The supply of convenience stores: challenges of short-distance routing within the constraints of working time regulations

Manuel Ostermeier

Angaben zur Veröffentlichung / Publication details:

Ostermeier, Manuel. 2023. "The supply of convenience stores: challenges of short-distance routing within the constraints of working time regulations." European Journal of Operational Research 314 (3): 997–1012. https://doi.org/10.1016/j.ejor.2023.11.004.

The supply of convenience stores: Challenges of short-distance routing within the constraints of working time regulations

Manuel Ostermeier

University of Augsburg, Resilient Operations, Universitätsstraße 12, 86159 Augsburg, Germany

1. Introduction

Grocery distribution is characterized by the supply of a variety of different types of store (e.g., hypermarkets, supermarkets, and city stores) and likewise a variety of products and segments (e.g., frozen, fresh, and ambient products). The supply of each store type has its own particularities, and retailers have to deal with these to ensure cost- and time-efficient distribution (Agrawal & Smith, 2015; Hübner et al., 2013). *Convenience stores* constitute the smallest but at the same time an important store type in an urbanized world. The range of convenience stores in Europe comprises small city markets (e.g., REWE to go, SPAR express), kiosks, and gas stations. The variety of types and locations results in a heterogeneous structure of opening hours and delivery restrictions. Convenience stores are usually situated in dense urban areas and characterized by small and frequent orders due to their limited store space and backroom capacities. This leads to frequent and heterogeneous deliveries as convenience stores offer – despite their small size – a large product variety, ranging from tobacco and magazines through frozen products to an increasing assortment of fresh products for takeaway. The heterogeneous orders across different temperatures and generally small order sizes call for a combination of the different product flows to leverage synergies and enable economies of scale. Multi-compartment vehicles (MCVs) enable this combination as they are designed to split up their loading area into different chambers (compartments), each dedicated to one temperature zone. This perfectly suits the supply of convenience stores. Thanks to their flexibility and the combination of different product flows, MCVs are used successfully in retail practice (see e.g., Grünrock-Kern (2013)) and for other areas of application (e.g., waste management (Henke et al., 2015; Zbib & Wøhlk, 2019)).

In addition to industry-specific requirements, there are legal restrictions for the driving and working times of drivers. These are generally controlled by Regulation (EC)561/2006 (European Union, 2006) as well as the Directive 2002/15/EC (European Union, 2002) of the European Union (EU). The first mainly concerns the driving periods and respective rest periods and break times, the latter provides additional provisions for working hours, breaks, and night work (Goel, 2018). These regulations therefore impact the possible route planning in short-distance last-mile delivery such as for the supply of convenience stores. We consider the daily routing at a retailer in our application and thus delivery tours that are characterized by frequent stops and respective

E-mail address: manuel.ostermeier@uni-a.de.

activities such that the driving is interrupted frequently. The regulations on uninterrupted driving periods of 4.5 h and rest periods between two consecutive days (see EU Regulation (EC)561/2006) can therefore be neglected for the daily route planning. Instead, restrictions on the working time (i.e., daily working hours) and the scheduling of breaks are central aspects for the routing problem discussed as they limit possible tour duration and dictate breaks during the tours that drivers have to take.

The requirements described need to be considered in distribution planning. The supply of convenience stores is a major challenge for retailers and has so far not been addressed, despite its relevance in modern retail practice. It requires tailored solution approaches to enable realistic planning of associated tours and to adhere to all regulatory and operational requirements: small order sizes across different temperature zones, multiple time windows, and the integration of breaks and maximum tour duration. While working hour regulations and driving time limitations have been considered in long-haul transportation (see e.g., Goel and Irnich (2017), Goel and Vidal (2014), Koç et al. (2018) and Tilk and Goel (2020)), these practical requirements are mostly neglected in short-distance distribution planning. Vehicle routing problem (VRP) variants, including VRPs with MCVs, often ignore working hour regulations or tour duration restrictions (see e.g., Ostermeier et al. (2021)). The consideration of these is, however, essential for actual planning in the retail industry. The integration of breaks impacts arrival times at stores and overall tour duration. This is critical when time windows have to be met and the duration of tours is limited. Neglecting mandatory breaks on tours may lead to significant delays of deliveries and to non-feasible tours as delivery time windows or store opening hours are not respected. This paper addresses this issue and takes into account the break time scheduling for the daily routing. We address the supply of convenience stores that occurs in grocery retailing. This study is based on a cooperation with a major European retailer. It reflects planning restrictions at our industry partner and the corresponding routing problem. Despite the underlying case, the setting and requirements are transferable to related distribution problems. We formulate a general multi-compartment vehicle routing problem with multiple time windows and breaks (MCVRP_TWB) that extends the classical capacitated vehicle routing problem (CVRP, see Toth and Vigo (2014)) and takes into account the particularities of the supply of convenience stores. This allows us to contribute to the existing literature by considering the following problem characteristics simultaneously:

- The supply of convenience stores (i.e., short-distance routing) with MCVs.
- The decision on joint and/or separate deliveries of product segments, i.e., the decision on the number and size of compartments.
- The delivery within predefined multiple time windows according to store types, employee availability, and opening hours.
- The adherence to working time regulations. This includes the adherence to maximum tour duration, the scheduling of breaks within tours, and the general decision on the duration of tours to control the need for breaks.

We present an adaptive large neighborhood search (ALNS) to solve the MCVRP_TWB for realistic problem sizes. The ALNS uses problem-specific operators to address the problem characteristics given and integrates break times within the search. We show that our solution approach outperforms existing state-of-the-art approaches for MCVRP.

The remainder of this paper is organized as follows. Section 2 describes the planning problem considered and Section 3 discusses literature related to our problem. Section 4 formulates a comprehensive model formulation for the MCVRP_TWB. The solution approach developed is presented in Section 5. Section 6 first analyzes the performance of the ALNS proposed by comparing it to a state-of-the-art approach and then examines the impact of working hour regulations for the routing in retail practice. We therefore provide a case study and further numerical experiments in our analysis. We conclude our work by summarizing our findings in Section 7.

2. Problem description

This section details the planning problem of supplying convenience stores when working hour regulations are considered. The setting described is motivated by the actual distribution problem of our partner in industry. We first describe the distribution system for the supply of convenience stores before detailing corresponding restrictions and legal regulations.

The supply of convenience stores. Most retailers supply their own (convenience) stores and customers via central or local distribution centers (DCs; see Fernie and Sparks (2009), Kuhn and Sternbeck (2013)). Further, distribution is carried out by the retailer's own distribution fleet, by external carriers, or a mix of both. The scheduling of tours is in all cases subject to the regional planners. Distribution starts and ends at the DC, where goods are loaded, and the deliveries are carried out by MCV tours to supply all stores with demands on the respective planning day. Convenience stores are small retail outlets with limited space and restricted accessibility in a mostly urban environment. This leads to high customer frequency and at the same time to a broad assortment in terms of product segments offered. Convenience stores thus require small (due to lack of storage/space) and frequent (due to high customer demand) deliveries with a heterogeneous structure. This means that orders comprise small amounts of individual products but at the same time across different product segments (i.e., temperature zones). The order of a gas station may comprise small amounts of frozen and fresh foods (e.g., single packs of ice cream and ready-made sandwiches), ambient goods plus tobacco products, as an example. A higher number of orders is combined on the same route, and consequently tours with up to 24 stops per tour are common. This contrasts with the supply of supermarkets, where usually around six stores are served (see, e.g., Hübner and Ostermeier (2019)), or the supply of hypermarkets, where even fewer stores are on the same tour due to frequent full-truck deliveries. The prevailing order structure for convenience stores is therefore predestined for the use of MCVs. These vehicles are beneficial for the delivery of small orders across multiple segments and especially multiple temperatures (see e.g., Ostermeier and Hübner (2018)) as they are able to combine the different product flows. In detail, the loading area of an MCV can be subdivided into several compartments, each dedicated to one temperature/product type, which enables the simultaneous transportation of different temperature zones. Orders across several zones can be combined on the same vehicle and store demands for multiple segments can be fulfilled by a single truck. The short distances and the high number of stores are especially beneficial for the use of MCVs as this ensures the use of all compartments with sufficient capacity usage. In contrast, the use of single-compartment vehicles leads to a higher number of deliveries (e.g., multiple deliveries for each temperature segment) or the use of cooling boxes requiring additional handling effort. The products ordered are commissioned at the DC in the respective warehouse sections of the associated segments (e.g., frozen, fresh, ambient, and tobacco), and all goods are consolidated within a buffer area at the loading ramp of the corresponding tour. Please note that products with cooling requirements (i.e., fresh and frozen goods) are loaded directly to vehicles as soon as the loading is possible such that the cooling chain is not interrupted. Drivers are responsible for the loading of their trucks, which consumes available working time and affects the feasible tour duration (see below). They load all orders of a tour into the compartments of the MCV and start the tour at the scheduled starting time. Drivers are a rare and costly resource these days. The objective of the distribution is therefore to minimize the overall time consumed. Fig. 1 illustrates the complete distribution process.

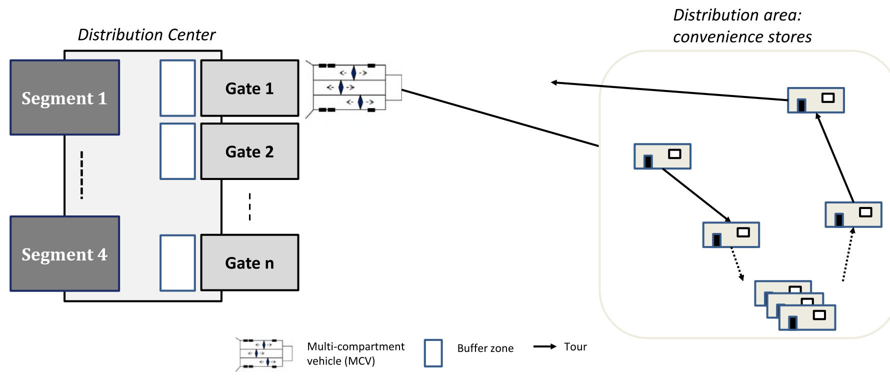

Fig. 1. Distribution system for the supply of convenience stores with MCVs.

Time restrictions for the distribution. The system has additional requirements that have to be respected within the planning process. The distribution process depicted in Fig. 1 is restricted by several time constraints that impact the routing decisions. To begin with, the arrival times at convenience stores are subject to delivery time restrictions. First, the opening hours of stores are heterogeneous across the different types of store. A gas station may be open 24 h a day, while small kiosks have restricted opening hours or can only be supplied at specified times due to limited accessibility or legal restrictions (e.g., deliveries in pedestrian zones only between 6 and 10 am or 6 pm and 9 pm). Second, core customers and corresponding stores may have contracted delivery time windows and therefore need to be served within the times defined as otherwise fines apply. Finally, the workforce in small stores is limited and stores may be dependent on defined delivery times such that enough workers are available. These time restrictions of the stores result in multiple time windows for the delivery throughout the day. Additionally, individual stores require individual service times as the service at stores is dependent on the site specifics. Some store deliveries may be hindered by limited accessibility or restricted unloading areas. The delivery process is consequently characterized by process- and store-specific service times.

