Trip Planner MODE(Multimodal Optimal Dynamic pErsonalized)

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Introduction Current free and subscription-based trip planners have focused on providing transit options to improve the first- and last-mile connectivity to the destination. However, those trip planners may not be multimodal to vulnerable road users (VRUs). Depending on the level of availability of digital twin of travelers' behaviors and sidewalk inventory, providing the personalized suggestion transit service route with reliability could be useful for riders and reduce rush hour congestion. In this paper, the adaptive trip planner considers the real-time impact of environment changes on pedestrian route choice (e.g., fatigue, weather conditions, unexpected construction, congestion) and tolerance level in response to transit service uncertainty.

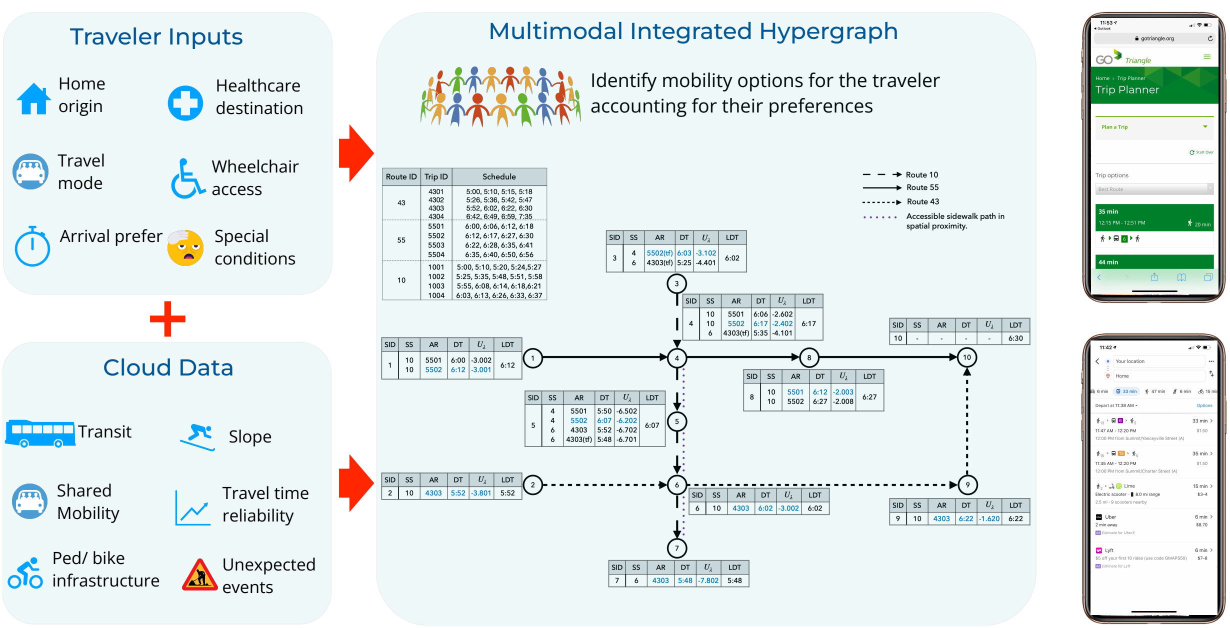

Figure 1 **The trip planner M^{2}ODE combines the two modes, considering the traveler's PAT at the final destination when finding the optimal sidewalk path for the pedestrian mode.**

Methodology Sidewalk inventory is integrated into a directed hypergraph on the General Transit Feed Specification (GTFS) to specify traveler utilities as weights on the hyperedge. A realistic assessment of the effect of the user-defined preferences on a traveler's path choice is presented for a section of the Boston transit network, with schedule data from the Massachusetts Bay Transportation Authority. Different maximum utility values are presented as a function of varying traveler's risk-tolerance levels. In response to unprecedented climate change, poverty, and inflation, this new trip planner can be adopted by state agencies to boost their existing public transit demand. The well-established hypergraph framework such as Nguyen, Pallottino, and Gendreau (1998), Noh, Hickman, and Khani (2012), Verbas, Mahmassani, and Hyland (2015), Opasanon and Miller-Hooks (2001) has modeled the transit schedule network satisfying temporal constraints according to arrival, transfer and departure times of transit vehicles. This study will further extend previously developed VRU Personalized Optimized Dynamic (VRUPOD) by Darko et al. (2022) to provide sidewalk route guidance for users who save personal information relevant to transportation needs.

The simulated test network has ten stops, two intersections and is served by three bus routes (43, 55, and 10), each with an inbound and outbound route. The available schedule data from the Massachusetts Bay Transit Authority's (MBTA) GTFS dataset shows that the period between 5:00 and 8:00 AM has approximately 24 trips belonging to these routes. We define each trip ID in the schedule data by a four-digit number, where the first two digits represent the route information, and the remaining digit represents the trip number. We characterize the sidewalk network for each pedestrian mode decision using sidewalk data from the Boston sidewalk inventory sid (2011). After the spatial region for the pedestrian mode is constructed, the sidewalk network in this region, characterized by the sidewalk data, is generated and used to find the optimal sidewalk path based on the users' preferences. The simulation-based evaluation for a typical day of the week (i.e., Tuesday) shows the best path with the normalized cost of each feasible path alternative, and the weights β on the cost ($\beta_1 = -2, \beta_2 = -1, \beta_3 = -2$).

Evaluation Using retrospective GTFS data, a temporal aggregation of link-level travel time is used to estimate the anticipated $IVTT$ variability which provides a more realistic representation of the anticipated travel-time variability. To evaluate the proposed pedestrian accessibility model independently, we conduct two experiments for different origin-destination pairs in an 8×8 sidewalk grid network (data from Boston sidewalk inventory) and then compute the total score for sidewalk surface type and slope. The users' preference concerning the sidewalk factors is set as: High rating for slope compared to width, length, and surface type. While User 1 prefers high rating for surface type compared to slope, width, and distance (the lower the sidewalk surface type score, the better the sidewalk path), User 2 prefers high rating for slope compared to width, surface type, and distance (the lower the sidewalk slope score, the better the sidewalk path).

