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A SIMULATION STUDY ON INLAND CONTAINER AND TRUCK SCHEDULING OPTIMIZATION

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Abstract
Inland container transportation, as a continuation of sea transportation, is crucial for ensuring the efficient flow of cargo entering and leaving ports. Optimizing the configuration of the inland transportation network and the organization of container dispatching services is vital for container shipping companies to ensure high-quality "door-to-door" service. This paper develops a container transportation network model incorporating an Inland Container Depot (ICD), then, establishes an inland container-truck scheduling model. A mixed integer programming model is developed to address the scheduling of imported empty containers, imported full containers, exported empty containers, exported full containers, and trucks. The model is validated using real data from a container shipping company, and the Variable Neighborhood Search (VNS) algorithm is proposed to solve the model efficiently. The simulation results indicate that establishing ICDs and planning truck and empty container scheduling within this transportation network can effectively reduce drayage transportation costs.
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Key Words: Container Scheduling, Vehicle Routing Problem, Transportation Network, Inland Container Depot, Variable Neighborhood Search

1. INTRODUCTION

With the continuous development of international trade, the volume of goods trade has increased, accompanied by severe environmental pollution and significant port congestion issues. The adjustment and upgrading of industrial layouts and the implementation of national carbon reduction strategies are imminent. Against this backdrop, to alleviate port congestion and adapt to changes in industrial layouts, ports, inland hinterlands, and Inland Container Depots (ICDs) are actively promoting the construction of a multimodal container transportation network. The construction of ICDs is playing an increasingly important role in container transportation networks. On one hand, ICDs, as key hubs connecting sea and land, can effectively integrate multiple transportation modes such as road, rail, and water, balancing the efficiency and cost of container transportation and achieving the goal of green and sustainable transport. On the other hand, the construction of ICDs can significantly alleviate port clearance pressure, enabling efficient and seamless interconnection across various multimodal transport stages. Hu et al. [1] noted that holistic optimization of container scheduling at ports and inland areas yields greater benefits than independent optimization, emphasizing the role of ICDs in leveraging advanced road networks and enhancing inland transport. Studies aim to improve demand responsiveness and reduce trucking costs.

In addition, various countries have introduced relevant policies and regulations. The European Commission proposed in 2011 that "by 2030, 30 % of road freight transport over 300 kilometres should shift to other modes, such as rail or water, and by 2050, this proportion should exceed 50 %". Boile et al. [2] demonstrated, using the New York-New Jersey port region as an example, that establishing inland empty container depots can effectively reduce empty truck travel distances and the total system cost of empty container dispatching. China's "Outline for Building a Strong Transportation Country", released in September 2019, explicitly requires the "promotion of rail-water, road-rail, road-water, and air-land multimodal transport development to achieve cost reduction and efficiency improvement". The "Implementation Opinions on Further Reducing Logistics Costs", released in 2020, emphasized increasing financial support for the construction of railroad sidings and multimodal transport hubs, and the formulation of design standards for railroad sidings in ports. Supported by these favourable policies, inland multimodal container transport has rapidly developed. Simultaneously, Kolar et al. [3] studied empty container dispatching in Central and Eastern Europe, showing multimodal transport's potential and the benefits of vertical and horizontal integration. Inland systems, though similar to maritime ones, are more complex. Optimizing ICDs and vehicle scheduling is key.

This paper jointly studies the scheduling of empty containers (hereinafter referred to as "empty containers") and trucks in the inland container transportation network. First, a container transportation network incorporating ICDs is constructed. On this basis, an inland container-truck scheduling model is established, addressing the scheduling of imported empty containers, imported full containers, exported empty containers, exported full containers, and trucks. The model is validated using real data from a container shipping company, and the Variable Neighborhood Search (VNS) algorithm is used to solve it. The final results indicate that establishing ICDs and planning truck and empty container scheduling within this transportation network can effectively reduce drayage transportation costs. Furthermore, based on the distribution characteristics of actual customers, three types of examples are generated to analyse the impact of different quantities of ICDs on total costs and the relationship between the layout of ICDs and total costs under different scenarios.

The remainder of this paper is organized as follows: Section 2 reviews the literature; Section 3 introduces the problem studied and the mixed-integer programming model established; Section 4 presents the algorithm design and numerical experiments to verify the algorithm's effectiveness; Section 5 validates the model's feasibility through simulation studies and examines the economic benefits of setting up ICD hubs; Section 6 concludes the paper.