Alongside store-specific restrictions, there are legal regulations with respect to the labor time of drivers. More precisely, there are limits for the total labor time (i.e., an absolute maximum of 10 h per day) and for break times during work that need to be respected for all employees. Total labor time limits the tour duration, which is further reduced due to other tasks a driver is responsible for (e.g., loading of the truck before the tour starts, return of empty roll cages). The working day of a driver is consequently separated into tasks at the DC (e.g., loading of goods, paperwork, return of empties) and the actual delivery tour. As such, the full working hours are not available for the tours. The mandatory break times further imply that breaks during the delivery tours are required between stops at stores if the tour length exceeds a defined duration (i.e., exceeds six working hours). The exact regulations are controlled by the respective authorities and differ between countries and regions (see e.g., Regulation (EC)561/2006 (European Union, 2006)). In the application considered, breaks can be taken between two consecutive stops, i.e., before or after a stop on the tour. The first and last (store) stop are an exception in this context: there must not be a break before the first nor after the last store on a tour. After the last stop, vehicles return straight to the depot. The mandated break times may be taken in one break (i.e., a single break of 45 min) or split into two smaller breaks (i.e., two breaks of 30 and 15 min). In any case, it needs to be ensured that a break of at least 30 min is scheduled during the first six hours of a tour in the event that the tour exceeds this duration.

The combination of break times and strict time windows for deliveries poses additional planning challenges. The overall tour duration as well as the arrival times at all subsequent stores are affected as soon as breaks are mandatory for tours. This complicates the planning as these times need to be integrated into the process such that delivery times are not violated and tour duration is not exceeded. Neglecting break times leads to non-feasible tours and in the worst case to failed deliveries (arrival after opening hours) or high fines (if service agreements are not met). The need for breaks (through the duration of tours) and the actual time when a break is taken is thus part of the decision problem. An example of breaks during a tour for the supply of convenience stores is illustrated in Fig. 2. It shows a tour visiting 20 stores (stops). The break time of 30 min may be taken any time between stop 1 (after) and stop 12. After stop 13 the duration of 6 h is exceeded and thus the 30-min break has to take place at a previous stop. The 15-min break on the other hand may happen any time on the tour (before stop 20 as the last stop). The tour duration is limited to 8 h and 45 min.

3. Related literature

This section discusses related literature and concludes with a summary that details the contribution of our work. The MCVRP_TWB extends the literature on MCVRPs and CVRPs with respect to time windows and working hour regulations. We therefore discuss related publications in these areas. For a detailed review on VRPs and their variants we refer to Toth and Vigo (2014), Laporte (2009), Pollaris et al. (2015) as well as (Golden et al., 2008), and to Ostermeier et al. (2021) for a detailed review of MCVRPs.

MCVRPs in grocery distribution. Our review focuses on MCVRPs in grocery distribution. Chajakis and Guignard (2003) present a first study on the supply of convenience stores with multiple temperatures. However, the authors do not explicitly consider MCVs but two alternatives, where either bulkheads are used to separate temperature zones or cooling boxes. They present the corresponding mathematical models and solve the variants using Lagrangean relaxation. Derigs et al. (2011) are the first to present a comprehensive mathematical model for the use of MCVs in fuel and grocery distribution. The authors present a solver suite of various solution methods (e.g., local search and large neighborhood search (LNS) components). They analyze the performance of different operator combinations in numerical experiments. Hsiao et al. (2017) consider a problem variant where the exact temperature setting within compartments is adjusted in addition to the compartment sizes. They analyze the impact of temperature and storage time on the goods, i.e., the quality of foods. Moreover, time windows and service times are taken into account. The problem is solved using biogeography-based optimization. Hübner and Ostermeier (2019) examine the impact of additional loading and unloading costs when MCVs are used and different shipping gates at the DC have to be approached. In contrast to our application, the warehouse and corresponding loading gates are organized according to the different temperature segments, and traveling between gates to collect different segments is necessary. They solve the corresponding MCVRP with loading and unloading costs with an LNS

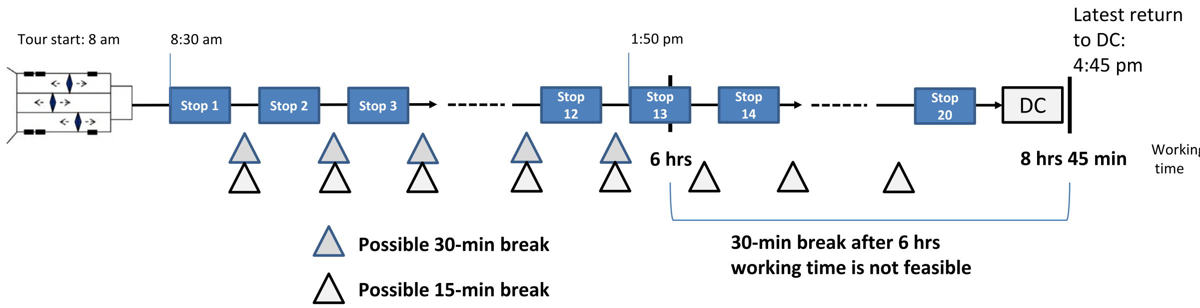

Fig. 2. Possible break times during a delivery tour (example).

and analyze the benefits of MCVs in grocery distribution. Further, Ostermeier and Hübner (2018) extend their previous work by selecting either single- or multi-compartment vehicles for delivery tours. In a similar problem setting, Ostermeier et al. (2018) study the impact of loading constraints on the distribution with MCVs. The authors present an exact approach for their problem formulation (branch-and-cut) as well as a neighborhood search that integrates loading restrictions. Chen et al. (2019) study an MCVRP for the distribution of perishable food. They take time windows into account and limit the number of stores to be visited to ensure the freshness of products. The problem is solved using an ALNS approach. Chen and Shi (2019) consider a problem variant for urban/last-mile delivery with time windows. They take into account orders for products that need to be separated due to odor or mutual contamination. The authors propose two variants of swarm optimization to solve the problem. Lastly, Martins et al. (2019) and Frank et al. (2021) study multi-period MCVRPs. The former work defines product-specific time windows and introduces an ALNS with daily and weekly operators to simultaneously address the routing and multi-period aspects of the problem. The latter work optimizes delivery patterns for the distribution with MCVs and analyzes the corresponding impact of combined product flows. The authors also use an ALNS to solve the multi-period problem. The existing publications highlight the importance of MCVs for grocery distribution and the increasing interest in this field of study. Yet, as pointed out in the MCVRP review by Ostermeier et al. (2021), publications in this area with respect to real-world limitations are lacking. None of the existing publications deals with the combination of duration constraints, store-individual (multiple) time windows and service times, and – in particular – no break times are considered.

VRPs with time windows. The VRP with time windows (VRPTW) is closely related to our problem variant. There are numerous publications on VRPTW as it represents one of the most studied VRP variants. We therefore refer to Desaulniers et al. (2014) for a more detailed survey on VRPTW. There are many different solution approaches due to the high number of publications. Besides exact approaches (see e.g., Baldacci et al. (2012)) there are various heuristics for the VRPTW (see e.g., Gendreau et al. (2008), Gendreau and Tarantilis (2010)). Heuristic approaches are required to solve large-scale problem instances of the complex routing problem. Among others, (A)LNS heuristics belong to the best-performing approaches (see e.g., Prescott-Gagnon et al. (2009), Ropke and Pisinger (2006)), and thus motivated the development of our ALNS approach.

VRPs with break considerations. In addition to VRPTW, VRPs with consideration of break times are related to our work. The literature on this topic can be divided into two streams: the vehicle routing and truck driver scheduling problem (VRTDSP), and the vehicle routing problem with break times. The VRTDSP combines the truck driver scheduling problem (TDSP) and classic VRPs for long-haul transportation. Drivers in long-haul transportation are required to adhere to given driving hours and rest periods to avoid excessively long driving times throughout the week or several consecutive days. The TDSP arose from the need to address different country- and region-specific regulations in long-haul transportation and thus different planning requirements for drivers (see e.g., Archetti & Savelsbergh, 2009; Bowden & Ragsdale, 2018; Goel, 2010; Goel et al., 2012; Goel & Kok, 2012; Kleff, 2019). The related works focus on the adherence to regulations for driver scheduling, i.e., they often assume a given sequence of nodes for which a valid schedule has to be determined for the planning horizon considered. Goel (2012) provides a general formulation of the minimum duration TDSP that can be flexibly applied to different sets of rules. The VRTDSP extends the TDSP by integrating routing decisions and time windows. The first work in this context was presented by Savelsbergh and Sol (1998), who consider lunch and night breaks within fixed time intervals and provide a solution approach based on a branch-and-cut algorithm. Following this early research, there are various publications that address model extension and different regulatory settings. Both exact approaches (see e.g., Goel & Irnich, 2017; Tilk & Goel, 2020) and heuristic approaches (see e.g., Goel, 2009; Goel & Vidal, 2014; Koç et al., 2018; Kok, Meyer, et al., 2010; Prescott-Gagnon et al., 2010; Rancourt et al., 2013; Xu et al., 2003) have been proposed to solve the VRTDSP efficiently. Kok, Hans, et al. (2010) study a problem for the driving times of daily routing, but the planning framework is based on long-haul transportation with driving time limits of 4.5 h. All these publications deal with explicit driver regulations due to the long-term horizon, i.e., extensive driving times for multiple hours. In contrast to our work, the driving itself (e.g., 4.5 h) is the bottleneck, and breaks as well as rest periods between consecutive stops/days need to be planned. In our problem context, we deal with daily delivery tours that are characterized by short-distance transportation and frequent stops with service requirements such that accumulated driving periods are not an issue. The working hour regulations that apply are not just valid for drivers but for all employees in Europe and comprise the complete working time, i.e., driving as well as service times. Breaks can be scheduled freely after each stop on the tour and a decision is required regarding when the break fits best (if mandatory), or if shorter routes are constructed to avoid breaks. This decision is labeled as break time scheduling. Moreover, the total break time may be split into multiple breaks (e.g., 15+30 min), which adds to both flexibility and complexity. We therefore consider the scheduling of break times in short-distance transportation as is the case for the supply of convenience stores. Publications that deal with a similar problem setting, i.e., break times during daily delivery tours, focus on lunch breaks. The first work that explicitly addresses break times in the form of lunch breaks is found in Sahoo et al. (2005). The authors consider single lunch breaks within waste management and model the breaks by adding a dummy node to the network that represents the break stop. The authors apply an iterative two-phase algorithm that is based on the insertion algorithm of Solomon (1987) and exchange operators of Taillard et al. (1997). Kim et al. (2006) extend this work and present a clustering-based algorithm for the problem. In the same field, Buhrkal et al. (2012) present another work for the consideration of lunch breaks. The authors add binary variables to their model to account for the position of break times. They use an ALNS to solve the corresponding VRP. Finally, Coelho et al. (2016) consider lunch breaks in the context of the furniture industry. They present a mixed integer linear program that does not use additional variables for breaks but an extended distance matrix that links all breaks with customers. The authors present a multi-start randomized local search heuristic as the solution approach. All of these publications consider break times, but break times are fixed to specific, predefined time windows (lunchtime) in each study. Break times are therefore restricted to time windows and not freely chosen during the tour. Further, breaks are inserted into all tours independent of the tour duration. This distinguishes our work from other publications and constitutes the genuine character of the MCVRP_TWB, where the need for breaks depends on the tour duration (i.e., if breaks become mandatory as tour duration exceeds a given threshold), and only the length of breaks, not the actual time of the breaks, is predefined.

Summary and contribution. The supply of convenience stores has similar requirements to that of standard grocery distribution, but also poses additional challenges. As such, we take into account small and frequent orders for short-distance transportation and the use of MCVs to address these requirements. In addition to the general distribution setting, we need to consider strict time restrictions due to time window requirements and the adherence to break times for workers. Review of the pertinent literature shows the importance of MCVs for grocery distribution and the consideration of both time windows and break times. Yet most publications dealing with break times focus on long-haul transportation and its specifics (e.g., rest and driving periods), while only a handful of publications consider breaks (i.e., lunch breaks) for daily routing. The consideration of working hour regulations is an important topic for retailers as it directly impacts routing decisions and the overall distribution planning. The insertion of break times impacts delivery times and – in combination with time windows – the planning of feasible routes. Break times and limited route duration need to be taken into account to provide applicable routing solutions and to enable a realistic evaluation of tours. There is no publication that deals with the integrated planning of breaks for the supply of convenience stores or other short-distance routing applications. Break times have also not been considered within MCVRP literature and the corresponding combination of different product flows. Our study fills this gap. It provides a general problem formulation for the integration of breaks into an (MC)VRP and analyzes the implications of the corresponding routing problem for direct application in the retail industry.

