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Location flexibility in parcel delivery operations: framework and empirical analysis

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In traditional parcel delivery operations, customers determine delivery locations and, hence, the performance of a transporter. We exploit this idea and show that customers can improve the efficiency of a transporter by giving the latter flexibility in choosing the delivery locations. Two possible policies to enable this flexibility are presented and evaluated. The first policy, conceptually similar to roaming vehicle routing, is related to the presence of alternative locations. The second policy is related to the possibility of aggregating/skipping some locations. We show that route optimization behind both policies can be modelled via the well-known generalized travelling salesman problem. Extensive computational experiments with real parcel delivery data are performed to evaluate the potential of the presented policies and to obtain insights for possible implementation in daily practice. The experiments show that under certain conditions, the two proposed policies can lead to 15 to 20% improvement in the route length and in extreme yet realistic cases up to 40 to 50%. Consequently, the concept of flexible delivery locations has potential for practice, especially in densely populated areas.

Keywords: parcel delivery; location flexibility; vehicle routing.

1. Introduction

After many years of a double-digit growth, the global turnover of business-to-customer e-commerce reached EUR 19.43 billion in 2015 (Kalinić *et al.*, 2016). Ordering from home (or work) and delivery by parcel has become a popular shopping practice in daily life (McLeod *et al.*, 2006). The rise of e-commerce leads to high fragmentation of shipments (Esser & Kurte, 2013; Schewel & Schipper, 2012), resulting in an unprecedented high number of parcel deliveries in last miles. Consequently, a huge pressure is imposed on current parcel delivery networks to improve their operational efficiency. However, in today's highly demanding environment, establishing an efficient last-mile parcel delivery network is a very challenging task, as confirmed by Gevaers *et al.* (2011) who claim that last-mile delivery is usually the least efficient part of supply chains. It is also considered one of the most expensive

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and polluting sections of the entire logistics (Gevaers *et al.*, 2014). According to Du *et al.* (2005), delivery in a business-to-consumer (B2C) e-commerce environment is fundamentally different from that in a business-to-business environment. The orders in an online B2C environment are mostly small in size, unique and diverse in terms of timing and location. This makes the coordination between sellers and customers extremely difficult. As a result, there are substantial challenges faced by parcel carriers (e.g. DHL, PostNL, UPS) to improve their performance in the last-mile parcel delivery.

Thus, a steadily increasing demand of parcel delivery services puts an increasingly high pressure on logistics service providers. This pressure is expressed not only in terms of costs (due to strong competition in this field, the margins are very low) but also in terms of ecological (e.g. CO_2 emissions) and social (e.g. traffic congestion) factors. The attempts of improving the efficiency of parcel delivery can be broadly classified into two main categories:

- route optimization: design of cheap, short, fast, etc. routes;
- fleet optimization: ensuring high vehicle utilization (full truck loads) and small fleet used.

Route optimization has a very rich history, and both shortest path and shortest tour problems can be solved quite efficiently to optimality, sometimes even in presence of complicating factors, such as additional restrictions or uncertainties, see e.g. Parmentier & Meunier (2014), Randour *et al.* (2014), Lozano *et al.* (2016), Liao (2019), Adulyasak & Jaillet (2016), Gendreau *et al.* (2016) and Xue *et al.* (2016). However, this also means that there is little room left for performance improvement of a transportation system by considering the traditional routing only.

Fleet optimization is also extensively addressed in the literature in the recent decades and is now a rather mature field. There are a variety of approaches, ranging from cross-docking (Belle *et al.*, 2012; Ladier & Alpan, 2016) and fleet mix optimization (usually integrated into vehicle routing, see e.g. Hoff *et al.*, 2010) to such 'exotic' ones as using taxis (Li *et al.*, 2015), public transport (Ghilas *et al.*, 2016) or drones (Ha *et al.*, 2018; Macrina *et al.*, 2020; Murray & Chu, 2015) for parcel delivery. Thus, we are getting close to the limits in this field, as well.

To sum up, due to impressive advances in the solution techniques, the performance of existing approaches reaches its natural limits (defined by the optimal solutions) while the volumes of parcel delivery grow steadily. This mismatch dictates the need for innovative approaches. What is common for a major part of the research on transportation is that it follows a *passive customer perspective*: the customer requests are assumed to be fixed and the transporter's goal is to fulfil them in an efficient way. On the contrary, we propose a more *pro-active customer perspective*: make customers adjust their requests to facilitate efficient transportation. At a first glance, this seems to have a negative impact on the service levels: customers just want comfort, they do not want to adjust. Yet, we present *two policies* leading to a win–win situation—more space for traffic optimization (flexibility of delivery locations) and an additional reward for the customers (e.g. improved service levels, discounted delivery charges) at the same time. In this perspective, the customer engagement facilitates the distribution of the parcels implicitly and explicitly. Besides certain logistic advantages, this can be seen as a step towards sustainable consumption because customers become involved in the logistics process and get both a feeling of the burden they create and an opportunity to relieve the related challenges. In a long run, this may trigger the customers to reconsider their ordering behaviour.

Yet, having an attractive concept is not enough. A thorough computational study involving realistic data is necessary to understand the limitations and the potential for practice. As shown in Turkensteen & Hasle (2017), simple logic and testing on small datasets do not always provide adequate insights in real-life performance of logistic concepts.

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The goal of this paper is to design a concept and its implementation (policies) of introducing a flexibility of delivery locations and to quantify its impact on the performance of parcel delivery services using historical data. A very large dataset is used and case-specific features are avoided as much as possible to reveal the general trends implied by the proposed policies. In addition, we show that the so-called concept of roaming delivery locations (Reyes *et al.*, 2017) is a special case of a more general concept of flexible locations.

