Transportation Research Part E xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Intelligent logistics integration of internal and external transportation with separation mode

Tijun Fan[a], Qianlan Pan[a], Fei Pan[a], Wei Zhou[b,c,*], Jingyi Chen[a]

[a] School of Business, East China University of Science and Technology, Shanghai 200237, China
[b] Information & Operations Management, ESCP Europe, Paris 75011, France
[c] Transportation Engineering, School of Naval Architecture, Ocean & Civil Engineering, Shanghai Jiaotong University, Shanghai 200240, China

ARTICLE INFO

Keywords:
Intelligent logistics
Container transportation
Integration
Separation mode

ABSTRACT

Many multinational companies operate their business in both domestic and overseas markets with different logistics modes, namely freight transportation by truck for domestic and short-haulage transshipment by container for overseas. To effectively optimize these operations for the two types of logistics systems, we propose an intelligent integration of external and internal transportation with the separation of drayage trucks and containers. The objective is to minimize the total cost, which includes both fixed and variable costs. The fixed cost occurs when the drayage truck is incurred in integrating transportation, and the variable cost is generated per travel distance increment. By dividing customers into different subsets and proposing a special penalty matrix, we provide an intelligent model that integrates the internal and external container transportation problems. A customized genetic algorithm is proposed. Based on the instances of real-life data on 888 orders, the results show that our approach can reduce the overall cost by 16.8%.

1. Introduction

As an emerging technology caused by rapid advances in modern information technology, internet of things (IoT) is widely concerned and applied in many areas including manufacturing and transportation. As for an important application of IoT, intelligent logistics plays an importation role in city life. Implementing intelligent logistics can meeting business requirements and make wise management of transportation.

In the contemporary globalized economy, an increasing number of multinational companies operate their businesses in both domestic and overseas markets with different logistics requirements and operational standards. This presents substantial operational challenges and tremendous opportunities to improve logistics. For the domestic market, freight transportation by truck between local suppliers and retailers is often needed. For the overseas market, short-haulage container transshipment is a popular transportation mode between terminals and shippers/receivers. The hybrid logistics requirements of the domestic and overseas markets increase companies' total operating costs. How to effectively integrate and optimize the operations of the two types of logistics systems thus becomes an important issue, especially in the emerging research field of intelligent logistics services.

This research studies a real company with production based in China (its name is withheld pursuant to a confidentiality agreement) that produces furniture, kitchen appliances and home accessories. This company covers both the Chinese local market

* Corresponding author at: ESCP Europe, Department of Information & Operations Management, 79 Avenue de la republique, 75011 Paris, France.
E-mail addresses: tjfan@ecust.edu.cn (T. Fan), ql.pan@mail.ecust.edu.cn (Q. Pan), feipan@mail.ecust.edu.cn (F. Pan), wzhou@escpeurope.eu (W. Zhou), jychen@mail.ecust.edu.cn (J. Chen).

https://doi.org/10.1016/j.tre.2019.10.011
Received 22 June 2019; Received in revised form 29 October 2019; Accepted 30 October 2019
1366-5545/

Please cite this article as: Tijun Fan, et al., Transportation Research Part E, https://doi.org/10.1016/j.tre.2019.10.011

and all major international markets. As it ships to retailers in both China and across the world, it is keen to investigate novel hybrid models and to find the optimal solutions that would yield higher efficiency and lower costs. With several suppliers in the city of Shanghai, for instance, the company operates freight transportation for the retailers in that city via truck and Shanghai's seaports via container. As the two incompatible transportation modes result in high operating costs, the company is determined to explore a novel and intelligent integrated container transportation solution for both markets.

The transportation problem for the domestic market belongs to the classical vehicle routing problem (VRP). The freight transportation for the overseas market, from hinterland shippers to container terminals, belongs to the container drayage problem (CDP). The major challenge is to integrate VRP and CDP with container transportation. Thanks to the recent advancement of IoT and GIS (Geographic Information System) technologies, practitioners are able to tackle this challenge by tracking and tracing the items, containers, along with the movement of vehicles and the status of the warehouses. How to optimize the integrated container transportation given the separation between drayage trucks and containers intelligently becomes a more important question, while the advanced technology ensure granularized information collection at the real-time and effective information sharing.

Based on the real-time data, we propose a novel intelligent logistics approach to integrate internal and external container transportation by adopting drayage trucks and containers during transportation. We consider the internal transportation between suppliers and retailers in the domestic market and the external transportation from shippers to terminals for the overseas market. The integrated container transportation system entails computational complexity and difficulty due to the routing differences between supplier/retailer and shipper/terminal. By introducing a new penalty matrix that maps to the start point and endpoint of freight with divisible subsets, we also make a methodological contribution by proposing a customized genetic algorithm as the solution method.

The remainder of the paper is organized as follows: we review the literature on container vehicle routing problems under the stay-with mode and separation mode in Section 2. We then present details of the proposed problem in Section 3. In Section 4, we formulate the mathematical model. In Section 5, we propose a heuristic algorithm to solve practical problems. A case study based on the analysis of our corporate data is presented in Section 6. Concluding remarks are in Section 7.

2. Related work

We categorize the relevant literature in three streams: the intelligent logistics, the vehicle routing problem, the container transportation problem under stay-with mode and the container transportation problem under separation mode.

2.1. Intelligent logistics

There is a number of studies which aim to improve logistics systems by applying intelligent methods. Some of the very early research in the field, such as Crainic et al. (2009), found that the Intelligent Transportation Systems (ITS) developments were largely hardware-driven and the development of the software component of ITS, models and decision-support systems was lagging behind. They emphasized that transportation planning and management disciplines, operations research played a key role to play to solve this challenge. He et al. (2014) presented a novel multilayered vehicular data cloud platform by using cloud computing and IoT technologies. Two innovative vehicular data cloud services, an intelligent parking cloud service and a vehicular data mining cloud service, for vehicle warranty analysis in the IoT environment are also presented. A conceptual model for customer orientation in intelligent logistics that focused on improving the role of the customer in logistics operations was proposed by McFarlane et al. (2016).

The integrated planning problem for intelligent food logistics systems was studied by Li et al. (2018). They applied the intelligent logistics to reduce food waste, improve food quality and safety. Computational results showed that the intelligent logistics methods they proposed if of effectiveness and efficiency. Recently, Wei and Max (2018) reviewed smart-city initiatives of governments, industry, national laboratories and academia. The results found that research opportunities have appeared when the smart-city movement transiting from the tech-oriented stage to the decision-oriented stage, including smart buildings, smart grid, smart mobility and new retail. In general, today's existing researches in this field have focused more on the information and communication technologies and we needed more research of business process, model, and methodology innovations. Barenji et al. (2019) investigated a intelligent E-commerce logistics platform that integrates intelligent distribution centers based on an agent technology. The platform served for decentralization and synchronization purposes and also optimized for the transportation and logistics of the overall system.

2.2. Vehicle routing problem

The vehicle routing problem was first proposed by Dantzig in 1959 (Dantzig and Ramser, 1959). The main task in the VRP is to determine a set of vehicle routes to perform all (or some) transportation requests with the given vehicle fleet at the minimum cost, in particular deciding which vehicles handle which requests in what sequence such that all vehicle routes can be feasibly executed (Toth et al., 2014). Since the VRP was proposed, it has received considerable attention from scholars. The VRP may be studied from either a static or dynamic perspective (Ghiani et al., 2003).

Numerous papers have been conducted to address different aspects of the static VRP. Gutierrez-Jarpa et al. (2010) considered a VRP with deliveries, selective pickups and time windows. The numerical computational results included 100 customers. Polat et al. (2015) studied the vehicle routing problem with simultaneous pickup and delivery with a time limit (VRPSPDTL). The problem determined a set of vehicle routes originating and terminating at a depot, and the objective was to minimize the total travel distance.

Salazar-Gonzalez and Santos-Hernandez (2015) introduced a new vehicle routing problem, which transferred one commodity between customers with a capacitated vehicle that was able to visit a customer more than once. Bula et al. (2017) focused on the heterogeneous fleet vehicle routing problem (HFVRP) for hazardous materials (HazMat) transportation. The results showed that the approach was competitive in terms of computational efficiency and quality. Qiu et al. (2018) studied a problem on practical logistics distribution that consisted of designing a least-cost set of routes to serve a given set of customers while respecting constraints on the vehicles' capacities.

Static vehicle routing problems assume that all relevant information or intelligence is determinate and can be exploited in the solution process; by contrast, the input data for a dynamic VRP are usually sourced online (Jaillet and Wagner, 2006) or in real-time (Yang et al., 1999). Meanwhile, competitive intelligence is an important part of developing and implementing organizational strategy (Kumar et al., 2019). So dynamic VRP is meaningful in practice. Franceschetti et al. (2013) considered the time-dependent pollution-routing problem (TDPRP) that consisted of routing a fleet of vehicles to serve a set of customers and determined the speed on each route. The cost function included emissions and driver costs while accounting for traffic congestion that changed vehicle speeds and increased emissions. Dalmeijer and Spliet (2018) presented a branch-and-cut algorithm for the time window assignment vehicle routing problem (TWAVRP), in which the problem of assigning time windows for delivery when demand volume was unknown. Zolfagharinia and Haughton (2017) investigated the impact of potential factors on carriers' operational efficiency in a dynamic pickup and delivery problem with full truckload (DPDFL) for local operators. The results showed that advanced load information and the decision interval had a marked influence on total costs. Sun et al. (2018) studied time-dependent pickup and delivery problems with time windows to optimize the service of a transportation provider under two types of operational flexibility. Subramanyam et al. (2018) proposed a two-stage stochastic optimization approach to assign time windows to customers in vehicle routing applications under operational uncertainty.

