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Research article

Optimization problems in liquefied natural gas transport and storage for multimodal transport companies

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Abstract: As a relatively clean energy source, liquefied natural gas (LNG) is experiencing a growing demand. The uneven global distribution of LNG often compels residents in regions without local sources to import it, underscoring the need to optimize the global LNG transportation network. Therefore, this study formulates a nonlinear mixed-integer programming model for a multimodal transport and storage problem to optimize LNG carrier allocation, LNG storage planning, and LNG transport planning, aiming to minimize the total cost of multimodal transport, minus the rewards offered by ports. In order to facilitate the solving of the model, some linearization methods are used to transform the nonlinear model into a linear model. To assess the efficiency of the linear model, we conduct computational experiments on small-scale instances with five inland cities, medium-scale instances with 15 inland cities, and large-scale instances with 60 inland cities. The results show that all small- and medium-scale instances can be solved to optimality within 427.50 s. Feasible solutions with a maximum gap value of 0.03% for large-scale instances can be obtained within 1 h. In addition, sensitivity analyses are conducted to identify the impacts of the cost of transporting LNG by vehicles, the charter cost of LNG carriers, and the rewards for shipping LNG. In general, higher cost of transporting LNG by vehicles and higher charter cost of LNG carriers lead to a higher objective value. It is also found that when the rewards for shipping LNG increase to a certain extent, such that the additional rewards exceed the additional multimodal transport cost incurred, the amount of LNG unloaded at the subsidized port increases.

Keywords: multimodal transport; transport and storage; decarbonization of energy; ship allocation and scheduling; LNG supply chain

1. Introduction

Energy is the cornerstone of a nation's economy, playing a pivotal role in promoting economic and social development [1]. Against the backdrop of reducing carbon emissions, the development of the global economy has placed greater emphasis on green and low-carbon, and the decarbonization of energy has gradually attracted the attention of countries around the world [2]. Compared with traditional fossil fuels such as coal and fuel oil, natural gas has the advantage of being clean and environmentally friendly, which means natural gas leads to fewer carbon dioxide (CO_2) emissions and air pollutants while generating the same amount of energy [3, 4]. Hence, if natural gas replaces more coal and fuel oil, it could contribute to reducing CO_2 emissions and improving air quality [5]. As a relatively clean-burning fossil fuel, natural gas shows an increasingly important trend in the energy structure, which enables the shift toward a more environmentally friendly future [6].

In recent decades, natural gas has gained significant popularity and is now extensively utilized in various areas, including power generation and fuel supply [7], etc., which leads to remarkable growth in its usage and transportation [8]. In order to ensure the safety of natural gas storage and transportation, technology is usually used to liquefy natural gas at approximately 112 kelvins, which increases its density by 600 times, resulting in liquefied natural gas (LNG) [9, 10]. LNG transportation is more flexible, allowing LNG to be supplied to customers in various locations [11]. Besides, the storage of LNG is more convenient, which enables it to resist demand fluctuations caused by seasonal changes. With these advantages, LNG has become one of the most important energy sources. Notably, after the outbreak of the conflict between Russia and Ukraine, Europe has reduced its dependence on the natural gas from Russia and turned to import more LNG from other countries to meet its energy demands, resulting in fluctuations in the global LNG supply chain. According to [12], the global LNG trade volume reached 401.5 million tons (MT) in 2022, with an increase of 25.4 MT compared to the previous year. Australia, the United States, and Qatar are the three largest LNG exporters in the world, supplying 80.9 MT, 80.5 MT, and 80.1 MT, respectively. Asia is the major global LNG market, and China, in particular, imported 63.7 MT of LNG in 2022. It is worth noting that the Chinese government is committed to making Shenzhen an LNG trading hub. To promote LNG trade and reduce shipping costs, the government offers incentives of 1 RMB (i.e., 0.14 USD) per ton for LNG unloaded at Shenzhen Port, with an upper limit of 5 million RMB (i.e., 690,500 USD) per year [13]. An example is used to illustrate the port's incentive rules. If the amount of LNG unloaded is 3 MT, the rewards calculated at 0.14 USD/ton are 420,000 USD, which are below the upper limit of 690,500 USD, so the actual rewards are 420,000 USD. However, if the amount of LNG unloaded is 6 MT, the rewards calculated at 0.14 USD/ton are 840,000 USD, which exceed the upper limit. In this case, the actual rewards are 690,500 USD.