4. Model development

This section presents the mathematical model of the MCVRP_TWB. We provide a general problem formulation for the consideration of multiple breaks and time windows, driving time restrictions, and store-individual service times that also applies to related short-distance routing problems in other regions, including single-compartment applications (i.e., assuming a single compartment). The MCVRP_TWB is defined on a complete, undirected, weighted graph $G = (N_0, E)$, where $N_0 = \{0, 1, \dots, n\}$ represents the set of nodes including the depot (node 0) and $N = N_0 \backslash \{0\}$ the set of store locations. $E = \{(i,j) : i,j \in N\}$ represents the set of edges, each weighted with the traveling time tt_{ij}. The traveling times satisfy the triangle inequality. All tours start and end at the depot. The planning horizon comprises one delivery day on which each tour has a maximum duration of T hours. Breaks are mandatory on a tour if the duration exceeds R hours. The break time is split up into a set of breaks B, and each break is associated with a break time r_b. This means that the complete break time required (e.g., 45 min) is the sum of all breaks, i.e., $\sum_{b \in B} r_b$. This allows us to model the possibility of a single break (i.e., $|B| = 1$) as well as the segmentation of break time into smaller breaks (e.g., 30 and 15 min). Breaks can only happen after the first and before the last stop at a store on the tour. Further, a certain share of breaks has to be taken within the first R working hours, which is represented by the subset $\overline{B} \subseteq B$. A sufficiently large, homogeneous set V of MCVs with capacity Q is available at the depot. The distribution comprises orders across a set of different product segments S. The subset $S_i \subseteq S$ summarizes all segments ordered by a store, i.e., the corresponding order quantity q_{is} is positive. The loading area of an MCV can be split into up to $\overline{c}$ compartments to accommodate the different segments (i.e., temperature zones). We assume $\overline{c} = |S|$, i.e., all segments considered can potentially be delivered jointly by a single MCV, and the set of segments S also represents the potential compartments on an MCV. However, the assignment of segments to vehicles is restricted by a maximum compartment capacity for individual segments ($Q_s, s \in S$, e.g., limited frozen compartments). Note that not all compartments that are potentially available have to be used. The number of available compartments defines the maximum number of possible compartments and their maximum capacity on a truck. Further, each store is associated with a fixed service time s_i^{f} and a variable service time s_{is}^{v} that depends on the store location and the order size of segment s. The supply of store i has to take place within a set of predetermined time windows TW_i, where $t \in TW_i$ is a time window denoted by $[\alpha_{it}, \beta_{it}]$, with α_{it} and β_{it} as the lower and upper bound, respectively.

For the mathematical formulation, we further introduce the following binary decision variables.

$$p_{biv} \begin{cases} = 1, & \text{if break } b \text{ is scheduled after store } i \text{ on tour (vehicle) } v \\ = 0, & \text{otherwise} \end{cases}$$

$$x_{ijv} \begin{cases} = 1, & \text{if vehicle } v \text{ travels from location } i \text{ to } j \\ = 0, & \text{otherwise} \end{cases}$$

$$y_{ist} \begin{cases} = 1, & \text{if store } i \text{ is supplied with segment } s \text{ in time window } t \\ = 0, & \text{otherwise} \end{cases}$$

$$z_{isv} \begin{cases} = 1, & \text{if store } i \text{ is supplied with segment } s \text{ by vehicle } v \\ = 0, & \text{otherwise} \end{cases}$$

Additionally, we introduce three auxiliary variables: The binary variable ψ_v indicates if a break is mandatory on tour v, i.e., if the tour length exceeds the duration R. The continuous variable w_{iv} represents the arrival time of vehicle v at store i, and d_v indicates the total tour duration of vehicle v. Using the defined sets, parameters, and variables, the MCVRP_TWB can be formulated as follows.

$$\min \ f = \sum_{v \in V} d_v \tag{1}$$

subject to

$$\sum_{j \in N} x_{0jv} \leq 1 \qquad v \in V \tag{2}$$

$$\sum_{i \in N_0} x_{ihv} = \sum_{j \in N_0} x_{hjv} \qquad v \in V, \ h \in N_0 \tag{3}$$

$$\sum_{v \in V} z_{isv} = 1 \qquad i \in N, \ s \in S_i \tag{4}$$

$$\sum_{s \in S} z_{jsv} \leq |S| \sum_{i \in N_0} x_{ijv} \qquad v \in V, \ j \in N \tag{5}$$

$$\sum_{i \in N} \sum_{s \in S} q_{is} \cdot z_{isv} \leq Q \qquad v \in V \tag{6}$$

$$\sum_{i \in N} q_{is} \cdot z_{isv} \leq Q_s \qquad v \in V, \ s \in S \tag{7}$$

$$\sum_{t \in TW_i} y_{ist} = 1 \qquad i \in N, \ s \in S_i \tag{8}$$

$$w_{iv} + tt_{i0} + s_i^{\mathrm{f}} + \sum_{s \in S} z_{isv} \cdot s_{is}^{\mathrm{v}} - w_{0v} - M \cdot (1 - x_{i0v}) \leq d_v \qquad v \in V, \ i \in N \tag{9}$$

$$d_v \leq T \qquad v \in V \tag{10}$$

$$d_v - R \leq M \cdot \psi_v \qquad v \in V \tag{11}$$

$$\sum_{i \in N} p_{biv} = \psi_v \qquad v \in V, \ b \in B \tag{12}$$

$$p_{biv} \leq M(1 - x_{i0v}) \qquad i \in N, v \in V, \ b \in B \tag{13}$$

$$w_{iv} + s_i^{\mathrm{f}} + \sum_{s \in S} z_{isv} \cdot s_{is}^{\mathrm{v}} - w_{0v} \leq R + M(1 - p_{biv}) \qquad i \in N, v \in V,\ b \in \overline{B} \quad (14)$$

$$w_{iv} \leq M \cdot \sum_{s \in S} z_{isv} \qquad v \in V,\ i \in N \quad (15)$$

$$w_{iv} + tt_{ij} + s_i^{\mathrm{f}} + \sum_{s \in S} z_{isv} \cdot s_{is}^{\mathrm{v}} + \sum_{b \in B} p_{biv} \cdot r_b - M \cdot (1 - x_{ijv}) \leq w_{jv} \qquad v \in V,\ i \in N_0,\ j \in N \quad (16)$$

$$w_{iv} + tt_{ij} + s_i^{\mathrm{f}} + \sum_{s \in S} z_{isv} \cdot s_{is}^{\mathrm{v}} + \sum_{b \in B} p_{biv} \cdot r_b + M \cdot (1 - x_{ijv}) \geq w_{jv} \qquad v \in V,\ i \in N_0,\ j \in N \quad (17)$$

$$\alpha_{it} \cdot y_{ist} - M(1 - z_{isv}) \leq w_{iv} \leq \beta_{it} \cdot y_{ist} + M(1 - z_{isv}) \qquad i \in N,\ t \in TW_i,\ v \in V,\ s \in S_i \quad (18)$$

$$x_{ijv} \in \{0,1\} \qquad i,j \in N_0,\ v \in V \quad (19)$$

$$y_{ist} \in \{0,1\} \qquad i \in N,\ s \in S,\ t \in TW_i \quad (20)$$

$$z_{isv} \in \{0,1\} \qquad i \in N,\ s \in S,\ v \in V \quad (21)$$

$$\psi_v \in \{0,1\}, d_v \geq 0 \qquad v \in V \quad (22)$$

$$p_{biv} \in \{0,1\} \qquad b \in B,\ i \in N,\ v \in V \quad (23)$$

$$w_{iv} \geq 0 \qquad i \in N_0,\ v \in V \quad (24)$$

The objective function of the MCVRP_TWB (1) minimizes the total duration of all tours. Constraints (2) and (3) ensure the start of each tour at the depot and the flow conservation. Each segment ordered by a store has to be delivered (Constraints (4)). A store needs to be visited by a vehicle if at least one segment ordered is assigned to the corresponding tour (Constraints (5)). The assignment of orders to vehicles is only possible within the given capacity restrictions of the vehicle and compartments (Constraints (6) and (7)). The term $\sum_{i \in N} q_{is} \cdot z_{isv}$ consequently indicates the actual compartment size used for segment s on vehicle v. Please note that Constraints (6) are only required if the theoretical capacity of all individual compartments exceeds the vehicle capacity ($\sum_{s \in S} Q_s > Q$). By allowing the sum of compartment capacities to exceed the total truck capacity, it is ensured that each compartment size can be chosen flexibly within the maximum truck and compartment capacities Q and Q_s. This means that each compartment can be set at any feasible size between 0 and $Q_s \leq Q$, where 0 indicates that the compartment is not used. Exactly one time window is assigned for the supply of segment s to store i, which is ensured by Constraints (8). Constraints (9) define the total tour duration d_v of vehicle v. The tour duration must not exceed the maximum duration of T working hours as indicated by Constraints (10). Constraints (11) to (14) concern the scheduling of breaks. First, breaks become mandatory on tour v if the tour duration exceeds R working hours. Second, in the event that breaks are required on a tour ($\psi_v = 1$), Constraints (12) ensure that all breaks $b \in B$ are set to active. Third, no breaks are allowed after the last store stop of the tour. Lastly, a certain share of breaks has to be scheduled within the first R working hours according to Constraints (14). Constraints (15)–(18) set the arrival times at stores, ensuring that travel, service, and break times (Constraints (16) and (17)) as well as the given time windows (Constraints (18)) are respected. Finally, the variable domains are defined in Constraints (19)–(24).

5. Solution approach

The MCVRP_TWB extends the classic CVRP and constitutes an NP-hard optimization problem (see Toth and Vigo (2014)). The use of standard solvers is limited to small problem instances with respect to number of stores, orders, segments, and vehicles. Heuristic solution approaches are usually applied for industry-relevant problem sizes with several hundred orders. We present an ALNS to solve the MCVRP_TWB for this purpose. ALNS approaches have successfully been used on various VRPs (see e.g., Amorim et al. (2014), Kovacs et al. (2014) and Ropke and Pisinger (2006)), for MCVRPs (see e.g., Alinaghian and Shokouhi (2018), Derigs et al. (2011) and Martins et al. (2019)), and also for VRPs with consideration of lunch breaks (see e.g., Buhrkal et al. (2012)). It can be classified as a state-of-the-art approach for rich routing problems. Typically, an ALNS comprises the following steps: (1) generation of initial solution (Section 5.1), (2) improvement phase by changing large parts of the incumbent solution (Sections 5.2 and 5.3), (3) acceptance of new solutions according to defined criteria (Section 5.5), and (4) update of operator scores according to their performance (Section 5.6). Our ALNS framework uses problem-tailored operators to steer the search for promising solutions. We further split the ALNS into two search phases: phase 1 solves the MCVRP without the consideration of break times, and phase 2 solves the complete MCVRP_TWB. This means that breaks are ignored for the initial solution and within the first phase. The breaks are then inserted before the second search phase starts. The allowed tour length in phase 1 is limited to the maximum total driving and service time for drivers, excluding the potential time required for breaks. Only after the first search phase, the allowed duration is increased to the maximum tour duration. This ensures feasibility of the break insertion. For example, if we assume a maximum tour duration (T) of 8 h and 45 min and a required (total) break time of 45 min, the maximum driving and service time is set at 8 h in the first search phase. Once the second phase starts, the maximum tour duration T is used. Moreover, the adherence to Constraints (11)–(14) is ensured using a dedicated break adjustment mechanism (Section 5.4). Algorithm 1 outlines the complete solution approach.

