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Mathematical Optimization of Carbon Storage and Transport Problem for Carbon Capture, Use, and Storage Chain

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Abstract: The greenhouse effect caused by carbon dioxide (CO_2) emissions has forced the shipping industry to actively reduce the amount of CO_2 emissions emitted directly into the atmosphere over the past few years. Carbon capture, utilization, and storage (CCUS) is one of the main technological methods for reducing the amount of CO_2 emissions emitted directly into the atmosphere. CO_2 transport, i.e., shipping CO_2 to permanent or temporary storage sites, is a critical intermediate step in the CCUS chain. This study formulates a mixed-integer programming model for a carbon storage and transport problem in the CCUS chain to optimally determine ship allocation, ship departure scheduling, and CO_2 storage and transport. Taking advantage of the structure of the problem, we transform the mixed-integer programming model into a simpler model that can be computed efficiently. To evaluate the performance of the simpler model, numerous computational experiments are conducted. The results show that all small-scale instances (each with 10 power plants) and medium-scale instances (each with 30 power plants) can be solved optimality by Gurobi within 14.33 s. For large-scale instances with 60 and 65 power plants, feasible solutions with average gap values of 0.06% and 6.93% can be obtained by Gurobi within one hour, which indicates that the proposed methodology can be efficiently applied to practical problems. In addition, important parameters, including the unit fuel price, the time-charter cost, and the ship sailing speed, are examined in sensitivity analyses to investigate the impacts of these factors on operations decisions. In summary, a lower fuel price, a lower charter cost, or a higher ship sailing speed can increase the profit of the CCUS chain.

Keywords: ship allocation and scheduling optimization; maritime decarbonization; carbon capture; utilization; storage

MSC: 90-10

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1. Introduction

As climate change continues to worsen, the need to establish a low-carbon society has become the consensus of the international community [1–6]. Globally, more and more countries and regions are taking action to issue corresponding policies for low-carbon development goals and implement various emission reduction measures. For example, the United States rejoined the Paris Agreement, committing to reduce greenhouse gas emissions by 50–52% from 2005 levels by 2030 [7]; the European Union issued the European Green Deal policy aimed at achieving carbon neutrality by 2050 [8]; China announced new goals related to carbon dioxide (CO_2) emissions which aim to reduce carbon intensity by more than 65% by 2030 from 2005 levels [9]. At the same time, an increasing number of companies are adopting low-carbon development strategies, such as reducing energy consumption, using renewable energy sources, and changing production methods, with the aim of lowering carbon emissions and achieving sustainable development [10–12].

As part of the effort to enable the realization of a low-carbon society, many countries, such as Norway [13], the Netherlands [14], and Sweden [15], are exploring CO_2 ship transportation, which is a part of the carbon capture, use, and storage (CCUS) chain. Specifically, CCUS technology refers to capturing CO_2 from emission sources, such as factories and power plants, and then utilizing or storing it, thereby reducing the amount of CO_2 emissions emitted directly into the atmosphere [16–18]. The aim of CCUS is to transport CO_2 emitted by emission sources to storage and reuse locations in a safe, cost-effective, and efficient manner. Although CCUS technology can reduce CO_2 emissions, its cost is high [19], which implies that technical innovation and operations management are needed to reduce costs. Fortunately, according to the estimates of the National Petroleum Council (NPC), by 2030, the cost of CCUS is expected to drop by 30–50% [20]. In terms of operations management, CO_2 ship transportation is an important intermediate step of CCUS because the CO_2 shipping cost is high. After capturing CO_2, if it cannot be transported to the storage and reuse locations safely and efficiently, the goal of CCUS cannot be achieved. Therefore, finding a way to optimize CO_2 operations management is crucial.

The deployment of CCUS technology has rapidly expanded over the past decade, with global CCUS contributing to the handling of 44 metric tons of CO_2 emissions in 2021 [18]. Moreover, global CCUS uptake needs to grow 120-fold by 2050, to at least 4.2 gigatons per annum of CO_2 captured, to achieve the net-zero CO_2 emissions target [21]. Faced with such a large volume of transport, shipping companies inevitably need to investigate cost control. Therefore, how to address the problem of carbon storage and transport optimization for the CCUS chain is crucial for the operations management of shipping companies.

Motivated by this real-world challenge in the development of the low-carbon society, this study focuses on a carbon storage and transport optimization problem for CCUS and proposes a mixed-integer programming (MIP) model to optimally determine ship allocation, ship departure scheduling, and CO_2 storage and transport planning. In order to accelerate the solving process, a proposition is found based on model characteristics and is used to transform the previous model into a simpler model, which can be solved quickly by Gurobi. Computational results show the proposed methodology meets the solution requirements for practical instances. Moreover, three important parameters, including the fuel price, the time-charter cost, and the ship sailing speed, are examined to seek useful managerial insights for CCUS companies.

The remainder of this study is organized as follows. Section 2 reviews and discusses related papers. Section 3 formulates an MIP model and converts the model to a simpler one based on a proposition. Computational experiments are conducted in Section 4. Section 5 summarizes the conclusions.

2. Literature Review

With the increase in greenhouse gas emissions, the need for efficient and effective solutions to deal with CO_2 has become a crucial issue. CCUS technology is currently the primary means of centralized CO_2 treatment. This complex system is capable of preventing CO_2 emissions from entering the atmosphere at a technical level by sequestering the captured CO_2 and making full use of CO_2 as chemical feedstock and injection fluid. Readers who are interested in comprehensive overviews of the CCUS technology problem can refer to [22–24]. To improve overall efficiency and reduce costs, numerous studies, such as [25–28], investigate how to optimize the CCUS chain from a techno-economic perspective. The existing literature, such as [24], finds that implementing an efficient transport network for the CCUS chain is important because transportation is a key component of this process. Pipeline transport and maritime transport are the two main methods used to transport CO_2. According to related studies [28–31], the choice between the above two methods depends on several factors, such as distance and transport volume. In general, when transporting a small amount of CO_2 over long distances, which conforms to the setting of this study, maritime transport is more cost-effective. Since this study focuses on maritime transport optimization in the CCUS chain, this study reviews two streams of related works: advantages, and operations management of CO_2 maritime transport.

