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Multi-day Planning in Cooperative Two-tier City Logistics Systems with Fairness Constraints

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Abstract. Two-tier city logistics systems (2T-CLSs) offer the potential for more efficient urban freight management. Since such systems necessitate substantial infrastructure and multiple Logistics Service Providers (LSPs) operate within a city, cooperation among these LSPs offers further opportunities for both economic cost savings and reducing environmental impact. However, establishing effective long-term cooperation among these LSPs requires ensuring that every LSP has an incentive to cooperate with other LSPs and feels fairly treated within the coalition. To tackle this challenge, we present a service network design formulation that addresses multi-day tactical planning in a 2T-CLS involving cooperating LSPs. This formulation includes various fairness constraints on the workload and costs of each LSP as well as constraints on the daily regularity in selecting services. In a numerical study, we show that cooperation leads to immense benefits in the form of cost savings of on average 22.4% and lower environmental impact. Furthermore, we quantify the impact of different fairness constraints and show that too strict fairness constraints harm the entire coalition and that lower cost increases occur when fairness constraints are enforced on average over multiple days rather than on each individual day. Our analysis further reveals that stable coalitions are only possible when fairness constraints are enforced in terms of both the workload and cost of each LSP. Based on these results, we derive valuable policy implications that are crucial for both LSPs and municipal authorities planning cooperative city logistics projects.

Keywords: city logistics, cooperative logistics, horizontal cooperation, service network design

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1 Introduction

Recent years have witnessed both rapid urbanization and increased e-commerce activity (Lone et al., 2021; United Nations, 2018). These trends are expected to continue in the future, leading to an increased volume of freight delivery in city logistics systems. As a result, numerous Logistics Service Providers (LSPs) traverse cities daily, delivering freight to customers. Despite its indispensable role in societies and economies, this practice contributes to traffic congestion, noise, pollution, and harmful emissions, negatively impacting the environment and public health (Savelsbergh and Van Woensel, 2016). In recent years, numerous public sector initiatives have been put forth to improve urban freights management (Holguín-Veras et al., 2020). A key challenge is finding solutions that consider the interests of various stakeholders (Galambos et al., 2024). While LSPs and their customers are primarily concerned with keeping transportation costs as low as possible, urban communities and residents focus on reducing the negative external effects caused by transportation. One way of increasing monetary and ecological efficiency and thus bringing together the interests of different stakeholders is the concept of Two-Tier City Logistics Systems (2T-CLSs) (Crainic et al., 2004). These systems involve larger urban vehicle services to deliver freight from City Distribution Centers (CDCs), located on the outskirts of a city, to satellite depots located within the city. The final delivery to the customer locations is conducted with smaller, environmentally-friendly vehicles, referred to as city freighters, starting from the satellite depots.

As these systems require extensive infrastructure and as several LSPs operate within a city, often without fully utilizing their resources, cooperation among them presents an opportunity to reduce both monetary costs for LSPs and their customers, as well as the negative environmental impact on the city and its residents. Building on this perspective, Browne et al. (2012) have also underscored the significant potential of cooperative delivery systems to alleviate the negative social and environmental consequences of urban freight transport. Although city logistics is seen as an integrated logistics system in which several different players operate within a city (Crainic et al., 2023), cooperative concepts and their fair design have so far received little attention in the literature. This fair design encompasses various aspects. Firstly, there is a monetary aspect in which cost savings are fairly distributed among the coalition of LSPs. Additionally, it involves a workload consideration, ensuring that the market shares of the LSPs should remain stable, with each LSP primarily serving its own customers to maintain customer contact.

Further, existing models on 2T-CLS primarily focus on a single planning horizon that often reflects only a day or a morning. This overlooks significant challenges, particularly in city logistics, where it may be desirable—or even necessary—for some urban vehicles, like trams, to operate regularly on each day. The existing literature overlooks the consequences of this service regularity, revealing a lack of insight into its impact on cost dynamics in city logistics systems. Furthermore, the multi-day setting is important to understand the impact of having to meet certain fairness criteria on average over a period of several days rather than on each individual day.

To summarize, there is a clear lack of insight into tactical planning in 2T-CLSs about the monetary and environmental impacts of cooperation, the inclusion of fairness aspects in decision support systems for LSPs' cooperation, and the regularity of services over a multi-day period.

For LSPs as well as for public authorities, it is essential not only to have detailed planning models but also general policies that give them guidelines on how such a cooperative 2T-CLS must be designed so that it works in the long term and is successful for every actor involved. Our paper aims to derive general guidelines and policy implications for cooperation in 2T-CLSs in a more realistic multi-day planning environment through appropriate numerical experiments, which are of great interest for LSPs as well as for urban communities and policymakers. Thereby, we answer the following major research questions:

- What is the impact of cooperation among LSPs on major KPIs that are relevant for different stakeholders within a city?
- How do different fairness constraints regarding the workload and the cost balance impact the total system?
- Is it beneficial to fulfill fairness constraints on average over several days rather than on a daily basis?
- What are the effects of service regularity?

We make five key contributions to existing literature by answering these research questions.

1. We introduce a new problem setting for fair multi-day tactical planning in a cooperative 2T-CLS.
2. We present a novel service network design formulation for a fair multi-day 2T-CLS with cooperating LSPs.
3. We formulate various fairness constraints regarding the workload and the costs of each LSP, as well as regarding the regularity of selecting services.
4. We conduct an extensive numerical study investigating the effects of cooperation, the impact of fairness constraints, and the consequences of service regularity based on several monetary and environmental criteria.
5. We derive valuable policy implications for the design of a cooperative city logistics system.

The paper unfolds as follows: Section 2 details the problem description, followed by a comprehensive literature review in Section 3. Section 4 introduces the service network design formulation. In Section 5, we analyze the benefits of cooperation, the impact of fairness constraints, and the consequences of service regularity. Based on the results, we then derive general policy implications in Section 6. Finally, Section 7 summarizes our study and gives an outlook on future research opportunities.

2 Problem description

In this section, we start with the general problem environment in 2T-CLSs in Section 2.1 before we focus on the cooperative and fairness aspects in Section 2.2.

2.1 Multi-day planning in two-tier city logistics

For the illustration of 2T-CLSs, we use the terms introduced by Crainic et al. (2009). We do the tactical planning for a 2T-CLS with inbound demand over a schedule length of several days. Each demand has an origin location outside the city, a destination within the city, and a specific demand volume. Further, time restrictions for each demand are considered. Specifically, there is a release date for each demand, on which the demand is available at the earliest at the CDCs, and a due date, on which each demand should arrive at its destination at the latest. We consider a multi-day perspective where different demands arise on each individual day and must be fulfilled on the exact same day they occur. The release and due dates are, therefore, related to time periods within one day.

In 2T-CLSs, these demands are first delivered from their origins to a CDC. These CDCs are usually located on the outskirts of a city, in a place that is easily accessible for large vehicles such as trucks or trams. For this, we assume costs for the initial demand delivery to a CDC. Starting from the CDCs, the first-tier delivery is operated by services using large urban vehicles of different vehicle types, such as trams or trucks of various modifications. These vehicles differ in terms of their capacity and their fixed and variable monetary and environmental cost components. Each service starts at a specific time period at a particular CDC and visits an ordered sequence of satellites. These satellites are typically located within the city, around the city center, to ensure efficient second-tier routing operations. The demands arrive at these satellites and are consolidated and prepared for the final second-tier delivery. Please note that each satellite has limited space, so there are capacity limits on the number of vehicles and demand volume that can be handled simultaneously on a satellite. Thus, satellites represent the meeting point between first and second-tier vehicles. Smaller, environmentally friendly vehicles, like cargo bikes or electric vehicles, operate the delivery to the final demand destinations. These start at a specific time at a satellite and travel to a sequence of demand destinations. However, the focus of our study is on tactical planning. To this end, we follow an established approach in the literature and do not solve the actual routing problem on the second tier, but rely on approximations (Fontaine et al., 2021; Crainic et al., 2020). We aim to provide decision support for selecting services and allocating demands to services, satellites, and CDCs on the first tier on each day of the schedule length.

