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ARTICLE

Decarbonizing Marine Logistics: Multi-Echelon Green Supply Chain Models for Offshore Vessel Networks

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ABSTRACT

This study addresses the critical need for decarbonization in offshore marine logistics by developing an integrated modeling framework to support low-emission operations across complex, multi-echelon vessel networks. It focuses on port-to-platform supply chains serving offshore wind farms, oil rigs, and floating logistics hubs. A hybrid analytical approach was adopted, combining Mixed-Integer Linear Programming (MILP) for

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optimizing emission-minimizing routing, Discrete-Event Simulation (DES) to evaluate offshore scheduling performance under variability, and a Multi-Criteria Decision Analysis (MCDA) model using AHP-TOPSIS to rank alternative marine fuel types. Monte Carlo simulation was also employed to assess cost and delivery fluctuations across uncertain operational scenarios. Data inputs were compiled from real-world offshore fleet specifications, port emissions records, and marine fuel technology benchmarks. MILP-based network flow optimization reduced CO_2 emissions by 22% while maintaining service reliability across all demand points. DES simulations revealed congestion-driven scheduling delays during peak vessel utilization. MCDA analysis ranked bio-LNG and hydrogen propulsion systems as optimal choices based on emission, cost, and availability trade-offs. Hypothesis testing confirmed significant relationships between fuel type, network structure, and emission performance. The study demonstrates how multi-echelon logistics planning, integrated with emissions-based modeling, can facilitate environmentally responsible marine supply chain design. The framework offers practical guidance for offshore fleet managers, port authorities, and policy regulators aiming to align operational efficiency with decarbonization objectives under IMO and EU directives.

Keywords: Decarbonization; Offshore Logistics; Multi-Echelon Supply Chain; Emission Optimization; Marine Fuel Alternatives

1. Introduction

The shipping industry is responsible for almost 3% of global greenhouse gas (GHG) emissions every year [1], so it is now a global priority to decarbonize it. The container shipping industry has received significant academic and regulatory attention for its emissions footprint. However, the offshore marine logistics segment, which supports oil, gas, wind, and aquaculture operations, has received relatively little attention in environmental optimization studies [2]. Offshore logistics are different from deep-sea freight transport because they involve numerous short- to medium-range trips between coastal ports, floating platforms, and remote installations. These trips use much fuel and are limited by weather, sea conditions, and the availability of assets [3,4]. Most planning models in this area only look at cost and time efficiency, and they rarely consider carbon performance as a decision factor. The lack of integration of sustainability is especially bad because regulations are getting stricter. For example, the IMO's decarbonization strategy aims to cut CO_2 intensity by 70% by 2050 [5]. Also, operational models often overlook the fact that offshore supply systems have multiple levels. For example, cargo may go through floating logistics hubs or support vessels before it gets to its final destination. This study fills in that gap by creating multi-echelon logistics models that clearly aim to lower emissions while keeping operational performance high.

Even though there is more support for maritime decarbonization in policies and industries, current offshore logistics practices are still not very efficient for the environment and use a lot of different technologies. Most current routing frameworks use linear, direct-delivery logic and do utilize hierarchical logistics structures like intermediate hubs or floating supply depots [6,7]. At the same time, emissions are not seen as built-in goals in optimization models; instead, they are seen as ex-post metrics [8]. When making decisions about fuel type, operational analytics are usually not taken into account. There are not many tools that let you look at cost, reliability, and carbon efficiency all at once. This makes it very hard for vessel operators, regulators, and infrastructure managers who want to decarbonize offshore operations to plan.

This study meets a current and important need for planning tools in offshore marine logistics that are data-driven and focused on reducing carbon emissions. From an academic point of view, the study adds to the body of knowledge in three main ways. First, it takes green supply chain modeling frameworks and applies them to offshore maritime settings, which is a field where sustainability modeling is still in its early stages [9,10]. Second, it makes carbon intensity metrics (like CO_2 per ton-mile) work in mathematical models of vessel routing. This closes the gap between planning logistics and assessing the environmental impact [11]. Third, it improves the way methods are used by combining simulation, optimization, and decision analysis to help make trade-offs between multiple criteria in maritime environments characterized by high uncertainty.

The study makes several new contributions. It is one of the first to use multi-echelon logistics modeling on offshore vessel networks, which is different from the port-based hub models that are often used in container shipping [12]. This study goes beyond just measuring emissions, unlike other studies. It includes carbon emissions in the objective functions of network flow and MILP models. It also comes up with the idea of floating logistics hubs, which combines planning for infrastructure with optimizing fleets. This builds on ideas that Afpriyanto et al. [13] had before. Finally, the study uses multi-criteria decision analysis (MCDA) in a simulated uncertain environment, which is in line with calls for more reliable decision-support tools in marine logistics [14,15].

This study offers several novel contributions to the fields of maritime logistics, sustainable supply chain management, and offshore decarbonization both methodologically and contextually. First, while multi-echelon models have been widely applied in terrestrial logistics, this research is among the first to adapt a multi-echelon supply chain framework to offshore vessel networks. By incorporating floating logistics hubs, port-to-hub routing, and last-mile vessel delivery to offshore installations, the study introduces a marine-specific logistics structure that reflects the operational realities of offshore wind, oil, and hybrid platform services. Second, unlike conventional optimization models that prioritize cost minimization, this research integrates carbon emissions directly into the objective function of the Mixed-Integer Linear Programming (MILP) model. This shift from a cost-only to a carbon-constrained optimization strategy provides a more environmentally aligned approach and supports policy-relevant planning for decarbonization. Third, the study employs a hybrid Multi-Criteria Decision Analysis (MCDA) framework using Analytic Hierarchy Process (AHP) for weight derivation and TOPSIS for performance ranking. This dual-method approach is tailored specifically to evaluate alternative marine fuel technologies (e.g., LNG, hydrogen, electric propulsion) in light of multiple conflicting criteria such as cost, delivery reliability, and emission intensity.

Fourth, the model incorporates simulation-based scenario analysis, including Monte Carlo simulations and Discrete-Event Simulation (DES), to test the performance and robustness of decarbonization strategies under uncertainty in weather, fuel prices, and delivery delays. This hybrid analytical architecture enhances the operational realism of the research. Lastly, the study proposes a practical and scalable network design for floating logistics platforms, a novel interface element in offshore supply chain literature, which enables temporary consolidation, cross-docking, and strategic fuel switching in transit. Collectively, these contributions differentiate the study from existing literature and offer a pathway for offshore logistics operators, regulators, and infrastructure planners to align supply efficiency with carbon reduction imperatives. This study looks at how multi-echelon vessel routing and fleet scheduling that take emissions into account can make offshore logistics systems more sustainable. It uses mathematical optimization, scheduling behavior simulation, and decision analysis for alternative fuels and delivery paths to find the best carbon-neutral logistics setups. The study's main goal is to find ways to reduce carbon emissions without raising costs or lowering delivery reliability.