We further allow non-feasible solutions with respect to the time window constraints during the search (see e.g., Vidal et al. (2012)). This means that early or late deliveries are possible but penalized. This results in the modified objective function $f' = f + \zeta \cdot \sum_{i \in N} u_i$, where ζ is a penalization weight and u_i the extent of time a store time window is missed. The parameter ζ is increased in regular intervals to steer the search towards a solution without violations by setting $\zeta = \exp^{(iterations/\delta)}$, where δ is used as a control parameter.

Please note that in our context the algorithm removes/inserts orders (i.e., a combination of store i and segment s) and not, as is common in single-product cases, complete customers (i.e., stores) from the solution. We define an order as a combination of store i and segment s in the remainder of this work.

5.1. Initial solution

The ALNS approach proposed is based on an initial set of routes. The initial route building is done by a variation of the well-known savings procedure of Clarke and Wright (1964). The savings algorithm has been successfully applied in other MCVRP and VRP variants (see e.g., Muyldermans and Pang (2010)), and especially serves as basis for modified heuristics in the context of time windows (see e.g., Solomon (1987), Van Landeghem (1988)). It was chosen as it provides a fast initial solution and a solid basis for the subsequent improvement phase of the ALNS. Our savings have been modified to take into account the arrival times within the predetermined time windows. It is defined by $s_{ij} := v_{ij}(tt_{i0} + tt_{0j} - tt_{ij})$, where tt_{ij} represents the travel times between two locations and v_{ij} the delivery time similarity between the two corresponding locations. The parameter $v_{ij} \in [0,1]$ indicates the share of time in which the time window(s) of the successor location is met with respect to the given time window(s) of the predecessor location. For instance, if store i has a time window between 6 am and 10 am (i.e., a time span of 4 h), and store j can be supplied between 6 am and 8 pm (i.e., time span 14 h), v_{ij} equals 1 as j can be reached at all possible start times from i ($v_{ij} = \frac{feasible\ start\ time\ from\ i}{time\ span\ i} = \frac{10-6}{4}$). The other way round, store i is only reached in time from store j if the vehicle starts at j between 6 am and $(10 - tt_{ji})$ am, i.e., $v_{ji} = \frac{10 - tt_{ji} - 6}{14}$. In this sense, v can be seen as the likelihood that store j is reached

Algorithm 1 ALNS – complete algorithm

Input: Order and customer data, time and distance matrix between locations;
Generate initial solution S (*no breaks*) ▷ Section 5.1
Set best solution $S^* = S$
Start first search phase (*no breaks*)
repeat
  Select a destroy-repair heuristic pair (d, r) based on adaptive weights (ρ_{dr})
  Apply pair (d, r) to generate new incumbent solution S' ▷ Section 5.2 & 5.3
  if $S' < S^*$ **then**
    Set $S^* = S'$ and $S = S'$
  else if S' meets acceptance criterion **then** ▷ Section 5.5
    Set $S := S'$
  end if
  Update performance of destroy-repair heuristic pair (d, r) ▷ Section 5.6
until Termination criterion is met
Insert breaks into tours while adhering to Constraints (11)–(14), update solution S^*
Start second search phase (*including breaks*)
repeat
  Select a destroy-repair heuristic pair (d, r) based on adaptive weights (ρ_{dr})
  Apply pair (d, r) to generate new incumbent solution S'
  if $S' < S^*$ **then**
    Apply break adjustment mechanism to generate S'' ▷ Section 5.4
    if $S'' < S^*$ **then**
      Set $S^* = S''$ and $S = S''$
    else if S'' meets acceptance criterion **then**
      Set $S := S''$
    end if
  else if S' meets acceptance criterion **then**
    Apply break adjustment mechanism to generate S''
    if S'' meets acceptance criterion **then**
      Set $S := S''$
    end if
  end if
  Update performance of destroy-repair heuristic pair (d, r)
until Termination criterion is met
return S^*

in time from store i. Please note that the savings are calculated for all store combinations regardless of the segments ordered while service times are neglected. The savings calculated are therefore equal for all segments (orders) of a store.

5.2. Destroy operators

The improvement phase of the ALNS starts by destroying parts of the current solution using destroy operators. We define two groups of destroy operators in our implementation: diversification and intensification. A total of five destroy operators are used.

Diversification. The diversification destroy operators aim at exploring different, random neighborhoods and therefore at broadening the search to overcome local minima. The first operator for diversification is *random removal*. It operates by randomly removing o orders from the current solution. Second, a *tour removal* operator is used to diversify the tours used. It randomly selects m existing tours and removes the tours completely, i.e., all corresponding orders are removed.

Intensification. Alongside diversification, the search needs to be intensified to exploit promising neighborhoods. The intensification operators make use of problem specifics and are tailored to the problem setting at hand. This enables a more guided search. We define three different operators for intensification: *penalty removal* and two versions of *relatedness removals*.

The *relatedness removals* are based on the original relatedness operators by Shaw (1997), Ropke and Pisinger (2006), and Pisinger and Ropke (2007). The first operator is denoted as *routing relatedness* and considers travel times between stores, order quantity, and order segment. The relatedness measure $R^1_{is_1js_2}$ is defined in Eq. (25) and indicates the relatedness between the order of store i for segment s_1 and the order of store j for segment s_2. The lower the value of R^1, the more two orders are related.

$$R^1_{is_1js_2} := \phi \cdot \frac{tt_{ij}}{tt_{\max}} + \epsilon \cdot \frac{|q_{is_1} - q_{js_2}|}{q_{max}} + \omega \cdot e_{s_1s_2}. \tag{25}$$

The first term considers the travel times, where $tt_{\max}$ indicates the maximum travel time across all stores. The second term compares the order quantities of orders for the corresponding segments of stores i and j, where q_{max} represents the maximum order quantity across all orders. Finally, the last term indicates whether the same segments are considered for both stores (i.e., if $s_1 = s_2$, $e_{s_1s_2} = 0$, 1 otherwise). Each term is weighted according to its relevance for the search, using the weights ϕ, ϵ, and ω. One order from the order(s) already removed is then chosen as the starting point for calculating the relatedness to all other orders not yet removed. The remaining orders are then sorted with respect to the calculated relatedness to the selected (already removed) order. If no order has yet been removed, the first order is chosen randomly. Further, following Shaw (1997), it is not the most related order that is chosen for removal. Instead, using the random number $z \in [0, 1)$ and the randomization parameter λ, the order $z^\lambda \cdot 100$ percent down the list is removed. This process is repeated until o orders are removed.

The second relatedness removal is denoted as *time relatedness* and has been developed to take into account the heterogeneous delivery times of stores. It is defined as

$$R^2_{is_1js_2} = \eta \cdot \frac{tt_{ij}}{\max(\mu, \gamma_{is_1js_2})} + (1-\eta) \cdot \frac{H}{\max(\mu, \gamma_{is_1js_2})}. \quad (26)$$

The first term indicates the relation of travel time and overlapping delivery times. Here, $\gamma_{is_1js_2}$ indicates the time span in which both stores i and j can be reached for the corresponding segments s_1 and s_2, i.e., the total overlapping delivery time. The higher $\gamma_{is_1js_2}$, the higher the similarity (which decreases $R^2_{is_1js_2}$). Further, in cases where store delivery times do not overlap ($\gamma_{is_1js_2} = 0$), μ represents a small number to ensure dissimilarity ($\mu < 0.1$). The second term represents the share of time in which both stores can be reached in relation to the complete planning horizon H. Again, the importance of the two terms is indicated using the weight η. The removal process follows the same logic as for the *routing relatedness*. Please note that, while the time windows are not segment-specific, the time relatedness removal concerns the removal of orders and is consequently calculated for each individual order (i.e., the combination of store and segment, see also above).

The *penalty removal* is a variation of the classical *worst removal* and considers the penalty costs incurred by early/late deliveries. The orders that cause penalties are ranked according to the penalty costs incurred (in decreasing order). Again, o orders from this list are removed from the current solution: it is not the most costly orders that are chosen for removal; instead, orders are selected using the randomization z^λ (see above).

5.3. Repair operators

After orders have been removed using one of the destroy operators, the routes need to be repaired by reinserting all orders removed. For repairing solutions we use two insertion operators: *greedy insertion* and *regret insertion*. Using the greedy insertion, the orders removed are inserted at the position that causes the least increase in costs. The order with the lowest cost increase is inserted first. The insertion of orders is repeated until all orders are reinserted. The regret insertion extends the logic of the greedy operator by applying a more foresighted insertion logic. In contrast to the greedy insertion, it is not the order with the least cost increase that is inserted, but the order with the highest regret. Regret is here defined as the opportunity costs if an order is not inserted at its best but only at the kth best position. The parameter k represents the degree of regret. Formally, the regret is defined in Eq. (27). The delta in the objective function value for inserting the order of store i for segment s at the best position (i.e., the position with the smallest cost increase) at the lth best tour, is denoted by Δ^l_{is}. This means that $l = 1$ is the tour with the lowest cost increase and would thus be chosen using the greedy operator, and $\Delta^l_{is} > \Delta^{l'}_{is}$, for $l > l'$.

$$regret^{is}_k := \sum_{l=2}^{k} (\Delta^l_{is} - \Delta^1_{is}) \quad (27)$$

The regret operator then chooses the order of store i for segment s with the highest regret according to Eq. (27) for reinsertion and repeats this process until all orders are reinserted. As the value of regret may change after each insertion, the regret values have to be calculated within each iteration of the insertion.

5.4. Break adjustment mechanism

The integration of breaks into the search is an essential part of the solution algorithm. The need for breaks is dynamic as the duration of tours changes with every iteration, i.e., with every removal and insertion of stores to tours. A continuous break-control during the search that adjusts breaks with every change applied is computationally costly and significantly increases runtimes. For example, the insertion of a store into a tour would require simultaneously checking the impact on tour duration, a possible removal/adding of breaks, a shift of breaks within tours (as mandatory breaks need to happen within the first R hours of a tour), arrival times at stores and possible time window violations, and finally, the cost implications of all these actions. We further found that not allowing insertions whenever break constraints are violated, restricts the search and hinders promising moves. As a consequence, we decided on a practical approach – the break adjustment mechanism – that controls break adherence whenever a promising solution was found, i.e., if a current solution is a candidate for a new incumbent solution (see acceptance criterion in Section 5.5). The adjustment mechanism operates only during the second search phase, as the first phase ignores breaks completely. The ALNS improves the routing solution when breaks are integrated into the second phase by removing and reinserting store orders using the operators introduced in Sections 5.2 and 5.3, and the adjustment mechanism shifts breaks within the routes according to the movement of orders. The mechanism consequently ensures that the breaks adhere to the given restrictions (see Section 4) and are moved within tours accordingly. At the same time, the mechanism represents an optimization of break times within tours as it moves all breaks to the cost-optimal position of the corresponding tour — even if a break does not violate any restriction. For this, we apply the mechanism to every tour found and check if i) breaks are mandatory on the tour, ii) breaks are scheduled at a feasible position of the tour, and (iii) breaks are at their cost-optimal position. Algorithm 2 details the break adjustment mechanism.

The procedure chosen significantly reduces computation times while it ensures adherence to working time regulations and minimizes possible time window violations through re-optimization of the break scheduling.