We assume that the demands for the entire schedule length of several days are known deterministically beforehand, with each day potentially having a different number of demands, different demand locations, and varying demand volumes. Any deviations between the forecasted demand and the demand actually occurring on the day are out of the scope of this study as different strategies have already been investigated (Crainic et al., 2016). In addition, we assume that the same set of potential services is provided by the LSPs on each day and can be selected. So, in contrast to the demands, where on every day different demands occur, the set of potential services stays the same for the entire schedule length, where each service can be selected on each day. The connection between the individual days is expressed through two aspects. Firstly, it may be desirable for services of the LSPs if at least some of their services operate regularly each day to plan in a more stable manner. Such policies are helpful both for services with trams, as they have to coordinate their schedules with passenger trams already running and should therefore not change their times every day, and for all services, as it enables more stable schedules and better planning for drivers and vehicles. The resulting impact on the whole system has not yet been considered in any study on 2T-CLSs. Further, the multi-day perspective also influences the cooperation of the LSPs, specified in the next section. Even if this is not explicitly the subject of our study, the multi-day planning described above could also be used for rolling horizon planning, where the rolling planning horizon consists of several days.

2.2 Cooperation in two-tier city logistics

We consider different LSPs that operate on the same infrastructure within this system. Each LSP has different demands on each day. Further, each LSP can provide a set of services capable of satisfying its own demands. Therefore, we assume that each LSP contributes both demands and transportation resources to the coalition, with the transportation resources comprising urban vehicle services and usable capacity at satellites.

As illustrated in Figure 1, the cooperation among LSPs occurs through mutually sharing demands and resources. This cooperation allows LSPs to exchange demands, enabling one LSP to fulfill the demands of another using its own services. Additionally, each LSP contributes its transportation resources to the coalition, which include vehicle fleets, service capabilities, and satellite capacity.

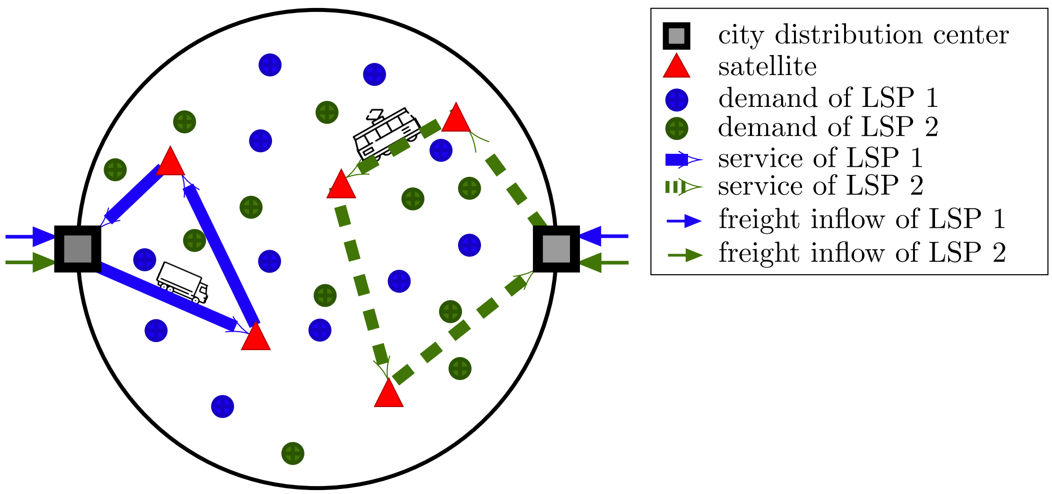

Figure 1: 2T-CLS with cooperating LSPs

We assume that each LSP itself is responsible for delivering its demands to a CDC, as well as subsequently delivering them from the satellite to their final demand locations. Cooperation thus takes place on the first tier through the joint provision of resources, as well as through demand sharing, which means that each LSP can also deliver demands from another LSP from the CDCs to the satellites.

It is assumed that these LSPs agree to cooperate under the guidance of a central coordinator, who is responsible for determining the optimal allocation of resources to achieve a system-wide optimum. This central coordinator could either be a third-party provider or a jointly managed entity operated by the participating LSPs. In either scenario, each LSP must be willing to share information regarding its demands and transportation resources.

Achieving a system optimum may result in solutions that individual LSPs perceive as unfair due to workload and cost distribution imbalances. Consequently, the challenge lies not only in minimizing total system costs but also in designing a framework where each LSP feels fairly treated. This includes both financial considerations, ensuring that each LSP gains a tangible benefit from the cooperation, and workload considerations, ensuring that no LSP faces significant disadvantages in areas such as market share or the ability to effectively serve its own demands In addition, the relative differences between the LSPs in cost savings and the gain or loss of market share should not be too far apart. Each LSPs should also supply a certain proportion of its own customers in order, firstly, to maintain customer contact and, secondly, to carry a large proportion of its own workload itself. In particular, situations should be avoided in which an LSP performs a large part of the executed services but only contributes a small proportion of the demands to the coalition and vice versa. Therefore, it should be ensured that there is a link between the services provided and executed and the demands brought into the coalition, which leads to fair cooperation from both a workload and a monetary perspective.

For this purpose, we consider fairness constraints to prevent an unjustified imbalance in workload and costs. Given that these constraints affect the decision model, we assess various fairness constraints by examining their effects on the total system costs and their implications for fairness. The multi-day perspective described above becomes essential when assessing the extent to which it matters whether these constraints must be met on each day or, on average, over several days.

3 Literature review

We structure the literature review as follows: Firstly, we delve into the existing literature concerning planning problems within 2T-CLSs in Section 3.1. Subsequently, Section 3.2 shows various approaches presented in the literature concerning cooperation in transportation, explicitly focusing on establishing fairness in cooperation. Lastly, Section 3.3 outlines the research gaps.

3.1 Two-tier city logistics systems

2T-CLSs were first introduced to the scientific literature by the work of Crainic et al. (2004). They considered the strategic positioning of satellite depots, formulated as a location-allocation problem. Since then, many publications have considered strategic, tactical, and operational planning problems. Crainic et al. (2009) presented the first general modelling framework for tactical planning in 2T-CLSs. Therefore, they considered the synchronization between the first and the second tier. Based on this, several studies have considered the exact operation synchronization of the first and second tiers (e.g., Grangier et al., 2016; Groß et al., 2020). Crainic et al. (2016) proposed a two-stage stochastic programming formulation to consider demand uncertainty in tactical planning. Crainic and Sgalambro (2014) presented a service network design formulation for the tactical planning in 2T-CLSs and discussed promising algorithmic solution perspectives. Fontaine et al. (2021) contributed a service network design model for a multi-modal 2T-CLS with inbound and outbound demand and solved it through a Benders decomposition algorithm. Studies on strategic issues focus mainly on the location of satellites (e.g., Gianessi et al., 2016). Fontaine et al. (2023) proposed a general methodological framework based on continuous approximation theory for the design of city logistics networks with multiple LSPs. Zhu et al. (2023) concluded in a study on city logistics that co-modality is especially suitable for the middle mile in city logistics. Furthermore, Nataraj et al. (2019) considered the location of urban consolidation centers in a horizontal cooperation scenario. Other innovative approaches in the literature even consider the integration of freight transport into bus networks, which implicitly also assumes a 2T-CLS in which the first tier is carried out by bus services (Machado et al., 2023; Masson et al., 2017).

For a broader overview of routing problems in the context of city logistics, we refer to Cattaruzza et al. (2017).

Regarding cooperation, Crainic et al. (2020) is the first publication that explicitly considers the cooperation of LSPs in a 2T-CLS so far. Their findings highlight that this cooperative approach resulted in noteworthy improvements in efficiency, both in terms of monetary and environmental impact.