The classical VRP does not provide solutions to the transportation integration problem of the separate modes of containers and trucks. Therefore, in the next subsection, we continue reviewing the literature of container transportation problem.

2.3. Container transportation problem under the stay-with mode

The stay-with mode is an importation operational mode in container transportation. Generally, the stay-with container transportation problem can be divided into static and dynamic variants. Some scholars have studies the static container transportation problem under the stay-with mode. Wang and Regan (2002) proposed a solution method for a multiple traveling salesmen problem with time window constraints (m-TSPTW), which provided a theoretical basis for the subsequent solution of container transportation problems. Imai et al. (2007) addressed a vehicle routing problem that arises in picking up and delivering full container loads from/to an intermodal terminal. The results showed that the procedure they developed can efficiently solve large-instance problems. Chung et al. (2007) studied some practical problems involved in road container road transportation in Korean trucking. The case indicated that the approach could be applied to operate and design container transportation systems in the real world. Caris and Janssens (2009) formulated the container drayage problem in the service area of an intermodal terminal as a full truckload pickup and delivery problem with time windows (FTPDPTW). Zhang et al. (2010) studied a truck scheduling problem for container transportation with multiple depots and multiple terminals while including containers as a transportation resource. Zhang et al. (2011a) investigated the problem faced by firms that transport containers by truck in an environment with resource constraints and developed an algorithm based on reactive tabu search (RTS) to solve the problem. Wang and Yun (2013) studied an inland container transportation problem using truck and train. They developed a mathematical graph model and proposed a hybrid tabu search. Nossack and Pesch (2013) investigated a truck scheduling problem in container transportation, where containers need to be transported between customers (shippers or receivers) and container terminals (rail or maritime) and vice versa. Lai et al. (2013) studied a drayage problem in which container loads were shipped from a port to importers or from exporters to the port by trucks carrying one or two containers under the stay-with mode. The metaheuristic performs a sequence of local search phases and improves the performance of carrier's decisions. Shiri and Huynh (2016) investigated a version of the drayage problem in which the intermodal terminal requires trucks to have an appointment, and the results showed that the adoption of an efficient truck appointment system could considerably reduce operating time for drayage firms.

The load balance for container loading problem was studied by Ramos et al. (2018). They treated load balance as a hard constraint and introduced vehicle specific diagrams. The multi-population biased random-key genetic algorithm (BRKGA) they proposed showed advantage in incorporating load balance. Moreover, the allocation of empty container resources due to uneven imports and exports in hinterland container drayage transportation has also been examined. Shintani et al. (2007) studied the design of container liner shipping service networks by considering empty container repositioning. Zhang et al. (2009) formulated a container truck transportation problem that involved multiple depots with time windows at both origins and destinations, including the reposition of empty containers. Shintani et al. (2010) considered saving container fleet management costs in repositioning empty containers by using foldable containers. The result revealed that foldable containers dramatically saved repositioning costs relative to standard containers. Moon et al. (2013) compared the repositioning costs of foldable containers to those of standard containers. The study demonstrated the economic feasibility of foldable containers and that their purchasing cost and transportation cost affect their use. Sterzik and Kopfer (2013) proposed a comprehensive mathematical formulation that simultaneously considered vehicle routing and scheduling and empty container repositioning. Numerical experiments indicated that for some data sets, the approach they proposed had considerable potential for reducing fixed costs. Zhang et al. (2018) incorporated foldable containers into drayage services. Their numerical experiments demonstrated that the use of four-in-one foldable containers can save approximately 10% on transportation costs.

By exploiting structural properties of the optimal solution, Galle et al. (2018)transformed the restricted Container Relocation Problem (CRP) o binary integer programming problem, which reduced the number of variables and constraints compared to existing formulations and improved efficiency significantly. Legros et al. (2019) studied a time-based policy for empty container management. from a practical point of view, they considered detention fees and cleaning costs in practice. Results showed the policy they proposed reduced container repositioning costs. Shintani et al. (2019) formulated a model of a minimum cost multi-commodity network flow problem which aimed to simultaneously determine the fleet sizes of standard and combinable containers and their empty container allocation/repositioning of combinable containers. Numerical experiments showed that mixed use of containers save cost significantly.

Several scholars have studied this problem in the dynamic setting. Mahr et al. (2010) applied two solution approaches, online optimization and an agent-based approach, to solve the drayage problem with time windows under two types of uncertainty, and the results demonstrated that the agent-based system outperformed on-line optimization when service time duration was highly uncertain. Zhang et al. (2011b) proposed approaches for incorporating informational and operational dynamics into intermodal drayage operations with flexible tasks, which helped a drayage firm to identify high-quality plans even when many tasks were initially unknown. Escudero et al. (2013) presented a method of using vehicle Global Positioning System(GPS) to solve this problem, which consistently allowed the planner to reassign tasks when the problem conditions changed. The results showed that the approach can reduce average operating costs by as much as 5%–13%. Zhang et al. (2014) introduced a determined-activities-on-vertex (DAOV) graph to study a container drayage problem with flexible orders. The results revealed that the window partition method could effectively solve the problem. Wong et al. (2015) derived with a yield-based container repositioning framework, followed by a constrained linear programming optimizing the container repositioning, and incorporated changes in the destinations of empty containers and adjustment factors to cope with surges in demand. Torkjazi et al. (2018) studied an approach for designing a truck appointment system (TAS) to serve both maritime container terminal operators and drayage operators that proved capable for solving problems subject to substantial uncertainty. Jeong et al. (2018) investigated an empty container management strategy in a two-way four-echelon container supply chain for bilateral trade between two countries. They also proposed a hybrid solution procedure based on accelerated particle swarm optimization and heuristic to solve the problem, which reduced the transshipment cost. Lee and Moon (2020) formulated a robust mode for the empty container repositioning problem considering foldable containers under demand uncertainty. Computational results indicated that the formulation performs well in terms of operating costs.

2.4. Container transportation problem under the separation mode

There is a small number of publications that investigated the container transportation problems under the separation mode. Cheung and Shi (2008) studied a cross-border drayage container transportation problem from the perspective of individual resources (e.g., driver, tractor, and chassis) and the composites of them (e.g., driver-tractor-chassis triplets) that needed to be managed simultaneously. The results showed that the benefit gained by relaxing regulatory policies is significant. Braekers et al. (2013) discussed a full truckload vehicle routing problem for transporting loaded and empty containers under a separation mode. The results demonstrated the advantage of using a two-phase algorithm for vehicle routing problems with hierarchical objectives. Xue et al. (2014) studied a local container drayage problem (LCDP) under an new operation mode in which a tractor could be detached from its companion trailer and assigned to a new task. In numerical experiments, the new operation mode reduced the total cost by at least 15.26%. Xue et al. (2015) investigated the problem again with a max–min ant colony optimization algorithm, which outperformed cplex in solution quality and computation time. Sterzik et al. (2015) compared the cost when trucking companies have access only to their own containers to the situation in which empty containers were permitted to be interchanged among several owners. The results indicated that container sharing between trucking companies leads to remarkable cost savings. Song et al. (2017) studied a new variant of the container drayage problem under the separation mode in which a container can be separated from the truck during (un) loading operations, while some emptied containers should be returned to the depot for maintenance. Numerical experiments showed that the separation mode has advantages over the stay-with mode.

Although some scholars have considered the container transportation problems under the separation mode, they have focused solely on the waiting time optimization when receivers/shippers unload or load freight. In contrast to existing related studies, our study treats the containers as an independent resource that can be used for both internal and external transportation.

3. Problem description

We consider a scenario with truck and container depots. In the separation mode, the company uses different trucks to fulfil transportation for local and international markets. The operation is shown in Fig. 1.

The internal transportation (transportation for the domestic market): a truck departs from the truck depot and picks up freight from the suppliers. Then, the truck drops the freight off at retailers and ultimately returns to the truck depot. A truck is allowed to visit several customers if the upper bound distance constraint is satisfied. In the lower part of Fig. 1, drayage trucks depart from the truck depot, then pass the container depot and pick up empty containers. Note that an empty container must be picked up before the truck drives to the shipper since a container is needed to load the freight destined for export. Then, each truck, after picking up a container, will load the export freight at the shippers, and finally drops off the full containers at the terminal. In this situation, the two types of transportation operate separately, which increases managerial complexity and transportation costs. According to Smilowitz (2006), the efficiency of a system can be improved if more tasks are present in a single system, thus generating more opportunities both for covering two flexible tasks with a single joint execution and eliminating trucks invalid transportation (Zhang et al., 2011b).