5.5. Acceptance criterion and termination

The acceptance criterion for new solutions is the efficient Record-to-Record Travel (RRT) proposed by Dueck (1993). The RRT has produced very good results for other MCVRP applications (see Derigs et al. (2011)) and represents a simple acceptance criterion that can easily be adjusted to different problem settings. The RRT only requires the definition of the threshold parameter δ, $\delta \in (0,1)$. A new solution (S') is then accepted as an incumbent solution if the cost delta to the best solution (S^*) found so far is equal to or less than $\delta \cdot S^*$, i.e., $S' - S^* \leq \delta \cdot S^*$. A particularity of our implementation is that the acceptance criterion is checked twice in the second phase (see Algorithm 1). First, the current solution S' is checked after the removal and reinsertion is finished. Second, if the acceptance criterion evaluation for S' as incumbent solution is positive, the break adjustment mechanism is performed, resulting in a new solution S'', and the check is repeated. The solution S'' is only accepted as incumbent solution if the condition still holds after the break adjustment. A new solution is of course accepted as new best solution if it is better than the current best solution. The search ends after both search phases are completed. The first search phase stops as soon as the routing solution has not been improved for a defined number of iterations ($limit_1$). Afterwards, search phase 2 starts and continues the search. Again, the search terminates if the limit of unsuccessful iterations ($limit_2$) is reached.

5.6. Adaptive search mechanism

The signature feature of the ALNS is the adaptation of the search to the given problem. The adaptive search assigns weights to destroy-repair operator pairs and evaluates the pairs' performance during the search. The performance is measured via the solution improvement induced by the operator pair used as introduced in Ropke and Pisinger (2006). To achieve this, a probability Φ_{dr} based on the weight ρ_{dr} is assigned to the destroy-repair operator pair (d, r), where d represents a

Algorithm 2 Break adjustment mechanism

```
Input: Current solution S, set of tours in S tours(S), sets of breaks B and B̄, break limit R;
for tour ∈ tours(S) do
    if length of tour ≥ R then                                              ▷ Break(s) mandatory?
        for b ∈ B̄ do
            Check break feasibility w.r.t. position and time (time(b))
            if non-feasible position or time(b) > R then                    ▷ Break needs to be re-positioned
                Check all feasible positions on tour with time(b) < R.
                Move b to cost-optimal position.
            else if Penalty of tour > 0 then                                 ▷ Possible improvement?
                Check all feasible positions on tour with time(b) < R.
                Move b to cost-optimal position.
            end if
        end for
        for b ∈ B\B̄ do                                                        ▷ Check remaining breaks
            Check break feasibility w.r.t. to position
            if non-feasible position then
                Check all possible positions on tour and impact on mandatory breaks b ∈ B̄.
                Move b to cost-optimal position that does not violate time restrictions of mandatory breaks.
            end if
        end for
    else
        Remove breaks if any breaks are on the tour
    end if
end for
return S with updated tours
```

destroy operator and r a repair operator (n_d, n_r indicating the number of destroy/repair operators). Φ_{dr} is defined as

$$\Phi_{dr} = \frac{\rho_{dr}}{\sum_{d'=1}^{n_d} \sum_{r'=1}^{n_r} \rho_{d'r'}}. \tag{28}$$

The weights ρ_{dr} are initialized with value 1 and updated during the search depending on the corresponding performance of the pair (d, r). The performance is measured by a dedicated score Ψ_{dr}, which is updated after every application of the operator pair according to the improvement achieved:

- A new best solution was found and the score Ψ_{dr} is increased by σ_1.
- A new solution is accepted as an incumbent solution and the score is increased by σ_2.
- A new solution is not accepted as an incumbent solution and the score does not increase.

Following Ropke and Pisinger (2006), scores are initialized with the value zero and updated after each iteration. Moreover, weights ρ_{dr} are updated using the current scores after a predefined number of iterations (e.g., 100 iterations), as defined in Eq. (29). Here, α represents a control parameter weighting the past and recent performance, and Θ_{dr} denotes the number of times the operator pair (d, r) was used. Scores are reset to zero after the update of weights.

$$\rho_{dr} := (1-\alpha)\rho_{dr} + \alpha \frac{\Psi_{dr}}{max(1, \Theta_{dr})} \tag{29}$$

6. Numerical analysis

Our numerical experiments analyze the performance of the ALNS proposed and the impact of breaks on routing. The ALNS is compared to an existing approach for an MCVRP in grocery distribution. The analysis shows the performance of our algorithm with respect to runtime and solution quality (Section 6.1). The second part of the numerical experiments is concerned with the impact of working hour regulations on distribution planning. We provide several tests to analyze how break times influence short-distance routing when strict time window restrictions have to be respected (Section 6.2). The analysis is based on real data from our industrial partner and therefore provides implications for actual planning in the retail industry.

Parameter setting. The ALNS was implemented in Java and all experiments were run on a 1.8 GHz PC with 16 GB RAM (Windows 10). The algorithm-specific parameters are set at the following values. The limit for unsuccessful iterations is set at $limit_1 = 200$ for the first and at $limit_2 = 2000$ for the second phase. The threshold parameter for the acceptance criterion is set at $\delta = 0.4\%$. The weights for the relatedness removals are defined as follows: $\phi = \omega = 1$, $\epsilon = 0.5$, $\eta = 0.66$. The randomization parameter λ equals 4 and two regret operators are used ($k = 2$ and $k = 3$). If not stated otherwise, the number of orders to be removed from the incumbent solution is randomly selected between 1 and $\min(4, \lfloor n/2 \rfloor)$ for tour removals (m), and between 2 and $\min(80, \lfloor 0.4 \cdot n \rfloor)$ for the other removal operators (o). The penalization weight ζ is increased every 100 iterations based on the control parameter $\delta = 500$. The values of the parameters have been tuned according to the case data specifics in pretests.

6.1. Benchmark comparison

The first set of experiments deals with the performance of our algorithm. We compare the solution quality of our ALNS to the existing approach of Hübner and Ostermeier (2019). The authors propose an LNS for an MCVRP in grocery distribution, where they explicitly deal with loading and unloading operations incurred by the use of MCVs. In contrast to our partner company, they consider a DC setup with dedicated shipping gates for individual product segments, which causes additional costs for loading and unloading operations. We adjust our objective function and restrictions to the reported MCVRP by Hübner and Ostermeier (2019) to enable fair comparison, i.e., we include loading and unloading costs and assess the overall distance traveled. The authors have shown the efficiency and effectiveness of their LNS for various problem settings. Moreover, they compare their approach to the solver suite of Derigs et al. (2011), and show that their LNS is able to match the results. We use the instances and solutions reported in their

Table 1
Runtime: comparison to LNS of Hübner and Ostermeier (2019).

Test instance	Runtime (in s)		Delta (in %)
	ALNS	LNS	of ALNS vs. LNS
10n_20o_7tu_4s	<1	<1	–
50n_100o_7tu_4s	5	14	−64%
100n_200o_7tu_4s	18	26	−32%
200n_400o_7tu_4s	140	144	−3%
400n_800o_7tu_4s	285	285	−0%

Table 2
Solution quality: comparison with scenarios of Hübner and Ostermeier (2019).

Test instance	Objective value		Delta (in %)
	ALNS	LNS	of ALNS vs. LNS
199n_400o_7tu_3s (TestA.1)	11,675	11,980	−2.5%
199n_400o_5tu_3s (TestA.2)	8,804	9,029	−2.5%
199n_400o_3tu_3s (TestA.2)	6,366	6,614	−3.8%
199n_400o_7tu_3s (TestA.2)	11,675	11,980	−2.5%
199n_400o_9tu_3s (TestA.2)	14,789	15,128	−2.2%
199n_400o_7tu_3s (TestB)	9,732	9,939	−2.1%
106n_198o_7tu_3s (TestC.1)	5,005	5,135	−2.5%
106n_106o_7tu_3s (TestC.2)	2,993	3,025	−1.1%
Average			−2.4%

work, publicly available on http://www1.ku.de/wwf/pw/forschung/. The benchmark instances comprise two sets of instances: a set for runtime performance, and a set for a detailed solution quality analysis. We would like to note that the order and customer (store) structure in their setting (e.g., six vs. 24 stores on a single tour) as well as the cost structure (i.e., considering loading and unloading cost and total travel costs vs. total tour duration as in our case) differ significantly from ours. The LNS formulation therefore addresses a different problem setting. Our comparison aims to show that our ALNS still performs well for this special case.

Runtime comparison. Hübner and Ostermeier (2019) provide runtime tests for instances with ten to 400 customers and two to four segments with up to 800 orders. We focus on the instances with four segments in our comparison as this is the more demanding setting. The instances are denoted as "performance analysis with randomly generated data". The results of the comparison are reported as the average values for ten runs and are summarized in Table 1. The instances are denoted according to the following logic: customers_orders_avg. order size_segments, where order sizes are indicated in transportation units (TUs). Vehicle capacity is set at 33 TUs.

The results show the efficiency of the ALNS compared to a state-of-the-art approach for an MCVRP in a related application. The ALNS outperforms the LNS for small instances and converges to the same runtime for the largest instances (400 customers, 800 orders). Even when four segments are available (vs. three in our application), a runtime below five minutes is acceptable for daily route planning.

Solution quality. The second analysis assesses the solution quality of our ALNS. The test instances are denoted as "experiments on the effects of loading and unloading costs" by Hübner and Ostermeier (2019). The instances comprise eight different test scenarios, varying with respect to the number of customers, orders, segments, as well as average order sizes. The results of our comparison are displayed in Table 2. Again, we report the average values across ten different runs.

The average delta of the ALNS compared to the LNS for the MCVRP with loading and unloading costs is 2.4% in favor of the ALNS. Our approach achieves a better solution across all instances and generates improvements of up to 3.8% (Test A.2 with 3tu). The significant saving for Test A.2 is especially notable as it comprises a scenario with small order sizes. Small order sizes are characteristic for the supply of convenience stores and are thus the focus of our work.

6.2. Detailed analysis

Case description. In the second part of the numerical experiments, we present a detailed analysis using the case data from our industry partner. The case company is a major German retailer that operates in several European countries. The data comprises five representative working days for a DC located in southern Germany. It covers more than 1200 store locations (i.e., convenience stores) with > 4100 orders for four segments: tobacco, fresh foods, frozen goods, and ambient goods. Tobacco and ambient goods are, however, consolidated and treated as a single segment for deliveries (belonging to the same compartment). The number of stores supplied on a single delivery day varies between around 160 and 260, covering orders across all segments. The capacity of the standard vehicles used is 3000 TUs, and compartment sizes are completely flexible within the total vehicle capacity (i.e., $Q_s = Q, \forall s \in S$). We assume that enough trucks to fulfill all demands are available. Order sizes vary greatly between 1 and 1700 TUs due to the variety of convenience stores supplied, resulting in an average order size of around 160 TUs across all delivery days. The delivery days and quantities of each store are predetermined. Each store supplied has a defined delivery time window or (as in most cases) multiple time windows in which the service needs to take place. The time windows depend on the type of store, opening hours, and additional service agreements (e.g., for premium customers). The actual time windows therefore range from a single 24-h window (e.g., gas station with 24-h service) through split delivery times (e.g., opening hours in the morning and/or afternoon) to tailored (i.e., store-individual) time windows defined by a service contract. For the case study, we test three different time window settings to analyze the implications of different company policies. In the base scenario (denoted as *opening hours*, OH), we relax time windows to opening hours of stores and therefore a less restricted planning. Additionally, we analyze two scenarios with stricter time windows. In the second scenario (denoted as *mixed time windows*, MTW), we consider a mix of opening hours and store-individual time windows, while in the third scenario (denoted as *store-individual time windows*, STW) we assume that only store-individual time windows apply. For STW, time windows have a length of two hours and there is one time window available in the morning and one in the afternoon. The tour length is restricted to 8 h 45 min, which represents the daily working hours available for the delivery. Break time is split into two breaks that are mandatory if a tour lasts more than six hours: one 30-min break that has to take place within the first six hours of a tour, and one 15-min break that may happen anytime during the tour, but not before the first nor after the last stop. Finally, the DC covers a large area of multiple cities with a maximum travel time of around 5 h between the two most remote locations.

