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Finished-vehicle transporter routing problem solved by loading pattern discovery

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Abstract This work addresses a new transportation problem in outbound logistics in the automobile industry: the finished-vehicle transporter routing problem (FVTRP). The FVTRP is a practical routing problem with loading constraints, and it assumes that dealers have deterministic demands for finished vehicles that have three-dimensional irregular shapes. The problem solution will identify optimal routes while satisfying demands. In terms of complex packing, finished vehicles are not directly loaded into the spaces of transporters; instead, loading patterns matching finished vehicles with transporters are identified first by mining successful loading records through virtual and manual loading test procedures, such that the packing problem is practically solved with the help of a procedure to discover loading patterns. This work proposes a mixed-integer linear programming (MILP) model for the FVTRP considering loading patterns. As a special class of routing models, the FVTRP is typically difficult to solve within a manageable computing time. Thus, an evolutionary algorithm is designed to solve the FVTRP. Comparisons of the proposed algorithm and a commercial MILP solver demonstrate that the proposed algorithm is more effective in solving medium- and large-scale problems. The proposed scheme for addressing the FVTRP is illustrated with an example and tested with benchmark instances that are derived from well-studied vehicle routing datasets.

Keywords Automotive logistics · Vehicle routing problem · Three-dimensional bin packing · Logistics management · Evolutionary algorithm

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1 Introduction

As the size of databases increases, data mining problems pose interesting challenges. Data analyzing and mining results generally explore useful insights and hidden patterns, contributing to practical decision making (Corne et al. 2012; Ergu et al. 2014). This work focused on the finished-vehicle transporter routing problem (FVTRP), which can be solved by utilizing loading patterns (loadable relations between transporter and finished vehicles) discovered from historical data. Anji Logistics (http://www.anji-logistics.com) is the largest finished-vehicle logistics (FVL) service provider in China and was used as an application example in this work. According to statistical data from the Chinese Association of Automobile Manufacturers (http://www.caam.org.cn/), 22.1 million vehicles were produced in 2013, of which 21,984.1 thousand were sold. China is the largest automobile market in the world. Anji Logistics has 17,000 employees, 10 special finished-vehicle transporter companies, and 50 finished-vehicle distribution centers and warehouses. In 2013, Anji Logistics transported 6,140 thousand finished vehicles from vehicle distribution centers to dealers. Anji Logistics owns approximately 3,000 transporters and can operate more than 12,000 transporters provided by contracted transporter companies. Classified by the shapes of finished vehicles and transporter spaces as well as their constraints, the number of finished-vehicle types and transporters both exceed 1,000. For large finished-vehicle logistics companies such as Anji Logistics, the FVTRP is becoming challenging, and decreasing logistics costs through optimization is important.

Focal issues for finished-vehicle distribution are to allocate finished vehicles to transporters and design routes for these transporters while considering supporting rotation directions as well as binding and shock absorption methods for secure transportation. As the shapes of finished vehicles and spaces of transporters are irregular, various vehicles are packed into a transporter's space to achieve a high loading ratio and generate the route with the lowest cost. Problems that integrate routing and packing problems have recently attracted considerable attention. To the best of our knowledge, however, this is the first work to consider the irregular shapes of finished vehicles and transporter spaces. When both shapes and spaces are regular, such as two-dimensional (2D) or three-dimensional (3D) boxes, many useful research results for the 2D capacitated vehicle routing problem (2D-CVRP) and 3D capacitated vehicle routing problem (3D-CVRP) are available (Fuellerer et al. 2009, 2010; Gendreau et al. 2006, 2008; Iori et al. 2007; Moura and Oliveira 2009; Tarantilis et al. 2009; Zachariadis et al. 2009; Vidal et al. 2013; Wei et al. 2014). Although the problems with packing irregular shapes have been identified (Valle et al. 2012; Hu and Sheng 2014), these problems do not combine both irregular spaces and irregular shapes. To address irregular shapes and spaces, this work developed a virtual loading tool in the form of an optimization and simulation system to match and simulate solutions that allocate finished vehicles to transporters. However, this approach is usually time consuming, and its validity remains unverified by manual loading tests. From another perspective, because successful loading data are available, a loading-pattern discovery approach can be applied using successful historical transport records to address the characteristics of irregular shapes and spaces.

The FVTRP is an extension of the classical VRP, which is one of the most widely studied combinatorial optimization problems. The packing aspects of the FVTRP are addressed by a loading-pattern discovery procedure, which contains the following subroutines: search for feasible loading patterns from the historical data; apply the virtual loading test to obtain feasible loading solutions; and verify the solutions using the manual loading process. In this work, by incorporating the loading pattern constraints into a specific VRP model, a mixed-integer linear programming (MILP) model is established, which can be solved by

MILP solvers. To cope with the poor performance for medium or large problem instances, an evolutionary algorithm is designed.

This work contributes to the finished-vehicle logistics and 3D-CVRP literature in the following ways. First, the FVTRP is proposed and formulated as an MILP model in the background of the finished vehicle distribution, and it shares common features with furniture, appliance, and other logistics systems with items that have irregular spaces or shapes. Second, the loading pattern as a strategy can reduce the complexity of matching criteria related to containers and items. Although the loading pattern is designed for the FVTRP, it can be extended to the 2D-CVRP, 3D-CVRP, and their variants to reduce computational complexity. Third, a loading-pattern discovery scheme, based on knowledge discovery, is proposed and applied to extract the available packing solution from historical packing data for the FVTRP. An integral framework incorporating loading pattern discovery and route optimization combines the techniques associated with information processing and operations research to solve practical problems. In summary, this work proposed a hybrid approach combining optimization and knowledge discovery techniques for a novel industrial problem, the FVTRP.

The remainder of this paper is organized as follows. Section 2 reviews finished-vehicle logistics and instances of the vehicle routing problem with packing constraints. Section 3 provides a detailed description of the finished-vehicle distribution issue. Loading pattern discovery as a solution methodology for packing is also presented. Section 4 establishes an MILP to formulate the FVTRP with loading patterns. Section 5 presents the proposed evolutionary algorithm for solving the FVTRP. Section 6 experimentally validates the proposed method. Finally, Sect. 7 offers conclusions and future research directions.

2 Literature review

The automobile industry is important to many economies worldwide, and it has been a source of many innovations in product design and manufacturing technologies (e.g., the assembly line, just-in-time inventory, and kan-ban management). Consequently, it has been the focus of numerous empirical studies. However, many studies have centered on production, procurement, or new product development processes. Many studies of operational performance in the automobile industry have focused on the assembly plant or the product design process rather than finished goods in downstream supply chains. For instance, Fisher and Ittner (1999) assessed the effect of product variety on work-in-process inventory using archival data from automotive plants belonging to a single company. MacDuffie et al. (1996) analyzed the impact of product variety on manufacturing productivity and consumer-perceived quality using data from 70 automobile assembly plants. Outbound logistics in the automobile industry has grown significantly (Mattfeld and Kopfer 2003; Keskin et al. 2014). As a key component of automobile outbound logistics, FVL involves designing routes for transporters. Moreover, a routing problem combined with a loading problem in which finished vehicles are distributed to dealers on this route must be loadable by the transporter by considering spatial constraints between the transporter and finished vehicles. Few studies have addressed FVL management or operational decision-making.

