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Vehicle selection for a multi-compartment vehicle routing problem

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This paper addresses the vehicle routing and selection problem of single and multi-compartment vehicles for grocery distribution. Retailers used to rely on single-compartment vehicles (SCV), and transported only one temperature-specific product segment with this vehicle type. Retailers now have the option of using multi-compartment vehicles (MCV) due to technological advances. Products requiring differing temperature zones can be transported jointly as the loading area is split into separate compartments. Both vehicle types cause different costs for loading, transportation and unloading. In literature either the use of SCVs or MCVs has been considered without a distinction between vehicle-dependent costs and the use of both vehicle types in the fleet to achieve a cost-optimal fleet mix. We therefore identify vehicle-dependent costs within empirical data collection and present an extended multi-compartment vehicle routing problem (MCVRP) for the vehicle selection. We solve the problem with a Large Neighborhood Search. Our numerical experiments are based on the insights we draw from a real-life case with a retailer. In further experiments we show that the mixed fleet is always better than an exclusive fleet of SCVs or MCVs and state which factors influence the cost reduction. A mixed fleet can reduce costs by up to 30%. As a result, mixed fleets are advisable in grocery distribution and vehicle selection should be part of the MCVRP.

1. Introduction

An efficient distribution system is essential for every grocery retailer as it amounts to around 20% of total logistics costs (Hübner, Kuhn, & Sternbeck, 2013; Kuhn & Sternbeck, 2013). Decisions concerning the delivery process are therefore a central problem for retailers, and cost-efficient solutions are needed. This paper develops a model and solution approach for the vehicle selection and routing for a delivery fleet in grocery distribution.

Grocery stores receive different product segments from the retailer's distribution center (DC). Each product segment has a particular temperature requirement (e.g., deep-frozen, chilled, ambient). These temperature requirements are defined by law (e.g., for chilled products) or by quality management (e.g., for longer shelf life). Each retailer differentiates further the transportation temperature and hence defines the constitution of a product segment. For instance, many retailers use multiple temperature zones for chilled products (e.g., meat at 2° and vegetables at 4–6° Celsius). In the past, retailers only used single-compartment vehicles (SCV). An SCV can transport products from one exact temperature zone. This means that, for example, there are trucks with a cooling system that only deliver deep-frozen goods, and trucks that only deliver ambient goods with no temperature regulation. Each customer is therefore approached several times if different product segments are ordered, receiving one product segment at a time. Nowadays the use of technically advanced multi-compartment vehicles (MCV) is an attractive alternative. MCVs enable the transportation of different product segments (e.g., frozen and ambient) jointly with one vehicle, and thus allow the joint delivery of several product segments for a customer at the same time. This is possible due to the separation of the loading area of a truck into multiple compartments. Each of the compartments can be dedicated to a specific temperature zone, independent of the other compartments on the same truck. The number of compartments and their size can be adjusted flexibly so that between one and five compartments can be set on a truck without any loss in capacity. An example of two possible layouts for an MCV to illustrate the compartment separation is given in Fig. 1, together with the layout of an SCV.

The features of SCVs and MCVs also imply different distribution costs. First of all, MCVs have slightly higher procurement costs, which impact the costs for transportation. This may be compensated by higher flexibility in routing. Each outlet with orders from different segments does not have to be approached several times for the delivery of each segment. This reduces the total number

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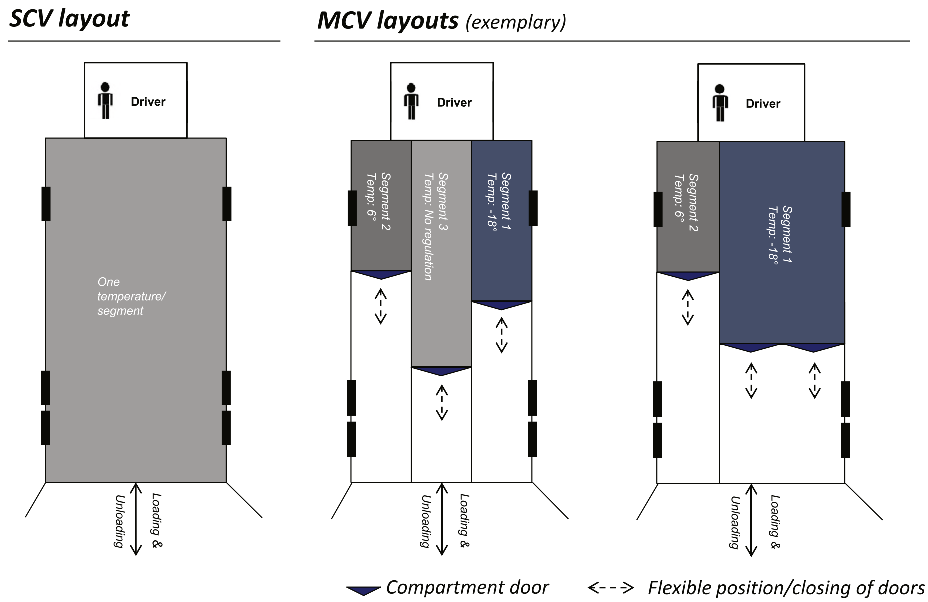

Fig. 1. Examples for the layout of MCVs and an SCV.

of stops as orders can be combined on the same vehicle. For instance, the use of an MCV might be beneficial if a customer orders various segments that all fit on a single vehicle. Joint delivery however requires additional loading actions at the DC as different segments are stored in temperature-specific sections. An MCV therefore has to approach multiple shipping gates to load orders from various segments. This results in higher loading costs. SCVs on the other hand have lower procurement costs, which result in lower transportation costs for certain routes and modes. SCVs are more economic if stores order full truckloads of one segment or if two neighboring customers order the same segment and require almost full truck capacity. Furthermore, only one loading process is needed as only one segment is transported. The differences in the delivery process and in cost have to be evaluated to select the optimal vehicle type for corresponding tours. Retailers can benefit from the advantages of both vehicle types if they apply a mixed fleet. They therefore need to decide what kind of vehicles should be used, and which is the optimal mix of vehicle types in their fleet.

Current literature on multi-compartment vehicle routing problems (MCVRP) only considers an MCV fleet. However, a mixed fleet of both vehicle types might be beneficial due to the differences described if the most economic vehicle for each tour can be chosen. This raises the question of which vehicles should be used for which routes and under which circumstances SCVs or MCVs are the better choice. We propose a model that takes into account the different costs for both vehicle types for evaluating the MCVRP and vehicle selection problem. Our new approach extends the literature with the introduction of the following characteristics:

- The selection of vehicle type, i.e., SCV or MCV for each delivery tour.
- The assignment of orders to vehicle types and flexible compartments.
- The identification of cost factors to account for costs related to processes and vehicle types that depend on the use of SCVs, MCVs and the number of segments transported together.

The routing of our MCVRP takes into account (i) demands for multiple heterogeneous product segments, and (ii) the use of different vehicle types. It therefore has to be determined (iii) whether different segments are combined on a vehicle or not, and (iv) which customer orders across the segments are combined. The MCVRP considered is an NP-hard problem as it is a generalization of the CVRP (see Toth & Vigo 2014). To solve our problem, we built upon a large neighborhood search (LNS) framework introduced by Derigs et al. (2011) and Hübner and Ostermeier (2018), as it has shown good results for MCVRP.

The outline of the paper is as follows. Section 2 describes the problem context and identifies the differences between SCVs and MCVs. The related literature is discussed in Section 3. Next, the formal definition of the problem and the solution approach is presented in Section 4. In Section 5, we analyze the impact of using both SCVs and MCVs for the distribution within various scenarios, including a case study with real-life data. Finally, the findings and conclusions are summarized in Section 6.

2. Problem description

Grocery retailers channel the overwhelming majority of volumes to their stores via DCs (Fernie & Sparks, 2009; Kuhn & Sternbeck, 2013). European discounters and most full-line supermarkets operate their own distribution networks consisting of several regional DCs from which the complete assortment is supplied (Klingler, Hübner, & Kempcke, 2016). DCs are organized according to temperature-specific product segments. A retail DC usually serves between 50 and 400 outlets (Glatzel, Großpietsch, & Hübner, 2012). The distribution process can be divided into three steps (see Hübner & Ostermeier, 2017): (1) the loading processes (=collection of goods from the DC), (2) the transportation of goods, and (3) the unloading process at the outlets. In the following we analyze the costs that occur for SCVs and MCVs in the specified flow of goods. The process and cost analysis was performed in a joint project with a German retailer.

(1) Vehicle-dependent loading costs at the DC. The first step for the distribution is the pickup of orders from the DC. Retailers organize warehouses by temperature zone. This also means that each temperature zone needs to be loaded separately. As a consequence, the collection of goods from the DC differs by SCV and MCV. The loading processes are displayed in Fig. 2.

