Impact of bot-return policies in truck-and-bot transportation systems

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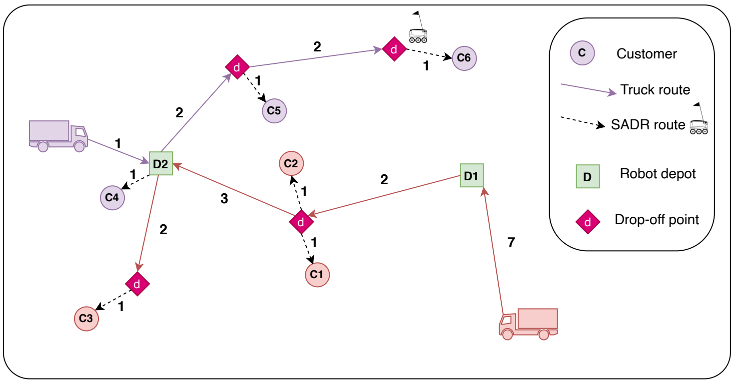
1 Introduction

Following the existing trend towards online shopping, home delivery services have been consistently increasing during the COVID-19 pandemic. This has created additional challenges for maintaining a satisfying supply level while meeting the growing expectations of stakeholders and customers for last-mile services. In Germany alone, it is forecast that by 2023, 4.4 billion shipments will need to be handled every year compared to 1.69 billion in 2000 (Boysen *et al.*, 2021). It is also worth noting the reluctant attitude of customers to accept higher prices, while they still demand for fast and efficient deliveries, as it is highlighted in Joerss *et al.* (2016). Given these ever-increasing challenges, alternative delivery modes, in substitution for traditional truck delivery systems, are likely to be beneficial from multiple viewpoints. New delivery modes have been made available in a recent past as a result of technology advances in domains such as digitization and automation. These new technologies are expected to play an important role in industrialized countries, where the aging population puts additional stress on the logistics job market, (Otto & Battaïa, 2017). In this work, we focus on small autonomous delivery robots (SADRs), when used in combination with trucks. SADRs, also named bots, travel at pedestrian speed along sidewalks, and they are transported to and released from trucks at appropriate drop-off points. We rely on a system characterized by the presence of bot stations, to which the bots return autonomously after completing a job, and where their batteries are swapped. Then, a truck picks the bots up again, loads a parcel into them, and transports them to their next drop-off point. Choosing the right return policy for the bots (*i.e.,* to which bot station they should return) is likely to heavily impact the required bot fleet size to achieve a given set of deliveries at a given service level. In this work, we evaluate and compare various bot return policies regarding their operational efficiency.



Destination	Origin	Start (t)	End (t)
C1	D1	7	10
C2	D1	7	10
C3	D1	12	15
C4	D2	1	2
C5	D2	1	4
C6	D2	1	6

Figure 1 – *Example of a given service plan and its resulting delivery jobs.*

2 Problem description

As shown by Boysen *et al.* (2018), when bot stations are available in the delivery network, the truck waiting time for bot to return after a delivery is drastically reduced compared to the situation where the bots would be picked up by the trucks themselves at determined pick-up points. In the same work and focusing on this situation, the authors provide truck routes together with bot scheduling solutions for a large set of various instances. We refer at this type of output solutions as *service plans*, which is the starting point for the present work. A service plan defines for a given set of customers to be served:

- a truck route visiting bot stations and drop-off points;
- a scheduling plan for the bots, which defines where and when they are picked up and released;
- a timing for the entire delivery process.

In Figure 1, we display the combination of two truck routes and associated bot scheduling plans, computed using the methodology introduced in (Boysen *et al.*, 2018). In order to make the bots as reusable as possible for other trucks later in their schedule, we focus in this work on evaluating different return bot policies for the bots, namely the *dedicated-station policy*, the *closest-station policy*, and the *most-suitable-station policy*.

We consider a set J of delivery jobs, in which each job $j \in J$ is defined by an origin o_j, a destination d_j, an initial time i_j, and an ending time e_j. Each job is performed by one bot $b \in B$. Ultimately, we aim at computing a solution that minimizes the bot fleet size and which is defined by two main components: an assignment a that matches each job of $j \in J$ to a bot $b \in B$, and the definition of the bot stations that are visited by a bot which performs two consecutive jobs j and j'. Let Ω^a be the set of job pairs (j, j') that are executed in direct succession by a same bot $b \in B$. An intermediate bot station s has to be determined for each $(j, j') \in \Omega^a$. A solution is considered feasible:

- If each job $j \in J$ is assigned to exactly one bot $b \in B$ in assignment a.
- When two jobs j and j' are assigned to the same bot to be executed in direct succession, then there must be enough time for the bot to visit its associated bot station $b_{j,j'}$ in between. In other words, it means that $i_{j'} \geq e_j + \delta(d_j, b_{j,j'}) + \delta(b_{j,j'}, o_{j'})$ must hold for each $(j, j') \in \Omega^a$, where $\delta(o, d)$ represents the bot travel time from o to d.