Supply chain issues and logistics network design problems in FVL have attracted considerable interest (Vilkelis and Jakovlev 2014). Eskigun et al. (2005) studied the design of a finished-vehicle outbound supply chain network while considering lead times, location of distribution facilities, and choice of transportation mode using Lagrangian heuristics. As a pioneering study on operations optimization and management of FVL, Holweg and Miemczyk (2002) assessed whether an FVL system could support a "build-to-order" business. Kim et al. (2010) presents an approach for RFID-enabled finished vehicle deployment planning at a shipping yard; the approach is based on a market-based decision-making framework with a multi-agent computational architecture to process and coordinate real-time changes in vehicle locations and to make timely decisions. Fischer and Gehring (2005) developed a multi-agent system that supports the planning of transshipments of imported finished vehicles *via* a seaport. Mattfeld and Kopfer (2003) developed an automated planning and scheduling system to support operations that transport finished vehicles from a transshipment hub by integrating the manpower planning and inventory control using a two-stage hierarchical approach. Mattfeld and Orth (2006) generated a planning model for optimizing the transportation and storage capacities at a vehicle transshipment hub using a greedy-based construction heuristic that assigns vehicles to storage locations. Finished-vehicle distribution is also a source of pollution. Nieuwenhuis et al. (2012) established a transport cost model to track CO_2 emissions along the built-up vehicle supply chain from the final assembly plant to a local distribution location. Due to economic and environmental protection, the loading ratio must be increased, and the routes of a road transporter for finished-vehicle distribution must be optimized. Although these studies investigated problems in FVL, the combination of transporter routing and the packing of finished vehicles on a transporter was not considered.

The FVTRP belongs to the category of practical routing models that are integrated with 3D loading constraints by considering irregular 3D shapes of the transporter and finished vehicles. In terms of combined vehicle routing and packing models, Iori et al. (2007) investigated the 2D-CVRP, with the aim of identifying a minimum-cost route set that satisfies customer demands and is composed of 2D boxes. For each of these routes, the decision-maker must generate a feasible orthogonal packing solution for shipped boxes on a vehicle. The authors solved the problem *via* an exact branch-and-cut algorithm for instances involving up to 30 customers and 90 boxes. Gendreau et al. (2008) applied a novel Tabu search method for larger 2D-CVRP instances. Zachariadis et al. (2009) solved the 2D-CVRP using a hybrid local search strategy, and Fuellerer et al. (2009) proposed an ant colony optimization approach for the same problem. Côté et al. (2014) described an exact algorithm for solving a two-dimensional orthogonal packing problem with unloading constraints, which occurs as a subproblem of mixed vehicle routing and loading problems. Dominguez et al. (2014) proposed an efficient multistart algorithm, with a reduced number of parameters, for solving 2D-CVRP). Gendreau et al. (2006) generalized the 2D-CVRP as a 3D-CVRP by introducing a routing model with 3D loading constraints. This 3D-CVRP model considers customer demands composed of orthogonal 3D boxes, which must be feasibly stacked into rectangular vehicle containers. Additional operational constraints are introduced to ensure the stability of stacked boxes, the secure transportation of fragile boxes, and easy unloading of boxes at the customer locations. To tackle the 3D-CVRP, the authors developed a Tabu search method that is effective for problems with up to 100 customers and 199 transported boxes. Metaheuristic approaches for the 3D-CVRP have also been proposed by Fuellerer et al. (2010) and Tarantilis et al. (2009). The routing model with 3D loading constraints introduced by Moura and Oliveira (2009), which is closely related to the 3D-CVRP, can be called the vehicle routing problem with time windows and loading problem (VRPTWL). Two algorithms are used to solve the VRPTWL. With the first, vehicle routes and container-packing patterns are generated simultaneously, whereas the second approach first constructs high-quality routes for the VRP with time windows (VRPTW), and then for each of the generated routes, feasible packing patterns are identified. Here, the two-stage approach generates routing and packing solutions sequentially. The packing solutions, namely, packing patterns, are generated by 3D packing algorithms for regular 3D shapes; however, this work tackles irregular spaces for transporters and irregular shapes for finished vehicles. Another integrated routing and packing problem, the Multi-Pile VRP (MP-VRP), is derived directly from a real-world distribution problem faced by an Austrian wood-products retailer (Doerner et al. 2007). The MP-VRP is solved by generating an optimal route set with minimum costs for delivering chipboards to customers. Due to the regular shapes of the transported boxes and the vehicle loading spaces, the original 3D loading problem with chipboard packing can be reduced to a suitably defined one-dimensional (1D) packing problem. To solve the packing sub-problem, Tricoire et al. (2011) used heuristic and exact-solution methods. Zachariadis et al. (2012) introduced and solved a novel transportation problem called the pallet-packing vehicle routing problem (PPVRP), which is a practical routing model with loading constraints, and assumed deterministic demands from customers in the form of 3D rectangular boxes. To develop feasible pallet-packing arrangements, an efficient packing heuristic is employed. The algorithmic speed is accelerated by using collected packing feasibility information. For a recent and complete survey of integrated routing-packing problems, interested readers are referred to the work by Iori and Martello (2010). Compared with traditional routing problems, packing constraints add new complexity, especially in computational performance. The above studies generally developed heuristic algorithms to solve difficult problems that combine routing and packing. This work attempts to use packing patterns in historical data to improve computational performance and the loading feasibility for irregular shapes.

Although many studies have attempted to solve the 3D-CVRP, the proposed methods cannot be applied to the FVTRP because of irregularly shaped containers and items in large real-world applications. When the length of a packed item is equal or almost equal to the length or width of a container space, loading feasibility can be determined by 2D bin packing approaches (Fuellerer et al. 2009; Leung et al. 2010, 2011; Yin and Tang 2009; Hu et al. 2015; Cui et al. 2015). When the sizes of the packed items vary widely but the container spaces are regular cubes, 3D bin packing algorithms can be applied (Bortfeldt 2012; Fuellerer et al. 2010; Tarantilis et al. 2009). Considering the packing problem in such VRPs is beneficial. However, the combination of two NP-hard problems (routing and packing) increases the solution difficulty. In practice, solutions generated for the 3D-CVRP require sophisticated operators to handle the loading/unloading processes. Additionally, the loading sequence will impose handling costs (Iori and Martello 2010; Tang et al. 2010; Wei et al. 2014), which are difficult to caculate in the solution.