Transportation is the foundation of LNG international trade, because it ensures the cross-border flow of LNG. With the rapid development of technology, the intertwined influence of policies and the increasing diversity of supply sources, cross-border LNG transportation, especially maritime transport through LNG carriers, has gradually gained popularity [14, 15]. As for onshore LNG transportation from ports to inland cities, rail and road transportation are typically adopted. Compared to railway transportation, road transportation for LNG is a more flexible and efficient way [16]. Hence, in this study, we consider the multimodal transport mode combining maritime transport and road transport. LNG is transported from a specific overseas port to coastal ports by LNG carriers, and then transported to inland cities by vehicles. Multimodal transport companies often face diverse challenges, such as the coordination of various transport links, differences in policies among different countries and regions, and the personalized customer demands. Particularly, the growing volume of LNG trade has led to a rise in the cost of transporting LNG, which has sparked an urgent need for the optimization of LNG transportation networks.

Faced with complex business scenarios, understanding how to optimize transport and storage decisions to reduce operational costs is particularly crucial for multimodal transport companies. Therefore, this study focuses on an LNG multimodal transport problem and proposes a mixed-integer programming (MIP) model to optimize LNG carrier allocation, LNG storage planning, and LNG transport planning, aiming to minimize the total cost of multimodal transport, minus the rewards offered by ports. Some linearization techniques are adopted to acquire a linear MIP model to simplify model-solving. Numerical experiments are conducted on small-, medium-, and large-scale instances that are randomly generated. In addition, we investigate the impacts of the cost of transporting LNG by vehicles, the charter cost of LNG carriers, and the rewards for shipping LNG, which provides scientific guidance for multimodal transport companies managing LNG transport and storage operations.

The structure of the remainder of this study is outlined as follows. Section 2 provides a thorough review and analysis of the related literature. Section 3 introduces the background of the problem, formulates a nonlinear MIP model, and transforms it into a linear one to accelerate the solution process. Section 4 carries out numerical experiments. Section 5 summarizes the whole study and presents future prospects.

2. Literature review

LNG is produced through a liquefaction process, during which it acquires the characteristic of low temperature. The energy generated from this low temperature can be used in applications such as air separation, seawater desalination, etc [17–19]. The related technologies of LNG transport and storage are indispensable for the rapid development of the LNG supply chain. Chen et al. [20] introduced the technological status of the oil and gas transport and storage (OGTS) engineering and predicted its future development trends. Sharafian et al. [21] analyzed the performance of LNG storage tanks in refueling stations based on practical parameters. According to [22], LNG is highly combustible, and leaks can easily result in severe accidents such as fires and explosions, resulting in casualties and economic losses. Therefore, it is essential to ensure the safety of LNG transport and storage. Wu et al. [23] developed a Bayesian-Catastrophe-EPE (energy transfer theory, preliminary hazard analysis, and evolution tree) model and systematically assessed the risk of LNG bunkering and storage in ports, aiming to prevent risks and avoid losses in advance. Yu et al. [24] concentrated on the risk assessment of LNG storage tank leakage and verified the performance of the proposed model with the case of LNG storage tank leakage in Tangshan. Besides, some scholars have devoted their efforts to studying LNG logistics from an economic perspective. Miana et al. [25] designed two methods, namely a physical model and an "intelligent" model, to predict the aging of LNG in the process of shipping. Upon observing the liberalization of the LNG market, Yuan et al. [26] identified more uncertainties in LNG prices and demand, and offered valuable decision support for fleet planning. Xu et al. [27] discussed the shipping capacity priority strategy for the freight market composed of a shipping company and two freight forwarders with differentiated capitals. Since this study focuses on the optimization of LNG transport and storage for multimodal transport companies, the following gives a comprehensive review of relevant studies from two aspects—multimodal transport and the operations management of LNG transport and storage.

Multimodal transport is defined as the sequential transportation of cargoes utilizing at least two distinct modes of transportation [28]. Interested readers can refer to [29–31], which give an overview of multimodal transport planning to gain a comprehensive understanding of multimodal transport. Hou et al. [32] introduced the accessibility index designed for foreign trade intermodal transport, which incorporated the ease of exporting goods via multimodal transport as well as the global attractiveness of goods, and delved into the influence of the COVID-19 pandemic on international trade logistics. Real et al. [33] investigated the design problem of multimodal hub networks with multiple alternative routes. A general MIP was proposed, which could be applied to the network design of different combinations of transportation modes such as maritime, railway, land, and air transport. Abbassi et al. [34] focused on the robust optimization of multimodal freight transport. Considering the uncertainties in utilization cost, transportation cost, and terminal capacity, an innovative approach combining a population-based simulated annealing algorithm with an exact algorithm was proposed and validated through a real case.