The rest of the paper is organized as follows. Section 2 positions this paper within the existing literature. In Section 3, we present two policies of introducing a flexibility of delivery locations. Sections 4 and 5 focus, respectively, on the model and the dataset used for the computational experiments summarized in Section 6. Finally, Section 7 provides a discussion of the results and managerial insights for a potential implementation.

2. Literature review

In the past decade, the improvement of last-mile performance has gained substantial attention in the literature, especially in the field of city logistics, see an overview in, e.g. Olsson *et al.* (2019). The existing literature addresses a broad range of topics related to the improvement of the last-mile performance, from network redesign (Ewedairo *et al.*, 2018) and new business models (Akeb *et al.*, 2018; Castillo *et al.*, 2018) to innovative vehicle solutions (de Mello Bandeira *et al.*, 2019; Ghilas *et al.*, 2016; Ha *et al.*, 2018; Li *et al.*, 2015; Macrina *et al.*, 2020; Simoni *et al.*, 2020) and route optimization with additional restrictions (Cerulli *et al.*, 2017).

We focus on the situation when a number of parcels have to be delivered from a central location (warehouse, transportation hub, etc.) to a number of geographically dispersed clients, i.e. the *one-to-many* transportation pattern. This is in contrast to the *many-to-many* pattern addressed for example in Allahviranloo & Baghestani (2019); Li *et al.* (2015).

Our contribution is closely related to the works on roaming delivery locations (see, e.g. Reyes *et al.*, 2017) and on crowd logistics (see, e.g., Akeb *et al.*, 2018).

The essence of the roaming delivery locations is that the destination address of every parcel changes over time. This provides some flexibility for the transporter (alternative delivery locations) but complicates the decision making because the timing has to be explicitly taken into account while constructing the vehicle routes. Route optimization with roaming delivery locations is computationally intractable for many practically relevant problem sizes, see Ozbaygin *et al.* (2017) for the performance of the exact approach. Hence, heuristic approaches have been developed for both the deterministic (Reyes *et al.*, 2017) and the stochastic version of the problem (He *et al.*, 2020; Lombard *et al.*, 2018; Sampaio *et al.*, 2019). In contrast to the concept of roaming delivery locations, we assume that the alternative addresses are available at any time (this assumption is justified in Section 3). This makes the timing irrelevant and simplifies the modelling and computations.

The concept of crowd logistics suggests involving the customers (or even more general public) in the process of parcel delivery (Mehmann *et al.*, 2015). The related literature focuses on grouping of the customers and determining the routes within the 'crowd', see for example Akeb *et al.* (2018). In our study, crowd logistics plays a complementary role within a combined transportation system involving both vehicle and crowd delivery. This is similar to the so-called dual-mode delivery (see, e.g. Nguyen *et al.*, 2019), but the walking part of the route, in our case, is performed by the customers rather than the driver.

The contribution of this study is two-fold. First, we propose a concept that generalizes the concepts of roaming delivery locations and crowd logistics. Second, we provide insights into realistic

performance of the concept. This is important because the datasets used in a majority of papers have at least one of the following features: (i) artificially generated data, (ii) aggregated data and (iii) small size of the dataset. In contrast, we use a large real-life dataset (see Section 5) containing precise locations of individual customers.

3. Location flexibility

In this section, we consider two policies of introducing a flexibility of delivery locations. It is assumed that the parcels are small and lightweight enough to be carried conveniently by one person: books, small utility goods, gadgets, etc. Further, although we speak mainly about reducing the distances travelled, it is important to keep in mind that distances are tightly connected to transportation costs and times, emissions and congestion (the more time vehicles spend on the road, the more congested the road is).

The *first policy* relies on a fact that customers usually do not spend the whole day in one place. For example, they may spend some time at home, at their workplace, at relatives, etc. In the classical setting, this creates challenges for logistics service providers, as they are restricted to a single address and a shorter time frame when the customer is available at the address. However, considered from a different perspective, this situation also creates opportunities. Imagine that a customer provides more than one address where he can pick up his parcel (also, the corresponding time frames). This makes the logistic service provider decisions more flexible by providing extra options for the delivery address and time. Even if only home–workplace alternatives are considered, the impact can be substantial, as the current trend is towards working at a distance from home. For example, the average home–workplace distance in The Netherlands is between 12 and 20 km, according to different estimates, see Centraal Bureau voor de Statistiek (2016a) and Centraal Bureau voor de Statistiek (2016b, p.24). Further, taking the rising popularity of public transportation (International Association of Public Transport, 2016) into account, lockers at railway or bus stations can be considered as another alternative for the delivery location. This alternative has an inherent advantage of having wide time windows: lockers are always accessible and the customers would normally pick up their parcels on their way back home in the late afternoon, thus leaving a major part of the day available for the delivery. Another possibility for an alternative address is the place of parents or close friends. Again, depending on the situation (e.g. retirement, working at home, etc.), the availability of the alternative address can be much higher than that of the original one, making the timing constraints (time windows) less important.

It should be mentioned that a similar concept of roaming delivery locations has been recently studied in Ozbaygin *et al.* (2017) and Reyes *et al.* (2017), but instead of alternative addresses the authors consider delivering to the trunk of a customer's car with a known itinerary. That setting, however, reduces the applicability of the policy to drivers and imposes a number of complications: tighter time windows, itineraries have to be known in advance (privacy issues) and itineraries usually change more often than addresses, implying more data to handle for the logistics service provider and longer forms to fill in for the customer.