The FVTRP is closely related to the 3L-CVRP and the VRPTWL in that it considers the distribution of finished vehicles with 3D irregular shapes to transporters with irregular spaces. Thus, a 3D-CVRP or VRPTWL instance can be viewed as an FVTRP instance that involves box-like finished vehicles and transporter spaces.

3 Finished-vehicle distribution

Outbound logistics for finished vehicles is a key component in the finished-vehicle supply chain (Fig. 1). By outbound logistics, new vehicles are distributed to customers. For outbound logistics of finished vehicles, storage and delivery tasks are typically outsourced to third party logistics (3PL) companies. In this study, Anji Logistics, as the largest 3PL in the automobile industry in China, is chosen. It has a giant logistics network for outbound finished vehicles.

FVL companies generally organize logistics operations using a two-stage distribution network (Fig. 2). In the first stage, new vehicles are transported from manufacturers to nearby warehouses and then from these warehouses to regional warehouses. In the second stage,

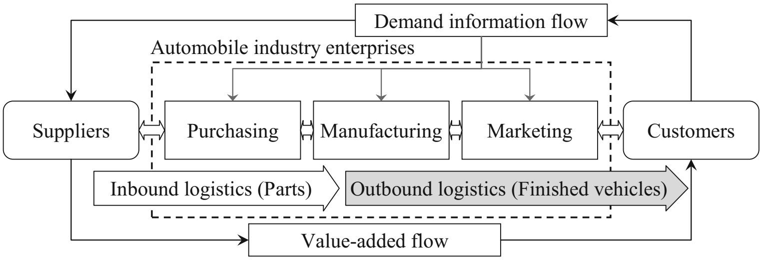

Fig. 1 New vehicle supply chain and logistics

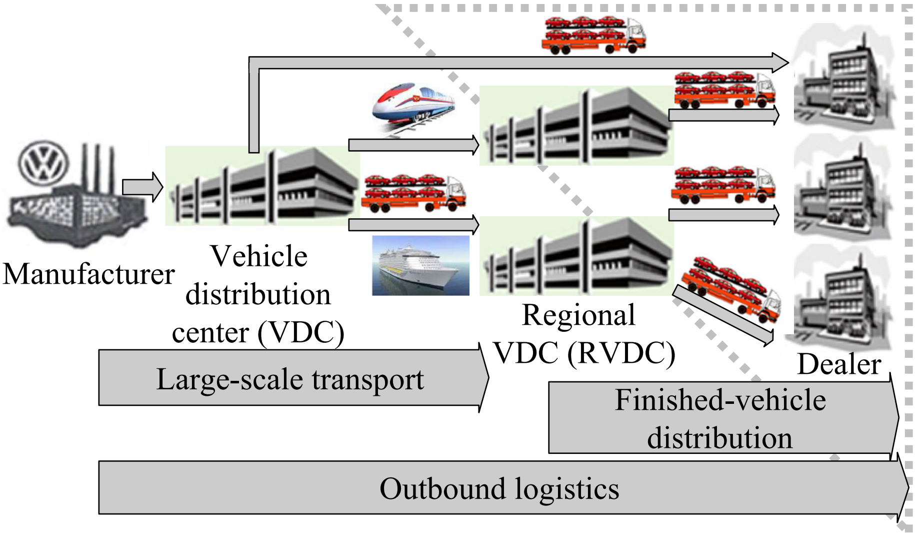

Fig. 2 Outbound logistics and finished-vehicle distribution

the finished vehicles are transported to dealers. Although ecommerce is now popular, buying vehicles is usually offline in China. Therefore, one need not design a logistics function to transport vehicles to final customers. In the first stage, large-scale transport is accomplished by road transporters, trains, shipping, or their integration, in which "multi-modal" transport can achieve better environmental and economic performance. The second stage is the distribution from one door (regional distribution center) to another door (dealer). Given rapid market development and attempts to reduce inventory levels, distribution should address multi-type and small-batch finished-vehicle flows. This work focuses on the routing and packing optimization problems in the distribution stage, which is the second stage. The FVTRP can be characterized as follows: some transporters are located at a regional vehicle distribution center (RVDC) for transporting finished vehicles to dealers; the dealers submit their orders of finished vehicles to a sales company, and the ordered cars are finally delivered to the RVDC; and the RVDC schedules the route for the orders in terms of packing feasibility and routing costs. Therefore, the FVTRP is a 3D-CVRP type with irregularly shaped container and goods.

As the capacity of the transporter is sufficiently large that it can load all the vehicles to be distributed, the FVTRP is simplified into an VRP, which focuses on optimizing the distribution routes and is an NP-hard problem. Hence, the FVTRP is an NP-hard problem that has difficult packing constraints. In the special packing constraints, both packing vehicle size and the transporter's space are irregular. These characteristics increase the complexity of the problem. In the FVTRP, the distribution route for each dealer and finished-vehicle loading pattern (i.e., the solution for the transporter to pack vehicles) are determined based on historical data of successful loads in the FVL database.

Loading pattern is introduced to reduce the complexity of the packing problem with irregular container spaces and packed items. In the application of a logistics system for furniture and finished vehicles, when packed items are considered as regular boxes, container space utilization will have a very low ratio. For FVL, the space utilization ratio may reach an extremely low value. Thus, transporters of finished vehicles are typically designed as framework-like containers with layers and special structures. To the best of our knowledge, few studies have examined the 3D-CVRP with irregular container spaces and packed items. The irregular spaces and shapes increase the complexity of the routing and packing problems. According to shape, a container space is usually separated into some small compartments for packed items. Similar to the 3D-CVRP, the loading solution should adhere to the loading and unloading sequence, keeping the handling costs low for order distribution (Duhamel et al. 2011; Mendoza et al. 2010; Muyldermans and Pang 2010a, b). Because FVL generally involves long distances, re-marshaling time can be overlooked when compared to traveling time in the FVTRP.

Generally, FVL information systems have historical distribution data containing successful loading records (pairs of transporters and a set of finished vehicles). Pairs of transporter type and vehicle type can be found in the data warehouse. Therefore, data mining technologies can be used to find successful loading patterns. In this study, a loading pattern for a transporter is a combination of various finished vehicles. Although "type of" for transporters or vehicles refers to the size and shape, the phrase can be extended to describe common loading feasibilities. *Via* loading patterns, the capacity of a transporter is determined by combinations of various finished vehicles types, not volume, weight, or quantity. Containerization, which is a technique associated with secondary packaging logistics, can be applied widely to other logistics fields.

