Multi-day Container Drayage Problem with Active and Passive Vehicles

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Abstract. We consider a real-world container drayage problem, where containers are transported between an intermodal terminal, a container terminal and customer locations. Given a fleet of trucks and trailers, the goal is to efficiently utilize these resources to complete a number of customer orders. Orders consist of several tasks with time windows, such as picking up a container at the terminal, delivering it to a customer, and bringing the processed container back. While generating daily plans is already a complex task, this paper introduces novel approaches for generating solutions for a whole week. Hereby we exploit the possibility to re-arrange parts of the order within the week that are not time-critical. The results show that this approach is highly efficient to decrease the operational costs and to service more customer orders with the same amount of resources.

Keywords: Container drayage problem · Multi-day solution · Active and passive vehicles · Variable neighborhood search

1 Introduction

Road transportation is a popular mode for freight transportation. But considering the current transportation volume and the caused pollution due to emissions, the aim is to shift a part of it to rail freight and/or to cargo [2]. Intermodal freight transportation, where multiple modes of transport (truck, rail and ships) are used in combination is an attractive alternative for long distance trips (more than 700 km). The fact that the first and last mile of such long distance trips (so called *drayage operation* [7]) causes a substantial part of the total costs shows the importance of proper and efficient planning of the first and last mile. Furthermore, inefficient drayage operations can cause shipment delays, congestion at the terminals or customer locations, and an increase of carbon emission. These concerns further emphasize the importance of drayage operation optimization.

The container drayage problem (CDP) considers the transportation of containers between an intermodal terminal, a container terminal and customer locations. In this work, we investigate a real-world application considering a multi-day container drayage problem (MDCDP) in the area of Vienna. There

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is a tri-modal transshipment center located at the port, where containers arrive and leave either by truck, train or ship and several carriers are responsible for the last-mile transport of the containers. The customer orders are distinguished into two categories: *import orders* and *export orders* as depicted in Fig. 1. Containers must be served at customer locations within a given time window and operational hours at the port and terminal must be met. The CDP belongs to the general class of pickup and delivery problems [11] which usually considers one resource. But in our case we have to deal with multiple resources such as trucks, drivers, trailers and containers. We model trucks and drivers as a single resource because each driver is assigned to his own truck. Trailers are a separate resource because at some customer locations it is allowed to uncouple the trailers while loading or unloading takes place. The containers are a separate resource as well and must meet the compatibility requirements between trailers and containers. Thus, we model our problem as an active-passive vehicle routing problem (VRP) [8,12], where passive vehicles refer to the trailers and active vehicles refer to the trucks, and these two must be synchronized. The given problem is static, thus all orders of one carrier are known in advance. Dynamic variants are considered in the literature as for example in [5,14], and a solution approach, which addresses the cooperation of multiple carriers is shown in [6]. Here, we consider the MDCDP and optimize the plan for several consecutive days (usually Monday to Friday). Existing literature on multi-day solution approaches consider only single resources problems [3,4].

In this work we deal with a rich set of constraints: the planning and synchronization of multiple resources, compatibility of trailers and containers, working time regulations, and the given time windows at the customer locations and the terminals. The aim is to improve the planning in order to reduce the operational costs of carriers and to increase the capacity of drayage operations within the planning horizon. The main contribution of this work is the extension of our previous CDP algorithm [10] to the MDCDP, so that several consecutive days are considered by solving the transitions between days efficiently.

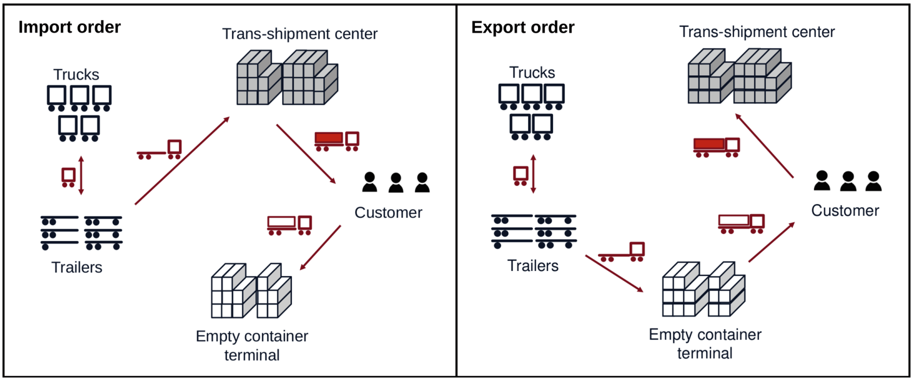

Fig. 1. Two categories of customer orders: *import orders* and *export orders*.