2. LITERATURE REVIEW

In container transportation, one of the major drawbacks is the imbalance in container usage demand resulting from imbalanced international trade, leading to a significant volume of empty container repositioning and substantial resource wastage. Reducing the cost of empty container repositioning and maximizing the utilization of containers to effectively improve the operational efficiency of the entire system has become a major research focus. This paper focuses on studies related to solution algorithms.

Most researchers have studied inland container dispatching issues by starting with the container transportation problem, which includes empty container repositioning. Inland container transportation refers to the movement of containers between customer locations, container terminals, and regional warehouses. Wang and Yun [4] examined the optimization problem of transporting containers between customer locations and container terminals via trucks and trains under hard time window constraints, and developed a mixed-integer programming model solved with a hybrid tabu search algorithm. Sterzik and Kopfer [5] created a mathematical model that simultaneously considers vehicle route scheduling and empty container repositioning, aiming to minimize truck operating time and used an efficient tabu search algorithm to solve the problem. Cordeau et al. [6] focused on the movement of containers from terminals to container trucks, developing a local search algorithm to optimize truck waiting time and total driving time. Fan et al. [7] investigated container repositioning between terminals and warehouses as well as between customer locations and warehouses, developing an intelligent model to minimize total costs and utilizing a customized genetic algorithm to solve the inland container transportation problem under a separated paradigm. Peng et al. [8] proposed an integer and linear programming model for container repositioning to maximize profits, solvable with CPLEX. Shan et al. [9] developed a robust model addressing demand uncertainty and empty container scheduling, using a branch and price algorithm for solution.

In the context of multimodal transportation, the construction of ICDs provides new perspectives for optimizing container scheduling. Dang et al. [10] researched the empty container repositioning problem under the inland multi-yard system, proposing four heuristic algorithms for inland empty container repositioning policies to minimize expected total costs, and solved the model with a genetic algorithm. Zehendner and Feillet [11] proposed a truck appointment system by constructing a mixed-integer programming model based on terminal network flows, aiming to minimize container delivery delays. Niu et al. [12] studied the separate and joint scheduling of yard trucks and containers, aiming to minimize truck waiting time. They solved the problem using particle swarm optimization and bacteria foraging algorithms and compared their effectiveness. Cao et al. [13] developed an integer linear programming model to optimize drayage transportation costs and reduce penalty costs for delayed container delivery by using ICDs as transshipment points, and solved it with CPLEX. The studies in [14] and [15] demonstrate the effectiveness of integrating and optimizing automotive inbound logistics and improving the tractor-to-semitrailer ratio, respectively, showing significant improvements in logistics efficiency and cost reduction. Xu et al. [16] discuss the implementation of hedging strategies in supply chains to mitigate risks in uncertain environments, while Wang et al. [17] examine the integration of green technologies in supply chain decisions and its effect on output variability and retail pricing. Song et al. [18] present an SSD-based system for detecting defects in carton packaging within the logistics supply chain, while Wu et al. [19] examine the relationship between environmental regulations, policy complexity, and the efficiency of technological innovation in the context of environmental sustainability. Hu et al. [20] developed a predictive model for greenhouse gas emissions from aquaculture wetlands, while Fu et al. [21] evaluated the management performance quality of urban water environment treatment projects. In addition, some scholars have also studied optimization strategies for ICD [22, 23].

In summary, current research on container scheduling mainly focuses on the repositioning of empty containers. Scholars analyse this issue from the perspectives of system composition, demand, and supply of empty containers, and establish mixed-integer programming models with objectives such as minimizing costs and maximizing profits. Further studies explore ways to reduce the cost of empty container repositioning and improve the efficiency of drayage operations in a multimodal transportation setting. Most researchers employ heuristic algorithms and CPLEX solvers to address these models, while a smaller number use exact algorithms such as branch-and-cut and branch-and-price solutions. These exact methods are generally applied to smaller-scale problems and tend to have longer solution times, which highlights the effectiveness of heuristic algorithms for this type of problem. Based on the research by the aforementioned scholars, this paper develops a VNS algorithm to solve the inland container-truck scheduling model.