The finished vehicles are distributed by a special transporter, which can load 1–24 vehicles by adjusting its framework or inner structure components to adapt to specific vehicles (top-left figure in Fig. 3). However, the design of new vehicles is far more flexible, whereas the transporter's flexibility is limited. Moreover, loaded vehicles may be damaged during moving. A motion simulation system simulates the loading and unloading processes (bottom-left figure in Fig. 3). In practice, without the support from mathematical modeling and algorithms, planners or drivers of new vehicles accumulate feasible loading patterns by experience.

A feasible solution for the FVTRP is obtained by incorporating information processing, modeling, and optimization techniques (Fig. 3). Due to the irregularly shaped containers and packed items, methods developed for 3D bin packing studies cannot be extended easily to the FVTRP. Figure 3 also indicates three proposed routines for the proposed loading patterns. First, loading pattern discovery is a base from which new loading patterns can be discovered using three steps; second, the successful loading patterns can be retained to update the pattern database; and third, existing patterns can be extracted from the database for the most efficient usage. This work primarily addresses the first routine. Its three-step method first generates feasible combinations of various vehicle types by 2D bin packing method with irregular shapes (Valle et al. 2012). Compared with the 3D bin packing problem, by determining the maximal number of packed vehicles, the 2D bin packing method can produce feasible solutions in several minutes. Then, the generated feasible loading patterns should be tested by simulation. The left two figures in Fig. 3 indicate these two steps. However, the principles and

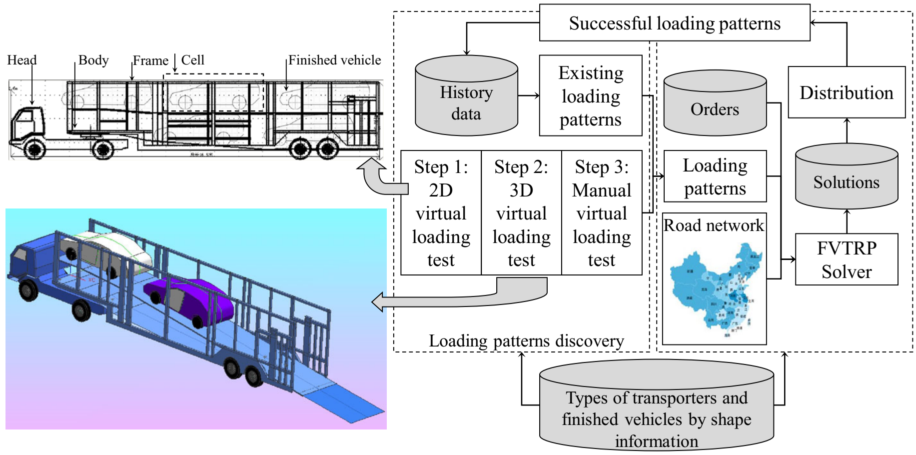

Fig. 3 Loading pattern discovery and updating procedures

implementation details are not the focus of this study. Verifying the solution and producing suggestions for the inner structure and loading and binding approaches via a manual test are costly. Compared to the manual test, the two steps are entitled virtual loading procedures. The model of the FVTRP solver is another key component and is studied in the following sections.

4 A formulation of FVTRP based on loading patterns

The FVTRP can be formulated based on traditional CVRP models (Toth and Vigo 2001). The loading pattern is added by new constraints. The set $V = \{0, 1, \ldots, n, n+1\}$ represents dealers ordering new vehicles and is indexed by i and j, where both 0 and $(n+1)$ represent the distribution center. Therefore, the dealer set can be denoted as N, $N = V \setminus \{0, n+1\}$. The transporter set is defined by K and is indexed by k. For simplicity, the transporter type set is not defined, and only the vehicle type set is denoted as Ω and is indexed by o. Finally, the set of loading patterns is E and is indexed by e. After establishing these sets, six groups of parameters are applied. First, $[L_i, U_i]$ is the time window for the dealer i, and $[L, U]$ denotes the time window for the distribution centers, namely, $[L, U] = [L_0, U_0] = \left[L_{n+1}, U_{n+1}\right]$. Second, P_i defines handling time at dealer i. Third, $T_{i,j}$ specifies the traveling time from dealer i to j. Fourth, $D_{i,o}$ is the demand of dealer i for finished vehicle type o, and the number of total demanded vehicles is denoted by D_i, $D_i = \sum_o D_{i,o}$. Fifth, $\Theta_{k,e,o}$ is the quantity of vehicle type o that can be loaded onto transporter k by a loading pattern e. Then, the available loading patterns for a transporter k are derived based on Θ, $\left\{e : \Theta_{k,e,o} > 0\right\}$. Let $CAP = \max_{k,e} \sum_o \Theta_{k,e,o}$. Any transporter cannot load vehicles more than CAP. Sixth, $A_{i,j}$ is defined to reduce the number of constraints: If a transporter cannot load the finished vehicles ordered by dealer i just before visiting j according to the restrictions of time windows and transporter capacity, then $A_{i,j} = 0$; otherwise, it is 1. For all $i \in N$ and $j \in N$, $A_{i,j}$ is computed by Eq. (1), and set $A_{0,\cdot} = 1$, $A_{n+1,\cdot} = 0$, $A_{\cdot,0} = 0$ and $A_{\cdot,n+1} = 1$. For model readability, the distribution center is denoted by $DP_1 = 0$ and $DP_2 = n+1$, and M indicates a big positive number. The model is to identify optimal routes and optimal assignments of finished vehicles to transporters. Therefore, three groups of decision variables are defined.

First, $x_{k,i,j} \in \{0, 1\}$ is a flow variable. When transporter k serves dealer j immediately after serving the dealer i, $x_{k,i,j}$ is one; otherwise, it is zero. Second, define $y_{k,e} \in \{0, 1\}$ as a packing pattern variable. When transporter k packs the vehicles by loading pattern $e \in E$, $y_{k,e}$ is one; otherwise, it is zero. Third, $\tau_{k,i}$ is the time variable when transporter k distributes new vehicles to dealer i. The total traveling time should be minimized, as in Eq. (2).

$$A_{i,j} = \begin{cases} 0, & \left(L_i + P_i + T_{i,j} > U_j,\, D_i + D_j > CAP\right) \\ 1, & else \end{cases} \tag{1}$$

$$\min f = \sum_{k,i,j} \left(T_{i,j} \cdot x_{k,i,j}\right) \tag{2}$$

We assume that the demand from each dealer cannot split. The flow balance constraints are defined by Eqs. (3)–(6). Every transporter starts from the distribution center and finally returns to it, as defined by Eqs. (3) and (4). Each dealer can be visited once and only once by a scheduled route, as defined by Eq. (6). The sequence of dealers on a route is constrained by Eq. (7). The time window of each dealer is constrained by Eqs. (8) and (9). The loading pattern is introduced as constraints in Eqs. (10) and (11) limiting the number of each vehicle type for a specific loading pattern and the assigned loading pattern to each transporter. To ensure the feasibility of the model, it is assumed that for all i, there exists at least one loading pattern e and one transporter k such that $D_{i,o} \leq \Theta_{k,e,o}$ for all o. However, Eq. (7) is nonlinear because it contains the product of two decision variables, variables $x_{i,j,k}$ and $\tau_{i,k}$, so it is transferred to Eq. (12) as a linear constraint.