The operations management of LNG transport and storage is crucial to the LNG supply chain. Jokinen et al. [35] developed an MIP model for the design of small-scale LNG supply chain with the aim of minimizing the total cost related to fuel procurement, which was applied to an actual case in Finland. Zhang et al. [16] was dedicated to optimizing the on-road LNG transportation network. The problem was able to be divided into two independent subproblems, including a big-order problem that met the needs for integral LNG trucks, which could be decomposed into a traditional transportation problem, and a small-order problem that satisfied partial demands, which could be viewed as a variant of the vehicle routing problem. The operations management of LNG transport and storage is related to inventory routing problems, which were reviewed in [36–39]. Andersson et al. [40] proposed a model with stricter lower bounds for the LNG inventory routing problem and designed a branch-and-bound algorithm, which performed better than the previous branch-price-and-cut algorithm. Shao et al. [41] explored a hybrid heuristic method for the LNG inventory routing problem, which could be applied to general maritime inventory routing problems, to facilitate decision-making in a short timeframe. It is important to note that the LNG inventory routing problem is studied by existing literature from the perspective of producers, whereas the LNG transport and storage problem from the perspective of buyers, discussed in this study, has not been studied in existing literature.

While most studies on LNG transport and storage focus on maritime transport, few explore the integration of multiple transportation modes, particularly the multimodal transport mode combining maritime and land transport essential for importing LNG from foreign countries to inland cities. Besides, the studies on multimodal transport rarely involve the optimization of LNG transport and storage, which is crucial to the global LNG supply chain. To address this issue, this study designs an MIP to provide decision support for LNG carrier allocation, LNG storage planning, and LNG transport planning involving both LNG carriers and vehicles, in order to achieve the goal of minimizing the total transport cost, minus the rewards given by the ports.

3. Problem description and model formulation

To meet the demand for LNG in inland cities, a company engaged in multimodal transport imports LNG from overseas and transports LNG to inland cities, involving both maritime transport and road transport. Therefore, this study focuses on an LNG multimodal transport problem and formulates a mathematical model to provide an optimal strategy that minimizes the total cost, i.e., the cost of maritime transport and road transport, minus the port rewards for importing LNG. This section first introduces the background of the problem in detail in Section 3.1 and then formulates a nonlinear MIP model in Section 3.2, which is subsequently transformed into a linear MIP model to facilitate the solving of the mathematical model in Section 3.3.

3.1. Problem background

We consider that a multimodal transport company ensures the supply of sufficient LNG to meet the demand of inland cities during a set T of months indexed by t, while taking into account the transport costs and ports' rewards. The company transports LNG from a certain foreign port to a set N of coastal ports, indexed by i, by LNG carriers, and then transports it to a set P of inland cities, indexed by j, by vehicles. This process involves two different modes of transport, namely maritime transport and road transport.

In the first stage, the multimodal transport company arranges shipping plans, utilizing LNG carriers of a set K of ship types. Each LNG carrier of type k has a specific capacity, which is denoted by w_k, $k \in K$. In order to promote coastal cities to become gas trading hubs, a set N' of ports indexed by i provides financial incentives for shipping LNG. Let a_i and r_i, $i \in N'$, represent the rewards for shipping a ton of LNG from overseas to port i, and the maximum rewards offered by port i, respectively. LNG unloaded from ships is temporarily stored in specialized gas tanks at port i, with a maximum storage capacity, denoted by v_i, $i \in N$.

In the second stage of multimodal transport, vehicles transport LNG placed in gas tanks to inland cities. LNG unloaded at multiple ports can serve the same inland city and meet the monthly demand of inland city j, which is denoted by m_{jt}, $j \in P$, $t \in T$. Let d_{ij} represent the distance from port i to city j for transporting LNG by vehicles, $i \in N$, $j \in P$. This study takes a month as a time period unit. All the gas tanks at the ports are empty at time 0 (before ship's arrival at the ports at the beginning of the first month), and the unloading of LNG from LNG carriers occurs at the beginning of each month. To simplify the problem, we suppose that the unloading of LNG at the ports is instantaneous, which means that the time required for the unloading process is 0. In addition, both LNG unloaded at the beginning of month t and the LNG that is not transported to inland cities in the previous time periods can be supplied to inland cities to meet the demand for LNG in month t.