3. PROBLEM DESCRIPTION AND MODEL DEVELOPMENT

3.1 Problem description

The container transportation network studied in this paper consists of four types of nodes: docks, yards, ICDs and customers. The ICD connects the yards to the inland hinterland and the inland hinterland to customer clusters. It functions to consolidate goods and store empty containers, and containers are transported by trucks between different nodes. Customer transport tasks can be categorized into two major types: domestic transport tasks and international transport tasks. Domestic transport refers to the transportation of containers between inland hinterland customers, known as the IC (Inland Container) transportation tasks. International transport refers to the round-trip transportation between the docks and customers.

Docks mainly handle the import and export transportation tasks of international customers. Depending on the loading status of the containers, international transport tasks can be further divided into four categories: IF (import full container), OF (export full container), IE (import empty container), and OE (export empty container).

(1) IE (Import Empty Container): The containers start from the docks and can be transported to the yard, ICD, or international customer location. (2) OE (Export Empty Container): The destination of the empty containers is unique, while the starting point can be any node, including the yard, ICD, and customer location. (3) IF (Import Full Container): The starting point is the dock and the destination is the customer location. (4) OF (Export Full Container): The starting point and destination are unique: the starting point is the shipper's location and the destination is the dock. Table I provides the classification and description of transport tasks. Yards and ICDs serve as storage locations for empty containers, servicing international and domestic transportation tasks respectively. The ICD is responsible for providing empty containers to domestic customers and receiving empty containers from other nodes.

Table I: Classification and description of transport tasks.

Task	IF	OF	IE	OE	IC
Starting Point	Terminal	Customer (Shipper)	Terminal	Any	Customer/ICD
Ending Point	Customer (Receiver)	Terminal	Any	Terminal	Customer/ICD

The transshipment process of different types of container transport tasks between various entities is shown in Fig. 1.

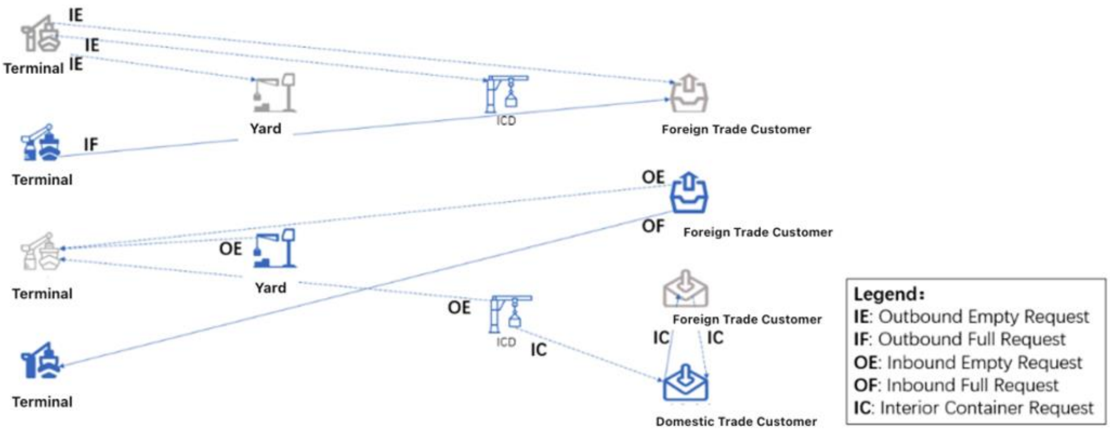

Figure 1: Transshipment process for different types of container transport tasks.

This paper aims to minimize the total cost, which includes truck transport costs and the lowest construction cost for ICDs. Given the predefined transport tasks and time windows, the internal and external transport tasks are matched with trucks and containers, optimizing the circulation of empty containers and the dispatch of trucks. For problem modelling, this paper considers using homogeneous vehicles to meet customer demands. It is assumed that each truck can move only one container at a time, all containers are 20 TEU, and the ICD has unlimited capacity, capable of storing a sufficient number of empty containers and trucks. Trucks start from the ICD, complete the transport tasks, and then return to the ICD. All transport requests are known before the transport begins, and vehicles must complete all transport tasks within the given time windows.

3.2 Model formulation

The input parameters of this model are defined in Table II.