$$\sum_{(j, A_{DP_1,j}=1)} x_{k,DP_1,j} = 1, \quad \forall k \tag{3}$$

$$\sum_{(i, A_{i,DP_2}=1)} x_{k,i,DP_2} = 1, \quad \forall k \tag{4}$$

$$\sum_{(i, A_{i,j}=1)} x_{k,i,j} = \sum_{(i, A_{j,i}=1)} x_{k,j,i}, \quad \forall j \in N, k \tag{5}$$

$$\sum_{(k,j,A_{i,j}=1)} x_{i,j,k} = 1, \quad \forall i \in N \tag{6}$$

$$x_{i,j,k}\left(\tau_{i,k} + P_i + T_{i,j} - \tau_{j,k}\right) \leq 0, \quad \forall k, i, j, A_{i,j} = 1 \tag{7}$$

$$L \leq \tau_{k,i} \leq U, \quad \forall k, i \in \{0, n+1\} \tag{8}$$

$$L_i \sum_{(j, A_{i,j}=1)} x_{k,i,j} \leq \tau_{k,i} \leq U_i \sum_{(j, A_{i,j}=1)} x_{k,i,j}, \quad \forall k, i \in N \tag{9}$$

$$\sum_i \left(D_{i,o} \cdot \sum_{j, A_{i,j}=1} x_{k,i,j}\right) \leq \sum_e \left(y_{k,e} \cdot \Theta_{k,e,o}\right), \quad \forall k, o \tag{10}$$

$$\sum_e y_{k,e} \leq 1, \forall k \tag{11}$$

$$\tau_{k,i} + P_i + T_{i,j} - \tau_{k,j} \leq \left(1 - x_{k,i,j}\right) \cdot M, \quad \forall k, i, j, A_{i,j} = 1 \tag{12}$$

Comparing to general CVRP models, the above proposed model has distinct features. First, the transporter capacity is not directly presented by weight or volume. Although we define *CAP* as a maximum number of finished vehicles to reduce constraints, the capacity of a transport is given by a loading pattern that the transporter can have. Second, by Eqs. (10) and

(11), the assignments of finished vehicles to a transporter are checked by the assignments of finished vehicles to a loading patterns, and the assignment of the loading pattern to a transporter.

By replacing Eq. (7) with Eq. (12), the proposed model [Eqs. (2)–(6) and (8)–(12)], an MILP incorporating loading patterns constraints, is an extension of the traditional VRP or CVRPTW models. Therefore, it can be solved by column generation, branch-and-bound, branch-and-price, Lagrangian relaxation or other hybrid exact algorithms. Genetic algorithm, simulated annealing algorithm, Tabu search, or other heuristic algorithms can also be applied to solve the problem. In the following section, an academic MILP solver demonstrates the features of the problem and model, and an evolutionary algorithm is designed for practical medium and large instances.

5 Evolutionary algorithm for routing

As mentioned, the FVTRP is an extension of the VRP. The VRP is an NP-hard problem, and only small instances of the VRP can be directly solved by MILP solvers. To solve medium or large instances of the FVTRP, an evolutionary algorithm is developed. To facilitate algorithm implementation, the model in Sect. 4 is adjusted and new assumptions are made. When the number of transporters for each loading pattern is sufficient, transporter set K and loading pattern set E can share the same definition. The transporter set can then be taken as a virtual set corresponding to the loading pattern set. In Algorithm 1, distribution routes are planned by the considered pattern and loading ratio.

Algorithm 1 (Evolutionary algorithm for the FVTRP)

Input: Population size, P_s; crossover probability, P_x; mutation probability, P_m; maximal iterations, P_g; and the sets and parameters defined in the model in Sect. 4.

Output: Optimal routes

Process

Step 1 Initialization: generate a population P with P_s individuals; set elite as $elite = \Phi$.

Step 2 Evaluation: compute the fitness of each individual by Eq. (2).

Step 3 Selection: choose $\lceil P_s/2 \rceil$ pairs of individuals by a tournament selection strategy.

Step 4 Crossover: for each pair of the $\lceil P_s/2 \rceil$ pairs, by probability P_x, apply the partially mapped crossover (PMX) operator to generate new individuals and replace the parents.

Step 5 Mutation: by probability P_m, perform mutation on new individuals by swapping two genes randomly.

Step 6 Evaluate the new population by Step 2.

Step 7 Update *elite* with the best individual.

Step 8 If the termination conditions are not met, go to Step 3; otherwise, return *elite*.

5.1 Encoding and decoding

Encoding converts the distribution route for the dealers into the chromosome, which is easily computed by the evolutionary algorithm. In detail, the sequence of dealers in $N = \{0, 2, \ldots, n\}$ is used for encoding, where each dealer represents a gene. For instance, assuming that three dealers need service, the sequence $\{0, 2, 1, 3\}$ means that the transporter begins at the distribution center and visits dealer 2, dealer 1, and dealer 3 sequentially and then returns to the distribution center. Therefore, any permutation of this sequence is a valid chromosome without duplicates. Decoding transforms genes in a chromosome into dealers to construct the route set. In this work, the adopted decoding strategy is based on shortest path algorithm for multi-type goods distribution (Liu et al. 2008).

This decoding strategy consists of three steps. First, an acyclic graph is created for routes based on the chromosome (a dealer list that starts and ends at the depot). Each route is then represented by a sequence of dealers whose start and end dealers are located in the chromosome [see Fig. 1 in Liu et al. (2008)]. Second, while considering the constraints of each route [e.g., Eqs. (2)–(12)], the route cost is computed. Third, the shortest path is computed on the acyclic graph, and the segments of the path are routes with minimum cost [see Fig. 2 in Liu et al. (2008)]. Within these steps, the computational method for cost should incorporate the specific model constraints. The cost of solution routes in the third step should be consistent with the cost of each route computed in the second step. A revised decoding approach and its specific cost computation method that considers the characteristics of the FVTRP are elucidated as follows.

The time cost of the route represented by a dealer sequence $r =< c_1, c_2, \ldots, c_k >$ is calculated by Eq. (13).