The aim of this study is to minimize the total cost of multimodal transport minus the rewards provided by the ports. The total cost of multimodal transport can be classified into two parts according to the mode of transportation: maritime transport cost and road transport cost. LNG carriers are chartered, and the cost of chartering an LNG carrier is calculated based on the type of ship. Let c_{ikt}, $i \in N$, represent the cost of chartering an LNG carrier of type k that arrives at port i at the beginning of month t, and then the maritime transport cost can be calculated by $\sum_{i\in N}\sum_{k\in K}\sum_{t\in T} c_{ikt}\varepsilon_{ikt}$, where ε_{ikt}, $i \in N$, is defined as the decision variable representing the number of LNG carriers of type k that arrive at port i at the beginning of month t. Let h and β_{ijt}, $i \in N$, denote the cost of transporting a ton of LNG per unit distance by vehicles, and the decision variable representing the amount of LNG transported by vehicles from port i to city j in month t, respectively. Road transport cost that arises from delivering LNG from the ports to inland cities can be calculated by $\sum_{i\in N}\sum_{j\in P}\sum_{t\in T} hd_{ij}\beta_{ijt}$. Besides, the rewards provided by the ports can be calculated by $\sum_{i\in N'} \min(r_i, \sum_{t\in T} a_i\alpha_{it})$, where α_{it}, $i \in N$ $(N' \subseteq N)$, is denoted as the decision variable representing the amount of LNG unloaded by LNG carriers at port i at the beginning of month t.

The constraints of this study can be divided into three groups, which are related to LNG carriers, coastal ports, and inland cities. The first group of constraints arises from the limited capacity of LNG carriers, which has an impact on the number of ships that need to be chartered. The second group of constraints related to ports is characterized by the decision variable representing the amount of LNG stored at port i, after unloading LNG from ships that arrive at the beginning of month t, which is denoted by δ_{it}, $i \in N$. We suppose that the amount of LNG in the gas tanks at time 0 is 0; hence, after unloading LNG from ships that arrive at the beginning of the first month, the amount of LNG stored at port i is equal to the amount of LNG unloaded from ships at port i, i.e., $\delta_{i0} = \alpha_{i1}$. For the second month and subsequent months, δ_{it} depends on the remaining amount from previous months, and the amount of LNG unloaded from ships that arrive at the beginning of month t. Specifically, the value of δ_{it} is equal to the amount of LNG stored at port i after unloading LNG from ships that arrive at the beginning of month $t-1$ minus the amount of LNG transported to inland cities during month $t-1$, plus the amount of LNG unloaded at port i at the beginning of month t. Notably, the amount of LNG stored at port i is subject to the capacity of the gas tanks, and it cannot be less than the amount of LNG transported from port i to all inland cities. As for the last group of constraints, we consider that the amount of LNG transported from the ports to inland cities must meet local demand.

In summary, this study explores a multimodal transport problem to optimally determine LNG carrier allocation, LNG storage planning, and LNG transport planning involving both LNG carriers and vehicles. An MIP model is developed with the objective of minimizing the total cost of multimodal transport, including the maritime transport cost and road transport cost, minus the rewards provided by the ports.

3.2. Model formulation

Based on the above analysis of the problem, we formulate a nonlinear MIP model in this section. This study uses two assumptions: (I) an LNG carrier can only unload LNG at one port [42], and (II) the LNG unloading time is 0 [43]. Before formulating the nonlinear MIP model for this problem, the notation used in this study is listed as follows.

Indices and sets:

- N set of all ports for unloading LNG, $i \in N$.
- N' set of ports that offer rewards for unloading LNG, $N' \subseteq N$, $i \in N'$.
- K set of all available ship types, $k \in K$.
- P set of all inland cities, $j \in P$.
- T set of all months in the planning horizon, $t \in T$.
- Z_+ set of all non-negative integers.

Parameters:

- a_i rewards for shipping a ton of LNG from overseas to port i (USD/ton).

c_{ikt} cost of chartering an LNG carrier of type k that arrives at port i at the beginning of month t (USD).

d_{ij} distance from port i to city j for transporting LNG by vehicles (km).

h cost of transporting a ton of LNG per unit distance by vehicles (USD/(ton · km)).

m_{jt} demand for LNG in city j in month t (ton).

r_i maximum rewards offered by port i (USD).

v_i maximum LNG storage capacity of port i (ton).

w_k maximum LNG capacity of an LNG carrier of type k (ton).

Decision variables:

α_{it} continuous, the amount of LNG unloaded by LNG carriers at port i, $i \in N$, at the beginning of month t, $t \in T$.

β_{ijt} continuous, the amount of LNG transported by vehicles from port i, $i \in N$, to city j, $j \in P$, in month t, $t \in T$.

ε_{ikt} integer, the number of LNG carriers of type k, $k \in K$, which arrive at port i, $i \in N$, at the beginning of month t, $t \in T$.

δ_{it} continuous, the amount of LNG stored at port i, $i \in N$, after unloading LNG from ships that arrive at the beginning of month t, $t \in T$, if any.