The selected bot return policy has an influence on the feasibility of a solution. Specifically, our three alternative policies add respective specific feasibility constraints to the problem:

- *Dedicated-station policy:* we assign each bot to a unique bot station. This means that for each bot $b \in B$, all jobs assigned to b must have their origin at the same bot station. Thus, $o_j = o_{j'}$ for all $(j, j)' \in J_b^a$, with $j \neq j'$, and where $J_b^a \subseteq J$ is the set of jobs assigned to bot b within assignment a.
- *Closest-station policy:* bots must return to the closest bot station after completing the job. This means that the distance $\delta(d_j, b_{j,j'})$ for all $(j, j') \in \Omega^a$ must be minimized among all existing bot stations.
- *Most-suitable-station policy:* with this policy, no additional constraints are added on the choice of the returning bot station as all of them are eligible.

Our bot fleet size problem seeks the smallest possible fleet size $|B|$, in the situation where the three above bot return policies are implemented.

3 Methodology

We define an alternative view of the problem making use of a minimum cost bipartite matching methodology, with adaptations depending on the bot return policy to evaluate.

Dedicated-station policy: as each bot returning to its original station is a strong constraint, the problem decomposes into multiple station-specific sub-problems (one for each bot station where jobs originate). We introduce a bipartite graph $G = (V, E, c)$ for each of these sub-problems, where V is composed by bot nodes and job nodes; edges E are the possible connection between nodes: *Bot2Bot*, *Bot2Job*, *Job2Job*, and *Job2Bot*, each characterized by a cost c. The graph G has bipartition (P, Q), where P represents the successors nodes and Q represents the predecessors nodes, with $|P| = |Q| = 2 \cdot |J'|$, and where $J' \subseteq J$ is the subset of jobs corresponding to the single bot station under consideration in this sub-problem. There exist $|J'|$ potentially usable bots (*i.e.,* upper bound), these are called *bot nodes.* In both the bipartitions P and Q, there is a given number of *job nodes* and the edges between these two bipartitions have the following meaning:

- *Bot2Bot:* indicates that this bot is not required in the solution; edge weight $c_e = 0$;
- *Bot2Job:* from P to Q, indicates that the job is the first one performed by that bot; edge weight $c_e = 1$;
- *Job2Job:* $j \in P$ is connected with a different $j' \in Q$, which indicates that j' is performed by the same bot after finishing j; edge weight $c_e = 0$.
- *Job2Bot:* job $j \in P$ is connected to bot in Q, which indicates that j is the last job performed by that bot; edge weight $c_e = 0$.

For the resulting bipartite graph, a minimum cost bipartite matching, where each node of P is matched with exactly one node of Q and the sum of selected edge weights is minimal, can be obtained in polynomial time using an adaptation of the well-known Hungarian method (Kuhn, 1955), which runs in $O(n^3)$, where $n = 2 \cdot |J'|$ in this case.

Closest-station policy: with bots (potentially) returning to different bot stations, the bot fleet sizing problem no longer decomposes into single-station sub-problems. We thus consider a unique graph G, where bipartition (P, Q) receives $|P| = |Q| = 2 \cdot |J|$ nodes as defined above (*i.e.,* $|J|$ bot nodes and $|J|$ job nodes). The only other alteration arises for the *Job2Job* edges, which are inserted between a job $j \in P$ and its successor job $j' \in Q$ only if $\overline{s}_j = o_{j'}$, where $\overline{s}_j$ refers to the bot station being the closest to job j, and $i_{j'} \geq e_j + \delta(d_j, \overline{s}_j)$ holds. The weights of these edges are set to $c_e = 0$.

Most-suitable-station policy: The most-suitable-station policy offers bots even more flexibility to switch between bot stations based on which one is the most convenient. Since multiple trucks are active in the same area, bot stations are chosen based on the truck routes and the demand for bots at the various stations, as long as these stations are reachable by the bots after completing their job.

4 Insights on results

We consider a large set of instances resulting from those generated and solved (regarding the scheduling dimension) in (Boysen *et al.*, 2018). By merging together several of the instances considered in Boysen *et al.* (2018), we are facing complex delivery networks, similar to those appearing in real situations, in which several trucks are serving customers with the use of SADRs. Our work quantitatively studies the critical impact played by the three considered bot-return policies on the minimum bot fleet required to fulfil a number of given set of jobs. We observe significant discrepancies when implementing these distinct return policies. These differences depend on the one hand on the pre-computed truck routes, and on the other hand on the heterogeneous network layouts that are considered, namely the distribution of the bot stations, the customers and the drop-off points. This aspect suggests that before setting up a two-echelon system based on truck and SADRs, it is of utmost importance to carefully analyze the geographic space and the demand distribution in order to establish a distribution of prospective bot stations and drop-off points. Observing that both the network layout and the bot-return policy influence the bot fleet size, our findings help in answering several questions that must be raised before implementing such novel truck-and-bot transportation systems for last-mile deliveries, which include:

- How many bot stations should be implemented to serve a given set of customers using n bots and m trucks?
- When only a limited number of bot stations can be opened, how should their location be determined?
- In which way the bots should be distributed between the available bot stations?
- Which impact has the chosen bot return policy on the required bot fleet size to satisfy a given set of jobs?

While studying formally the best feasible return bot strategies to be implemented for truck-and-bots delivery systems, focusing on the above aspects helps us provide useful information for decision-makers in this context.

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