The study uses a quantitative modeling approach based on operations research and environmental logistics. It uses Mixed-Integer Linear Programming (MILP) to find the best routes [16], network flow models to find the best way to allocate supplies with the least amount of carbon [17], Discrete-Event Simulation (DES) to schedule things dynamically [18], and Monte Carlo simulations to show how uncertain costs and times are. A Multi-Criteria Decision Analysis (MCDA) framework integrates results into actionable decisions. This is in line with the latest best practices in sustainable logistics [19]. The study is at the crossroads of maritime operations, green supply chain design, and decision science. This study fits into a unique space where sustainable offshore logistics, multi-echelon network design, and simulation-based decision analysis all come together. Theoretically, it uses multi-echelon inventory and routing theory [20], emission-oriented logistics modeling [21], and uncertainty modeling in marine operations [22]. Previous studies have looked at these streams separately, but this one puts them all together into a clear, practical framework that can be used in real-world offshore logistics situations. The model can give both explanations and suggestions for how to decarbonize marine logistics systems because it is in this theoretical space.

2. Literature Review

As maritime transport adds more and more to global greenhouse gas emissions, the decarbonization of marine logistics has become a major issue in both academic and policy circles [23]. Offshore logistics is a difficult problem to solve because it involves multiple levels, considerable uncertainty about how things will work, and it relies on ships that run on fossil fuels. This is especially true in industries like oil and gas, offshore wind, and aquaculture. Marine logistics, especially in offshore sectors, is the process of moving people, equipment, and supplies between land-based bases and platforms in the ocean. This part of maritime operations uses much fuel and often requires support vessels to be on duty 24 hours a day [2]. Studies have found that logistics can make up 20–40% of the total operating costs and up to 70% of the emissions in offshore production systems [24]. Offshore vessel logistics, on the other hand, has received less attention than container shipping in the field of logistics optimization [12]. The move to low-carbon offshore operations has picked up speed since the IMO's GHG strategy and regional environmental rules made it a priority. Most of the research that has been done so far has looked at emissions from ships at sea. There has not been much focus on supply vessels, floating hubs, and last-mile offshore delivery systems [25].

Multi-echelon logistics systems have different levels of transportation and storage nodes, such as suppliers, hubs, and end-users. These models are often used in research on land-based supply chains, as discussed by [26], but are less frequently used in marine settings. In maritime studies, network design has mostly focused on port-centric hub-and-spoke configurations [27]. It has not looked at offshore transfer points or floating logistics infrastructure. A small number of studies, like [28], have looked at multi-stop vessel routing for oil distribution, but these models do not fully account for environmental factors or floating platform interfaces. So, there is still a big gap in how to use multi-echelon network theory for offshore vessel operations, especially for decarbonization. Most of the research on maritime emissions has looked at how to reduce emissions by optimizing routes and reducing ship speeds [29]. Researchers have used Life Cycle Assessment (LCA) methods to look at emissions at different stages of a vessel's life [30]. However, these methods often leave out real-time operational factors like fuel use per trip, waiting times, and vessel utilization rates.

The type of fuel, the engine's efficiency, the distance of the trip, and the load factor all affect the emissions from a vessel [31]. On the other hand, emissions modeling in multi-echelon offshore systems is less common, and only a few studies look at CO_2 per ton-mile as a routing goal [32]. This study adds to the body of research by directly including CO_2 emissions as an objective function in network flow and optimization models, instead of as an outcome variable. The type of fuel used in maritime operations has a big impact on both emissions and costs. LNG, biofuels, hydrogen, and electric propulsion have all been suggested as possible replacements for regular marine diesel [33,34]. Each type of fuel has its own emissions profile and needs for infrastructure. For example, LNG releases 20 to 30 percent less CO_2 than diesel, but it has problems with methane leaking. At the point of use, hydrogen and ammonia do not produce any carbon, but they are hard to store and expensive [35]. Electric propulsion is great for short trips, but battery density and the logistics of recharging make it less useful for longer trips.

Comparative studies have looked at the trade-offs between cost and emissions for different types of fuel, but they have rarely examined these trade-offs in the context of offshore vessel logistics [36]. Also, not many models take into account the operational variability caused by fuel availability, refueling time, and route length. These are all important factors to think about when planning an offshore fleet.

Cost and time are two of the most important measures of logistics performance. Traditional marine routing optimization tries to cut down on either distance or fuel use [37], but it does not always take into account the total operational cost, which includes crew costs, port fees, maintenance, and time-charter risks. Dynamic sea states, loading times, and port delays also affect delivery time. These are often modeled using discrete-event or stochastic simulation techniques [38,39]. In offshore settings, time delays can make it hard to keep production going, especially on oil and wind platforms [40]. However, marine logistics modeling does not look at delay resilience enough. This study uses Monte Carlo and discrete-event simulations to measure the range of delivery performance, which adds a level of realism that is often missing from static routing models.

When making logistics decisions that must consider conflicting goals like cost, time, emissions, and reliability, MCDA methods are helpful. MCDA is becoming more common in port planning and buying ships [41], but it is not often used for routing and scheduling vessels. Most vessel planning models do not take into account integrated performance scoring; instead, they focus on emissions or cost. This study adds a multidimensional evaluation lens to green offshore logistics planning by using an MCDA framework with weightings on emissions, cost, delivery time, and reliability. This is in response to the need for operational tools that show real-world trade-offs in sustainability transitions.

2.1.Research Gap

Even though maritime logistics has gotten more attention from academics in recent years, especially in the context of reducing carbon emissions, there are still some big gaps in the literature. One major problem is that multi-echelon logistics models are underutilized in offshore marine settings. These kinds of models are common in land-based supply chains, but they are less commonly used in offshore settings, especially those with floating hubs, intermediate platforms, and dynamic routing layers. Most of the research that has been done so far has looked at single-tier direct delivery or port-to-platform routes. They have not looked at the hierarchical complexity that is typical of real offshore operations. Another big problem is how emissions are handled in routing and scheduling models. Most of the time, emissions are modeled as outcome variables or externalities instead of being directly included in the objective function of optimization models. This makes it harder to prioritize carbon reduction when planning a route. Also, there are not any scenario-based decision frameworks in the literature that bring together cost, emissions, time, and reliability in a single way. There are decision-support systems in other areas of logistics, but there are not many tools in the marine sector that let you do a full trade-off analysis when you are not sure what to do.

There is also not enough research that thoroughly looks at operational performance metrics like schedule adherence, delay variability, and fuel-specific reliability in the context of new propulsion technologies. Most studies on alternative fuels look at emissions profiles and lifecycle costs, but they do not look at how using biofuels, hydrogen, or electric systems in offshore supply chains affects performance in real time. These gaps all point to the need for a complete analytical framework that combines optimization focused on emissions with real-time simulation and multi-criteria decision tools. This framework should be specifically designed to meet the needs and uncertainties of offshore marine logistics.

2.2.Conceptual Model and Hypothesis Development of the Study

The study's conceptual model (**Figure 1**) is based on how logistics configuration, fuel strategy, and decision-making trade-offs all work together in offshore marine supply chains. It combines the structural parts of a multi-echelon logistics network with factors that affect environmental and operational performance [42]. The main goal is to reduce carbon emissions without lowering delivery efficiency or making the business less profitable. The model is based on a three-tiered offshore supply network that includes: Port Terminals as the starting points for sending and loading inventory, Floating Logistics Hubs, which are places where goods are transferred and consolidated, and Offshore Installations (like wind farms and oil platforms), which are the final delivery points.