For a given loading pattern $e \in E$ and route r generated by the decoding algorithm, $Q(r, e)$ computes the compatibility between the route and loading pattern, as defined in Eq. (14), where the assessed compatibility is true only when the quantity of every vehicle type does not exceed the loading amount of the same vehicle type. Thus, the loading ratio $\eta(r, e)$ of the route r by a specific loading pattern e is computed by Eq. (15). Moreover, $\eta(r)$ records the loading pattern with the maximal loading ratio.

The permutation of dealer set $\{1, 2, \ldots, n\}$ is denoted as γ, which is updated by inserting the distribution center index as the first and last component. To disconnect the two indices for the distribution center, set $T_{0,n+1} = \infty$. Notably, $\gamma_{i,j}$ denotes the subsequence from component $(i + 1)$ to component j. Moreover, $C_{i,j}$ and $\eta_{i,j}$ simply represent $C\left(\gamma_{i,j}\right)$ and $\eta\left(\gamma_{i,j}\right)$, respectively, where $C_{i,j}$ is computed by Eq. (16) and where P_c is the time limit for a route.

$$C(r) = T_{DP_1,c_1} + \sum_{i \in \{1,2,\ldots,k-1\}} \left(T_{c_i,c_{i+1}}\right) + T_{c_k,DP_2} \tag{13}$$

$$Q(r, e) = \wedge_{o\in\Omega}\left(\sum_{c\in r} \left(D_{c,o}\right) \le \Theta_{e,e,o}\right) \tag{14}$$

$$\eta(r, e) = Q(r, e) \cdot \left(\sum_{c\in r, o\in\Omega} D_{c,o} \Big/ \sum_{o\in\Omega} \Theta_{e,e,o}\right) \tag{15}$$

$$C_{i,j} = \begin{cases} C\left(\gamma_{i,j}\right), & \eta\left(\gamma_{i,j}\right) > 0 \wedge C\left(\gamma_{i,j}\right) \le P_c \\ \infty, & else \end{cases} \tag{16}$$

Therefore, for a given route γ representing a sequence of dealers, by setting $C_{i,j}$ as the "distance" between any two "nodes", the set of roads from the first "node" (starting from the distribution center) to the last "node" (returning to the distribution center) represents the set of routes with the maximal loading ratio.

When decoding a chromosome (a permutation of the dealer set) with Eqs. (14)–(16), the packing patterns are considered for each route under constraints Eqs. (3)–(11). The infeasible routes will not be generated by the generation procedure of the acyclic graph based on the method proposed by Liu et al. (2008). The shortest path on an acyclic graph defining a set of optimal routes can be computed in $O\left(n^2 \log(n)\right)$ time (Liu et al. 2008).

5.2 Selection and crossover operators

The selection and crossover operators create new individuals based on the current population. The tournament selection strategy (Ryvkin 2010) is applied to generate new pairs, followed by operations of a partially matched crossover (PMX) (Ting et al. 2010). Crossover probability is controlled by P_x. The new pairs are then used to update the original parents.

5.3 Mutation operator

The population updated by selection and crossover operations is subjected to a mutation process by swapping any two randomly chosen genes by the mutation probability, P_m. The mutation operator generates new individuals more independently than the crossover operator with the existing population. The operator guarantees that it is possible to generate individuals who have new characteristics that differ from those of old populations. New solutions can always be found by jumping from local solutions.

5.4 Control parameters

The evolutionary process is controlled by the following parameters: population size, P_s; crossover probability, P_x; mutation probability, P_m; and maximal iterations, P_g. Prins (2004), who examined the parameter configuration of an evolutionary algorithm for the VRP, found that the encoding and decoding strategies, evolutionary operators, and assessment criteria for cost and other measures have strong effects on convergence and evolution speed. Setting P_s to 60, P_x to 0.8, and P_m to 0.2 is proper for the algorithm to operate efficiently based on empirical data. However, when encoding and decoding, the evolutionary operators are devised differently, and the optimal parameters can differ.

6 Case and computational results

For demonstration, 10 dealers and the distribution center are located in a 500×500 space (the grey circle in Fig. 4 represents the depot). Table 1 presents the locations, time windows, handling times and demands for three vehicle types between the dealers and distribution center. To visualize the routes, time windows are all set to $[1, \infty]$. Table 2 presents the time matrix among the 12 nodes (including dealers and the distribution center). In total, 9 loading patterns are provided and can be found and tested by the proposed approaches in Sect. 3 (Table 3).

With the commercial MILP solver Gurobi 4.6, the model defined by Eqs. (2)–(12) is solved to obtain the routes (Fig. 4). The square grid in Fig. 4 displays the related dealer, the time window, handling time, and demands for vehicles of three types. For each transporter, the route, the route number, loading pattern number, and the corresponding maximal quantities of the three vehicle types are listed in another grid. Figure 4 displays two routes. The first route uses loading pattern No. 1 and distributes finished vehicles to dealers 5, 2, 6, 3, and 7 sequentially. This loading pattern can load 15 finished vehicles; thus, this route loads 15 finished vehicles, and the loading ratio is 100 %. The second route uses loading pattern No. 7, distributing finished vehicles to dealers 8, 9, 4, 10, and 11 with a loading ratio of 50 %