On the left, the loading for an SCV is illustrated. An SCV approaches only one shipping gate as segments cannot be combined

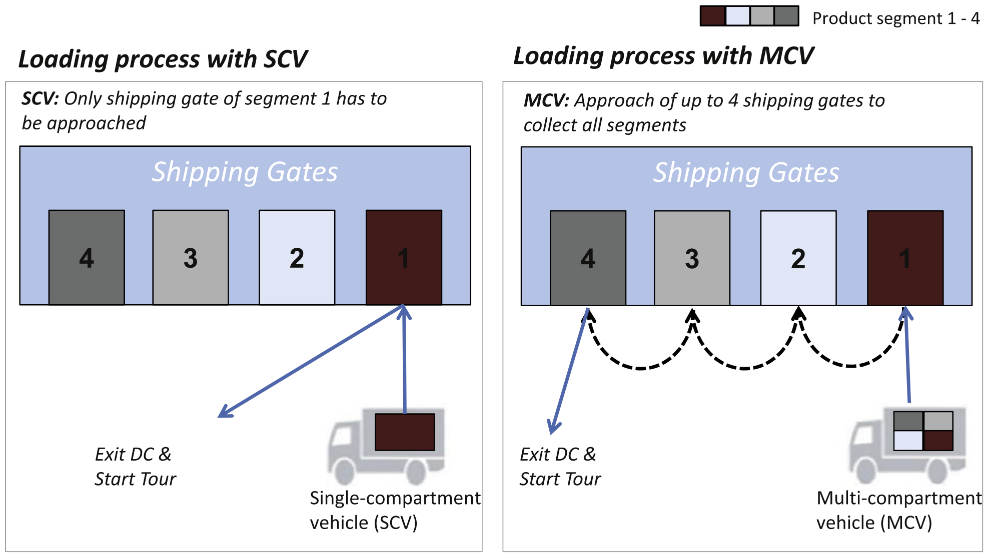

Fig. 2. Loading process with SCVs and MCVs at the DC.

on this truck type due to the temperature requirements. Each tour therefore starts with the approach of exactly one shipping gate to collect all orders for the corresponding tour. This requires no rearrangement of the truck at the DC. Vehicles are ready to leave for the tour after exactly one loading process.

On the right, the MCV loading procedure is illustrated for a tour with four different segments. In this case, the MCV has to approach four different shipping gates. This involves four separate loading steps and the vehicle traveling between the gates. Each loading step involves the loading of all orders of one segment as otherwise the same shipping gate would have to be approached multiple times. The pickup at the DC is therefore driven by multiple loading processes and accordingly with higher loading costs dependent on the number of segments and compartments. These additional costs have to be taken into account within the routing.

Some loading aspects are equal for both vehicle types. Each vehicle has to approach a loading gate in reverse as the loading can only be done from the rear of the truck. The actual loading of goods (i.e., the loading of pallets or roll-cages) depends on the order size of the different customers. It requires the same actions regardless of the vehicle type and thus is not decision relevant.

(2) Vehicle-dependent transportation costs. Vehicle-dependent routing costs have to be considered to determine the cost-minimal transportation fleet. The special technical features of MCVs lead to higher procurement costs in comparison to SCVs. The price of an MCV is higher than for an SCV due to the need to isolate separation walls plus multiple cooling devices. As a consequence, higher investment costs are one of the main drivers of higher MCV costs. Further, fixed costs for insurance and maintenance differ and therefore impact overall costs. In the end, these fixed costs need to be considered when selecting a particular vehicle type for distribution. We therefore propose a vehicle-specific transportation cost rate per distance unit to map the corresponding investment and maintenance costs. This cost calculation includes both variable and fixed costs, and is translated into costs per kilometer. For the fixed costs we consider all costs for one life cycle of a vehicle and divide them by the expected vehicle miles traveled. Further, variable costs are added based on driver and fuel costs. The total transportation costs included in this way are also equivalent to a rate that is paid per kilometer if a truck is leased. Furthermore, we would like to note that the use of MCVs does not lead to additional capacity restrictions. As the number and size of compartments can be adjusted flexibly, there is no loss in capacity. Retailers use standardized carriers for transportation (e.g., roll-cages or pallets) that are indicated in transportation units (TU). The smallest size of a compartment can be set to one TU, the biggest size of one compartment to full vehicle capacity.

(3) Vehicle-dependent unloading costs. The delivery process for SCVs involves the approach of stores that have ordered the corresponding segment on the tour. Orders of these customers for other segments cannot be included in the tour as the transportation of only one segment is possible. Furthermore, it is not possible to load orders for other segments from other customers, even if these would fit onto the truck or the customers are in close proximity. These orders are therefore supplied on different tours. This may result in higher transportation kilometers and the use of more vehicles. The delivery process with SCVs is illustrated on the left of Fig. 3.

An example of a tour for the joint delivery of four product segments with an MCV is displayed on the right of Fig. 3. The MCV combines customers with orders for different segments on the same tour. If capacity is sufficient, joint delivery makes it unnecessary to approach a customer several times and therefore saves transportation kilometers and unloading time. This results in fewer customer stops and thus in lower unloading costs for the use of MCVs.

Summary. The selection of vehicle type – whether SCV or MCV – impacts distribution costs. Table 1 summarizes the cost differences between both types, where "–" indicates that the vehicle type has lower costs in this dimension, and "+" the opposite. These costs need to be taken into account to achieve an evaluation of routing costs that reflects the operational processes needed. We therefore show the need to distinguish between loading, transportation and unloading costs of SCVs and MCVs.

Table 1
Schematic overview of cost differences between SCVs and MCVs.

Vehicle type	Loading	Transportation		Unloading
		Costs per kilometer	Travel distance	
SCV	–	–	+	+
MCV	+	+	–	–

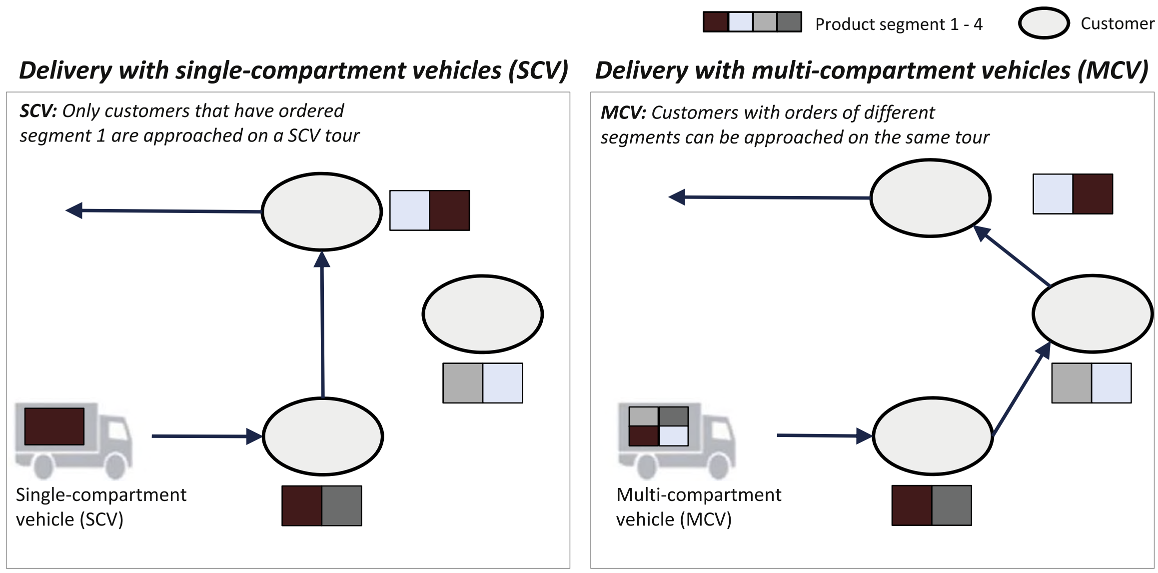

Fig. 3. Delivery process of SCVs and MCVs on example routes.

Please note also, that each MCV can be used as SCV if only one compartment is used, i.e., only one product type is transported. MCVs offer a higher flexibility compared to SCVs and therefore have a higher degree of freedom for the planning and routing.

3. Related literature

The MCVRP considered is a generalization of the classical CVRP. For an overview of VRP and CVRP we refer to Golden, Raghavan, and Wasil (2008); Laporte and Semet (2001); Toth and Vigo (2014) and Pollaris, Braekers, Caris, Janssens, and Limbourg (2015). The current literature on MCVRP can be divided into publications considering fixed and flexible compartment sizes.

MCVRPs with fixed compartment sizes. The majority of MCVRP literature focuses on problems with fixed compartments. A typical field of application for MCVRP with fixed compartments is the distribution of fuel. These MCVRP instances are applied for truck types where the compartment sizes are fixed in advance, but the assignment of product segments to compartments is part of the decision problem. Coelho and Laporte (2015) provide a classification of different MCVRPs focusing on fuel distribution. They distinguish between split and unsplit compartments and tanks. Split compartments means that the content of one compartment can be distributed to more than one customer. This is not the case with unsplit compartments (see e.g., Brown & Graves, 1981). Split tanks indicate that the requirements for one order of one customer can be delivered by multiple trucks. Furthermore, Coelho and Laporte (2015) propose models and a branch-and-cut algorithm to formulate and solve different problem variants. In the context of fuel distribution, too, Avella, Boccia, and Sforza (2004) consider the supply of fuel pumps with MCVs and solve the corresponding problem with a branch-and-price algorithm. Furthermore, Cornillier, Boctor, Laporte, and Renaud (2008) develop heuristic approaches for solving the multi-period petrol station replenishment problem, considering trucks with different compartments.