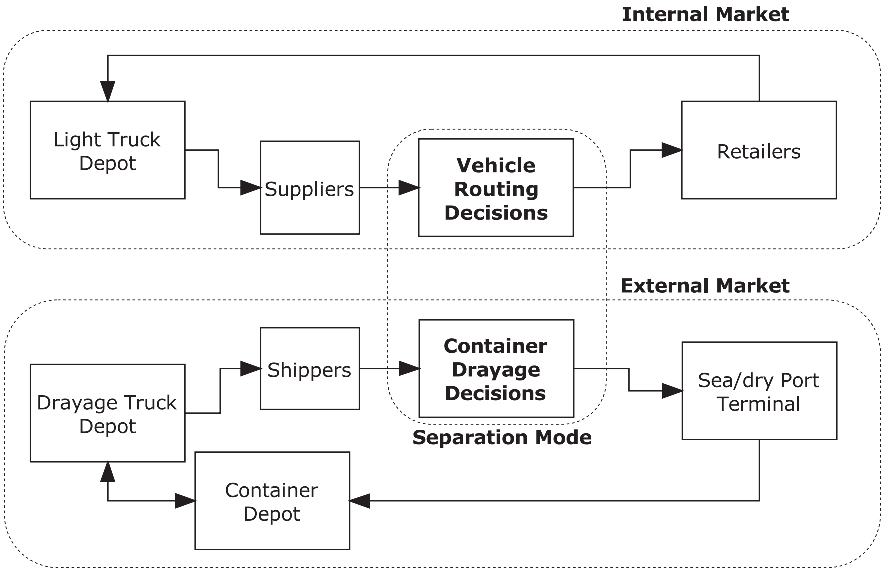


Fig. 1. Current situation.

Based on that, we intend to integrate internal and external transportation. As shown in Fig. 2.

Two scenarios may exist after integrating the two logistics systems. In Fig. 2, the drayage truck departs from the truck depot and picks up an empty container at the container depot, then drives to supplier to load the freight and transport it to the retailer. After finishing the internal transportation task, the drayage truck might drive to shipper or supplier to execute the next task if the upper bound of the distance constraint is not exceeded. In the second scenario, the drayage truck departs from the truck depot for the container depot. After picking up an empty container, the drayage truck drives directly to shipper and then delivers the freight to the terminal. If the upper bound on distance permits, the drayage truck can continue to execute other tasks, driving to the container depot to pick up another empty container for the next shipment or return to the truck depot. During the entire operation process, the information of drayage truck will transfer to the intelligent decision center and the decision information will be returned to truck. In the integrated situation, we use the homogeneous truck (the drayage truck) for integrated transportation, which can dramatically reduce total costs.

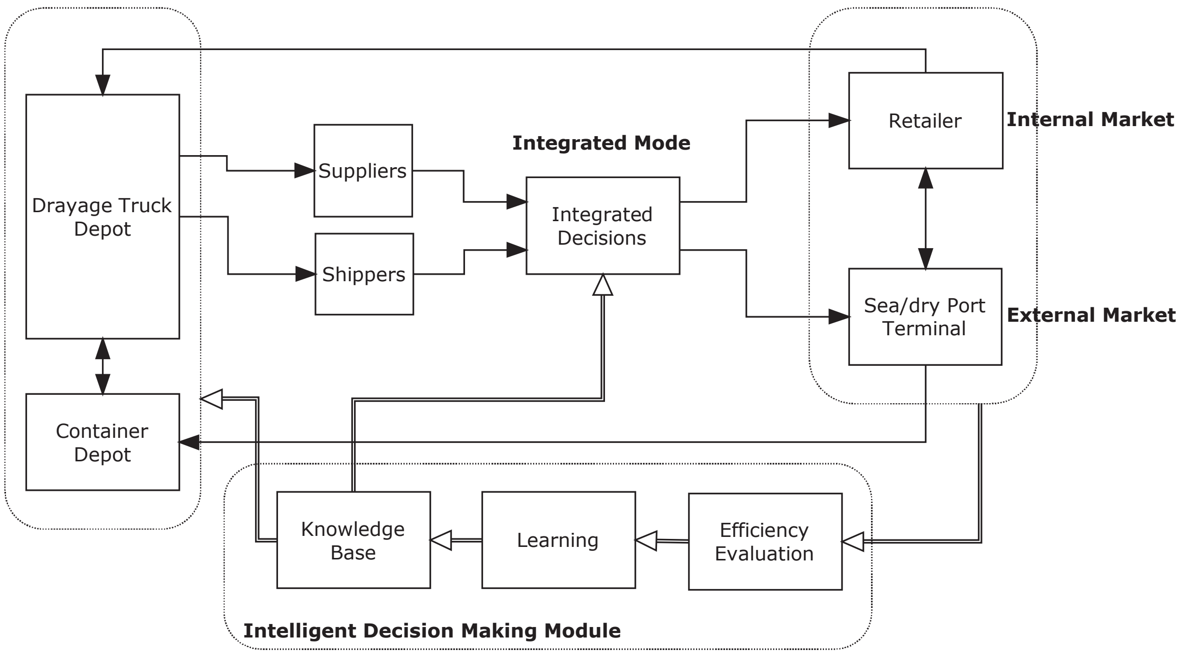


Fig. 2. Optimized operation process.

Table 1
Notations.

Sets and indices	
V_1	set of the container depot, $V_1 = \{1, 2, \ldots, n_1\}$
V_2	set of suppliers, $V_2 = \{n_1 + 1, n_1 + 2, \ldots, n_1 + n_2\}$
V_3	set of retailers, $V_3 = \{n_1 + n_2 + 1, n_1 + n_2 + 2, \ldots, n_1 + 2n_2\}$
V_4	set of shippers, $V_4 = \{n_1 + 2n_2 + 1, n_1 + 2n_2 + 2, \ldots, n_1 + 2n_2 + n_3\}$
V_5	set of terminals, $V_5 = \{n_1 + 2n_2 + n_3 + 1, n_1 + 2n_2 + n_3 + 2, \ldots, n_1 + 2n_2 + 2n_3\}$
V	set of all points, including all types of set have mentioned before,and these sets are completely separate. $V = \{0, V_1, V_2, V_3, V_4, V_5\}$, where 0 represents the truck depot
i, j	nodes, $i \in V, j \in V$
i'	nodes, $i' \in V$, i' is not the same point as i
$\Im$	set of trucks, $\Im = \{1, 2, \ldots, K\}$
k	truck, $k \in \Im$
Parameters	
c_1	fixed cost
c_2	variable cost
L	upper bound on distance
d_{ij}	distance from i to j
M_{ij}	penalty matrix
Decision variable	
x_{ijk}	truck k travels from i to j

4. Modelling

4.1. Assumptions and notations

(1) Transportation information such as locations and the orders of suppliers, retailers, shippers, and terminals is already known. The number of trucks and the upper bound of the distance traveled by drayage truck is already given.
(2) The location set is divided into several subsets:0, V_1, V_2, V_3, V_4 and V_5. The truck depot is denoted by 0. V_1 represents the set of container depots, V_2 is the set of suppliers, V_3 represents the set of retailers, V_4 denotes the set of shippers, and V_5 represents the set of terminals. Furthermore, $V = 0, V_1, V_2, V_3, V_4$ and V_5.
(3) For each internal transportation task, freight is transported from start point to the corresponding endpoint; for example, the freight from the supplier should be transported to the corresponding retailer. We do not consider cases such as one-to-many or many-to-one transportation.
(4) For external container transportation, each container loads the freight required by one overseas customer, regardless of whether doing so entails an instance of less than container load (LCL).
(5) The truck departs from the truck depot and then needs to return to the truck depot after completing the transportation task or when it reaches the upper bound on distance.
(6) The number of empty containers is infinite, and the truck picks up empty containers from container depot when needed.

The following notations are used in Table 1.

4.2. Mathematical modelling

We describe in detail our model to quantitatively characterize integrated internal and external container transportation under the separation mode.

$$\min\ total\_cost = c_1 K + c_2 \sum_{k\in\Im} \sum_{i\in V} \sum_{j\in V} x_{ijk} d_{ij} M_{ij} \tag{1}$$

$$\sum_{k\in\Im} \sum_{j\in V} x_{ijk} = 1,\ \ \forall\ i \in V_2 \cup V_3 \cup V_4 \cup V_5 \tag{2}$$

$$\sum_{j\in V\setminus\{0\}} x_{0jk} = 1,\ \ \forall\ k \in \Im \tag{3}$$

$$\sum_{i\in V\setminus\{0\}} x_{i0k} = 1,\ \ \forall\ k \in \Im \tag{4}$$

$$\sum_{i\in V} x_{ijk} = \sum_{i'\in V} x_{ji'k}, \ \forall k \in \Im, \ \forall j \in V\backslash\{0\} \tag{5}$$

$$\sum_{i\in V}\sum_{j\in V} d_{ij}x_{ijk} \leqslant L, \ \forall k \in \Im \tag{6}$$

As shown in Eq. (1), the objective minimizes the overall integrated transportation costs, which include fixed and variable costs of internal and external container transportation. c_1 is the fixed cost for each drayage truck, K is the given number of trucks, both of which are given parameters, and c_1K represents the fixed cost of integrated container transportation. Similarly, the second part of Eq. (1) (i.e., $c_2 \sum_{k\in\Im}\sum_{i\in V}\sum_{j\in V} x_{ijk}d_{ij}M_{ij}$) represents the variable cost of this integrated transportation, where c_2 is the variable cost per unit distance, and a given parameter; $\Im$ represents the truck set, $\Im = \{1, 2, ..., K\}$; the vertex set V includes the truck depot (denoted by 0), the set of container depots (V_1), the set of suppliers (V_2), the set of retailers (V_3), the set of shippers (V_4), and the set of terminals (V_5), i.e., $V = \{0, V_1, V_2, V_3, V_4, V_5\}$; the independent variable x_{ijk} is a boolean variable that is equal to one if the k-th truck departs from point i to point j ($i \in V, j \in V$), zero otherwise; d_{ij} is the distance from point i to point j; and $d_{ij} = d_{ji}$, because for a specific internal or external trip, the start point may be the point i and the endpoint may be point j, but for another trip, the start point and the endpoint are vice versa, i.e., the start point is the point j and the endpoint is point i. The above symbols in Eq. (1) are basically consistent with the traditional vehicle routing problem, but these expressions cannot describe the difference between our proposed integrated transportation model and the existing vehicle routing problem (VRP), such as traditional VRP or the vehicle routing problem with simultaneous pickup and delivery (VRPSPD). Therefore, we introduce a new punishment M_{ij} parameter to portray the directionality of transportation. When the drayage truck is allowed to travel from point i to point j, M_{ij} equals 1; otherwise M_{ij} is M. This parameter will be introduced in detail in Section 4.3.

