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ORIGINAL ARTICLE

Public transport crowdshipping: moving shipments among parcel lockers located at public transport stations

Alexander Wyrowski[1] · Nils Boysen[1] · Dirk Briskorn[2] · Stefan Schwerdfeger[3]

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Abstract
In view of success stories of unicorn startups from the sharing and gig economy such as Airbnb, DiDi, or Uber, it is not surprising that postal service providers try to transfer the sharing idea toward their last-mile delivery services: owners of underused assets (here private crowdshippers traveling anyway) are connected with users willing to pay for the use of these assets (here postal service providers having to deliver parcels). In this paper, we consider a special form of crowdshipping where public transport users, steered by a smartphone app, pick up parcels from parcel lockers, take these shipments with them on their subway rides, and deposit these parcels into other lockers. Finally, the actual recipients can pick up their shipments from their most convenient parcel lockers, e.g., on their own way back home from work. We formulate the optimization problem that matches crowdshipping demand and supply and determines the routes along lockers and crowdshippers each parcel takes. Specifically, we allow that each parcel is moved by multiple cooperating crowdshippers and solve this problem with different objective functions capturing the individual aims of the main stakeholders: shippers, crowdshippers, recipients, and the platform provider. We evaluate the relationship of these objectives and quantify the efficiency loss of a more restricted matching policy, where only a single crowdshipper can be assigned to each parcel's complete path between origin and destination. Finally, we also explore the impact of delays and investigate whether specific objectives protect against unforeseen events.

Keywords Transportation · Urban logistics · Crowdshipping · Public transport

1 Introduction

Crowdshipping, defined as the application of individuals for delivery of other peoples' shipments on trips they would make anyway (Behrend and Meisel 2018), has received much attention in the recent years. This is mainly triggered by the following general trends:

Extended author information available on the last page of the article

(i) *Increasing parcel volumes:* In Germany, for instance, a study predicts that by 2024 5.1 bn shipments will need to be processed per year compared to 2.47 bn in 2011 (Statista 2022). Managing this sharp increase with the traditional courier service infrastructure seems barely possible, especially in the aging societies of many developed countries. Therefore, many postal service providers are on the lookout for novel forms of last-mile delivery.
(ii) *Gig economy:* Large sharing platforms like Uber, Lyft, and AirBnB enjoy increasing popularity. In Europe, the sharing economy is estimated to have generated a total sales volume of €28 bn in 2015 (Vaughan and Daverio 2016). A sharing platform connects owners of under-used assets, such as cars, spare room, or parking spaces, with users willing to pay for the use of these assets. Naturally, unused transport capacity is also a potential asset to be shared.
(iii) *Ecological awareness:* Road transport is among the most serious emission sources. It is estimated to contribute a 20% share of all CO_2-emissions (Schroten et al. 2012). Obviously, utilizing unused transport capacity on trips made anyway is a simple means to reduce traffic volume and thus emissions.

Given these trends, crowdshipping is the attempt of retailers (e.g., Amazon Flex or Walmart), logistics companies (e.g., DHL), and specialized online platforms offering a matching of supply and demand as a service (e.g., Uber Freight or postmates.com) to transfer the basic idea of the sharing economy to transport services, especially on the last mile. In this context, this paper treats a specific form of crowdshipping, which we call *public transport crowdshipping*.

On the demand side of public transport crowdshipping, we have shipments, e.g., parcels with goods ordered online, which have to be transported toward suitable parcel lockers. We assume that these lockers are located directly in the access paths of public transport, so that recipients can conveniently receive their shipments, e.g., on their way back home after work. Initially, the shipments to be transported are placed in other parcel lockers close to their origins. For instance, a small brick-and-mortar store also running an online sales channel can place an online order in a parcel locker close to the store and can announce their transport demand on the crowdshipping platform. Alternatively, the platform organizer could also offer the service to pick up larger shipment volumes, e.g., at a distribution center of a retail chain, and place the parcels into well-frequented lockers where many potential crowdshippers pass by. On the supply side, public transport users can register on the central crowdshipping platform and announce their travel behavior, e.g., their daily commute to and from work via the metro system, in a smartphone app.

Once a sufficient number of potential crowdshippers is collected, the platform matches supply and demand, e.g., with the help of the solution procedures provided in this paper, and announces transport requests onto the smartphones of selected crowdshippers. Such a request advises a crowdshipper via the smartphone to pick up a shipment at a specific parcel locker and also contains the access code to open the respective locker compartment. The crowdshipper can accredit the pickup by scanning a bar code on the parcel via the smartphone app, which is also the signal that the respective locker compartment is available again. Then, the crowdshippers take the parcels with them on their public transport rides. Once arrived, they place the parcels into other parcel lockers advised by the app and accredit the deposit by scanning the bar codes of parcels and locker compartments. These lockers can either be the parcels' final destinations where they are picked up by the parcels' actual recipients, or they are just intermediate lockers where the parcels wait for other crowdshippers to be moved onward.

The big advantage of public transport crowdshipping is its sustainability. Compared to road transportation, trains are eco-friendly means of transportation (Schroten et al. 2012) and, since public transport users make their trips anyway, this form of parcel delivery does not produce any additional traffic. Thus, especially environmentally aware travelers get intrinsically motivated and may request no high monetary compensation for their crowdshipping services, so that public transport crowdshipping can also become a low-cost parcel delivery mode. Long-term invest is only required for the development of the smartphone app, the setup of the IT infrastructure, and the parcel lockers to be positioned in stations of public transport. On the negative side, many crowdshipping platforms struggle with providing secure, scalable, and reliable transport services (Le et al. 2019). They depend on the volatile participation of crowdshippers, which varies from day to day and is hard to forecast. Ways to take on this challenge are, for instance, discussed by Savelsbergh and Ulmer (2022).

The basic idea of public transport crowdshipping is formulated in different publications, e.g., (Gatta et al. 2019a, b; Zhang et al. 2017), and companies such as Amazon (ParcelHero 2016) and HistSystem Co. (2019) have announced their intentions to establish a network of parcel lockers in public transport stations. However, the (to the best of the authors' knowledge) only company that established parts of the public transport crowdshipping concept is the French platform Chronobee. Public transport users can register on the Chronobee platform (https://app.chronobee.com/) with their daily commute and are matched to transport requests also announced on the platform. However, parcel pickup and delivery are not organized via parcel lockers (but via direct interaction) and there is no option for multiple crowdshippers sharing the transport of a single parcel.

In this paper, we investigate the basic optimization problem of public transport crowdshipping and provide suitable solution methods to match crowdshipping supply and demand. The matching task also includes the planning of each parcel's route through the public transportation network and its utilization of different parcel lockers as well as crowdshippers until finally reaching the destination locker in time. Specifically, we formulate six alternative objective functions that consider the aims of different stakeholders. While the crowdshipping platform aims to maximize their profit consisting of postal charges for each delivered parcel minus crowdshipping fees, crowdshippers rather focus on their own crowdshipping fees. The customers of parcel delivery services, instead, prefer reliable services and want to avoid that parcel handovers between crowdshippers are missed in case of train delays. We formulate our public transport crowdshipping problem and provide computational complexity results for all problem versions. Furthermore, we provide a heuristic decomposition approach that is easily adaptable to solve all problem versions. This allows us to investigate the relationship of the stakeholders' objectives. Furthermore, we compare our cooperative crowdshipping policy that allows multiple subsequent crowdshippers to jointly transport a parcel from origin to destination with a more restrictive policy that excludes crowdshipper cooperation. Finally, we also investigate the impact of train delays and explore which of our objectives produces robust plans where only a few parcels miss their recipients.

Thus, our paper makes the following contributions to the literature: (a) We detail the operational processes and the basic matching task of a novel form of crowdshipping: public transport crowdshipping. (b) We provide suitable solution methods for the basic matching task with six different objectives to cover the aims of all main stakeholders. (c) We apply our solution methods in a comprehensive computational study in order to identify critical success factors. Here, we show that a large crowdshipper base of volunteering public transport users must be recruited, explore the different aims of the main stakeholders, investigate how to protect against stranded parcels due to unforeseen train delays, and evaluate the gains of cooperative transport where parcels take multiple legs with different crowdshippers toward their destination lockers.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 defines our public transport crowdshipping problem with its six alternative objectives and explores computational complexity. In Sect. 4, we provide the basic model formulation and report on necessary adaptions when dealing with the different objectives. Our heuristic decomposition approach is introduced in Sect. 5. Insights into the computational performance and managerial issues are provided in Sect. 6 and 7, respectively. Finally, Sect. 8 concludes the paper.

2 Literature review

The sharing and gig economy in general and crowdshipping in particular have attracted a lot of research in the recent years. Thus, we refer the reader to the following in-depth survey papers: Dablanc et al. (2017) (on-demand deliveries), Le et al. (2019) as well as Savelsbergh and Ulmer (2022) (crowdshipping), Boysen et al. (2019) (matching of supply and demand in the sharing industry), and Boysen et al. (2021) (last-mile delivery). For an overview on different crowdshipping applications, our own literature review, first, elaborates on the different user groups that are targeted as potential crowdshippers:

(i) *Hired drivers:* Some crowdshipping platforms hire independent drivers, who are hourly paid, contribute their own vehicle, and sign up in advance for prefixed time-slots. These platforms are either directly operated by large retailers like Amazon (with their Amazon Flex service) or by third-party companies offering a matching of supply and demand as a service (e.g., Uber Freight or postmates.com). Optimization approaches matching crowdshipping supply and demand as well as planning delivery routes are, for instance, provided by Archetti et al. (2016) and Arslan et al. (2018). The main disadvantage of this form of crowdshipping is that parcel delivery is not processed on trips made anyway. Instead, extra traffic is generated and, from an environmental perspective, nothing is gained compared to traditional delivery modes.

(ii) *Occasional drivers:* This disadvantage is avoided, if pickup and delivery requests of customers are properly integrated into existing trips, e.g., of private drivers with their own cars having some flexibility regarding the timing of their regular (independently planned) journeys (Zehtabian et al. 2022) or taxis offering additional freight services (Li et al. 2014).

(iii) *In-store customers:* Attracting a sufficiently large external driver base can produce a lot of effort (Le et al. 2019). Hence, it can be advantageous if specific groups of people, e.g., customers of large retail outlets, can directly be offered crowdshipping participation, e.g., for the purchases of their neighbors. Applications are reported for retail chain Walmart (Dayarian and Savelsbergh 2020), and optimization approaches are, for instance, provided by Gdowska et al. (2018).

(iv) *Employees:* Large brick-and-mortar retail outlets or distribution centers of online retailers employ hundreds of workers, who can increase their earnings by crowdshipping online orders to neighbors on their way back home from work. Test runs are reported for Walmart, and decision support matching parcels and employees is provided by Boysen et al. (2022).

(v) *Air passengers:* To exploit price differences between different countries and save on air mail freight tariffs, crowdshipping platforms such as `piggybee.com` broker crowdshipping air passengers with free luggage space.

(vi) *Public transport users:* In this paper, we consider public transport users as potential crowdshippers. The literature in this specific area of crowdshipping is summarized in more detail in the following.

The main factors influencing the willingness to participate in public transport crowdshipping are investigated in (Gatta et al. 2019a, b). They report on a survey from Rome (Italy) and state that about 50% of the questioned metro users are willing to participate. A brief review on further empirical studies on crowdshipping participation is provided by Punel et al. (2019). In the following, we only focus on operations research contributions.

A combination of delivery by traditional delivery vans and public transport is considered by (Ghilas et al. 2016b, a, c, 2018). Here, company-owned delivery vans cooperate with public transport operating on fixed timetables. Shipments can be handed over and, after transport, received from public transport, which acts as an additional intermediate transport option. A problem definition and a first MIP is presented by Ghilas et al. (2016b). The same problem is tackled by Ghilas et al. (2016a) and Ghilas et al. (2018) with adaptive large neighborhood search and branch-and-price, respectively. A stochastic problem version is treated by Ghilas et al. (2016c). A similar problem setting for alternative vehicles, i.e., cargo bikes and buses, is investigated by Masson et al. (2017); Azcuy et al. (2021) as well as Schmidt et al. (2022). Kou et al. (2022) investigate the peculiarities of combining delivery vans and public transport in a rural setting. In our problem setting, we have no delivery vans (or cargo bikes), and we decouple the handover process by parcel lockers. Two crowdshippers cooperating in the transport of a specific parcel need to subsequently access the locker, but not at the same time. This leads to a completely different problem structure.