Test overview. The detailed analysis aims at providing insights into the ALNS performance and the integration of breaks when time window restrictions exist. We conduct several tests to assess different settings relevant to industry. Table 3 summarizes the tests performed.

6.2.1. Algorithm analysis

Operator frequency. This test analyzes the use of operators within the ALNS and as such the contribution of single operators for the search. Operators are chosen with respect to their performance (see Section 5.6), and therefore their frequency is a good performance indicator. We conduct two tests for the operator analysis. First, we apply the ALNS without breaks, i.e., only the first search phase is used with $limit_1 = 2000$. Second, we apply the complete ALNS (including breaks) with the limits specified above. The tests are executed for scenario OH. Figs. 3 and 4 illustrate the corresponding operator frequencies.

Random removal is the most frequently used operator for the ALNS without breaks. Together with the routing and time relatedness measure, it accounts for 94% of removal operators used. This shows the need for both intensification and diversification operators and their

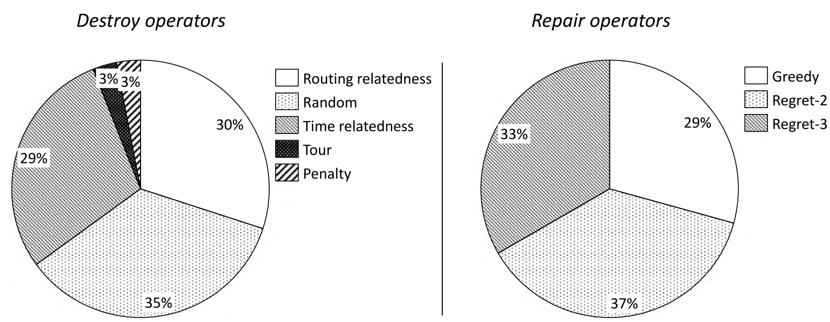

Fig. 3. Operator frequency for unrestricted routing (ALNS without breaks).

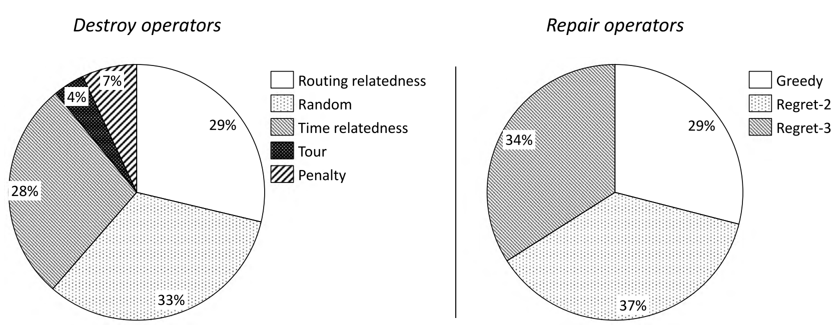

Fig. 4. Operator frequency for integrated breaks (ALNS with breaks).

Table 3
Overview of detailed analysis.

Section	Experiment	Description
6.2.1	Algorithm analysis	Analysis of operator frequency setting; analysis of search phase and operator setting;
6.2.2	Integration of break times	Impact of integrating break times on routing; status quo without breaks and scenario analysis; comparison with ex-post consideration of breaks
6.2.3	Impact of break setting	Impact of break time length on routing solutions, i.e., impact of extended long break (60+15 min), and 45-min break vs. two breaks (30+15 min)

Table 4
Scenario STW – Comparison of ALNS with and without first search phase.

Day	ALNS w/o first search phase		ALNS proposed		
	# tours/ incl. break	Late delivery[b]	Delta (in %)[a]	# tours/ incl. break	Late delivery[b]
1	16/7	–	−2,29%	15/6	–
2	25/9	–	−3,57%	23/11	–
3	21/11	–	−0,84%	18/11	–
4	24/13	–	−3,24%	22/13	–
5	23/9	–	−5,49%	21/10	–
Total	109/49	–	−3,14%	99/51	–

[a] Improvement in favor of ALNS proposed, i.e., complete algorithm including all operators and search phases.
[b] Extent to which deliveries are late (in minutes).

combination to improve results. The analysis also shows that the tour and penalty removal operators are used less frequently with a total share of around 6%. The most frequent repair operator is regret-2 insertion with 37%, closely followed by regret-3 (34%) and greedy (29%).

Operator use within the ALNS including breaks paints a similar picture. Repair operator use is almost identical to the case without breaks. Please note that a total frequency above 100% results from rounding. Again, random removal as well as the relatedness removals are used most frequently, at around 30% each. However, when breaks are considered, the importance of the penalty removal increases, resulting in a frequency of 7%. This can be attributed to the increased violation of time windows due to the time consumed by breaks. A repair operator for violated time windows therefore becomes more important. The tour removal frequency slightly increases from 3% to 4%. At first glance it seems that the removal of complete trucks does not significantly help the search to improve results. Yet additional tests without tour removal show that tour removal is needed for a diversified search as it helps to restructure the solutions found (see below).

Impact of first search phase. Subsequent to the operator frequency, we analyze the ALNS performance when only the second search phase is used. This means that breaks are added to the search right after the initial solution was found and $limit_1$ is set at 0. The tests are applied for Scenario STW since it is the most challenging scenario with respect to break times. Table 4 displays the comparison of the ALNS with and without the first search phase.

The ALNS proposed, i.e., including both search phases, outperforms the ALNS version without the first search phase by around 3% for the complete planning week. This shows the importance of the first search phase, where no breaks are considered. The first search phase builds a valuable basis for the subsequent search as it first solves an MCVRP without break times and thus a less restricted search for good routing solutions. Alongside the improvement of the overall solution quality, the search using both phases reduces the number of tours by 10 across the week. If only the second phase is used, the search for improved solutions is hindered by the breaks and tends to use more tours to compensate for the break times.

Table 5
Scenario STW – Comparison of ALNS including and excluding tour and penalty removal operators.

Day	ALNS excl. tour/penalty removal		ALNS proposed		
	# tours/ incl. break	Late delivery[b]	Delta (in %)[a]	# tours/ incl. break	Late delivery[b]
1	14/7	–	−4,16%	15/6	–
2	26/13	–	−5,40%	23 /11	–
3	22/12	–	−9,10%	18/11	–
4	23/13	–	−1,65%	22/13	–
5	25/10	–	−8,51%	21/10	–
Total	110/55	–	−5,73%	97/54	–

[a] Improvement in favor of ALNS proposed, i.e., complete algorithm including all operators and search phases.
[b] Extent to which deliveries are late (in minutes).

Reduced removal operator set. The final algorithm analysis provides insights into the use of the tour and penalty removal. In general, these operators are used less frequently than the other removal operators. We therefore compare the ALNS performance when the two operators are excluded to the complete ALNS proposed. Table 5 displays the results of the comparison.

The results show that the two removal operators significantly contribute to the overall performance of the ALNS. The ALNS including all operators performs 5.7% better than the setting without tour and penalty removal across the planning week. The penalty removal becomes more important with a more restrictive time setting. The tour removal is further a central operator to decrease the number of tours (110 vs. 97 tours across the planning week) and thus to concentrate the deliveries on fewer trucks. The removal of complete tours enables a new assignment of orders to other (existing) tours. The removal is therefore most important for the start of the improvement phase as otherwise the algorithm struggles to remove tours with a suboptimal setting. The reduction of tours is a secondary goal in retail practice, and in particular at our case company. Using fewer tours leads to additional savings as fewer drivers (and thus a more limited workforce) are needed.

6.2.2. Integration of break times

Subsequent to the algorithm performance, this section analyzes the impact of break times on short-distance routing with time window constraints. We examine the general impact of breaks and compare the results of the time window scenarios defined with and without the integrated consideration of breaks. In the event that break times are not integrated within the search – which resembles the prevailing approach in literature – an ex-post insertion is applied. This means that the routing problem is solved without break restrictions (i.e., the ALNS is reduced to search phase one), and after a final routing solution is obtained, breaks are inserted according to the requirements given (see Section 4). This may however lead to non-feasible results, i.e., a violation of delivery time restrictions (time windows and tour duration). We therefore allow a violation of time windows and assess the overall solution using the modified objective function f'. This allows us to directly compare the results and assess the magnitude of delays when breaks are neglected in the planning. We apply a linear penalty proportional to the extent of the delay to account for possible recourse in the event of time window violations, i.e., the penalization weight ζ is set at 1 for the final evaluation. A ten-minute delay thus results in a time penalty of ten minutes as well. Note that a violation of time windows represents a non-feasible solution in industry as hard time limits are contracted/mandatory. Simply adding a linear penalty to the solution underestimates actual costs as possible compensations would weigh considerably higher. The results are reported for each weekday of the case study and reveal the best solution for ten runs per instance.

Table 6
Status quo: route planning without break considerations.

Day	OH scenario		MTW scenario		STW scenario	
	Total duration	# tours/ tours > 6 h	Total duration	# tours/ tours > 6 h	Total duration	# tours/ tours > 6h
1	3,978	10/7	4,377	12/7	4,864	14/7
2	6,096	15/11	6,558	16/13	8,127	24/14
3	5,711	15/9	5,842	15/10	7,004	21/10
4	6,278	15/11	6,531	16/13	7,497	21/12
5	5,324	14/9	5,913	15/10	7,034	20/11
Total	29,475	69/47	31,607	74/53	36,956	100/54

Status quo - no breaks. We first evaluate the solution of the case study without break consideration. This means that the MCVRP_TWB presented is solved excluding break restrictions, i.e., the problem is reduced to an MCVRP with time windows. This enables us to assess the status quo for route planning and to analyze how many tours actually require breaks. Table 6 presents the results of the corresponding MCVRP with time windows.

The status quo analysis shows that up to 81% (MTW, day 2) of tours exceed 6 h of working time, which means break time is mandatory. Even in the STW scenario with the highest number of tours, and thus shortest routes, over 50% take more than 6 h. The distribution planning presented is consequently not feasible as it is not aligned with European regulations and could not be operated as planned. The consideration of breaks is therefore highly relevant for route planning in industry and needs to be integrated into route planning. We analyze how this integration impacts routing in the following scenarios.

Scenario OH. The results of the comparison for OH are displayed in Table 7. It shows that considering breaks increases overall tour duration by 7.19% (ex-post) and 6.4% (integrated) across the complete week. This represents a substantial impact on the distribution planning and the availability of drivers and vehicles. The additional time needed can be reduced by up to 1.4% (day 3) on a single day, and by 0.85% across the complete week when breaks are integrated in the search (vs. ex-post evaluation). Looking at the best solutions of the ex-post approach, a feasible solution (i.e., a solution without delayed deliveries) was obtained for three out of five delivery days as for days 1 and 5 a delay of around eight and 26 min occurs. The integrated approach always achieves feasible solutions. It further requires one tour less (68 tours), and the number of tours including breaks (i.e., tours that last more than 6 h) is 44 compared to 47 for the ex-post solutions. Table A.12 provides additional information on central tour characteristics of the OH scenario.

Scenario MTW. The MTW scenario additionally considers service agreements for individual stores. It is therefore more restricted than OH with respect to delivery times and offers a more realistic setting, resembling the prevailing situation at the retailer. Table 8 summarizes the results.