Lahyani, Coelho, Khemakhem, Laporte, and Semet (2015) study MCVRP with a branch-and-cut algorithm for olive oil collection. El Fallahi, Prins, and Wolfler Calvo (2008) consider fixed compartments and the fixed assignment of product types to compartments in the context of animal food distribution. A memetic algorithm and tabu search is applied to solve the problem. Caramia and Guerriero (2010) use a two-part heuristic to investigate milk collection with fixed compartment sizes and without a given assignment of product types to compartments. Chajakis and Guignard (2003) propose a heuristic based on Lagrange relaxation for the supply of convenience stores. An extension of MCVRP by stochastic demand models is given by Mendoza, Castanier, Guéret, Medaglia, and Velasco (2010, 2011). They develop several construction procedures. In a similar way, Goodson (2015) proposes a simulated annealing algorithm. Only recently, Mirzaei and Wøhlk (2016) present a branch-and-cut algorithm for two variants of an MCVRP. The first one considers the delivery of all segments with only one MCV per customer, i.e., each customer is only approached once, while the second one allows the delivery of each segment with different MCVs. Silvestrin and Ritt (2017) also consider an MCVRP with single visits to customers and present a tabu search to solve the corresponding problem. The only publications that consider the delivery of multiple goods on either the same or separate vehicles are Muyldermans and Pang (2010) and Archetti, Campbell, and Speranza (2016). The first regards the collection of waste from firms that produce different types of waste. Their research focuses on the question of when co-collection (i.e., the joint collection of different wastes) is better than separate collection (i.e., only collecting one type of waste per vehicle). In contrast to our problem specification they do not differentiate between different costs for SCVs and MCVs, but apply a CVRP for the single-commodity case. It is solved by a guided local search. Archetti et al. (2016) study the impact on transportation costs if single or multi-commodity vehicles are used. Further, they analyze the possibility of splitting deliveries if vehicles can transport multiple commodities. Again, no differentiation between vehicle-dependent costs was made in their work, and they regard problems where either single- or multi-commodity vehicles are used. The selection of vehicles for routing was therefore not considered.

MCVRPs with flexible compartments. The available literature is still very limited for an MCVRP with flexible compartments. A model that uses flexible compartments for the distribution of both food and fuel was presented by Derigs et al. (2011). They introduce a solver suite including an LNS, a local search and several construction heuristics within an adaptive search procedure. Their approach has been tested on various benchmark instances and provides further insights into the performance of different operators for the

Table 2
Notation.

Index sets		
	$L^* = L \cup \{0\}$:	Set of locations where $L = \{1, \ldots, n\}$ is the set of customers, and vertex 0 is the depot
	P:	Set of product segments $p \in P$
	O:	Set of orders $o \in O$
	N_j:	Set of orders for customer j ($N_j \subseteq O$)
	S_p:	Set of orders for segment p ($S_p \subseteq O$)
	K:	Set of vehicle types $k \in K$
	V_k:	Set of vehicles of each type $k \in K$, $v \in V_k$
	C:	Set of compartments $m \in C$
	C_k:	Set of compartments for each vehicle type $k \in K$, $c \in C_k$ ($C_k \subseteq C$)
Parameters		
	d_{ij}:	Distance between locations i and j [in distance units]
	q_o:	Quantity volume of order o [in transportation units]
	Q_k:	Vehicle capacity of vehicle type k [in transportation units]
Cost parameters		
	lc_m:	Loading cost dependent on the number of compartments m used on a vehicle [in currency units]
	tc_v :	Transportation cost dependent on the vehicle v [in currency units]
	ulc_v :	Unloading cost dependent on the vehicle v [in currency units]

search. Henke, Speranza, and Wäscher (2015b) present an MCVRP for the collection of glass waste. Their formulation considers flexible compartment sizes, but the variation in size is limited to predefined steps. This means that compartments are not fully flexible but can vary between given sizes. They developed a variable neighborhood search to solve the corresponding problem. Henke, Speranza, and Wäscher (2015a) develop a branch-and-cut approach to this problem. Further, Koch, Henke, and Wäscher (2016) present a genetic algorithm for a similar problem setting to collect multiple products from customers. Only recently, Hübner and Ostermeier (2018) presented an MCVRP with different costs for loading and unloading processes for MCVs. They show that compartment-dependent costs for MCVs are decision relevant and significantly influence the routing solution. However, they only regard MCV-specific costs and do not include the vehicle selection in their decision problem. They present an LNS to solve the MCVRP with loading and unloading costs. Ostermeier, Martins, Amorim, and Hübner (2018) extend the model and solution approach by including loading constraints to reflect required loading and unloading sequences. However, vehicle selection with MCVRP for flexible compartments has not been studied so far in any of the publications.

Heterogeneous VRPs. Besides MCVRPs our work is also inspired by research on fleet size and mix. The general stream of literature concerning this problem is classified as heterogeneous VRP (HVRP). The first ones to consider the problem of an VRP with an heterogeneous fleet are Golden, Assad, Levy, and Gheysens (1984). Different types of heterogeneous VRPs are identified by Baldacci, Battarra, and Vigo (2008). In their work, Baldacci et al. (2008) provide a classification of five major subclasses for VRPs with an heterogeneous fleet. Following their classification, our work could be seen as a Fleet Size and Mix VRP with Vehicle Dependent Routing Costs (FSMD). This means, that we consider a fleet of unlimited size and choose the optimal fleet mix according vehicle dependent costs. We base our work on the MCVRP formulation and search for the optimal mix between MCVs and SCVs. Hence, our model formulation is directly related to the MCVRP formulations and inspired by the HVRP problem class.

Summary and contribution. Overall, specific problems considered in the MCVRP context are quite heterogeneous. To the best of our knowledge, the only contributions that deal with flexible compartment sizes and assignments of orders to vehicles are Derigs et al. (2011); Henke et al. (2015a,b) and Hübner and Ostermeier (2018). However, they do not make any fleet mix decision. Muyldermans and Pang (2010) and Archetti et al. (2016) present studies on the use of either single- or multi-compartment vehicles for fixed compartments. However, they neither specify decision-relevant loading and unloading costs nor do they differentiate the transportation costs for SCVs and MCVs.

To evaluate the choice of vehicles for the routing, it is necessary to take into account different costs dependent on the vehicle types. We therefore analyze these cost differences and derive the costs that are decision relevant for an optimal choice of vehicles. These costs are integrated in a decision model that is solved by applying a suitable solution approach for MCVRP. We base our model on Hübner and Ostermeier (2018) as they provide the most comprehensive formulation of total costs.

4. Model development and solution approach

4.1. MCVRP with vehicle selection

Our vehicle selection problem can be formulated as an extension of the MCVRP that includes vehicle-dependent loading, transportation and unloading costs. We therefore use an MCVRP formulation that allows the possibility to choose between SCVs and MCVs to determine the optimal vehicle mix. The model for MCVRP with Vehicle Selection (MCVRP _VS) thus minimizes total costs by determining the tours, selecting the vehicle for each tour and assigning orders to compartments of vehicles. Table 2 summarizes the notation that will be used for the model development.

The MCVRP _VS can be formulated as follows: Let $G = (L^*, E)$ be an undirected, weighted graph consisting of a vertex set $L^* = \{0, 1, \ldots, n\}$, representing the location of the DC ($\{0\}$) and the locations of n customers ($L = \{1, \ldots, n\}$), and a set of edges $E = \{(i, j) : i, j \in L^*, i < j\}$, representing the connection between different locations. Each edge is associated with a non-negative distance d_{ij} to account for the driving kilometers between customer locations.

Orders are defined by customers, product segments and quantity. The set of orders is denoted by O and the set of product segments by P. In our case, a product segment consists of items (=products) that belong to one temperature zone, and hence items that can be transported jointly within one compartment. Each customer $j = 1, \ldots, n$ may place one or several orders, each referring to a particular product segment. The set N_j, $N_j \subseteq O$ represents all orders of customer j, while the set S_p, $S_p \subseteq O$ represents all orders of product segment p. A positive demand q_o is given for each order $o \in O$. The orders have to be collected from the DC and transported to the customers. A customer may be visited several times (i.e., during different tours) in order to deliver different product segments. A split delivery of an order of one product segment of a single customer is not possible. Each customer, $j \in L$, places at least one order. Further, each product segment available is at least ordered by one customer. This also means that not all customers need to order each segment.

Vehicles are defined by the vehicle type k, the number of compartments m used on the vehicle and a given transportation capacity for each vehicle type (Q_k). The set of vehicle types $K = \{k_1, k_2\}$ includes SCVs (denoted by k_1) and MCVs (denoted by k_2). The set of vehicles per type is denoted by V_k, $k \in K$. It involves a sufficient number for all vehicle types to meet customer demand. Further, the set of available compartments C_k is defined for each vehicle type. If an SCV is used, the number of compartments is limited to one compartment ($|C_{k_1}| = 1$). If an MCV is used, a predefined number of compartments is available for each vehicle, i.e., $|C_{k_2}| = \bar{c}$. Total vehicle capacity for MCVs (Q_{k_2}) can then be divided into a limited number of a maximum of $\bar{c}$ compartments for each vehicle. The number of compartments used per MCV and their size is not predefined. If a compartment $c \in C_{k_2}$ is used, its size can vary between 1 transportation unit and the total vehicle capacity. If it is not used, the compartment size is zero. Different segments cannot be mixed in the same compartment. The loading of a new segment therefore also requires the opening of a new compartment. As loading/unloading processes are a central aspect of the MCVRP _VS, we further introduce loading costs lc_m for a number of compartments m, $m \in C$ and unloading costs ulc_v of vehicle $v, v \in V_k$. The number of compartments determines the number of loading processes at the DC. More specifically, lc_m can be regarded as a cost vector representing loading costs for each vehicle, and their value is determined by the number of active compartments. It is therefore denoted as lc_m, where the costs of each vehicle depend on the number of active compartments with $m = \sum_{c \in C_k} a_{vc}$. The binary auxiliary variable a_{vc} indicates if a compartment c is active on vehicle v ($a_{vc} = 1$). This is required to sum up all active compartments on a vehicle. Additionally, vehicle-type-dependent transportation costs tc_v, $v \in V_k$ and vehicle-type-dependent unloading costs ulc_v, $v \in V_k$, are applied.