Research on CO_2 shipping began in the early 2000s. CO_2 maritime transport has unique advantages, which are summarized in Table 1. For example, according to [24], when pipeline technology is impractical, ships with low sunk costs can be used as an alternative. This is because pipeline transport requires high capital expenditures, especially in areas where the geology is unsuitable for pipeline construction. However, when transporting a small amount of CO_2 over long distances, the impact of potential sunk costs related to shipping is significantly reduced, making maritime transport a more cost-effective option. Moreover, according to [32], maritime transport is cost-effective in areas where CO_2 sources are decentralized. In addition, according to [33], the CO_2 shipping system involves multiple regional and even national stakeholders. Due to the flexibility of CO_2 maritime transport, the CO_2 shipping system can be adjusted to better satisfy the need of each region over time. Furthermore, CO_2 maritime transport may enable industrial clusters that release a large amount of CO_2 emissions, especially those lacking sufficient spaces for CO_2 storage, to achieve industrial decarbonization and comply with relevant emission standards. Similarly, for regions with CO_2 storage capacity exceeding the required amount, carbon management and storage services can be offered to other countries by CO_2 maritime transport.

Table 1. Summary of the advantages of shipping CO_2.

Literature	Advantages of Shipping CO_2
[24]	Ships with low sunk costs can replace pipelines for CO_2 transport, especially in areas where the geology is unsuitable for pipeline construction.
[32]	Shipping CO_2 is cost-effective in areas where CO_2 sources are decentralized.
[33]	Shipping CO_2 is flexible to satisfy the need of each region.

Few studies explore the operations management of CO_2 maritime transport. Ref. [34] indicates that CO_2 maritime transport plays a key role in commercialized CO_2 capture and storage projects, as well as demonstration projects. Ref. [35] claims that it is more financially efficient for ships to carry CO_2 throughout the voyage than to sail with ballast on the return voyage. Additionally, according to [36], transporting CO_2 by ship is similar to the way liquified natural gas (LNG) is transported by LNG carriers, which is a widely studied process. According to [37], ships carrying CO_2 follow the same international standards and regulations as ships carrying LNG. Ref. [38] studies a short-term LNG delivery problem and proposes an MIP model with the aim of maximizing the net profit to determine cargo selection, speed optimization, and fleet deployment. Ref. [39] studies a capacitated vehicle routing problem to optimize distribution routes of small-scale LNG carriers and conducts an economic analysis on five mobile power plants located in remote areas of western Indonesia. Furthermore, Ref. [40] considers a scenario in which dual-purpose ships can carry CO_2 on the return trip after transporting LNG to the destination. These papers and their research contents are summarized in Table 2. Unlike the LNG transport problem, which only considers delivery targets, the CCUS problem allows for two CO_2 processing approaches, i.e., CO_2 transported by ship and CO_2 directly emitted into the atmosphere, which means that both the amount of CO_2 transported by ship and the amount of CO_2 emitted into the atmosphere need to be determined in this study. This feature complicates the original CO_2 maritime transport problem, making the CCUS problem require a new methodology to deal with the unique feature.

Table 2. Related works on shipping CO_2 and LNG.

Literature	CO_2 Capture	CO_2 Transport	CO_2 Storage	LNG Transport
[34]		√	√	
[35]		√	√	
[36]	√		√	
[38]				√
[39]				√
[40]		√		√

In summary, existing studies related to the CCUS problem focus on techno-economic analysis and planning. Although few studies optimize the management of CO_2 maritime transport in the CCUS chain, they do not provide a quantitative methodology for the ship allocation and scheduling problem in the CCUS chain. To fill this research gap, this study proposes an MIP model to optimize the allocation and scheduling of CO_2 maritime transport, as well as the storage and transport planning of CO_2.

3. Problem Description and Model Formulation

CO_2 maritime transport is an intermediate step in the CCUS chain and can be achieved by ship. Therefore, this study focuses on a carbon storage and transport problem to optimally determine ship allocation, ship departure scheduling, and CO_2 storage and transport planning. This section first introduces the problem background in Section 3.1 and formulates an MIP model in Section 3.2.

3.1. Problem Background

We consider a network consisting of a set N of power plants indexed by i and a storage location indexed by 0. These power plants generate electricity by burning fossil fuels during a planning horizon containing a set T of time periods, emitting tremendous CO_2. A time period in the planning horizon is defined as a day and indexed by t. Let w_{it} represent the amount of CO_2 produced by power plant i in day t. CO_2 produced by all power plants can be treated in two ways. First, CO_2 can be captured and transported to the storage location, i.e., through the CCUS chain. Second, CO_2 can be emitted directly into the atmosphere. Specifically, CO_2 produced by all power plants can be transported to the storage location (i.e., location 0) by ships of a set of K ship types. As shown in Figure 1, CO_2 produced does not have to be immediately transported to the storage location, which means that CO_2 produced by power plant i can be temporarily stored in the power plant whose storage capacity is denoted by q_i and then transported to the storage location, i.e., 0. Furthermore, there are benefits to transporting CO_2 to the storage location rather than emitting CO_2 directly into the atmosphere. Thus, let the benefit of transporting a ton of CO_2 from power plants to the storage location compared to emitting a ton of CO_2 into the atmosphere be denoted by r.

Let a_k, b, c_k, and m_k represent the fuel consumption per unit distance traveled by ships of type k, unit fuel price, time-charter cost of renting a ship of type k for $|T|$ days, and the CO_2 tank capacity of ships of type k, respectively. Let l_i, and v_k represent the total length of a trip from power plant i ($i \in N$) to the storage location 0 and then back to the power plant, and the sailing speed of ships of type k, respectively. Therefore, the sailing time (day), represented by n_{ik}, of ships of type k, $k \in K$, to complete a trip from power plant i ($i \in N$) to the storage location 0 and then back to the power plant can be calculated by $n_{ik} = \lceil l_i / 24v_k \rceil$.

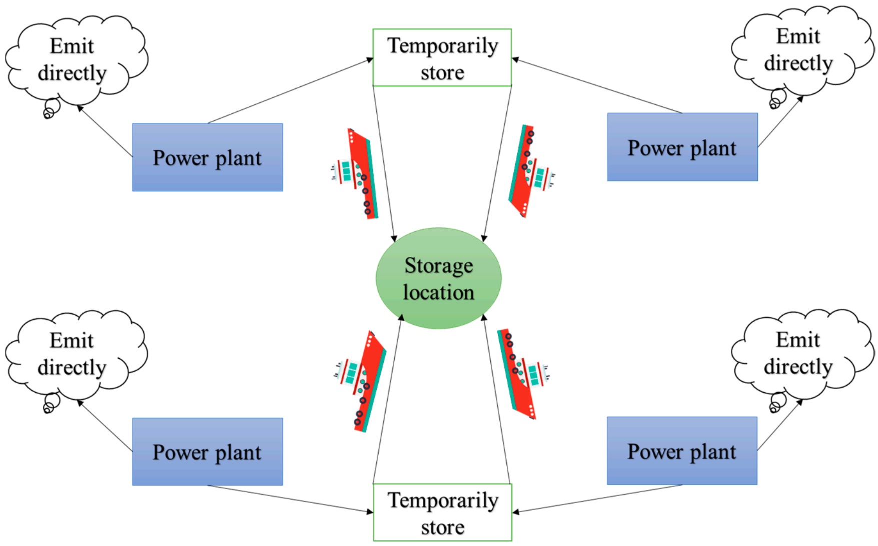

Figure 1. Schematic diagram of CO_2 maritime transport.