2 Problem Description

In the MDCDP a set of available trucks (together with their drivers) and a set of available trailers are given. The operating times of these two resources depend on the given driver regulations (daily and weekly regulations for working and driving times must be met). Each truck belongs to a given emission standard class and there exist several types of trailers with a different number of axes. All trucks and trailers are located at a single depot. Additionally, a set of orders is known before the start of the week. We consider two different order types: import order and export order as illustrated in Fig. 1. Each order consists of two parts, where each of them requests a container transport between two locations. An *import order* requires moving a full container from the port to the customer and later moving the emptied container from the customer to the container terminal. Whereas an *export order* initially moves an empty container from the container terminal to the customer where goods are loaded. The full container is then moved from the customer to the port. Another characteristic of an order is the given situation at the customer location. There are three possibilities for the (un-)loading process. The different pre- and post-conditions of tasks must be considered in the planning of truck routes, see Fig. 2:

- **Waiting:** The truck+trailer must wait at the customer location while the container is processed (e.g. space restrictions).
- **Uncoupling:** It is allowed to uncouple the trailer, which has the container loaded at the customer location. This allows leaving the truck to perform other tasks. After the (un-)loading process any truck is allowed to continue with the second task of the order.
- **Lifting:** Some customers have a crane which can lift the container from the trailer. Thus, the truck+trailer can leave the container at the customer's location and go on to perform other tasks. Another truck with a compatible trailer can be sent to pick up the container after (un-)loading has finished.

Each order has a given time window which defines when the service at the customer location must take place. Furthermore, the service time for all locations, the type of the loading process, the required time for (un-)loading, and the container type (important for trailer compatibility) is given.

Since the available resources are limited, not all orders of a week can be completed. However, maximizing the number of completed orders has top priority. Each truck has to execute a sequence of tasks, which is already challenging because of the given time windows, driver regulations, and different order types (arising pre- and post-conditions). But providing the sequence of tasks with feasible trailers is also a complex decision. This depends on the containers that have to be transported, the availability of trailers, and the toll costs on the highway. The latter depend on the emission class of the truck and the number of axes of the trailer. Finally, the overall goal is to optimize the routing of trucks and trailers such that all constraints are met, as many orders are completed as possible, and the total operational costs are minimized.

3 Solution Approaches

Here, we present our solution approaches for the given real-world MDCDP. First we describe the approach generating daily solutions and then we introduce the approach for solutions considering multiple consecutive days.

3.1 Solution Representation

In a feasible solution for the MDCDP, containers of the orders must be assigned to trailers respecting the compatibility and the availability of the trailer. Since trailers are passive vehicles, they must be assigned to available trucks. Thus, a solution consists of a set of truck routes and a set of trailer routes which must be synchronized. For an efficient solution representation we group the tasks of an order to so called *trailer nodes*. For example, in the case of *uncoupling* only the truck leaves and the trailer has to stay at the customer while the container is processed. Thus, the two tasks can be combined to one trailer node. For each trailer node we calculate the respecting time window, the service duration (including all service, loading and travel times), the trailer type, the start and end location. For the truck routes, we generate so called *truck nodes*, by splitting the nodes of the trailer routes whenever it is allowed for a truck to leave the trailer. Analogously, each truck node has a time window, a service duration, and a start and end location. Note, that required times to fulfill the pre- or post-conditions (e.g., time for decoupling) are included into the truck node as well.

3.2 Single Day Solution

A single-day solution of the CDP is generated by a combination of heuristics. First, the trailer routes are computed by a construction heuristic and all trailer nodes which cannot be feasibly inserted into a trailer route are stored on a so-called *dummy route*, i.e., the corresponding orders are unfulfilled. In order to obtain a complete solution, feasible truck routes are computed from the given trailer routes by the PILOT heuristic [13]. For further improvement of the solution we apply a variable neighborhood search algorithm (VNS) [9]. The key concept of our approach is the close interaction between the improving trailer

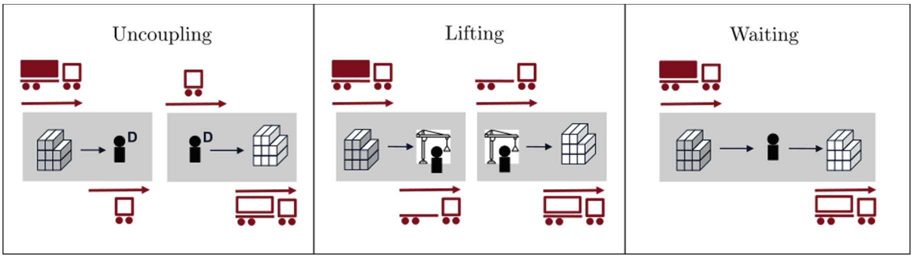

Fig. 2. Three possibilities of the (un-)loading process at the customer location.