We introduce two decision variables with x_{ovc}, indicating whether an order o is assigned to compartment c on vehicle v and b_{ijv}, indicating whether customer j is visited directly after customer i with vehicle v. Please note that the vehicle type k is included in the vehicle set $v \in V_k$.

$$x_{ovc} \begin{cases} = 1, & \text{if order } o \text{ is assigned to compartment } c \text{ on vehicle } v \\ = 0, & \text{otherwise} \end{cases}$$

$$b_{ijv} \begin{cases} = 1, & \text{if vehicle } v \text{ is traveling from customer } i \text{ to } j \\ = 0, & \text{otherwise} \end{cases}$$

Further auxiliary variables are used. There is the binary auxiliary variable a_{vc} (see above) that indicates if a compartment c is active on vehicle v and the integer variable u_{iv} accounts for the position of each customer i on the tour of vehicle v.

$$a_{vc} \begin{cases} = 1, & \text{if compartment } c \text{ is active on vehicle } v \\ = 0, & \text{otherwise} \end{cases}$$

$$u_{iv} = t, \quad t \in \{1, \ldots, |L^*|\} \text{ representing the position } t \text{ of customer } i \text{ on tour/vehicle } v$$

The objective function and constraints are formulated as follows:

$$\min \ \text{Total Costs} = \sum_{k \in K} \sum_{v \in V_k} \left[lc_{\sum_{c \in C_k} a_{vc}} + tc_v \left(\sum_{i \in L^*} \sum_{j \in L^*} d_{ij} \cdot b_{ijv} \right) + ulc_v \left(\sum_{i \in L^*} \sum_{j \in L} b_{ijv} \right) \right] \quad (1)$$

subject to

$$\sum_{j \in L} b_{0jv} \leq 1 \quad v \in V_k, \quad k \in K \quad (2)$$

$$\sum_{i \in L^*} b_{ihv} = \sum_{j \in L^*} b_{hjv} \quad v \in V_k, \quad k \in K, \quad h \in L^* \quad (3)$$

$$u_{iv} - u_{jv} + |L^*| \cdot b_{ijv} \leq |L| \quad v \in V_k, \quad k \in K, \quad i \in L^*, \quad j \in L \quad (4)$$

$$u_{0v} = 1 \quad v \in V_k, \quad k \in K \quad (5)$$

$$\sum_{o \in O} \sum_{c \in C_k} q_o \cdot x_{ovc} \leq Q_k \quad v \in V_k, \quad k \in K \quad (6)$$

$$\sum_{k \in K} \sum_{v \in V_k} \sum_{c \in C_k} x_{ovc} = 1 \quad o \in O \quad (7)$$

$$\sum_{o \in N_j} \sum_{c \in C_k} x_{ovc} \leq |O| \cdot \sum_{i \in L^*} b_{ijv} \quad v \in V_k, \quad k \in K, \quad j \in L \quad (8)$$

$$\sum_{o \in O} x_{ovc} \leq |O| a_{vc} \quad c \in C_k, \quad v \in V_k, \quad k \in K \quad (9)$$

$$\sum_{o \in S_p} x_{ovc} \leq |O| \cdot (1 - x_{rvc}) \quad v \in V_k, \quad k \in K, \quad c \in C_k, \quad p, q \in P : p \neq q, \quad r \in S_p \quad (10)$$

$$a_{vc} \in \{0, 1\} \quad v \in V_k, \quad c \in C \quad (11)$$

$$b_{ijv} \in \{0, 1\} \quad i, j \in L^*, \quad v \in V_k \quad (12)$$

$$u_{iv} \in \{1, \ldots, |L^*|\} \quad i \in L^*, \quad v \in V_k \quad (13)$$

$$x_{ovc} \in \{0, 1\} o \in O, \quad v \in V_k, \quad c \in C_k \quad (14)$$

The objective function (1) of the MCVRP _VS minimizes the total costs across all vehicles used v, $v \in V_k$, $k \in K$. The first term considers total loading costs. Loading costs lc depend on the number of active compartments $\sum_{c \in C_k} a_{vc}$ on each vehicle v. In the second term, the total transportation costs are calculated. The costs are represented by tc_v and depend on the chosen vehicle $v, v \in V_k$ as well as on the distance (d_{ij}) between locations i and j and the customer sequence b_{ijv}. Finally, the third term represents the total costs for unloading at all customers supplied. The total costs for unloading consist of the vehicle-dependent unloading costs ulc_v multiplied by the number of stops on the corresponding tour. The unloading costs differ between vehicle types k. Please note that the objective function presented is non-linear.

Constraints (2) and (3) ensure that every vehicle $v, v \in V_k$ can only depart once from the DC ($i = 0$), and that every vehicle that arrives at a customer location j, $j \in L^*$ also departs from there. Restrictions (4) and (5) are used to eliminate sub-tours by indicating the position of location i on the tour of vehicle v and setting the DC as the start and end point of each tour. This is imposed by the fact that the position of location j is higher than that of i if the vehicle v travels from i to j. Constraints (6) ensure that the orders loaded into all compartments of vehicle v do not exceed the vehicle capacity Q_k of each type k. Each order o can only be assigned to one compartment c on a vehicle v and therefore Eqs. (7) are needed. Constraints (8) ensure that customer j has to be visited if an order o of customer j is loaded on vehicle v. Constraints (9) ensure that compartment c on vehicle v is set to active if an order o is assigned to it. The incompatibility restrictions (10) ensure that incompatible orders from different segments p and q, p, $q \in P, p \neq q$, are not assigned to the same compartment. This is done by ensuring that an order o from the set of orders S_p, which comprises all orders of product segment p, is not combined in one compartment with an order r from the set O_q, which comprises all orders of product segment q. Lastly, the domains of the decision variables are given by (11)–(14).

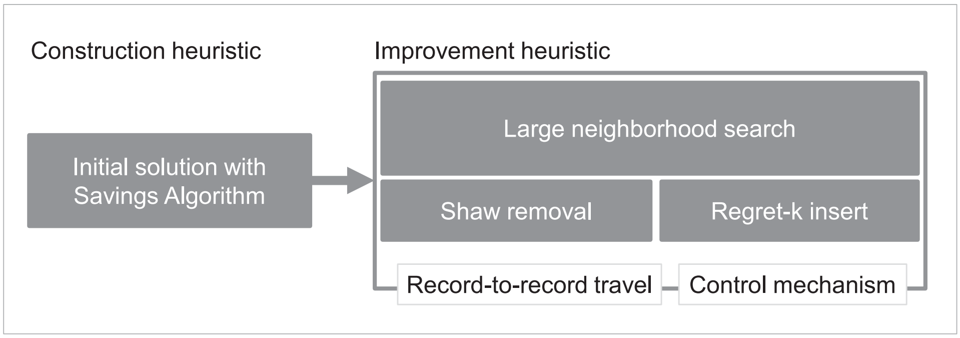

Fig. 4. Overview of solution approach.

4.2. Solution approach

The MCVRP presented for the selection of vehicles is an NP-hard problem and therefore only small problems can be solved exactly. Heuristic approaches are needed for problem sizes relevant in practice. We choose an LNS for our solution approach. Various LNS formulations have been successfully developed for VRP and MCVRP (see Derigs et al. (2011) and Hübner and Ostermeier (2018)). Based on the framework of Hübner and Ostermeier (2018), we develop an LNS for the vehicle selection. The outline and operators of the heuristic approach are presented in Fig. 4.

Initial solution. The parallel savings algorithm by Clarke and Wright (1964) is used as a construction heuristic to create an initial solution. It is also a widely applied construction heuristic for MCVRP (e.g., Derigs et al. (2011); Muyldermans and Pang (2010)) and is able to produce a fast, feasible solution.

Large neighborhood search. An LNS is used as improvement heuristic. LNS have been successfully used by Derigs et al. (2011) and Hübner and Ostermeier (2018) for MCVRP. We base our approach on these works. The LNS is constituted by (1) a removal operator, (2) an insertion operator and (3) the guidance of the search procedure. These will be detailed in the following.

(1) Remove operator. For the removal of orders we chose Shaw removal presented by Shaw (1997) as it enables the consideration of similarities between orders and therefore a directed search. This means that we can highlight different characteristics between orders as the affiliation of orders to the same or different customers and/or segments. This is essential for the search as these differences have a high impact on routing costs.