Mathematical model:

Based on the above definition of parameters and decision variables, a nonlinear MIP model **[M1]** is formulated as follows.

$$\textbf{[M1]}\ \min \sum_{i\in N}\sum_{k\in K}\sum_{t\in T} c_{ikt}\varepsilon_{ikt} + \sum_{i\in N}\sum_{j\in P}\sum_{t\in T} hd_{ij}\beta_{ijt} - \sum_{i\in N'} \min(r_i, \sum_{t\in T} a_i\alpha_{it}) \tag{3.1a}$$

$$\text{s.t. } \alpha_{it} \le \sum_{k\in K} w_k\varepsilon_{ikt}, \qquad \forall i \in N, t \in T \tag{3.1b}$$

$$\delta_{i1} = \alpha_{i1}, \qquad \forall i \in N \tag{3.1c}$$

$$\delta_{it} = \delta_{i,t-1} - \sum_{j\in P}\beta_{ij,t-1} + \alpha_{it}, \qquad \forall i \in N, t \in T \setminus \{1\} \tag{3.1d}$$

$$\delta_{it} \le v_i, \qquad \forall i \in N, t \in T \tag{3.1e}$$

$$\delta_{it} \ge \sum_{j\in P}\beta_{ijt}, \qquad \forall i \in N, t \in T \tag{3.1f}$$

$$\sum_{i\in N}\beta_{ijt} = m_{jt}, \qquad \forall j \in P, t \in T \tag{3.1g}$$

$$\alpha_{it}, \delta_{it} \ge 0, \qquad \forall i \in N, t \in T \tag{3.1h}$$

$$\beta_{ijt} \ge 0, \qquad \forall i \in N, j \in P, t \in T \tag{3.1i}$$

$$\varepsilon_{ikt} \in Z_+, \qquad \forall i \in N, k \in K, t \in T. \tag{3.1j}$$

Objective (3.1a) minimizes the total cost of transporting LNG by LNG carriers and vehicles, minus the rewards of ports. Constraints (3.1b) guarantee that the amount of LNG transported by LNG carriers to port i at the beginning of month t cannot be greater than the total amount of LNG that can be accommodated by all types of LNG carriers, which arrive at port i at the beginning of month t. Constraints (3.1c)–(3.1d) characterize the flow variation of LNG stored at port i. Constraints (3.1e) guarantee that the amount of LNG stored at port i cannot exceed the maximum LNG storage capacity of port i. Constraints (3.1f) ensure that there is enough LNG stored at port i to supply inland cities. Constraints (3.1g) ensure that the amount of LNG transported by vehicles from all ports to city j in month t meet the demand for LNG in city j in that month. Constraints (3.1h)–(3.1j) define the decision variables and restrict the ranges of the decision variables.

3.3. Model linearization

In order to enable the model to be directly solved by commercial solvers, such as Cplex and Gurobi, some linearization methods are used to transform **[M1]** proposed in Section 3.2 into a linear model. It is easy to observe that the objective function is nonlinear and the nonlinear part in objective (1) is $\sum_{i\in N'}$ $\min(r_i, \sum_{t\in T} a_i\alpha_{it})$. First, we define a new variable.
Newly defined variables:

θ_i continuous, $i \in N'$, the smaller value between r_i and $\sum_{t\in T} a_i\alpha_{it}$.

According to the new notation, several new constraints are introduced as follows.
Newly defined constraints:

$$\theta_i \le r_i, \qquad \forall i \in N' \tag{3.2}$$

$$\theta_i \le \sum_{t\in T} a_i\alpha_{it}, \qquad \forall i \in N' \tag{3.3}$$

$$\theta_i \ge 0, \qquad \forall i \in N'. \tag{3.4}$$

Then, $\sum_{i\in N'} \min(r_i, \sum_{t\in T} a_i\alpha_{it})$ is transformed to $\sum_{i\in N'} \theta_i$. And the final version of the objective is shown as follows.

$$\min \sum_{i\in N}\sum_{k\in K}\sum_{t\in T} c_{ikt}\varepsilon_{ikt} + \sum_{i\in N}\sum_{j\in P}\sum_{t\in T} hd_{ij}\beta_{ijt} - \sum_{i\in N'}\theta_i \tag{3.5}$$

As a result, we obtain the linear MIP model **[M2]**:
[M2] objective (3.5), subject to constraints (3.1b)–(3.1j), (3.2)–(3.4).

4. Computational experiments

In order to evaluate the performance of the proposed mathematical model, computational experiments are conducted on a PC (14 cores of CPUs, 2.5 GHz, Memory 32 GB). The model introduced in Section 3 is implemented in the commercial solver Gurobi 10.0.0 (Anaconda, Python). This section first shows the value setting of the parameters in Section 4.1, displays experimental results in Section 4.2, and carries out sensitivity analyses to investigate beneficial managerial insights in Section 4.3.