Some constraints are basically the same as those in the traditional VRP and the VRPSPD. Eq. (2) ensures that each point, representing suppliers, retailers, shippers or terminals, is assigned to exactly one truck, i.e., for any endpoint i (i.e., $i \in V_2 \cup V_3 \cup V_4 \cup V_5$), only one truck departs from this point, and the independent variable x_{ijk} should satisfy Eq. 2. Eq. (3) ensures that each truck departs from the truck depot once and returns to the depot after servicing the last customer demand once; therefore, x_{0jk} and x_{i0k} should satisfy constraint (3) and constraint (4), respectively. From constraint (3) and constraint (4), we obtain that

$$\sum_{k\in\Im}\sum_{j\in V\backslash\{0\}} x_{0jk} = \sum_{k\in\Im}\sum_{i\in V\backslash\{0\}} x_{i0k} = K.$$

In Eq. (5), i and i' both belong to V, but they are different points. Eq. (5) is a flow equilibrium constraint that represents every point j has the same in-degree and out-degree. According to Eq. (6), based on firms' actual operating needs, each truck should return to the truck depot before its driving distance reaches the upper bound (Avella et al., 2004; Laporte et al., 1984). Therefore, the constraint (6) should be satisfied, where L is the upper bound on the distance traveled by trucks.

4.3. Penalty matrix (M_{ij})

This subsection further expands on the penalty matrix (M_{ij}). Although the distance matrix (d_{ij}) in the traditional vehicle routing problem can reflect the directionality (one or two way roads) of roads, it cannot express two specific container trips (plans) moving in the opposite direction, i.e., the start point of one container trip (plan) is the other's endpoint, and vice versa. In other words, the traditional VRP cannot describe transportation from a specific start point to an endpoint. Furthermore, the VRPSPD can reflect this pickup and delivery problem between a given start point to the corresponding endpoint (Toth et al., 2014), such as internal transportation. However, the VRPSPD cannot describe external container transportation because the truck needs to load the container at the container depot before picking up the freight at the start point of the external container trip, and the newly added container loading operation exceeds the scope of the VRPSPD. Therefore, the penalty matrix (M_{ij}) is proposed to describe integrated internal and external container transportation.

The penalty matrix (M_{ij}) is defined as follows:

$$M_{ij} = \begin{cases} 1, & i \in 0 \text{ and } j \in V_1 \\ 1, & i \in V_1 \text{ and } j \in V_2 \cup V_4 \\ 1, & i \in V_2 \text{ and } j \in V_3 \\ 1, & i \in V_3 \text{ and } j \in V_2 \cup V_4 \\ 1, & i \in V_4 \text{ and } j \in V_5 \\ 1, & i \in V_5 \text{ and } j \in \{0\} \cup V_1 \\ M, & \text{otherwise} \end{cases} \tag{7}$$

where the parameter M is penalty (a very large positive number). Case one in Eq. (7) indicates that a drayage truck departing from the truck depot (0) must drive to the container depot (V_1). In case two, a truck departing from the container depot (V_1) must drive to the supplier (V_2) or the shipper (V_4). In case three, a truck departing from the supplier (V_2) must drive to the retailer (V_3). Case four shows that a truck departing from the retailer (V_3) can drive to another supplier (V_2) or the shipper (V_4). In case five, a truck departing from the shipper (V_4) must drive to the terminal (V_5). In case six, a truck departing from the terminal (V_5) can drive to the truck depot (0) or the container depot (V_1). Other cases are not feasible or allowed, therefore penalties need to be imposed. To provide further detail, the penalty matrix (M_{ij}) is explained through a specific example. Suppose that the number of elements in the sets V_1, V_2, V_3, V_4 and V_5 is

Table 2
A specific example of the penalty matrix (M_{ij}).

	0	1	2	3	4	5
0	1	M	M	M	M	M
1	M	M	1	M	1	M
2	M	M	M	1	M	M
3	M	M	1	M	1	M
4	M	M	M	M	M	1
5	1	1	M	M	M	M

one. These five points are denoted by 1 to 5 in order, and 0 represents the truck depot. Therefore, the penalty matrix (M_{ij}) of this sample is shown in Table 2.

The reason that the penalty matrix (M_{ij}) is proposed to describe the directionality of the integrated internal or external transportation is that (1) it simplifies the mathematical description of our established model; (2) it avoids conflicts between the non-directionality of the road and the directionality of the trip (plan); and (3) it does not impose an additional burden on the calculation of the objective function, because $d_{ij}M_{ij}$ in Eq. (1) can be considered as a whole, which is the Hadamard product of the distance matrix (d_{ij}) and the penalty matrix (M_{ij}).

5. Solution method

In the previous section, we presented a customized algorithm to quantitatively solve the proposed mathematical model for integrated internal and external container transportation. This model is a special case of the VRP, which is NP-hard (Lenstra and Kan, 1981). Therefore, our model is an NP-hard problem and requires a heuristic solution (Russell, 1995).

Lawrence and Mohammad (1996) first applied the genetic algorithm to effectively solve the traditional VRP. Introduced by Holland in 1975 (Holland, 1975; Cheng et al., 2018), the genetic algorithm has a key characteristic to update solutions (or chromosomes) through selection, crossover and mutation. The genetic algorithm with the natural number coding method is now a mainstream solution method for the VRP (Cheng and Yu, 2013). Although it can solve the proposed mathematical model, its computational efficiency is extremely poor. We will further explain the reason of such inefficiency through the example presented in Section 4.3.

For the permutation of five different types of points, there are 120 different possibilities. However, among the 120 possibilities, only two are feasible solutions of the proposed mathematical model, i.e., “0→1→2→3→4→5→0” and “0→1→4→5→2→3→0”(see Fig. 3). Therefore, it is necessary to improve the coding method of the genetic algorithm according to the characteristics of the integrated internal and external container transportation problem.

Compared with the traditional VRP, the central problem studied in this paper possesses two major characteristics. Firstly, for each internal or external container trip, there is a unique start point and a unique endpoint. The transportation direction is one-way and runs only from the start point to the endpoint as shown in Eq. (7). The start point and the endpoint of a trip (plan) can be considered as a whole and represented by a natural number. Therefore, as long as the number of trips (plan) is given, the specific transportation route can be uniquely determined. Secondly, due to the separable characteristics of containers and trucks, the drayage truck must load the container at a container depot before the trip (plan) is implemented, i.e., a truck must visit the container depot set (V_1) before visiting the set of suppliers (V_2) or shippers (V_4). Based on these two characteristics, the genetic algorithm with an improved coding method is proposed, which can be briefly summarized as follows:

Step1: Data reading. The distance matrix and all trips (plans), which include the set of suppliers, retailers, shippers and terminals of the internal and external container transportation systems are input.
Step2: Population initialization. A population is generated based on the improved coding method. The population can be mutated into hundreds of chromosomes, and each chromosome represents a feasible solution of the integrated internal and external container transportation.
Step3: Fitness value calculation. According to the transportation (plan) data that have been read, each chromosome is compiled into the transportation routes of all trucks, and then the fitness value (also called the objective function value) of the transportation routes of all trucks is calculated according to Eq. (1).
Step4: Population update. The population evolves through selection, crossover, mutation and re-inserting.

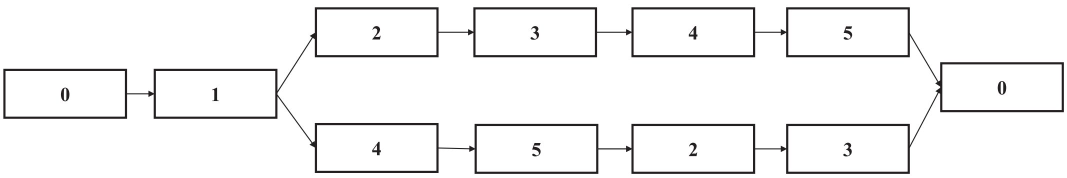


Fig. 3. All feasible solutions of the example in Section 4.3.

Step5: If the continuously unchanged number of the minimum fitness value in the population or the total number of all iterations reaches the given upper bound, the algorithm terminates. The latest minimum fitness value in the population and its corresponding chromosome are considered the outputs.

The main steps of the algorithm in our model are provided in Fig. 4.

In what follows, we will further discuss the population initialization in Step 2 and the crossover and mutation in Step 3, which are related to the improved coding method and different from those of the genetic algorithm with the natural number coding method.