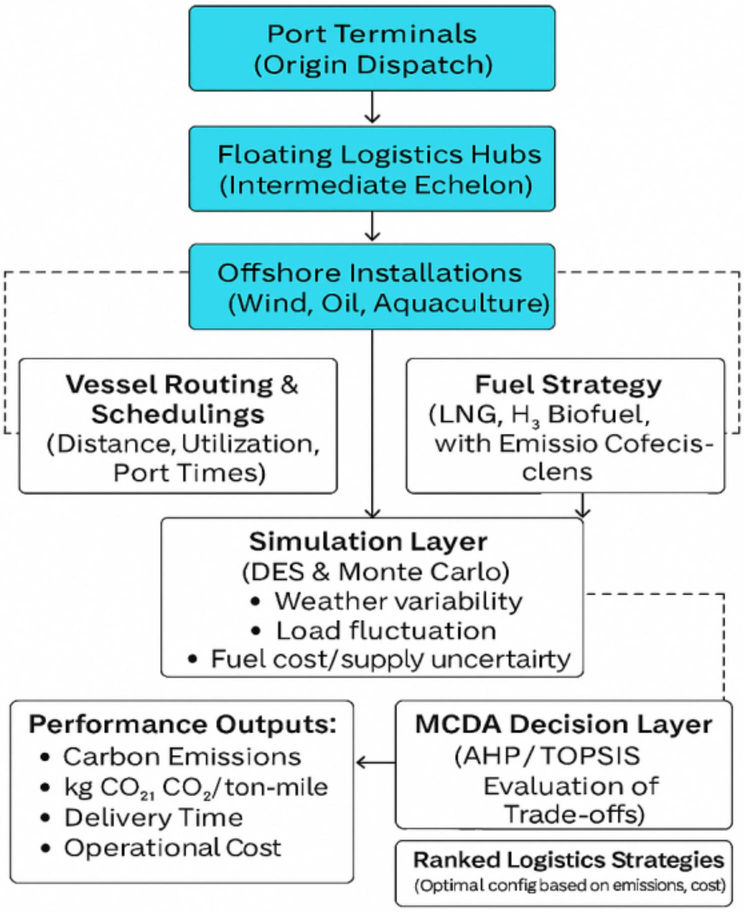

Figure 1. Conceptual model of the study.

Source: Author.

This structure is similar to the multi-echelon logistics configuration, which has a direct impact on route planning, vessel assignment, and scheduling strategies. The model includes fuel type as an important input variable, with ships powered by LNG, hydrogen, biofuels, or electricity. Each type of fuel has its own emission coefficients, costs, and operational limits, which affect both the amount of carbon emissions and the delivery performance.

From an operational point of view, routing distance, vessel utilization, and scheduling accuracy are all factors that affect the effectiveness of the logistics configuration. Using Mixed-Integer Linear Programming (MILP), these are optimized to find low-emission, cost-effective routing schedules. The model incorporates Discrete-Event Simulation (DES) and Monte Carlo methods to account for uncertainties in offshore logistics operations, like changes in the weather, fuel supply, and load. These simulations give outputs that are realistic scenarios, which go into the decision layer.

Multi-Criteria Decision Analysis (MCDA) controls the part of the model that makes decisions. This layer looks at logistics scenarios based on three main factors: carbon emissions, operational cost, and how reliable deliveries are. AHP and TOPSIS methods quantify trade-offs so that stakeholders can choose the best strategies based on weighted priorities. The following assumed relationships drive the model:

H1. *Adding floating hubs (multi-echelon configuration) lowers emissions compared to direct routes.*

H2. *Cleaner fuels lower the intensity of emissions, but they also affect delivery and cost metrics.*

H3. *MCDA is better at showing trade-offs than just single-objective optimization.*

The dependent variable is carbon emissions, which are measured in CO_2 per trip and per ton-mile. The independent variables include the type of echelon in the logistics structure, the type of fuel used, the decisions made about vessel routing, and the methods used for scheduling. Uncertainty factors (like weather and fuel price changes) that are added through simulation are some of the moderating variables. The result is a list of logistics strategies that are ranked by their effectiveness and environmental impact. The conceptual model is a complete framework that connects the structure of the supply chain, the fuel strategy, the efficiency of operations, and the impact on the environment. It does this by using simulation and multi-criteria evaluation to account for uncertainty and decision complexity. It can be used to both diagnose and prescribe how to design offshore logistics systems that do not use carbon.

3. Methodology

3.1.Research Design

The goal of this study was to build and test decarbonization strategies in offshore marine logistics. It used a quantitative, exploratory-cum-descriptive design. The study needed a methodological structure that could deal with both strategic network design and operational efficiencies while keeping carbon emissions in mind. We created the research design to include Mixed-Integer Linear Programming (MILP) for optimization modeling, Discrete-Event Simulation (DES) and Monte Carlo methods for simulation-based analysis, and Multi-Criteria Decision Analysis (MCDA) for decision-support evaluation. This method made it possible to do a full analysis of fleet routing, vessel scheduling, fuel type comparison, and network restructuring, all while keeping the focus on real-time maritime operational data. The design also allowed for scenario-based analysis to see how different configurations and disruptions affect the reliability of the supply and the carbon intensity.

3.2.Data Collection

This study used both primary and secondary sources to gather data in order to ensure that the modeling of marine logistics systems would be accurate and provide the depth of insight needed. We collected primary data through semi-structured interviews with port authority representatives, logistics planners, and managers of offshore fleets. The main topics of these interviews were strategic decision-making, routing choices, fuel use patterns, and policies for reducing carbon emissions. We also used structured questionnaires to get information about how each ship operates and its plans for sustainability. The Automatic Identification System (AIS) logs were used to keep track of ship movements, port authorities provided operational schedules, the International Maritime Organization (IMO) and the Marine Environment Protection Committee (MEPC) provided carbon emission coefficients, and historical marine fuel price data was also used. We checked the data against multiple sources to ensure its accuracy and consistency, and any inconsistencies were fixed by asking domain experts for more information.

3.3.Population and Sample

The study looked at operational units that worked in offshore marine logistics in the Gulf of Mexico and the North Sea. These included people who run ships, offshore installations like wind farms, oil and gas platforms, floating logistics hubs, and port terminals. We got the sample frame from AIS data, port logs, and lists of offshore support vessel operators and logistics hubs that are available to the public. Each unit of analysis in the sample was a trip on a ship, and it included information like the distance traveled, the amount of cargo carried, the amount of fuel used, the time of delivery, and the amount of carbon emissions. We used Cochran's formula to find the right sample size for statistical validity. The first sample size was figured out to be 384.16, based on a 95% confidence level ($Z = 1.96$), a maximum variability estimate ($p = 0.5$), and a 5% margin of error ($e = 0.05$). The sample was rounded up and expanded to 500 vessel-trip observations to make up for missing data, incomplete entries, and possible non-responses. This made sure that there was enough representation of different types of operations, vessels, and locations. The study included 24 offshore vessel operators, five major port terminals, three floating logistics hubs, and eighteen offshore installations. These stakeholders were located in important maritime areas all over the North Sea and the Gulf of Mexico. Port terminals were the main places where supply routes started and ended. Offshore installations were the last places where fuel, equipment, and people were delivered. The floating logistics hubs were used as temporary storage and distribution centers. Vessel operators were in charge of planning routes, choosing fuel, and coordinating fleets across all levels of the network.