The *second policy* is based on a rather different idea but has the same outcome—it provides alternatives for delivery locations. This policy relies on two assumptions. First, customers would agree to pick up their parcels from a neighbour located within a short distance, in exchange for some reward for the inconvenience. This reward is not necessarily expressed in monetary terms, like a one-time discount or a membership card. Instead (or in addition), customers can be motivated by increased service levels, by their contribution to a 'greener' consumption or to solving traffic problems (in their district), etc. The second assumption is that a customer receiving a parcel would not mind receiving some more parcels for other customers who will come to pick them up. In fact, a similar practice already takes

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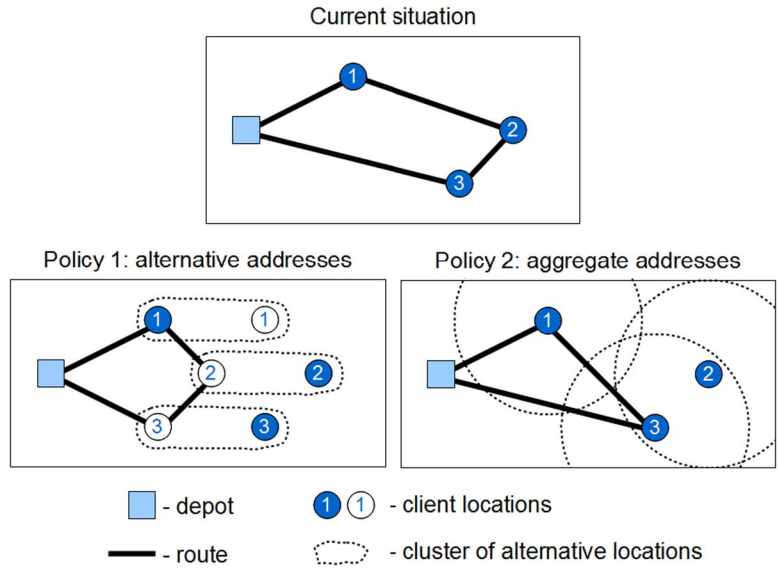


FIG. 1. An overview of the proposed policies.

place in The Netherlands and some other countries: if a parcel cannot be delivered (the customer is not at home), then it is delivered at the neighbours. This is currently a back-up activity, however. In principle, a logistic service provider can plan a route to visit fewer customers and to leave there the parcels for their neighbours. This flexibility in choosing which customers to visit provides advantages both in the distance travelled and in the time spent at customers. Also, this reduces the number of delivery stops—one of the main factors causing the inefficiency of the last mile, according to Aljohani & Thompson (2020). At a late stage of working on this paper, we became aware that a similar concept is implemented: ViaTim (see www.viatim.nl for details).

Thus, the major difference between the two policies is as follows. In the first policy, the potential gain results from choosing a location where each customer is served, while the total number of visited locations is fixed. In the second policy, the gain results from visiting fewer locations (customers). Figure 1 visualizes this point. Despite this dissimilarity, it will become apparent in the next section that from a modelling, and thus computational, perspective the policies are essentially equivalent.

Though both policies have a time-related component (time windows for the first one, service times for the second), it is not considered in this paper, and we focus on the spatial aspect. This choice is governed by the following major reasons. First of all, our dataset contains only spatial information. Including fictitious timing would compromise the realistic nature of the dataset and make the outcomes questionable. Also, timing is very case specific: some locations are easier for parking than others, some customers are immediately accessible from the street, for some others the courier has to go through corridors and levels. Time windows are very personal and vary a lot. Yet, the most attractive cases are when the alternative addresses have wide time windows (lockers at stations, relatives who spend most of the time at home, etc.) thus making time windows less relevant. So, including the timing (even if it is realistic) severely limits the generality of the outcomes. Another reason is the tractability of the

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related optimization problems. Given the large size of the dataset (5428 routes), it is crucial to keep the computational complexity as low as possible.

4. Research methodology

In order to have a common base for modelling the policies introduced in Section 3, it is useful to define the notion of a *cluster*—a set of locations such that at least one location from this set must be visited. Given this definition, in the first policy, a cluster associated to a customer is a set of alternative addresses of this single customer. Generally speaking, customers are independent and each pair of clusters has an empty intersection (see Fig. 1). Even if some locations are geographically close to each other or coincide (e.g. lockers or collection points), they can be treated as separate locations in the model. The size of a cluster is determined by the number of alternative addresses of the corresponding customer, usually 2 or 3. In the second policy, a cluster associated to a customer contains the location of this customer and those of all neighbours within a certain fixed distance (an input for the model). Thus, the clusters do intersect, unless all customers are distant from each other. The clusters may vary in size greatly: customers within densely populated areas have larger clusters than those living in rural areas.

The goal of the model under consideration is to find a shortest route that starts and ends at a depot and visits each cluster at least once (*cluster constraints*). The depot is assumed to be assigned a cluster containing that single location. In the first policy, it is necessary to visit each cluster exactly once. Yet, under realistic assumptions (distances satisfy the triangle inequality, which holds for Euclidean and, mostly, for road distances) the strict equality is ensured by the objective. For the second policy, having an inequality in the cluster constraints is crucial because overlapping clusters may require some of them to be visited more than once. Thus, for the sake of consistency, cluster constraints are inequalities for both policies.

4.1 *Model formulation*

The model can be defined on a complete directed graph $G(V, A)$, where vertex set V contains the depot and all customer locations, each arc $a = (i, j) \in A$ $(i, j \in V)$ is associated with weight w_a representing the distance between the corresponding vertices (locations). We have chosen for a directed version of the problem as it corresponds to reality more closely, we will come back to this discussion in Section 6. Furthermore, the input for the model contains a set of clusters $C = \{V_1, \ldots, V_K\}$ $(V_k \subset V, k = 1, \ldots, K)$. If we denote the depot by 0, then the cluster containing the depot is $V_0 = \{0\}$.

In our model, variables x_a $(a \in A)$ define if the corresponding arc is traversed or not, and variables y_v $(v \in V)$ define if location v is visited. For any set $S \subset V$, $\delta^+(S)$ and $\delta^-(S)$ denote all arcs entering or exiting set S, respectively.