Suppose it is day 0 now, all power plants have no CO_2 temporarily stored, and all ships are at the allocated power plant. All power plants are assumed to produce CO_2 and emit CO_2 via the above mentioned two ways. Furthermore, CO_2 loading and unloading time is assumed to be 0. Therefore, all scheduled ships depart from the power plant at the beginning of each day. An MIP model is formulated in the next section to maximize the benefit of CCUS minus the associated costs. Specifically, the CCUS benefit can be calculated by $\sum_{i\in N}\sum_{t\in T}\gamma_{it}r$, where γ_{it} is defined as the amount of CO_2 transported by ships departing from power plant i to the storage location in day t. In terms of the associated costs, two types of costs are considered. The first type of cost is the time-charter cost which can be calculated by $\sum_{i\in N}\sum_{k\in K}c_k\alpha_{ik}$, where α_{ik} is defined as the number of charter-in ships of type k, $k\in K$, allocated to power plant i, $i\in N$. The second type of cost is the fuel cost which can be calculated by $\sum_{i\in N}\sum_{k\in K}\sum_{t\in T}\varepsilon_{ikt}ba_kl_i$, where ε_{ikt} represents the number of ships of type k, $k\in K$, departing from power plant i, $i\in N$, at the beginning of day t, $t\in T$.

For constraints, several factors need to be considered. Specifically, CO_2 flow calculation at each power plant on each day is first introduced. Let δ_{it} represent the amount of CO_2 stored at power plant i at the end of the day t, $t\in T\cup\{0\}$, and $\delta_{i0}=0$ because all power plants have no CO_2 temporarily stored on day 0. Therefore, δ_{it} at power plant i, $i\in N$, at the end of the day t, $t\in T$, can be calculated by $\delta_{i,t-1}+w_{it}-\beta_{it}-\gamma_{it}$, where β_{it} is denoted as the amount of CO_2 emitted by power plant i to the atmosphere at the beginning of day t. Moreover, the amount of CO_2 stored at power plant i at the end of the day t cannot exceed the CO_2 storage capacity of power plant i, i.e., q_i. For ship chartering constraints, we assume that once a ship is chartered in a power plant, it needs to be chartered in that power plant for the entire planning period, and each ship can serve only one power plant during the entire planning period. Moreover, the total number of charter-in ships of type k allocated to all power plants cannot be greater than the maximum number of ships of type k that can be chartered in, represented by d_k. Finally, the total number of ships sailing along the trip from power plant i to the storage location and back to the power plant each day cannot be greater than the total number of charter-in ships allocated to power plant i. For CO_2 transport constraints, the total amount of CO_2 transported from each power plant on each day cannot be greater than the total capacity of all ships departing on that day.

In summary, this study investigates a carbon storage and transport problem for the CCUS chain to optimally determine ship allocation, ship departure scheduling, and CO_2 storage and transport planning. From the perspective of the power plants' profitability, this study develops an MIP model to maximize the benefit of the CCUS chain minus the associated costs, including the time-charter cost and fuel cost.

3.2. Model Formulation

Based on the above analysis of the problem, we formulate an MIP model in this section. This study assumes that CO_2 loading and unloading time is 0. Before formulating the mathematical model for this problem, we list the notation used in this paper as follows.

Indices and sets:

N set of all power plants, $i \in N$.
0 index of the storage location.
K set of all ship types, $k \in K$.
T set of all days in the planning horizon, $t \in T$.
Z_+ set of all non-negative integers.

Parameters

a_k fuel consumption per unit distance traveled by ships of type k (ton/n mile).
b unit fuel price (USD/ton).
c_k time-charter cost of renting a ship of type k for $|T|$ days (USD).
d_k maximum number of ships of type k that can be chartered in.
l_i total length of a trip from power plant i ($i \in N$) to the storage location 0 and then back to the power plant (n mile).
m_k CO_2 tank capacity of ships of type k (ton).
v_k sailing speed of ships of type k ($k \in K$) (n mile/hour).
q_i CO_2 storage capacity of power plant i (ton).
r benefit of transporting a ton of CO_2 from power plants to the storage location (i.e., 0) compared to emitting a ton of CO_2 into the atmosphere (USD/ton).
n_{ik} sailing time of ships of type k to complete a trip from power plant i ($i \in N$) to the storage location 0 and then back to the power plant, which is related to l_i and v_k (day).
w_{it} amount of CO_2 produced by power plant i in day t (ton).

Variables

α_{ik} integer, the number of charter-in ships of type k, $k \in K$, allocated to power plant i, $i \in N$.
ε_{ikt} integer, the number of ships of type k, $k \in K$, departing from power plant i, $i \in N$, at the beginning of day t, $t \in T$.
β_{it} continuous, the amount of CO_2 emitted by power plant i to the atmosphere at the beginning of day t.
γ_{it} continuous, the amount of CO_2 transported by ships departing from power plant i to the storage location in day t.
δ_{it} continuous, the amount of CO_2 stored at power plant i at the end of the day t, $t \in T \cup \{0\}$, where, by convention, δ_{i0}:=0 .

Mathematical model

Based on the above definition of parameters and variables, an MIP model is formulated as follows.

[M1]
$$\text{Max} \sum_{i \in N} \sum_{t \in T} \gamma_{it} r - \sum_{i \in N} \sum_{k \in K} c_k \alpha_{ik} - \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} \varepsilon_{ikt} b a_k l_i \quad (1)$$
subject to:
$$\sum_{i \in N} \alpha_{ik} \leq d_k \quad \forall k \in K \quad (2)$$
$$\sum_{t' \in T(t-n_{ik}<t' \leq t)} \varepsilon_{ikt'} \leq \alpha_{ik} \quad \forall i \in N, k \in K, t \in T/\{1,2,\cdots,n_{ik}-1\} \quad (3)$$
$$\sum_{t'=1}^{t} \varepsilon_{ikt'} \leq \alpha_{ik} \quad \forall i \in N, k \in K, t \in \{1,2,\cdots,n_{ik}-1\} \quad (4)$$
$$\delta_{it} = \delta_{i,t-1} + w_{it} - \beta_{it} - \gamma_{it} \quad \forall i \in N, t \in T \quad (5)$$
$$\delta_{i0} = 0 \quad \forall i \in N \quad (6)$$
$$\gamma_{it} \leq \sum_{k \in K} m_k \varepsilon_{ikt} \quad \forall i \in N, t \in T \quad (7)$$
$$\delta_{it} \leq q_i \quad \forall i \in N, \forall t \in T \cup \{0\} \quad (8)$$
$$\alpha_{ik} \in Z_+ \quad \forall i \in N, k \in K \quad (9)$$
$$\varepsilon_{ikt} \in Z_+ \quad \forall i \in N, k \in K, t \in T \quad (10)$$
$$\beta_{it}, \gamma_{it} \geq 0 \quad \forall i \in N, t \in T \quad (11)$$
$$\delta_{it} \geq 0 \quad \forall i \in N, t \in T \cup \{0\} \quad (12)$$