Table II: Parameters and node sets.

Param.	Description / Formula	Param.	Description / Formula
s	number of shippers	r	number of receivers
sr	number of shippers in the domestic network	sr'	number of receivers in the domestic network
n	$s+r$	n'	$sr+sr'$
m	$n+n'$	E_i	number of IE containers
E_o	number of OE containers	d	number of depots
p	number of ICD	v	$m+n+E_i+E_o$
K	$\{1,\dots,k\}$	t_{ij}	travel time from *i* node to *j*
S_i	service time at node *i*	$[a_i,b_i]$	time window at node *i*
T_{ik}	time when vehicle *k* arrives at node *i*	L_{ic}	time when container *c* arrives at node *i*
l	time spent loading/unloading a container	p_i	time for filling/emptying a container at node *i*
m_i	initial number of vehicles at depot *i*	o_i	initial number of vehicles at ICD *i*
d_k^{tru}	starting depot/ICD for vehicle *k*	E_i^d	initial number of empty containers at depot *i*
E^d	total initial number of empty containers at depots	E_i^{icd}	initial number of empty containers at ICD *i*
E^{icd}	total initial number of empty containers at ICD	V	$V_T\cup V_D\cup V_{ICD}\cup V_C\cup V_{C'}$
V_s	$\{1,\dots,s\}$	V_r	$\{s+1,\dots,n\}$
V_C	$V_s\cup V_r$	$V_{s'}$	$\{n+1,\dots,n+sr'\}$
V_r	$\{n+sr'+1,\dots,n+n'\}$	$V_{C'}$	$V_{s'}\cup V_{r'}$
V_{OF}	$\{m+1,\dots,m+s\}$	V_{IF}	$\{m+s+1,\dots,m+n\}$
V_{OE}	$\{m+n+1,\dots,m+n+E_o\}$	V_{IE}	$\{m+n+E_o+1,\dots,m+n+E_o+E_i\}$）
V_T	$V_{OF}\cup V_{IF}\cup V_{OE}\cup V_{IE}$	v	$m+n+E_i+E_o$
V_{D_s}	$\{v+1,\dots,v+d\}$	V_{D_e}	$\{v+d+1,\dots,v+2d\}$
V_D	$V_{D_s}\cup V_{D_e}$	V_{ICD_s}	$\{v+2d+1,\dots,v+2d+p\}$
V_{ICD_e}	$\{v+2d+p+1,\dots,v+2d+2p\}$	V_{ICD}	$V_{ICD_s}\cup V_{ICD_e}$
δ_j^s	scenario where ICD is disrupted	p^s	probability of scenarios
D^s	number of areas covered under scenarios	a_{ij}	indicator whether ICD *j* covers area *i*
x_j	indicator whether an ICD is built at node *j*	C	$\{1,\dots,r+E_i+E^d+E^{icd}\}$
C_i^d	$\sum_{i\in V_{D_s}} C_i^d=\{r+E_i+1,\dots,r+E_i+E^d\}$	C_i^{icd}	$\sum_{i\in V_{ICD_s}} C_i^{icd}=\{r+E_i+E^d+1,\dots,r+E_i+E^d+E^{icd}\}$
T_{ik}	time when vehicle *k* arrives at node *i*	L_{ic}	time when container *c* arrives at node *i*

The decision variables are as follows:

$$x_{\boldsymbol{ijk}} \coloneqq \begin{cases}1 & \text{if vehicle } k \text{ travels from node } i \text{ to node } j\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

$$y_{\boldsymbol{ijc}} \coloneqq \begin{cases}1 & \text{if container } c \text{ is transported from node } i \text{ to node } j\\ 0 & \text{otherwise}\end{cases} \tag{2}$$

The service time S_i at each node is related to the pickup and delivery locations of container tasks. Service time comprises two parts: the time spent loading/unloading a container *l* and the time spent filling/emptying a container p_i. The service time S_i is defined as shown in Table III.

Table III: Definition of node service time S_i.