5.1. Population initialization

Due to the directionality and uniqueness of the trip (plan), the start point and endpoint of the internal or external container transportation (plan) can be represented by an order number, which can reduce the dimensionality of solutions and simplify the structure of solutions. Suppose that the number of trucks is K; the number of unique elements in set V_1 is n_1; the number of the internal order is n_2, which is equal to the number of the V_2 and equal to the number of set V_3; and the number of external orders is n_3, which is equal to the number of set V_4 and equal to the number of set V_5. Next, a truck depot is denoted by 0; a container depot is represented by a natural number between 1 and n_1; an internal order is denoted by a natural number between $n_1 + 1$ and $n_1 + n_2$; and an external order is represented by a natural number between $n_1 + n_2 + 1$ and $n_1 + n_2 + n_3$. We use an example to illustrate the process of solving the genetic algorithm. In the following process, the number 0 represents the truck depot, and 1 represents container depot. We have three internal orders, coded by the numbers 2, 3, 4 and two external container orders which are recorded as the numbers 5 and 6. There are 3 trucks available for these tasks. Generate a feasible solution (i.e., a chromosome in the population) as follows:

Step1: Order sorting. A random permutation of natural numbers from $n_1 + 1$ to $n_1 + n_2 + n_3$ is generated, which contains n_2 internal orders and n_3 external orders, as shown in Fig. 5(a).

Step2: Truck allocation. In this random permutation of length $n_2 + n_3$, $K - 1$ locations are randomly selected from $n_2 + n_3 - 1$ gaps. Then, $K - 1$ zeros are inserted into these locations, and two zeros are added to both ends of this random permutation. A vector of length $n_2 + n_3 + K + 1$ is obtained, which contains $K + 1$ zeros. The sequence of natural numbers between any two adjacent zeros in this vector is the order fulfilment process of a truck, as shown in Fig. 5(b).

Step3: Allocating container depots. In the vector of length $n_2 + n_3 + K + 1$ obtained in Step 2, insert a natural number between 1 and n_1 after the zero because both internal and external orders need to be transported in empty containers. Moreover, since a container containing freight will be left at the terminal, if a drayage truck continues to execute another task, it needs to pick up another empty container. Traveling in the opposite direction, a number that represents a container depot needs to be inserted between the external order and another number except zero. Because the total number of the marked natural numbers is n_3, the number of newly inserted natural numbers is n_3. Finally, a vector of length $n_2 + 2n_3 + K + 1$ is generated, as shown in Fig. 5(c).

The initial feasible solution generated in this section satisfies the requirements for the integrated internal and external container transportation problem and permits a more flexible extraction of containers, as long as the transportation is container-based. Moreover, it reflects the integration optimization of internal and external transportation, as processing the location in the form of the order makes it easier to achieve integration optimization.

5.2. Crossover and mutation

Crossover and mutation are important operations in the genetic algorithm and can help to maintain the diversity of the population and avoid falling into local optimums (Cuevas et al., 2002; Bajpai and Kumar, 2010). However, their designs are directly related to the structure of the initial solution (i.e., a chromosome in the population), and existing crossover and mutation operators, such as partially mapped crossover, order crossover and position-based crossover, cannot guarantee that each chromosome in the offspring population is a feasible solution.

First, the steps of a specific crossover operator in our proposed algorithm are as follows:

Step1: Two chromosomes are randomly selected from the current population, and they are denoted Parent Chromosome 1 and Parent Chromosome 2, as shown in Fig. 6(a).

Step2: A gene fragment between two adjacent zeros is randomly selected from Parent Chromosome 1, as shown in Fig. 6(b).

Step3: The genes, which are less than or equal to n_1 and appear in the selected gene fragment from Step 2, [1] are removed from the copy of Parent Chromosome 2, as shown in Fig. 6(c).

Step4: In the remaining genes in Step 3, $K - 2$ locations are randomly selected from the gaps. Next, $K - 2$ zeros are inserted into these locations, and two zeros are added to both ends of these genes, as shown in Fig. 6(d).

Step5: Then, the genes (i.e., natural numbers) greater than $n_1 + n_2$ are marked. Finally, a natural number between 1 and n_1 is inserted after each zero and between any two adjacent transportation tasks, as shown in Fig. 6(e).

[1] The genes that are less than or equal to n_1 represent the truck and container depot.

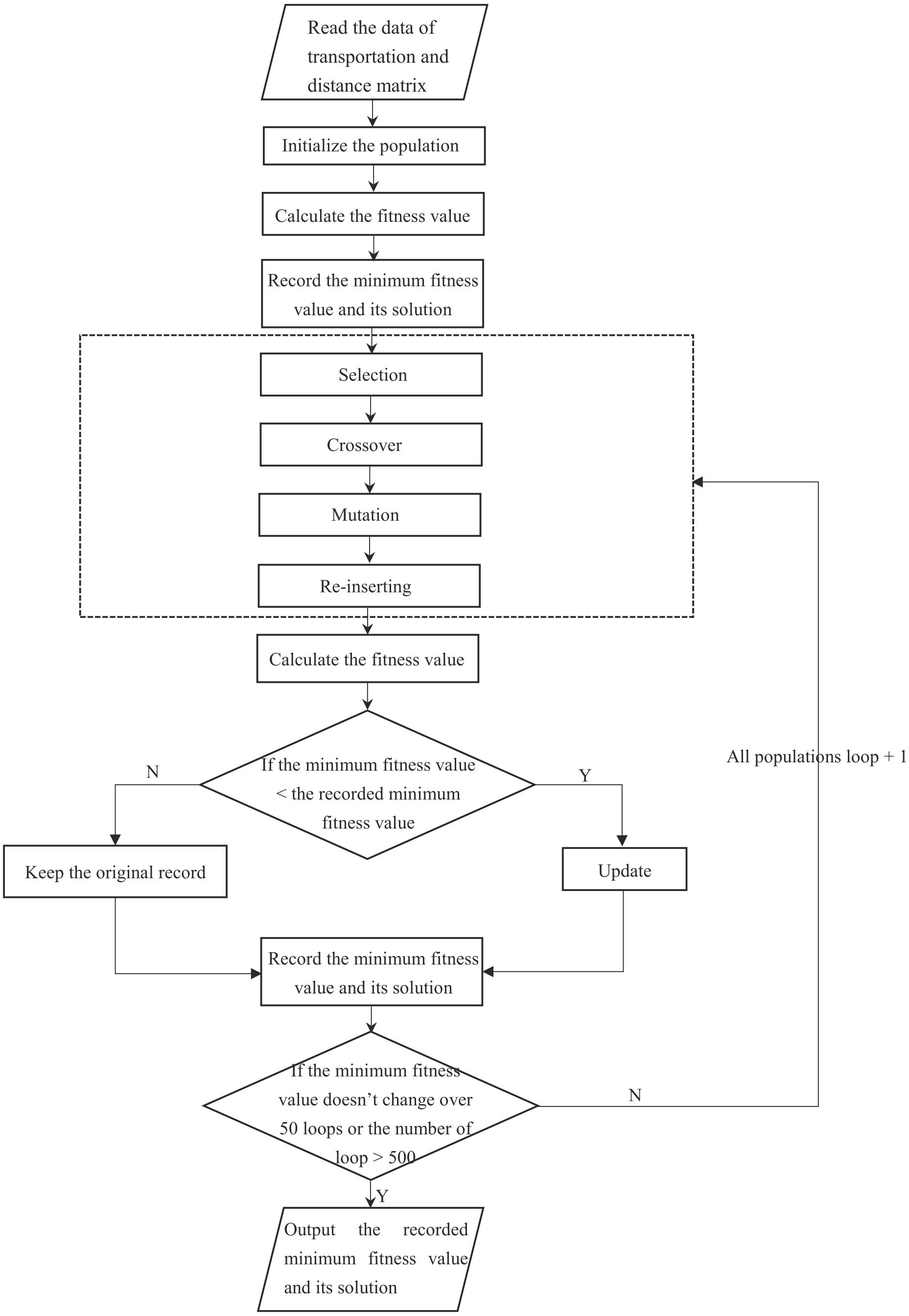


Fig. 4. Flowchart of the Genetic Algorithm.

2	5	3	4	6

(a) Order sorting

0	2	5	0	3	4	0	6	0

(b) Truck allocation

0	1	2	5	0	1	3	4	0	1	6	0

(c) Allocating container depots for external orders

Fig. 5. Population initialization.

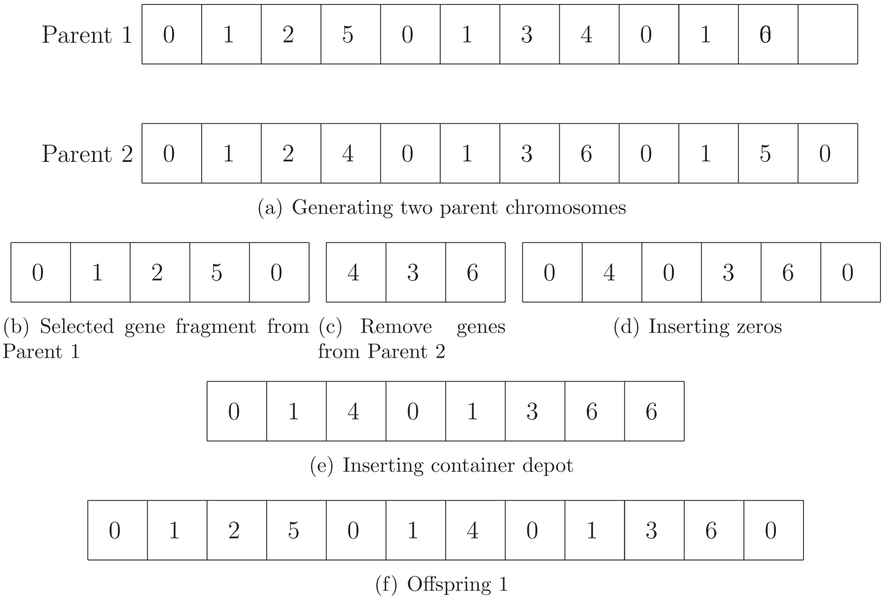


Fig. 6. Crossover.