Crowdshipping between different parcel lockers is also considered by Chen et al. (2017) and Chen et al. (2016). They, however, consider taxis and not public transport users as potential crowdshippers. This requires an additional coordination of parcel delivery with people transport and leaves more flexibility, because taxis are not bound to fixed timetables. Furthermore, crowdshipping between parcel lockers without any time constraints is considered by Wang et al. (2016) and Zhang et al. (2017). Finally, Kızıl and Yıldız (2022) consider the problem to decide the location of parcel lockers, that is to choose the stations where parcel lockers are to be installed, and evaluate solutions, including backup services with zero-emission vehicles for parcels that are not crowdshipped, using a scenario-based approach. The problem is formulated as a two-stage stochastic program and solved by a branch-and-price approach.

The existing crowdshipping literature also includes transshipment nodes into operational routing and assignment problems (e.g., Macrina et al. 2020; Vincent et al. 2022). These nodes add flexibility where shipments, delivered by company owned vehicles, are finally picked up by the crowdshippers. In our problem setting, the origin position at the first parcel locker is fixed for each shipment. Instead, we allow that multiple crowdshippers can participate in delivering shipments to their destinations by handing the parcel over at intermediate lockers. This transshipment option rather relates our problem setting to multi-hop ridesharing (e.g., Masoud and Jayakrishnan 2017; Wang et al. 2023), where passengers can hitch multiple subsequent rides to finally reach their destinations. In this domain, however, vehicles (crowdshippers) typically do not operate on predefined routes without any time flexibility and have a capacity for more than one passenger (parcel).

It can be concluded that the crowdshipping literature provides no suitable optimization procedures where public transport users with known travel behavior are coordinated to crowdship other peoples' parcels between parcel lockers.

Finally, there are other optimization problems from other domains that share some important structural similarities with our optimizations problem for public transport crowdshipping. However, we come back to these similarities after having defined this problem in the following section.

3 Problem definition

The critical element of any crowdshipping solution is a central IT platform that matches supply and demand. This also holds true for our specific crowdshipping application, where public transport users pick up and deliver parcels among parcel lockers located in stations $s \in S$ with given locker capacity L_s for storing shipments in locker compartments.

(i) On the *demand* side, we have a set J of parcels. Beginning from release date r_j, parcel $j \in J$ is available at the parcel locker at origin station α_j. To deliver a parcel successfully, it needs to arrive at the parcel locker at destination station ω_j no later than deadline d_j, which is the point of time when the parcel's actual recipient passes the lockers at station ω_j, e.g., on the way back home from work. If parcel $j \in J$ is successfully delivered, the platform receives a postal charge p_j. If a parcel cannot be forwarded to its destination on time, it cannot be accepted for crowdshipping services and the platform receives no postal charge.

(ii) On the *supply* side, we have a set I of public transport users who have registered at the crowdshipping platform and are willing to participate in parcel delivery; we call them crowdshippers. Each crowdshipper $i \in I$ is associated with a time-stamped path defining i's movement through the public transportation network. Specifically, the time-stamped path is given as a sequence of tuples each referring to a departure time at a specific station. We presuppose that only those station visits are added to the time-stamped path, where the respective crowdshipper has enough time to pickup and/or deposit a parcel at a parcel locker. Hence, we do not explicitly consider a specific pickup and deposit duration. Furthermore, we only consider those stations where a parcel locker is located and where a parcel is to be picked up or delivered to (or at least one other crowdshipper can access the locker). When traversing a travel leg between two subsequent stations according to a time-stamped path, a crowdshipper has a capacity to carry at most one parcel.

We refer to the joint travel of a crowdshipper i and a parcel j starting with i picking j up at station $s \in S$, moving from s to another station $s' \in S$, and finally depositing j at station s' as an *entrainment*. For each entrainment, an entrainment fee f is paid to the crowdshipper by the platform. For a station s and a point in time t a crowdshipper passes through s, we say that $n_{s,t}$ is the number of parcels stored in the lockers at s immediately after t. This number $n_{s,t}$ is composed of (i) parcels that originate from station s and have not been picked up yet at t, of (ii) parcels that have been intermediately deposited in s until t, but have not been picked yet, and of (iii) parcels with delivery station s that have already reached their destination until t and have not been picked up by the recipient yet since $d_s > t$.

A parcel is moved from its origin to its destination station not necessarily by a single entrainment. Instead, a solution to our crowdshipping problem is a sequence σ_j of entrainments assigned to each parcel $j \in J$. An empty sequence σ_j reflects that parcel j is not delivered at all. We say a solution is delivery-feasible, if for each parcel $j \in J$ with non-empty sequence (a) the first entrainment starts at station α_j and does not start before release date r_j, (b) each other entrainment starts at the station where the previous entrainment ended and does so not before the end time of the previous entrainment, and (c) the last entrainment ends at station ω_j and does not end after deadline d_j.

Furthermore, we say a solution is capacity-feasible, if (i) the crowdshippers' capacity is not exceeded. This means that for each crowdshipper i and each station s on the path there is at most one entrainment involving i that starts at s or a previous station on the path and ends at a station that is reached after s. Furthermore (ii), the parcel lockers' capacities are not exceeded. That is for each station s and each point in time t where a crowdshipper passes through s, there are at most L_s parcels in the locker and we have $n_{s,t} \leq L_s$.

Finally, we say a solution is feasible, if it is both delivery-feasible and capacity-feasible. Since we have different involved stakeholders, i.e., crowdshippers, recipients, and the platform provider, there may be different views on what is a good solution among the feasible ones. We consider six problem versions in the following:

(1) *MAX-PROFIT:* The problem is to find a feasible solution maximizing profit. The profit associated with a feasible solution is the total postal charge for successfully delivered parcels (i.e., those with non-empty sequences of entrainments) minus the entrainment fees for the crowdshippers (i.e., the total number of entrainments multiplied by fee f). This objective mirrors the aim of a crowdshipping platform maximizing its own profit.
(2) *MAX-PARCELS:* The problem is to find a feasible solution with a profit of at least a given threshold P that maximizes the number of delivered parcels. This objective aims to maximize the number of satisfied customers while granting the platform a minimum profit.
(3) *MAX-INVOLVEMENT:* The problem is to find a feasible solution with a profit of at least a given threshold P that maximizes the number of crowdshippers with at least one entrainment. This objective aims to engage a maximum number of crowdshippers, while granting the platform a minimum profit P.
(4) *MIN-TOTAL-ENTRAINMENTS:* The problem is to find a feasible solution with a profit of at least a given threshold P that minimizes the total number of entrainments over all parcels. Since each entrainment involves a failure risk, e.g., a parcel missing its subsequent entrainment due to a delayed train, this objective reduces the risk of stranded parcels. This is something both the platform and the recipients prefer to avoid.
(5) *MIN-MAX-ENTRAINMENTS:* The problem is to find a feasible solution with a profit of at least a given threshold P that minimizes the maximum length of entrainment sequences among all parcels. A parcel is only successfully delivered toward its destination, if all its entrainments are successfully completed. Thus, reducing the number of entrainments per parcel should promote the number of successful deliveries by protecting against uncertainty. An obvious disadvantage of this objective is that in the worst case a single shipment with a large number of inevitable entrainments removes the optimization pressure from all other shipments. It will be part of our computational study in Sect. 7.3 to explore how severely this deteriorating effect impacts average results.
(6) *MAX-MIN-SLACK:* For each successfully delivered parcel $j \in J$, we consider the minimum slack time at ω_j and at each station j where it is picked up by a crowdshipper (including α_j). The slack time of parcel j at each such station s is the time it spends there in the locker between delivery and pickup. For the sake of convenience, we say that for each other pair of parcel j and those stations where j is not handled the slack time is infinite, so that they do not influence the minimum slack time. The problem is to find a feasible solution, which maximizes the minimum slack time among all pairs of parcels and stations while granting at least a minimum profit of P to the platform. Slack time protects against delays of trans and crowdshippers, and the larger the slack, the more delay of entrainments is acceptable without leading to stranded parcels. Note that in the field of robust optimization adding slack (buffer) time is one prominent approach to achieve solution-robustness (e.g., see Briskorn et al. 2011; Kouvelis and Yu 1996). Fur-

ther note that again a single shipment that can only be feasibly transported if handed over among two specific crowdshippers with zero slack time removes the optimization pressure from all other parcels. It will be the task of our computational study in Sect. 7.3 to explore whether this disadvantage significantly deteriorates average results.

Example: Consider the example instance given in Fig. 1(a). Here, we have three crowdshippers a, b, and c traveling along three subway lines (blue, green, and orange) with the crowdshippers' departure times given next to their person icons. It is assumed that travel between two neighboring stations of a line takes one time unit, so that crowdshipper b leaves the origin station at the upper left at 5 and arrives at the destination at the upper right station at 8. Two parcels A and B are to be delivered, where the lower (higher) number within the respective parcel icon indicates the earliest departure (latest arrival) at its origin (destination) station. Parcel pickup and deposit at a parcel locker is assumed to take negligible time, and the locker capacity is assumed to be non-restrictive. A solution that is both delivery-feasible and capacity-feasible is depicted in Fig. 1(b). The numbers in the parcel icons indicate their departure at the respective station (or the arrival time at a destination). Parcel B, for instance, leaves its origin station in the lower left with crowdshipper c on the blue line, is deposited at time 6 in the station where the blue and green line meet, and travels its final leg with crowdshipper b. This solution leads to the following objective values:

(1) *MAX-PROFIT:* If we assume that the crowdshipping platform receives postal charge $p_j = 5$ for each parcel $j \in J$ and each crowdshipper receives $f = 1$ money unit per parcel entrainment, our solution results in a total profit of 6 money units.
(2) *MAX-PARCELS:* If we assume that the given minimum platform profit P does not exceed 6 money units, then both parcels are successfully processed and the objective value is 2. A profit of $P > 6$, however, cannot be achieved and, hence, the solution in Fig. 1(b) would not meet the profit requirement.
(3) *MAX-INVOLVEMENT:* For $P \leq 6$, we have all three public transport users involved in crowdshipping.

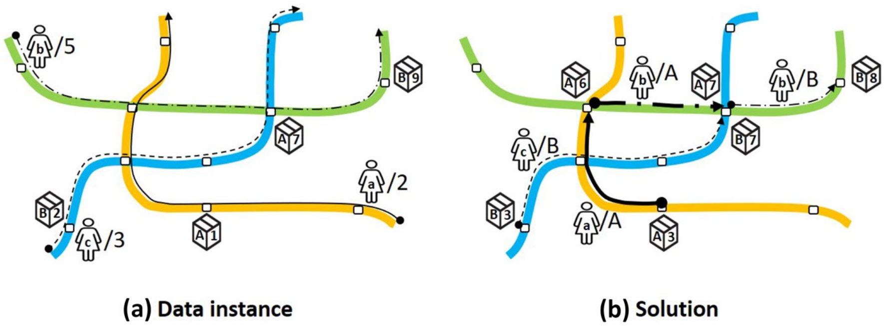

Fig. 1 Example for public transport crowdshipping

(4) *MIN-TOTAL-ENTRAINMENTS:* For $P \leq 6$, our solution involves a total number of four entrainments.
(5) *MIN-MAX-ENTRAINMENTS:* For $P \leq 6$, the maximum number of entrainments per parcel amounts to 2, which is achieved by both parcels.
(6) *MAX-MIN-SLACK:* While the slack time of parcel A's handover (departure) where the yellow and green lines meet (at its origin locker) is 1 (2) time unit(s), it arrives at its destination right at the deadline. Hence, parcel A's minimum slack is 0. Parcel B has a slack time of 1 time unit at all its relevant lockers (i.e., at its destination in the lower left, at its handover locker where the blue and green lines meet, and at its destination in the upper right). Hence, in total we have a minimum slack time of 0 (provided that $P \leq 6$).

Our crowdshipping problem is based on a few (simplifying) assumptions and prerequisites, which we discuss in the following:

(i) We presuppose deterministic information on the crowdshipper's movement through the public transportation network. Thus, we assume that crowdshippers register at the platform and announce their time-stamped paths, e.g., before they head to work. Naturally, this assumption causes problems whenever crowdshippers cannot realize their announcement and are delayed. We address this type of uncertainty by our robustness-oriented objectives MIN-TOTAL-ENTRAINMENTS, MIN-MAX-ENTRAINMENTS, and MAX-MIN-SLACK. We test their abilities to protect against delays in Sect. 7.
(ii) We only consider a static problem setting, which can, for instance, be applied to decide on order acceptance at the previous day, while the deterministic travel information is only applied to anticipate the shipments' prospective traversal through the public transportation network. The operational routing based on continuously updated information, e.g., on delayed trains, canceled requests, or missing crowdshippers, is then left to another optimization task including dynamic and stochastic information. Even in a dynamic environment, however, our static problem version can be applied on a rolling planning horizon whenever new information occurs. Furthermore, the static version can be used to train a neural network to make online decisions or to establish bounds on the solution value of the dynamic version of the problem, which will facilitate the evaluation of heuristic approaches. Naturally, we only provide a first contribution to public transit crowdshipping that aims at inspiring further research.
(iii) We presuppose the most basic compensation scheme for crowdshippers, which is very easy to communicate: a fixed entrainment fee f. Alternative schemes, for instance, influenced by parcel characteristics (e.g., weight or urgency), crowdshippers (e.g., their reliability rating or membership duration), and/or transportation legs (e.g., scarcity of crowdshippers on rarely used parts of the transportation network or the length of an entrainment) are possible, but left to future research.

