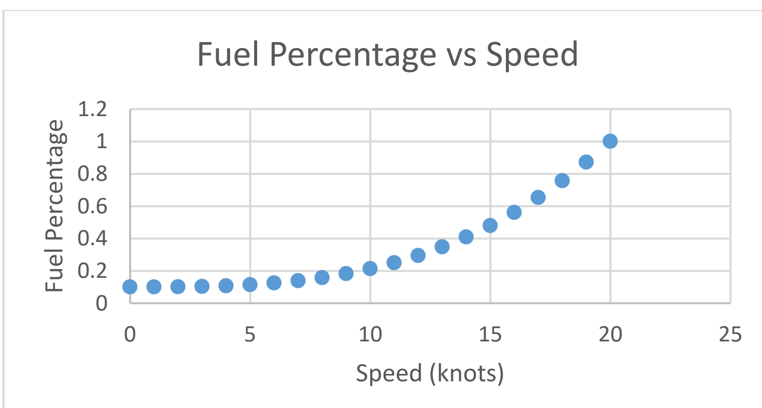

Figure 3. Variation of Fuel Percentage with Ship Speed (knots)

5. Case Study

To evaluate the simulation model, we set up the model to run three different scenarios for a non-green ship.

- Scenario 1: The ship is sailing in calm sea without any weather condition;
- Scenario 2: The ship is sailing in ocean current with tidal effects;

- Scenario 3: The ship is sailing in ocean current with tidal effects, but with increased ship sailing speed to match the overall ship sailing duration in Scenario 1.

In the first scenario, the ship is sailing in a calm sea without considering any additional ocean current or tidal resistance. In this case, the ship will sail smoothly to its destination. In the second scenario, the ship will be slowed down due to the involuntary speed loss it experiences according to the respective ocean current block that it passed through in the simulation. As the ship experiences a slowdown, additional time will be incurred without any speed increase to make up for the added resistance. In the third scenario, the speed of the ship is adjusted so that it makes up for the lost time, to ensure that the voyage time remains consistent with the first scenario. With the speed increase, the ship will no longer operate at its optimum speed.

Figure 4 shows the sailing path of the ship. Due to the islands around Singapore waters, the sailing path of the ship is not a straight line, as it needs to navigate through the water to avoid any collision with the islands. The model can also be configured such that the sailing ship can avoid anchorages and other neighboring ships, to simulate more realistic real-world marine traffic and obstruction. If the features are turned on, the built-in A*algorithm for ship navigation will search for other routes to prevent entering anchorages or collisions with nearby ships.

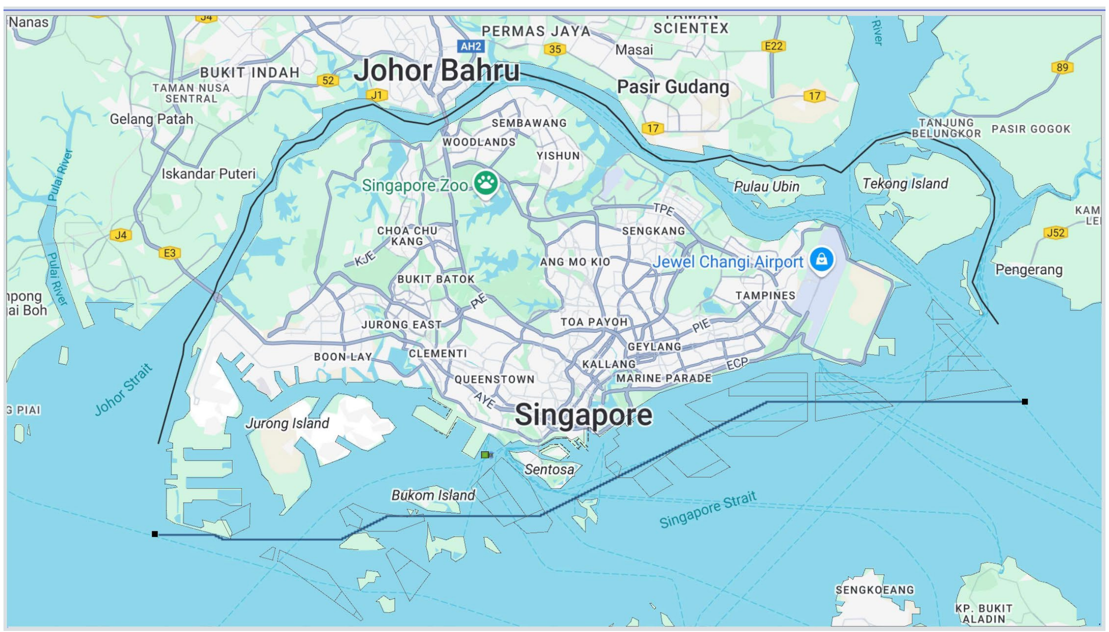

Figure 4. A Ship Sailing in Calm Sea from a West Location to an East Location

Figure 5 shows the ship sailing under the influence of ocean current effects. Ocean current blocks are defined to capture the tidal conditions. Each ocean current block will contain the speed and direction of the tidal waves. When a ship enters a block, the speed and direction of the ocean current will influence the sailing speed of the ship. The time taken for the ship will thus vary as they face different weather conditions, which change their speed.