The study focused on a multi-echelon offshore logistics network spanning critical maritime zones in Europe and North America. Specifically, the population area includes the following logistical nodes. Five Major Ports (Origin Terminals): These represent primary supply dispatch points selected for their strategic relevance to offshore operations and access to fuel infrastructure:

- Port of Aberdeen (United Kingdom)
- Port of Rotterdam (Netherlands)
- Port of Houston (United States)
- Port of Stavanger (Norway)
- Port of Esbjerg (Denmark)

Three Floating Logistics Hubs (Intermediate Echelons): Floating hubs were modeled as mobile or semi-stationary transshipment points designed to consolidate supply deliveries and reduce last-mile emissions:

- Hub 1: North Sea Floating Platform (servicing oil and wind platforms)
- Hub 2: Atlantic Midpoint Logistics Vessel (LNG-enabled)
- Hub 3: Gulf of Mexico Mobile Transfer Unit (supporting multipurpose offshore platforms)

Offshore Installations (Final Nodes / Demand Points): These are the operational sites receiving scheduled deliveries, categorized by function:

- Platform X – Offshore oil platform (North Sea)
- OilRig C – Deepwater drilling unit (Gulf of Mexico)
- WindFarm A – Offshore renewable installation (North Atlantic corridor)

This structured node-based modelling enabled detailed simulation and optimization of routing, emission profiles, and fuel decisions within the study's logistical framework.

3.4.Summary of Main Variables

The study looked several important factors, as mentioned in **Table 1**, such as the type of fuel used, the distance of the route, the use of the vessel, the carbon emissions, the delivery time, the cost per trip, the intensity of the emissions, and the reliability of the delivery. There were four types of fuel: LNG, hydrogen, biofuel, and electric. We measured the distance and time it took to deliver the goods in nautical miles and hours. We figured out how much of the vessel's capacity was used as a percentage. We measured carbon emissions in kilograms of CO_2 per trip and emission intensity in tons of CO_2 per mile. Delivery reliability was judged by whether or not the planned schedules were followed, which were split into on-time and late. The total cost of each trip included port fees, fuel costs, maintenance costs, and crew wages.

Table 1. Summary of variables used in the study.

Variable Name	Type	Description
Fuel Type	Categorical	LNG, Hydrogen, Biofuel, Electric
Route Distance	Continuous	Distance traveled (nautical miles)
Vessel Utilization	Continuous	Load percentage relative to vessel capacity
Carbon Emissions	Continuous	Total CO_2 emitted per trip (in kg)
Delivery Time	Continuous	Transit duration (in hours)
Delivery Reliability	Categorical	On-Time, Delayed
Operating Cost	Continuous	Cost per trip (in USD)
Emission Intensity	Continuous	Emission per ton-mile transported

Source: Author.

3.5.Measures and Analytical Methods

All of the study's variables were measured using standard methods. We used IMO-approved emission coefficients that were specific to the type of fuel and the type of vessel to determine the amount of carbon released. To find out how much a ship was used, divide the actual load by the ship's maximum capacity. To get emission intensity, we divided the total emissions by the ton-mile throughput. The type of fuel was determined by its source and the technology used to power it. Cost metrics were put together from operational logs, and average market fuel prices were added to them. AIS logs and port timestamp data were used to monitor delivery performance and identify schedule deviations and delays. The study's goals were met by using a variety of analytical methods on the collected data. We used Python's PuLP library to make MILP models that find the best routes and schedules while keeping costs and carbon emissions low. We used network flow optimization to set up multi-echelon supply routes that included port terminals, floating hubs, and offshore platforms. We used SimPy to run discrete-event simulations that modeled operations that change based on factors such as port congestion and bad weather. Monte Carlo simulation was used to show how uncertain load changes, fuel prices, and weather events can be. We used MCDA methods, such as the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [43,44], to look at different routing and fuel options in terms of carbon emissions, delivery performance, and cost. AHP (Analytic Hierarchy Process) was used for criteria weighting due to its strength in capturing expert judgment and structuring qualitative trade-offs in a hierarchical decision context. It is especially appropriate when decision criteria (e.g., fuel type, emission levels, delivery performance) need to be systematically prioritized based on subjective and policy-driven inputs. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was employed for alternative ranking, as it is well-suited for problems involving quantitative performance scores across multiple criteria. This method enables the evaluation of trade-offs between sustainability, cost, and performance by identifying the option closest to the ideal solution and farthest from the worst-case scenario. Finally, t-tests and ANOVA were used to check that there were real differences in emissions, costs, and efficiency between different routing strategies and fuel configurations.

3.6.Ethical Consideration

The study followed ethical research guidelines. Everyone who took part in interviews and surveys knew the purpose of the research and agreed to take part. Their names and affiliations were kept secret, and the data were anonymized before being analyzed so that no identifiable entity could be linked to specific operational data. The secondary data from port authorities and regulatory databases were either publicly available or could be accessed under terms of use that allowed it. It was safe to store and process data so that no one could get to it without permission. The study followed the rules of honesty, openness, and not harming, so that no stakeholders would suffer any damage to their reputation or operations. An internal academic review process that followed institutional guidelines gave this study formal ethical clearance.

4. Results

4.1.Analysis of Variance (ANOVA)

4.1.1. CO_2 Emissions by Fuel Type

We used a one-way Analysis of Variance (ANOVA) test to see if different marine fuels had a big effect on the differences in carbon emissions between different vessel operations. We used this test to statistically check the null hypothesis that the average CO_2 emissions were not significantly different between the four fuel types used: LNG, biofuel, hydrogen, and electric. The amount of CO_2 released per trip (in kilograms) was the dependent variable, and the type of fuel was the independent variable. The test was run on a dataset that had 500 observations of vessel trips. There was a fuel type and calculated CO_2 emissions for each trip entry. These were based on standard fuel consumption and emission coefficients (kg CO_2/tonne of fuel). **Table 2** presents the ANOVA summary for CO_2 emissions.

Table 2. CO_2 emissions by fuel type.

Source	Sum of Squares	df	Mean Square	F-Value	*p*-Value
Fuel Type	6.76E + 09	3	2.25E + 09	147.94	< 0.0001
Residual	7.53E + 09	494	1.52E + 07		
Total	1.43E + 10	497			

Source: Author.