Under the above notations, the model is formulated as follows:

$$\min\{\sum_{a \in A} w_a x_a\} \tag{1}$$

subject to

$$\sum_{a \in \delta^+(\{v\})} x_a = y_v \qquad \forall v \in V \tag{2}$$

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$$\sum_{a\in\delta^-(\{v\})} x_a = y_v \qquad \forall v \in V \tag{3}$$

$$\sum_{v\in V_k} y_v \geqslant 1 \qquad \forall k \in \{1,\ldots,K\} \tag{4}$$

(Subtour elimination constraints) (5)

$$x_a, y_v \in \{0,1\} \qquad \forall v \in V, a \in A \tag{6}$$

For the sake of efficiency, we use subtour elimination constraints both in their clique form

$$\sum_{a\in S\times S} x_a \leqslant \sum_{v\in S\setminus\{v'\}} y_v, \quad S \subset V,\ |S| \geqslant 2,\ 0 \notin S,\ v' \in S \tag{7}$$

or, if $V_k \subseteq S$ holds for some $k \in \{1,\ldots,K\}$

$$\sum_{a\in S\times S} x_a \leqslant \sum_{v\in S} y_v - 1, \quad S \subset V,\ |S| \geqslant 2,\ 0 \notin S, \tag{8}$$

and in their cut form

$$\sum_{a\in\delta^-(S)} x_a \geqslant y_v, \quad v \in S,\ 0 \notin S,\ |S| \geqslant 2. \tag{9}$$

If subset S is small enough, constraints (7) and (8) are more compact than constraint (9). Also, identifying cliques from connected components is faster than finding minimum cuts.

It can be seen that formulation (1)–(6) is very similar to the formulation of the generalized TSP (see, e.g. Fischetti *et al.*, 1995). The only difference is that we do not assume non-intersection of clusters and consider a directed version of the problem.

In order to make the model more computationally efficient, valid inequalities are added to the formulation during the solution process. We use the following special case of the so-called comb inequalities (Grötschel & Padberg, 1979):

$$\sum_{a\in H} x_a + \sum_{l=1}^{L}\sum_{a\in T_l} x_a \leqslant \sum_{i\in H} y_i + \left\lfloor \frac{L}{2} \right\rfloor, \tag{10}$$

where 'handle' $H \subset V$ and 'teeth' $T_l \subset V$ ($l \in \{1,\ldots,L\}$, L - odd) are such that $|T_l| = 2$ and $|T_l \cap H| = 1$. This special case corresponds to the so-called 2-matching inequalities (Edmonds, 1995). According to our experience, these constraints reduce the duality gap from about 10% to few percent.

4.2 *Heuristic*

Due to the fact that the GTSP is an NP-hard problem (Fischetti *et al.*, 1995), we expected not being able to solve all instances to optimality within a reasonable time frame. That is why, alongside with the exact method, a variant of the variable neighbourhood search (VNS) heuristic (see e.g. Pisinger & Ropke,

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TABLE 1 *Outline of the heuristic*

`Initialisation`	Construct an initial tour using a nearest neighbour heuristic. Remember it as the best solution. It is also the current solution.
`repeat`	Apply one of four operators to modify the current solution. If the current solution is feasible and better than the best one, update the best solution.
`until`	The time limit is reached.

2007) was considered. The general structure of our heuristic is given in Table 1, a detailed explanation of its elements is provided in the rest of this section.

The nearest neighbour heuristic for generating the starting solution works as follows: starting from the depot, extend the tour with the nearest vertex belonging to an unvisited cluster, until all clusters are visited.

Two removal and two insertion operators were implemented. Before applying an operator, each node $i \in V \setminus \{0\}$ is assigned two ranks $r_{len}(i)$ and $r_{cov}(i)$ calculated as follows:

- if i belongs to the current tour:
  - $r_{len}(i)$ is the difference between the length of the current tour and the tour with vertex i removed;
  - $r_{cov}(i)$ is the difference between the number of visited (covered) clusters in the current tour and the tour with vertex i removed;
- if i does not belong to the current tour:
  - $r_{len}(i)$ is the difference between the length of the tour with vertex i inserted and the length of the current tour;
  - $r_{cov}(i)$ is the difference between the number of visited (covered) clusters in the tour with vertex i inserted and the current tour.

Each operator inserts or removes a randomly chosen vertex to/from the current tour. For the insertion operators, the probability of vertex i not included in the tour being chosen is either inversely proportional to $r_{len}(i)$ or proportional to $r_{cov}(i)$—hence two insertion operators (one using $r_{len}(i)$, another using $r_{cov}(i)$). For the removal operators, the probability of vertex i included in the tour being chosen is either proportional to $r_{len}(i)$ or inversely proportional to $r_{cov}(i)$—hence, two removal operators (one using $r_{len}(i)$, another using $r_{cov}(i)$).

An operator to apply at each step is randomly chosen with a probability depending on whether the current solution is feasible or not, see Table 2. These probabilities were found by applying a random search procedure to several instances. An interesting conclusion from the table is that most of the time the heuristic alternates between inserting and removing. For example, the probability of having two consecutive removals is 0.091. This 'greedy' behaviour is not just assumed, but results from parameters tuning on our dataset. Note also that our goal was not to design the most efficient heuristic for the GTSP, but to implement a reasonably performing tool suitable for the computational experiments reported in Section 6.

