Dynamic capacity planning for demand-responsive multimodal transit

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Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 29, 2024

Keywords: Multimodal transit, Public transport, On-demand mobility, Stochastic optimization, Large-scale optimization

1 INTRODUCTION

This work studies a mixed transport system where public transport (i.e., transit) and on-demand vehicles are optimized in a synchronized and integrated manner. This type of system, also known as On-Demand Multimodal Transit System (ODMTS), has been actively studied in recent years (Bertsimas *et al.*, 2020, Dalmeijer & Van Hentenryck, 2020, Steiner & Irnich, 2020, Calabrò *et al.*, 2023). The rise of digitalization capabilities, the need to address new and changing commuting patterns, and the higher customer expectations underscore the potential value of such systems. Pilot projects have proven the viability of ODMTS in practice (Van Hentenryck *et al.*, 2023), but modeling and planning these systems at scale remains a challenge, and most of the studies consider different assumptions to be able to solve such models (Banerjee *et al.*, 2021, Sumalee *et al.*, 2011). Among others, the large-scale models focus on a deterministic scenario and consider homogeneous fleets within modal systems (Lienkamp & Schiffer, 2023). One of the areas for improvement from ODMTS is dimensioning the system capacity accurately. Running half-empty vehicles or overcrowded ones hinder the offered service level to passengers. Adjusting the frequency of the transit lines is one way of adapting the system capacity to the demand. However, this may not be enough, and it is also susceptible to unexpected variations in demand. We believe that planning and sizing a heterogeneous fleet can be a more efficient approach to optimize the system capacity and offer a better level of service. This also fits with the needs of many transit operators to renew their fleets and the model we present can be seen as an opportunity to make such decisions effectively.

The public transport system is seen as the core part of an ODMTS where demand-responsive vehicles act as a complement to transit rather than a replacement. Sizing the system's fleet is a strategical decision, whereas operating on-demand services is an operational one as they do not rely on planning in advance. This brings us to formulate the system as a two-stage model formulation in which we make strategic decisions in the first stage (i.e., system fleet sizing and scheduling) and operational decisions in the second stage (i.e., planning of on-demand vehicles and passenger routing) to respond to demand uncertainty.

We address two main research questions in this study:

1. Can a model for ODMTS with heterogeneous fleet planning decisions and stochasticity in demand lead to better passenger service levels and lower transport operations costs?

2. What are the benefits this model can bring and how can it operate in practice?

The first question is about how can we leverage the uncertainty realization and additional operational flexibility to plan the system capacity more efficiently. The second question is about quantifying the value of integrating on-demand mobility systems into public transportation line and timetable planning. This value addresses all the actors involved: (i) operational costs for operators, (ii) passenger level of service for customers, and (iii) environmental and congestion impact for the society.

This study aims at making the following contributions:

1. New model: *Demand-responsive multimodal transit with heterogenous fleet and stochastic demand*: A two-stage stochatic optimization model.

2. Efficient exact algorithm: A solution method based on double (i.e., Benders and Dantzig-Wolfe) decomposition.

3. High-quality solutions on large real-life instances.

4. Practical impact: Benefits of integrated multimodal planning versus independent planning of public transport and demand-responsive services.

2 TWO-STAGE STOCHASTIC OPTIMIZATION

We present a two-stage stochastic problem formulation that defines the transit schedule and its required fleet in the first stage, and plans the on-demand vehicles and passenger routing at the trip level in the second stage.

$$\begin{aligned}
\min \quad & \text{Transit fleet and schedule costs} + \text{expected operational and travel costs} && (1)\\
\text{s.t.} \quad & \text{Passenger mode assignment constraints} && (2)\\
& \text{Mode service operating constraints} && (3)\\
& \text{Vehicle capacity constraints} && (4)\\
& \text{Passenger flow constraints} && (5)
\end{aligned}$$

2.1 First stage

The first stage problem covers strategical decisions including, (i) which schedule and (ii) with which fleet should we operate the transit system, and (iii) which transit lines and/or on-demand vehicle serve each passenger origin-destination. It minimizes both transit operational costs and the expected travel costs of passengers.

We consider a set of public transport lines to operate (e.g., bus or tram) formed by a set of stations that operate in both directions. Each line can operate different schedules at different frequencies, and with different types of vehicles (differing in capacity).

We divide the passenger demand in different origin-destination pairs and aggregate the demand flow during the operating time period.

Based on this setup, this first stage minimizes, on one hand, the operational costs of operating the transit schedule, which depend primarily on the frequency (i.e., number of vehicles needed) and vehicle type used, and on the other hand, the a-priori costs of assigning the aggregated origin-destination flow to be served by a specific line(s), on-demand vehicle, or both. We model all these decisions using binary variables and linear constraints ensuring that each line operates one schedule, and that its capacity can cover the assigned demand.