(iv) We assume that a crowdshipper can transport at most one parcel at a time. Naturally, it may also be possible to transship two small parcels instead of one large shipment, but again this problem extension is left to future research.

(v) We assume that capacity restrictions L_s can be measured in number of parcels that fit into a locker at station $s \in S$. This implies that differently sized parcels (and suitable locker compartments to hold them) are not differentiated. Since parcels are restricted in their size and weight to be conveniently handled by crowdshippers in public transport anyway, we assume that each parcel fits any compartment. Integrating differently sized parcels and compartments (or multiple shipments per customer) into our solution concepts seems straightforward, but is left to future research.

(vi) We presuppose that parcels that end up with empty entrainment sequences do not occupy locker capacity at their origins. Since they cannot be feasibly crowdshipped, alternative delivery options beyond public transport must be utilized (e.g., a traditional postal service provider). Analogously, we assume that parcels with a slack of 0 at origin, handover, or destination lockers occupy no capacity. They are directly handed over among the persons meeting in front of the lockers.

(vii) We do not include the shipments' delivery toward the first locker and their final travel legs after the final locker. We assume that they are executed by the shippers hiring crowdshipping services and the recipients, respectively. Naturally, when comparing public transport crowdshipping with other last-mile delivery modes (e.g., regarding their costs and emissions) these legs must not be forgotten. However, the choice of the first (last) locker where a sender induces a shipment into the system (a recipient picks up a shipment) could be part of the operational decision (analogously to Macrina et al. 2020; Vincent et al. 2022) to circumvent scarce locker capacity. To extract the basic optimization setting, however, we leave this additional flexibility to future research.

Given this problem setting, the following paragraphs provide an analysis of computational complexity.

Theorem 3.1 *MAX-PARCELS is strongly NP-hard even if* $P = f = 0$, $L_s = \infty$ *for each* $s \in S$, *and* $r_j = 0$, $d_j = \infty$, *and* $p_j = 1$ *for each* $j \in J$.

We show NP-completeness of the decision version of MAX-PARCELS, which asks whether we can deliver all parcels by reduction from the problem to find a number of edge-disjoint paths in a directed acyclic graph, namely DISJOINT-PATHS, which is strongly NP-complete (see Slivkins 2010) and is restated in the following.

Given a directed graph $G = (V, E)$ with n nodes and m arcs, and k pairs of terminals $(s_1, t_1), \dots, (s_k, t_k)$, DISJOINT-PATHS is to determine whether there exist a directed path from s_l to t_l for each $l = 1, \dots, k$, such that these paths do not share any edges. DISJOINT-PATHS is implied to be (strongly) NP-complete by Even et al. (1976), even if G is acyclic.

Proof Given an instance I of DISJOINT-PATHS with G being acyclic, we construct an instance I' of MAX-PARCELS as follows. We set $P = f = 0$ and assume that nodes in V are numbered according to a topological ordering, that is if there is an arc leading from v to v', then $v' > v$.

- We have a station $v \in S$ for each node $v \in V$ in G with $L_v = \infty$.
- We have a crowdshipper $e \in I$ for each arc $e \in E$ in G. The path of crowdshipper $e = (v, v')$ leads from station v directly to station v' and does not visit any other stations. We do not fully specify the time-stamps, here, but set them such that no crowdshipper leaves from $v \in V$ before each crowdshipper reaching v has arrived. This can be done easily since G is acyclic.
- Finally, we have $J = \{1, \dots, k\}$ and each parcel $j \in J$ has $p_j = 1$, $\alpha_j = s_j$, $\omega_j = t_j$, $r_j = 0$, and $d_j = \infty$.

Note that each feasible solution to I' achieves the required profit of $P = 0$ since $f = 0$. Note, furthermore, that a delivery-feasible solution to I' with each parcel delivered has a sequence of entrainments for each delivered parcel $j \in J$, which reflects a path from s_j to t_j in G. Since each crowdshipper can carry at most one parcel, these paths are arc-disjoint.

Now, it is not hard to see that the answer to I is yes, if and only if all parcel can be delivered in I'. This completes the proof. □

With Theorem 3.1, we can easily conclude Corollary 3.1.

Corollary 3.1 *MAX-PROFIT is strongly NP-hard and determining whether a feasible solution to MAX-INVOLVEMENT, MIN-TOTAL-ENTRAINMENTS, MIN-MAX-ENTRAINMENTS, or MAX-MIN-SLACK exits is strongly NP-complete, even if* $f = 0$, $L_s = \infty$ *for each* $s \in S$, *and* $r_j = 0$, $d_j = \infty$, *and* $p_j = 1$ *for each* $j \in J$.

It is not hard to see that MAX-PROFIT with $f = 0$ and $p_j = 1$ for each parcel $j \in J$ is equivalent to MAX-PARCELS with $P = 0$. MAX-INVOLVEMENT, MIN-TOTAL-ENTRAINMENTS, MIN-MAX-ENTRAINMENTS, and MAX-MIN-SLACK generalize the decision version of MAX-PARCELS. We can set f and the profit threshold P in the former problems to 0 and the value achieved when all parcels are delivered, respectively, in order to determine whether it is possible to deliver all parcels.

4 Mixed integer programs

This section presents a basic mixed integer program (MIP) for MAX-PROFIT and details on necessary modifications to address the other objectives. We, first, introduce parts of the notation summarized in Table 1.

Beside sets J, I, and S of parcels, crowdshippers, and stations as introduced in Sect. 3, we use various subsets. Sets S_i and S_i' contain all stations visited by

Table 1 Notation for MAX-PROFIT-MIP

J	set of parcels
I	set of crowdshippers
S	set of stations
S_i	set of stations visited by $i \in I$
S_i'	set of stations visited by $i \in I$ except the last station of i
I_s	set of crowdshippers who visit $s \in S$
I_s'	set of crowdshippers who pass through or end at $s \in S$ (and do not start in s)
I_j^1	set of crowdshippers who are at α_j not earlier than r_j and, hence, can pick up j from α_j
I_j^2	set of crowdshippers who arrive at ω_j not later than d_j and, hence, can deliver j to ω_j
$I_{i,s}^-$	set of crowdshippers who are at $s \in S$ before or at the same time as $i \in I_s$ (including i)
$I_{i,s}^+$	set of crowdshippers who are at $s \in S$ after or at the same time as $i \in I_s$ (including i)
$J_{i,s}$	set of parcels such that $j \in J_{i,s}$ if and only crowdshipper i is at station $s \in S_i$ in $[r_j, d_j]$
L_s	locker capacity of station $s \in S$
α_j	origin of parcel $j \in J$
ω_j	destination of parcel $j \in J$
r_j	release date of parcel $j \in J$
d_j	deadline of parcel $j \in J$
p_j	postal charge of parcel $j \in J$
$t_{i,s}$	point of time when crowdshipper $i \in I$ is at $s \in S_i$
f	fixed entrainment fee
$\mathbf{s}_{i,s}^-$	station visited by $i \in I$ immediately before $s \in S$, $i \in I_s'$
$\mathbf{s}_{i,s}^+$	station visited by $i \in I$ immediately after $s \in S_i'$
$x_{i,s,j}$	binary variable: 1, if crowdshipper $i \in I$ moves parcel $j \in J_{i,s}$ from station $s \in S_i'$ toward $\mathbf{s}_{i,s}^+$; 0, otherwise
$y_{i,s}$	continuous variable: at least 1, if crowdshipper $i \in I$ picks up a parcel at station $s \in S_i'$; at least 0, otherwise

crowdshipper $i \in I$ on the fixed path and all stations visited but the last one on the path, respectively. The latter, thus, contains those stations where i can pick up a parcel. Sets I_s and I_s' represent the set of crowdshippers visiting station $s \in S$ and the set of crowdshippers visiting but not starting in s, respectively. The latter, hence, contains all crowdshippers who can deliver a parcel to s. Sets I_j^1 and I_j^2 contain those crowdshippers who can pick up parcel $j \in J$ at its origin station α_j, that is who leave α_j not earlier than r_j, and who can deliver j timely to its destination ω_j (i.e., they reach ω_j not later than d_j), respectively. Sets $I_{i,s}^-$ and $I_{i,s}^+$ represent the set of crowdshippers who are present at s the same time or earlier than i and the set of crowdshippers who are present at s the same time or later than i, respectively. That is, crowdshipper i can pick up a parcel at s delivered to s by any crowdshipper in $I_{i,s}^-$, and a parcel delivered to s by i can be picked up by each crowdshipper in $I_{i,s}^+$. Finally, we have $J_{i,s} = \emptyset$ if crowdshipper i does not visit station s, and $J_{i,s} = \{j \mid r_j \le t_{i,s} \le d_j\}$ otherwise.

We employ two type of variables. First, we consider binary variable $x_{i,s,j}$ for each crowdshipper $i \in I$, each station $s \in S_i'$ visited by i except the last one on the path, and each parcel $j \in J_{i,s}$ which is compatible with $r_j \leq t_{i,s} \leq d_j$. Binary variable $x_{i,s,j}$ equals 1, if crowdshipper $i \in I$ moves parcel $j \in J_{i,s}$ from station $s \in S'_i$ toward $\mathbf{s}^+_{i,s}$, and 0 otherwise. Second, we have continuous variable $y_{i,s}$ for each crowdshipper $i \in I$ and station $s \in S'_i$ where i might pick up a parcel (that is, each station $s \in S'_i$ visited by i except the last one on the path). Continuous variable $y_{i,s}$ takes a value of at least 1, if crowdshipper $i \in I$ picks up a parcel at station $s \in S'_i$, and a value of at least 0 otherwise. We will argue, however, that in optimum solutions $y_{i,s}$ takes only binary values.

Applying the notation summarized in Table 1, our MAX-PROFIT-MIP consists of objective function (1) and constraints (2) to (10).

$$\text{MAX-PROFIT-MIP: Maximize } \sum_{j \in J} \sum_{i \in I^1_j} p_j \cdot x_{i,\alpha_j,j} - \sum_{i \in I} \sum_{s \in S'_i} f \cdot y_{i,s} \tag{1}$$

$$\text{s.t.} \sum_{j \in J_{i,s}} x_{i,s,j} \leq 1 \qquad \forall\, i \in I; s \in S'_i \tag{2}$$

$$\sum_{i \in I : J_{i,s} \ni j} x_{i,s,j} \leq 1 \qquad \forall\, j \in J; s \in S \tag{3}$$

$$x_{i,s,j} - \sum_{i' \in I^+_{i,\mathbf{s}^+_{i,s}}} x_{i',\mathbf{s}^+_{i,s},j} \leq 0 \qquad \forall\, i \in I; s \in S'_i; j \in J_{i,s} \, : \, \mathbf{s}^+_{i,s} \neq \omega_j \tag{4}$$

$$\sum_{i \in I^1_j} x_{i,\alpha_j,j} - \sum_{i \in I^2_j} x_{i,\mathbf{s}^-_{i,\omega_j},j} = 0 \qquad \forall\, j \in J \tag{5}$$

$$\begin{aligned} &\sum_{\substack{j \in J, \\ \alpha_j = s, t_{i,s} \geq r_j}} \sum_{i' \in I^1_j} x_{i',\alpha_j,j} + \sum_{i' \in I^-_{i,s} \cap I'_s} \sum_{\substack{j \in J_{i',\mathbf{s}^-_{i',s}} : \\ \omega_j \neq s}} x_{i',\mathbf{s}^-_{i',s},j} \\ &+ \sum_{i' \in I^-_{i,s} \cap I'_s} \sum_{\substack{j \in J_{i',\mathbf{s}^-_{i',s}} : \\ \omega_j = s, d_j \geq t_{i,s}}} x_{i',\mathbf{s}^-_{i',s},j} - \sum_{i' \in I^-_{i,s}} \sum_{j \in J_{i',s}} x_{i',s,j} \leq L_s \qquad \forall\, i \in I; s \in S_i \end{aligned} \tag{6}$$

