Dynamic capacity allocation for cargo-hitching in urban public transportation systems

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1 INTRODUCTION

As urban populations grow and cities become more interconnected, the demand for efficient public transit rises (United Nations, 2019). Moreover, this population increase leads to significant growth of e-commerce transactions whose transportation contributes up to 15% of urban road transport (Dablanc, 2011). As a consequence, cities suffer from overloaded transportation systems, whose negative externalities cause environmental harm via CO_2 emissions, health dangers via particulate matters and NO_x, and economic harm through working hours lost in congestion (Levy *et al.*, 2010). Public transit systems (PTSs) offer sustainable mobility solutions with low emissions per passenger compared to individual mobility solutions (Noussan *et al.*, 2022). However, the sustainability of the PTSs depends on their utilization. To mitigate low PTS utilization during off-peak hours and relieve heavily congested road networks, partially occupied by freight trucks, this work studies the concept of *cargo-hitching* where a municipality equips its PTS such that it accommodates intermodal freight transportation. In this context, we allow the dynamic allocation of public transportation (PT) capacity such that municipalities can sync the allocation with the varying transit demand and freight mainly occupies excess capacity at off-peak hours.

Scientific literature on the strategic planning of cargo-hitching is sparse and predominantly focused on selecting suitable PT lines (see e.g., Delle Donne *et al.*, 2023), or determining the sharing mode of PT vehicles (Di *et al.*, 2022, Li *et al.*, 2023) — here the capacity allocation is implicitly determined by the sharing mode and remains constant during operations. Studies considering the dynamic allocation of capacity are missing.

In this context, we develop an algorithmic framework for the strategic planning tasks of a municipality to enable cargo-hitching in their PTS. Figure 1 illustrates our setting in which logistic service providers transport freight to selected stops of the PTS, ship it via the PT vehicles to the city center, and complete the last-mile with city freighters. To do so, the municipality needs to transform their PTS by adding *hybrid transportation units (HTUs)* that can transport freight and passengers. We focus on HTUs with a flexible interior that can be changed between trips. For example, an HTU can be a specifically designed subway train wagon (cf. Kelly & Marinov, 2017).

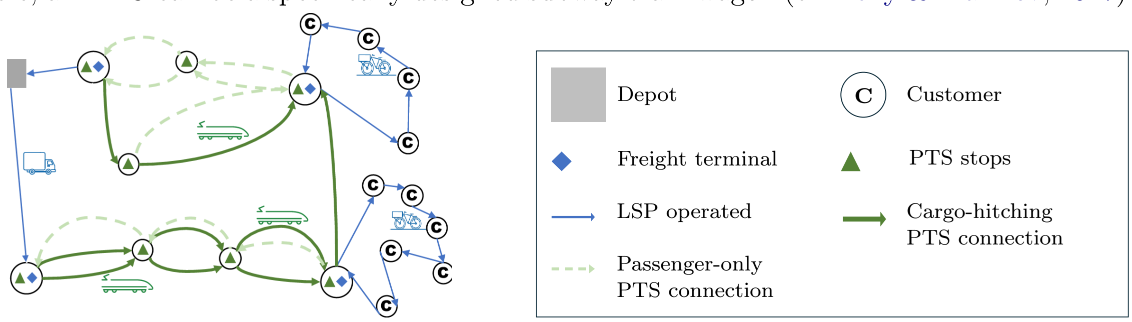

Figure 1 – *Schematic cargo-hitching illustration*

Changing the interior in between trips allows the system operator to allocate capacity between passengers and freight. We make the following contributions: first, we define a novel strategic planning problem for a municipality enabling cargo-hitching with dynamic capacity allocation to increase the system utilization during off-peak hours. Second, we introduce a new algorithmic framework with a state-of-the-art graph expansion and develop both a Price-and-branch (P&B) and Branch-and-price (B&P) algorithm to solve real-world problem instances. Third, we derive managerial insights from a case study using real-world data for the city of Munich, Germany.