routes and constructing the truck routes. All neighborhood structures operate on the trailer routes, whereas every move is evaluated by computing the corresponding truck routes using the PILOT heuristic. In the VNS, all neighborhood structures are traversed in a random order and with a *next improvement strategy*. Only better solutions are accepted, thus the move is only executed if the resulting truck solution has a better objective value than the current solution. The neighborhood structures, operators and settings for the VNS and PILOT heuristic are described in more detail in [10].

3.3 Multi-day Solution

Considering the problem over a multi-day horizon adds more flexibility and thus creates additional optimization potential. The most important new flexibility comes from the fact, that tasks at the transshipment center and at the empty container terminal are usually not as time-critical as tasks at customer locations. For example, returning an empty container to the container terminal does not strictly have to be accomplished on the same day as the corresponding import order. It can be postponed to the following day, where it can then be performed in combination with another task. This enables planning more efficient tours which either save operational costs or fulfill additional customer orders.

Figure 3 shows the two possibilities: If the first task of an order is allowed to process the day before the given customer's time window, it may be beneficial to already pick up the container on the previous day and place it at an intermediate facility (usually the depot) overnight. The remaining tasks are served on the next day. We call this a *pre-carriage* operation. The other possibility is named *post-carriage* operation. In this case, the last task of an order is allowed to process on the day after. In the solution, the according trailer nodes are added.

The **base algorithm (BA)** simply applies the VNS algorithm for every day of the week. To obtain a feasible weekly solution, the working and driving hours at the end of day are considered on the next day. But in order to exploit the advantage of combining tasks of orders between two consecutive days we introduce a **greedy algorithm (GA)**. The algorithm takes the solution of the BA and sequentially considers all transitions between two days. It iterates over all routes and examines for each route if *pre-carriage* or *post-carriage* opera-

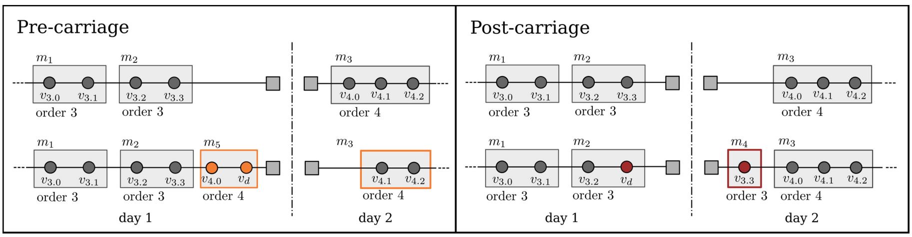

Fig. 3. Two possibilities how to combine trailer tasks of two consecutive days.

tions yield to an improvement of the objective value. If there is an improvement, the better one will be applied. Even tough the GA yields slightly better results, the disadvantage of this approach is its sequential/greedy nature and that it considers only tasks which are already inserted in the solution. Therefore we introduce a novel local search based algorithm, called **multi-day local search (MDLS)**. The MDLS also takes the BA as starting solution and selects a transition between two days randomly. Then it applies one of four defined operators (also selected randomly) in order to improve the solution. After a given number of non-improving iterations, the algorithm stops. The first two operators select two routes randomly (one of the current day and one of the next day) and apply either a *pre-carriage* or a *post-carriage* operation to the last and first task of the routes. Note, that in the case of two different trailer routes, the container compatibility of all tasks must be verified. The latter two operators insert unserved orders from the dummy route into the solution. They randomly select an order from the dummy route and try to insert it either as a *pre-carriage* or a *post-carriage* operation. Following a *next improvement strategy*, the accordingly generated trailer nodes are inserted into two randomly selected trailer routes.

4 Computational Experiments

We tested the algorithms (implemented in Java 8) on a set of instances based on real-world data. The fleet consists of 14 trucks of different emission classes (3, 4, 5, EEV), and 22 chassis of 8 different types with 1-3 axes. The costs per km of a truck is set to 1.2 € and the toll costs on Austrian highways depend on the emission class of the truck and the total number of axes [1]. While the resources are fixed, the instances vary in the number of orders (100–300 orders per week) and are generated randomly with the following parameters: The split of import and export orders is fifty-fifty. At 20% of the customer locations decoupling is not allowed and one-third of the customer locations have a crane for lifting the containers. Each order has a given time window of 30 min, a given container type which must meet the compatibility properties with the chassis, a loading time of 1, 2, or 3 h, and a given service time of 10 min at every location. Table 1 shows the average results of 15 instances per set of 10 runs per instance. For space reasons, the full results are in an external table[1].