3.2 Fairness in cooperative transportation

In general, the efficiency gains resulting from modern algorithmic solutions have led to increased attention being paid to the fair distribution of these efficiency gains among the groups involved. (De-Arteaga et al., 2022). In the context of cooperation between LSPs, a distinction can be made between centralized and decentralized cooperation (Gansterer and Hartl, 2018). In centralized cooperations, the decisions of the coalitions are made by a central authority. In contrast, in decentralized cooperations, the participants cooperate individually or are supported by a central authority that does not have full information. In decentralized cooperations, auction models are mainly used to manage the exchange of demands. Thereby, the exchange of demands is ensured by a shared pool in which each player submits the demands it wants to trade. From this pool, the individual demands are then traded among the players by means of auctions (e.g., Gansterer and Hartl, 2016; Gansterer et al., 2020; Li et al., 2015; Karels et al., 2020). However, our study considers centralized planning, where a central authority has full information about all LSPs. The literature already investigates the fact that centralized cooperation can reduce overall system costs in different kinds of routing and transportation problems (e.g., Cruijssen et al., 2007; Krajewska et al., 2008; Padmanabhan et al., 2022). In their survey about collaborative vehicle routing Gansterer and Hartl (2018) concluded that in most studies on centralized collaborations potential benefits of 20-30% are identified. With regard to cooperation at satellite depots, Bruni et al. (2024) investigated the benefits of vertical and horizontal cooperation and found significant cost savings for both forms of cooperation. In the context of service network design models, Zhang et al. (2024) investigated the benefits of cooperation between carriers with uncertainty in demands. However, existing studies rarely consider how to ensure that the cooperation is perceived as fair for all involved participants. There are two main approaches to ensuring fairness within centralized cooperation. First, cost allocation methods can be used to allocate the total costs incurred in the system to the individual LSPs according to a previously defined method (Guajardo and Rönnqvist, 2016). The simplest methods are proportional cost allocation methods, in which the costs are allocated proportionately to a previously defined reference value. Furthermore, more advanced methods from cooperative game theory are introduced in the literature like the Shapley Value (Shapley, 1953), the Nucleolus (Schmeidler, 1969) and the Equal Profit Method (Frisk et al., 2010). In the context of 2T-CLSs, Gückel et al. (2024) compared different cost allocation methods and outlined the diverging interests of different sized LSPs in selecting a cost allocation method. For a general review of cost allocation methods, we refer to Guajardo and Rönnqvist (2016).

However, since cost allocation methods focus exclusively on a financial aspect, and other essential aspects (e.g. changes in market shares or the fulfillment of predominantly own demands) are disregarded, we pursue a different approach. This includes the introduction of constraints directly within the decision support system that balance the workload and/or cost of each coalition member. Within this context, Mancini et al. (2021) considered workload- and profit balance constraints for a vehicle routing problem with cooperative carriers. They concluded that workload balance constraints and minimum profit constraints over the whole planning horizon only slightly increase total system cost. In Crainic et al. (2020), constraints are added that ensure lower and upper bounds for the service costs and the workload of each LSP in the coalition. They reported significant impacts on the total cost, especially when the capacity constraints are tight. Further Matl et al. (2019) analyzed different equity functions for workload resources in a vehicle routing context. Recently, Soriano et al. (2023) considered a multi-depot vehicle routing problem in which they added a fairness objective function. This function aims to maximize, among all depots, the worst profit variation concerning the stand-alone solution to the classical cost minimization function. In a vehicle routing context, Sánchez et al. (2022) considered models quantifying different fairness and efficiency criteria of the individual routes.

3.3 Research gap

As highlighted, numerous studies have explored various planning problems across different levels within 2T-CLSs. However, research explicitly focusing on cooperation within 2T-CLSs remains notably limited. Specifically, there is a gap in the literature regarding the integration and impact of fairness constraints in multi-day planning to ensure that no LSP feels unfairly treated. Furthermore, current research lacks evidence on the effects of multi-day planning in which certain constraints related to both service regularity and fairness must be adhered to over several days. We close this research gap and explicitly model cooperation in a multi-day setting. This includes incorporating fairness constraints as well as considering the limited daily flexibility in the selection of services. This approach provides new insights into the design of cooperative 2T-CLSs, thereby contributing significantly to the existing body of literature.

4 Mathematical problem formulation

Section 4.1 introduces the notation. Section 4.2 presents the problem formulation, including the base model for full cooperation and additional constraints on cooperation fairness and service regularity.

4.1 Notation

This section establishes the key sets and parameters for our base model. Additional notation that is only used for the additional constraints regarding workload and cost balance as well as regarding the service regularity is introduced in the respective sections for better readability.

Sets

We consider a set of LSPs, denoted as $\mathcal{N}$. The physical infrastructure is represented by a set of CDCs, denoted as $\mathcal{E}$, and satellite facilities, denoted as $\mathcal{Z}$. The first-tier delivery from CDCs to satellites is operated by a set of urban vehicle services $\mathcal{R}$. Each service in this set can potentially be provided on every day within the schedule length. On the contrary, the set $\mathcal{D}$ represents the demands within the whole schedule length but can be further divided into subsets of the demands for each individual day. Each service is operated by one of the urban vehicles. Thereby, $\mathcal{M}$ represents the set of vehicle types that differs by capacity and cost components. The time dimension is considered through the set $\mathcal{T} = \{1, 2, ..., |\mathcal{T}|\}$ that represents the days in the schedule length and the set $\mathcal{P} = \{1, 2, ..., |\mathcal{P}|\}$ that represents the time periods during each day. In general, the set $\mathcal{T}$ does not necessarily have to refer to days but can also be understood as a consistency interval within which several sets of periods are connected. However, in the course of our study, driven by the problem definition, we will continue to refer to days.

Subsets

Each LSP n contributes its own subset of demands $\mathcal{D}(n)$ and its own subset of services, denoted as $\mathcal{R}(n)$, to the coalition. Additionally, the demands associated with day t are represented by the set $\mathcal{D}(t)$. These demands need to be fulfilled on the exact same day on which they occur.

Concerning services, distinct subsets are created: $\mathcal{R}(d, z)$ represents services that meet the release and due date requirements for demand d at satellite z. The release and due dates are periods during the day. Note that the due date of each demand is transferred to the satellites depending on the time-distance to the satellites (e.g., Fontaine et al., 2021). $\mathcal{R}(p, z)$ covers services operating during period p at satellite z, which is determined by the arrival time plus service time of the service at the satellite. $\mathcal{R}(p, e, m)$ encompasses services that operate during period p, originating from CDC e, and utilizing urban vehicle type m. Please note that some parameters of the services, e.g., service times or start and end times, do not appear in the optimization model but are only used in advance as a pre-processing step to generate these subsets, which is why they are not explicitly introduced in the following. Further, in contrast to the demands, the same services are offered daily, and therefore, there is no explicit subset of services for a specific day.

Parameters
Each service r is associated with a specific vehicle type m_r, originates from a specific CDC e_r, and follows a sequential pattern of satellite visits. Each vehicle type m is associated with a specific capacity u_m. The volume of each demand d is denoted by v_d. For every satellite z, the following capacity-related parameters are introduced: a_{zpn} denotes the maximum number of services that LSP n can handle during period p at satellite z, and b_{zpn} represents the maximum demand volume that LSP n can handle during period p at satellite z. Additionally, h_{emn} reflects the number of urban vehicles owned by LSP n of vehicle type m available at CDC e.

Cost considerations are integrated as follows: Each service r is defined by its operating costs c_r, encompassing financial and environmental expenses linked to negative external effects. The cost attributed to assigning demand d to satellite z and service r is denoted as s_{dzr}. These costs encapsulate the approximated second-tier routing expenses from satellite z to the final demand destination (e.g., Crainic et al., 2020). Furthermore, the costs associated with delivering demand d from its origin to CDC e are represented by f_{de}.

4.2 Mathematical problem formulation

We introduce our base model for full cooperation where resources and demands are shared without restriction (Section 4.2.1). Subsequently, we incorporate fairness constraints related to workload (Section 4.2.2) and costs (Section 4.2.3). Then, we introduce constraints related to the regularity in selecting services (Section 4.2.4).

4.2.1 Base model

Our model utilizes the following binary decision variables: y_{rt}, which equals 1 if service $r \in \mathcal{R}$ operates on day $t \in \mathcal{T}$, and 0 otherwise. Additionally, x_{dzr} equals 1 if demand $d \in \mathcal{D}$ is assigned to satellite $z \in \mathcal{Z}$ and service $r \in \mathcal{R}$, and 0 otherwise. We do not need to include the day index t for the assignment variable x_{dzr} because our model formulation ensures that demands are assigned on the exact day they arise.