2.2 Second stage

The second stage tackles the operations of the on-demand services and the actual routing of the demand at the passenger level given the transit schedule defined in the first stage. This stage is divided into a set of scenarios, each scenario corresponding to a different realization of the passenger demand with a given probability. Each passenger request in this stage is characterized by an origin, destination, and request time. To capture each passenger's door-to-door trip, we use a time-expanded network where each node represents a time instant, spatial location, and mode of transport. We define multiple sets of arcs defining, walking and waiting time, (off)-boarding of vehicles and running times of the transport modes. A simplified example of such network is

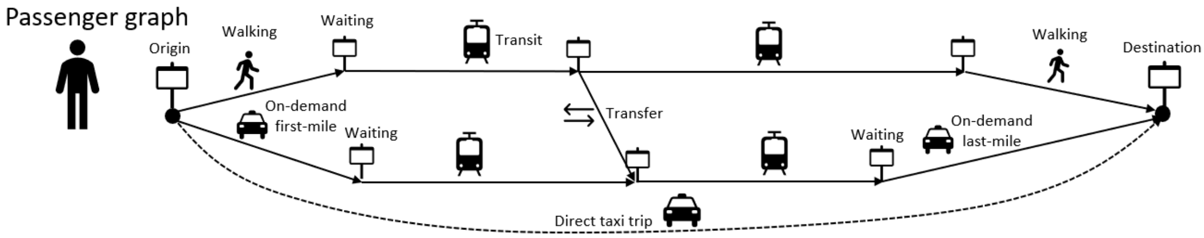

Figure 1 – *Example of a passenger graph.*

shown in Figure 1.

The model has one set of binary variables depicting the arcs used by each passenger trip. The second stage minimises the generalized cost of travel for the passengers (Desaulniers & Hickman, 2007) and the operational costs of the on-demand vehicle routes. We operate the on-demand vehicles in a first/last-mile or a door-to-door manner, and ensure capacity at the vehicle level for the transit vehicles. Finally, we link the first and second stage with activating constraints that link the different transit schedules and demand mode choices to the corresponding arc sets in the time-space graph.

3 A DOUBLE DECOMPOSITION ALGORITHM

To solve large-scale instances of the model, we exploit the decomposability of problem, and in particular, of the second-stage graph. First, we can apply Benders decomposition to the entire two-stage problem. The first-stage problem becomes the Benders Master Problem (BMP) and the second-stage problem becomes the Benders Sub-problem (BSP). Leveraging this decomposition, we can reformulate the second-stage problem as a set partitioning formulation where variables refer to paths instead of arcs in the time-space graph. Each path corresponds to a passenger trip from origin to destination.

Given the complexity of the second stage, enumerating all path-based variables is not tractable. Therefore, we opt to generate them dynamically using column generation.

Due to the reformulation, we only convexify the flow-conservation constraints for passenger trips, meaning that the pricing problem (PP) is a shortest path problem in a directed and acyclic graph (DAG). Therefore, we can use efficient label-setting algorithms to solve them. We acknowledge that, when the PP is a pure shortest path problem, column generation does not provide a benefit in terms of root node relaxation (i.e., solving the root node with column generation and solving the relaxed version of the original formulation provide equal bounds), but we foresee to solve the root node faster.

Once the column generation and Benders decomposition procedures converge, if the solution is still fractional, we solve the integer version of the BSP to guarantee an integer feasible solution. The BSP formulation is tight in itself, and therefore, we expect the integrality gap to also be tight.

Table 1 – *Model benchmark comparison.*

ODMTS vs.	Transit fleet costs	On-demand service distance	Transit users	Average passenger delay	Number of direct taxi trips
Deterministic equivalent	+0%	-21.4%	x15.3	+4.3%	-27.9%
Non-integrated system	+0%	-11.8%	x1.3	-1.7%	-18.6

4 PRELIMINARY RESULTS

We compare our two-stage stochastic model for ODMTS, with two different benchmarks. On one side, to assess the value of the stochastic optimization, we compare our model with a deterministic equivalent, and on the other side, to evaluate the value of integrating multiple modes of transport, we compare ODMTS with a system in which transit and on-demand services are planned separately. The results in Table 1 show a comparison of the out-of-sample solutions in a relatively small test case (three lines, tens of stops, and hundreds of passengers) in the city of Zurich, Switzerland. Thanks to the additional planning flexibility, our model is able to drastically improve the transit ridership while maintaining a similar level of service and without the need to increase the system capacity. This translates in a significant reduction of the operating costs (i.e., distance) of on-demand services, which can also translate in reduced consgestion and pollution.

For the results conducted so far, the model could be solved directly using commercial solvers, but the decomposition-based method presented is expected to scale real-life city-scale instances efficiently. We also plan to conduct detailed assessments on the value of fleet heterogeneity and the potential of ride-pooling on first/last mile on-demand services.

In overall, results suggest that ODMTS can become a relevant solution in the current mobility ecosystem and provide benefits to users, operators and society as a whole.

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