Shaw removal is based on the concept of similarity and therefore a problem-specific distance measure (R_{os}) is defined. It evaluates the difference between any two orders o and s (either from the same customer or different customers) using $o, s \in O$. Additionally, a randomization step is integrated into the approach to achieve higher diversification for the search. For the description of the procedure we divide the set of all orders O into removed orders (O^-) and assigned orders (O^+), such that $O^+, O^- \subseteq O$, $O^+ \cup O^- = O$ and $O^+ \cap O^- = \emptyset$. The distance measure R_{os} is given in Eq. (15).

$$R_{os} := \phi \cdot \frac{cost_{os}}{cost_{max}} + \omega \cdot prod_{os} + \psi \cdot \frac{|q_o - q_s|}{q_{max}} \quad (15)$$

R_{os} considers the three main characteristics for orders: *distance cost*, *product segment* and *order size*. First, *distance cost* indicates the distance between the customers whose orders o and s are being considered. If customers are located close to each other (or if the orders belong to the same customer), the similarity between orders is rated higher as the distance between customers has a high impact on transportation but also on unloading costs if orders are from the same customer. Second, the *product segment* indicates whether the orders belong to the same product segment and can therefore be assigned to the same compartment. It is defined as $prod_{os} = 1$ if segment of order o is different from segment of order s, 0 otherwise. The *product segment* is most influential for loading costs as the combination of different segments requires multiple compartments on a truck and therefore the use of an MCV. Finally, the *order size* represents the fact that swapping orders of the same size tends to provide feasible solutions more quickly. The highest order quantity across all orders is represented by q_{max}. Weights ϕ, ω, and ψ are applied to represent the importance of each of the three components. In this way, a higher value of R_{os} corresponds to a higher difference between order characteristics and therefore less similarity.

The overall removal procedure operates in the following way. A set number of r orders has to be removed from the incumbent solution. The first order o to be removed is chosen randomly from all orders O. Please note that for the start of the removal process the set O^+ is equal to O. After the initial step, the removal is based on similarity to one of the orders already removed. Orders in O^+ are ranked according to the defined similarity to the randomly chosen order $o \in O^-$ in descending order, i.e., the most similar order at the top and the least similar order at the bottom. The selection of the next order for removal is then based on the similarity plus a random number $z \in [0, 1)$ and a parameter α. For the selection of a new order, it is not the order with the highest similarity that is chosen but one that can be found z^α percent down the similarity ranking. If the resulting position is not integer, the result is rounded to the next integer value. The randomization is applied for diversification of the search: the higher the α, the more diversified the search.

(2) Insertion operator. The insertion operator for our LNS is based on the regret-k insertion by Ropke and Pisinger (2006). Following our notation, orders removed ($o \in O^-$) are reinserted with a regret-k operator to the set O^+.

We modified the regret insertion of Ropke and Pisinger (2006) to evaluate all vehicle-dependent costs if an order is assigned to a tour. This involves the influence on loading and unloading costs as well as transportation costs if an order is assigned to either an SCV or MCV. The insertion uses a regret value $regret_k$ for theoretical reinsertion for each removed order $o \in O^-$. For this, Eq. (16), with $k \geq 2$ is used to calculate the potential costs of reinsertion. It is the sum of differences between the best option (represented by the lowest total tour costs $totalcost_{v_1}$) and k-best options (represented by $totalcost_{v_u}$). Here, $totalcost_{v_u}$ are the total tour costs of the uth best tour v if order s is inserted there and $totalcost_{v_u} \leq totalcost_{v_t}$, $\forall u < t$.

$$regret_k := \sum_{u=2}^{k} (totalcost_{v_u} - totalcost_{v_1}) \quad (16)$$

The order that shows the highest regret value according to the calculated $regret_k$ is chosen for reinsertions. As the regret insertion not only considers the insertion of an order in the actual solution but also a possible later insertion, it offers a cost evaluation with greater foresight. The calculation of the regret value has to be repeated after each insertion as the options and costs for reinsertion may have changed. This process is iterated until all orders are reinserted (i.e., $O^- = \emptyset$).

(3) Guiding the search procedure.

Record-to-record travel. To govern the process of finding a solution improvement using the LNS, the record-to-record travel (RRT) meta-heuristic is used. It was shown that the RRT delivers good solutions for MCVRP (Derigs et al., 2011). The RRT is defined according to Dueck (1993) and controls the improvement steps by setting a limit for the acceptance of declining solution values. This means that a solution is only accepted if it lies within a defined deviation D from the best result found so far. Even though the RRT approach is quite simple, it does not seem to be inferior to other methods used (Derigs et al., 2011).

Runtime limits and diversification. The search terminates if a given number of iterations without solution improvement is reached. Further, we use a large destroy step to avoid local minima. It is called every time a given number of iterations without improvement is reached. In this step, the value for the orders to remove (r) is set to a large number (e.g., half of the order list). In this way, big parts of the incumbent solution are destroyed and the search diversified.

Summary. The complete structure of our LNS is displayed in Algorithm 1.

Algorithm 1 Large Neighborhood Search for MCVRP _VS.

Input: (Initialize Solution S, set remove parameter r, set regret parameter k)
  $S_{best} := S$
  Shaw removal $SR(r)$
  Regret insertion $RI(k)$
  ResetCounter $m := 1$
  Set allowed deviation D according record-to-record travel $RRT()$
  while improving = **true do**
    $S' := S$
    Remove r orders from S' using $SR(r)$
    Reinsert orders removed into S' using $RI(k)$
    if $ObjectFunction(S') < ObjectFunction(S_{best})$ **then**
      $S_{best} = S'$
      $S = S'$
      Reset number of unsuccessful runs to zero and m to 1
    else if $ObjectFunction(S') \leq ObjectFunction(S_{best})$ plus accepted deviation D **then**
      $S := S'$
      Increase number of unsuccessful runs
    else
      Increase number of unsuccessful runs
      Continue with original solution S
    end if
    if Number of unsuccessful runs = limit **then**
      Set improvement **false**
    else if Number of unsuccessful runs = reset limit multiplied by m **then**
      Remove high number of orders from S using $SR(r)$
      Reinsert orders removed into S using $RI(k)$
      m = m+1
    end if
  end while
  return S_{best}

5. Numerical experiments

In this section, we present numerical analyses for vehicle selection within an MCVRP for different data settings. First we apply tests with real-life data from a case study with a major German retailer in Section 5.1. We will generalize these findings in further tests. We use randomly generated data that are informed by the joint project with the retailer. The main experiments for the impact of vehicle selection are presented in Section 5.2. We consider two different settings, one for urban areas with shorter distances and one for larger distances corresponding to rural areas. Following these results, we complete further experiments for different order structures and settings that take into account the particularities of SCVs and a mixed fleet in Section 5.3.

Runtime parameters. The computational results were obtained on a 1.8 gigahertz PC with 8 gigabytes memory running on Windows 10. The implementation of the LNS algorithm has been realized in Java. The heuristic-specific parameters are set as follows. For the Shaw removal, the weights for the calculation of the similarity measure R_{os} were set to $\phi = \omega = 0.4$ and $\psi = 0.2$ and $\alpha = 4$. This choice of weights is based on the higher influence of distance costs and product segments compared to order size. Using this setting we obtained good results in various pretests. The number of items removed r is chosen randomly using uniform distribution. This results in a variation of between 5 and 30 orders removed for the studies with simulated data and tests with 100 customers. The regret parameter has been set at $k = 2$. Furthermore, the termination limit is 2000 and the limit for a solution reset is 500 for all LNS applications. The maximum deviation D allowed for the RRT equals 0.4% for all tests. We further refer to Hübner and Ostermeier (2018) and Derigs et al. (2011), who have shown that the defined parameter settings perform efficiently for related MCVRPs.

5.1. Case study

The first analysis is based on a joint case study with a retailer. We used empirical data collection to obtain cost parameters, order structures and customer data.

Cost parameters. A central aspect of the MCVRP_VS are the differing cost factors for SCVs and MCVs. As described in Section 2, costs depend on the vehicle type and in the case of MCVs also on the number of compartments used. The exact parameters are subject to non-disclosure agreements with the retailer. We therefore report the relative cost parameters in relation to the transportation costs tc_{k_1} of SCVs. This means that the transportation costs for SCVs are set to $tc_{k_1} = 1.00$ currency units.

Cost parameters for the loading and unloading costs for the different vehicle types were obtained by a time and motion study. These values originate from the process analysis at the retailer's sites. Representative tours have been accompanied and the times for the different processes have been measured. We refer to our description in Section 2 for the processes and additional handling involved. All measurements of our case study for loading and unloading costs have been translated into monetary terms by evaluating the times obtained with the corresponding personnel costs. *Loading costs* are fixed at 2.55 currency units per loading process for SCVs ($lc_{k_1} = 2.55$ currency units). Loading costs of MCVs (lc_{k_2}) additionally depend on the number of compartments used m and therefore on the number of loading steps needed. The costs identified are displayed in Table 3.

Table 3
Loading costs lc_{k_2} of MCVs per compartment, *normalized to* tc_{k_1}.

Number of Compartments	1	2	3	4
Loading costs in currency units	2.62	5.25	7.80	10.35

Table 4
Results of the case study.