$$x_{i,s,j} - x_{i,\mathbf{s}^-_{i,s},j} \leq y_{i,s} \qquad \forall\, s \in S'_i; i \in I'_s; j \in J_{i,s} \tag{7}$$

$$x_{i,s,j} \leq y_{i,s} \qquad \forall\, i \in I; s \in S'_i; i \notin I'_s; j \in J_{i,s} \tag{8}$$

$$x_{i,s,j} \in \{0, 1\} \qquad \forall\, i \in I; s \in S'_i; j \in J_{i,s} \tag{9}$$

$$y_{i,s} \geq 0 \qquad \forall\, i \in I; s \in S_i' \tag{10}$$

Objective function (1) defines the aim of the platform provider, which is the maximization of the total profit consisting of the sum of postal charges for all successfully delivered parcels minus the total entrainment fees to be paid to the crowdshippers. Note that for given x-variables $y_{i,s}$ gets assigned the smallest feasible value in optimum solutions due to (1). Constraints (2) enforce the capacity of (at most) a single parcel per travel leg for each crowdshipper. Only a single crowdshipper can move a parcel j from a specific station s due to (3). Naturally, this can be crowdshipper $i \in I$, if and only if parcel j is an element of $J_{i,s}$, which contains all parcels that can be moved from station s by i. Constraints (4) guarantee that each parcel j moved to a station s will be carried further unless $\omega_j = s$, that is if s is its destination. Note that $i \in I_{i,s}^+$ and, hence, (4) covers the case where a parcel travels through s without being put in a locker. Note, furthermore, that (4) implies that a sequence of entrainments can only end at a parcel's destination. Note, finally, that (4) together with (3) implies that parcels cannot travel in circles and, hence, each parcel that is picked up at all gets assigned a sequence of entrainments ending at the parcel's destination. Constraints (5), then, ensures that such a parcel is transported from its origin. Violations of lockers' capacities are prevented by constraints (6). The left side reflects $n_{s,t_{i,s}}$, that is the number of parcels in the lockers at s immediately after crowdshipper i has left s. The first sum counts the parcels which start at s ($\alpha_j = s$) and have been put into a locker until $t_{i,s}$ ($t_{i,s} \geq r_j$). The second sum counts the parcels which do neither start nor end at s ($\omega_j \neq s$) and have been transported to s until $t_{i,s}$ ($i' \in I_{i,s}^- \cap I_s'$). The third sum counts the parcels which end at s ($\omega_j = s$), arrived at s until $t_{i,s}$ ($i' \in I_{i,s}^- \cap I_s'$), and have not been taken out of the locker by the recipients until $t_{i,s}$ ($d_j \geq t_{i,s}$). Finally, the fourth sum counts the parcels that have been transported from s until immediately after $t_{i,s}$. Note that a parcel which travels through s without ever being put into a locker at s never contributes to the capacity load. Constraints (7) and (8) enforce that $y_{i,s} \geq 1$ if j is picked up by i at s and s is not i's first station and s is i's first station, respectively. Note that in this case we obtain $y_{i,s} = 1$ in optimum solutions, since $y_{i,s}$ will get assigned a value as small as feasibly possible due to the objective function. Finally, (9) and (10) define the variables' domains. If neither (7) nor (8) enforce $y_{i,s} \geq 1$, then we obtain $y_{i,s} = 0$ in optimum solutions, again, due to the objective function.

Note that it is not enforced that the sequence of entrainments actually starts at the parcel's origin. We can, however, cut all entrainments leading to the parcel's origin without decreasing the objective value or losing feasibility. We suggest to add Constraints (11) and (12) to MAX-PROFIT-MIP to restrict the solution space.

$$\sum_{i \in I'_{\alpha_j} : j \in J_{i,\mathbf{s}^-_{i,\alpha_j}}} x_{i,\mathbf{s}^-_{i,\alpha_j},j} \leq 0 \quad \forall j \in J \tag{11}$$

Table 2 Additional notation for other objectives

M	large value (BigM)
P	minimum platform profit
F_i	binary variables: 1, if crowdshipper $i \in I$ moves any parcel $j \in J$; 0, otherwise
F^e	continuous variable: maximum number of entrainments among all crowdshippers
F^s	continuous variable: minimum slack among all crowdshippers
$z_{i,j}$	binary variables: 1, if crowdshipper $i \in I$ moves parcel $j \in J$; 0, otherwise

Table 3 Extended MIP formulations for the remaining objectives

Problem	Objective and new constraints in addition to (2)-(13)	
MAX-PARCELS	Maximize $\sum_{j \in J} \sum_{i \in I_j^1} x_{i,\alpha_j,j}$	
MAX-INVOLVE-MENT	Maximize $\sum_{i \in I} F_i$	
	$\sum_{s \in S_i'} \sum_{j \in J_{i,s}} x_{i,s,j} \geq F_i$	$\forall\, i \in I$
	$F_i \in [0, 1]$	$\forall\, i \in I$
MIN-TOTAL-ENTRAINMENTS	Minimize $\sum_{i \in I} \sum_{s \in S_i'} y_{i,s}$	
MIN-MAX-ENTRAINMENTS	Minimize F^e	
	$\sum_{s \in S} z_{s,j} \leq F^e$	$\forall\, j \in J$
	$x_{i,s,j} - x_{i,\mathbf{s}_{i,s}^-,j} \leq z_{s,j}$	$\forall\, i \in I, s \in S_i'$
	$z_{s,j} \geq 0$	$\forall\, j \in J; s \in S$
MAX-MIN-SLACK	Maximize F^s	
	$(2 - x_{i,s,j} - x_{i',\mathbf{s}_{i,s}^+,j}) \cdot M + (t_{i',\mathbf{s}_{i,s}^+} - t_{i,\mathbf{s}_{i,s}^+}) \geq F^s$	$\forall\, i \neq i' \in I; s \in S_i'; \mathbf{s}_{i,s}^+ \in S_{i'}'; j \in J_{i,s} \cap J_{i',\mathbf{s}_{i,s}^+}$
	$(1 - x_{i,\alpha_j,j}) \cdot M + (t_{i,\alpha_j} - r_j) \geq F^s$	$\forall\, i \in I; s \in S_i'; j \in J_{i,s}; s = \alpha_j$
	$(1 - x_{i,s,j}) \cdot M + (d_j - t_{i,\omega_j}) \geq F^s$	$\forall\, i \in I; s \in S_i'; j \in J_{i,s}, \mathbf{s}_{i,s}^+ = \omega_j$

$$\sum_{i \in I'_{\omega_j} : j \in J_{i,\omega_j}} x_{i,\omega_j,j} \leq 0 \quad \forall j \in J \tag{12}$$

Constraints (11) cut solutions where the sequence of entrainments does not start at the parcel's origin. Constraints (12) do not cut any solutions but make it explicit that a sequence of entrainments must end at a parcel's destination. Preliminary computational test have shown that these extensions lead to a speed up of standard solver Gurobi, so that all computational tests reported in Sect. 6 include these valid inequalities.

Given our basic model MAX-PROFIT-MIP, the adaptions in order to cover our five alternative objectives are truly straightforward. While MAX-PROFIT directly aims to maximize the profit, the other problems rather have a minimum platform profit P that must be ensured by additional constraint

$$\sum_{j\in J}\sum_{i\in I_j^1} p_j \cdot x_{i,\alpha_j,j} - \sum_{i\in I}\sum_{s\in S_i'} f \cdot y_{i,s} \geq P. \tag{13}$$

Given constraints (2)-(13) and the notation reported in Table 2, the modified objective functions and the necessary additional constraints for our five alternative objectives are summarized in Table 3.

Due to the complexity status of our problem versions, we cannot expect that our MIPs are solvable for an off-the-shelf solver if the numbers of parcels and crowdshippers reach dimensions relevant to real-world crowdshipping platforms. Therefore, the following section provides an additional heuristic solution procedure.

5 A heuristic decomposition framework for all objectives

A suitable solution procedure should cover all of our six problem versions with only minor adaptions, and it should deliver close to optimal solutions in acceptable time even for considerable numbers of parcels and crowdshippers. Our suggestion to meet these requirements is a heuristic decomposition framework that consists of two stages. On the first stage, which we describe in more detail in Sect. 5.1, we introduce a modification of Dijkstra's algorithm to generate a pool of single-parcel tours through a given public transportation network. On the second stage (see Sect. 5.2), we apply a standard solver to select parcel tours from the pool by solving a MIP similar to the well-known set packing problem.

5.1 Generating a pool of single-parcel tours

In the first stage, we generate a pool of single parcel tours for all parcels. If each parcel tour was optimized individually, then most of them would utilize the central resources where most traffic passes. Therefore, we apply a special mechanism where also tours via less central resources are generated to ensure diversity within the pool. Specifically, we consider a sequence π of all parcels in J and generate a tour for parcels one by one in the order indicated by π. When generating a tour for the k-th parcel in π, we account for capacities of crowdshippers occupied by tours for the first $k-1$ parcels. Virtually, whenever a part of a crowdshipper's path is occupied by the k-th parcel, we consider each remaining part of this path as a distinct crowdshipper (who is available throughout this path) for the $(k+1)$-th parcel.

For a specific parcel $j \in J$, we then generate a path from α_j to ω_j respecting release date r_j, deadline d_j, and the crowdshippers' time-stamped paths as follows. The scheme loosely follows Dijkstra's algorithm and the A*-algorithm (Ikeda et al. 1994) with stations corresponding to nodes in a graph and paths of crowdshippers corresponding to paths in that graph. Rather than restricting ourselves to a purely time-driven evaluation of paths for j, we consider $\phi_s = w_\mu \cdot \mu_s + w_d \cdot q_s + w_t \cdot t_s$ for each station $s \in S$, where μ_s is the number of entrainments on the path of j from α_j to s, q_s represents the Manhattan distance between stations s and ω_j, t_s is time parcel j reaches s on the path, and w_μ, w_d, and w_t are weights.

We designed ϕ_s to reflect various aspects relevant for the different objectives. Furthermore, we maintain for each station $s \in S$ the crowdshipper i_s, which brought j to s. Initially, we set $\phi_{\alpha_j} = w_\mu \cdot 0 + w_d \cdot q_{\alpha_j} + w_t \cdot r_j$ and $\phi_s = \infty$ for each $s \neq \alpha_j$ and initialize $i_s = \cdot$ for each $s \in S$ with a dummy. In each iteration, the procedure then determines a station s^* to which the best path is then fixated. Furthermore, we update the best found paths to stations which can be reached be traveling one station with a crowdshipper from s^*, given that s^* is reached at time t_{s^*}. In the course of the procedure, $\overline{S}$ represents the set of stations with fixated paths toward them. Initially, we have $\overline{S} = \emptyset$.

In each iteration, s^* is determined as $s^* = \arg\min \left\{ \phi_s \mid s \in S \backslash \overline{S} \right\}$. If $s^* = \omega_j$ and $t_{s^*} \leq d_j$, we have found the (feasible) path from α_j to ω_j. If $s^* = \omega_j$ and $t_{s^*} > d_j$, the procedure failed to find a feasible path. Finally, if $s^* \neq \omega_j$, we determine the set I_{s^*} of crowdshippers starting from s^* not before t_{s^*}. For each $i \in I_{s^*}$ and the corresponding station $\mathbf{s}^+_{i,s^*}$ to which i travels from s^*, we determine the implied value $\phi_{\mathbf{s}^+_{i,s^*},i}$ of $\phi_{\mathbf{s}^+_{i,s^*}}$ as

$$\phi_{\mathbf{s}^+_{i,s^*},i} = \begin{cases} w_\mu \cdot \mu_{s^*} + w_d \cdot q_{\mathbf{s}^+_{i,s^*}} + w_t \cdot t_{i,\mathbf{s}^+_{i,s^*}} & i = i_{s^*} \\ w_\mu \cdot (\mu_{s^*} + 1) + w_d \cdot q_{\mathbf{s}^+_{i,s^*}} + w_t \cdot t_{i,\mathbf{s}^+_{i,s^*}} & i \neq i_{s^*}. \end{cases}$$

In both cases, $q_{\mathbf{s}^+_{i,s^*}}$ reflects the distance between the next station $\mathbf{s}^+_{i,s^*}$ and ω_j, and $t_{i,\mathbf{s}^+_{i,s^*}}$ represents the time parcel j would reach the next station $\mathbf{s}^+_{i,s^*}$ if it is carried from s^* by crowdshipper i. In the upper case, this crowdshipper i is the same as the one that brought j to s^* (that is, j travels through s^* with i) and, hence, $\mu_{\mathbf{s}^+_{i,s^*}} = \mu_{s^*}$. In the lower case, crowdshipper i picks up j at s^* and, hence, $\mu_{\mathbf{s}^+_{i,s^*}} = \mu_{s^*} + 1$. Note that the same station s might be the next station for multiple crowdshippers in I_{s^*} and the implied values might differ among them. We update all path information for station $\mathbf{s}^+_{i,s^*}$ for each $i \in I_{s^*}$, if

$$\phi_{\mathbf{s}^+_{i,s^*}} > \min \left\{ \phi_{\mathbf{s}^+_{i',s^*},i'} \mid i' \in I_{s^*}, \mathbf{s}^+_{i,s^*} = \mathbf{s}^+_{i',s^*} \right\},$$

that is if the best implied path by any crowdshipper traveling from s^* to $\mathbf{s}^+_{i,s^*}$ yields a lower value of $\mathbf{s}^+_{i,s^*}$.