Figure 5. A Ship Sailing in Ocean Current Effects from a West Location to an East Location

As there is no random effect in the model, each scenario is run once with one ship. At the end of the ship's voyage, the results of sailing duration, fuel consumption and gas emissions will be recorded by the model. The experiment results in Table 1 show that the travelling duration lengthens as the ship sails under the effect of ocean current conditions. As the duration is increased, fuel consumption and gas emissions will also increase accordingly. Increasing the sailing speed of the ship under ocean current conditions will ensure that the ship can arrive at the destination location on time (as in Scenario 1). However, the fuel consumption and the gas emissions will also increase greatly. Comparing Scenario 3 with Scenario 2, the speed of the ship has increased by 19%, but the fuel consumption and gas emissions have increased by 99%.

Table 1. Results of sailing duration, fuel consumption and gas emission

Scenario	Speed (knots)	Duration (hrs)	Fuel Consumption (kg)	Gas Emission (kg)					
				CO_2	SO_x	NO_x	CH_4	*CO*	N_2O
1. Calm Sea	12	2.58	0.84	2.6861	0.1147	0.2476	0.0002	0.0008	0.0005
2. Ocean current with tides	12	3.20	1.04	3.3252	0.1420	0.3065	0.0002	0.0009	0.0006
3. Ocean current with tides and Increased Speed	14.3	2.58	2.07	6.6326	0.2832	0.4185	0.0003	0.0013	0.0009

Further experiments can be carried out to study the optimization of the operations for different types of ships, as well as different types of ship operations such as towing, delivery and maintenance.

6. Conclusion

This paper described the development of the prototype MSODSS, built using the FlexSim simulation system, which supports various ship types, including non-green, hybrid-electric, and full-electric vessels. Its simulation capabilities account for complex real-world variables such as weather conditions, propulsion types, and environmental impacts. A case study demonstrated the system's functionality by simulating ship operations in different scenarios, including calm seas, ocean current tidal conditions, and increased speed adjustments to maintain voyage duration. Results revealed that increasing speed under adverse weather significantly raised fuel consumption and emissions, emphasizing the trade-offs in operational decision-making.

The ships used in the current prototype are based on the vessel particulars of a container ship, and no information on the health status of the equipment onboard the ship was taken into account in the simulation model. The scenarios presented in the experiment also consider only one objective, which is the sailing duration. Future development efforts will focus on refining the simulation-based optimization model to add different types of harbour craft and also include additional factors such as hull degradation and alternative energy sources while improving the efficiency of computations using surrogate machine-learning models. Further case studies in real-world industry scenarios, such as electric harbour craft, will validate the system's practicality and provide insights into optimizing operations under different conflicting constraints. We will also explore deploying MSODSS beyond Singapore's maritime context to other regions or ocean-going vessels, as well as other application scenarios such as optimization of maintenance operations for a fleet of ships. This work highlights the potential of MSODSS to transform ship operations, contributing to more sustainable and efficient maritime practices. By continuing to refine and expand the system, we aim to address the evolving challenges of the maritime industry and support the transition towards greener and more efficient ship operations.

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Biographies

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Dr Chin Soon Chong is currently a Research Fellow with the Singapore Institute of Technology (SIT). He graduated from the City University, UK with a BSc (Electrical and Electronic) in 1990, from Nanyang Technological University with a MEng (Mechanical) and a PhD (Electrical and Electronic). He has over 20 years of research and industrial experience in simulation, scheduling and optimisation as applied in the domain areas of container port, factory and warehouse, semiconductor manufacturing, MRO inventory optimisation. He specialises in simulation-based scheduling and cost optimisation using meta-heuristics including genetic algorithm, bee colony, tabu search and simulated annealing. He has obtained ACTA training and certification.

Changjun Yang is a Senior Professional Officer with the Singapore Institute of Technology (SIT). She received her Master in High Performance Computation for Engineered Systems (HPCES) from the National University of Singapore. She developed the optimization engine for a vehicle routing software, and she worked with MINDEF to develop the simulation model to plan the army's underground warehouse. Currently, she is teaching the simulation module in SIT.

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Dr. Wei Zhang is currently an Associate Professor with the Information and Communications Technology Cluster, Singapore Institute of Technology (SIT). Before joining SIT, he was a Scientist at the Agency for Science, Technology, and Research (A*STAR), Singapore. From 2015 to 2017, he was a Research Fellow at NTU, Singapore. Dr. Zhang received the Ph.D. degree in computer science from the School of Computer Science and Engineering, Nanyang Technological University (NTU), Singapore, in 2015. Dr. Zhang serves as the Programme Leader of the Bachelor of Science with Honours in Computing Science programme. He also serves as an Associate Editor for the IEEE Internet of Things Journal (IoT-J) as well as the Area Chair, Track Chair, Review Committee Member, and TPC members of the top conferences such as IJCAI, GLOBECOM, and ICME. His research interests lie in utilizing artificial intelligence (AI) for industrial applications, especially smart grid and smart buildings, towards improved user experience and enhanced sustainability.