Container type	Pickup location	Delivery location
OF	$l+p_i+l$	l
OE	l	l
IF	l	$l+p_i+l$
IE	l	l
IC	$l+p_i+l$	$l+p_i+l$

For example, for an export full task, the truck needs to first unload the empty container at the shipper's location, then load the full container and deliver it to the terminal. Thus, the service time at the pickup and delivery locations for an export full task is $l + p_i + l;\ l$, respectively. In international transport, when a truck performs two consecutive import/export container tasks, it needs to visit a depot to unload/load empty containers, with the travel time being the sum of the round trip time to the depot and the time spent loading/unloading the empty container. The special cases for travel time t_{ij} in international transport are calculated as shown in Table IV.

Table IV: Calculation of special cases for travel time t_{ij} in international transport.

Path node	**Travel time**
$i \in V_r \cup V_{IE}, j \in V_{IF} \cup V_{IE}$	$\min_{d \in V_D} (t(i,d) + t(d,j)) + l$
$i \in V_{OF} \cup V_{OE}, j \in V_s \cup V_{OE}$	$\min_{d \in V_D} (t(i,d) + t(d,j)) + l$

In mixed international-domestic transport, trucks need to visit a depot/ICD in the following cases: (1) When the previous task was a domestic transportation task and the new task is an import task (IF/IE), the truck needs to unload the empty container at the nearest depot/ICD before performing the import task. (2) When the previous task was an export task (OE/OF), the truck needs to pick up an empty container at the nearest depot/ICD after unloading the container at the terminal and then start the next domestic transportation task. The special cases for travel time t_{ij} in mixed international-domestic transport are shown in Table V.

Table V: Calculation of special cases for travel time t_{ij}.

Path node	**Travel time**
$i \in V_{r'}, j \in V_{IF} \cup V_{IE}$	$\min_{d \in V_D \cup V_{ICD}} (t(i,d) + t(d,j)) + l$
$i \in V_{OF} \cup V_{OE}, j \in V_{s'}$	$\min_{d \in V_D \cup V_{ICD}} (t(i,d) + t(d,j)) + l$

Objective function:

$$min\ z = \partial_1 \left(\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} x_{ijk} t_{ij} - \sum_{i \in V} \sum_{j \in V} \sum_{c \in C} y_{ijc}\, t_{ij} \right) + \partial_2 \sum_{i \in V} \sum_{j \in V} \sum_{c \in C} y_{ijc}\, t_{ij} \quad (3)$$

4. SIMULATION EXPERIMENT

4.1 Simulation process

Since the problem studied in this paper is an NP-hard problem, an optimization algorithm must be used to solve the model. Optimization algorithms are divided into exact and heuristic algorithms. Exact methods have a geometric growth in time complexity and are typically only suitable for solving small-scale scenarios. For the scenario in this paper, heuristic algorithms are more suitable. To solve large-scale instances, this paper develops a Hybrid Heuristic Algorithm combining Fixed Optimization and VNS. Fixed Optimization is a heuristic algorithm that calculates an approximate optimal solution by decomposing variables. However, traditional Fixed Optimization methods heavily rely on a single initial feasible solution, making them prone to local optima. On the other hand, the VNS algorithm, a meta-heuristic algorithm, improves local search algorithms and can effectively avoid local optima. It alternates between different neighbourhood structures, balancing intensification and diversification, finding local optima during the descent phase, and escaping corresponding valleys during the perturbation phase. Therefore, this paper adopts a hybrid heuristic algorithm to optimize the search direction and intensity, thus improving the solution quality.

This paper first uses the Relaxed Fixed Method to obtain an initial feasible solution, then, starting from this feasible solution, fixes part of the 0-1 variables, and solves the remaining 0-1 variables. Choosing the appropriate variables for decomposition is crucial for optimizing the solution efficiency. The decision variables in this paper's model are twofold: one concerning vehicles and one about containers. Based on the decomposition strategy of vehicles and containers, let represent the 0-1 variables related to vehicles that have been fixed, while the 0-1 variables with subscripts in are the decision variables to be optimized. For example, in the truck set K, use the roulette algorithm to randomly select the k^{th} truck, fix its related decision variables to reduce the model's computation, and then solve the remaining decision variables. The roulette algorithm selection process is as follows: Each truck in the set is selected with a probability inversely proportional to its corresponding fitness function value. Each time the k^{th} truck is selected, its probability accumulates, and the fitness function value increases, reducing the probability of being selected in the next round. This ensures sufficient jumping out of the neighbourhood to obtain the global optimal solution. The algorithm process in this paper follows as shown in Table VI.