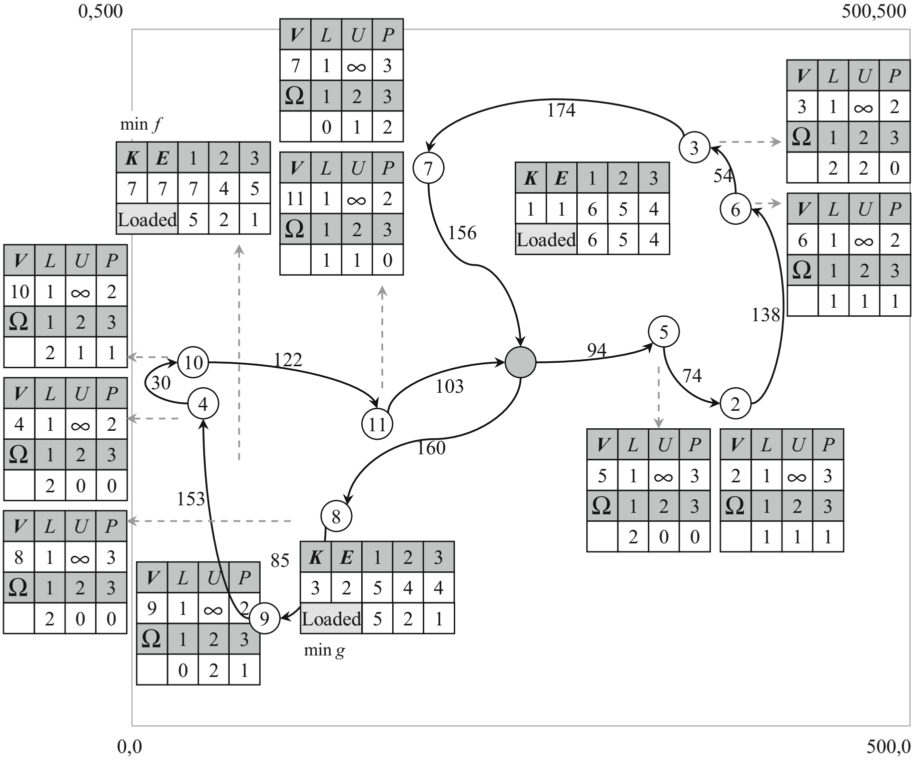

Fig. 4 Routes returned by Gurobi 4.6 for demonstration

Table 1 Locations of, demands from and other service information of dealers

V	x	y	L/min	U/min	P/min	Ω 1	2	3
1	250	250	0	0	2	0	0	0
2	388	222	1	∞	3	1	1	1
3	364	408	1	∞	2	2	2	0
4	46	219	1	∞	2	2	0	0
5	340	278	1	∞	3	2	0	0
6	388	360	1	∞	2	1	1	1
7	191	394	1	∞	3	0	1	2
8	134	140	1	∞	3	2	0	0
9	85	71	1	∞	2	0	2	1
10	39	248	1	∞	2	2	1	1
11	155	210	1	∞	2	1	1	0
12	250	250	0	∞	1	0	0	0

(8/16). The value of the cost (traveling time) of each road is attached near the road (Fig. 4). The transport costs of the first and second routes are 690 and 653, respectively. When the objective is to maximize the loading ratio, as in Eq. (17), the loading patterns are 1 and 2,

Table 2 Time matrix (unit: minute)

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	141	195	206	94	176	156	160	243	211	103	0
2	141	0	188	342	74	138	262	267	339	350	233	141
3	195	188	0	370	132	54	174	353	438	362	288	195
4	206	342	370	0	300	370	227	118	153	30	109	206
5	94	74	132	300	0	95	189	248	328	302	197	94
6	176	138	54	370	95	0	200	336	419	367	277	176
7	156	262	174	227	189	200	0	260	340	211	187	156
8	160	267	353	118	248	336	260	0	85	144	73	160
9	243	339	438	153	328	419	340	85	0	183	156	243
10	211	350	362	30	302	367	211	144	183	0	122	211
11	103	233	288	109	197	277	187	73	156	122	0	103
12	0	141	195	206	94	176	156	160	243	211	103	0

Table 3 The loading patterns and their configurations for loadable vehicles

Ω	1	2	3
1	6	5	4
2	5	4	4
3	4	6	5
4	5	6	3
5	4	5	6
6	3	7	4
7	7	4	5
8	6	4	5
9	5	7	2

and the loading ratios are improved to 1 and 8/13. The total loading ratio increases from 75 to 80.7 %; i.e., the empty loading rate declines by 5.7 % compared with those of the previous routes.

$$\min g = \sum_{k,o}\left(\sum_{e}\left(y_{k,e}\cdot\Theta_{k,e,o}\right)-\sum_{i}\left(D_{i,o}\cdot\sum_{j,A_{i,j}=1}x_{k,i,j}\right)\right) \tag{17}$$

The FVTRP is an extension of the VRP, such that the model for which it is established in Sect. 4 is difficult to solve because it is an NP-hard problem. When the available loading patterns and the size of the dealer set are increased, the model cannot be solved by general MILP solvers (e.g., Gurobi) with ideal performance within an acceptable time. Notably, this work does not compare the differences among various commercial and academic MILP solvers. In Sect. 5, an evolutionary algorithm is designed for this problem. In the following experiments, 100 dealers are located in the 500 × 500 space, and the distribution center is located at the center. The distance between any two dealers is measured as Euclidean distance. After a series of tests, the control parameters for the algorithm are set as $P_s = 30$, $P_x = 0.7$, $P_m = 0.4$, and $P_g = 20{,}000$. Table 4 lists the available loading patterns. After 20,000

Table 4 The loading patterns and their configurations for loadable vehicles

Ω	1	2	3	Maximal vehicles
1	6	5	7	18
2	5	4	6	15
3	4	6	5	15
4	3	6	8	17
5	6	2	5	13
6	5	4	6	15
7	7	4	5	16
8	3	2	8	13
9	9	3	4	16

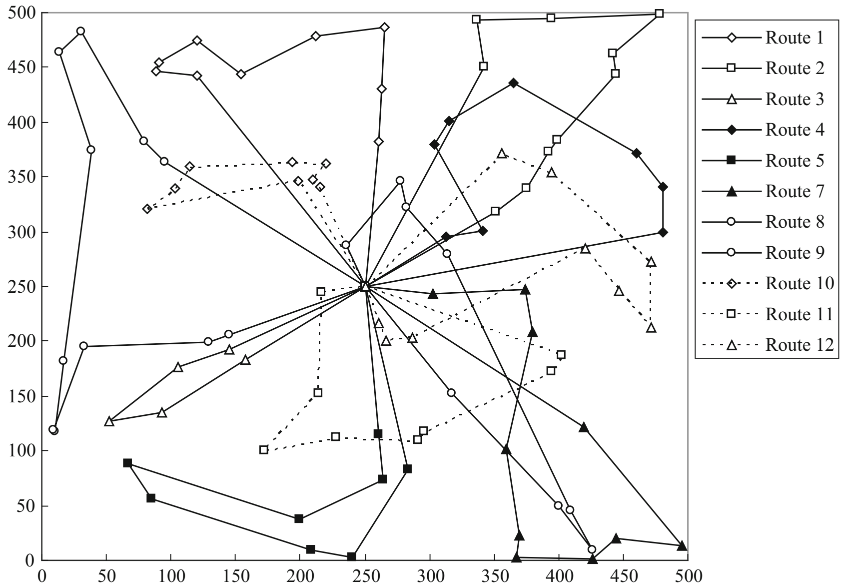

Fig. 5 The routes returned by the evolutionary algorithm

iterations, 12 routes are returned (Fig. 5). Table 5 lists the loading pattern, loading ratio, transport cost, and other information for each route. The average loading ratio for all 12 routes is 0.830. Six loading patterns are used: 4 routes take pattern No. 1, and 3 routes take pattern No. 2. With loading pattern No. 1, the ratios of the three vehicle types are balanced. Thus, this pattern is chosen due to its highest probability, likely because demands are also uniformly generated. Figure 6 displays the optimum and average fitness values for the 20,000 generations. After 10,000 iterations, both curves are stable.

