Robust Route Planning in Intermodal Urban Traffic

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Abstract. Passengers value reliable travel times but are often faced with delays in intermodal urban traffic. To improve their mobility experience, we propose a robust route planning tool that provides routes guaranteeing a certain probability of on-time arrival and satisfying additional constraints. The constraints can limit the number of transfers, time-dependent trip costs and other relevant resources. To find such routes, we extend the time-dependent reliable shortest path problem by adding constraints on time-dependent and stochastic edge weights. An exact solution method based on multi-objective A* search is proposed to solve this problem. By applying our algorithm to a showcase featuring an actual city, we hope to answer relevant questions for policy-makers and contribute to smarter mobility in the future.

Keywords: Urban Mobility, Travel Time Reliability, Constrained Shortest Path Problem, Multi-Objective A* Search

1 Introduction

Urban transport passengers value reliable travel times [1]. However, travel times in urban transport are uncertain due to a range of factors such as the traffic situation or infrastructure defects. A robust route planning tool that takes reliability into account can therefore help to improve passengers' mobility experience in cities and enable smarter mobility. However, current tools typically don't consider reliability and base their advice on deterministic public transport schedules and expected car travel times.

Our contribution is the development of a route planner that finds robust routes in intermodal urban traffic. We define a network model that reflects intermodal specifics such as uncertain travel times that vary over time and a flexible set of constraints. These constraints can limit the number of transfers, time-dependent trip costs and other resources. Subsequently, we extend the work of Chen et al. [2] and develop an exact algorithm based on multi-objective A* search [3] that finds robust routes satisfying the constraints. Reliability is reflected by setting a minimum probability for on-time arrival.

2 Related Work

Reliable route planning is a stochastic shortest path problem [4] in a network with time-dependent travel times [5]. Many variants of this problem exist. Firstly, paths defined

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a priori can be distinguished from adaptive decision rules that define a successor based on realized arrival times [5]. We focus on a priori paths, which are more practical than complex decision rules. Secondly, many optimization criteria were proposed, e.g., expected time [5, 6], a combination of expected time and variance [7], worst- [8] and best-case time [9] as well as criteria based on on-time arrival probability [10, 11].

Limiting cost or walking time creates a constrained problem. In its well-studied deterministic version [12] it is NP-complete [13] and can include waiting in some variants [14]. It was recently extended to the stochastic case [15, 16].

Main solution approaches for the unconstrained problem include mixed integer programming [11, 15, 17] and label-correcting algorithms [2, 9, 10, 18]. For example, Chen et al. [2] use an A* search approach to find a shortest path with on-time arrival guarantees and also apply it to a weighted combination of time and cost.

The constrained problem has been addressed with mixed integer programming to minimize expected time [15] and with genetic algorithms to maximize on-time arrival probability [16], both assuming constant weights. Building on Chen et al. [2], our contribution is to develop an exact solution method for the problem with on-time arrival guarantees, applicable to constant as well as time-dependent and stochastic weights.

3 Problem Definition

We use a weighted multi-layer digraph $G = (N, E, L, \Omega, D, W)$ to model intermodal networks. Locations are represented by nodes $i \in N$ and passengers can travel between locations on directed edges $(i, j) \in E \subseteq N \times N$. Each node belongs to a layer $l \in L$ that corresponds to a transport mode, e.g., walking or a train line. Edges within a layer represent travel using that mode and edges between layers model transfers.

Departures and arrivals at nodes are assumed to happen at discrete times t within a finite time horizon $\Omega = \{0, 1, \dots, t_{max}\}$ and travel times are described by discrete random variables. To reflect time-dependence, functions $D_{ij}(t)$ assign such random variables to each edge (i, j) depending on the time $t \in \Omega$ at which it is used. In addition, each edge is labeled with time-dependent discrete random variables $W_{ijk}(t), k \in \{1, \dots, K\}$ representing a diverse set of non-negative weights such as distance or (time-dependent) fees.

Finding robust routes translates into a discrete and stochastic optimization problem:

$$\max_{p, t_{start}} \quad t_{start} \tag{1}$$

$$s.t. \quad P\left(T_d^p(t_{start}) \leq t_{target}\right) \geq \alpha \tag{2}$$

$$P\left(C_{dk}^p(t_{start}) \leq c_k\right) = 1, \forall k \in \{1, \dots, K\} \tag{3}$$

$$t_{start} \in \Omega, \;\; p \in SP_{od} \tag{4}$$

The goal is to find a path p in the set of simple paths SP_{od} from origin $o \in N$ to destination $d \in N$ that leaves the origin at the latest possible time t_{start} and reaches the destination before or at a given time $t_{target} \in \Omega$ with a probability of at least α while satisfying additional constraints on, e.g., the number of transfers, cost or walking time.