We formulate the problem as a service network design formulation as follows:

$$min \qquad \sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} c_r \cdot y_{rt} + \sum_{d\in\mathcal{D}}\sum_{z\in\mathcal{Z}}\sum_{r\in\mathcal{R}}(s_{dzr} + f_{de_r}) \cdot x_{dzr} \tag{1}$$

$$\sum_{z\in\mathcal{Z}}\sum_{r\in\mathcal{R}} x_{dzr} = 1 \qquad \forall d \in \mathcal{D} \tag{2}$$

$$\sum_{z\in\mathcal{Z}}\sum_{r\in\mathcal{R}\setminus\mathcal{R}(d,z)} x_{dzr} = 0 \qquad \forall d \in \mathcal{D} \tag{3}$$

$$\sum_{z\in\mathcal{Z}} x_{dzr} \le y_{rt} \qquad \forall d \in \mathcal{D}(t), r \in \mathcal{R}, t \in \mathcal{T} \tag{4}$$

$$\sum_{d\in\mathcal{D}(t)}\sum_{z\in\mathcal{Z}} v_d \cdot x_{dzr} \le u_{m_r} \cdot y_{rt} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{5}$$

$$\sum_{r\in\mathcal{R}(p,e,m)} y_{rt} \le \sum_{n\in\mathcal{N}} h_{emn} \qquad \forall e \in \mathcal{E}, m \in \mathcal{M}, p \in \mathcal{P}, t \in \mathcal{T} \tag{6}$$

$$\sum_{d\in\mathcal{D}(t)}\sum_{r\in\mathcal{R}(p,z)} v_d \cdot x_{dzr} \le \sum_{n\in\mathcal{N}} b_{zpn} \qquad \forall z \in \mathcal{Z}, p \in \mathcal{P}, t \in \mathcal{T} \tag{7}$$

$$\sum_{r\in\mathcal{R}(p,z)} y_{rt} \le \sum_{n\in\mathcal{N}} a_{zpn} \qquad \forall z \in \mathcal{Z}, p \in \mathcal{P}, t \in \mathcal{T} \tag{8}$$

$$x_{dzr} \in \{0,1\} \qquad \forall d \in \mathcal{D}, z \in \mathcal{Z}, r \in \mathcal{R} \tag{9}$$

$$y_{rt} \in \{0,1\} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{10}$$

The objective function (1) minimizes the total costs, which consist of the service operating costs (first sum) and the cost of assigning each demand to a service-satellite combination (second sum). Constraints (2) ensure that each demand is assigned to exactly one service, while Constraints (3) make sure that demands can only be assigned to services that fulfill the release and due dates for the demand. We need two sets of constraints for this instead of one, as otherwise, multiple assignments would make it possible to circumvent the fairness constraints introduced later. Constraints (4) state that on each day, demands can only be assigned to a service if the service is selected on this day. Constraints (5) ensure that the capacity of the services is not exceeded. Additionally, these constraints guarantee that if a demand is assigned to a service, that service must operate on the day the demand arises. This ensures that demands match the available service capacities for that specific day on which they occur, maintaining an accurate daily alignment between services and demands. Constraints (6) limit the number of urban vehicles that are available at each CDC. Constraints (7) and (8) are the capacity constraints of the satellites. Thereby, Constraints (7) limit the demand volume that operates at satellite z in period p on day t while Constraints (8) limit the number of urban vehicles that can be handled at satellite z in period p on day t. These capacity constraints result from the available capacities across all LSPs. Constraints (9) and (10) specify the binary value domain of the decision variables.

4.2.2 Workload balance constraints

We follow the terminology of Mancini et al. (2021) by referring to constraints that limit the shifts in workload among the LSPs compared to the initial situation without cooperation as workload balance constraints. Let β be a parameter that sets a lower limit for the number of demands assigned to the services of each LSP, relative to the number of demands the LSP brings into the coalition. Specifically, $\beta = 1$ enforces that each LSP fulfills exactly as many demands by its own services as it brings into the coalition. Let α be a parameter that determines the share of each LSP's own demand volume that its own services must fulfill. At $\alpha = 1$, there is no demand sharing between the LSPs in the coalition as each LSP must fulfill 100% of its own demand volume by its own services, while $\alpha = 0$ allows for complete demand sharing.

For balancing the workload of the LSPs over the schedule length, we consider the following constraints regarding the number of demands that each LSP must fulfill and the share of own demand volume that each LSPs must fulfill by its own services.

$$\beta \cdot |D_n| \leq \sum_{d \in \mathcal{D}} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}(n)} x_{dzr} \qquad \forall n \in \mathcal{N} \tag{11}$$

$$\alpha \cdot \sum_{d \in \mathcal{D}(n)} v_d \leq \sum_{d \in \mathcal{D}(n)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}(n)} x_{dzr} \cdot v_d \qquad \forall n \in \mathcal{N} \tag{12}$$

Constraints (11) ensure a lower limit for the number of demands assigned to the services of each LSP. They guarantee that the number of demands assigned to each LSP's services is greater than β times the number of demands of that LSP. However, the fulfilled demands do not have to correspond to the demands brought into the coalition by the respective LSP but can also represent demands from other LSPs. This ensures that each LSP does not lose too many demands and thereby too much market share compared to the initial situation without cooperation. Constraints (12) represent an even stricter restriction. They ensure that each LSP satisfies at least a particular share α of their own demand volume through their own services.

So far, these balance constraints hold on average over all days in the schedule length and ensure workload balance on average over these days. To ensure that on each individual day, the workload balance constraints are met, we can replace them as follows:

$$\beta \cdot |\mathcal{D}(n) \cap \mathcal{D}(t)| \leq \sum_{d \in \mathcal{D}(t)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}(n)} x_{dzr} \qquad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{13}$$

$$\alpha \cdot \sum_{d \in \mathcal{D}(n) \cap \mathcal{D}(t)} v_d \leq \sum_{d \in \mathcal{D}(n) \cap \mathcal{D}(t)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}(n)} x_{dzr} \cdot v_d \qquad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{14}$$

4.2.3 Cost balance constraints

Further, we consider constraints related to the total cost of each LSP in order to have a fair distribution of cost savings among the LSPs. The costs that an LSP n bears are made up of the operating costs of its services ($\sum_{r \in \mathcal{R}(n)} \sum_{t \in \mathcal{T}} c_r \cdot y_{rt}$) as well as the cost to deliver own demands to a CDC and the final delivery cost to deliver the demands from the satellite to their final location ($\sum_{d \in \mathcal{D}(n)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr}$).

Let C_n be the standalone cost for each LSP n when acting independently without cooperating with other LSPs in the coalition. Thereby, C_n must be determined beforehand by solving the model for the sets and parameters of LSP n in isolation. The total standalone cost for all LSPs acting independently $C_{\mathcal{N}}$ is defined by $C_{\mathcal{N}} = \sum_{n \in \mathcal{N}} C_n$.

Let γ be a parameter that provides flexibility in the cost distribution, allowing a maximum percentage markup on the costs that would be allocated to the LSP in the case of exact equal relative cost savings among all LSPs. Setting γ to 0 could lead to no feasible solution, as it might not be possible to have a solution in which each LSP has the exact same relative cost savings.

$$\sum_{r \in \mathcal{R}(n)} \sum_{t \in \mathcal{T}} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}(n)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr} \leq C_n \qquad \forall n \in \mathcal{N} \tag{15}$$

$$\sum_{r \in \mathcal{R}(n)} \sum_{t \in \mathcal{T}} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}(n)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr} \leq$$
$$(1+\gamma) \cdot \frac{C_n}{C_{\mathcal{N}}} \cdot (\sum_{r \in \mathcal{R}} \sum_{t \in \mathcal{T}} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr}) \qquad \forall n \in \mathcal{N} \tag{16}$$

Constraints (15) ensure that each LSP bears at most the cost that would incur if the LSP would act independently without cooperating with other LSPs in the coalition. Constraints (16) are stricter. They ensure that the costs for LSP n must be smaller or equal to the costs $(1+\gamma) \cdot C_n / C_{\mathcal{N}}$ times the total cost of the coalition.