2 PROBLEM SETTING

Formally, we consider a set of requests $\mathcal{R} = \mathcal{R}^{\mathrm{P}} \cup \mathcal{R}^{\mathrm{F}}$, which is the union of two distinct subsets: passenger requests $\mathcal{R}^{\mathrm{P}}$ and freight requests $\mathcal{R}^{\mathrm{F}}$. Every request is defined as a quintuple $r = (o^r, d^r, q^r, e^r, l^r)$. Here, o^r denotes the request's origin, d^r its destination, q^r its demand, and e^r as well as l^r define the interval $[e^r, l^r]$ in which the request must be processed, with e^r being the earliest start time and l^r marking the latest service completion time. The PTS consists of a set of stops $s \in \mathcal{M}$. Moreover, a fleet of PT vehicles, denoted by $\mathcal{H}$, operates on this network with every PT vehicle $h \in \mathcal{H}$ following a specific sequence of stops. Each route corresponds to a PT vehicle's path through the PTS during the planning horizon and the times at which it services the constituent stops. We define a PT vehicles' route as a sequence of stops $\langle s_1, \dots, s_n \rangle$ with corresponding arrival times $\langle t_1, \dots, t_n \rangle$, where n represents the number of stops on that route. Accordingly, we define the route of a PT vehicle h as a sequence of tuples $L_h = \langle (s_1, t_1), \dots, (s_n, t_n) \rangle$ and the set of temporal stops as $\mathcal{L} := \bigcup_{h \in \mathcal{H}} \{(s,t) : (s,t) \in L_h\}$. Requests pass the PTS on paths $p \in \mathcal{P}$ where paths can be represented as a sequence of temporal stops. The set of paths $\mathcal{P} = \tilde{\mathcal{P}} \cup \hat{\mathcal{P}}$ is the union of passenger paths $\tilde{\mathcal{P}}$ and freight paths $\hat{\mathcal{P}}$.

A solution is a quadruple (y, x, g, z) where $y \in \mathbb{N}_0^{|\mathcal{H}|}$ encodes the design decision such that y yields the number of HTUs per PT vehicle. The vector $x \in \mathbb{N}^{|\mathcal{L}|}$ dynamically allocates the flexible capacity given by the HTUs. Vectors $g \in \mathbb{R}^{|\tilde{\mathcal{P}}|}$ and $z \in \{0,1\}^{|\hat{\mathcal{P}}|}$ denote the flow associated to a path for a passenger request, or freight request respectively. A solution is feasible if

i. the sum of passenger flow must exceed a service level
ii. the sum of flows g and z adheres to the capacity limits evolving from the dynamic allocation
iii. design variables y are subject to an upper bound vector κ, and propagate these limits accordingly to the capacity allocation variables x.

We aim to find solutions that minimize the total system cost, which includes a design cost for each deployed HTU, a penalty cost for each rejected freight request $r \in \mathcal{R}^{\mathrm{F}}$, and a distance-proportionate routing cost per unit of freight transported through the PTS.

3 METHODOLOGY

We develop an algorithmic framework that bases on a temporal and spatial graph expansion.
Graph expansion: To devise an effective algorithm, we encode some of the problem's temporal and spatial complexity by using a problem-specific graph representation. We use a temporal graph expansion in which vertices represent a combination of location and time, and combine it with a spatial expansion in which we separate different vehicles' routes through the PTS into $|\mathcal{H}| + 1$ different graph layers. The expanded graph contains one separate layer of temporally expanded vertices for every vehicle $h \in \mathcal{H}$, and one additional layer that we call holding layer. The holding layer enables keeping requests at stops and is the only connection between different vehicle layers such that all transfers pass the holding layer. Moreover, we represent a request's origin and destination as temporal vertices (o^r, e^r), and (d^r, l^r). We link the origin and destination vertices to the holding layer. Furthermore, we apply the following preprocessing steps. First, we pre-compute a set of paths for passengers $\tilde{\mathcal{P}}$ such that it contains the k shortest paths for every request $r \in \tilde{\mathcal{P}}$. Second, we contract the graph's arcs such that the arc set $\mathcal{A}$ contains all arcs allowing for freight transportation. Additionally, $\mathcal{A}^{\mathrm{F}} \subset \mathcal{A}$ denotes the capacity restricted