Table VI: VNS algorithm process.

VNS algorithm process	
1)	Generate initial solution S
2)	Set the current optimal solution as the initial solution S
3)	while not reaching the termination time do
4)	Fix the subscript k
5)	If $S'<$ global optimal solution then
6)	Set the current optimal solution as S' and the global optimal solution as S' $m \leftarrow 1$
7)	else if ($k < k_{max}$)
8)	$m \leftarrow m+1$
9)	Perform perturbation search for a new solution S'' from the neighbourhood structure of S
10)	else if ($S''<$ current optimal solution)
11)	Set the current optimal solution as S'' and the global optimal solution as S''
12)	else
13)	Set the global optimal solution as the initial solution S
14)	end if
15)	end while
16)	Output: global optimal solution

First, use the heuristic algorithm to generate an initial solution S and define its neighbourhood structure Nm. Then, using the Fixed Optimization method, randomly select the q^{th} and s^{th} trucks and fix their paths in the initial solution S, solving for the remaining trucks' delivery paths to generate a new solution S'. Subsequently, compare the new solution with the current optimal solution. If it is better than the new solution, then S' becomes the new current optimal solution; otherwise, enter the next neighbourhood for a new search to find another new solution S' and perform a new comparison operation until the maximum computation time is reached, then output the current optimal solution as the global optimal solution.

4.2 Simulation analysis

To verify the algorithm's effectiveness, this paper designs two types of cases based on different ICD quantity scales, referring to the parameter settings methods used by Zhang et al. (2010) and Xu et al. (2020), determining the number of customers to be 38. Customers are randomly generated within a rectangle based on the map of China. The number of container trucks is set to 10, and the number of ICDs ranges from 1 to 15. The K-Means clustering method is used, with customer demand as the weight and the sum of squared errors (SSE) as the stopping condition for generating candidate locations. The formula is:

$$SSE = \sum_{c=1}^{p} \sum_{V \in (V_C + V_{C'})} N_{task} |V - p_c|^2 \tag{4}$$

where N_{task} is the weight coefficient representing the customer task volume, V represents the customer point, and p_c is the cluster center.

Table VII: Results for different ICD quantity scales.

TYPE	ICD Quantity	CPLEX			VNS			GA			CPLEX	VNS	GA
		Total travel cost	Vehicle full-box distance	Optimization effect	Total travel cost	Vehicle full-box distance	Optimization effect	Total travel cost	Vehicle full-box distance	Optimization effect	Runtime		
Small scale	3	17192	1472	22 %	19130	1787	21 %	41030	3872	19 %	22.46.90	12.47.00	52.06.2
	5	15398	1319	22 %	18520	1726	21 %	18500	3619	19 %	1.34.54	0.39.32	0.40.90
	7	14838	1263	23 %	18150	1689	21 %	37016	3470	19 %	1.09.61	0.12.23	0.21.95
Medium scale	9	14888	1268	22 %	17580	1632	21 %	37386	3507	19 %	1.09.19	0.28.77	0.55.03
	11	14262	1203	24 %	17530	1627	21 %	37226	3491	19 %	1.05.95	0.29.63	0.55.58
	12	13946	1181	23 %	17530	1627	21 %	37066	3475	19 %	1.43.44	0.34.75	1.08.43

By horizontally comparing the data of the three methods in Table VII, it can be seen that the results of CPLEX and VNS are relatively close and significantly better than the inland container transportation network without ICDs. Compared to the traditional scheduling transportation network without ICDs, the total travel cost for container trucks can be reduced by about 10 % to 15 %. The VNS algorithm can significantly improve the empty travel distance of container trucks in traditional container transportation networks, noticeably increasing resource utilization and producing a more reasonable scheduling plan. Additionally, comparing the runtime of CPLEX, GA, and VNS reveals that VNS has a shorter runtime than CPLEX for solving instances and outperforms both GA and CPLEX for medium-scale instances. The results indicate that the VNS algorithm can effectively optimize the total travel cost for container trucks and reduce the empty travel distance of vehicles. Additionally, it has higher solving efficiency compared to other methods.