	Delivery day	Scenario: tc_{k_2}(low) Delta in total costs SCV vs. MF (%)	MCV vs. MF (%)	Fleet mix (SCV (%) / MCV (%))	Scenario: tc_{k_2}(high) Delta in total costs SCV vs. MF (%)	MCV vs. MF (%)	Fleet mix (SCV (%) / MCV (%))
Case study	1	5.5	0.1	30 / 70	4.9	0.4	35 / 65
	2	13.2	0.0	18 / 82	12.8	0.4	29 / 71
	3	7.2	0.0	18 / 82	6.5	0.5	34 / 66
	4	4.2	0.0	23 / 77	3.7	1.6	39 / 61
	5	3.4	0.3	32 / 68	3.0	0.6	42 / 58
	6	4.6	0.5	36 / 64	3.9	1.9	60 / 40

Unloading costs are set to $ulc_{k_1} = 2.26$ currency units for SCVs and $ulc_{k_2} = 2.33$ currency units for MCVs. Please note that these values may be retailer- and DC-specific and may only serve as a guideline for the cost parameters in a general setting. For other DCs these may vary significantly, e.g., if the temperature-specific warehouses are not at the same location and there is a longer travel time between gates.

We took a total costs approach for the calculation of the *transportation costs* of each vehicle type as denoted in Section 2. Both vehicle types have a certain mileage during the life time of the truck, based on the past experience of the retailer. This given total mileage allows the conversion of fixed costs for procurement, maintenance and insurance into costs per distance units. Further variable costs that depend on the distance and travel time are fuel and personnel costs for the driver. These can be translated into costs per distance unit as well. For further details we refer to Section 2. Higher procurement costs for MCVs are thus translated into higher transportation costs tc. We consider two different cost scenarios for the transportation costs of MCVs (tc_{k_2}). In the low cost case, MCVs are only 0.9% more expensive than SCVs (at tc_{k_2}(low)=1.009 currency units) and in the high-cost case, MCVs are 4.7% higher (at tc_{k_2}(high)=1.047 currency units). We apply these two scenarios, as the retailer has two different offers and contracts with truck suppliers. The actual costs are highly dependent on the bargaining position of individual retailers.

Order and customer data. The data set covers orders from a specific DC for a complete delivery week. This comprises six different delivery days and therefore six instances. Altogether, this involves 406 customers with orders for four different product segments and a volume of over 4500 orders. The number of orders per day reaches a maximum of over 900 orders from almost all customers. The capacity of all vehicles is identical, at 33 transportation units. The average order size across all product segments and weekdays amounts to around 6 transportation units. Furthermore, the maximum distance between two locations amounts to 346 kilometers.

Results of case study. We analyze three different fleet options. First we consider solutions where only SCVs are available (with $V_{k_2} = \{\}$, denoted as "SCV"). In the second scenario only MCVs (with $V_{k_1} = \{\}$, denoted as "MCV") are used. The third option operates with a mixed fleet making use of vehicle selection (denoted as "MF"). The last one allows the selection of SCVs and MCVs. This highlights the advantages of introducing vehicle selection for the problem, and presents potential savings for retailers. We solve the corresponding routing problem with the heuristic approach presented in Section 4.2 with respect to the formulated mathematical model in Section 4.1.

Table 4 summarizes the results for the scenario with low transportation costs on the left and high transportation costs on the right. For the scenario with lower transportation costs (tc_{k_2}(low)), the impact of using a mixed fleet reveals a maximum of 0.5% in cost reduction. However, the impact for three delivery days is very small. The reason for this is the higher share of MCVs used for distribution, at up to 82%. If higher transportation costs are considered (tc_{k_2}(high)), the cost reduction achieved reaches a maximum of around 2% for day 6 and 1.6% for day 4. The average order size on these days is around 7 transportation units, which is above the weekly average. Additionally, the share of SCVs is higher for the tc_{k_2}(high)-scenarios. Day 6 has an especially high SCV usage of around 60%. The average computational time needed across the six days of the week amounts to 4.2 minutes for the tc_{k_2}(low)-scenario and 6.4 minutes for the tc_{k_2}(high)-scenario.

Table 5
Range of order quantity per segment (in transportation units).

Segment	1	2	3	4
Minimum quantity	1	1	5	10
Maximum quantity	5	10	20	25

5.2. Generalization of the findings of the MCVRP with vehicle selection

In this section, we will generalize our findings. The numerical experiments are based on randomly generated data that allows us to draw managerial insights from different settings. We will apply two basic scenarios for a setting with urban customers and with rural structures. We analyze the vehicle selection within the MCVRP and the influence on total costs. We consider ten different instances for all tests, and apply the LNS ten times to each problem. We will detail the data generation process before the analysis itself.

5.2.1. Data generation and parameter setting.

Order data. We assume that four segments are available for each customer. For the order pattern, we distinguish between one and four orders per customer. If customers order only one segment, they randomly choose one among the available four segments. If they order four segments, each available segment is ordered once. The available order sizes are based on our insights from the case study. In grocery distribution, the order sizes between segments are heterogeneous. Therefore we assume different ranges for the order sizes of different segments. The sizes follow uniform distribution between the set minimum and maximum order sizes. Details are given in Table 5. By way of example, segment 4 could resemble ambient products and segment 1 deep-frozen. The share of sales for ambient products is substantially higher than sales for deep-frozen goods, and the corresponding order volumes differ accordingly.

Distance data. The distances between customers are split into two scenarios: an urban and a rural delivery area. For the urban area distances are chosen randomly between 20 and 65 kilometers. We assume distances of between 40 and 200 kilometers for rural deliveries, and the corresponding routing costs. Please note, that the distances are chosen randomly, however the triangular inequality is taken into account during the generating of distances.

Table 6
Test overview for rural and urban deliveries (Ø values).

Test	Transportation	Delta in total costs		Fleet mix
scenario	costs[a]	SCV vs. MF (%)	MCV vs. MF (%)	(SCV (%) / MCV (%))
Urban	tc_{k_2}(low)	20.87	0.14	9 / 91
	tc_{k_2}(high)	18.46	0.32	15 / 85
Rural	tc_{k_2}(low)	22.40	0.13	8 / 92
	tc_{k_2}(high)	19.85	0.43	13 / 87

[a] Different costs for MCVs.

5.2.2. Results of basic experiments. First, instances for urban deliveries are considered. Second, we analyze rural deliveries. In both settings we apply the two cost scenarios for the MCV transportation costs introduced in the previous subsection (tc_{k_2}(low) and tc_{k_2}(high)). As before, we compare the three different fleet options with SCVs only (SCV), MCVs only (MCV) or with a mixed fleet (MF). We assume a vehicle capacity of 33 transportation units for all our tests, as in the case study.

Urban deliveries. Table 6 summarizes the findings for both transportation cost scenarios for urban delivery areas. We have significant savings potential if a mixed fleet is possible compared to the use of SCVs only (see SCV vs. MF). The cost savings potential is around 20%. The second comparison regarding the use of MCVs only or a mixed fleet yields different results (see MCV vs. MF). In this case, with a solution improvement of 0.14% for tc_{k_2}(low) and 0.32% for tc_{k_2}(high), the difference between a fleet with only MCVs or a mixed fleet is small. This can be attributed to the high share of MCVs with up to 92% used for distribution even if SCVs are available. Only a few SCVs are used if the fleet can be chosen freely, and therefore transportation costs only have a minor influence.

Rural deliveries. Similar results compared to those of urban areas can be observed for rural areas. Comparing MF to an SCV fleet, the improvement for both cost scenarios lies at around 20%, with up to 22.40% in the first transportation cost scenario. The same holds true for the comparison between MF and an MCV fleet. No significant difference in costs was revealed in the case of low transportation costs. If higher transportation costs are considered, a mixed fleet yields an average solution improvement of 0.43%.

5.3. Further experiments with varying order and customer data

Further tests for different data structures were analyzed in addition to the base tests in the previous section. First, the influence of order sizes on the fleet mix is examined. Second, we apply changes to the order structure so that each customer only orders one of the available segments. We focus on rural transportation for the tests, i.e., long distances between customers, as this was also the focus of the case study.

5.3.1. Order sizes. For the base test the order sizes were chosen randomly between different order sizes. To further analyze the impact of order sizes, we chose to consider two alternative scenarios. For this, small order sizes ranging from 1 to 10 transportation units for all segments are considered in the first scenario. In the second scenario larger order sizes ranging from 3 to 33 transportation units are chosen, with a slight variation per segment. In detail, we assume order sizes from 3 to 20 transportation units for the first segment, 5 to 25 transportation units for segment 2 and 3 and 10 to 33 transportation units for the last segment. Based on the results of our tests in Section 5.2, we only apply the higher transportation costs of MCVs (tc_{k_2}(high)).

Small order sizes. The use of SCVs is costlier for smaller order sizes. As orders are smaller it is more likely that the combination of different segments is beneficial on the same tour. Using MCVs would therefore be preferable for most tours, and in fact in our tests for small orders MCVs were used exclusively. As a consequence, the improvement in the solution value lies above 30% if a mixed fleet is used. As only MCVs are used, there is no difference in costs between a mixed and an MCV fleet. The results are summarized in Table 7.

Large order sizes. In contrast to small order sizes, larger orders have a positive impact on the use of SCVs. As displayed in Table 7, the potential cost reduction goes down to an average of 4.81% compared to a cost reduction of 30.69% in the case of small orders. Larger orders allow fewer combinations of different segments on the same tour and therefore the use of MCVs becomes less beneficial. Best results can be achieved again if a mixed fleet is applied. The improvement compared to using only MCVs amounts to an average of 1.75%. Table 8 details our results with large orders, indicating the best solution found for each instance.