Objective (1) maximizes the benefit of the CCUS chain minus the time-charter cost and fuel cost. Constraints (2) guarantee that the total number of charter-in ships of type k allocated to all power plants cannot exceed the maximum number of ships of type k that can be chartered in. Constraints (3)–(4) ensure that the total number of ships sailing along the trip from power plant i to the storage location and back to the power plant on each day cannot exceed the total number of charter-in ships allocated to power plant i. Constraints (5) are the CO_2 flow constraints at each power plant on each day. Constraints (6) guarantee that all power plants have no CO_2 temporarily stored on day 0. Constraints (7) ensure that the total amount of CO_2 transported from each power plant on each day cannot be greater than the total capacity of all allocated ships departing on that day. Constraints (8) guarantee that the amount of CO_2 stored at power plant i on each day cannot exceed the CO_2 storage capacity of power plant i. Constraints (9)–(12) state the ranges of the defined decision variables.

Proposition 1. *The following model [M2] is equivalent to the previous model [M1].*

[M2]	*Objective* (1)
subject to:	*Constraints* (2), (3), (5)–(12).

Proof. For Constraints (3), when the value of t is equal to n_{ik}, we have $\varepsilon_{ik1} + \varepsilon_{ik2} + \cdots + \varepsilon_{ik(n_{ik}-1)} + \varepsilon_{ikn_{ik}} \leq \alpha_{ik}, \forall i \in N, k \in K$. All Constraints (4) are summarized as follows:

$$\begin{gathered} \varepsilon_{ik1} \leq \alpha_{ik}, \forall i \in N, k \in K \\ \varepsilon_{ik1} + \varepsilon_{ik2} \leq \alpha_{ik}, \forall i \in N, k \in K \\ \vdots \\ \varepsilon_{ik1} + \varepsilon_{ik2} + \cdots + \varepsilon_{ik(n_{ik}-1)} \leq \alpha_{ik}, \forall i \in N, k \in K. \end{gathered}$$

Since $\varepsilon_{ikt} \in Z_+$, and for any $i \in N$, any $k \in K$, and any $t \in T$, we have $\varepsilon_{ik1} \leq \varepsilon_{ik1} + \varepsilon_{ik2} \leq \cdots \leq \varepsilon_{ik1} + \varepsilon_{ik2} + \cdots + \varepsilon_{ik(n_{ik}-1)} \leq \varepsilon_{ik1} + \varepsilon_{ik2} + \cdots + \varepsilon_{ik(n_{ik}-1)} + \varepsilon_{ikn_{ik}}$. If constraints (3) are satisfied, constraints (4) must be satisfied. Therefore, constraints (4) can be removed, and model [M2] is equivalent to the previous model [M1]. □

4. Computational Experiments

Numerous computational experiments are conducted on a PC (14 cores of CPUs, 2.5 GHz, Memory 64 GB) to assess the proposed model. The mathematical model proposed in this study is implemented in Gurobi 10.0.0 (Anaconda, Python). This section first summarizes the value setting of the parameters in Section 4.1, reports experimental results in Section 4.2, and carries out sensitivity analyses to seek managerial insights in Section 4.3.

4.1. Experimental Setting

The total duration of the planning horizon is set to one week, namely 7 days. A 300 by 300 (n mile) simulation environment is developed to simulate a network area. All power plants and a storage location are uniformly distributed over the network area. The total length of a trip from a power plant to the storage location and then back to the power plant (l_i) is the Euclidean distance. Then, values of n_{ik} can be calculated by $n_{ik} = \lceil l_i / 24 v_k \rceil$. Since a 25-year-old coal-fired 425 megawatt (MW) power plant in Australia currently produces about two million tons per annum (Mtpa) of CO_2 [41], the average value of the amount of CO_2 produced by each power plant on each day is set to 6040 tons (a normal distribution with a standard deviation of 200). [41] indicates that the value of the CCUS benefit is described as the carbon social cost or the real value of the damage caused to society by a ton of CO_2 emitted to the atmosphere. According to a technical guidance document issued by an interagency working group on the social cost of greenhouse gases (SC-GHG) reconvened by the Biden administration [42], the new interim value for the social cost of CO_2 is 51 USD per metric ton of CO_2 at a 3% discount rate. Therefore, r is set to 46.3 USD/ton. Three types of ships are available in the computational experiments, and the value settings of relevant parameters, namely v_k, a_k, m_k, c_k, and d_k, are summarized in Table 3. The setting of parameters v_k, a_k, m_k, and c_k is the same as the setting in [43]. Since the average price of very low sulfur fuel oil (VLSFO) in 20 global ports from the beginning of September 2021 to the end of August 2022 is 717 USD/ton [44], the unit fuel price (b) is set to 717 USD/ton. The average value of the CO_2 storage capacity of each power plant is set to 10,000 tons (a normal distribution with a standard deviation of 100).

Table 3. Setting summary of five parameters.

Ship Type	1	2	3
Ship size	small	medium	large
v_k (n mile/hour)	13	14	16
a_k (ton/n mile)	0.0641	0.0893	0.1172
m_k (ton)	9400	11,000	15,000
c_k (USD)	46,900	54,600	74,550
d_k	20	20	20

4.2. Experimental Results

Model [M2] is directly solved by Gurobi. We conduct 10 sets of small-scale instances (each with 10 power plants), 10 sets of medium-scale instances (each with 30 power plants), and 10 sets of large-scale instances (five with 60 power plants and five with 65 power plants). The solution time limit for each computational instance is one hour.