Step6: A new chromosome is generated by combining 0, the selected gene fragment in Step 2 and the genes obtained in Step 4, which are denoted Offspring 1. Offspring 2 can be obtained in a similar way, as shown in Fig. 6(f).

Second, the steps of a specific mutation operator are as follows:

Step1: A certain chromosome is selected from the population with a very low probability, as shown in Fig. 7(a)
Step2: The genes that are less than or equal to n_1 are removed from this selected chromosome, as shown in Fig. 7(b)
Step3: From the remaining genes from Step 2, two genes are randomly selected, and their locations are exchanged.
Step4: Step 2 and Step 3 of generating a feasible solution are performed on the genes obtained in the previous step, as shown in Fig. 7(c)

Through the mutation operation, some genes on the chromosomes are changed, which means that the current feasible solution has changed. Through the mutation operation, the obtained solution can emerge from the local optimal solution, and then we may find a better global solution. By decoding the solution represented by the order number and querying the location and order matrix, we can obtain a sequence of the optimal solution represented by location.

6. Case study

6.1. Data

The purpose of this research is to solve the integrated internal and external transportation problem for a multinational group that designs and sells ready-to-assemble furniture. We acquired transportation information from a company in the Shanghai area, including 444 internal transportation and 444 external container transportation tasks. Data preprocessing is performed to ensure that the data are valid through the following calculation.

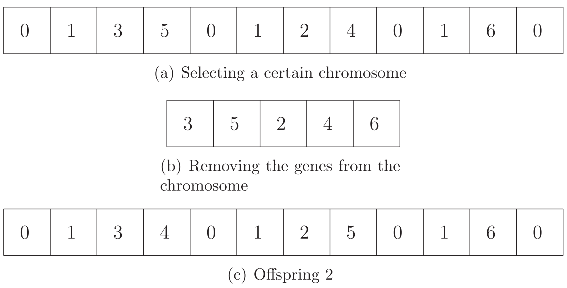


Fig. 7. Mutation.

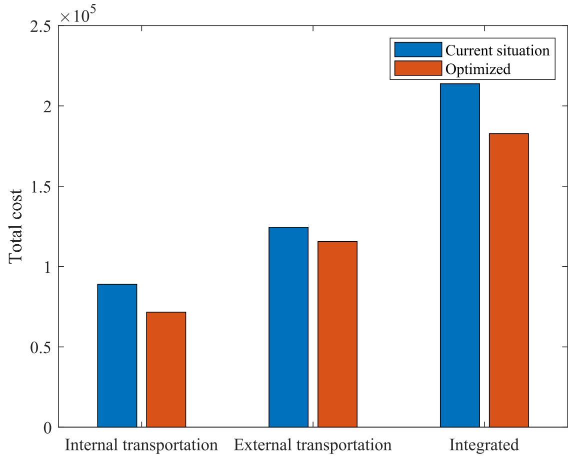


Fig. 8. Results.

6.2. Analysis of results

As mentioned above, the company separately operates the internal transportation and the external container transportation, while our approach optimizes the transportation logistics by integrating internal and external container transportation with the separation mode. When comparing the optimal result that we obtained with the current situation, we find that we can achieve a 16.80% improvement. To obtain the optimal solution, we set various parameters, including the number of trucks (k), an upper bound on distance (L) and the ratio of fixed to variable costs (w). We assume that the variable cost is equal to 1 unit. The results show that when k is 390, L is 1320 km and w equals 0, the optimal result is 182773.11. Under the same setting of cost parameters, the company's cost under the status quo is 213523.9. Therefore, the result achieves 16.80% optimization when the unit cost is equal to 1. Moreover, in reality, the unit cost is larger than the value we assumed, meaning that our method can achieve a further improvement in the real-world case.

To further verify our approach, we apply it to optimize the current situation without integration. The results show that our approach is also appropriate for the problem without integration, which achieves optimization results of 19.39% and 7.16% for internal and external container transportation, respectively. It demonstrates that our proposed method can significantly reduce transportation costs. However, integrated transportation is better than non-integrated transportation. Our results reveal that integrating internal and external transportation can save approximately 2.4% more costs than when applying our method to two types of transportation. Fig. 8 depicts the results for the separate and integrated optimization.

As Fig. 8 shows, by using our methods, we can reduce costs when internal and external container transportation are considered separately, while adopting the integrated approach can achieve a further total cost savings.

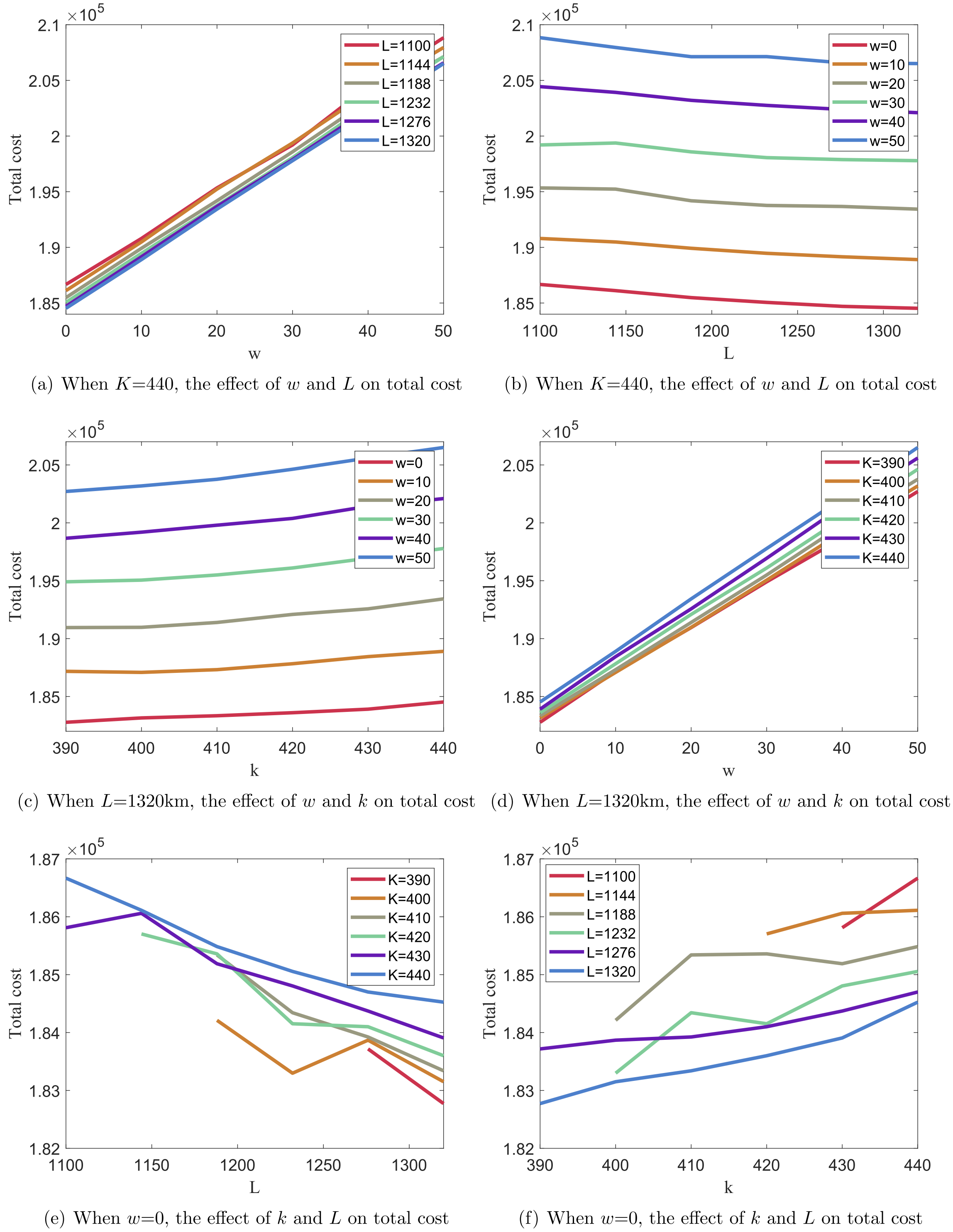
6.3. Sensitivity analysis

In this paper, three key parameters are involved: the number of trucks (k), the upper bound on distance (L) and the ratio of fixed to variable costs (w). To explore the parameters' effects on total costs, the values of the other two parameters are fixed and the influence of the third, remaining parameter on the total cost is explored.

The relationships between w and L and *totalcost* are shown in Fig. 9(a), (b) when $K = 440$. The vertical axis represents the *totalcost*. In Fig. 9(a), the horizontal axis represents the different values of w. Different lines represent different results under different values of L. The *totalcost* increases in w, which means that fixed and variable costs significantly influence the *totalcost* because w is equal to fixed cost over the variable cost. In fact, w has an approximately linear relationship with *totalcost*. According to the objective function Eq. (1), w is a coefficient. Thus, as w increases, the total cost also increases. Therefore, it is meaningful for enterprises to control their fixed and variable costs, especially their fixed costs. The different lines overlap, which means that L have no obvious effect on *totalcost* when k is fixed. We observe the same tendency in Fig. 9(b): as L increases, the *totalcost* remains constant after a slight initial drop. Regarding the different lines, which refer to different values of w, they share the same slope.