The findings of MTW paint a different picture from that of OH. While the overall increase in duration is comparable for both approaches at around 8% and 7.8%, the ex-post approach fails to find a feasible solution for any of the weekdays. In fact, the total delay across the complete week amounts to 2.65 h. This highlights that considerable changes to route planning are needed to implement break restrictions and adhere to time windows at the same time. This is demonstrated especially in the case of day 3, where the integrated approach leads to a 2.2% longer duration. While this result is counterintuitive at first glance, it shows the ability of the integrated approach to incorporate tighter time restrictions and to rebuild tours accordingly. In detail, an additional tour is required to adhere to the time restrictions. This enables a feasible delivery schedule and contrasts with the delay of 45 min in the ex-post scenario. The 45-min delay and the corresponding penalty can be compensated for by the shorter routes that are possible when breaks are neglected in the search. This solution is, however, not

Table 7
Scenario OH – Impact of break times for integrated vs. ex-post consideration.

Day	Ex-post			Integrated			
	Ex-post vs. w/o breaks	# tours/ incl. break	Late delivery[a]	Integrated vs. w/o breaks	Integrated vs. ex-post	# tours/ incl. break	Late delivery[a]
1	7.51%	10/7	8	6.67%	−0.90%	10/7	–
2	7.51%	15/11	–	7.04%	−0.51%	15/9	–
3	6.62%	15/9	–	5.35%	−1.36%	14/9	–
4	7.31%	15/11	–	6.75%	−0.61%	15/11	–
5	7.07%	14/9	26	6.16%	−0.98%	14/8	–
Total	7.19%	69/47	34	6.40%	−0.85%	68/44	–

[a] Extent to which deliveries are late (in minutes).

Table 8
Scenario MTW – Impact of break times for integrated vs. ex-post consideration.

Day	Ex-post			Integrated			
	Ex-post vs. w/o breaks	# tours/ incl. break	Late delivery[a]	Integrated vs. w/o breaks	Integrated vs. ex-post	# tours/ incl. break	Late delivery[a]
1	7.31%	12/7	30	7.29%	−0.02%	11/8	–
2	8.85%	16/13	52	7.71%	−1.24%	17/12	–
3	7.81%	15/10	45	9.84%	2.20%	16/10	–
4	8.59%	16/13	29	8.27%	−0.35%	16/12	–
5	7.12%	15/10	3	5.73%	−1.50%	16/11	–
Total	8.01%	74/53	159	7.82%	−0.21%	76/53	–

[a] Extent to which deliveries are late (in minutes).

Table 9
Scenario STW – Impact of break times for integrated vs. ex-post consideration.

Day	Ex-post			Integrated			
	Ex-post vs. w/o breaks	# tours/ incl. break	Late delivery[a]	Integrated vs. w/o breaks	Integrated vs. ex-post	# tours/ incl. break	Late delivery[a]
1	9.00%	14/7	166	3.73%	−5.79%	15/6	–
2	9.53%	24/14	226	5.17%	−4.81%	21 /14	–
3	8.32%	21/10	186	5.35%	−3.24%	18/11	–
4	10.58%	21/12	347	10.12%	−0.52%	22/13	–
5	9.10%	20/11	209	1.35%	−8.52%	21/10	–
Total	9.36%	100/54	1,134	5.39%	−4.37%	97/54	–

[a] Extent to which deliveries are late (in minutes).

feasible as time windows are violated. The number of tours required to accommodate breaks increases by two trucks across the complete week, with 74 trucks (ex-post) vs. 76 (integrated).

Scenario STW. The last scenario represents the most restrictive time window setting, with store-individual time windows of two hours across all stores. Table 9 illustrates the results.

The impact of an even stricter time window setting accentuates the results of MTW. The extent to which deliveries are late for the ex-post approach increases significantly with store-individual time windows. The time involved in late deliveries exceeds 18 h across the complete week, and results in an additional duration of 9.4%. As such, the building of shorter routes (ex-post) is not able to compensate for the resulting time accounted for by late deliveries. The integrated approach is able to compensate for the break time, resulting in feasible solutions for all days and an additional duration of only 5.4%. This highlights the strong need to already integrate break times in route building as otherwise non-feasible solutions with a significant amount of delay are obtained. This is also reflected in the comparison of solution values. The possible savings of the integrated search are 4.37% across the week, with a maximum of more than 8% (day 5). Moreover, the integrated search reduces the number of vehicles (tours) needed, while the number of tours including breaks equals 54 for both approaches. A reduction of tours is possible as break times can also be used as buffer time to reach the time windows of stores.

Scenario comparison. Our results highlight the complexity of the planning problem with break times and time windows. Route planning requires the minimization of tour duration and the feasibility of delivery times at the same time. The adherence to time restrictions when breaks are needed shows the tradeoff between shorter tours and punctual deliveries. Comparing the results of all three scenarios, we see that the need for integrating breaks increases with a more restricted time window setting. Otherwise, delays and thus non-feasible solutions have a significant impact on routing costs, culminating in more than 18 h of delay for the complete planning week. Moreover, the different scenarios show that the retailer's time window policy has a major impact on route planning. The number of tours rises from 68 (OH, integrated approach) to 97 (STW, integrated approach). At the same time, possible savings increase when using an integrated planning approach. Summarizing our findings, we can state that the consideration of break times may be neglected if no strict time window agreements exist. However, integrated planning is indispensable in a setting with store-individual time windows for some (MTW) or all stores (STW).

6.2.3. *Impact of break setting*

The final analysis addresses the impact of break settings. The model approach (see Section 4) enables the use of multiple breaks of different lengths. So far, we focused on two breaks of 30 and 15 min, as used at our partner in industry. We compare this standard setting to a possible scenario with an increased break time of 60 min plus 15 min as well as to a one-break policy. Both comparisons are conducted for the STW scenario since it is the most restrictive setting and most sensitive to break times.

Table 10
STW scenario: Impact of extended break time.

Day	Ex-post		Integrated		
	# tours/ incl. break	Late delivery[a]	Integrated vs. ex-post	# tours/ incl. break	Late delivery[a]
1	14/6	246	−1,89%	14/7	–
2	20/12	890	0,84%	22 /15	–
3	19/11	716	−3,25%	21/12	–
4	20/13	892	−7,12%	22/12	–
5	20/10	570	−2,79%	19/12	–
Total	93/52	3,315	−2,85%	98/58	–

[a] Extent to which deliveries are late (in minutes).

Table 11
STW scenario: Advantage of multiple breaks.

Day	45-min break	30- & 15- min breaks		Improvement for 30+15
	# tours/ tours incl. break	# tours/ tours incl. break	# combined breaks[a]	
1	14/7	15/6	2	−1.73%
2	22/13	22/13	13	–
3	20/13	18/11	6	−1.64%
4	21/11	21/11	11	–
5	20/9	21/10	7	−2.90%
Total	97/53	97/51	39	−1.16%

[a] 30-min and 15-min breaks combined to one 45-min break, i.e., scheduled consecutively.

Extended long break. The first analysis of the break setting considers the case when a 60 min break instead of a 30 min break is needed as long break. The short break of 15 min stays unchanged. This could, for instance, reflect the need for lunch breaks or a longer period of time where stores are closed during the day. We further extend the total tour duration by 30 min (i.e., 9 h 15 min) to enable the same tour duration with respect to driving and service time of 8 h and to reflect the longer break time. Table 10 summarizes the comparison of the ex-post evaluation and the integrated approach.

The experiment endorses the results of our tests for the standard setting. The extent of late deliveries further increases due to the longer break times and intensifies the issue of non-feasible deliveries. The lateness of deliveries sums up to more than 55 h for the complete week, and to more than 14 h for a single delivery day (day 4). The longer the break time needed, the longer are the resulting lateness and potential penalties in the event that breaks are neglected within the route planning.

One-break policy. The second analysis reduces the number of breaks to one. This setting allows us to assess the advantages of a more liberal two-break setting compared to a predetermined single break. We therefore apply a single break of 45 min (total break length as in the standard setting) that has to be taken within the first six hours of the tour in the event a break is needed. Table 11 displays our findings.

The comparison of break settings shows that a flexible setting (30+15) leads to improvements of up to 2.9% and an overall improvement of 1.16% compared to a strict one-break policy. For three out of five days, an improvement is possible when breaks are split, while for two days the best solution found can be achieved when breaks are combined, i.e., a 45-min break is used. Interestingly, also for days 3 and 5, 54% and 70% of breaks are combined to a 45-min break in the two-break setting. The results indicate that even for a higher degree of freedom with respect to break times, many breaks are combined and result in 45-min breaks.

7. Conclusion

The work presented addresses a delivery problem relevant in practice for the supply of convenience stores. Besides this special application, our model and solution approach are relevant for similar applications in the retail industry and short-distance routing. It further provides an essential contribution to existing VRP and MCVRP literature. We consider the actual distribution requirements for a large European retailer that mostly supplies gas stations, kiosks, and other variants of convenience stores. We formulate the MCVRP_TWB to address all relevant distribution requirements. The model takes into account multiple time windows for the supply of stores, ranging from opening hours to strict delivery time windows. Moreover, we integrate working hour regulations for drivers that are strictly regulated and thus need to be considered in distribution planning to obtain feasible routing solutions. Despite their relevance for practical applications, break times have not been considered sufficiently within VRP literature for daily routing. The MCVRP_TWB is solved using a tailored ALNS formulation that applies problem-specific operators and a break adjustment mechanism step. The ALNS outperforms an existing state-of-the-art approach for MCVRPs by up to 3.8%. Our solution approach is further able to solve different problem settings with respect to break requirements effectively and provides feasible solutions when time windows are restrictive and breaks are needed.

In our numerical experiments, we leverage a case study and show the impact of break times on planning when time restrictions exist. Assessing the status quo for distribution planning, we show that breaks are needed in up to 81% of tours planned and thus highlight the need to take break times into account. We compare our integrated approach to a solution where breaks are inserted ex-post once the routing has been solved. In the event that breaks are not integrated within the search, non-feasible solutions are obtained for all delivery days. This leads to more than 18 h of late deliveries for a complete planning week in the most restrictive scenario, which is not acceptable from a practical point of view. The integrated search on the other hand provides feasible solutions (i.e., meeting all time window requirements) while integrating break times into the routing solutions. This results in the opportunity to make time savings of up to 4.2% compared to an ex-post insertion. Our experiments demonstrate the important tradeoff between an integrated planning of breaks for in-time deliveries (i.e., respecting time window and tour duration restrictions), and a complete focus on an improved routing without breaks, risking penalties for delayed deliveries. The latter may only be beneficial when no tight time restrictions exist (e.g., wide opening hours of stores without delivery time windows).

Following our work, there are various opportunities for future areas of research. The integration of break times and further practice-driven restrictions are often neglected in related routing problems. These requirements should, however, be integrated into other applications and problem variants to ensure feasible solutions and to analyze their impact on distribution planning. This may be especially true for applications in last-mile delivery when customers are supplied directly. We further assume predetermined travel and service times. The consideration of stochastic times further contributes to more realistic planning for industry, and break times may be used as buffer times for possible uncertainties during delivery. A further step towards solutions for real-world problems would be an extension to consider different vehicle types. Retailers often operate mixed fleets with small trucks for deliveries in inner cities and larger ones for deliveries in rural areas. In general, MCVs are considered to be fuel-powered. The use of electric vehicles in this context and a possible combination of recharging and break times are interesting options for future research. Finally, we apply an ALNS to solve realistic problem sizes. The development of exact approaches for smaller problem sizes could help to further assess the impact of break times and different settings on the overall planning problem.

Acknowledgments

The author is grateful to the retailer, i.e., the case company that we collaborated with on this project, for their support and many helpful contributions. We would like to extend our special thanks to the logistics department and their valuable recommendations, which significantly improved our research.