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TABLE 2 *Probabilities for the LNS operators*

Solution	Removal		Insertion	
	r_{len}	r_{cov}	r_{len}	r_{cov}
Feasible	0.400	0.600	0.000	0.000
Infeasible	0.036	0.055	0.727	0.182

TABLE 3 *Basic characteristics of the dataset*

Number of operating days	35
Number of routes	5428
Number of deliveries	468374
Number of locations	105500

TABLE 4 *Distance-related characteristics of the dataset*

Average distance per customer, km	1.49
Average distance per route, km	92.46
Average distance per day, km	15014
Total distance, km	495488

5. An analysis of the dataset

The dataset provided by an anonymous Dutch parcel delivery company includes 5428 routes, represented as a sequence of delivery locations visited. All routes start and end at the same depot; each location is defined by its geographic coordinates (latitude, longitude). There are in total 468374 delivery locations, 105500 of which are unique, i.e. some locations have multiple deliveries. The time span of the data is from 19 May 2015 to 17 July 2015 and contains 35 operating days. Table 3 summarizes the basic characteristics of the dataset. The dataset can be made available on request in an anonymized form.

As real distances travelled are not included in the dataset, they had to be computed. Given the size of the data, it was not feasible to compute the shortest path distances on the real road network for all routes, so the following approximation is used. First, the geographic coordinates are projected to a plane using the Mercator projection (Osborne, 2013), then the Euclidean metric is used to calculate the distance between the resulting points. The projection of original points is needed for the experiments reported in Subsection 6.1 and is also useful for visualization purposes. To illustrate the error of this approximation, real road distances were computed for several routes from the dataset using Google API tools (Inc, 2017) and compared to the approximated ones. Figure 2 shows that our approximation gives a rather centred estimate for the geographic region of interest. In contrast, the often used great circle approximation (Weisstein, 2017) systematically underestimates the distances.

Based on the approximated distances and the data from Table 3, some distance-related characteristics were calculated, as presented in Table 4. The average distance per customer is calculated as a ratio between the total distance travelled and the number of customers. The other characteristics are self-explanatory. Figure 3 characterizes the dataset in terms of the number of deliveries per route and route lengths.

It is observed that the routes from the dataset have a large variety in the following aspect. In some routes, the depot is located within or close to a ‘cloud’ of the delivery locations. In others, the distance

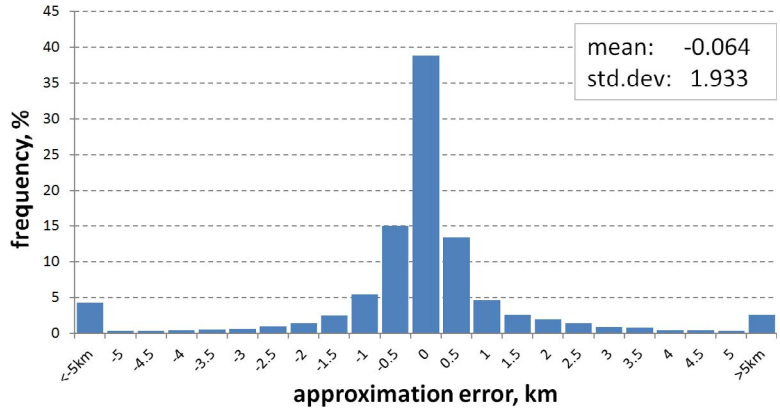


FIG. 2. Distribution of the difference between the approximated and the real road distances. The histogram is based on 200000 distances.

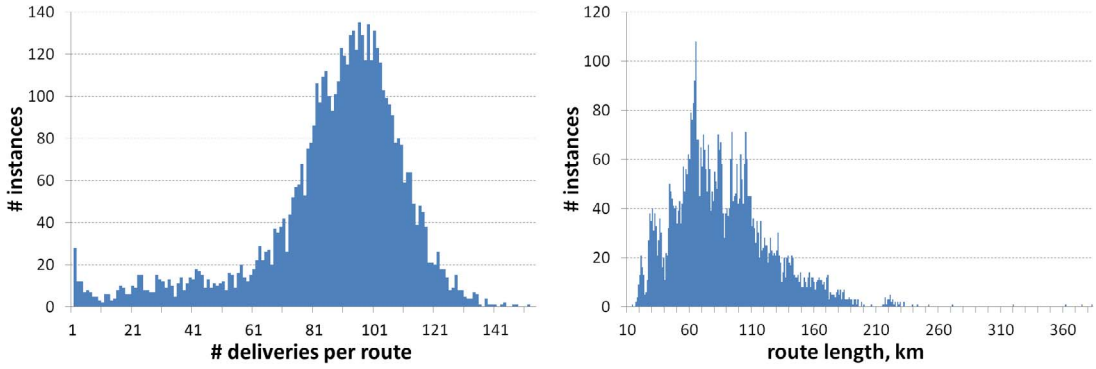


FIG. 3. Distributions of the number of deliveries per route and route lengths, respectively.

between the depot and the delivery locations is much larger than the distance between any two delivery locations. As this aspect has an impact on the performance of the second policy, it is necessary to quantify it. For this purpose, we introduce the *closeness ratio*

$$\rho = \frac{\max\limits_{i,j \in V \setminus \{0\}} (w_{i,j} + w_{j,i})}{\min\limits_{i \in V \setminus \{0\}} (w_{0,i} + w_{i,0})}, \tag{11}$$

where 0 represents the depot as defined in Section 4, $w_{i,j}$ is the distance between locations i and j. Figure 4 characterizes the dataset in terms of the closeness ratio.

A low closeness ratio value means that a route has long first and last legs, so routing between customers has a smaller contribution to the tour length than distances between the depot and the first and the last customers. From Fig. 4, it is apparent that the majority (see two leftmost columns) of the routes have a low closeness ratio. This abundance of routes with low closeness ratio can be seen as an

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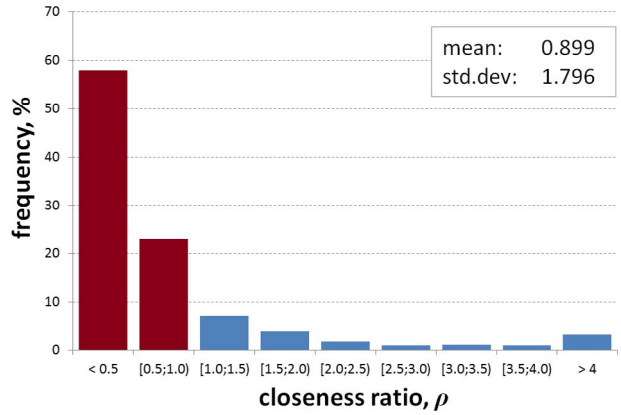


FIG. 4. Distribution of the closeness ratio for the dataset.

argument for redesigning the supply chain of the company, so that the depots are shifted closer to the customers.