4.1. Experimental setting

We consider a duration of six months in the planning horizon. Three types of LNG carriers are available, which are categorized as small (k = 1), medium (k = 2), and large (k = 3) based on their sizes. Table 1 shows the parameter settings including w_k and c_{ikt} for these LNG carriers, which are in line with the setting in [44]. The charter cost of each type of LNG carriers can be estimated based on the daily charter rate and the duration of voyage. We assume that all LNG carriers depart from Qatar and sail towards the destination ports in China, with a sailing distance of approximately 5845 nautical miles, and LNG carriers typically sail at a speed of 19.5 knots [26]. So it takes approximately 13 ($\frac{5845}{19.5\times 24} = 13$) days for the LNG carriers to complete a one-way transportation. Since the daily charter rate of the three types of LNG carriers is \$6700, \$7800, and \$10,650 [44], respectively, the cost of chartering the three types of LNG carriers (c_{ikt}) for one-way transportation is \$87,100, \$101,400, and \$138,450, respectively.

Table 1. Parameter settings for LNG carriers.

Ship type	w_k (ton)	c_{ikt} (USD)
Small	9400	87,100
Medium	11,000	101,400
Large	15,000	138,450

The LNG carriers can unload LNG at three different ports. Each port's maximum LNG storage capacity (v_i) is set to 30,000 tons. Among these ports, only one port provides a reward of \$0.14 for each ton of LNG unloaded (a_i), with a maximum reward (r_i) of \$345,070 [13]. Given a simulated 500 km by 500 km square region to simulate a road transport network area, two ports are located at the northeast corner and the southeast corner of the network area, while a third port with rewards is located at the midpoint of the line connecting the other two ports. Small-scale experiments for instances with five inland cities, medium-scale experiments for instances with 15 inland cities, and large-scale experiments for instances with 60 inland cities are conducted in Section 4.2. In each instance, the locations of the inland cities are randomly generated to ensure a uniform distribution throughout the simulated area. The distance from port i to city j for vehicles (d_{ij}) is the Euclidean distance [43]. The average monthly demand of each city is set to 1000 tons (a normal distribution with a standard deviation of 100). According to [45], the average transportation cost of an LNG vehicle with a capacity of 50 cubic meters (i.e., 22.5 ton) is 5 RMB/km (i.e., 0.69 USD/km). Hence, the cost of transporting a ton of LNG per unit distance by vehicles (h) is 0.03 ($\frac{0.69}{22.5} = 0.03$) USD/(ton · km).

4.2. Experimental results

In order to evaluate the efficiency of the model, Gurobi is utilized to solve model **[M2]**. Computational experiments are conducted, which are divided into three groups based on the number of inland cities included in each instance. We carry out 10 sets of small-scale instances, 10 sets of medium-scale instances, and 10 sets of large-scale instances, corresponding to five inland cities, 15 inland cities, and 60 inland cities, respectively. The time limit for Gurobi to solve each instance is set to 1 h, namely 3600 s. All the experimental results are summarized in Table 2. To clearly present the experimental results, the objective values are recorded as integers, and the CPU time is rounded to two decimal places. The gap value that denotes the relative difference between the current best solution and the current best dual bound is formatted as a percentage with two decimal places. As can be seen from Table 2, the difficulty of solving the problem varies with the number of inland cities. All small- and medium-scale instances are able to achieve optimality within 427.50 s. To be specific, the solution time for small-scale instances with five inland cities does not exceed 0.15 s. The time required to obtain the optimal solution for medium-scale instances with 15 inland cities varies, with the shortest time being

2.99 s and the longest time being 427.50 s. Among large-scale instances with 60 inland cities, 3 out of 10 instances can be solved to optimality within 80.08 s, while the remaining 7 instances can obtain feasible solutions with a maximum gap value of 0.03% within 1 h, which meets the needs of practical problems. Therefore, the computational experiments demonstrate the efficiency of the proposed model and its applicability to real-world scenarios.

Table 2. Experimental results of different scale instances.

Scale type	Number of inland cities	ID	Objective value (USD)	CPU time (s)	Gap (%)
Small	5	1	518,831	0.14	–
		2	588,471	0.09	–
		3	558,657	0.07	–
		4	544,187	0.06	–
		5	542,201	0.07	–
		6	611,257	0.15	–
		7	474,380	0.11	–
		8	490,518	0.04	–
		9	531,664	0.07	–
		10	524,550	0.05	–
Medium	15	1	1,531,755	427.50	–
		2	1,627,092	98.21	–
		3	1,474,203	92.34	–
		4	1,517,073	15.99	–
		5	1,614,876	306.83	–
		6	1,520,864	2.99	–
		7	1,617,992	17.08	–
		8	1,525,397	27.27	–
		9	1,601,062	209.24	–
		10	1,655,131	352.04	–
Large	60	1	6,237,178	3600.15	0.02
		2	6,087,725	3600.09	0.01
		3	5,998,054	0.17	–
		4	5,838,319	3600.13	0.02
		5	5,934,333	3609.39	0.03
		6	6,302,486	3606.50	0.02
		7	6,012,028	80.08	–
		8	6,324,634	3600.36	0.02
		9	6,422,527	21.15	–
		10	6,379,079	3600.20	0.02

Note: – denotes that an optimal solution is found within 1 h.