5.3.2. Number of segments ordered. The next tests with randomly generated data comprise the analysis of instances where only one segment is ordered out of four available ones. For each customer, the segment ordered is assigned randomly following uniform distribution. As in the previous tests, we apply tc_{k_2}(high) due to the impact on vehicle selection. We analyze the influence of segments ordered per customer for random order sizes as in the base test (see Section 5.2), as well as for large and small order sizes as in the previous tests. The results are presented in Table 9, giving the average cost delta and fleet mix for each scenario.

The tests show that the number of segments ordered per customer has little influence on the cost savings if a mixed fleet is used as the main driver for potential savings is again the order size. If only one segment per customer is ordered, the effects for larger orders are slightly increased as the number of SCVs increases (51% SCVs for large orders and one segment ordered). This is due to the fact that if each customer orders only one segment there is no possible cost saving from combining different segments for the same customer on one tour. Therefore it is more likely that tours dedicated to one segment are created, combining only customers with the shortest distances but not mixing different segments. As a consequence, the average cost reduction for the comparison of MCV and MF is 1.80% for large orders and 0.55% for random order sizes. No significant cost reduction can be achieved for small orders as 97% of vehicles are MCVs. Further, it is noticeable that the potential saving for the comparison of SCV and MF in the case of small orders is significantly lower than for tests with four ordered segments. This can be attributed to the fact that the benefits of combining different segments on one truck is less beneficial if the orders are from different customers. MCVs are most profitable if orders from the same customer can

Table 7
Test overview for small and large order sizes (Ø values).

Test	Transportation	Delta in total cost		Fleet mix
scenario	costs[a]	SCV vs. MF (%)	MCV vs. MF (%)	(SCV (%) / MCV (%))
Small orders	tc_{k_2}(high)	30.69	0.00	0 / 100
Large orders	tc_{k_2}(high)	4.81	1.75	48 / 52

[a] Considering higher transportation costs: tc_{k_2}(high).

Table 8
Test details for rural deliveries for larger orders and tc_{k_2}(high).

Test scenario	Instance	Delta in total costs		Fleet mix	Ø runtime
		SCV vs. MF (%)	MCV vs. MF (%)	(SCV (%) / MCV (%))	in seconds (MF)
Large orders	1	4.19	1.36	48 / 52	38
	2	4.91	1.72	49 / 51	37
	3	4.53	1.42	49 / 51	39
	4	5.65	1.81	47 / 53	44
	5	5.31	1.75	48 / 52	41
	6	5.19	1.70	52 / 48	37
	7	4.50	1.91	46 / 54	54
	8	6.28	1.73	40 / 60	40
	9	4.49	1.86	50 / 50	44
	10	4.45	1.77	48 / 52	37
	Ø	4.81	1.75	48 / 52	41

Table 9
Test overview for one ordered segment (Ø values, tc_{k_2}(high)).

Test scenario	Order size	Delta in total cost		Fleet mix
		SCV vs. MF (%)	MCV vs. MF (%)	(SCV (%) / MCV (%))
1 out of 4 segments ordered	Small	6.45	0.03	3 / 97
	Random	9.66	0.55	23 / 77
	Large	4.59	1.80	51 / 49

Table 10
Test details for tests with one ordered segment and large order sizes (tc_{k_2}(high)).

Test scenario	Instance	Delta in total costs		Fleet mix	Ø runtime
		SCV vs. MF (%)	MCV vs. MF (%)	(SCV (%) / MCV (%))	in seconds (MF)
1 out of 4 segments ordered (Large orders)	1	5.17	1.94	55 / 45	8
	2	6.51	1.64	52 / 48	10
	3	5.22	2.18	61 / 39	7
	4	3.77	1.73	52 / 48	8
	5	3.08	1.90	58 / 42	11
	6	5.06	1.96	52 / 48	8
	7	3.56	1.87	54 / 46	11
	8	5.30	1.80	39 / 61	11
	9	7.10	1.69	45 / 55	8
	10	4.41	1.44	40 / 60	8
	Ø	4.59	1.80	51 / 49	9

be combined. For a more detailed overview of the test results with larger orders, we provide details per instance in Table 10, using the best solution for each instance.

5.3.3. Special case: Analysis with larger order sizes, rural areas and high loading/unloading costs. This final analysis investigates the effects if the factors that are beneficial for an SCV fleet are combined. As shown above, it is advantageous to use more SCVs if there are larger order sizes, longer transportation distances and higher loading costs. This scenario constitutes an upper bound of possible cost savings by fleet mix optimization. This scenario is typical for rural regions. There are usually larger stores that require larger order volumes. This is further intensified due to longer travel distances that require the bundling of orders to obtain lower delivery frequencies. Moreover, loading and unloading costs are assumed to be 50% above the costs indicated in Table 3. Loading costs increase particularly if the temperature-specific DCs are not co-located and the vehicle needs to pick up the orders at different locations (e.g., in different cities). Unloading costs increase if processes at the stores are not lean (e.g., no ramps, complicated parking).

The detailed results are summarized in Table 11. The extreme scenario shows that under the given circumstances the gap between an SCV and MCV fleet decreases significantly. Looking at the averages over all instances, MF improves the SCV solution by 2.63% and the MCV solution by 2.01%. The SCV solution proved even better than the MCV solution for three instances (instances 1, 2 and 6). However, we show that a mixed fleet provides the lowest cost solutions in all cases.

5.4. Summary

Our tests analyzed different scenarios to map various requirements from practice and to consider different influences on the use of SCVs and MCVs. To do this we considered rural and urban delivery areas with varying order sizes and order structures. The numerical experiments showed that a mixed fleet is always the best option. Furthermore, an exclusive MCV fleet yields better results than an exclusive SCV fleet. More precisely, costs can be reduced by up to 30% with a mixed fleet compared to a fleet composed exclusively of SCVs, and by up to 2% compared to a fleet made up exclusively of MCVs. Mixing the fleet is particularly beneficial in cases with longer transport distances and higher order volumes. In these cases SCVs become more beneficial and therefore the share of SCVs impact the savings potential from a mixed fleet compared to a fleet made up exclusively of MCVs. If solutions have a higher share of SCVs, a mixed fleet becomes more beneficial as transportation and loading costs can be reduced compared to an MCV fleet.

The case study and further experiments above allow us to deduce the following managerial insights for the use of SCVs and MCVs in grocery distribution.

- *Mixed fleet superior to SCV/MCV fleet.* In all our tests, the use of a mixed fleet is significantly better than an SCV fleet. The

Table 11
Test details for extreme scenario (tc_{k_2}(high)).

Test scenario	Instance	Delta in total cost SCV vs. MF (%)	Delta in total cost MCV vs. MF (%)	Fleet mix (SCV (%) / MCV (%))	Ø runtime in seconds (MF)
Special case	1	2.49	2.57	61 / 39	9
	2	1.75	1.77	63 / 37	9
	3	2.44	1.65	55 / 45	7
	4	4.80	2.01	37 / 63	7
	5	3.59	1.61	49 / 51	8
	6	2.04	2.43	67 / 33	8
	7	2.87	2.23	55 / 45	9
	8	3.35	1.66	43 / 57	6
	9	3.40	1.41	53 / 47	7
	10	2.86	2.31	65 / 35	7
	Ø	2.63	2.01	55 / 45	8

same holds true for the use of an MCV fleet, even if the potential savings are more moderate. The higher the share of SCVs in the optimal fleet, the higher the potential savings of a mixed model.

- *Mixed fleet required for larger order sizes and rural areas.* The possibility of selecting vehicles provides a significant improvement especially for rural areas with larger stores and therefore a higher order volume. The cost reduction of a mixed fleet compared to an MCV fleet increases as more SCVs are used in these scenarios. The effect is intensified if the order structure of customers is more heterogeneous.
- *Mixed fleet required for order structure with fewer orders per customer.* A mixed fleet provides the best results in order structures where each customer does not order the same segments. Where each customer orders only one segment, it becomes harder to combine several segments on the same truck and deliveries with SCVs become more beneficial. A mixed fleet to cover both multi-segment and single-segment deliveries is therefore required to achieve a cost-optimal solution.
- *A heterogeneous fleet is required in most applications.* The main implication of our tests is that a mixed fleet is needed in all applications. It provides a cost-optimal solution as it combines the advantages of both SCVs and MCVs.

Overall, the use of a mixed fleet is advisable for retailers in grocery distribution. Vehicle selection should therefore be part of the routing problem to achieve a cost-optimal solution with an efficient distribution fleet.

6. Conclusion

This paper introduced vehicle selection for an MCVRP with flexible compartments. The objective of our research was to show the benefits of considering both SCVs and MCVs for distribution fleets. We therefore presented an extended MCVRP to account for the different vehicle types and the corresponding costs incurred by their use. We identified the relevant costs and evaluated them within a case study. The resulting problem was solved with an LNS that has shown good results for different MCVRP variants. We analyze the impact of including vehicle selection within the MCVRP in various numerical experiments. It was shown that a mixed delivery fleet yields significant savings potential compared to a fleet with only SCVs or MCVs. We first analyzed vehicle selection for a case study with a major German retailer. In this case, it was possible to confirm the advantages of selecting SCVs and MCVs for distribution in a practical application. This is expressed in possible savings of up to 2% for one delivery day. Second, we applied tests with randomly generated data to analyze the advantages of vehicle selection for different scenarios. This comprised tests for urban and rural areas, variations in order sizes as well as scenarios with varying order structures. We showed that a mixed fleet of SCVs and MCVs is superior to a fleet with only one vehicle type in each of the experiments. For instance, the potential savings of a mixed fleet amount to a maximum of 30% compared to a fleet composed exclusively of SCVs if small order sizes are considered. Summing up, we were able to show the benefits of considering a mixed fleet of SCVs and MCVs for distribution. The extended model including the vehicle-specific cost factors yields significant savings potential for retailers.