The presented constraints hold over all days in the schedule length and ensure cost balance on average over these days. To ensure that on each individual day, these balances hold, we replace them by Constraints (17) and (18). Thereby, C_{nt} represents the standalone cost of LSP n on day t, while $C_{\mathcal{N}t} = \sum_{n \in N} C_{nt} \forall t \in \mathcal{T}$ represents the cumulative standalone cost of all LSPs of the coalition $\mathcal{N}$ on day t.

$$\sum_{r \in \mathcal{R}(n)} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}(n) \cup \mathcal{D}(t)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr} \leq C_{nt} \qquad \forall n \in \mathcal{N}, t \in \mathcal{T} \quad (17)$$

$$\sum_{r \in \mathcal{R}(n)} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}_n \cup \mathcal{D}(t)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr} \leq$$

$$(1+\gamma) \cdot \frac{C_{nt}}{C_{\mathcal{N}t}} \cdot (\sum_{r \in \mathcal{R}} c_r \cdot y_{rt} + \sum_{d \in \mathcal{D}(t)} \sum_{z \in \mathcal{Z}} \sum_{r \in \mathcal{R}} (s_{dzr} + f_{de_r}) \cdot x_{dzr}) \qquad \forall n \in \mathcal{N}, t \in \mathcal{T} \quad (18)$$

4.2.4 Service regularity constraints

To prevent the execution of entirely different services each day, we include constraints on the regular operation of services. For this purpose, we introduce the binary auxiliary decision variable $\hat{Y}_r$, set to 1 if service $r \in \mathcal{R}$ operates on every day $t \in \mathcal{T}$.

We incorporate a service regularity parameter, θ, to specify the proportion of selected services that should operate each day. For example, $\theta = 0.7$ indicates that 70 percent of all selected services should be those that operate every day. To enforce this, we introduce the following constraints:

$$\hat{Y}_r \cdot |\mathcal{T}| \leq \sum_{t \in \mathcal{T}} y_{tr} \qquad \forall r \in \mathcal{R} \quad (19)$$

$$\theta \cdot \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}} y_{tr} \leq \sum_{r \in \mathcal{R}} \hat{Y}_r \cdot |\mathcal{T}| \quad (20)$$

$$\hat{Y}_r \in \{0,1\} \qquad \forall r \in \mathcal{R} \quad (21)$$

Constraints (19) enforce that if a service is defined as a permanent service ($\hat{Y}_r = 1$), then it must be selected on each day ($y_{tr} = 1 \forall t \in \mathcal{T}$). Constraint (20) ensures that at least a fraction θ of the selected services must be defined as permanent services. Accordingly, $\theta = 0.7$, for example, means that at least 70% of the services selected in the schedule length ($y_{tr} = 1$) must be services that operate on every single day ($\hat{Y}_r = 1$). Constraints (21) ensure the binary value domain.

5 Numerical study

Within this numerical study, our goal is to generate insights into both the general impacts of cooperation on monetary and environmental KPIs and to investigate the effects of the introduced fairness constraints in a multi-day setting on the overall system as well as on the individual LSPs. In addition, we want to quantify the effects of the service regularity. These numerical experiments provide the basis for the policy implications formulated in Section 6. We start by describing the problem-specific instances in Section 5.1 and the numerical setup in Section 5.2. Section 5.3 shows the impact of cooperation on major KPIs. Afterward, Section 5.4 analyzes the effects on total system costs when adding workload and cost balance constraints to the base model. Section 5.5 discusses the effects of these constraints from a financial and a workload perspective. In Section 5.6, we investigate the impact of integrating constraints regarding the service regularity.

5.1 Instance generation

To generate instances for the problem at hand, we are guided by similar publications in the field of 2T-CLSs (e.g., Fontaine et al., 2021; Crainic et al., 2004) and generate our instances based on a real city.

We consider a schedule length of six days and three LSPs operating in that system. During the days, we consider $|\mathcal{P}| = 72$ periods, each having 10 minutes, representing one business day (12 operating hours). We generate a network containing three CDCs and six satellites. Distances between demand locations, satellites, and CDCs are determined by the Euclidean distance.

We consider four different urban vehicle types: small tram, large tram, small truck, and large truck, with capacities of 50 for small and 75 for large vehicles. The cost of the services c_r depends on the vehicle type and the travel distance. We set the fixed cost for the vehicles as follows: 10 for small trams, 15 for large trams, 13 for small trucks, and 18 for large trucks. The variable costs are determined by multiplying the travel distance by 1.2 for small trams, 1.5 for small trucks, 1.7 for large trams, and 2.0 for large trucks. The lower cost of trams is justified by their lower environmental impact cost. Additionally, the travel speed for trams is set to 25 km/h and 20 km/h for trucks to account for traffic conditions. Services are generated based on plausible routes that connect the CDCs with a sequence of satellites. Services operated by trams can only travel to satellites that are located on a tram stop. Each service is replicated three times within the day. The first starting period is randomly set between periods 5 and 15. The following replication starts 15 periods later. We assume a service time of two periods for each satellite.

The three LSPs have different numbers of demands. Specifically, LSP 1 has between

12 and 15 demands per day, LSP 2 has between 17 and 20 demands per day, and LSP 3 has between 22 and 25 demands per day, respectively, leading to $51 \leq |\mathcal{D}(t)| \leq 60 \forall t \in \mathcal{T}$ and consequently $306 \leq |\mathcal{D}| \leq 360$ in each instance. Note that the demands vary from day to day and differ in number, volume, and location. All demand volumes are randomly set between 5 and 10. Thereby, each value is uniformly distributed across the specified range. Each demand's release date (RD) is randomly set between periods 0 and 50. The due date (DD) is then determined by $DD = RD + \text{randint}(12, 22)$ to ensure time feasibility. LSP 1 provides 21 services, while LSP 2 provides 27 services, and LSP 3 provides 33 services. The assignment costs s_{dzr} are determined by the Euclidean distance between the satellite z and the location of demand d. For capacity constraints, we assume that each LSP is allowed to operate one vehicle per period at each satellite (a_{zpn}) and a demand volume of 30 units (b_{zpn}). Furthermore, we limit the number of vehicles of each type m available at CDC e for all LSPs to one (h_{emn}). Within this framework, we generate ten different instances, which we will use for all our numerical experiments in the upcoming sections.

5.2 Numerical setup

We implemented the mathematical model in Python 3.12 using Gurobi 11 as a solver. All experiments are carried out on an AMD Ryzen 9 5950X 16-Core Processor, 3.40 GHz with 128 GB RAM. All experiments were performed on six threads. We set a time limit of 60 minutes for Gurobi. With this setting, Gurobi could solve some of the experiments in the upcoming sections exactly, while minor GAPs remained in others. The average GAP across all experiments was 0.28%, and the maximum GAP was 1.4%. Particularly the experiments in which constraints were in force, which apply over the entire period and thus connect the individual days with each other, were hard to solve.

5.3 General effects of cooperation

In this section, we identify the impact of cooperation on various KPIs. We have included cost-based KPIs, which are particularly relevant for LSPs and their customers, as they want their deliveries to be as cheap as possible, and environment-based KPIs, which are particularly relevant for the municipal authority and the city's residents, as they are primarily interested in minimizing negative impacts.

We achieve this by solving the base model (Section 4.2.1) for each LSP separately and aggregating the results (No Coop.), as well as by solving the base model collectively for all LSPs (Coop.).

As shown in Table 1, cooperation leads to lower costs in all cost components, with total system costs falling by as much as 22.4%. This underscores the benefits of cooperation,

KPI	**Definition**	**No Coop.**	**Coop.**	**Δ [%]**
Total system cost	Objective function (1)	4518.2	3507.7	-22.4
Service operating cost	$\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} c_r \cdot y_{rt}$	2330.9	1516.6	-34.9
CDC assignment cost	$\sum_{d\in\mathcal{D}}\sum_{z\in\mathcal{Z}}\sum_{r\in\mathcal{R}} f_{de_r} \cdot x_{dzr}$	893.2	869.0	-2.7
Second tier cost	$\sum_{d\in\mathcal{D}}\sum_{z\in\mathcal{Z}}\sum_{r\in\mathcal{R}} s_{dzr} \cdot x_{dzr}$	1294.2	1122.1	-13.3
No. of selected services	$\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} y_{rt}$	57.4	40.8	-28.9
Utilization of services [%]	$\frac{\sum_{d\in\mathcal{D}} v_d}{\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} u_{m_r}\cdot y_{rt}}$	78.7	97.1	23.4
Share of large vehicles* [%]	$\frac{\sum_{r\in\acute{\mathcal{R}}}\sum_{t\in\mathcal{T}} u_{m_r}\cdot y_{rt}}{\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} u_{m_r}\cdot y_{rt}}$	28.5	61.4	115.4
Share of trams* [%]	$\frac{\sum_{r\in\hat{\mathcal{R}}}\sum_{t\in\mathcal{T}} u_{m_r}\cdot y_{rt}}{\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} u_{m_r}\cdot y_{rt}}$	55.3	69.5	25.7
Driven distance of services [km]	$\sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} distance(r) \cdot y_{rt}$	889.5	466.5	-47.6

*$\acute{\mathcal{R}}$ represents the subset of services operated by large urban vehicles and $\hat{\mathcal{R}}$ the subset of services operated by trams.