4.3. Sensitivity analyses

The values of several parameters of the mathematical model fluctuate according to real-world conditions. However, in the above experiments, all parameters are considered fixed. Hence, in order to explore the impacts of the parameters on decision-making, we select the instance with five inland cities labeled as ID 1 to conduct sensitivity analyses on the parameters, including the cost of transporting LNG by vehicles (h), the charter cost of each type of LNG carriers (c_{ikt}), and the rewards for shipping LNG (a_i).

To begin with, this study explores the impact of the cost of transporting LNG by vehicles on LNG transport and storage planning. The value of the cost of transporting a ton of LNG per unit distance by vehicles (h) is set to 0.03 (USD/(ton · km)) in Section 4.2. Taking into account the changes in fuel price, the value of the cost of transporting a ton of LNG per unit distance by vehicles (h) is assumed to vary from 0.01 (USD/(ton · km)) to 0.06 (USD/(ton · km)). From Figure 1(a), we can see that the higher the cost of transporting LNG by vehicles, the higher the objective value, which makes sense because the cost of transporting a ton of LNG per unit distance by vehicles increases, leading to the increase in the road transport cost, which is an important component of the objective value. Hence, the objective value also increases.

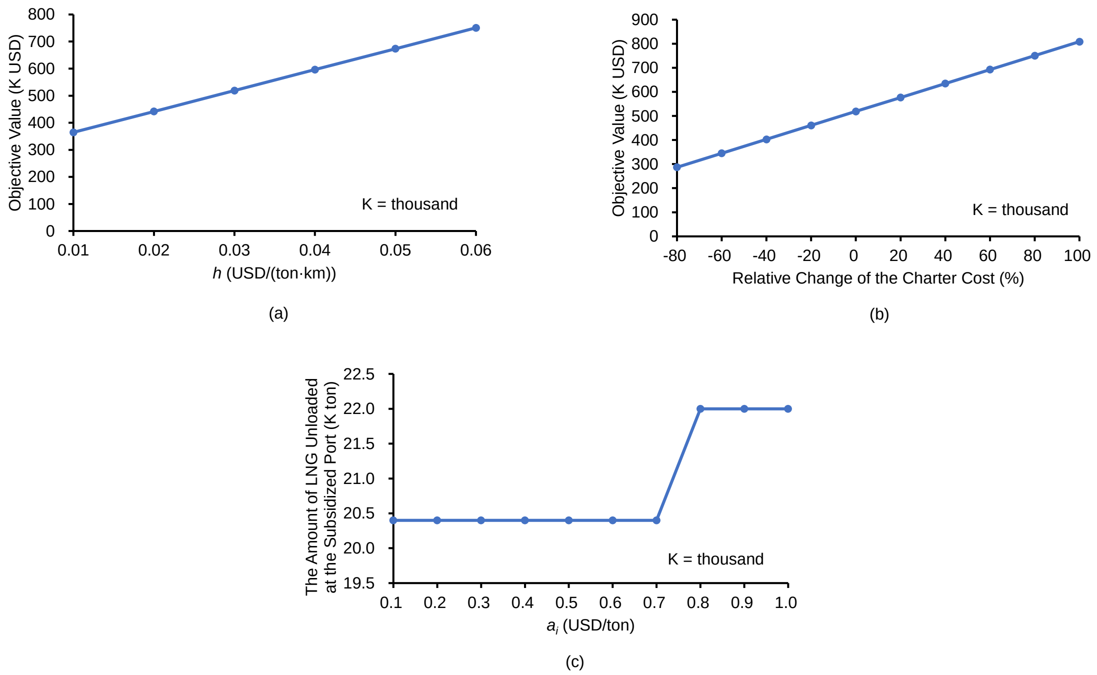

Figure 1. Impacts of the cost of transporting LNG by vehicles (h), the charter cost of each type of LNG carriers (c_{ikt}), and the rewards for shipping LNG (a_i).