arc set. We denote the graph with the contracted arc set and its node set $\mathcal{V}$ as $G(\mathcal{V}, \mathcal{A})$.
Algorithm: We solve a path-based mixed integer program (MIP) with a P&B approach as shown in Algorithm 1. First, the algorithm solves the continuous relaxation of the given path-based formulation (1-12) via Column Generation (CG) with partial pricing. Every 5 iterations, we enhance the partial pricing by conducting a full pricing iteration that allows us to update both the upper bound and the lower bound. Our CG component utilizes the dual solution from a restricted master problem (RMP) to solve the decomposed pricing problems and add new columns to the RMP (6). After the CG has terminated (4), the algorithm branches on the obtained continuous solution in order to enforce integer feasible solutions (13).

Algorithm 1 Price-and-branch

```
1:  relaxation ← ContinuousRelaxation
2:  rmp ← InitializeRMP(relaxation)                 ▷ Ensures feasibility throughout CG
3:  LB, UB ← 0, ∞
4:  while OptimalityGap > ϵ and SolveTime > 0 do
5:      duals ← SolveRMP(rmp)                        ▷ Warmstarting at previous solution
6:      cols ← Price(duals)
7:      rmp ← AddColumns(rmp, cols)
8:      UB ← UpdateBounds(rmp)                       ▷ Solution value of RMP
9:      if FullPricingIteration then                 ▷ No update in partial pricing iterations
10:         LB ← UpdateBounds(rmp, duals)
11:     end if
12: end while
13: return solution ← BranchAndCut(rmp)              ▷ No further updates of lower bound
```

The pricing problems are shortest path problems on the static graph G for all requests $r \in \mathcal{R}^{\mathrm{F}}$:

$$\min_{f} \quad q^r \Big[\sum_{(i,j)\in\mathcal{A}} c_{i,j} f^r_{i,j} - \sum_{(i,j)\in\mathcal{A}^{\mathrm{F}}} \alpha_{i,j} f^r_{i,j} \Big] - \eta^r \tag{1a}$$

$$\text{s.t.} \quad \sum_{j\in\mathcal{N}^+(i)} f^r_{i,j} - \sum_{j\in\mathcal{N}^-(i)} f^r_{j,i} = \begin{cases} 1, & \text{if} \quad i = (o^r, e^r), \\ -1, & \text{if} \quad i = (d^r, l^r), \\ 0 & \text{otherwise.} \end{cases} \qquad \forall i \in \mathcal{V}, \tag{1b}$$

$$f^r_{i,j} \in \{0, 1\}, \qquad \forall (i,j) \in \mathcal{A} \tag{1c}$$

Here, $\alpha_{i,j}$, $(i,j) \in \mathcal{A}^{\mathrm{F}}$ are the duals associated to the capacity restricting constraints while dual variables η^r, $r \in \mathcal{R}^{\mathrm{F}}$ belong to the convexity constraints in the RMP. We provide an admissible distance approximation that allows us to solve the pricing problems efficiently via the A* algorithm and implemented a full B&P algorithm as a benchmark.

4 RESULTS

We design a case study based on the subway network in Munich, Germany. In this context, we use the fleet composition, routes, and time-tables published by the system operator, and 10,000 passenger travel requests from the simulation tool MITO (cf. Moeckel *et al.*, 2020). Additionally, we sample freight demand based on population and income distributions. The sizes of the sampled instances differ by the number of sampled freight requests — we generate $n = 15$ experiments with different seeds for every instance size in $[250, 500, 1000, 2000, 3000]$ freight requests.
Computational analysis: Table 1 compares the P&B approach with the B&P algorithm and a commercial solver's branch-and-cut algorithm on an equivalent MIP formulation.