Appendix. Statistics on routing solution

Table A.12 summarizes essential information on the capacity utilization and shares of compartments for the base scenario (OH). It shows an average utilization of 81% across the entire planning week, with full trucks on every delivery day (utilization ≥ 99%).

Table A.12
Scenario OH: tour statistics for the planning week.

Day	Capacity Utilization			Average share of		
	Average	Max	Min	Segment 1	Segment 2	Segment 3
1	80%	99%	39%	82%	5%	13%
2	87%	99%	50%	83%	6%	11%
3	81%	99%	32%	80%	6%	13%
4	78%	100%	30%	82%	6%	13%
5	80%	100%	19%	79%	9%	12%
All	81%	100%	19%	81%	6%	12%

References

Agrawal, N., & Smith, S. A. (2015). Retail supply chain management: quantitative models and empirical studies. *International Series in Operations Research & Management Science*, Springer US.

Alinaghian, M., & Shokouhi, N. (2018). Multi-depot multi-compartment vehicle routing problem, solved by a hybrid adaptive large neighborhood search. *Omega*, *76*, 85–99.

Amorim, P., Parragh, S. N., Sperandio, F., & Almada-Lobo, B. (2014). A rich vehicle routing problem dealing with perishable food: a case study. *TOP*, *22*(2), 489–508.

Archetti, C., & Savelsbergh, M. (2009). The trip scheduling problem. *Transportation Science*, *43*(4), 417–431.

Baldacci, R., Mingozzi, A., & Roberti, R. (2012). Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints. *European Journal of Operational Research*, *218*(1), 1–6.

Bowden, Z. E., & Ragsdale, C. T. (2018). The truck driver scheduling problem with fatigue monitoring. *Decision Support Systems*, *110*, 20–31.

Buhrkal, K., Larsen, A., & Ropke, S. (2012). The waste collection vehicle routing problem with time windows in a city logistics context. *Procedia - Social and Behavioral Sciences*, *39*, 241–254, Seventh International Conference on City Logistics, June 7-9, 2011, Mallorca, Spain.

Chajakis, E. D., & Guignard, M. (2003). Scheduling deliveries in vehicles with multiple compartments. *Journal of Global Optimization*, *26*, 43–78.

Chen, L., Liu, Y., & Langevin, A. (2019). A multi-compartment vehicle routing problem in cold-chain distribution. *Computers & Operations Research*, *111*, 58–66.

Chen, J., & Shi, J. (2019). A multi-compartment vehicle routing problem with time windows for urban distribution – a comparison study on particle swarm optimization algorithms. *Computers & Industrial Engineering*, *133*, 95–106.

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., Gagliardi, J. P., Renaud, J., & Ruiz, A. (2016). Solving the vehicle routing problem with lunch break arising in the furniture delivery industry. *Journal of the Operational Research Society*, *67*(5), 743–751.

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.

Desaulniers, G., Madsen, O. B., & Ropke, S. (2014). Chapter 5: The vehicle routing problem with time windows. In P. Toth, & D. Vigo (Eds.), *MOS-SIAM series on optimization*: *vol. 18*, *Vehicle routing: Problems, methods, and applications* (2nd ed.). (pp. 119–159). Society for Industrial and Applied Mathematics.

Dueck, G. (1993). New optimization heuristics. *Journal of Computational Physics*, *104*(1), 86–92.

European Union (2002). Directive 2002/15/EC of the European Parliament and of the Council of 11 March 2002 on the organisation of the working time of persons performing mobile road transport activities. *Official Journal of the European Communities, L80*, 35–39.

European Union (2006). Regulation (EC) No 561/2006 of the European Parliament and of the Council of 15 March 2006 on the harmonisation of certain social legislation relating to road transport and amending Council Regulations (EEC) No 3821/85 and (EC) No 2135/98 and repealing Council Regulation (EEC) No 3820/85. *Official Journal of the European Union L 102*.

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.

Frank, M., Ostermeier, M., Holzapfel, A., Hübner, A., & Kuhn, H. (2021). Optimizing routing and delivery patterns with multi-compartment vehicles. *European Journal of Operational Research*, *293*, 495–510.

Gendreau, M., Potvin, J. Y., Bräumlaysy, O., Hasle, G., & Løkketangen, A. (2008). Metaheuristics for the vehicle routing problem and its extensions: A categorized bibliography. In B. Golden, S. Raghavan, & E. Wasil (Eds.), *Operations research/Computer science interfaces series*: *vol. 43*, *The vehicle routing problem: Latest advances and new challenges* (pp. 143–169). Springer.

Gendreau, M., & Tarantilis, C. D. (2010). Solving large-scale vehicle routing problems with time windows: The state-of-the-art. Technical report CIRRELT 2010-04.

Goel, A. (2009). Vehicle scheduling and routing with drivers' working hours. *Transportation Science*, *43*(1), 17–26.

Goel, A. (2010). Truck driver scheduling in the European Union. *Transportation Science*, *44*(4), 429–441.

Goel, A. (2012). The minimum duration truck driver scheduling problem. *EURO Journal on Transportation and Logistics*, *1*(4), 285–306.

Goel, A. (2018). Legal aspects in road transport optimization in Europe. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 144–162.

Goel, A., Archetti, C., & Savelsbergh, M. (2012). Truck driver scheduling in Australia. *Computers & Operations Research*, *39*(5), 1122–1132.

Goel, A., & Irnich, S. (2017). An exact method for vehicle routing and truck driver scheduling problems. *Transportation Science*, *51*(2), 737–754.

Goel, A., & Kok, L. (2012). Truck driver scheduling in the United States. *Transportation Science*, *46*(3), 317–326.

Goel, A., & Vidal, T. (2014). Hours of service regulations in road freight transport: An optimization-based international assessment. *Transportation Science*, *48*(3), 391–412.

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.

Grünrock-Kern, U. (2013). Deutscher Logistik-Preis 2013 fuer Lekkerland. URL http://www.bvl.de/presse/meldungen/archiv-2013/deutscher-logistik-preis-2013-fuer-lekkerland.

Henke, T., Speranza, M. G., & Wäscher, G. (2015). The multi-compartment vehicle routing problem with flexible compartment sizes. *European Journal of Operational Research*, *246*, 730–743.

Hsiao, Y. H., Chen, M. C., & Chin, C. L. (2017). Distribution planning for perishable foods in cold chains with quality concerns: formulation and solution procedure. *Trends in Food Science & Technology*, *61*, 80–93.

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.

Hübner, A., & Ostermeier, M. (2019). A multi-compartment vehicle routing problem with loading and unloading costs. *Transportation Science*, *53*, 282–300.

Kim, B. I., Kim, S., & Sahoo, S. (2006). Waste collection vehicle routing problem with time windows. *Computers & Operations Research*, *33*(12), 3624–3642.

Kleff, A. (2019). *Scheduling and routing of truck drivers considering regulations on drivers' working hours* (Ph.D. thesis), Karlsruher Institut für Technologie (KIT).

Koç, Ç., Jabali, O., & Laporte, G. (2018). Long-haul vehicle routing and scheduling with idling options. *Journal of the Operational Research Society*, *69*(2), 235–246.

Kok, A. L., Hans, E. W., Schutten, J. M. J., & Zijm, W. H. M. (2010). A dynamic programming heuristic for vehicle routing with time-dependent travel times and required breaks. *Flexible Services and Manufacturing Journal*, *22*(1–2), 83–108.

Kok, A. L., Meyer, C. M., Kopfer, H., & Schutten, J. M. J. (2010). A dynamic programming heuristic for the vehicle routing problem with time windows and European community social legislation. *Transportation Science*, *44*(4), 442–454.

Kovacs, A. A., Parragh, S. N., & Hartl, R. F. (2014). A template-based adaptive large neighborhood search for the consistent vehicle routing problem. *Networks*, *63*(1), 60–81.

Kuhn, H., & Sternbeck, M. G. (2013). Integrative retail logistics: an exploratory study. *Operations Management Research*, *6*(1–2), 2–18.

Laporte, G. (2009). Fifty years of vehicle routing. *Transportation Science*, *43*(4), 408–416.

Martins, S., Ostermeier, M., Amorim, P., Hübner, A., & Almada-Lobo, B. (2019). Product-oriented time window assignment for a multi-compartment vehicle routing problem. *European Journal of Operational Research*, *276*, 893–909.

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*, 93–103.

Ostermeier, M., Henke, T., Hübner, A., & Wäscher, G. (2021). Multi-compartment vehicle routing problems: State-of-the-art, modeling framework and future directions. *European Journal of Operational Research*, *292*, 799–817.

Ostermeier, M., & Hübner, A. (2018). Vehicle selection for a multi-compartment vehicle routing problem. *European Journal of Operational Research*, *269*, 682–694.

Ostermeier, M., Martins, S., Amorim, P., & Hübner, A. (2018). Loading constraints for a multi-compartment vehicle routing problem. *OR Spectrum*, *40*, 997–1027.

Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & Operations Research*, *34*(8), 2403–2435.

Pollaris, H., Braekers, K., Caris, A., Janssens, G. K., & Limbourg, S. (2015). Vehicle routing problems with loading constraints: State-of-the-art and future directions. *OR Spectrum*, *37*, 297–330.

Prescott-Gagnon, E., Desaulniers, G., Drexl, M., & Rousseau, L. M. (2010). European driver rules in vehicle routing with time windows. *Transportation Science*, *44*(4), 455–473.

Prescott-Gagnon, E., Desaulniers, G., & Rousseau, L. M. (2009). A branch-and-price-based large neighborhood search algorithm for the vehicle routing problem with time windows. *Networks*, *54*(4), 190–204.

Rancourt, M. E., Cordeau, J. F., & Laporte, G. (2013). Long-haul vehicle routing and scheduling with working hour rules. *Transportation Science*, *47*(1), 81–107.

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.

Sahoo, S., Kim, S., Kim, B. I., Kraas, B., & Popov, A. (2005). Routing optimization for waste management. *INFORMS Journal on Applied Analytics*, *35*(1), 24–36.

Savelsbergh, M., & Sol, M. (1998). Drive: Dynamic routing of independent vehicles. *Operations Research*, *46*(4), 474–490.

Shaw, P. (1997). *A new local search algorithm providing high quality solutions to vehicle routing problems*. Glasgow, Scotland, UK: APES Group, Dept of Computer Science, University of Strathclyde.

Solomon, M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research*, *35*, 254–265.

Taillard, E., Badeau, P., Gendreau, M., Guertin, F., & Potvin, J. Y. (1997). A tabu search heuristic for the vehicle routing problem with soft time windows. *Transportation Science*, *31*(2), 170–186.

Tilk, C., & Goel, A. (2020). Bidirectional labeling for solving vehicle routing and truck driver scheduling problems. *European Journal of Operational Research*, *283*(1), 108–124.

Toth, P., & Vigo, D. (2014). *MOS-SIAM series on optimization*, *Vehicle routing: Problems, methods, and applications* (2nd ed.). Society for Industrial and Applied Mathematics.

Van Landeghem, H. (1988). A bi-criteria heuristic for the vehicle routing problem with time windows. *European Journal of Operational Research*, *36*(2), 217–226.

Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., & Rei, W. (2012). A hybrid genetic algorithm for multidepot and periodic vehicle routing problems. *Operations Research*, *60*, 611–624.

Xu, H., Chen, Z. L., Rajagopal, S., & Arunapuram, S. (2003). Solving a practical pickup and delivery problem. *Transportation Science*, *37*(3), 347–364.

Zbib, H., & Wøhlk, S. (2019). A comparison of the transport requirements of different curbside waste collection systems in Denmark. *Waste Management*, *87*, 21–32.