Table 4 records the computing time and objective values of the solutions obtained by Gurobi. To enhance readability and better highlight the results, we keep objective values as integers and round the computing time to two decimal places in the following tables. The "Gap" value is expressed as a percentage, representing the relative difference between the current best solution and the current best dual bound. As shown in Table 4, the number of power plants has a significant impact on the difficulty of solving the proposed MIP model. A small increase in the number of power plants may greatly affect the solution quality of the model. All small- and medium-scale instances can be solved to optimality by Gurobi within 14.33 s. Specifically, for small-scale instances with 10 power plants, the problems can be solved quickly (within 3.56 s). The solution time of medium-scale instances with 30 power plants varies. The fastest-solving and slowest-solving medium-scale instances can be solved to optimality within 6.27 s and 14.33 s, respectively. For large-scale instances with 60 and 65 power plants, feasible solutions with average gap values of 0.06% and 6.93% can be obtained by Gurobi within one hour, which is by far enough to meet the solution requirements of practical examples. Hence, the solution efficiency of the proposed mathematical model for small-, medium-, and large-scale computational instances is verified.

Table 4. Comparison of Different Scale Instances.

Scale Type	Number of Power Plants	No.	Objective Value (USD)	Time (s)	Gap (%)
Small	10	1	18,488,070	3.51	–
		2	18,685,312	0.61	–
		3	18,718,096	0.50	–
		4	18,932,070	0.48	–
		5	18,680,620	0.58	–
		6	18,610,402	3.56	–
		7	18,609,668	0.64	–
		8	18,637,785	0.53	–
		9	18,896,223	0.62	–
		10	18,737,553	0.53	–

Table 4. *Cont.*

Scale Type	Number of Power Plants	No.	Objective Value (USD)	Time (s)	Gap (%)
Medium	30	1	56,453,748	6.27	–
		2	56,661,330	6.62	–
		3	56,404,237	7.23	–
		4	56,200,587	6.83	–
		5	55,932,114	11.45	–
		6	56,180,227	14.33	–
		7	56,141,059	7.58	–
		8	55,905,737	11.47	–
		9	56,315,341	12.51	–
		10	56,223,681	9.03	–
Large	60	1	112,083,178	3600.50	0.04
		2	111,322,988	3605.51	0.08
		3	111,676,064	3603.92	0.05
		4	111,193,998	3605.55	0.05
		5	111,616,979	3605.57	0.07
	65	1	111,943,020	3600.73	7.03
		2	112,109,654	3603.69	6.85
		3	112,178,272	3604.25	6.94
		4	111,723,484	3606.13	6.98
		5	112,352,265	3603.52	6.83

Note: The en dash denotes an optimal solution is found within one hour.

4.3. Sensitivity Analyses

In the above computational experiments, some critical parameters, such as the unit fuel price (b), the time-charter cost of renting a ship k for $|T|$ days (c_k), and the ship sailing speed (v_k), are set fixed, even though they are not always the same in real life. As a result, we use the instance with 10 power plants (No.10) in Table 4 to conduct sensitivity analyses on these parameters to explore their impacts on operations decisions.

4.3.1. Impact of the Fuel Price

First, the impact of the fuel price on the allocation and scheduling of ships transporting CO_2 is investigated. In the experiments in Section 4.2, the unit fuel price (b) is set to 717 USD/ton. Since the highest and lowest prices of VLSFO in 20 global ports from the beginning of September 2021 to the end of August 2022 are 1021 USD/ton and 491 USD/ton, respectively [44], the unit fuel price (b) in this analysis varies from 450 to 1050. As shown in Table 5, the objective value decreases as the fuel price increases, which implies that a higher fuel price leads to a higher fuel cost, further leading to a lower profit for the CCUS chain. This is reasonable because the fuel cost is one of the main operating costs and is in line with the conclusions of [45].

Table 5. Impact of the fuel price on the profit of the CCUS chain.

b (USD/Ton)	Objective Value (USD)
450	18,864,030
550	18,816,661
650	18,769,291
750	18,721,921
850	18,674,552
950	18,627,182
1050	18,579,813

4.3.2. Impact of the Time-Charter Cost

Next, this study investigates the impact of the time-charter cost on the allocation and scheduling of ships transporting CO_2. In the experiments in Section 4.2, the time-charter costs of renting a ship k for $|T|$ days (c_k) are set to 46,900 USD, 54,600 USD, and 74,550 USD, corresponding to ship types 1, 2, and 3, respectively. Table 6 shows the objective value when the relative change of the charter cost (namely the current charter cost minus the original charter cost and then divided by the original charter cost) ranges between –60% and +60%, which is consistent with the setting in [43]. It can be concluded from Table 6 that the higher the time-charter cost, the lower the objective value, which is reasonable because the objective value is the revenue of the CCUS chain minus the time-charter cost and fuel cost, and a greater relative change in the charter cost leads to a higher time-charter cost, further leading to a lower objective value.

Table 6. Impact of the time-charter cost on the profit of the CCUS chain.

Relative Change of Charter Cost	Objective Value (USD)	Relative Change of Charter Cost	Objective Value (USD)
−60%	19,018,953	10%	18,690,653
−50%	18,972,053	20%	18,643,753
−40%	18,925,153	30%	18,596,853
−30%	18,878,253	40%	18,549,953
−20%	18,831,353	50%	18,503,053
−10%	18,784,453	60%	18,456,153

4.3.3. Impact of the Ship Sailing Speed

Finally, this study investigates the impact of ship sailing speed on the allocation and scheduling of ships transporting CO_2. In the experiments in Section 4.2, ship sailing speeds (v_k) of ship types 1, 2, and 3 are set to 13 n mile/hour, 14 n mile/hour, and 16 n mile/hour, respectively. Considering the variation of the ship sailing speed under different conditions in related studies [43,46], this study adopts eight different speed combinations of three ship types to carry out this sensitivity analysis. Relevant results are recorded in Table 7, which records sailing speeds of ship types 1, 2, and 3, represented by "v_1", "v_2", and "v_3", respectively. From Table 7, it can be seen that the objective value goes up with the increase in ship sailing speed, but when values of v_1, v_2, and v_3 exceed 10, 11, and 12, respectively, the objective value does not change. This is reasonable because the higher the ship sailing speed, the shorter the ship sailing time. Increasing the profit of the CCUS chain by transporting more CO_2 outweighs the increasing fuel cost, resulting in an increase in the objective value. As ship sailing speed increases to a certain level where the increased profit of the CCUS chain is in balance with the increased fuel costs, the objective value remains the same.

Table 7. Impact of the ship sailing speed on the profit of the CCUS chain.