The P&B approach solves all instances within 90 minutes to a median integrality gap of less than 1.0%. The commercial solver runs into memory bounds quickly and solves only the small instances with 250 requests consistently. Moreover, the P&B algorithm is almost as good as the B&P at lower computational cost. In summary, our algorithmic framework allows solving larger instances than a commercial solver at lower computational effort than a full B&P. The difference

Table 1 – *Benchmark Results (n = 15)*

Instance size	Median integrality gap [%]			Median solve time until first feasible solution [s]			Solved instances		
	MIP	**P&B**	**B&P**	**MIP**	**P&B**	**B&P**	**MIP**	**P&B**	**B&P**
250	0.69%	0.74%	0.87%	1,870.40	452.71	456.56	15	15	15
500	0.80%	0.73%	0.62%	2,790.19	515.07	559.23	13	15	15
1,000	-	0.84%	0.49%	-	641.31	684.75	0	15	15
2,000	-	0.86%	0.45%	-	965.17	1000.30	0	15	15
3,000	-	1.00%	0.65%	-	1286.11	1386.50	0	15	15

in solvable instance sizes reaches a factor of 6, i.e., increases from 500 to 3,000 freight requests.
Managerial insights: Figure 2 shows the system utilization over time in our base scenario, the utilization of one vehicle over the studied period, and the most important system components by transported freight volume per day.

First, we find that our framework schedules freight requests to be transported, and thus also increases utilization, predominantly at off-peak hours. The passenger transportation curve peaks around 8am and the freight transportation curve shows two peaks before and after that. Second, allowing to dynamically allocate HTU capacity enables the algorithmic framework to assign freight requests to PT vehicles such that passenger service remains undisturbed. Third, our results yield the most utilized system components and thereby allow planners to implement cargo-hitching step-wise starting with the most important components. Moreover, we conducted a sensitivity analysis that indicates cargo-hitching is worthwhile if truck-based transport occurs at an externality cost of more than 1.6 € per vehicle and kilometer, and loading and unloading costs of less than 2 € per passenger equivalent.

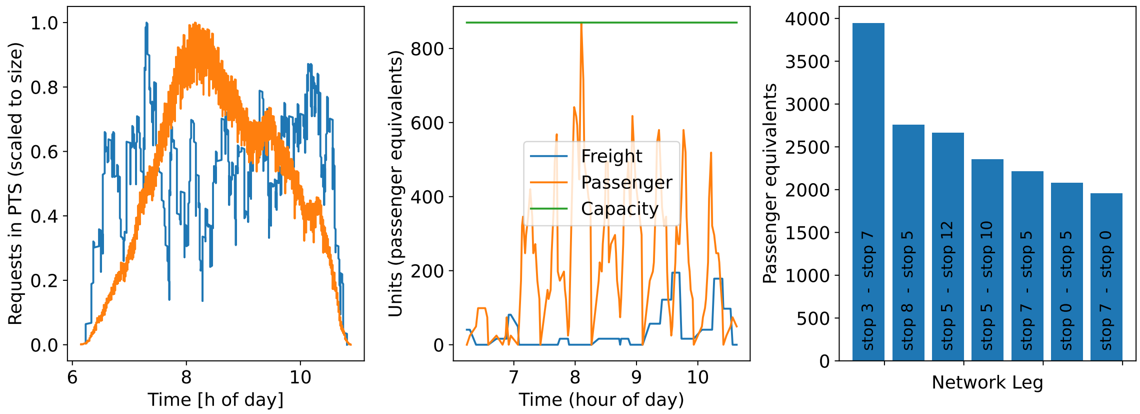

Figure 2 – *System utilization, single vehicle utilization, and network analysis*

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