Table 1: Impact of cooperation on major KPIs

particularly for the LSPs, as it enables them to save monetary costs. Additionally, the other KPIs relating to the negative external effects on the cities also show positive effects. Both the number of vehicles and the distance traveled by the services decrease significantly. In addition, cooperation leads to a shift in the urban vehicle fleet with a significant increase in the proportion of capacity provided by services operated by large vehicles and trams.

The impact on these KPIs shows that cooperation not only leads to monetary savings but also significantly reduces the negative impact on the environment, such as noise, CO2 pollution, traffic congestion, etc., through the more efficient use of vehicles, which is particularly important in the context of city logistics.

Despite the clear positive effects of cooperation, the outcomes can also lead to unfair distribution of costs and market shares, and without considering that each LSP should fulfill its own demand volume primarily through its services. In Table 2, we show the average minimum and average maximum values for the relative cost savings, the relative deviation in market share, and the share of own demand volume allocated to own services across the LSPs. The average minimum value, therefore, indicates how low this KPI is on average for the LSPs with the lowest value.

As can be seen, there are large deviations in all three KPIs. This indicates clear unfairness and instability within the coalition of LSPs, highlighting the urgent need for additional fairness constraints. Further, each service provider only satisfies a small fraction of its own demands, as the base model does not take this allocation into account.

KPI	Avg. minimum	Avg. maximum
Relative cost savings [%]	6.3	37.6
Relative deviation in market shares [%]	-38.8	47.1
Share of own demand volume [%]	17.8	50.7

Table 2: Average minimum and maximum value of the LSPs for various KPIs

These results show that full cooperation without taking the before-introduced fairness constraints into account does not lead to acceptable results for every LSP and that embedding appropriate constraints is necessary.

5.4 Impacts of fairness constraints on total system cost

We examine the impact of the workload (Section 5.4.1) and cost balance (Section 5.4.2) constraints on the total system costs by adding them to the base model with different parameter settings. For this, we distinguish between three scenarios in the following experiments:

1. The constraints that ensure daily workload/cost balance are enforced (referred to as *Individual day*).
2. We divide the schedule length into two and three-day segments. The model is solved individually for each segment, whereby the constraints that ensure average workload/cost balance over these segments are enforced. We report the results as a sum over the segments (referred to as *Two days* and *Three days*).
3. The constraints that ensure average workload/cost balance over the entire schedule length of six days are enforced (referred to as *All days*).

5.4.1 Workload balance

We start our investigation by analyzing the influence of Constraints (11) and (13) that limit the loss of market share, as they are less restrictive and focus exclusively on the number of demands and do not consider their volume or affiliation to an LSP. In our analysis, we gradually increase β from 0.7 (each LSP must be assigned at least 70% as many demands as it contributes to the coalition) to 1. Figure 2 shows the results.

We find that, on average, the inclusion of these constraints leads to an increase in total system costs of up to 1.75% when β is set to 1, and the constraints are enforced individually on each day. These results are consistent with the results obtained by Gansterer and

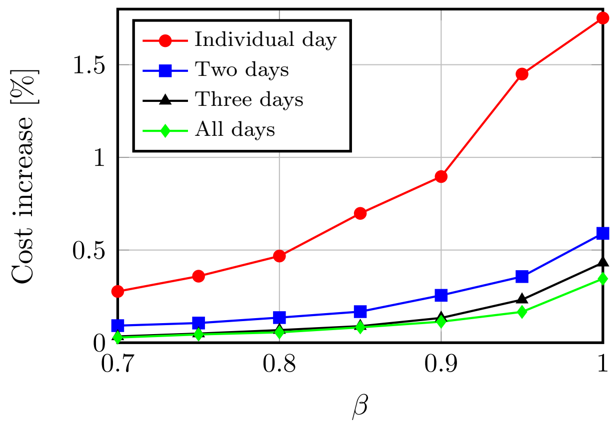

Figure 2: Cost impact of varying β

Hartl (2018) with the introduction of similar workload balance constraints in a vehicle routing context, as they also observe only minor cost increases. In addition, it further shows that the more days over which the constraints hold on average, the lower the increase in costs. Furthermore, we find that a large part of the increase only occurs with a very restrictive $\beta \geq 0.9$.

In the next step, we determine the impact on the total system cost of Constraints (12) and (14), which restrict the demand sharing of LSPs. These are more restrictive as they consider both the demand volume and the LSP to which the demands belong.

We increase α gradually from 0.7 (each LSP must satisfy at least 70 percent of its own demand volume with its own services) to 1 (no demand sharing possible). Figure 3 shows the results. In contrast to the previous analysis, we now see a very high impact on total system costs. When demand sharing is totally restricted ($\alpha = 1$), the total cost across all instances increases by 21.9% on average. Furthermore, we find that for all α values less than one, it is significantly cheaper to enforce these constraints over a more extended period of time rather than on each individual day. Even stretching the constraints over two days leads to significant savings. We also find that by sharing only a small portion of the demand volume, a large portion of the potential cost savings that would be possible by full demand sharing can be realized. This is demonstrated by the significant increase in total system costs for $\alpha > 0.8$.

Overall, these two analyses show that the inclusion of constraints that only affect the number of demands leads merely to a slight increase in total system costs, while constraints that limit demand sharing are associated with a high increase in costs. Furthermore, we find that for both constraints, a large part of the cost increase only happens when the constraints are enforced with strict α and β parameter settings.

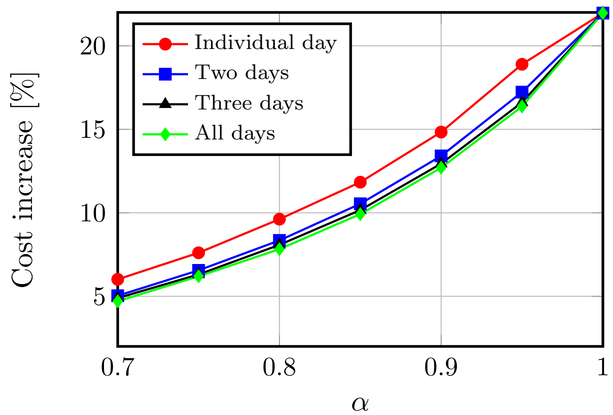

Figure 3: Cost impact of varying α

5.4.2 Cost balance

We start our investigation by including the less restrictive cost-balance Constraints (15) and (17) that ensure that the cost of each LSP is not greater than its stand-alone cost. Table 3 shows the cost increase compared to the base model without these constraints.

Individual day	Two days	Three days	All days
0.36%	0.14%	0.11%	0.08%

Table 3: Cost impact of stand-alone cost constraints

We find that including these constraints leads to a marginal increase in total system costs close to zero. Even if these constraints are enforced every single day, the total cost only increases by 0.36%. This shows that including this simple fairness criterion, namely that every LSP must benefit financially from the cooperation, causes almost no additional costs.

In the next step, we include the more restrictive constraints on the relative cost savings (Constraints (16) and (18)). We gradually increase γ from 1 to 6 percent. The results are shown in Figure 4.

We find that even for $\gamma = 1\%$ with daily enforcement of the constraints, the total system cost only increases by 1.6%. As soon as the constraints are stretched over segments of two or more days, resulting in balancing effects, the cost increases are close to zero.

Overall, these two experiments show that the inclusion of constraints regarding the cost distribution of LSPs only leads to marginal cost increases that are close to zero as soon as they are stretched over several days or as soon as the constraints are provided with less strict parameter settings.