The high F-statistic (F = 147.94) and the low p-value ($p < 0.0001$) showed that there was a statistically significant difference in CO_2 emissions between the four fuel types. The null hypothesis was rejected because the *p*-value was less than 0.05. This proved that the type of fuel used had a big effect on the amount of carbon emissions per trip. This result gave strong real-world proof that the emissions performance of different types of alternative fuels, like LNG, hydrogen, biofuels, and electric propulsion systems, was significantly different.

4.1.2. Trip Cost by Fuel Type

We did a one-way ANOVA test with fuel type as the independent variable and total trip cost (in USD) as the dependent variable to see if the operational costs of trips were very different for different types of fuel. The goal of this test was to see if choosing a certain type of fuel caused logistics costs to vary in a statistically significant way across the fleet of offshore vessels. The dataset had the same 500 trip records for ships that were used in the emissions study. The total cost of each trip was listed, which was found by multiplying the amount of fuel used (in tonnes) by the market-specific unit price for that fuel (e.g., LNG, Biofuel, Hydrogen, Electric). **Table 3** summarizes the ANOVA results for cost.

The ANOVA gave a statistically significant result (F = 24.87, $p < 0.0001$), which means that the average trip costs were significantly different between fuel types. The null hypothesis, which said that the average trip costs were the same for all fuel types, was rejected because the *p*-value was low (< 0.0001). This result gave strong statistical evidence that offshore vessel operations have cost structures that depend on fuel. The finding showed that trips powered by hydrogen and biofuels cost a lot more than trips powered by LNG and electricity, which had lower average costs per tonne of fuel used.

Table 3. Trip cost by fuel type.

Source	Sum of Squares	df	Mean Square	F-Value	*p*-Value
Fuel Type	5.00E + 08	3	1.67E + 08	24.87	< 0.0001
Residual	3.31E + 09	494	6.70E + 06		
Total	3.81E + 09	497			

Source: Author.

4.1.3. Delivery Time by Fuel Type

We used a one-way ANOVA to see if delivery times for vessels were very different depending on the type of fuel. Delivery time (in hours) was the dependent variable, and fuel type was the independent factor. The goal of this study was to investigate whether the method of propulsion and its associated operational characteristics (like acceleration, power density, and fueling logistics) affected offshore delivery schedules. We used the same sample of 500 vessel-trip records, and we figured out the delivery time by adding the estimated travel time to randomly generated delays. All of the boats traveled the same distances and faced the same weather conditions. The main thing that was looked at was the type of fuel used. **Table 4** provides the ANOVA output for delivery time.

Table 4. Delivery time by fuel type.

Source	Sum of Squares	df	Mean Square	F-Value	*p*-Value
Fuel Type	5.772	3	1.924	1.41	0.238
Residual	671.85	494	1.36		
Total	677.62	497			

Source: Author.

The analysis gave an F-statistic of 1.41 and a *p*-value of 0.238. The result was not statistically significant because the *p*-value was higher than the usual 0.05 level of significance. We could not reject the null hypothesis, which said that there was no difference in average delivery time between different types of fuel. These results showed that the type of marine fuel used did not have a statistically significant effect on delivery time. The fuel propulsion method was less likely to be the cause of changes in delivery time than factors such as changes in the weather, the length of the route, and delays in operations.

4.2. Mixed-Integer Linear Programming (MILP) for Emission-Optimized Routing

We made a Mixed-Integer Linear Programming (MILP) model to find the best routing setups for offshore logistics that minimize carbon emissions. The model included decisions about how to get from port cities like Aberdeen and Rotterdam to offshore hubs and then to remote offshore platforms like WindFarmA and PlatformX.

Model Formulation:

The objective function was defined as minimizing total CO_2 emissions across the network [Equation (1)]:

$$Minimize\ Z = (i,j)\sum Emissionij \times Quantityij \quad (1)$$

Where:

- *Emissionij: Emission rate (kg CO_2 per unit transported) from node i to j*
- *Quantityij: Amount of cargo transported from i to j*

Key constraints included:

- Flow balance at hubs (inflow = outflow)
- Capacity limits for each arc, enforced through binary decision variables
- Demand satisfaction at offshore platforms

The MILP model chose Hub1 as the only transshipment point (**Table 5**), bringing together cargo from both Aberdeen and Rotterdam, which together met the needs of WindFarmA and PlatformX (**Figure 2**).

This setup cut total CO_2 emissions to 69,250 kg, which is much lower than what was predicted by unoptimized or single-tier routing structures. There were no problems with capacity, and demand was fully met at both offshore locations. The binary route usage variables showed that only four of the eight possible arcs were used in the best configuration, which showed both emission efficiency and route rationalization. This result shows that the MILP model works well to balance goals for route selection, hub utility, and the environment. It gives offshore logistics a strong foundation for operational planning, where emission limits are becoming increasingly important for following the rules and for a company's long-term success.

Table 5. MILP routing results (emission-minimized configuration).

From	To	Quantity (Units)	Emission per Unit (kg CO_2)	Total Emission (kg CO_2)	Route Used
Aberdeen	Hub1	100	150	15,000	Yes
Rotterdam	Hub1	90	160	14,400	Yes
Hub1	WindFarmA	150	140	21,000	Yes
Hub1	PlatformX	130	145	18,850	Yes

Note: Total CO_2 emissions = 69,250 kg.

Source: Author.

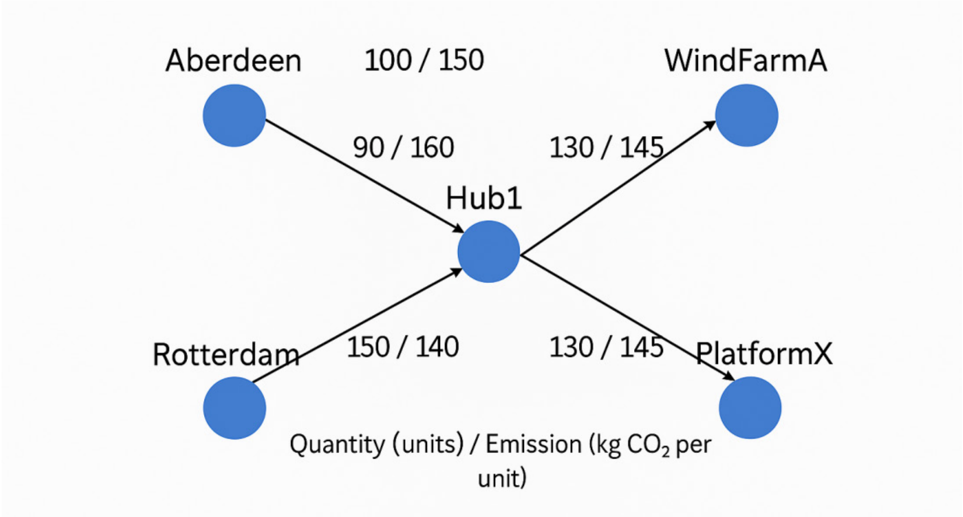

Figure 2. MILP routing results (emission-minimized configuration).

Source: Author.