To generate a pool with multiple tour candidates for each parcel, we repeatedly draw a random sequence π and employ the procedure detailed above for four different weight sets $(w_\mu, w_d, w_t) = (1/3, 1/3, 1/3), (1/3, 2/3, 0), (0, 1/2, 1/2), (0, 2/3, 1/3)$. These weight sets haven proven most effective in preliminary tests, which (for a matter of conciseness are not reported in this paper). A tour is admitted to the pool, if it generates a profit, that is if the postal charge exceeds the total entrainment fees. The pool is complete once we gathered 10 tours per parcel on average. The latter choice, too, has proven as a reasonable compromise between runtime and solution quality in preliminary tests not reported in this paper.

Table 4 Additional notation for stage 2

$\mathcal{T}_j$	set of single-parcel tours for each parcel $j \in J$
c_ψ	profit of tour $\psi \in \mathcal{T}_j$, $j \in J$
$\Xi_{i,s,\psi}$	binary parameters: 1, if crowdshipper $i \in I$ moves parcel $j \in J$ from station $s \in S'_i$ toward $\mathbf{s}^+_{i,s}$ according to tour $\psi \in \mathcal{T}_j$; 0, otherwise
$\Delta_{i,s,\psi}$	binary parameters: 1, if parcel $j \in J$ is stored in a locker at $s \in S$ when $i \in I$ leaves s according to tour $\psi \in \mathcal{T}_j$; 0, otherwise
Γ_ψ	minimum slack in tour $\psi \in \mathcal{T}_j$, $j \in J$
Y_ψ	number of entrainments in tour $\psi \in \mathcal{T}_j$, $j \in J$
ϵ_ψ	binary variables: 1, if tour $\psi \in \mathcal{T}_j$, $j \in J$, is selected; 0, otherwise

5.2 Combining single-parcel tours

After generating a set $\mathcal{T}_j$ of single-parcel tours for each parcel $j \in J$ as detailed in Sect. 5.1, we use an off-the-shelf solver and a MIP model formulation in order to combine single-parcel tours to a feasible solution. We present the MIP model formulation in the following, while using the additional notation summarized in Table 4.

Again, we describe our basic MIP for objective MAX-PROFIT first and report on necessary adaptions for our alternative objectives afterward.

$$\text{MAX-PROFIT-SELECT: Maximize } F(\epsilon) = \sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} c_\psi \cdot \epsilon_\psi \tag{14}$$

$$\text{s.t.} \sum_{\psi \in \mathcal{T}_j} \epsilon_\psi \leq 1 \quad \forall j \in J \tag{15}$$

$$\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} \Xi_{i,s,\psi} \cdot \epsilon_\psi \leq 1 \quad \forall i \in I; s \in S'_i \tag{16}$$

$$\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} \Delta_{i,s,\psi} \cdot \epsilon_\psi \leq L_s \quad \forall i \in I; s \in S'_i \tag{17}$$

$$\epsilon_\psi \in \{0, 1\} \quad \forall \psi \in \mathcal{T}_j, j \in T \tag{18}$$

Our MAX-PROFIT-SELECT model uses binary variable ϵ_ψ for each $\psi \in \mathcal{T}_j$, $j \in J$, which takes value 1 if tour ψ is selected and value 0 otherwise. At most one tour can be selected per parcel $j \in J$, see (15), that is each parcel is delivered at most once. Two tours concerning different parcels cannot be selected simultaneously, if they occupy the same crowdshipper on the same travel leg, see (16). Similarly, at each relevant point of time no more than L_s parcels can be stored in a locker at station s,

Table 5 Extended set packing formulations for the different objectives

Problem	Objective and new constraints in addition to (15)-(19)	
MAX-PARCELS	Maximize $\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} \epsilon_\psi$	
MAX-INVOLVEMENT	Maximize $\sum_{i \in I} F_i$	
	$\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} \sum_{s \in S'_i} \Xi_{i,s,\psi} \cdot \epsilon_\psi \geq F_i$	$\forall\, i \in I$
	$F_i \in [0, 1]$	$\forall\, i \in I$
MIN-TOTAL-ENTRAINMENTS	Minimize $\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} (p_j - c_\psi)/f \cdot \epsilon_\psi$	
MIN-MAX-ENTRAINMENTS	Minimize F^e	
	$(p_j - c_\psi)/f \cdot \epsilon_\psi \leq F^e$	$\forall \psi \in \mathcal{T}_j, j \in J$
MAX-MIN-SLACK	Maximize F^s	
	$\Gamma_\psi \cdot \epsilon_\psi + (1 - \epsilon_\psi) \cdot M \geq F^s$	$\forall \psi \in \mathcal{T}_j, j \in J$

see (17). Finally, objective function (14) represents the goal to maximize the total profit achieved.

To represent our five alternative objectives, additionally a minimum total profit P is ensured by constraint

$$\sum_{j \in J} \sum_{\psi \in \mathcal{T}_j} c_\psi \cdot \epsilon_\psi \geq P. \tag{19}$$

Given constraints (15) to (19) and the notation listed in Table 4, our modified objective functions as well as the additional constraints are specified in Table 5.

Our MIP formulations extend the famous set packing problem (see Garey and Johnson 1979). Today's default solvers are generally known to be quite capable in solving this kind of model. The computational performance analysis reported on in the following section explores whether this claim can be confirmed in our case.

6 Performance of algorithms

In this section, we test the performance of our solution approaches. Since no established testbed is available for our public transport crowdshipping problem, we first elaborate how our instances have been generated in Sect. 6.1. Afterward, in Sect. 6.2, we benchmark the performance of our heuristic decomposition procedure with a standard solver solving our MIP models.

All computations have been executed on a 64-bit PC with an 7-3770 3.40 GHz CPU and 16.0 GB of RAM. All solution methods have been implemented using VisualBasic (Visual Studio 2019), and off-the-shelf solver Gurobi (version 9.1.2) has been applied for solving the MIP models with a general time limit of 300 s, if not explicitly stated otherwise.

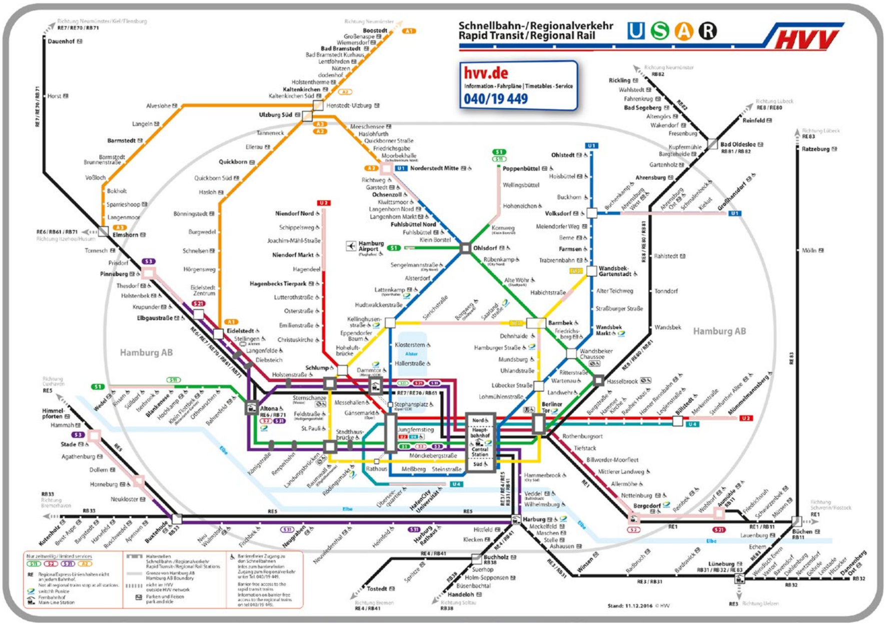

Fig. 2 Public transport system of Hamburg [Source: HVV]

6.1 Data generator

This section reports on our data generator, which is based on the public transport system of Hamburg (Germany). Our data generator receives the number of parcels $|J|$ and the number of crowdshippers $|I|$ as its own input data. Given this input, each single instance is obtained as follows.

- *Public transport network:* Given the railway system of Hamburg, we utilize subway lines U1, U2, U3, and U4 as well as urban railway lines S1, S21, S3, and S31 (see Fig. 2). Each line $l \in L$ is defined by a sequence of stations $S_l \subseteq S$, so that our test bed consists of $|S| = 147$ stations in total. These stations of set S are partitioned into two subsets $S = S_C \cup S_S$. Stations of sets S_C and S_S represent inner city and suburban stations and they are marked in gray and pink, respectively. For each line $l \in L$, we use frequency f_l given by the original schedule of the HVV during the working hours (i.e., $f_{U1} = f_{U2} = f_{U3} = 5$), and $f_l = 10$ for the rest of the time. The travel times between any two consecutive stations of a line are drawn from $\mathcal{U}\{1, 2, 3\}$, which is in line with the vast majority of real-world stations. Finally, our planning horizon is set to 10 hours, i.e., $T = 600$ minutes.
- *Lockers:* For each station $s \in S$, we draw a locker capacity L_s proportional to the crowdshipper traffic. Parameter L_s is initially determined by normalized ratio v_s^{norm}, defined as the 'number of lines' divided by the 'sum of corresponding frequencies'. Subsequently, L_s is finally established through $L_s = \frac{1}{8}|J| + \frac{1}{4}|J| \cdot v_s^{norm}$.

This ensures that the minimum capacity is $\frac{1}{8}|J|$, while the maximum capacity is $\frac{3}{8}|J|$.

- *Parcels*: For each parcel $j \in J$, we draw a release date $r_j \sim \mathcal{U}\{1, \ldots, |T|/10\}$ and a deadline $d_j \sim \mathcal{U}\{9 \cdot |T|/10, \ldots, |T|\}$. We assume that with a probability of 50% a parcel has to be transported from a city center to a suburban station, where origin and destination stations are randomly chosen from sets S_C and S_S, respectively, and with 50% vice versa. For each successfully delivered parcel, the platform receives a constant postal charge of $p_j = p = 5$.
- *Crowdshippers*: We assume that 40% of the crowdshippers move during the morning hours, i.e., we determine their departure time t_i by drawing from a uniform distribution: $t_i \sim \mathcal{U}\{1, \ldots, 3 \cdot |T|/10\}$. Another 40% of crowdshippers move during the late hours ($t_i \sim \mathcal{U}\{6 \cdot |T|/10 + 1, \ldots, 9 \cdot |T|/10\}$), and the remaining 20% of crowdshippers move during main working hours ($t_i \sim \mathcal{U}\{3 \cdot |T|/10 + 1, \ldots, 6 \cdot |T|/10\}$).

  Crowdshippers of the morning hours needs to travel from a suburban area to a city center station (with a probability of 60%), while 30% move in the opposite direction, and 10% travel entirely within the city center. The origin and destination stations are randomly selected from sets S_C and S_S.

  During the late hours, the selection of origin and destination station is reversed, so that 60% move from the city center to the suburban area, while 30% move in the opposite direction, and again 10% stay in the city center.

  For crowdshippers that travel during the main working hours, we assume that they travel with equal probability from a suburban area to the city center, the other way round, or within the city center.

  Given the origin station, departure time, and destination of crowdshipper $i \in I$, we determine the shortest path by the standard Dijkstra algorithm through our network in order to determine their time-stamped paths $t_{i,s}$. The fixed entrainment fee is $f = 1$.

Finally, we set the repetition counter to ten for each data setting defined by the number of parcels $|J|$ and the number of crowdshippers $|I|$. Hence, ten instances, each derived as defined above, are returned by our data generator.