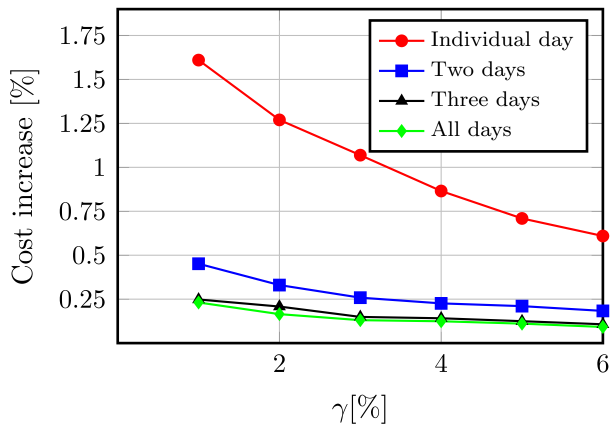

Figure 4: Cost impact of varying γ

5.5 Impact of fairness constraints on financial and workload aspects

In this section, we discuss the impact of the fairness constraints under both financial (Section 5.5.1) and workload (Section 5.5.2) aspects. Further, we investigate the daily variation effects on workload and costs when constraints are met over the entire period rather than on each individual day (Section 5.5.3).

5.5.1 Cost aspects

In this section, we take fairness considerations regarding the individual relative cost savings of the LSPs into account. We do this by comparing the individual cost savings of the LSPs for three cases: In Case 1, we solve the base model without any additional fairness constraints. In Case 2, we include Constraints (11) with β set to 1 and Constraints (12) with α set to a moderate value of 0.8. In Case 3, we include the Constraints (16) with γ set to 1%. Figure 5 depicts the results as boxplots. These boxplots show the distribution of the individual relative cost savings of the three LSPs across all instances (LSP 1 is the smallest, LSP 2 the medium, LSP 3 the largest).

As can be seen, the individual cost savings in Case 1 are subject to extreme fluctuations. In some cases, the individual cost savings are close to 0, or even in the negative range, which represents an extreme violation of the most straightforward fairness criterion that each LSPs should have financial benefits. In Case 2, individual savings are no longer subject to such strong fluctuations, as it is ensured that each LSP bears at least a particular share of the costs since each LSP must satisfy as many demands as it contributes to the coalition. However, the mean values of the savings are lower overall, as these constraints significantly increase the total system costs, as already shown. Further,

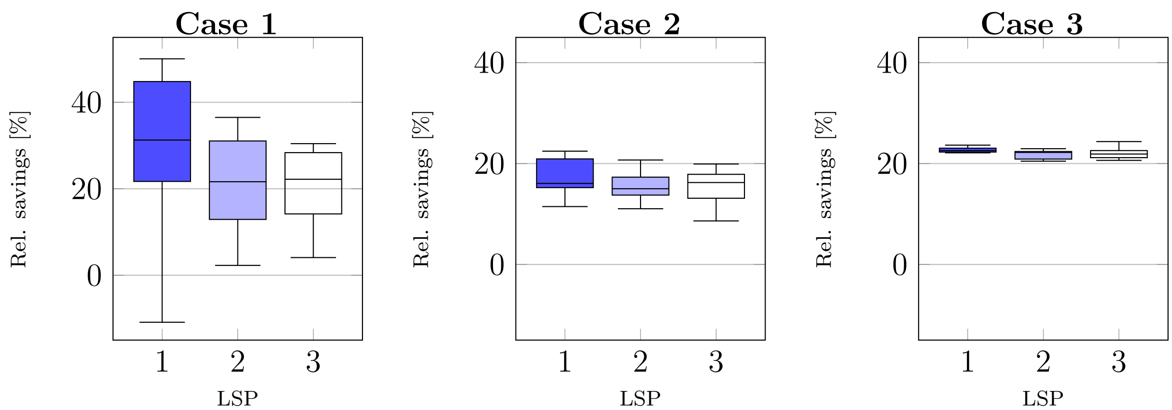

Figure 5: Relative cost savings of LSPs for the different cases [%]

there are still large deviations in the relative cost savings among the LSPs on individual instances. Only in Case 3 is it ensured that each LSP has a relative financial advantage of almost the same size without the total system cost rising sharply.

5.5.2 Workload aspects

In this section, we examine the percentage deviations in the number of assigned demands of the individual LSPs for the exact same three cases. Figure 6 shows the results. A value of, e.g., 20% means that the LSP has 20% more demands assigned than it contributes to the coalition.

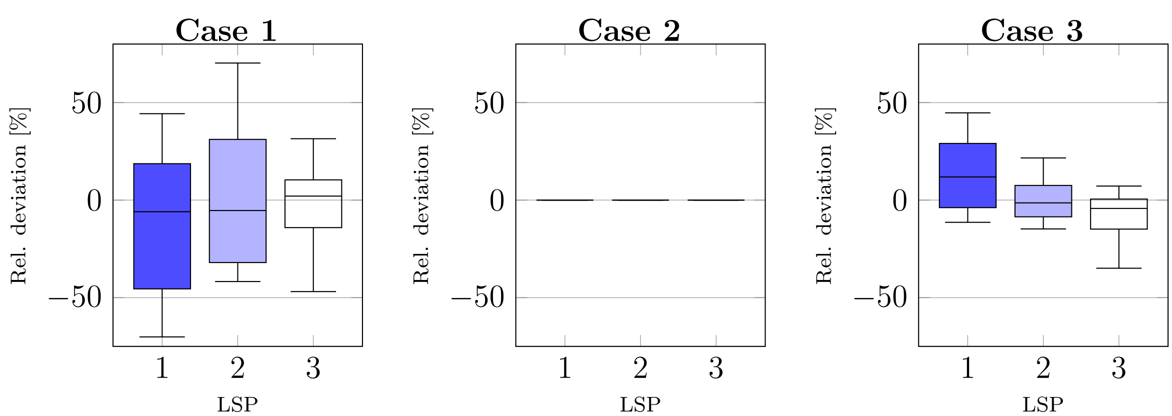

Figure 6: Relative deviation in the number of assigned demands for the different cases [%]

In Case 1, the relative changes in the number of demands for all three LSPs are subject to huge fluctuations as no single constraint limits the workload for any of the LSPs.

In Case 3, the fluctuations due to the introduction of cost balance constraints are much smaller but still significant. This shows that introducing the cost balance constraints also leads to a certain balance in the workload but still allows deviations in the number of demands. In addition, no consideration is given to whether the demands assigned to an LSP are also the respective own demands of this LSP. Only in Case 2 does the introduction of constraints result in absolutely no change in market shares, as changes in market shares are forbidden due to the constraints.

Overall, our results show that both workload and cost balance constraints are necessary to enable a fair coalition in both aspects. We illustrated that cost-based fairness constraints only insufficiently consider workload aspects implicitly and vice versa.

5.5.3 Daily fluctuations under multi-day fairness constraints

The inclusion of constraints that apply on average over a horizon of multiple days rather than on each individual day allows daily fluctuations. Therefore, we examine the daily fluctuations for the three LSPs if these fairness constraints are enforced on average over the whole schedule length. To do this, we solve the base model, including the respective constraints regarding costs and workload, with the parameter settings described below.

Figure 7 shows the distribution of the number of daily demands that the respective LSPs satisfy with their own services relative to the number of demands they bring into the coalition on the respective day. A value of 1, therefore, means that exactly as many demands are fulfilled by services of an LSP as the respective LSP contributes to the coalition on that day. For this analysis, we include Constraints (11) and set $\beta = 1$ to ensure that each LSP satisfies exactly as many demands with its services over the entire schedule length as it contributes to the coalition.

Figure 8 shows the distribution of the daily own share of demand volume, which the LSPs satisfy with their own services. For this analysis, we include Constraints (12) and set $\alpha = 0.8$.

Figure 9 shows the distribution of the daily cost savings of the coalition as a whole ($\mathcal{N}$) and for the respective LSPs. For this analysis, we include Constraints (16) and set $\gamma = 1\%$.