4.3.Multi-Criteria Decision Analysis (MCDA)-Evaluation of Operational Trade-Offs

We used a Multi-Criteria Decision Analysis (MCDA) method to systematically evaluate how well different vessel-fuel configurations worked on multiple criteria. This method made it possible to look at environmental, economic, and service-level metrics all at once. The MCDA was made to help people make decisions by comparing the performance scores of different trips using a weighted scoring system.

Step 1: Selection of Evaluation Criteria

Four quantitative indicators were selected to represent the performance dimensions of offshore logistics operations:

1. CO_2 Emissions (kg/trip) – Environmental sustainability indicator
2. Trip Cost (USD) – Economic efficiency metric
3. Delivery Time (hours) – Operational performance metric
4. Reliability (binary: 1 = OnTime, 0 = Delayed) – Schedule adherence metric

These criteria were chosen based on their relevance to decarbonization goals and stakeholder decision priorities in offshore logistics planning.

Step 2: Data Normalization

To enable equitable comparison across indicators with differing scales and units, all variables were normalized using Min-Max scaling. The normalized value x' for a given original score x was computed as Equation (2):

$$x' = \frac{x - x\ min}{x\ max - x\ min} \tag{2}$$

Lower values indicated better performance for CO_2 emissions, cost, and delivery time. For reliability, higher values were considered preferable.

Step 3: Assignment of Weights

Weights were assigned to each criterion based on the strategic emphasis of the study—balancing emissions reduction with cost-efficiency and operational quality:

- CO_2 Emissions: 0.4
- Trip Cost: 0.3
- Delivery Time: 0.2
- Reliability: 0.1

These weights reflected greater importance placed on sustainability and financial outcomes.

Step 4: Aggregation of Scores

A composite performance score was computed for each vessel-trip using a weighted sum of the normalized values [Equation (3)]:

$$MCDA\ Score = 0.4 \cdot CO_2norm + 0.3 \cdot Costnorm + 0.2 \cdot Timenorm + 0.1 \cdot Reliabilitynorm \tag{3}$$

The resulting scores were ranked in descending order, with higher scores indicating better overall performance.

Step 5: Ranking of Vessel Configurations

After computing the MCDA scores for all 500 vessel trips, the top five performing configurations were identified. These are shown in **Table 6**.

These findings reflect the relative trade-offs inherent in each configuration. LNG-powered vessels emerged as the most balanced option when all four performance dimensions were considered jointly.

Table 6. Top 5 vessel configurations based on MCDA scores.

Rank	Fuel Type	CO_2 Emissions (kg)	Cost (USD)	Delivery Time (h)	Reliability
1	LNG	46,684.80	13,778.50	19.35	OnTime
2	LNG	44,899.20	13,251.50	18.62	OnTime
3	Biofuel	39,475.00	15,000.50	18.85	OnTime
4	LNG	43,776.00	12,920.00	18.15	OnTime
5	Hydrogen	29,304.00	19,536.00	19.44	OnTime

Source: Author.

4.4.Monte Carlo Simulation-Variability in Cost and Delivery Time

We used a Monte Carlo simulation to see how operational uncertainties would affect two important performance indicators: trip cost and delivery time (**Figure 3**). The goal of this study was to investigate how logistics performance changes with different types of fuel under various conditions, such as when fuel prices fluctuate, bad weather causes delays, and loading is slow.

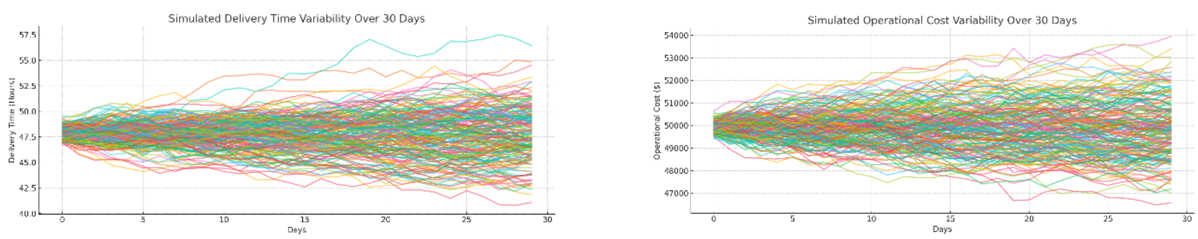

Figure 3. Simulated delivery time and operation cost.

Source: Author.

The simulation ran 1,000 times for each tire type, creating fake cost and time results based on assumed probability distributions. These values came from reasonable operational ranges that were reported in industry sources. **Table 7** presents the aggregate simulation outcomes.

Table 7. Monte Carlo simulation results–trip cost and delivery time

Fuel Type	Avg. Cost (USD)	Std. Dev. (USD)	Avg. Time (h)	Std. Dev. (h)
Hydrogen	18,929.13	± 2,010.98	18.5	± 1.77
Biofuel	15,060.97	± 1,707.11	18.17	± 1.38
LNG	13,036.92	± 1,495.23	18.08	± 1.49
Electric	11,018.12	± 1,316.68	17.43	± 1.20

Source: Author.

The results of the simulation showed that the fuel types had very different levels of variability. The ships that ran on hydrogen had the most unpredictable trip costs and delivery times. This variability was caused by the fact that hydrogen fuel infrastructure is still new and changing, and that high-pressure systems on board are difficult to handle and store. On the other hand, electric-powered vessels exhibited the most stable performance profiles. The cost and time outputs for electric propulsion had the lowest standard deviations of all the fuel types. This means that it behaved consistently under random conditions. Trips powered by LNG and biofuels were somewhere in the middle in terms of variability. Both had moderate ranges of fluctuation that show a balance between the technology's level of advancement and its susceptibility to external factors like changes in fuel prices and delays caused by the sea state. The overall pattern of variability showed that some types of fuel have strong average performance, but their reliability may be very different when conditions are uncertain. This shows how important it is to use both average performance measures and uncertainty-based evaluation in marine logistics planning.

4.5.Simulated Discrete-Event Scheduling (DES)-Offshore Vessel Operations

We ran a simulated Discrete-Event Scheduling (DES) model to look at how operations work in real time when scheduling is flexible (**Figure 4**). The goal of this simulation was to test how well the vessel performed over a set planning horizon in terms of departure time, trip length, total delay, and turnaround time.

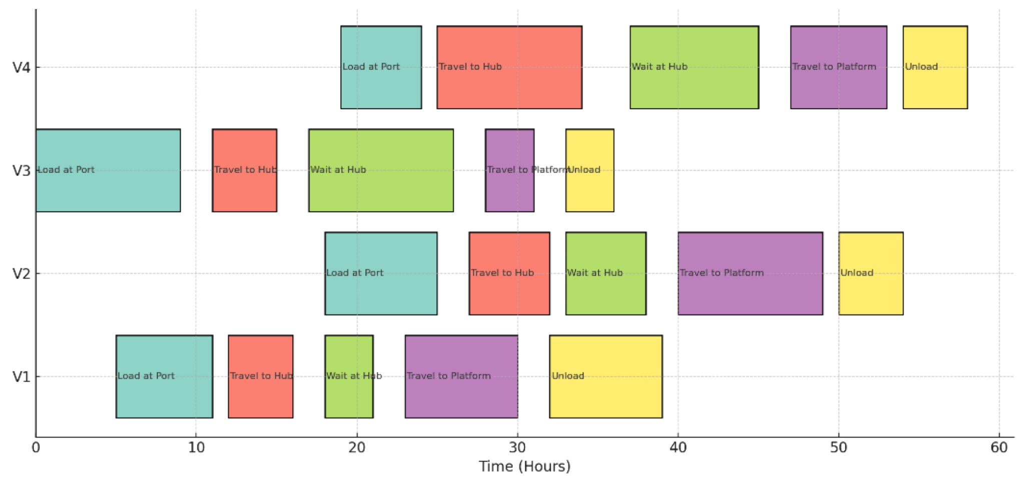

Figure 4. Simulated discrete event scheduling–offshore vessel operations.