6. Computational experiments

The major aim of the computational experiments is to verify the potential of both proposed policies in a realistic environment. This is done using the dataset of 5428 real parcel delivery routes. The impact on the transportation performance is quantified for each policy as the difference between the costs of routes visiting each location and costs resulting from the two policies.

Formulations (1)–(6) was solved using Xpress-MP as a general-purpose MILP solver; procedures for the separation of valid inequalities were coded in C++. Given the complexity of the problem and the large size of the dataset, a limit of 1 hour was imposed on the running time of the model. Whenever the time limit was reached, we used the heuristic described in Section 4.2 implemented in C++ with a time limit of 1 minute (again, for the performance considerations). The upper bound from the MILP solver or from the heuristic (whichever was better) was compared to the lower bound from the MILP solver to calculate the duality gap. The duality gaps are mostly below 1% (95% cases), so the solution quality is acceptable for the purposes of this paper. Note also that the duality gaps overestimate the real gaps. Figure 5 gives an overview of typical running times and duality gaps for the instances considered.

6.1 *Computational results for the first policy (alternative addresses)*

To identify the impact of the first policy, the input data have to be extended to incorporate alternative addresses for customers. This was done by generating random additional addresses for each customer. A natural question is how the distance between alternative addresses influences the objective. In order to answer this question, the following setup is used. For each customer i having coordinates (x_i, y_i), alternative locations are drawn from a uniform distribution on the following set:

$$B(x_i, y_i) = \left\{(x, y) \mid \mu((x, y), (x_i, y_i)) \leqslant R_{alt}\right\}, \tag{12}$$

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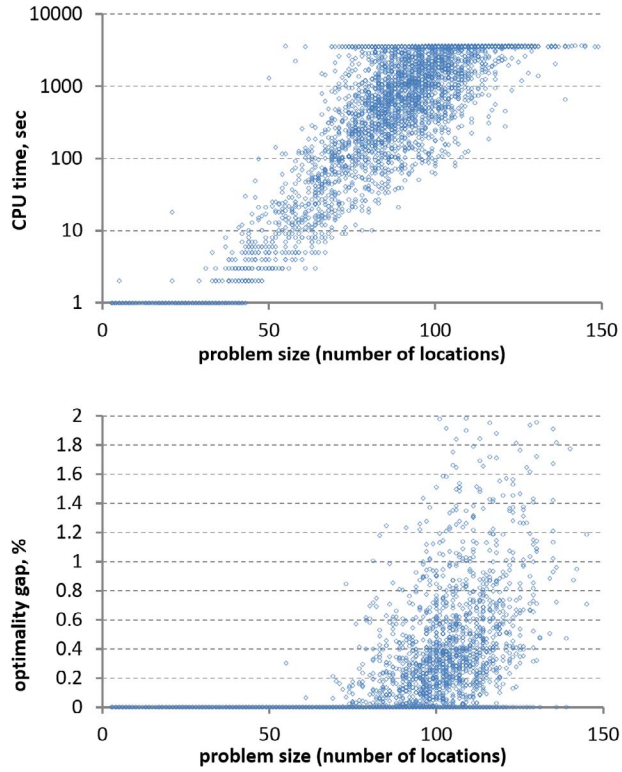


FIG. 5. Dependence between the performance and the input size for the dataset. Each point corresponds to one instance; the input size is expressed as the total number of vertices in the input graph.

where $\mu(.,.)$ - is the Euclidean distance. By varying the value of R_{alt}, the impact of the distance between alternative locations was studied. Note, however, that in this setting R_{alt} is an upper bound on the distance, rather than its exact value.

A case with two locations per customer was chosen: the main location from the real-life data and one (pseudo-)randomly generated alternative location. For a fixed value of R_{alt} and a fixed set of main locations, 1000 random instances were generated and solved. Based on each 1000 solutions, the average and the best values were calculated. The results of this series of experiments are summarized in Fig. 6. It is seen from the figure that, on average, the highest improvement is achieved if alternative addresses are relatively close to the main ones (within 2 km). At the same time, the curve reflecting the best cases reaches its minimum at around R_{alt} =6 km and shows a substantially larger performance improvement. This implies that the mutual location of all addresses is critical. To further illustrate this point, a similar series of experiments was carried out, but with alternative addresses distributed within the bounding box of the original set of locations, i.e.

$$B(x_i, y_i) = \left\{(x, y) \mid \mu((x, y), (x_i, y_i)) \leqslant R_{alt}\right\} \cap X, \tag{13}$$

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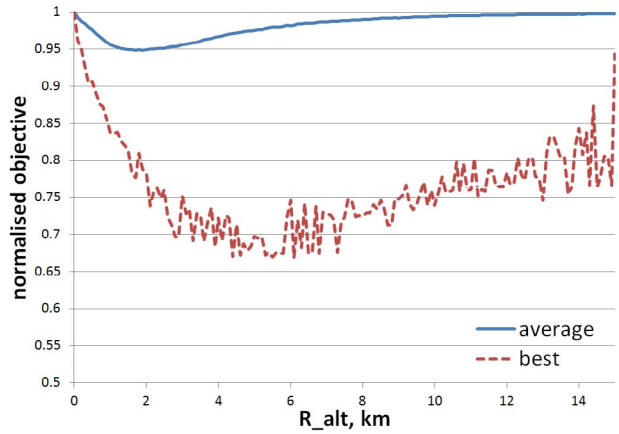


FIG. 6. Impact of the distance between alternative locations (R_alt).