Overall, it can be seen that enforcing the constraints over a period of several days results in high deviations on a daily basis. In all three analyses, these are particularly strong for the smallest LSP (LSP 1), as the balancing effects are most pronounced for it in relative terms. If these effects are undesirable or pose a problem, both the constraints that hold on average over the schedule length and the constraints relating to individual days can be enforced simultaneously so that even within the individual days, the fluctuations

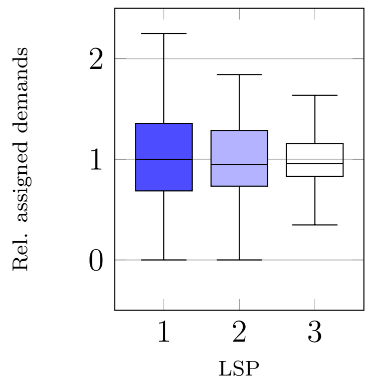

Figure 7: Distribution of the daily number of demands assigned to own services relative to the own number of demands for $\beta = 1$

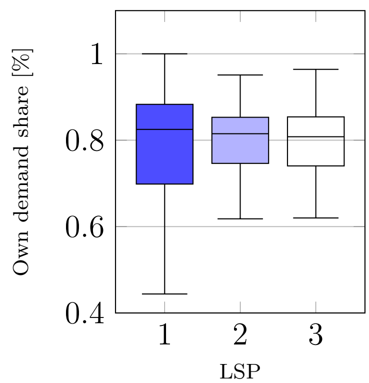

Figure 8: Distribution of the daily share of own demand volume assigned to own services for $\alpha = 0.8$

only occur in a certain interval.

5.6 Impact of service regularity

In this section, we examine the effects of regularly operated services over the entire schedule length. To do this, we add the Constraints (19) and (20) to the base model and gradually increase θ from 0 (no regularity) to 1 (complete regularity). We distinguish between two cases. In the first case (moderate fluctuation), we take the instances we have used for previous experiments. In the second case (high fluctuation), we modify these instances by randomly removing between 0 and $3 \cdot (60 - |\mathcal{D}(t)|)$ demands each day t. This approach increases the fluctuation of daily demand, removing more demands on days with fewer already and fewer on days close to the maximum of 60 demands. Additionally, we multiply the demand volumes v_d by a different random number between 0.7 and 1.3 each day. With this approach, we achieve a higher daily fluctuation in both

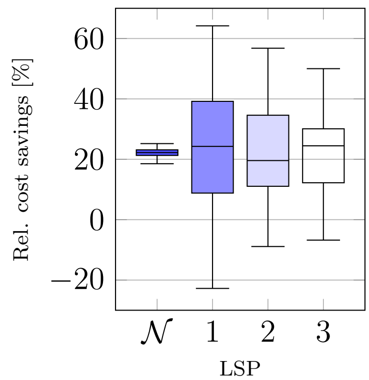

Figure 9: Distribution of daily relative cost savings [%] for $\gamma = 1\%$

the number of demands and the demand volume, allowing us to evaluate whether this has an effect on the costs of service regularity. The results are shown in Figure 10.

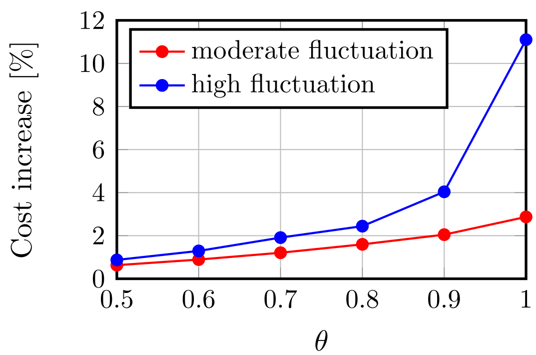

Figure 10: Cost impact of varying θ [%]

We see that in case of moderate fluctuation, the cost increase with complete service regularity amounts to almost 3% on average. In addition, we observe that for all values of θ, the cost increase in case of high fluctuation is significantly higher. With complete regularity, the costs increase by over 11%. In particular, a very high increase between $\theta = 0.9$ and $\theta = 1$ can be seen, which is due to the fact that there are no compensation options for fluctuating demand if all services have to be operated regularly. This clearly indicates that the regularity of the services is particularly detrimental to the system if there are strong fluctuations in the demand structures between days, as the service capacity provided cannot then adapt to the demand fluctuations between days. This shows that service regularity makes particular sense if there is also a corresponding demand regularity. Detailed analysis further revealed the following environmental impact in case of high fluctuation when comparing $\theta = 0$ and $\theta = 1$: the average number of selected services increases by 27,4%, the average utilization of the services decreases by 24.1%, and the driven distance of the services increases by 10,8%.

Overall, the results show that complete service regularity leads to both monetary cost increases and higher environmental impact costs. However, most of the cost increases only occur with high parameter settings for θ, and this effect is stronger the greater the daily fluctuation in the demand structure is.

6 Policy implications

Based on the results of our numerical experiments, we derive the following policy implications that are relevant for LSPs as well as for policymakers.

Cooperation leads to monetary and environmental cost savings: Our results show that cooperation leads to huge improvements in monetary as well as non-monetary KPIs. These result from more efficient use of services, higher utilization of urban vehicles, and economies of scale through cooperation. It is particularly important that cooperation is not limited to the use of shared infrastructure but also includes demand sharing, as this can lead to considerable cost savings even when established on a small scale.

Balance fairness over time: Our numerical experiments consistently demonstrate that adhering to fairness criteria on average over an extended period of several days yields significant cost savings compared to enforcing them on a daily basis. Even an extension of the constraints to a segment of two days enables balancing effects that mitigate the impact of the constraints on the total system cost. Although these balancing effects reduce overall costs, they lead to considerable daily fluctuations in workload and cost distributions for LSPs, particularly for the smaller LSPs in the coalition. This holds for both workload and cost-related fairness criteria.

Mitigate the impact of too strict constraints: We show that too strict constraints increase the total system cost and thus harm all LSPs of the coalition. Fairness constraints should, therefore, not be too strict to reduce negative effects on the coalition as a whole. Across all experiments, moderate settings of these constraints have little to almost no impact on the total system cost.

Consider cost and market shares: Focusing solely on costs or solely on market shares does not lead to acceptable coalitions for all LSPs. In order to ensure a stable coalition, both aspects must therefore be taken into account in the decision support system so that none of the LSPs is disadvantaged in terms of cost and workload aspects.

Allow flexibility over time in the selection of services: We demonstrate that cooperative city logistics systems need flexibility in selecting services over time. Regularly operated services might be wishful, but too strict constraints on this lead to a dramatic increase in total system cost and therefore harm the entire system as well. Especially when there are high fluctuations in the daily demand structure, flexibility is necessary as otherwise there will be immense additional costs as the selection of services can no longer be adapted to the specific demand structures of each day. Therefore, service regularity relies on demand regularity to prevent significant increases in total system costs. In this context, too, the majority of cost increases occur when flexibility is severely restricted. Conversely, a moderate restriction, where some services have to be operated regularly, only leads to a slight increase in costs.

7 Conclusion

In the existing body of literature on city logistics, numerous models and problem settings have been explored that implicitly assume a cooperative logistics system. However, our study is the first to explicitly address the area of cooperation between LSPs in a more realistic multi-day scenario, considering both fairness and service flexibility constraints.

Throughout our investigation, we analyzed the impact of different constraints regarding the fair design of a cooperative city logistics system. The crux of our findings underscores the importance of integrating both cost-based and workload-based constraints for the establishment of fair and sustainable cooperations in city logistics. Our numerical experiments clearly revealed that fairness should be considered on average over a horizon of several days rather than on a daily basis. Furthermore, it became evident from our results that excessively stringent constraints not only compromise total costs but also negatively impact all LSPs engaged in the coalition. Based on these results, we derived policy implications that are of great importance from the perspective of both the LSPs and the public policymakers in order to realize successful city logistics projects.

In conclusion, we were able to show that cooperation between LSPs has the potential to benefit all stakeholders, including LSPs, customers, communities, and city residents, and to have a positive impact on the environment. As we peer into the future, a vast landscape for further research unfolds, particularly in broadening considerations beyond financial and workload aspects. Exploring dimensions such as joint risk protection or reciprocal remuneration when serving demands of another LSP holds promising potential.

Finally, we would like to motivate further research in cooperative city logistics. By tackling these challenges together and offering valuable recommendations to both LSPs and public policymakers, we can contribute to more sustainable, efficient, and consequently more liveable cities.

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