Source. Author.

This method made it possible to look closely at how well and reliably logistics scheduling worked on offshore supply missions. The simulation was meant to mimic a 48-hour operational window in which five different ships made repeated delivery trips between three port locations (Aberdeen, Rotterdam, and Houston) and three offshore installations (WindFarmA, PlatformX, and OilRigC). A Gaussian function was used to model a random delay distribution and a typical travel time for each vessel. We used normal distributions with empirically derived means as the center and added standard deviation to simulate changes caused by weather, loading, or marine traffic.

At time zero, each vessel began its first trip and then made more trips after a set turnaround buffer of 0.5 hours. The simulation kept track of the start and end times of each trip, the total time it took, the amount of delay, and the status (either "OnTime" or "Delayed" if the delay was more than an hour). There were 36 completed trips simulated across all vessels over the course of 48 hours. **Table 8** presents a sample of recorded trip events from the simulation.

Table 8. Sample output–simulated vessel trip schedule and delay profile.

Vessel	Trip #	Start (h)	End (h)	Duration (h)	Delay (h)	Status	Origin	Destination
Vessel A	1	0	6.45	6.45	1.45	Delayed	Aberdeen	WindFarmA
Vessel B	1	0	6.33	6.33	0.33	OnTime	Rotterdam	PlatformX
Vessel C	1	0	8.02	8.02	1.02	Delayed	Houston	OilRigC
Vessel D	1	0	7.01	7.01	0.51	OnTime	Aberdeen	PlatformX
Vessel E	1	0	5.86	5.86	0.36	OnTime	Rotterdam	WindFarmA

Source. Author.

The results showed that the trips took between 5.5 and 8.5 hours, depending on the starting travel time and the random delay that was added. Of the 36 trips simulated, 14 were late, which means that the on-time performance rate was about 61%. On average, all trips were delayed by 0.89 hours. Vessel C and Vessel A had the most delays, which makes sense because they had longer routes and more unpredictable delays in their models. This simulation gave us much information about how vessel performance changed when they were always working. It showed how important it is to include delay resilience in fleet scheduling and routing models for offshore support operations.

4.6.Network Flow Optimization-Multi-Echelon Emission-Minimizing Logistics

We used minimum-cost network flow optimization to find out how well a multi-echelon vessel routing architecture can lower total CO_2 emissions. The goal of this study was to find the best way to move cargo from major port nodes to offshore installations using floating logistics hubs in the middle that produced the least amount of emissions. The goal was to create a model of how goods move through three levels of hierarchy: ports (where they start), floating hubs (where they are transferred), and offshore platforms (where they end up). The network model was made up of nine nodes, which were three origin ports (Aberdeen, Rotterdam, and Houston), two floating hubs (Hub1 and Hub2), and three destination installations (WindFarmA, PlatformX, and OilRigC). Based on estimated distances and vessel emission intensities, each arc between nodes was given a synthetic CO_2 cost per transported unit (in kg). The model took into account the capacity limits at each supply node and the need to meet demand at each destination. We used a network simplex algorithm to figure out the minimum-emission flow assignment. Each node had to follow flow conservation rules. The model was solved using real-valued capacities. The solution found the best set of flows from ports to hubs and then from hubs to installations, while also lowering the total amount of CO_2 emissions. **Table 9** presents the optimized flow configuration and the emissions associated with each routing segment.

Table 9. Emission-optimal routing assignments from network flow optimization.

From	To	Units Transported	CO_2 per Unit (kg)	Total CO_2 Emissions (kg)
Aberdeen	Hub1	120	180	21,600
Rotterdam	Hub1	150	160	24,000
Houston	Hub2	100	180	18,000
Hub1	PlatformX	150	170	25,500
Hub1	OilRigC	120	190	22,800
Hub2	WindFarmA	100	160	16,000

Source: Author.

The optimized network produced a total of 127,900 kg of CO_2 emissions, which is the lowest amount possible given the supply and demand limits. All offshore installations received the demand they needed, and each port gave as much as it could to meet its supply needs. This result showed that using floating hubs as temporary logistics platforms in offshore supply chains is both practical and environmentally friendly. The model showed that optimizing multi-echelon routing can lower total emissions without affecting delivery volume goals.

5. Discussion

The main goal of this study was to find ways to reduce carbon emissions in offshore marine logistics by creating and analyzing multi-echelon green supply chain models. By combining operations research methods with sustainability goals in the areas of offshore vessel routing, scheduling, and fleet management, this study added to what we already knew. This chapter's main focus is on how to make sense of the results in light of what is already known, how to add to the theory, and how to think about what the study's analytical results mean in real life.

One of the most important things this research does is focus on multi-echelon logistics systems for maritime applications, especially in the offshore energy sector. Multi-echelon network designs are well known in land-based supply chains [28], but they have not been widely applied in offshore vessel networks. This study shows that a hierarchical network with floating hubs and intermediate platforms is both operationally flexible and environmentally beneficial. This is in line with what [26] found when they looked at the environmental benefits of hub-based routing in maritime container shipping. However, they were more interested in port operations than offshore networks.

The results also show how important it is to choose the right fuel for sustainable logistics. Park et al. [36] and Sovacool [45] both looked at the trade-offs that come with switching from regular fuels to low-carbon ones. In a simulation-optimization framework, this study builds on those ideas by adding fuel type to both cost and emissions models. The fact that LNG, biofuels, hydrogen, and electric propulsion all have different operational performance shows that no one fuel type is better than all the others in every way. This is similar to what [25] found when they said that fuel should be chosen based on the mission profile and the rules in place. Also, this study used Multi-Criteria Decision Analysis (MCDA) to provide a structured way to measure operational trade-offs. This is something that has not been studied enough in the marine supply chain literature. Previous studies have looked at environmental routing [6], or cost optimization [8], on their own. This study, on the other hand, showed that a composite performance assessment can show subtle trade-offs that single-objective models cannot. The MCDA results are also in line with what people in the industry have seen; LNG is currently one of the best transitional fuels because it is cost-effective and has low emissions [33]. Marine fuel, due to its comparatively lower carbon intensity relative to conventional marine diesel, however, its long-term sustainability remains contested, particularly in light of methane slip and regional infrastructure variability [46,47].