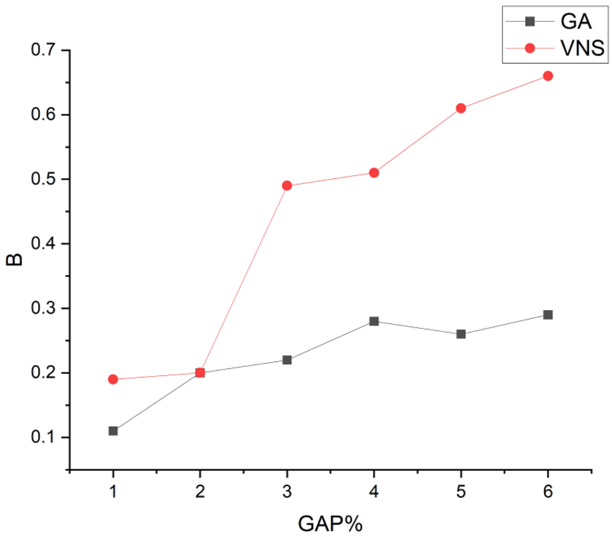

Figure 2: Algorithm performance comparison.

The performance comparison of the three solving methods is shown in Fig. 2. The horizontal axis "gap" indicates the difference between an algorithm's solving result for a case and the current optimal result, defined as $gap = \frac{best-result}{best} \times 100$ %, where "best" indicates the best result among all heuristic algorithms for a case, and "result" indicates the solving result of the algorithm. The maximum value on the horizontal axis represents the largest gap value of all algorithms for all cases. The vertical axis represents the proportion of cases where the algorithm achieves a certain gap level, with values ranging between [0, 1]. Each curve in the figure represents a solving method, and the intercept (the vertical value when the horizontal axis is 0) indicates the proportion of cases for which the algorithm achieved the best result among all heuristic algorithms. Curves located further to the upper left indicate that the corresponding algorithm achieved a higher solving level for more cases.

5. RESULTS AND DISCUSSION

To validate the results of this study, we selected data from a container transportation company and conducted simulation calculations. After screening and cleaning the customer data, the specific parameters are set as shown in Table VIII.

Table VIII: Parameters of the case study.

Distribution of customer points	**Clustering**
p (Number of ICDs)	4
d (Number of Terminal Yards)	3
E_i (Number of Import Empty Containers)	3
E_o (Number of Export Empty Containers)	3
s (Number of OF Customers)	3
r (Number of IF Customers)	3
sr (Number of IC Inland Shipping Customers)	6
sr' (Number of IC Inland Receiving Customers)	6
k (Number of Container Trucks)	10
m_i (Initial Number of Vehicles at Each Yard)	(2, 2, 2)
o_i (Initial Number of Vehicles at Each ICD)	(1, 1, 1, 1)
E_i^d (Initial Number of Empty Containers at Each Yard)	(3, 3, 3)
E_i^{icd} (Initial Number of Empty Containers at Each ICD)	(3, 3, 3, 2)
l (Time for Loading/Unloading Containers, min)	15
p_i (Time for Filling/Emptying Containers)	[30, 60]
Customer Point Distance (measured in min)	[0, 300]
Time Window (min)	[0, 1500]

When the number of ICDs is set to 4, the problems were solved using both CPLEX and a hybrid algorithm. The results are shown in Table IX.

Table IX: Results of the case study.

Number of ICDs	**Total travel cost**	**Vehicle fully loaded distance**	**Vehicle empty distance**
0	20122	1846	277
4	13970	1238	265
Optimization Effect	30.57 %	32.94 %	4.33 %

Simultaneously, when no ICDs are established, CPLEX was used to solve the problem and analyse the metrics such as the total travel cost of container trucks. The efficacy of ICDs in the inland container network was compared and analysed, with the results shown in Fig. 3. From Table IX, it is evident that setting up hub ICDs in the original inland container transportation network can optimize the network, significantly reducing the total transportation cost and the vehicle fully loaded travel distance. Specifically, the total cost of vehicle transportation decreased by 30.57 %, the fully loaded travel distance of vehicles decreased by 32.94 %, and the empty travel distance of vehicles decreased by 4.33 %. In the original container transportation network, after completing the distribution and collection tasks, trucks need to transport containers to the terminal or terminal yard. In the optimized network with ICDs, trucks can directly store containers at ICDs after completing tasks, significantly enhancing the optimization of fully loaded travel distances.