Our work on MCVRP for the consideration of a mixed fleet represents a contribution to the still young field of research on MCVRP with flexible compartments. There are numerous aspects of MCVRP that have not yet been considered in literature. This study considered a mixed fleet. A possible next step could be to extend the problem to a heterogeneous fleet with differing vehicle capacities. Further, as MCVs have to approach several loading gates, this might lead to an increased traffic situation at the DC and higher waiting times. As a consequence, the balancing of departures could be a worthy extension of the presented MCVRP. Most publications, especially when considering flexible compartments, focus on single period problems. There is a lack of literature on MCVRP for multiple periods. Extensions with stochastic and varying demand also constitute a valuable path (see e.g., Mendoza et al. (2010, 2011)). As MCVs can combine different customer orders on the same vehicle, new possibilities for order and delivery frequency are given. The impact of combined orders on inventory and delivery patterns should therefore be examined (see e.g., Holzapfel, Hübner, Kuhn, & Sternbeck, 2016). Additionally, a change in the delivery frequency and/or order sizes impacts operations at the stores. Further applications could address the MCVRP for home deliveries of online orders and store orders (see e.g., Hübner, Holzapfel, & Kuhn, 2016a; Hübner, Wollenburg, & Holzapfel, 2016b). This should be integrated in the decision model.

Several extensions are possible as for classical VRP formulations. This includes the consideration of time-windows, stochastic demands or backhauls. Finally, existing solution approaches can always be improved. Alternative heuristic solution approaches and exact approaches (such as Henke et al. (2015a)) to compare and address different MCVRP variations need to be considered.

References

Archetti, C., Campbell, A. M., & Speranza, M. G. (2016). Multicommodity vs. single–commodity routing. *Transportation Science, 50*(2), 461–472.

Avella, P., Boccia, M., & Sforza, A. (2004). Solving a fuel delivery problem by heuristic and exact approaches. *European Journal of Operational Research, 152*(1), 170–179.

Baldacci, R., Battarra, M., & Vigo, D. (2008). Routing a heterogeneous fleet of vehicles. In B. Golden, S. Raghavan, & E. Wasil (Eds.), *The vehicle routing problem: Latest advances and new challenges* (pp. 3–27). US: Springer.

Brown, G. G., & Graves, G. W. (1981). Real-time dispatch of petroleum tank trucks. *Management Science, 27*(1), 19–32.

Caramia, M., & Guerriero, F. (2010). A milk collection problem with incompatibility constraints. *Interfaces, 40*(2), 130–143.
Chajakis, E. D., & Guignard, M. (2003). Scheduling deliveries in vehicles with multiple compartments. *Journal of Global Optimization, 26*(1), 43–78.
Clarke, G., & Wright, J. W. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research, 12*(4), 568–581.
Coelho, L. C., & Laporte, G. (2015). Classification, models and exact algorithms for multi-compartment delivery problems. *European Journal of Operational Research, 242*(3), 854–864.
Cornillier, F., Boctor, F. F., Laporte, G., & Renaud, J. (2008). A heuristic for the multi-period petrol station replenishment problem. *European Journal of Operational Research, 191*(2), 295–305.
Derigs, U., Gottlieb, J., Kalkoff, J., Piesche, M., Rothlauf, F., & Vogel, U. (2011). Vehicle routing with compartments: Applications, modelling and heuristics. *OR Spectrum, 33*, 885–914.
Dueck, G. (1993). New optimization heuristics. *Journal of Computational Physics, 104*(1), 86–92.
El Fallahi, A., Prins, C., & Wolfler Calvo, R. (2008). A memetic algorithm and a tabu search for the multi-compartment vehicle routing problem. *Computers & Operations Research, 35*(5), 1725–1741.
Fernie, J., & Sparks, L. (Eds.), (2009). *Logistics & retail management: Emerging issues and new challenges in the retail supply chain*. (3rd Ed.). London and Philadelphia: Kogan Page Ltd.
Glatzel, C., Großpietsch, J., & Hübner, A. (2012). Higher margins through efficient supply chains. *Akzente, 2*, 16–21.
Golden, B., Assad, A., Levy, L., & Gheysens, F. (1984). The fleet size and mix vehicle routing problem. *Computers & Operations Research, 11*(1), 49–66.
Golden, B. L., Raghavan, S., & Wasil, E. A. (2008). The vehicle routing problem: latest advances and new challenges. *Operations Research/Computer Science Interfaces Series*. Springer.
Goodson, J. C. (2015). A priori policy evaluation and cyclic-order-based simulated annealing for the multi-compartment vehicle routing problem with stochastic demands. *European Journal of Operational Research, 241*(2), 361–369.
Henke, T., Speranza, M. G., & Wäscher, G. (2015a). A branch-and-cut algorithm for the multi-compartment vehicle routing problem with flexible compartment sizes. *Working paper no. 04/2017*. Magdeburg: Otto-von-Guericke-University.
Henke, T., Speranza, M. G., & Wäscher, G. (2015b). The multi-compartment vehicle routing problem with flexible compartment sizes. *European Journal of Operational Research, 246*(3), 730–743.
Holzapfel, A., Hübner, A., Kuhn, H., & Sternbeck, M. (2016). Delivery pattern and transportation planning in grocery retailing. *European Journal of Operational Research, 252*, 54–68.
Hübner, A., Holzapfel, A., & Kuhn, H. (2016a). Distribution systems in omni-channel retailing. *Business Research, 9*(2), 255–296.
Hübner, A., & Ostermeier, M. (2017). Compartmentalized trucks cut the cost of grocery distribution. *Supply Chain Management Review August 2017*.
Hübner, A., & Ostermeier, M. (2018). A multi-compartment vehicle routing problem with loading and unloading costs. *Transportation Science*. Forthcoming doi: 10.1016/j.cor.2016.12.023
Hübner, A., Wollenburg, J., & Holzapfel, A. (2016b). Retail logistics in the transition from multi-channel to omni-channel. *International Journal of Physical Distribution & Logistics Management, 46*(6/7), 562–583.
Hübner, A. H., Kuhn, H., & Sternbeck, M. G. (2013). Demand and supply chain planning in grocery retail: An operations planning framework. *International Journal of Retail & Distribution Management, 41*(7), 512–530.
Klingler, R., Hübner, A., & Kempcke, T. (2016). *End-to-end supply chain management in grocery retailing*. European Retail Institute.
Koch, H., Henke, T., & Wäscher, G. (2016). A genetic algorithm for the multi-compartment vehicle routing problem with flexible compartment sizes. *Working paper no. 04/2016*. Magdeburg: Otto-von-Guericke-University.
Kuhn, H., & Sternbeck, M. G. (2013). Integrative retail logistics: An exploratory study. *Operations Management Research, 6*(1–2), 2–18.
Lahyani, R., Coelho, L. C., Khemakhem, M., Laporte, G., & Semet, F. (2015). A multi-compartment vehicle routing problem arising in the collection of olive oil in Tunisia. *Omega, 51*, 1–10.
Laporte, G., & Semet, F. (2001). Classical heuristics for the capacitated VRP. In P. Toth, & D. Vigo (Eds.), *The vehicle routing problem* (pp. 109–128). Society for Industrial and Applied Mathematics.
Mendoza, J. E., Castanier, B., Guéret, C., Medaglia, A. L., & Velasco, N. (2010). A memetic algorithm for the multi-compartment vehicle routing problem with stochastic demands. *Computers & Operations Research, 37*(11), 1886–1898.
Mendoza, J. E., Castanier, B., Guéret, C., Medaglia, A. L., & Velasco, N. (2011). Constructive heuristics for the multicompartment vehicle routing problem with stochastic demands. *Transportation Science, 45*(3), 346–363.
Mirzaei, S., & Wøhlk, S. (2017). Erratum to: A Branch-and-Price algorithm for two multi-compartment vehicle routing problems. *EURO Journal on Transportation and Logistics, 6*(2), 185–218.
Muyldermans, L., & Pang, G. (2010). On the benefits of co-collection: Experiments with a multi-compartment vehicle routing algorithm. *European Journal of Operational Research, 206*(1), 93–103.
Ostermeier, M., Martins, S., Amorim, P., & Hübner, A. (2018). Loading constraints for a multi-compartment vehicle routing problem. *Working paper, Catholic University Eichstaett-Ingolstadt*.
Pollaris, H., Braekers, K., Caris, A., Janssens, G., & Limbourg, S. (2015). Vehicle routing problems with loading constraints: State-of-the-art and future directions. *OR Spectrum, 37*, 297–330.
Ropke, S., & Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science, 40*(4), 455–472.
Shaw, P. (1997). *A new local search algorithm providing high quality solutions to vehicle routing problems*. Glasgow, Scotland, UK: APES Group, Department of Computer Science, University of Strathclyde.
Silvestrin, P. V., & Ritt, M. (2017). An iterated tabu search for the multi-compartment vehicle routing problem. *Computers & Operations Research, 81*(Supplement C), 192–202.
Toth, P., & Vigo, D. (2014). Vehicle routing: problems, methods, and applications. *MOS-SIAM series on optimization* (2nd ed.). Society for Industrial and Applied Mathematics.