No.	v_1 (n Mile/Hour)	v_2 (n Mile/Hour)	v_3 (n Mile/Hour)	Objective Value (USD)
1	6	7	8	18,549,953
2	8	9	10	18,724,714
3	10	11	12	18,737,553
4	12	14	15	18,737,553
5	14	16	17	18,737,553
6	16	18	19	18,737,553
7	18	20	21	18,737,553
8	20	22	23	18,737,553

4.4. Summary of Test Results and Managerial Insights

This study first conducts 10 sets of small-scale instances (each with 10 power plants), 10 sets of medium-scale instances (each with 30 power plants), and 10 sets of large-scale instances (five with 60 power plants and five with 65 power plants). The results show that the proposed model can be solved quickly by Gurobi, namely within 14.33 s for all small- and medium-scale instances. For large-scale instances with 60 and 65 plants, feasible solutions with average gap values of 0.06% and 6.93% can be obtained within one hour, which is by far enough to meet the solution requirements for practical examples. Then, this study conducts sensitivity analyses with three important parameters, including the fuel price, the time-charter cost, and the ship sailing speed, to obtain useful managerial insights for CCUS companies. Through our sensitivity analysis experiments, we find that the total profit decreases as the fuel price or the time-charter cost increase. Furthermore, the total profit increases with the increase in ship sailing speed, but when sailing speeds of ships of types 1, 2, and 3 exceed 10, 11, and 12, respectively, the total profit remains unchanged as the speeds increase.

5. Conclusions

The greenhouse effect with increasing CO_2 emissions is a major environmental problem for mankind. To address the greenhouse effect issue, CCUS technology is an important means of centralized CO_2 treatment. However, most of the existing studies focus on the techno-economic analysis and planning of CCUS. Although few studies explore how to optimize the management of CO_2 transport by ship in the CCUS chain, they lack quantitative approaches to the ship allocation and scheduling problems in the CCUS chain. To fill this research gap, this study first formulates an MIP model [M1] and transforms it to an equivalent model [M2] based on a proposed proposition to optimize ship allocation, ship departure scheduling, and CO_2 storage and transport planning in a carbon storage and transport problem for the CCUS chain.

Contributions of this paper are summarized in the following two aspects: first, the proposed model [M1] may help CCUS companies to optimally determine the number of charter-in ships allocated to each plant, the number of ships departing from power plants, the amount of CO_2 emitted to the atmosphere, the amount of CO_2 transported by ship, and the amount of CO_2 stored at power plants. Taking advantage of the structure of the problem, we transform the mixed-integer programming model [M1] into a simpler model [M2] that can be computed efficiently. The model [M2] can be solved quickly by Gurobi, which is by far enough to meet the solution requirements for practical examples. Second, sensitivity analyses with three important parameters, i.e., the fuel price, the time-charter cost, and the ship sailing speed, are conducted to obtain useful managerial insights for CCUS companies. In general, a lower fuel price, a lower charter cost, or a higher ship sailing speed can increase the profit of the CCUS chain.

However, this study has some potential extensions for the current methodology. First, a real case study with realistic settings could be conducted for more managerial insights. Second, the study does not take into account the uncertainty of the fuel price [47–51]. Considering the fuel price uncertainty may make the study more realistic as the fuel price fluctuates with time, refueling location, and other factors [52]. Third, this study assumes that ships sail at a constant speed. However, ship sailing speed has a significant impact on ship fuel consumption and thus influences the fuel cost [53], which may be considered in future studies. Finally, the applications of multi-purpose ships in CO_2 transport [35], big data [54–62], digitalization technologies [48,63,64], as well as blockchain in logistics [65–67], and green supply chain management [68–71] can be studied in the future.

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References

1. Carvalho, M.G.; Bonifacio, M.; Dechamps, P. Building a low carbon society. *Energy* **2011**, *36*, 1842–1847. [CrossRef]
2. Xiao, J.; Zhen, Z.; Tian, L.; Su, B.; Chen, H.; Zhu, A.X. Green behavior towards low-carbon society: Theory, measurement and action. *J. Clean. Prod.* **2021**, *278*, 123765. [CrossRef]
3. Gabrielli, P.; Campos, J.; Becattini, V.; Mazzotti, M.; Sansavini, G. Optimization and assessment of carbon capture, transport and storage supply chains for industrial sectors: The cost of resilience. *Int. J. Greenh. Gas Control* **2022**, *121*, 103797. [CrossRef]
4. Ogland-Hand, J.D.; Cohen, S.M.; Kammer, R.M.; Ellett, K.M.; Saar, M.O.; Bennett, J.A.; Middleton, R.S. The importance of modeling carbon dioxide transportation and geologic storage in energy system planning tools. *Front. Energy Res.* **2022**, *10*, 275. [CrossRef]
5. Chaudhari, U.; Bhadoriya, A.; Jani, M.Y.; Sarkar, B. A generalized payment policy for deteriorating items when demand depends on price, stock, and advertisement under carbon tax regulations. *Math. Comput. Simul.* **2023**, *207*, 556–574. [CrossRef]
6. Dey, B.K.; Datta, A.; Sarkar, B. Effectiveness of carbon policies and multi-period delay in payments in a global supply chain under remanufacturing consideration. *J. Clean. Prod.* **2023**, *402*, 136539. [CrossRef]
7. Fact Sheet: President Biden Sets 2030 Greenhouse Gas Pollution Reduction Target Aimed at Creating Good-Paying Union Jobs and Securing U.S. Leadership on Clean Energy Technologies. Available online: https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/ (accessed on 1 May 2023).
8. A European Green Deal: Striving to Be the First Climate-Neutral Continent. Available online: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en (accessed on 1 May 2023).
9. China's Xi Targets Steeper Cut in Carbon Intensity by 2030. Available online: https://www.reuters.com/world/china/chinas-xi-targets-steeper-cut-carbon-intensity-by-2030-2020-12-12/ (accessed on 1 May 2023).
10. Wu, B.; Liu, P.; Xu, X. An evolutionary analysis of low-carbon strategies based on the government–enterprise game in the complex network context. *J. Clean. Prod.* **2017**, *141*, 168–179. [CrossRef]
11. Zhang, S.; Liu, L.; Zhang, L.; Zhuang, Y.; Du, J. An optimization model for carbon capture utilization and storage supply chain: A case study in northeastern China. *Appl. Energy* **2018**, *231*, 194–206. [CrossRef]
12. Zhang, W.; Zhang, M.; Wu, S.; Liu, F. A complex path model for low-carbon sustainable development of enterprise based on system dynamics. *J. Clean. Prod.* **2021**, *321*, 128934. [CrossRef]
13. The Longship CCS Project. Available online: https://ccsnorway.com/the-project/ (accessed on 2 May 2023).
14. CO_2 Reduction through Storage under the North Sea. Available online: https://www.porthosco2.nl/en/ (accessed on 2 May 2023).
15. Karlsson, S.; Normann, F.; Odenberger, M.; Johnsson, F. Modeling the development of a carbon capture and transportation infrastructure for Swedish industry. *Int. J. Greenh. Gas Control* **2023**, *124*, 103840. [CrossRef]
16. Ostovari, H.; Müller, L.; Mayer, F.; Bardow, A. A climate-optimal supply chain for CO_2 capture, utilization, and storage by mineralization. *J. Clean. Prod.* **2022**, *360*, 131750. [CrossRef]
17. Ma, Z.; Chen, B.; Pawar, R.J. Phase-based design of CO_2 capture, transport, and storage infrastructure via SimCCS$^{3.0}$. *Sci. Rep.* **2023**, *13*, 6527. [CrossRef] [PubMed]
18. Carbon Capture, Utilisation and Storage. Available online: https://www.iea.org/fuels-and-technologies/carbon-capture-utilisation-and-storage (accessed on 3 May 2023).
19. Is Carbon Capture too Expensive? Available online: https://www.iea.org/commentaries/is-carbon-capture-too-expensive (accessed on 3 May 2023).
20. Carbon Capture, Use, and Storage (CCUS) Report. Available online: https://dualchallenge.npc.org/downloads.php (accessed on 3 May 2023).
21. Scaling the CCUS Industry to Achieve Net-Zero Emissions. Available online: https://www.mckinsey.com/industries/oil-and-gas/our-insights/scaling-the-ccus-industry-to-achieve-net-zero-emissions (accessed on 3 May 2023).
22. Rahman, F.A.; Aziz, M.M.A.; Saidur, R.; Bakar, W.A.W.A.; Hainin, M.; Putrajaya, R.; Hassan, N.A. Pollution to solution: Capture and sequestration of carbon dioxide (CO_2) and its utilization as a renewable energy source for a sustainable future. *Renew. Sustain. Energy Rev.* **2017**, *71*, 112–126. [CrossRef]
23. Tapia, J.F.D.; Lee, J.Y.; Ooi, R.E.H.; Foo, D.C.Y.; Tan, R.R. A review of optimization and decision-making models for the planning of CO_2 capture, utilization and storage (CCUS) systems. *Sustain. Prod. Consum.* **2018**, *13*, 1–15. [CrossRef]
24. Al Baroudi, H.; Awoyomi, A.; Patchigolla, K.; Jonnalagadda, K.; Anthony, E.J. A review of large-scale CO_2 shipping and marine emissions management for carbon capture, utilisation and storage. *Appl. Energy* **2021**, *287*, 116510. [CrossRef]
25. Middleton, R.S.; Keating, G.N.; Viswanathan, H.S.; Stauffer, P.H.; Pawar, R.J. Effects of geologic reservoir uncertainty on CO_2 transport and storage infrastructure. *Int. J. Greenh. Gas Control* **2012**, *8*, 132–142. [CrossRef]
26. Leung, D.Y.C.; Caramanna, G.; Maroto-Valer, M.M. An overview of current status of carbon dioxide capture and storage technologies. *Renew. Sustain. Energy Rev.* **2014**, *39*, 426–443. [CrossRef]