Second, we analyse the effect of w and k on *totalcost* when L is equal to 1320 km in Fig. 9(c), (d). In Fig. 9(c), the horizontal axis represents k. It is clear that *totalcost* increases when the number of trucks (k) increases, but the trend is not obvious. In Fig. 9(d), the horizontal axis represents the value of w, and the vertical axis represents the *totalcost*. The different lines reflect different values of k. When we increase w, *totalcost* also increases, which is in accord with Fig. 9(a).

We explore the relation among k, L and *totalcost* in Fig. 9(e), (f) when w equals 0. In Fig. 9(e), we find that L affects *totalcost* when k is limited. When k is small, along with an increase in L, the *totalcost* decreases rapidly. When L is large enough, providing more trucks reduce the cost slightly. In Fig. 9(f), *totalcost* is increasing in k, so using a reasonable number of trucks is necessary.



(a) When K=440, the effect of w and L on total cost (b) When K=440, the effect of w and L on total cost

(c) When L=1320km, the effect of w and k on total cost (d) When L=1320km, the effect of w and k on total cost

(e) When w=0, the effect of k and L on total cost (f) When w=0, the effect of k and L on total cost

Fig. 9. The effect of different parameters on total costs.

Ultimately, our analysis reveals that the w has a negative effect on $totalcost$. Regarding k and L, when there are enough trucks, increasing the upper bound on distance contributes little to cost savings, and vice versa. Thus, the company need to take more factors into account when it selects the proper values of k and L. Increasing the duration of drivers' trips does not necessarily reduce the total cost.

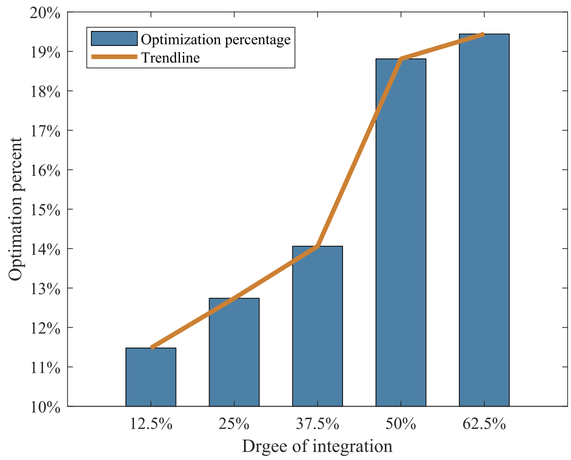


Fig. 10. Influence of different degrees of integration.

6.4. Influence of different degrees of integration

Moreover, we explore the influence of different degree of integration, which means integrating different numbers of internal and external orders. Specifically, the cases that we studied include 50 internal orders and 350 external orders, 100 internal orders and 300 external orders, 150 internal orders and 250 external orders, 200 internal orders and 100 external orders and 250 internal orders with 150 external orders, which represent integration percentages of 12.5%, 25%, 37.5%, 50% and 62.5%, respectively.

In Fig. 10, the abscissa represents different degrees of integration, while the ordinate represents the optimization percentage. When the degree of integration increases, the optimization percentage also increases, which means that when more internal orders involved, greater optimization can be achieved when the total number of orders is fixed. Furthermore, when the degree of integration is high, the growth rate of the degree of optimization slows. When the numbers of internal and external orders are nearly equal, the optimization percentage increases sharply. Thus, the company should choose a reasonable number of orders to optimize.

7. Conclusion

In this paper, we studied an intelligent logistics problem of an integrated internal and external transportation with the separation mode. To minimize the total cost in the operations process, we developed a novel model that integrates the internal and external container transportation problems by dividing customer points into different subsets and proposing a special penalty matrix. A customized genetic algorithm was proposed to solve the problem. Based on the instances of real-life data on 888 orders, the proposed method helps to reduce the overall cost by 16.8%. We also applied this method to optimize internal and external transportation, respectively. Although considerable optimization improvement may be achieved by separately applying the approach to two transportation situations, the results from the intelligent integrated model renders better performance. Sensitivity analysis was conducted by comparing the impacts of the three parameters: ratio of fixed to variable costs (w), number of drayage trucks (k), and upper bound of distance (L). The results show that the total cost increases significantly by w. Secondly, when number of trucks k is sufficient, increasing upper bound of distance L contributes little to cost savings and vice versa, meaning that there is trade off between k and L. We also conducted multiple rounds of calculation with different numbers of internal and external orders, to represent varying integration levels.

The research problem that we studied in this paper could not only help the practitioners to save logistics cost but also improve their business processes when both internal and external demands exist. To be more specific, the proposed model can help finding the optimized number of trucks and the upper bound of distance that would jointly affect the total cost. As the result, increasing the upper bound of distance may not lead to cost reduction. From the point of view of managing the fleet drivers' jobs, therefore, setting a reasonable upper bound of distance can help the company to meet its maximum work-duration policy for the drivers, and in the meanwhile help to minimize the total cost. From the point of view of transportation system management, integrated transportation can continuously help saving the system management costs through the self-learning adaptive decision support mechanisms.

Future research can be conducted to extend the separation mode problem, especially by considering more factors that exist in the integrated internal and external transportation system. In general, the separation mode allows drayage trucks to travel to another point while the container is in the process of loading/unloading, conforming to more practical scenarios. The research problem becomes more realistic but complex when the uncertainty of traffic conditions and road network information are taken into account. In addition, Artificial Intelligence(AI) is getting more and more importance in modern business operations (Luo et al., 2019) and large-scale numerical computing capabilities have become available. Therefore another future research of this topic can be directed to the continuous investigation of more enabling technologies and their data analytics mechanisms.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (71431004, 71972071) and the Fundamental Research Funds for the Central Universities.