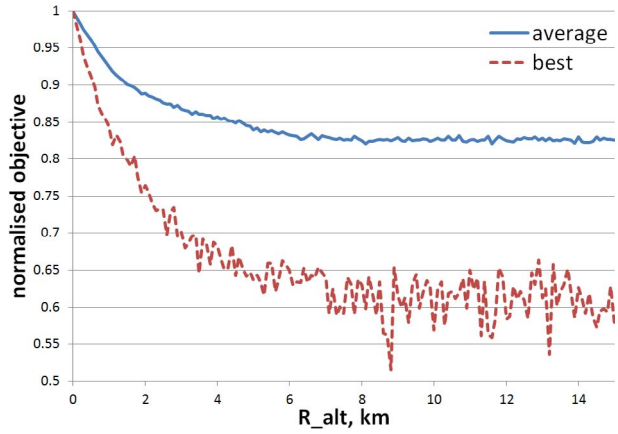


FIG. 7. Impact of the distance between alternative locations (R_alt); all generated locations are restricted to the bounding box of the original ones.

where

$$X = \{(x, y) \mid \min_{i \in V} x_i \leqslant x \leqslant \max_{i \in V} x_i,\ \min_{i \in V} y_i \leqslant y \leqslant \max_{i \in V} y_i\}. \tag{14}$$

Figure 7 shows that this restriction leads to a substantial performance improvement. The average improvement exceeds 15% for larger values of R_{alt}, while in Fig. 6 the improvement vanishes as R_{alt} exceeds 3 km.

6.2 *Computational results for the second policy (aggregate addresses)*

The second policy suggests collaboration between existing customers, so no additional spatial data is needed. The only parameter for this case is the distance threshold (*collaboration/aggregation radius*)

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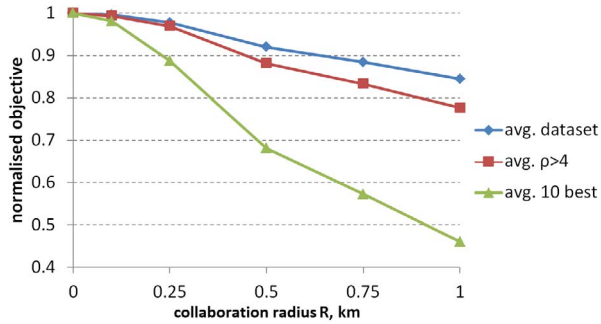


FIG. 8. Relative impact of the collaboration radius: averaged over the dataset (5428 instances), averaged over instances with high closeness ratio ($\rho > 4$, 170 instances), averaged over 10 best cases, respectively.

within which customers collaborate. We denote this parameter as R and each location $v \in V$ is assigned a cluster $V_v := \{i \in V : (w_{(i,v)} + w_{(v,i)})/2 \leqslant R\}$. As mentioned in Section 4.1, the depot 0 is assigned a cluster $V_0 := \{0\}$.

Figure 8 presents the results for this policy. The horizontal axis corresponds to values of the collaboration radius R. The focus is on the one kilometre range because, to our perception, it covers both the walking and the driving distance that people would accept. This range also covers the walking distances used in public transport planning, see e.g. El-Geneidy *et al.* (2014). The vertical axis corresponds to the objective values, normalized relative to the no-collaboration case (equivalent to having $R = 0$). From the figure, it can be seen that the average improvement in the performance is limited by 15%. This is caused by spatial characteristics of the dataset. First, the majority of the instances have a low closeness ratio $\rho < 1$, see Fig. 4. Second, in some instances, a single route visits several towns, resulting in several spatially distant clusters of locations. In this case, the relative improvement is very limited (similar to the instances with low values of ρ) even though they may have a high closeness ratio. In particular, this explains the small difference between two upper curves in Fig. 8. Note also that the middle curve is not very reliable as it is based on a relatively small sample (170 instances). Yet, if the customers are clustered in a proximity of the depot, the collaboration can lead to a substantial relative improvement in the distances travelled, as seen from the lower curve.

Figure 9 is similar to Fig. 8, except that the vertical axis reflects the absolute decrease in distance per customer served (the length of the tour divided by the number of customers). This performance measure is not sensitive to the closeness ratio that is why the instances with high values of ρ are not shown with a separate curve in the figure. It follows from the figure that the collaboration within a walking distance reduces the average travel distance per customer by more than 0.5 km, which is more than one third of the current average distance per customer of 1.49 km, see Table 4.

The qualitative discrepancy between the average relative performance (small improvement) and average absolute performance (substantial improvement) is due to the interplay of the distribution of the number of locations per route and distances. Few long distances per route have a minor impact on the distance per customer (for a reasonably large number of customers) but contribute substantially to the total length of the route, thus diminishing the effect of the policy.

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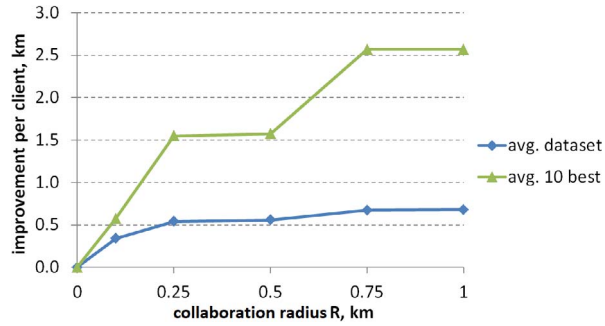


FIG. 9. Absolute impact of the collaboration radius: averaged over the dataset (5428 instances), averaged over 10 best cases, respectively.