The random variable $T_i^p(t)$ in (2) describes the arrival time at node i if starting at time t along path $p = (o, \ldots, i, j, \ldots d)$. With $T_o^p(t) = t$, it is calculated as follows:

$$T_j^p(t) = T_i^p(t) + D_{ij}(T_i^p(t)), \quad \forall j \in p \backslash o \tag{5}$$

In (3), accumulated weights, described by time-dependent random variables $C_{ik}^p(t)$, $\forall k \in K$ are limited to c_k. With $C_k^p(t) = 0, \forall k \in K$, they are calculated as follows:

$$C_{jk}^p(t) = C_{ik}^p(t) + W_{ijk}(T_i^p(t)), \quad \forall j \in p \backslash o, \forall k \in \{1, \ldots, K\} \tag{6}$$

The sums of random variables in (5) and (6) can be calculated using time-dependent convolution. For example, the probability of reaching node j on path p at time w is calculated as follows:

$$P\big(T_j^p(t) = w\big) = \sum_{v \in \Omega, v \leq w} P\big(T_i^p(t) = v\big) P\big(D_{ij}(v) = w - v\big), \forall\, w \in \Omega \tag{7}$$

This requires a sufficiently large time horizon and the assumption of independent edge travel times along paths. However, for scheduled modes, travel times are likely dependent. For example, a train that is delayed on one trip segment might try to get back on schedule on the subsequent segment by driving at top speed. To reflect such dependencies and still maintain the independence assumption, we represent entire journeys on one transportation line with a single edge. The travel time on that edge includes waiting before boarding and total time on board.

Waiting at nodes is often not allowed [2, 18]. However, it can improve the solution in the constrained problem: for example, waiting for congestion charges to drop after rush hour can allow passengers with a limited budget to use a faster mode of transport and thus accelerate their journey. We call this *strategic* waiting, as it is voluntary and thus distinguished from *transfer* waiting, i.e., waiting for a scheduled vehicle. We introduce strategic waiting by replacing $T_i^p(t)$ in (5) and (6) with a random variable $S_i^p(T_i^p(t), s_i)$ representing arrival time after strategic waiting. It depends on the original arrival time $T_i^p(t)$ and waiting parameter $s_i \in \Omega, \forall i \in N$. s_i is an additional decision variable and models that the passenger waits until s_i if arriving before s_i.

4 Solution Approach

We will build on the work of Chen et al. [2], who iteratively solve the closely related forward problem in which t_{start} is fixed and t_{target} is minimized. After several iterations with different starting times, a solution to the original problem is found.

The forward problem will be converted to a multi-objective problem by turning the weight constraints into objective functions. The set of non-dominated solutions to this associated multi-objective problem contains a solution to the constrained problem [19].

To find the non-dominated solutions, we will generalize the A* approach in [2] and apply multi-objective A* search [3]. A* search is defined for additive attributes, but can be extended to convolutions if they are order-preserving [20]. Given two paths p_1, p_2 from o to a node $i \in N \backslash o$ with p_1 dominating p_2 and any path p_3 starting at i, the order-preserving property (OPP) implies that the extended path p_1p_3 dominates the extended path p_2p_3. Given the OPP, dominated paths can be pruned in the algorithm.

Without constraints, the OPP holds if distributions are FIFO[1] [2]. As this is not always true with constraints and general weight functions, we will define conditions for which the OPP holds and structure our proofs along three hypotheses:

- The OPP holds for FIFO travel times and non-decreasing, deterministic weights.
- For deterministic weights that are non-decreasing until time t' and decrease afterwards (e.g., a congestion charge during rush-hour), strategic waiting parameters can be set such that the combined waiting and travel times satisfy the OPP.
- The OPP holds for time-dependent stochastic weights if $t' > t$ implies for all edges that $W_{ijk}(t) \leq W_{ijk}(t'), \forall k \in K$ regarding first-order stochastic dominance (FSD)[2].

5 Next Steps and Expected Contributions

So far, this research in progress has defined the constrained time-dependent reliable shortest path problem with time-dependent and stochastic weights to model robust route planning in urban intermodal traffic. In addition, we outlined an exact solution method.

We will continue to implement this approach and support it with required proofs. Numerical experiments will be conducted to evaluate the algorithm's speed given different network sizes and problem setups. This will include a comparison with the less complex unconstrained problem that was solved within seconds for real-world instances [2]. Furthermore, solutions will be benchmarked against deterministic routing advice. Finally, we plan to set up a showcase for an actual city with travel times sampled from, e.g., real-time public transport data or car trajectories. We expect that this will help to answer important questions for policy-makers such as:

- Which measures are most effective for improving reliability? For example, how does the effect of increasing train reliability compare to that of higher trip frequencies?
- How does reliability affect mode choice? And can mode choice be effectively influenced by improving the reliability of certain modes (e.g., bus or bike sharing)?

By answering these questions, we hope to make a significant contribution to smarter urban mobility in the future.

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[1] At any confidence level, travelers arrive at the end of a link in order of departure.

[2] Given discrete random variables X and X' with cumulative distribution functions F_X and $F_{X'}$: X dominates X' regarding FSD $\Leftrightarrow \forall x: F_X(x) \geq F_{X'}(x)$ and $\exists x: F_X(x) > F_{X'}(x)$ [21]

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