6.2 Computational results

Our performance tests benchmark our heuristic decomposition procedure (see Sect. 5) with off-the-shelf solver Gurobi when fed with the MIPs of Sect. 4. Our complete tests have shown that there are no significant performance differences of both competitors for the different objectives. To not overload this paper, we therefore decided to only report the performance results of objective MAX-PROFIT. When comparing the performance of these solution approaches in Table 6, we report on the average optimality gap in percent determined by Gurobi (column 'gap'), the average gap in percent to the best solution found among both competitors (column 'gap_b'), the number of instances where the approach found the best solution among

Table 6 Performance test of Gurobi and the heuristic decomposition procedure for objective MAX-PROFIT

		Gurobi						Decomposition heuristic				
$\|J\|$	$\|I\|$	gap	gap_b	best	opt	feas	sec	gap_b	best	opt	feas	sec
20	20	0.00	0.00	10	10	10	0.72	2.33	8	8	10	3.56
20	40	0.00	0.00	10	10	10	1.51	14.19	2	2	10	2.42
20	60	0.00	0.00	10	10	10	3.52	7.03	1	1	10	1.85
30	30	0.00	0.00	10	10	10	1.58	7.90	3	3	10	3.85
30	60	0.00	0.00	10	10	10	5.82	5.82	4	3	10	3.31
30	90	0.00	0.00	10	10	10	26.82	3.55	2	1	10	3.49
40	40	0.00	0.00	10	10	10	3.40	2.40	5	5	10	5.50
40	80	0.29	0.00	10	9	10	115.57	7.54	1	0	10	4.92
40	120	1.61	0.10	9	7	10	377.50	5.42	3	1	10	5.61
50	50	0.00	0.00	10	10	10	14.12	6.96	2	2	10	7.80
50	100	2.52	2.55	6	6	10	457.02	4.65	4	0	10	7.68
50	150	7.60	0.85	8	0	10	920.24	4.60	3	0	10	9.00
60	60	0.00	0.00	10	10	10	18.64	5.21	1	1	10	9.25
60	120	4.52	0.00	10	0	10	918.19	8.00	0	0	10	11.12
60	180	17.71	5.13	4	0	10	935.84	1.91	7	0	10	13.98
70	70	0.38	0.00	10	8	10	315.41	7.31	1	1	10	11.69
70	140	8.43	0.00	10	0	10	925.98	6.36	0	0	10	16.25
70	210	31.33	12.20	1	0	10	952.31	0.29	9	0	10	20.48
80	80	0.41	0.00	10	7	10	387.24	6.50	0	0	10	16.20
80	160	21.74	2.65	4	0	10	935.14	1.27	7	0	10	22.00
80	240	91.68	69.93	0	0	10	977.49	0.00	10	0	10	27.83
90	90	1.62	0.00	10	5	10	672.58	6.47	0	0	10	19.79
90	180	49.20	18.87	2	0	10	952.45	0.00	10	0	10	29.19
90	270	55.77	27.59	0	0	9	1015.92	0.00	10	0	10	41.56
100	100	4.40	0.00	10	0	10	921.50	4.55	0	0	10	25.54
100	200	55.38	24.13	0	0	9	968.71	0.00	10	0	10	37.91
100	300	79404.22	3027.54	0	0	8	1743.52	0.00	10	0	10	54.09

both competitors (column 'best'), the number of solutions proven to be optimal (column 'opt'), the number of instances where at least one feasible solution with an objective value ≥ 0 was obtained (column 'feas'), and the average CPU-seconds (column 'sec'). Note that time limit of the default solver was set to 15 min and the CPU-seconds of the heuristic include the preprocessing time of pool generation. In our study, we vary the number of parcels $|J|$ and the number of crowdshippers $|I|$. For each combination of these parameters, ten instances as described in Sect. 6.1 have been obtained, so that in total 270 instances constitute this testbed. The results summarized in Table 6 suggest the following findings:

- *Gurobi:* Default solver Gurobi performs very well when handling smaller instance sizes of $|J| \leq 30$ parcels. Here, it is able to verify all optimal solutions within short computational times. However, Gurobi struggles with larger instance sizes of $|J| \geq 70$ parcels, especially with a large crowdshipper base. Here, gaps as well as runtimes increase and less best solutions are obtained. For larger instances with fewer crowdshippers, however, Gurobi still outperforms our heuristic. Unfortunately, our computational evaluation in Sect. 7.1 will show that a large crowdshipper base is required to move a substantial number of parcels. In these cases, our heuristic seems the better option. Note that these results did not improve significantly in further tests, where we allowed the default solver longer running times up to one hour.
- *Decomposition heuristic:* Our heuristic, instead, produces a good compromise between solution quality and time, especially for large instances with many parcels and crowdshippers. It determines feasible solutions for all instances and requires less than one minute even for the largest instance sizes. The (optimality) gaps are reasonably small.

We conclude that both solution approaches seem an appropriate choice for our crowdshipping problem. Especially, for large instances with many shipments and potential crowdshippers, our heuristic seems the better choice, especially when fast decisions are required.

7 Managerial issues

This section is dedicated to managerial issues. We want to identify critical factors for the successful diffusion of public transport crowdshipping. Specifically, we explore how many volunteering crowdshippers must be recruited in order to successfully deliver a given amount of parcels in Sect. 7.1, we provide a relationship analysis between the different objectives in Sect. 7.2, and we address robustness issues to avoid stranded parcels in case of unforeseen train delays in Sect. 7.3. Finally in Sect. 7.4, we compare a splitting of a shipment's travel from origin to destination among multiple crowdshippers with direct single-crowdshipper transports. The latter promise a better protection against unforeseen train delays but offer less planning flexibility.

If not explicitly stated otherwise, we generate our instances as described in Sect. 6.1 for a varying number of parcels $|J|$ and available crowdshippers $|I|$. To not spoil our investigations by heuristic gaps, we decided to apply Gurobi (with a time limit of one hour) on smaller instances with up to $|J| \leq 60$ parcels only.

7.1 How many crowdshippers need to be recruited?

Among the outstanding challenges to successfully establish crowdshipping as a reliable every-day delivery option is certainly the volatile participation of volunteering

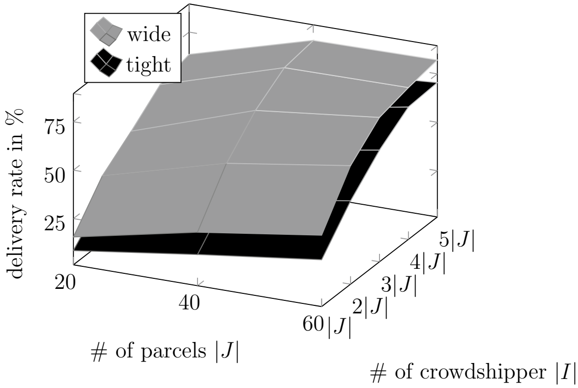

Fig. 3 Delivery rates of parcels in % depending on the number of parcels |*J*|, participating crowdshippers |*I*|, and wide or tight deadlines

crowdshippers (Le et al. 2019; Savelsbergh and Ulmer 2022). Therefore, recruiting a large enough base of participating crowdshippers is an important task for the successful diffusion of public transport crowdshipping. The specific means how to successfully attract public transport users for crowdshipping (e.g., a media campaign advertising the positive environmental impact and/or attractive entrainment fees) go beyond this paper. In this specific context, however, we want to explore how large the base of volunteering crowdshippers must be to successfully deliver a substantial amount of parcels via public transport crowdshipping.

To do so, we relate the parcel-to-crowdshipper-ratio to the delivery rate of successfully crowdshipped parcels in Fig. 3. Specifically, we solve instances with $|J| = \{20, 40, 60\}$ parcels to be transported, a volunteering crowdshipper base of $|I| = \{|J|, 2|J|, 3|J|, 4|J|, 5|J|\}$, and compare wide deadlines (as described in Sect. 6.1) and tight deadlines with $d_j = r_j + 2 \cdot |T|/3$. Our optimization objective is MAX-PROFIT, and we report on the delivery rate, i.e., the number of successfully crowdshipped parcels divided by all parcels in %. The results of our computational test, summarized in Fig. 3, show us basically four things:

(1) *Low impact of tighter deadlines:* The urgency of deliveries impacts the size of the crowdshipper base that is necessary to reach substantial delivery rates, but not to a large extent. Tight deadlines reduce the flexibility to involve crowdshippers in public transport crowdshipping, but this effect reduces the delivery rates only by a few percentage points.

(2) *More traffic on the platform increases the matches:* We can also observe a phenomenon, which is widely known for all kinds of matching problems (e.g., when organizing live kidney donations, see Roth et al. 2004). In Fig. 3, we can clearly observe that at a constant parcel-to-crowdshipper-ratio more traffic on the platform (i.e., more registered parcels and thus more volunteering crowdshippers, but at a constant ratio) increases the delivery rates. The larger the pool of volunteering crowdshippers and requested deliveries, the larger the flexibility to identify better matches.

(3) *Large crowdshipper base required:* Our results show that a crowdshipper base of significant size is required to reach noteworthy delivery rates. If we have the same number of crowdshippers than parcels (i.e., $|I| = |J|$), then only less than 38% of the registered shipments can feasibly be crowdshipped. At least twice as many crowdshippers than parcels are required to successfully crowdship about 62% of the parcels, and delivery rates of about 80%, instead, already require about five times more crowdshippers (wide deadlines).
(4) *The positive impact of additional crowdshippers quickly diminishes:* Finally, our results also indicate that the marginal returns of an increasing crowdshipper base reduce quickly. If we have just a small crowdshipper base (i.e., $|I| = |J|$), then adding another $|J|$ crowdshippers to the participants almost doubles the delivery rates. The same increase of $|J|$ additional crowdshippers if we already have a crowdshipper base of $|I| = 3|J|$ volunteers, instead, only leads to marginal additional returns around 10%. This effect implies that even with a very large crowdshipper base it cannot be expected that all registered parcels can be feasibly crowdshipped.

Naturally, these results should not be mistaken as precise target values for the number of crowdshippers to be recruited. The results are also impacted by other factors, such as the size of the public transport network and the pricing scheme. Nonetheless, our first experiment leads us to the following managerial take-home message:

Actionable insights: To not disappoint large parts of shippers seeking crowdshipping services for their parcels, a platform must recruit an active daily base of reliable crowdshippers that is considerably larger than the amount of parcels to be moved. Before investing into (IT and parcel locker) infrastructure, a crowdshipping platform for public transport should thus critically evaluate whether it is actually realistic to recruit such a substantial crowdshipper base. If this evaluation is positive, however, even an excessively large crowdshipper base cannot guarantee that all shipments can feasibly be crowdshipped. Thus, the need for a flexible and reliable fall-back option (e.g., a professional postal service provider) must either openly be communicated to the shippers (if they must take care of rejected parcels by themselves) or must additionally be organized by the platform.

7.2 Relationship of objectives in a deterministic world

If we presuppose a deterministic world where no unforeseen delays occur and all shipments are crowdshipped just as planned, then we see the following match between the main stakeholders of public transport crowdshipping and our objectives:

(i) *Platform provider ⇔ MAX-PROFIT:* A private platform provider with the intention of earning money for organizing crowdshipping services certainly prefers the MAX-PROFIT objective. Despite this general fit, we openly admit that other objectives can also be important for the platform. For instance, especially in early phases of the life cycle it could also be reasonable to involve as many shippers and crowdshippers as possible in order to gain publicity and investor awareness. However, MAX-PROFIT is certainly the most obvious choice for a profit-seeking platform.

(ii) *Shippers, recipients, and general public ⇔ MAX-PARCELS:* Since public transport crowdshipping only applies transport capacities of public transport users on trips they make anyway, any parcel feasibly crowdshipped saves conventional delivery traffic. Hence, the MAX-PARCELS objective seems a good proxy for reducing the negative impact (e.g., greenhouse gas emissions) coming along with van-based parcel delivery. Therefore, for environmentally aware recipients, the general public, and shippers aiming to advertise their sustainable delivery services the MAX-PARCELS objective seems a good fit.

(iii) *Crowdshippers ⇔ MAX-INVOLVEMENT:* Finally, crowdshippers may not exclusively be intrinsically motivated to protect the environment; at least an additional aim could be to earn money for their crowdshipping services. In this case, one possible objective is to maximize the number of involved crowdshippers, so that as many of them as possible can profit. Note that we leave even more involved objectives also including the sum of entrainment fees and fairness issues out of consideration.