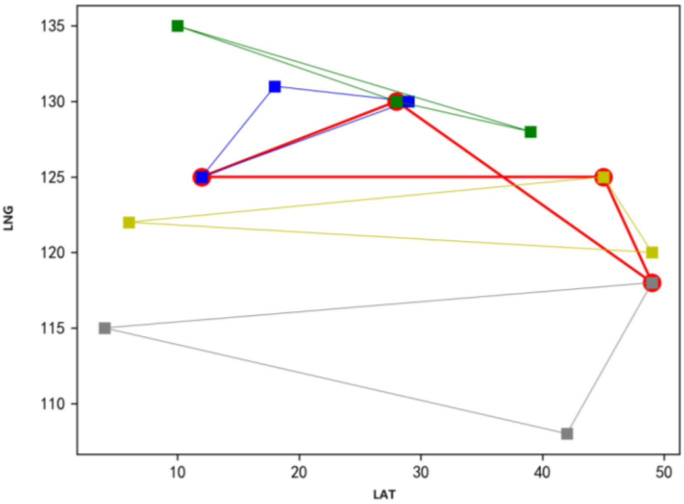

Figure 3: Results of the case study.

Considering the substantial construction cost of ICDs, this study investigates the relationship between the number of ICDs and total cost under three different distribution scenarios, with given time windows of 1500, 1900, and 2300 as shown in Fig. 4.

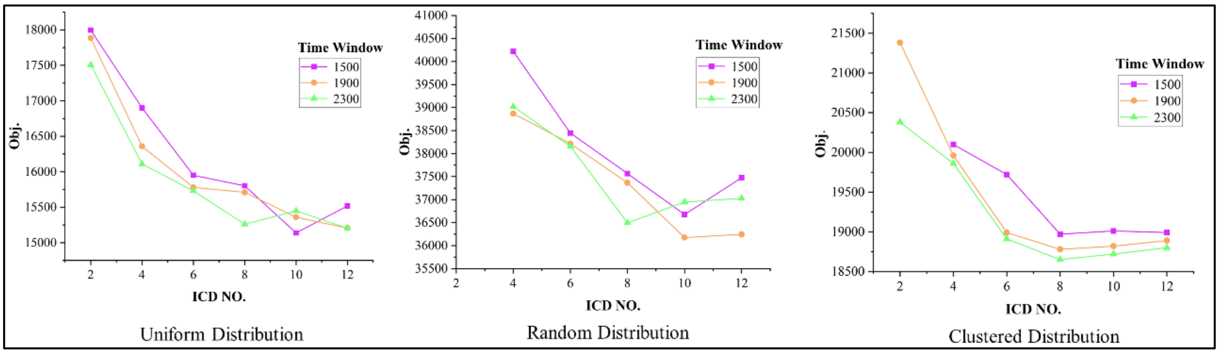

Figure 4: Impact of ICD setup on total cost across customer distributions.

Overall, setting up ICDs can effectively reduce the total cost, with the total cost showing an initial decrease followed by an increase. As the number of ICDs increases, the total cost initially decreases, reaching an optimal setup number, after which the additional optimization effect of new ICDs is less than the fixed construction cost, causing the total cost to start increasing. Additionally, for all three customer distribution types, the smaller the given time window, the higher the cost.

6. CONCLUSION

Inland container transportation, as an extension of maritime transportation, is crucial for ensuring the efficient flow of goods in and out of ports. Setting up hub ICDs in the existing inland container transportation network can fully utilize the developed comprehensive transportation system of the inland areas, enhancing the efficiency of inland container transportation and reducing the construction and total vehicle transportation costs of the inland container transportation network.

This study establishes an inland container transportation network with ICDs and investigates the scheduling of empty containers and trucks within this network. A mixed integer programming model is formulated, and a VNS algorithm combining fixed optimization algorithms is developed to solve the model. The effectiveness of the algorithm was first verified through instances of different scales. Subsequently, the model was validated based on real data from a container transportation company. The results show that establishing ICD hubs in the inland container transportation network can effectively reduce total costs and decrease vehicle empty travel distances. Specifically, the total transportation cost of vehicles was reduced by 30.57 %, the fully loaded travel distance by 32.94 %, and the empty travel distance by 4.33 %.

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