27. da Silva, F.T.F.; Carvalho, F.M.; Corrêa, J.L.G.; Merschmann, P.R.D.; Tagomori, I.S.; Szklo, A.; Schaeffer, R. CO_2 capture in ethanol distilleries in Brazil: Designing the optimum carbon transportation network by integrating hubs, pipelines and trucks. *Int. J. Greenh. Gas Control* **2018**, *71*, 168–183. [CrossRef]
28. Becattini, V.; Gabrielli, P.; Antonini, C.; Campos, J.; Acquilino, A.; Sansavini, G.; Mazzotti, M. Carbon dioxide capture, transport and storage supply chains: Optimal economic and environmental performance of infrastructure rollout. *Int. J. Greenh. Gas Control* **2022**, *117*, 103635. [CrossRef]
29. Weihs, G.A.F.; Kumar, K.; Wiley, D.E. Understanding the economic feasibility of ship transport of CO_2 within the CCS Chain. *Energy Procedia* **2014**, *63*, 2630–2637. [CrossRef]
30. Nogueira, T.; Rochedo, P.R.R.; Szklo, A. Evaluation of offshore CO_2 transport alternatives in Brazil. *Int. J. Greenh. Gas Control* **2022**, *116*, 103629. [CrossRef]
31. Weihs, G.A.F.; Ho, M.; Kambanis, J.; Wiley, D.E. Scoping study of the economics of CO_2 transport and storage options for steel manufacturing emissions in eastern Australia. *Int. J. Greenh. Gas Control* **2022**, *114*, 103592. [CrossRef]
32. Aspelund, A.; Mølnvik, M.J.; de Koeijer, G. Ship transport of CO_2: Technical solutions and analysis of costs, energy utilization, exergy efficiency and CO_2 emissions. *Chem. Eng. Res. Des.* **2006**, *84*, 847–855. [CrossRef]
33. Calvillo, C.; Race, J.; Chang, E.; Turner, K.; Katris, A. Characterisation of UK industrial clusters and techno-economic cost assessment for carbon dioxide transport and storage implementation. *Int. J. Greenh. Gas Control.* **2022**, *119*, 103695. [CrossRef]
34. Yoo, B.Y.; Choi, D.K.; Kim, H.J.; Moon, Y.S.; Na, H.S.; Lee, S.G. Development of CO_2 terminal and CO_2 carrier for future commercialized CCS market. *Int. J. Greenh. Gas Control* **2013**, *12*, 323–332. [CrossRef]
35. Gola, S.; Noussia, K. From CO_2 sources to sinks: Regulatory challenges for trans-boundary trade, shipment and storage. *Resour. Conserv. Recycl.* **2022**, *179*, 106039. [CrossRef]
36. Scott, V.; Gilfillan, S.; Markusson, N.; Chalmers, H.; Haszeldine, R.S. Last chance for carbon capture and storage. *Nat. Clim. Change* **2013**, *3*, 105–111. [CrossRef]
37. International Code for the Construction and Equipment of Ships Carrying Liquefied Gases in Bulk (IGC Code). Available online: http://www.imo.org/en/OurWork/Safety/Cargoes/CargoesInBulk/Pages/IGC-Code.aspx (accessed on 27 February 2022).
38. Msakni, M.K.; Haouari, M. Short-term planning of liquefied natural gas deliveries. *Transp. Res. Part C Emerg. Technol.* **2018**, *90*, 393–410. [CrossRef]
39. Budiyanto, M.A.; Riadi, A.; Buana, I.G.N.S.; Kurnia, G. Study on the LNG distribution to mobile power plants utilizing small-scale LNG carriers. *Heliyon* **2020**, *6*, e04538. [CrossRef]
40. Datta, A.; de Leon, R.; Krishnamoorti, R. Advancing carbon management through the global commoditization of CO_2: The case for dual-use LNG-CO_2 shipping. *Carbon Manag.* **2020**, *11*, 611–630. [CrossRef]
41. Hardisty, P.E.; Sivapalan, M.; Brooks, P. The environmental and economic sustainability of carbon capture and storage. *Int. J. Environ. Res. Public Health* **2011**, *8*, 1460–1477. [CrossRef]
42. Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide–Interim Estimates under Executive Order 13990. Available online: https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf (accessed on 20 September 2022).
43. Wen, M.; Pacino, D.; Kontovas, C.A.; Psaraftis, H.N. A multiple ship routing and speed optimization problem under time, cost and environmental objectives. *Transp. Res. Part D Transp. Environ.* **2017**, *52*, 303–321. [CrossRef]
44. World Bunker Prices. Available online: https://shipandbunker.com/prices/av/global/av-g20-global-20-ports-average (accessed on 19 September 2022).
45. Fagerholt, K.; Psaraftis, H.N. On two speed optimization problems for ships that sail in and out of emission control areas. *Transp. Res. Part D Transp. Environ.* **2015**, *39*, 56–64. [CrossRef]
46. Fuel Consumption by Containership Size and Speed. Available online: https://transportgeography.org/contents/chapter4/transportation-and-energy/fuel-consumption-containerships/ (accessed on 8 March 2023).
47. Qi, J.; Wang, S.; Psaraftis, H. Bi-level optimization model applications in managing air emissions from ships: A review. *Commun. Transp. Res.* **2021**, *1*, 100020. [CrossRef]
48. Wang, W.; Wu, Y. Is uncertainty always bad for the performance of transportation systems? *Commun. Transp. Res.* **2021**, *1*, 100021. [CrossRef]
49. Hassan, L.A.H.; Hewitt, M.; Mahmassani, H.S. Daily load planning under different autonomous truck deployment scenarios. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *166*, 102885. [CrossRef]
50. Huang, D.; Wang, S. A two-stage stochastic programming model of coordinated electric bus charging scheduling for a hybrid charging scheme. *Multimodal Transp.* **2022**, *1*, 100006. [CrossRef]
51. Liu, B.; Li, Z.C.; Wang, Y. A two-stage stochastic programming model for seaport berth and channel planning with uncertainties in ship arrival and handling times. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *167*, 102919. [CrossRef]
52. Lashgari, M.; Akbari, A.A.; Nasersarraf, S. A new model for simultaneously optimizing ship route, sailing speed, and fuel consumption in a shipping problem under different price scenarios. *Appl. Ocean. Res.* **2021**, *113*, 102725. [CrossRef]
53. Yuan, Z.; Liu, J.; Zhang, Q.; Liu, Y.; Yuan, Y.; Li, Z. Prediction and optimisation of fuel consumption for inland ships considering real-time status and environmental factors. *Ocean Eng.* **2021**, *221*, 108530. [CrossRef]
54. Chen, Y.; Huang, Z.; Ai, H.; Guo, X.; Luo, F. The impact of gis/gps network information systems on the logistics distribution cost of tobacco enterprises. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *149*, 102299. [CrossRef]