Our other three objectives, i.e., MIN-TOTAL-ENTRAINMENTS, MIN-MAX-ENTRAINMENTS, and MIN-MAX-SLACK, rather aim to protect against delays. In a deterministic world, however, unforeseen delays do not occur, so that we leave these objectives out of consideration for the moment and come back to them in the next section. Given our remaining three objectives and the underlying aims of the stakeholders discussed above, it is interesting to see how strong following one objective deteriorates the aims of the other stakeholders. In other words, this section explores whether there is a compromise objective that fits the aims of all people involved without leading to significant losses of specific groups. If this is given, we do not have to fall back on a multi-objective approach (including all negative aspects coming along with such a more complex approach) when aiming to satisfy all (or at least most) stakeholders.

To explore this matter, we plot the percentage of parcels that are successfully crowdshipped and the percentage of volunteering crowdshippers whose services are

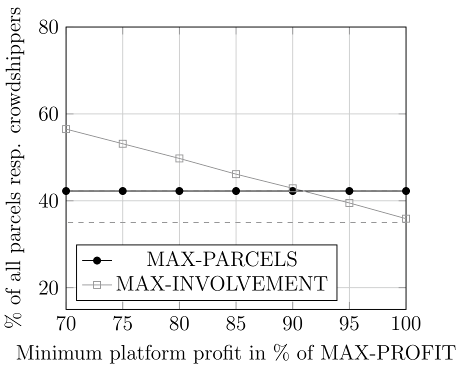

Fig. 4 Impact of minimum platform profit P when set to different percentage values of the optimal MAX-PROFIT solution value for objectives MAX-PARCELS and MAX-INVOLVEMENT

actually selected when solving problems MAX-PARCELS and MAX-INVOLVEMENT for different values of minimum platform profits P in Fig. 4. The different P-values are derived by setting them to 70, 80, 90, 100 % of the maximum platform profit gained via MAX-PROFIT. Note that we furthermore presuppose $|J| = 40$ parcels and a volunteering crowdshipper base of $|I| = 2|J|$. We can observe that a strong focus on the profit of the crowdshipping platform (i.e., by selecting a large percentage value when fixing minimum platform profit P) significantly reduces the number of participating crowdshippers (i.e., represented by MAX-INVOLVEMENT) but has no impact on the number of feasibly crowdshipped parcels (i.e., represented by MAX-PARCELS). These results suggest the following finding.

Actionable insights: Next to providing the relevant infrastructure, the matching of crowdshipping demand and supply is certainly the essential service provided by a crowdshipping platform. When implementing a matching procedure, e.g., with the help of one of our optimization approaches, it is thus likely that a platform follows their own primary target and applies the MAX-PROFIT objective. A sharing platform's elementary matching approach is typically not openly revealed in order to protect against copycat competitors. Therefore, fairness aspects among the diverging aims of stakeholders are typically hard to judge for outsiders and a platform barely needs to expect negative effects when they opt for the MAX-PROFIT objective. When they do, this has the following effects on the other stakeholders: The revenue side of the profit is determined by the postal charges earned for feasibly crowdshipped parcels. Therefore, the profit increases the more parcels are crowdshipped. Hence, the MAX-PROFIT objective tends to also support the aims of all sustainability-oriented stakeholders who aim to reduce the negative effect of traditional van-based deliveries. The cost side, on the other hand, is constituted by the entrainment fees to be paid to the crowdshippers. They are reduced the fewer entrainments are involved, which tends to also reduce the total number of selected crowdshippers. Thus, a crowdshipping platform opting for the MAX-PROFIT objective must be aware that they do this against the general aims of the crowdshippers. Fewer of them get actively involved, which may negatively impact their motivation to further volunteer for crowdshipping each day. A large crowdshipper base has been identified as a mission-critical resource in our previous experiment. Thus, at least in earlier phases of the life cycle, when public transport users need to be accustomed to crowdshipping, following the MAX-INVOLVEMENT objective with a lower minimum platform profit P to get more crowdshippers involved seems a valid option.

7.3 Impact of unexpected train delays

The real world is not deterministic. In public transport crowdshipping in particular, it is unforeseen train delays that jeopardize the realization of planned crowdshipping schedules. Delayed trains can lead to stranded parcels placed late into some locker, so that they get missed either by the finial recipient or a successor crowdshipper. In this case, recovery missions and compensation payments for delayed parcels produce additional costs that reduce the planned platform profit. To protect against these costs, this paper introduces three objective, namely

MIN-TOTAL-ENTRAINMENTS, MIN-MAX-ENTRAINMENTS, and MAX-MIN-SLACK (see Sect. 3). This section investigates whether these objectives actually lead to more robust crowdshipping schedules in case of unforeseen delays and which of them performs best.

Specifically, our experiment is set up as follows. Using our instance generator of Sect. 6.1, we generate 10 instances with $|J| = 30$ registered parcels and $|I| = 2|J|$ volunteering crowdshippers. The resulting instances are solved with each of our six objectives and each resulting solution undergoes the following simulation process where parameters P^d and d steer the occurrence of unforeseen train delays. $P^d \in \{5, 15\}$ defines the probability in % that each single train applied by the crowdshippers is delayed. If this is the case, a delay of $d \in \{3, 10\}$ minutes occurs, so that all crowdshipper riding on this train place their parcels later into the designated locker. This may lead to stranded parcels, which reduce the planned profit by the postal charge to be restituted to the shipper. We assume that no further compensation payments on top of the restituted postal charges are required and presuppose that all entrainment fees are still paid to all crowdshippers even if they are delayed or

Table 7 Post-delay profit of objectives MAX-PARCELS (MP), MAX-INVOLVEMENT (MI), MIN-TOTAL-ENTRAINMENTS (MTE), MIN-MAX-ENTRAINMENTS (MME), and MAX-MIN-SLACK (MMS) in relation to MAX-PROFIT in % depending on the percentage δ of the maximum post-delay profit of MAX-PROFIT, delay probability P^d in %, and delay duration d in minutes

δ	P^d	d	MP	MI	MTE	MME	MMS
90	5	3	92.25	90.64	98.93	95.45	93.05
92	5	3	92.25	93.32	95.72	96.52	96.26
94	5	3	93.32	94.65	97.86	99.47	94.92
96	5	3	96.79	96.79	97.06	97.06	97.06
98	5	3	102.67	100	103.74	100.27	101.6
100	5	3	101.34	104.01	102.67	**105.35**	**105.35**
90	15	3	95.47	82.2	108.41	99.35	93.2
92	15	3	93.85	95.15	104.53	97.41	98.71
94	15	3	93.53	95.15	105.5	109.06	95.47
96	15	3	99.35	97.73	99.68	102.91	94.82
98	15	3	104.85	100	**107.77**	101.94	101.94
100	15	3	103.24	106.47	103.24	**114.56**	**111.33**
90	5	10	88.08	86.45	94.85	89.97	87.53
92	5	10	90.79	90.51	97.02	96.48	92.14
94	5	10	91.87	91.87	97.83	98.1	92.14
96	5	10	91.33	95.39	97.02	95.66	94.31
98	5	10	95.93	97.29	97.02	96.21	94.85
100	5	10	98.64	98.64	97.29	**100**	**100**
90	15	10	86.27	78.87	100.35	90.49	80.28
92	15	10	91.55	84.15	101.41	93.66	93.31
94	15	10	91.2	84.15	98.94	**104.58**	93.31
96	15	10	88.73	88.73	97.89	97.89	92.61
98	15	10	98.24	96.48	97.89	96.83	93.31
100	15	10	100	98.24	94.72	103.52	101.76

miss their dedicated parcels due to a delayed predecessor crowdshipper. We call the resulting profit that includes restitutions for stranded parcels the *post-delay profit*.

In Table 7, we list the post-delay profits of objectives MAX-PARCELS (MP), MAX-INVOLVEMENT (MI), MIN-TOTAL-ENTRAINMENTS (MTE), MIN-MAX-ENTRAINMENTS (MME), and MAX-MIN-SLACK (MMS) divided by the post-delay profit of MAX-PROFIT. Thus, a value larger (smaller) than 100% indicates that the respective objective delivers a better (worse) post-delay solution than MAX-PROFIT. This performance measure is reported for different minimum platform profits P that are determined by varying the percentage $\delta \in \{90, 92, \dots, 100\}$ of the MAX-PROFIT objective value, the probability P^d in % that a train is delayed, and the duration d in minutes of a train delay. These results suggest the following findings:

(a) *The minimum platform profit should be set to 100%:* Next to the choice of the right objective, the platform must also decide on the minimum platform profit. We expect a trade-off: One the one hand, it is to be expected that a higher minimum profit leads to more and tighter handovers, so that more stranded parcels and thus higher compensation payments occur. Thus, it should be advantageous to relinquish a few percent of pre-delay profit to give the objective more flexibility to better protect against unforeseen delays. On the other hand, if we relinquish too much pre-delay profit, we also give up parcels that are actually not affected by delays. Given this trade-off, our results suggest that the latter effect prevails, so that we should not give up too much pre-delay profit. There are only a few exceptions, where a minimum profit of 100% does not lead to the highest post-delay profit.

(b) *MIN-MAX-ENTRAINMENTS delivers the best post-delay profits:* Given the best minimum platform profit for each objective, the bold-marked results of Table 7 highlight the best options. From these results, we can conclude that the MIN-MAX-ENTRAINMENTS objective (with a minimum platform profit of 100%) offers the best protection against unforeseen delays. Actually, this objective is the only one that consistently outperforms the MAX-PROFIT objective in all four delay scenarios. Even if it is just an average profit increase of 5,86 % over MAX-PROFIT (on average over all four delay scenarios with a minimum platform profit of 100%), it is easily earned money, because the platform only has to slightly alter the matching objective.

Actionable insights: The handling of stranded parcels is certainly another critical success factor for public transit crowdshipping. Recovery missions and compensation payments reduce the planned platform profit but are also a threat for the reputation of a platform. A simple means to successfully reduce the occurrence of stranded parcels in case of unforeseen delays is to apply the MIN-MAX-ENTRAINMENTS objective with a maximum platform profit. Since each handover of a parcel among subsequent crowdshippers provides a stranding opportunity, reducing these events via the MIN-MAX-ENTRAINMENTS objective leads to more robust plans.

However, there may be even better objectives and the best choice among them is certainly only one lever. Future research should thus evaluate the impact of other objectives and further countermeasures, such as a dynamic replanning once delays have occurred with altered entrainment missions for crowdshippers already underway. The right compensation scheme, which properly trades off the impact of stranded parcels on customer satisfaction with losses of platform profit, is certainly an important choice.

7.4 Comparison with the single-crowdshipper-per-parcel policy

French public transport crowdshipping platform Chronobee (see Sect. 1) applies the single-crowdshipper-per-parcel (SCPP) policy. This means that an accepted parcel is brought from origin to destination exclusively by a single crowdshipper. On the positive side, SCPP offers more protection against unforeseen delays. Train delays can still lead to parcels missing the deadlines at their destinations, but at least the handover risk of crowdshippers missing each other is eliminated. Our research provides optimization approaches under the multi-crowdshipper-per-parcel (MCPP) policy, where asynchronous parcel handovers via lockers between multiple crowdshippers are allowed. The asset of the MCPP policy is certainly the larger flexibility to move parcels with multiple crowdshippers. This promises higher delivery rates but increases the risk of stranded parcels. This section benchmarks both policies regarding their profits with and without train delays.

Specifically, our experiment is set up as follows. Using our instance generator of Sect. 6.1, we generate 10 instances with $|J| = 30$ registered parcels and $|I| = 2|J|$ volunteering crowdshippers. To obtain the profits of both policies in a deterministic world where no unforeseen delays occur, these instances are solved with two approaches. For MCPP, we apply the approach that proved best in the previous section. This means, we utilize the MIN-MAX-ENTRAINMENTS objective with a minimum platform profit equal to the maximum profit obtained by MAX-PROFIT to solve the instances and record the resulting profit. Another advantage of the SCPP policy is a much easier matching task, which constitutes a linear assignment problem that can efficiently be solved, e.g., by the famous Hungarian method (Kuhn 1955). Here, we assign crowdshippers to parcels, where the assignment profit is either the parcel charge minus a single entrainment fee if

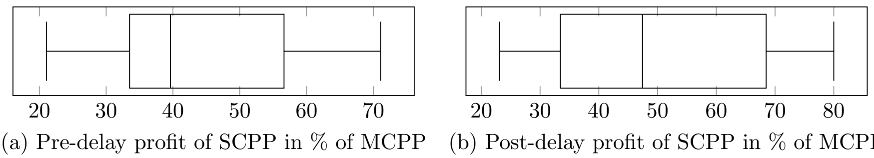

Fig. 5 Benchmark of MCPP and SCPP before (left) and after (right) delays: Profit of SCPP in % of MCPP's profit (obtained by the MIN-MAX-ENTRAINMENTS objective with a minimum platform profit equal to the maximum profit obtained by MAX-PROFIT) in %

the crowdshipper timely travels along the parcel's origin and destination or zero if no feasible transport by a specific crowdshipper is possible. Solving the max-profit linear assignment problem delivers the optimal profit of the SCPP policy. To also compare both policies if unforeseen train delays occur and stranded parcels may reduce the profit, we apply the high-risk-small-delay setting (i.e., with a delay risk of $P^d = 15\%$ and $d = 3$ minute delays) and determine the actual profit of both solutions if the respective delays occur. In Fig. 5, we depict the pre-delay (i.e., deterministic world without delays) and the post-delay (i.e., actual profit including compensation for stranded parcels in case of delays) profits. The box plots show the distribution of the profit of SCPP divided by the profit of MCPP in % over the solved instances. Hence, a value below (above) 100% indicates that SCPP realizes a lower (higher) profit than MCPP.