Based on the loading patterns (Table 4) and the above algorithm parameters, the dealer networks in the experiments adopt the instances used in the study by Ngueveu et al. (2010) for medium problems and those in the study by Prins (2004) for large problems. The demands by each dealer are generated randomly by a uniform distribution $U[0, 3]$ for each vehicle type. The computational results for the 12 instances obtained with Gurobi 4.6 and Algorithm

Table 5 The stowage result

Route	Loaded			Loading pattern				Loading ratio	Cost	Dealers
	1	2	3	No.	1	2	3			
1	2	4	8	4	3	6	8	0.824	708	9
2	4	5	6	1	6	5	7	0.833	751	10
3	4	2	4	5	6	2	5	0.769	468	5
4	5	4	4	2	5	4	6	0.867	705	8
5	3	2	6	8	3	2	8	0.846	851	8
6	3	4	4	2	5	4	6	0.733	539	6
7	6	5	7	1	6	5	7	1.000	850	10
8	4	4	5	2	5	4	6	0.867	774	8
9	6	4	7	1	6	5	7	0.944	1,006	11
10	2	5	5	3	4	6	5	0.800	504	8
11	2	3	7	4	3	6	8	0.706	616	8
12	5	5	4	1	6	5	7	0.778	692	9
								Average: 0.830	Average: 705	

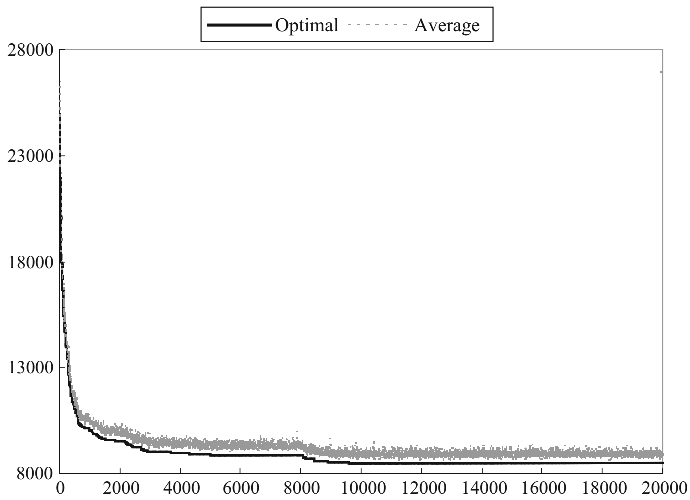

Fig. 6 Evolution curves of optimum and average fitness

1 are compared. Computation time of performing the Algorithm 1 is the time when the fitness value is unchanged further during 2,000 generations. Gurobi 4.6 solved the four problems within 10 h, which is more time than that consumed by the Algorithm 1. The computation times for instances solved by the Algorithm 1 are much shorter than those for instances solved by Gurobi 4.6, meaning that the Algorithm 1 is more efficient than Gurobi 4.6, especially for medium instances (Table 6). Furthermore, when the number of the dealers exceeds 120 (Table 6), Gurobi 4.6 cannot solve the problem within 10 h. However, the Algorithm 1 can obtain convergence results during this time. Therefore, the proposed algorithm can be applied to solve practical FVTRPs with more than 100 dealers. Anji Logistics, the largest RVDC near

Table 6 Test instances and results

Source	Instance	Dealers	Gurobi		Algorithm 1		
			f	Time (s)	f	$avg(f)$	Time (s)
Medium instances (Ngueveu et al. 2010)	CMT1	50	2,586	416	2,583	2,477	317
	CMT2	75	2,807	2,918	2,757	2,656	512
	CMT3	100	5,243	5,421	5,109	4,709	893
	CMT4	150	5,785	–	5,885	5,397	2,107
	CMT5	199	7,319	–	7,319	7,017	3,419
	CMT11	120	7,819	–	7,819	7,363	1,543
	CMT12	100	4,379	5,721	4,359	3,790	877
Large instances (Prins 2004)	GWKC1	240	–	–	57,827	52,977	3,637
	GWKC5	200	–	–	122,983	101,093	3,389
	GWKC10	323	–	–	6,923	6,524	4,322
	GWKC15	396	–	–	8,013	7,171	4,732
	GWKC20	420	–	–	7,631	6,373	5,231

Shanghai, will distribute approximately 200–500 finished vehicles to approximately 50–100 dealers everyday (statistics are estimated based on questionnaires and surveys; http://www.anji-logistics.com). Given this scale of practical problems, the proposed algorithm is effective for real problems.

Based on the procedures that combine routing and pattern discovery (Fig. 3), the Algorithm 1 as well as the experimental results, application techniques and limitations are discussed.

(1) Although the pattern discovery procedure reduces the computational complexity of the 3D-VRP with irregular containers and shapes, the virtual loading test procedures are time-consuming and contribute to the discovery of new patterns. Therefore, utilization of the three virtual loading test methods determines the performance of the proposed approach.

(2) This work focuses on the aspects of management and operational optimization, whereas the application of the proposed methods depends on information flows and the evolution of a database of loading patterns. Therefore, an information system incorporating these procedures or modules is critical for successful applications. Based on the proposed models and algorithm, a comprehensive decision support system was devised and applied to Anji Logistics.

(3) The proposed model and algorithm impose few changes to the routing problem when compared with the changes to the packing problem. However, computational performance of the routing procedure markedly affects the computational times of the Algorithm 1. In practice, the routing procedure can be improved by using historical data and by interaction with sophisticated scheduling operators.

7 Conclusions

This work examined the FVTRP and developed a model and algorithm to solve it. The proposed method helps solve medium and large problems encountered by large FVL companies such as Anji Logistics. In conclusion, there are additional skills that can be used to further reduce the computational complexity. For instance, the loading patterns in real cases can be reduced by matching vehicle types and loading patterns, and the relationships between loading patterns can be utilized to reduce the size of the loading pattern database. Additionally, because transporters are typically limited to specific regions by contracts, the entire problem can be divided into medium or small problems for specific regions. Feasible routes can also be generated first to transform the routing problem into a set covering problem; thus, computational strategies such as column generation can be applied efficiently.

Notably, in addition to reducing distribution cost, some additional benefits are gained from loading pattern discovery and routing optimization. First, the proposed method can help design transporter loading patterns (e.g., in the experiment, the number of transporters with loading pattern No. 1 should be increased). Second, with the accumulated knowledge of loading/unloading in the process of loading pattern discovery, handling efficiency can be improved. Third, during loading/unloading and transportation, damage can be reduced.

As discussed, for a real-world large problem, the model and algorithm should be combined with other techniques to improve their performance. First, the convergence speed of the proposed algorithm can be accelerated by incorporating local search strategies. To make the problem and solution framework lean and simple, some heuristics were tested; however, these heuristics and their test results were not reported in this manuscript. Second, the idea of a loading pattern can be extended to solve general 3D-VRPs, which is an interesting direction for future research. Third, more practical constraints and successful FVL strategies can be employed and examined theoretically in further studies.

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