The results show that our algorithms are able to find solutions with a high rate of served orders. Improvements are achieved when pre- or post-carriage operations are applied (GA and MDLS). The GA yields 1.3% improvement on average of total costs. Since the GA does not re-insert unfulfilled orders from the dummy route, no improvements w.r.t. served orders are possible. MDLS improves the results regarding the number of served orders, but the total costs may increase because of a higher mileage and longer working hours for the drivers. Given that the MDLS yields better results regarding the primary objective of maximizing the number of served requests, it clearly outperforms the other two approaches. Currently, a typical day of operation consists of 20-25 orders a day. Figure 4

[1] https://github.com/hkoller/ritzingeretal_mdcdp_2022.

Table 1. The average results for all approaches and instances: the percentage of served orders (ord^b), the truck costs per km ($cost^{km}$), the toll costs ($cost^t$), and the costs for drivers ($cost^d$) for the BA. Then, the improvements of costs (imp^{km}, imp^t, imp^d) and the improvement of total costs (imp^c) for the GA and the MDLS, and improvements for the percentage of served requests for the MDLS in (ord^m).

n	Base algorithm				Greedy algorithm				MDLS algorithm				
	ord^b	$cost^{km}$	$cost^t$	$cost^d$	imp^{km}	imp^t	imp^d	imp^c	ord^m	imp^{km}	imp^t	imp^d	imp^c
	[%]	[€]	[€]	[€]	[€]	[€]	[€]	[%]	[%]	[€]	[€]	[€]	[%]
100	100.0	10236.6	2553.7	4514.0	–150.3	–39.5	–12.1	1.2	100.0	–356.0	–99.6	–13.5	2.7
150	99.8	15371.9	3845.3	6620.5	–225.4	–63.2	–12.6	1.2	99.9	–580.7	–166.8	–15.4	3.0
200	95.7	17945.3	4505.7	8179.2	–316.6	–92.8	–20.6	1.4	96.8	–163.7	–50.3	140.3	0.2
250	86.4	18958.2	4710.4	9090.7	–312.0	–88.9	–21.7	1.3	87.1	–295.3	–113.4	126.3	0.8
300	78.1	19209.4	4789.5	9601.2	–324.7	–93.8	–32.5	1.3	78.7	–113.3	–74.2	165.8	0.0

shows an example plan: colored bars are the tasks performed by the trucks, light gray are the driving times between the locations and dark grey are waiting times. This output can be used for the planner either as a decision support or a quick estimation of resource utilization.

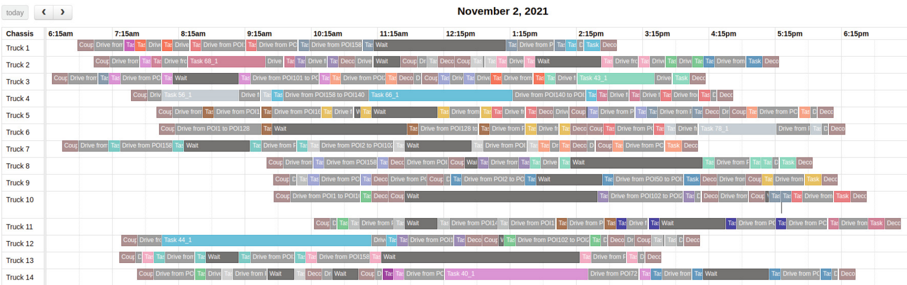

Fig. 4. Example for a daily plan with 14 trucks, 22 trailers, and 40 customer orders.

5 Conclusion

In this work, we investigated the MDCDP and presented three approaches for providing an efficient weekly solution for trucks and trailers. The primary goal was to serve as many customer orders as possible while efficiently utilizing the resources to minimize operational costs. We modeled our problem as an active-passive VRP and implemented a VNS algorithm for computing truck and trailer routes. Additionally, we presented novel approaches for generating solution for a whole week, resulting in larger instances with additional constraints on driver regulations. The results show that starting with the basic approach of considering the weekdays independently, the greedy algorithm is able to decrease the operational costs. This is achieved by incorporating *pre-carriage* and *post-carriage* operations that forwards or delays parts of the order that are not time-critical.

In addition, the MDLS algorithm is a powerful approach to increase the number of served orders with the same resources. In the future, we want to integrate the MDLS directly into the VNS algorithms to further improve the results.

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