References

Avella, P., Boccia, M., Sforza, A., 2004. Resource constrained shortest path problems in path planning for fleet management. J. Mathe. Modell. Algorithms 3 (1), 1–17.
Bajpai, P., Kumar, M., 2010. Genetic algorithm-an approach to solve global optimization problems. Indian J. Comput. Sci. Eng. 1 (3), 199–206.
Barenji, A.V., Wang, W.M., Li, Z., Guerra-Zubiaga, D.A., 2019. Intelligent E-commerce logistics platform using hybrid agent based approach. Transport. Res. Part E: Logist. Transport. Rev. 126, 15–31.
Braekers, K., Caris, A., Janssens, G.K., 2013. Integrated planning of loaded and empty container movements. OR Spectrum. 35 (2), 457–478.
Bula, G.A., Prodhon, C., Gonzalez, F.A., Afsar, H.M., Velasco, N., 2017. Variable neighborhood search to solve the vehicle routing problem for hazardous materials transportation. J. Hazard. Mater. 324, 472–480.
Caris, A., Janssens, G.K., 2009. A local search heuristic for the pre-and end-haulage of intermodal container terminals. Comput. Oper. Res. 36 (10), 2763–2772.
Cheng, A., Yu, D., 2013. Genetic algorithm for vehicle routing problem. In: ICTE 2013: Safety, Speediness, Intelligence, Low-Carbon, Innovation, pp. 2876–2881.
Cheng, F., Fan, T., Fan, D., Li, S., 2018. The prediction of oil price turning points with log-periodic power law and multi-population genetic algorithm. Energy Econ. 72, 341–355.
Cheung, R.K., Shi, N., 2008. An attribute-decision model for cross-border drayage problem. Transport. Res. Part E: Logist. Transport. Rev. 44 (2), 217–234.
Chung, K.H., Ko, C.S., Shin, J.Y., Hark, H.K., Kime, H., 2007. Development of mathematical models for the container road transportation in Korean trucking industries. Comput. Ind. Eng. 53 (2), 252–262.
Crainic, T.G., Gendreau, M., Potvin, J.Y., 2009. Intelligent freight-transportation systems: Assessment and the contribution of operations research. Transport. Res. Part C: Emerg. Technol. 17 (6), 541–557.
Cuevas, F.J., Sossa-Azuela, J.H., Servin, M., 2002. A parametric method applied to phase recovery from a fringe pattern based on a genetic algorithm. Opt. Commun. 203 (3–6), 213–223.
Dalmeijer, K., Spliet, R., 2018. A branch-and-cut algorithm for the time window assignment vehicle routing problem. Comput. Operat. Res. 89, 140–152.
Dantzig, G.B., Ramser, J.H., 1959. The truck dispatching problem. Manage. Sci. 6 (1), 80–91.
Escudero, A., MunUzuri, J., Guadix, J., et al., 2013. Dynamic approach to solve the daily drayage problem with transit time uncertainty. Comput. Ind. 64 (2), 165–175.
Franceschetti, A., Honhon, D., Van Woensel, T., Bekta?, T., Laporte, G., 2013. The time-dependent pollution-routing problem. Transport. Res. Part B: Methodol. 56, 265–293.
Galle, V., Barnhart, C., Jaillet, P., 2018. A new binary formulation of the restricted container relocation problem based on a binary encoding of configurations. Eur. J. Oper. Res. 267 (2), 467–477.
Ghiani, G., Guerriero, F., Laporte, G., Musmannob, B., 2003. Real-time vehicle routing: Solution concepts, algorithms and parallel computing strategies. Eur. J. Oper. Res. 151 (1), 1–11.
Gutierrez-Jarpa, G., Desaulniers, G., Laporte, G., Marianov, V., 2010. A branch-and-price algorithm for the vehicle routing problem with deliveries, selective pickups and time windows. Eur. J. Oper. Res. 206 (2), 341–349.
He, W., Yan, G., Da Xu, L., 2014. Developing vehicular data cloud services in the IoT environment. IEEE Trans. Ind. Informat. 10 (2), 1587–1595.
Holland, J.H., 1975. Adaptation in natural and artificial systems: an introductory analysis with applications to biology. In: Ann Arbor, M.I. (Ed.), Control, and Artificial Intelligence. University of Michigan Press, pp. 439–444.
Imai, A., Nishimura, E., Current, J.A., 2007. Lagrangian relaxation-based heuristic for the vehicle routing with full container load. Eur. J. Oper. Res. 176 (1), 87–105.
Jaillet, P., Wagner, M.R., 2006. Online routing problems: Value of advanced information as improved competitive ratios. Transport. Sci. 40 (2), 200–210.
Jeong, Y., Saha, S., Chatterjee, D., Moon, I., 2018. Direct shipping service routes with an empty container management strategy. Transport. Res. Part E: Logist. Transport. Rev. 118, 123–142.
Kumar, V., Saboo, A.R., Agarwal, A., Kumar, B., 2019. Generating competitive intelligence with limited information: a case of the multimedia industry. Prod. Oper. Manage.
Lai, M., Crainic, T.G., Francesco, M.D., Zuddasae, P., 2013. An heuristic search for the routing of heterogeneous trucks with single and double container loads. Transport. Res. Part E: Logist. Transport. Rev. 2013 (56), 108–118.
Laporte, G., Desrochers, M., Nobert, Y., 1984. Two exact algorithms for the distance-constrained vehicle routing problem. Networks 14 (1), 161–172.
Lawrence, S., Mohammad, A., 1996. Parametric experimentation with a genetic algorithmic configuration for solving the vehicle routing problem. In: Proceedings Annual Meeting of the Decision Sciences Institute. Decis Sci Inst, pp. 488–490.
Lee, S., Moon, I., 2020.. Robust empty container repositioning considering foldable containers. Eur. J. Oper. Res. 280 (3), 909–925.
Legros, B., Bouchery, Y., Fransoo, J., 2019. A time- based policy for empty container management by consignees. Prod. Oper. Manage. 28 (6), 1503–1527.
Lenstra, J.K., Kan, A.R., 1981. Complexity of vehicle routing and scheduling problems. Networks 11 (2), 221–227.
Li, Y., Chu, F., Feng, C., Chu, C., Zhou, M., 2018. Integrated production inventory routing planning for intelligent food logistics systems. IEEE Trans. Intell. Transport. Syst. 99, 1–12.
Luo, S., Lin, X., Zheng, Z., 2019. A novel CNN-DDPG based AI-trader: Performance and roles in business operations. Transport. Res. Part E: Logist. Transport. Rev. 131, 68–79.
Mahr, T., Srour, J., Weerdt, M.D., Zuidwijk, R., 2010. Can agents measure up? A comparative study of an agent-based and on-line optimization approach for a drayage problem with uncertainty. Transport. Res. Part C: Emerg. Technol. 18 (1), 99–119.
McFarlane, D., s Giannikas, V., Lu, W., 2016. Intelligent logistics: Involving the customer. Comput. Ind. 81, 105–115.
Moon, I., Ngoc, A.D., Konings, R., 2013. Foldable and standard containers in empty container repositioning. Transport. Res. Part E: Logist. Transport. Rev. 49 (1), 107–124.
Nossack, J., Pesch, E., 2013. A truck scheduling problem arising in intermodal container transportation. Eur. J. Oper. Res. 230 (3), 666–680.
Polat, O., Kalayci, C.B., Kulak, O., Gnther, H.O., 2015. A perturbation based variable neighborhood search heuristic for solving the vehicle routing problem with simultaneous pickup and delivery with time limit. Eur. J. Oper. Res. 242 (2), 369–382.
Qiu, M., Fu, Z., Eglese, R., Tang, Q., 2018. A Tabu Search algorithm for the vehicle routing problem with discrete split deliveries and pickups. Comput. Oper. Res. 100, 102–116.
Ramos, A.G., Silva, E., Oliveira, J.F., 2018. A new load balance methodology for container loading problem in road transportation. Eur. J. Oper. Res. 266 (3), 1140–1152.
Russell, R.A., 1995. Hybrid heuristics for the vehicle routing problem with time windows. Transport. Sci. 29 (2), 156–166.
Salazar-Gonzalez, J.J., Santos-Hernandez, B., 2015. The split-demand one-commodity pickup-and-delivery travelling salesman problem. Transport. Res. Part B: Methodol. 75, 58–73.
Shintani, K., Konings, R., Imai, A., 2010. The impact of foldable containers on container fleet management costs in hinterland transport. Transport. Res. Part E: Logist. Transport. Rev. 46 (5), 750–763.
Shintani, K., Imai, A., Nishimura, E., Papadimitriouc, S., 2007. The container shipping network design problem with empty container repositioning. Transport. Res. Part E: Logist. Transport. Rev. 43 (1), 39–59.
Shintani, K., Konings, R., Imai, A., 2019. Combinable containers: A container innovation to save container fleet and empty container repositioning costs. Transport.

Res. Part E: Logist. Transport. Rev. 130, 248–272.
Shiri, S., Huynh, N., 2016. Optimization of drayage operations with time-window constraints. Int. J. Prod. Econ. 176, 7–20.
Smilowitz, K., 2006. Multi-resource routing with flexible tasks: an application in drayage operations. Iie Trans. 38 (7), 577–590.
Song, Y., Zhang, J., Liang, Z., Yeb, C., 2017. An exact algorithm for the container drayage problem under a separation mode. Transport. Res. Part E: Logist. Transport. Rev. 106, 231–254.
Sterzik, S., Kopfer, H., 2013. A tabu search heuristic for the inland container transportation problem. Comput. Oper. Res. 40 (4), 953–962.
Sterzik, S., Kopfer, H., Yun, W.Y., 2015. Reducing hinterland transportation costs through container sharing. Flexible Serv. Manuf. J. 27 (2–3), 382–402.
Subramanyam, A., Wang, A., Gounaris, C.E., 2018. A scenario decomposition algorithm for strategic time window assignment vehicle routing problems. Transport. Res. Part B: Methodol. 117, 296–317.
Sun, P., Veelenturf, L.P., Hewitt, M., Van Woensel, T., 2018. The time-dependent pickup and delivery problem with time windows. Transport. Res. Part B: Methodol. 116, 1–24.
Torkjazi, M., Huynh, N., Shiri, S., 2018. Truck appointment systems considering impact to drayage truck tours. Transport. Res. Part E: Logist. Transport. Rev. 16, 208–228.
Toth, P., Vigo, D., Toth, P., Vigo, D., 2014. Vehicle Routing: Problems, Methods, and Applications, second ed. Society for Industrial and Applied Mathematics.
Wang, X., Regan, A.C., 2002. Local truckload pickup and delivery with hard time window constraints. Transport. Res. Part B: Methodol. 36 (2), 97–112.
Wang, W.F., Yun, W.Y., 2013. Scheduling for inland container truck and train transportation. Int. J. Prod. Econ. 143 (2), 349–356.
Wei, Q., Max, Z.J., 2018. A smart-city scope of operations management. Prod. Oper. Manage.
Wong, E.Y.C., Tai, A.H., Raman, M., 2015. A maritime container repositioning yield-based optimization model with uncertain upsurge demand. Transport. Res. Part E: Logist. Transport. Rev. 82, 147–161.
Xue, Z., Zhang, C., Lin, W.H., Miao, L., Yang, P., 2014. A tabu search heuristic for the local container drayage problem under a new operation mode. Transport. Res. Part E: Logist. Transport. Rev. 62, 136–150.
Xue, Z., Lin, W.H., Miao, L., Zhang, C., 2015. Local container drayage problem with tractor and trailer operating in separable mode. Flexible Serv. Manuf. J. 27 (2–3), 431–450.
Yang, J., Jaillet, P., Mahmassani, H., 1999. On-line algorithms for truck fleet assignment and scheduling under real-time information. Transport. Res. Rec.: J. Transport. Res. Board 1667, 107–113.
Zhang, G., Smilowitz, K., Erera, A., 2011b. Dynamic planning for urban drayage operations. Transport. Res. Part E: Logist. Transport. Rev. 47 (5), 764–777.
Zhang, R., Lu, J.C., Wang, D., 2014. Container drayage problem with flexible orders and its near real-time solution strategies. Transport. Res. Part E: Logist. Transport. Rev. 61 (1), 235–251.
Zhang, R., Yun, W.Y., Kopfer, H., 2010. Heuristic-based truck scheduling for inland container transportation. OR Spectrum. 32 (3), 787–808.
Zhang, R., Yun, W.Y., Moon, I., 2009. A reactive tabu search algorithm for the multi-depot container truck transportation problem. Transport. Res. Part E: Logist. Transport. Rev. 45 (6), 904–914.
Zhang, R., Yun, W.Y., Moon, I.K., 2011a. Modeling and optimization of a container drayage problem with resource constraints. Int. J. Prod. Econ. 133 (1), 351–359.
Zhang, R., Zhao, H., Moon, I., 2018. Range-based truck-state transition modeling method for foldable container drayage services. Transport. Res. Part E: Logist. Transport. Rev. 118, 225–239.
Zolfagharinia, H., Haughton, M.A., 2017. Operational flexibility in the truckload trucking industry. Transport. Res. Part B: Methodol. 104, 437–460.