7. Insights and conclusions

To study the impact of a flexibility of delivery locations, two policies for implementing this flexibility are presented and evaluated through computational experiments with realistic parcel delivery data. The location flexibility can be seen as a special case of the more general concept of customers engagement.

A number of simplifying assumptions were made. Concerning our approximation of the distances, it was found that it provides a centred estimate of the real distances with a reasonably low standard deviation. Note that the distances are often used as a proxy for travel times, costs and emissions that are influenced by uncertain factors (e.g. traffic conditions). From this perspective, using exact distances is not more meaningful than a good approximation thereof. Another simplification we made is due to considering each route separately instead of optimizing several routes simultaneously. First of all, it fits within the popular cluster-first-route-second approach and can still be used within a broader framework. In practice, assignment of clients or geographical areas to vehicles can be fixed (to our experience, this is not uncommon), so we avoid unnecessary complication of the model.

From the modelling perspective, it is found that a single optimization model (the generalized travelling salesman problem) can be used for both policies. The fact that this model is well studied and can be efficiently solved to optimality for moderately large inputs may foster their implementation. The results of our computational study suggest that relatively simple solution methods (both exact and heuristic) perform well on realistic input data. In most cases, optimal solutions were obtained within 1 hour; otherwise, the estimated optimality gaps were of the order of 1%.

It is found that the first policy, suggesting that each customer has two alternative locations, can lead to a 15% expected improvement in case the locations of all clients are densely grouped (and $R_{alt} \geqslant 4$ km). Otherwise, the expected improvement is much smaller, around 5%. The latter result is achieved if the alternative addresses of any single client are at most 3 kilometres apart ($R_{alt} = 3$). In practice, daily demands usually exceed vehicles capacities and requests are assigned to several routes, using either clustering techniques or some variant of the vehicle routing problem as an optimization model. This ensures that locations assigned to a route are 'reasonably' grouped, thus increasing the impact of alternative locations.

A relative impact of the second policy, suggesting that customers cooperate and accept parcels for their neighbours, largely depends on a spatial clustering of the delivery locations. In essence, the distance from the depot to the nearest customer imposes a lower bound on the length of a route. This bound does not depend on a collaboration between the customers. If this distance is substantially larger than

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distances between the customers, a relative performance improvement is very limited, even in case only one customer has to be visited. This feature is quantified via the closeness ratio. For inputs with high closeness ratio ($\rho > 4$) and a single cluster of delivery locations, a relative performance improvement can exceed 30% if the customers accept collecting their parcels within a 0.5 km neighbourhood (a walking distance). An average absolute improvement per customer exceeds 0.5 km which is substantial, compared to the current average distance per customer of 1.49 km. Wider neighbourhoods lead to even higher improvements. Another important point is that besides shorter distances this policy provides for time-related benefits. Each stop takes some amount of time that may vary greatly depending on the ease of parking, accessibility of customers (ground floor vs. some higher level), etc. By reducing the number of stops, the second policy reduces both the travel time and the customer service time.

7.1 *Implications for practitioners*

Both policies have a potential for considerably improving the performance of a parcel delivery system. For each of them, it was possible to reduce the route lengths by at least one quarter. In addition, they potentially simplify parcel handling and reduce the related service times. In the first policy, this reduction is due to a co-location of alternative addresses. For example, it might happen that the alternative addresses of some customers are very close, and several customers can be served from a single stop of the vehicle. The more alternative addresses the customers provide, the higher the probability of this happening. For instance, choosing lockers at a public place as a delivery address further facilitates this. In the second policy, a reduction in service times is an inherent feature due to fewer customers visited. Note that these policies are not mutually exclusive, and some combination of them can be implemented.

Thus, the logistics service providers should not ignore this opportunity. However, the implementation of the concept depends also on the e-commerce sector. For example, e-shops should give their customers an opportunity to enter several addresses while ordering goods, their return and insurance policies have to be properly adjusted, etc.

A crucial issue for the e-commerce sector is the level of trust and familiarity of their customers, see e.g. Gefen (2000). We believe that our policies score well from this perspective. From the customers' viewpoint, the only change is that they have an option of providing more than one delivery address. This is still an option, rather than an obligation, and people generally like when they have a choice of following their usual way. In case of the second policy, the customers have to accept that their parcel may be delivered to somebody else and they may get somebody's parcels. On one hand, this is already the practice in some countries. On the other hand, it is perfectly possible to let them choose if they want to participate in this scheme for each particular order.

Another important conclusion is that the spatial distribution of delivery locations has a large impact. First of all, this means that the assignment of customers to routes is critical to the overall performance. Also, the largest impact is achieved in a densely populated urban setting, while in rural areas the effect may be less pronounced. Figure 8 provides quantitative insights into the effect of the collaborating clients. This can be useful for the strategic planning: how many collaborating clients are required to reach the performance goals of a transportation company. In case of ViaTim, this information can be used to adjust the rewards for the participants in order to find a balance between the transportation and the collaborations costs.

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7.2 *Implications for research*

For a practical application of our approach, some further progress extending beyond the scope of this paper has to be made. One direction, related to the first policy, is to introduce the time windows component into the model: if each location is associated with a time window, the impact of having alternative locations can be even more pronounced, if their time windows do not overlap. Quantifying this requires a representative dataset with time windows. Furthermore, the compromise between the total distance and the total time (travel time plus service time) remains an open question, the answer to which largely depends on the customers service times and is therefore highly case specific.

Another future research direction is related to a collaboration of customers. Clearly, they need some incentives to collaborate. Alongside with motivation, one possibility is to give the collaborating customers some refund or discount. This induces a problem of finding a fair scheme for costs and benefits sharing. Cooperative game theory techniques can be applied here.

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