The results of Fig. 5 indicate that MCPP clearly outperforms SCPP. The loss in flexibility if only a single crowdshipper may transport each parcel reduces the median profit of SCPP to only 40% of MCPP's profit in a deterministic world. As expected, this disadvantage reduces if unforeseen delay occur, but the median profit of SCPP still merely reaches 47% of MCPP's profit. However, there are three instances with high risk and long delays where the higher robustness of SCPP leads to even better results than MCPP. On average, however, our experiment shows a clear advantage of MCPP, which leads us to our final managerial take-home message.

Actionable insights: The current business practice to only apply the SCPP policy should be reconsidered. Our computational results show that the increase of flexibility enabled by the parcel handover among multiple crowdshippers clearly overcompensates the higher risk of stranded parcels in case of unforeseen delays.

8 Conclusions

This paper investigates public transport crowdshipping and provides matching methods to select shipments and their ways through a public transportation network when accompanying crowdshippers on their commute. Based on a computational study applying these methods, we identify the following critical success factors for this innovative last-mile delivery concept:

(a) A large crowdshipper base of volunteering public transport users must be recruited that is significantly larger than the number of parcels to be transported. However, even if such a base can successfully be gathered, a platform cannot expect that all parcels can be transported. Thus, a reliable and flexible fall-back option must be at hand.

(b) Unfortunately, there is no single objective that can satisfy all involved stakeholders equally. When only focusing on the platform profit, this tends to also maximize the number of successfully crowdshipped parcels (and thus the positive environmental impact) but reduces the number of involved crowdshippers. This can get in the way of our previous success factor.

(c) To account for unforeseen train delays and to protect against stranded parcels, we identify the MIN-MAX-INVOLVEMENT objective, which restricts the maximum number of handovers among crowdshippers per parcel, as best suited.
(d) Finally, we show that allowing parcels to take multiple travel legs with more than a single crowdshipper greatly increased planning flexibility and promises much more transported parcels as well as higher platform profits than the single-crowdshipper-per-parcel policy of current business practice.

Future research could take up our research in multiple ways: Other optimization objectives and more complex methods including multiple objectives and explicitly involving stochastic delay information should be developed. In this way, matchings that better serve all involved stakeholders, even if unforeseen delays occur, could be obtained. Furthermore, our solution methods should be challenged, such that they are suitable for large real-world crowdshipping platforms with thousands of shipments and even more crowdshippers.

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References

Archetti C, Savelsbergh M, Speranza MG (2016) The vehicle routing problem with occasional drivers. Eur J Oper Res 254:472–480
Arslan AM, Agatz N, Kroon L, Zuidwijk R (2018) Crowdsourced delivery-a dynamic pickup and delivery problem with ad hoc drivers. Transp Sci 53:222–235
Azcuy I, Agatz N, Giesen R (2021) Designing integrated urban delivery systems using public transport. Trans Res Part E: Logist Trans Rev 156:102525
Behrend M, Meisel F (2018) The integration of item-sharing and crowdshipping: Can collaborative consumption be pushed by delivering through the crowd? Trans Res Part B: Methodol 111:227–243
Boysen N, Briskorn D, Schwerdfeger S (2019) Matching supply and demand in a sharing economy: Classification, computational complexity, and application. Eur J Oper Res 278:578–595
Boysen N, Emde S, Schwerdfeger S (2022) Crowdshipping by employees of distribution centers: Optimization approaches for matching supply and demand. Eur J Oper Res 296:539–556
Boysen N, Fedtke S, Schwerdfeger S (2021) Last-mile delivery concepts: a survey from an operational research perspective. OR Spectrum 43:1–58
Briskorn D, Leung J, Pinedo M (2011) Robust scheduling on a single machine using time buffers. IIE Trans 43:383–398
Chen C, Pan S, Wang Z, Zhong RY (2017) Using taxis to collect citywide e-commerce reverse flows: a crowdsourcing solution. Int J Prod Res 55:1833–1844

Chen C, Zhang D, Ma X, Guo B, Wang L, Wang Y, Sha E (2016) Crowddeliver: planning city-wide package delivery paths leveraging the crowd of taxis. IEEE Trans Intell Transp Syst 18:1478–1496
Dablanc L, Morganti E, Arvidsson N, Woxenius J, Browne M, Saidi N (2017) The rise of on-demand 'instant deliveries' in European cities. Supply Chain Forum: An Int J 18:203–217
Dayarian I, Savelsbergh M (2020) Crowdshipping and same-day delivery: Employing in-store customers to deliver online orders. Prod Oper Manag 29:2153–2174
Even S, Itai A, Shamir A (1976) On the complexity of timetable and multicommodity flow problems. SIAM J Comput 5:691–703
Garey MR, Johnson DS (1979) Computers and intractability. Freeman, San Francisco
Gatta V, Marcucci E, Nigro M, Patella SM, Serafini S (2019) Public transport-based crowdshipping for sustainable city logistics: Assessing economic and environmental impacts. Sustainability 11:145
Gatta V, Marcucci E, Nigro M, Serafini S (2019) Sustainable urban freight transport adopting public transport-based crowdshipping for B2C deliveries. Eur Transp Res Rev 11:13
Gdowska K, Viana A, Pedroso JP (2018) Stochastic last-mile delivery with crowdshipping. Trans Res Procedia 30:90–100
Ghilas V, Cordeau JF, Demir E, Van Woensel T (2018) Branch-and-price for the pickup and delivery problem with time windows and scheduled lines. Transp Sci 52:1191–1210
Ghilas V, Demir E, Van Woensel T (2016) An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows and scheduled lines. Comput Ope Res 72:12–30
Ghilas V, Demir E, Van Woensel T (2016b) The pickup and delivery problem with time windows and scheduled lines. INFOR: Information Systems and Operational Research **54**, 147–167
Ghilas V, Demir E, Van Woensel T (2016) A scenario-based planning for the pickup and delivery problem with time windows, scheduled lines and stochastic demands. Trans Res Part B: Methodol 91:34–51
HistSystem Co. (2019) On Korean Bizwire website: Seoul metro to begin parcel delivery service. http://koreabizwire.com/seoul-metro-to-begin-parcel-delivery-service/148909 (last access: November 2023)
Ikeda T, Hsu MY, Imai H, Nishimura S, Shimoura H, Hashimoto T, Tenmoku K, Mitoh K (1994) A fast algorithm for finding better routes by AI search techniques, in: Proceedings of Vehicle Navigation and Information Systems Conference, pp. 291–296
Kızıl KU, Yıldız B (2022) Public transport-based crowd-shipping with backup transfers. Transp Sci 57:174–196
Kou X, Zhang Y, Long D, Liu X, Qie L (2022) An investigation of multimodal transport for last mile delivery in rural areas. Sustainability 14:1291
Kouvelis P, Yu G (1996) Robust Discrete Optimization and Its Applications. Nonconvex Optimization and Its Applications, Springer, US
Kuhn HW (1955) The Hungarian method for the assignment problem. Naval Research Logistics Quarterly 2:83–97
Le TV, Stathopoulos A, Van Woensel T, Ukkusuri SV (2019) Supply, demand, operations, and management of crowd-shipping services: A review and empirical evidence. Trans Res Part C: Emerg Technol 103:83–103
Li B, Krushinsky D, Reijers HA, Van Woensel T (2014) The share-a-ride problem: People and parcels sharing taxis. Eur J Oper Res 238:31–40
Macrina G, Pugliese LDP, Guerriero F, Laporte G (2020) Crowd-shipping with time windows and transshipment nodes. Comput Ope Res 113:104806
Masoud N, Jayakrishnan R (2017) A decomposition algorithm to solve the multi-hop peer-to-peer ride-matching problem. Trans Res Part B: Methodol 99:1–29
Masson R, Trentini A, Lehuédé F, Malhéné N, Péton O, Tlahig H (2017) Optimization of a city logistics transportation system with mixed passengers and goods. EURO J Trans Logist 6:81–109
ParcelHero (2016) Amazon's Prime Ambition. https://www.parcelhero.com/content/downloads/pdfs/amazon/amazons-prime-ambition-parcelhero-industry-report.pdf (last access: November 2023)
Punel A, Ermagun A, Stathopoulos A (2019) Push and pull factors in adopting a crowdsourced delivery system. Transp Res Rec 2673:529–540
Roth AE, Sönmez T, Ünver MU (2004) Kidney exchange. Q J Econ 119:457–488
Savelsbergh MW, Ulmer MW (2022) Challenges and opportunities in crowdsourced delivery planning and operations. 4OR **20**, 1–21
Schmidt J, Tilk C, Irnich S (2022) Using public transport in a 2-echelon last-mile delivery network. European Journal of Operational Research , to appear

Schroten A, Warringa G, Bles M (2012) Marginal abatement cost curves for heavy duty vehicles. Background Report, CE Delft, Delft

Slivkins A (2010) Parameterized tractability of edge-disjoint paths on directed acyclic graphs. SIAM J Discret Math 24:146–157

Statista (2022) Paketsendungen erreichen neuen Rekordwert. https://de.statista.com/infografik/9992/in-deutschland-von-den-paket-und-kurierdiensten-befoerderten-sendungen/ (Accessed: November 2023)

Vaughan R, Daverio R (2016) Assessing the size of the collaborative economy in Europe. https://publications.europa.eu/en/publication-detail/-/publication/2acb7619-b544-11e7-837e-01aa75ed71a1 (Accessed: November 2023)

Vincent FY, Jodiawan P, Redi AP (2022) Crowd-shipping problem with time windows, transshipment nodes, and delivery options. Trans Res Part E: Logist Trans Rev 157:102545

Wang D, Wang Q, Yin Y, Cheng T (2023) Optimization of ride-sharing with passenger transfer via deep reinforcement learning. Trans Res Part E: Logist Trans Rev 172:103080

Wang Y, Zhang D, Liu Q, Shen F, Lee LH (2016) Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. Trans Res Part E: Logist Trans Rev 93:279–293

Zehtabian S, Larsen C, Wøhlk S (2022) Estimation of the arrival time of deliveries by occasional drivers in a crowd-shipping setting. Eur J Oper Res 303:616–632

Zhang C, Du Z, Parmar MD, Bai Y (2017) Pocket-switch-network based services optimization in crowd-sourced delivery systems. Comput Electr Eng 62:53–63

Authors and Affiliations

Alexander Wyrowski[1] · Nils Boysen[1] · Dirk Briskorn[2] · Stefan Schwerdfeger[3]

✉ Nils Boysen
nils.boysen@uni-jena.de
https://www.om.uni-jena.de/en/NilsBoysen.html

Alexander Wyrowski
alexander.wyrowski@uni-jena.de
https://www.om.uni-jena.de/en/alexanderwyrowski

Dirk Briskorn
briskorn@uni-wuppertal.de
http://www.prodlog.uni-wuppertal.de

Stefan Schwerdfeger
stefan.schwerdfeger@uni-jena.de
https://www.om.uni-jena.de/en/StefanSchwerdfeger

1 Friedrich-Schiller-Universität Jena, Lehrstuhl für Operations Management, Carl-Zeiß-Straße 3, 07743 Jena, Germany

2 Bergische Universität Wuppertal, Professur für BWL, insbesondere Produktion und Logistik, Rainer-Gruenter-Str. 21, 42119 Wuppertal, Germany

3 Friedrich-Schiller-Universität Jena, Lehrstuhl für Operations Management and Lehrstuhl für Management Science, Carl-Zeiß-Straße 3, 07743 Jena, Germany