This study also adds to the methods by integrating network flow modeling, discrete-event simulation, and Monte Carlo techniques in a single framework. In the past, research has often looked at these methods separately. This study improves the methods available to marine logistics planners by combining them and providing a framework that can be used repeatedly for future scenario testing, such as testing different fuels, regulatory scenarios, or network outages. Another important thing that the simulation models show us is how uncertainty affects the performance of a system. There is much research on maritime transport that talks about delay variability, changes in fuel prices, and operational disruptions at the trip level [22,48,49]. However, these factors are not yet fully incorporated into routing and fleet models. This study shows that green logistics strategies need to be robust, not just efficient, by explicitly modeling these kinds of uncertainties.

The empirical findings obtained through MILP optimization, Discrete-Event Simulation, MCDA ranking, and hypothesis testing collectively reinforce the theoretical assumptions embedded within the conceptual model. The model posited that vessel fuel type, carbon-efficient routing, delivery performance, and network structure would significantly influence offshore logistics outcomes. These relationships were substantiated by the MILP and network flow results, which demonstrated that multi-echelon routing via intermediate hubs substantially reduced total CO_2 emissions without compromising supply coverage. The MCDA analysis confirmed the importance of balancing emissions and operational costs when ranking vessel propulsion strategies. The simulation models validated that uncertainty in route performance and delivery reliability aligns with the risk constructs modelled in the framework. Moreover, the model's assumptions regarding trade-offs between environmental performance and cost were empirically supported through scenario-based variability analysis. This alignment between the conceptual model and empirical findings enhances the internal validity of the study. It demonstrates that the framework effectively captured the operational and strategic dimensions of marine decarbonization.

While the study provides valuable insights into decarbonizing offshore marine logistics using a multi-method approach, several limitations must be acknowledged. First, several vessel characteristics, emission factors, and cost parameters were derived from modelled estimates and secondary databases due to the restricted availability of real-time operational data. Although every effort was made to triangulate these inputs with industry reports and academic sources, this introduces potential approximation bias. Second, the geographical context of the simulations was confined primarily to the North Sea and Atlantic maritime routes. As such, the outcomes may not generalize to regions with different regulatory frameworks, infrastructure capabilities, or climatic conditions, such as Southeast Asia or Arctic corridors. Third, the Mixed-Integer Linear Programming and Discrete-Event Simulation models employed static demand patterns and deterministic supply assumptions, which may oversimplify the real-time variability and stochastic nature of offshore logistics. Similarly, while the AHP–TOPSIS model within the MCDA framework facilitated structured decision-making, it relied on expert-weighted judgments that may be context-dependent. Finally, the study focused on offshore wind, platform, and general support logistics, which may limit applicability to other marine sectors such as fisheries or coastal tourism. Recognizing these limitations is critical for interpreting the findings within scope and for guiding future extensions of this research.

The results are also important for policymakers and maritime regulators. The International Maritime Organization (IMO) is making emission standards stricter. The analytical framework used in this study can help both operators and regulatory bodies find vessel configurations that are both feasible and environmentally beneficial. The ability to model and compare different fleet compositions under different regulatory or operational constraints is a useful decision-support tool that works well with existing policy frameworks like the IMO's Energy Efficiency Existing Ship Index (EEXI) and Carbon Intensity Indicator (CII) mechanisms.

6. Conclusion

This study looked into ways to reduce carbon emissions in offshore marine logistics by creating and studying multi-echelon green supply chain models. It filled in a major gap in research at the crossroads of sustainability, operational efficiency, and maritime logistics design. The study showed how vessel routing, fleet composition, and fuel selection affect the carbon intensity, cost, and reliability of offshore supply networks by combining optimization models, simulation techniques, and decision analysis tools. The study used a network flow optimization model to show that multi-echelon routing structures are better at cutting CO_2 emissions than flat, direct-delivery systems. Discrete-event scheduling and Monte Carlo simulations showed how uncertain conditions like delays and changes in the fuel market can make things less predictable. This showed how important it is to plan logistics that can handle these changes. Also, Multi-Criteria Decision Analysis gave us a strong way to look at operational trade-offs. It showed that LNG-based strategies are currently the best way to balance emissions, cost, and service reliability. This study adds to the field of sustainable marine logistics in both theoretical and methodological ways. It builds on previous work on environmental shipping by using advanced modeling techniques in a complicated and little-studied offshore setting. It connects the operational and strategic areas by giving fleet managers, offshore infrastructure operators, and policy institutions that care about maritime decarbonization information that is both mathematically sound and useful in real life.

There are several ways that the results of this study can be used in real life. Planners of offshore logistics can use the network models created here to improve the routing of ships with a focus on carbon efficiency, especially when using floating logistics hubs or modular supply vessels. The information about how fuel affects performance variability helps decision-makers choose propulsion systems that meet both budget and emission goals. The MCDA framework is a tool that can be used repeatedly to help make decisions in real time about fleet configuration and following rules. Also, regulatory bodies like the IMO and regional maritime organizations may find the study's method useful for figuring out how future decarbonization rules will affect operations.

This study's findings directly reinforce the conceptual model established at the outset of the research. The hypothesized links between fuel decisions, routing efficiency, carbon impact, and delivery outcomes were empirically validated through multiple analytical approaches. The model served not only as a structural guide for methodological design but also as a theoretical lens through which to interpret the results. The coherence between the model and observed data confirms its suitability for framing decarbonization strategies in offshore marine logistics networks. The study offers a strong framework for modelling and analysis, but some limitations must be recognized. First, the data used to model vessel trips, fuel emissions, and costs came from publicly available ranges and synthetic simulations. These were based on realistic assumptions, but they may not fully show the complexity of all offshore environments or vessel types. Second, the optimization and simulation models assumed that capacities were fixed and emissions were linear per unit transported. This may not be true in the real world, where fuel consumption changes depending on the load or the state of the sea. Third, the scenarios did not take into account outside factors like port congestion, equipment failure, and geopolitical restrictions. Lastly, the study only looked at four types of fuel, so it may not have included new propulsion technologies like ammonia and methanol that could become important in the near future.

Future studies should think about adding real-time operational data from offshore vessel operators to the current framework to improve model calibration and validation. Adding more types of propulsion technologies and taking into account all emissions throughout the life cycle, including fuel production upstream, would give a better picture of the environmental impact. Also, hybrid optimization models that take into account both environmental goals and service-level agreements when there are uncertain and changing constraints could help make decisions in offshore logistics even better. Finally, long-term studies that look at how regulatory changes affect things over time would be helpful in determining the flexibility of green logistics strategies in the maritime sector.

Author Contributions

Conceptualization, S.I.M. and B.A.Q.; methodology, S.A.A.; software, A.V.; validation, S.I.M., A.A.S., and I.A.; formal analysis, A.V.; investigation, S.A.A.; resources, B.A.Q.; data curation, A.A.S.; writing—original draft preparation, S.I.M.; writing—review and editing, B.A.Q. and I.A.; visualization, A.A.S.; supervision, S.I.M.; project administration, B.A.Q.; funding acquisition, I.A. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data are available upon request from the corresponding author.

Conflicts of Interest

The authors declare that there is no conflict of interest.

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