55. Yan, R.; Wang, S.; Zhen, L.; Laporte, G. Emerging approaches applied to maritime transport research: Past and future. *Commun. Transp. Res.* **2021**, *1*, 100011. [CrossRef]
56. Demissie, M.G.; Kattan, L. Estimation of truck origin-destination flows using GPS data. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *159*, 102621. [CrossRef]
57. Lyu, N.; Wang, Y.; Wu, C.; Peng, L.; Thomas, A.F. Using naturalistic driving data to identify driving style based on longitudinal driving operation conditions. *J. Intell. Connect. Veh.* **2022**, *5*, 17–35. [CrossRef]
58. Wang, S.; Tian, X.; Yan, R.; Liu, Y. A deficiency of prescriptive analytics—No perfect predicted value or predicted distribution exists. *Electron. Res. Arch.* **2022**, *30*, 3586–3594. [CrossRef]
59. Wang, S.; Yan, R. A global method from predictive to prescriptive analytics considering prediction error for "predict, then optimize" with an example of low-carbon logistics. *Clean. Logist. Supply Chain* **2022**, *4*, 100062. [CrossRef]
60. Wang, S.; Yan, R. "Predict, then optimize" with quantile regression: A global method from predictive to prescriptive analytics and applications to multimodal transportation. *Multimodal Transp.* **2022**, *1*, 100035. [CrossRef]
61. Yan, R.; Wang, S. Integrating prediction with optimization: Models and applications in transportation management. *Multimodal Transp.* **2022**, *1*, 100018. [CrossRef]
62. Yang, Y.; Jia, B.; Yan, X.Y.; Li, J.; Yang, Z.; Gao, Z. Identifying intercity freight trip ends of heavy trucks from GPS data. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *157*, 102590. [CrossRef]
63. Li, Y.; Li, S.E.; Jia, X.; Zeng, S.; Wang, Y. FPGA accelerated model predictive control for autonomous driving. *J. Intell. Connect. Veh.* **2022**, *5*, 63–71. [CrossRef]
64. Yalcin, H.; Daim, T.U. Logistics, supply chain management and technology research: An analysis on the axis of technology mining. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *168*, 102943. [CrossRef]
65. Niu, B.; Mu, Z.; Cao, B.; Gao, J. Should multinational firms implement blockchain to provide quality verification? *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *145*, 102121. [CrossRef]
66. Choi, T.M.; Siqin, T. Blockchain in logistics and production from Blockchain 1.0 to Blockchain 5.0: An intra-inter-organizational framework. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *160*, 102653. [CrossRef]
67. Liu, S.; Hua, G.; Kang, Y.; Cheng, T.E.; Xu, Y. What value does blockchain bring to the imported fresh food supply chain? *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *165*, 102859. [CrossRef]
68. Yi, W.; Wu, S.; Zhen, L.; Chawynski, G. Bi-level programming subsidy design for promoting sustainable prefabricated product logistics. *Clean. Logist. Supply Chain* **2021**, *2021*, 100005. [CrossRef]
69. Yi, W.; Zhen, L.; Jin, Y. Stackelberg game analysis of government subsidy on sustainable off-site construction and low-carbon logistics. *Clean. Logist. Supply Chain* **2021**, *2021*, 100013. [CrossRef]
70. Zhang, L.; Guan, L.; Long, D.Z.; Shen, H.; Tang, H. Who is better off by selling extended warranties in the supply chain: The manufacturer, the retailer, or both? *Ann. Oper. Res.* **2020**, 1–27. [CrossRef]
71. Zhang, J.; Long, D.Z.; Wang, R.; Xie, C. Impact of penalty cost on customers' booking decisions. *Prod. Oper. Manag.* **2021**, *30*, 1603–1614. [CrossRef]