Then, this study investigates the impact of the charter cost on LNG transport and storage planning. In Section 4.2, the charter cost of the three types of LNG carriers (c_{ikt}) for one-way transportation is set to \$87,100, \$101,400, and \$138,450, respectively. According to [46], the time-charter rate of LNG carriers almost doubled in 2021, which shows that the charter cost of LNG carriers fluctuates greatly in the shipping market. The relative change of the charter cost of each type of LNG carriers (c_{ikt}) (i.e., the current charter cost minus the original charter cost and then divided by the original charter cost) ranges between –80% and +100%. It can be seen from Figure 1(b) that as the charter cost increases, the objective value also increases. This is because the charter cost is an important factor in determining the total cost of multimodal transport. Therefore, an increase in the charter cost leads to higher objective value.

Finally, the impact of the rewards for shipping LNG on LNG transport and storage planning is investigated. In Section 4.2, the rewards for shipping LNG from overseas to each subsidized port i (a_i) are set to 0.14 USD/ton. Due to possible policy adjustments, the rewards for shipping a ton of LNG (a_i) fluctuate within the range of 0.1 USD/ton to 1.0 USD/ton in the sensitivity analyses. From Figure 1(c), it can be seen that when the value of a_i is no more than 0.7 USD/ton, there is a difference in the amount of LNG unloaded at the subsidized port compared with when the value of a_i is greater than or equal to 0.8 USD/ton, which is reasonable because the increase in rewards exceeds the additional multimodal transport cost incurred. In other words, when the value of a_i increases from 0.7 USD/ton to

0.8 USD/ton, it is profitable to increase the amount of LNG unloaded at the subsidized port. However, when the value of a_i fluctuates within the range of 0.1 USD/ton to 0.7 USD/ton, or within the range of 0.8 USD/ton to 1.0 USD/ton, even if the rewards increase, the additional rewards cannot offset the resulting increase in multimodal transport cost. Therefore, the amount of LNG unloaded at the subsidized port remains unchanged at this point.

5. Conclusions

With the increasing environmental concerns, the use of LNG becomes more popular, highlighting the significance of its transport and storage operations management. Although some studies have been conducted on the transport and storage of LNG, they focus on maritime transport, lacking consideration of the combination of maritime and land transport, as well as the incentive policies of ports for shipping LNG. To address this challenge, this study investigates the LNG multimodal transport and storage problem, and proposes a mathematical model to help multimodal transport companies find the optimal logistics strategies.

The main contributions lie in the following two aspects:

1) We propose a nonlinear MIP model **[M1]** to assist multimodal companies to design LNG transport network. This model encompasses LNG carrier allocation, LNG storage planning, and LNG transport planning, including both LNG carriers and vehicles. It aims to minimize the total multimodal transport cost minus the rewards provided by the ports. Since it is hard to solve the nonlinear model **[M1]**, we transform it to a linear MIP model **[M2]** that can be directly solved by Gurobi. The computational results indicate that all small- and medium-scale instances can obtain optimal solutions within 427.50 s. For large-scale instances, feasible solutions with gap values less than 0.03% can be obtained within 1 h, which shows that the model **[M2]** is able to deal with practical operational problems.

2) Sensitivity analyses are conducted to investigate the impacts of the cost of transporting LNG by vehicles, the charter cost of each type of LNG carriers, and the rewards for shipping LNG. In short, higher cost of transporting LNG by vehicles and higher charter cost of LNG carriers lead to a higher objective value. Additionally, it is found that when the rewards for shipping LNG increase to a certain extent, such that the additional rewards exceed the additional multimodal transport cost incurred, the amount of LNG unloaded at the subsidized port increases.

However, future studies may further improve on the basis of this study. First, this study assumes that an LNG carrier calls at only one unloading port, but in actual operations, an LNG carrier may unload LNG at multiple ports [47], which can be considered in the future. In addition, the design of the LNG transport network with uncertain demand [48, 49], uncertain LNG purchase price [50], and uncertain ship travel time [51], needs more discussion. Furthermore, realistic data can be used for experimental setting, enhancing the practical value of the research findings [52]. Besides, more attention will be paid to sustainability metrics on LNG transport and storage planning, and potential collaborations with industry stakeholders to facilitate the practical implementation of the research findings. Finally, Gurobi is adopted to solve the LNG multimodal transport problem in this study, but as the scale of the instances increases, Gurobi struggles to obtain solutions within a reasonable time range. In future studies, we will utilize more advanced optimization algorithms, such as hybrid heuristics and metaheuristics [53, 54], self-adaptive algorithms [55], island algorithms [56], polyploid algorithms [57], hyper-heuristics [58], etc. These algorithms are widely applied in transportation [59,60], medicine [61,62], data classification

[63], and many other fields, and have been proved to be effective in the aforementioned domains. We plan to try these advanced optimization algorithms and design numerical experiments to compare the efficiency of these advanced optimization algorithms with the proposed method in this study for the LNG multimodal transport problem in the future.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare there are no conflicts of interest.

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