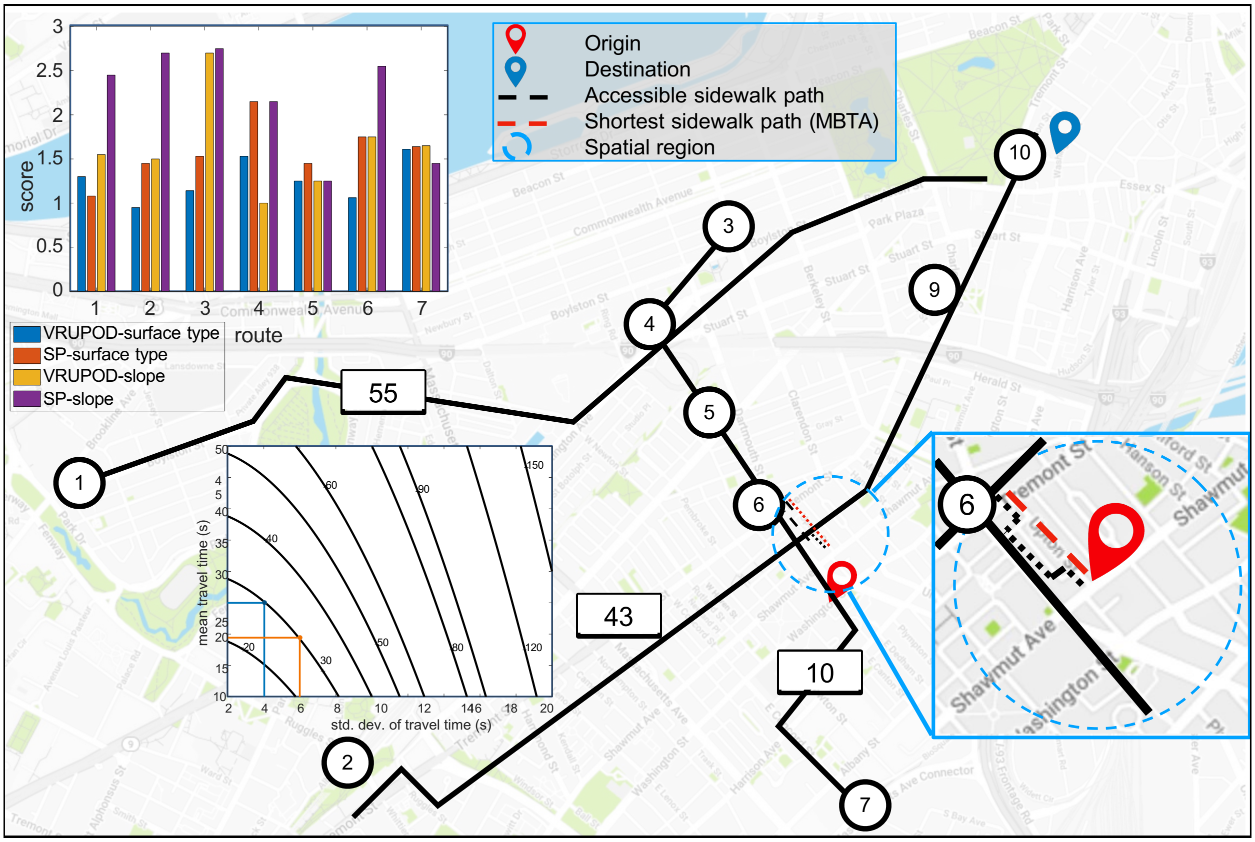

Figure 2 **(1) Variation of travelers' cost for different risk-tolerance. (2) Indifference curves considering risk-tolerance coefficient ($\lambda = 0.6$). (3) path options for risk-tolerance coefficients λ = 0.2 and 1.0.**

Figure 2 summarizes three results. 1. The traveler's cost decreases with decreasing uncertainty (i.e., standard deviation) in travel time, indicating that the traveler will prefer a route with less volatility. We also see that the higher the risk-tolerance coefficient, the higher the traveler's sensitivity to anticipated travel-time variability. Therefore, travelers with high risk-tolerance coefficient are less likely to select options with high standard deviations. 2.Points on the curves represent different mean and standard deviation combinations of travel time. For routes whose variability profiles result in the same cost, the traveler is indifferent to choosing among the routes. Such alternatives present the same level of inconvenience willing to be experienced by the traveler. 3. For the pedestrian mode decisions, user preferences concerning the sidewalk parameters were set as follows; High rating for slope and surface type compared to width and distance

The results for trips from all stops (origins) to one designated destination (All-to-one). We assume a destination stop 10, PAT = 6:30 a.m, and PAT time window dt = 15 min. Each route has a total of 4 trips that contribute to sub-paths satisfying the PAT with two transfer points (4 and 6). Walking from locations 7 to 6 is based on the optimal sidewalk path. The waiting time at a stop in each feasible path is calculated as the difference between scheduled departure time and the expected arrival time. For example, when vehicles are instructed to wait at stops when vehicle arrival time is less than the scheduled departure time, we can assume that the normal distributed $IVTT$ between two consecutive stops will mostly lead to a log-normal distributed waiting time at the successive stops. The anticipated travel-time variability defined by the mean and variance for $IVTT$ for each physical path in a feasible path is computed from the results of the retrospective GTFS data, equal to the sum of the mean and variances of travel time of links forming the path. The best path (vehicle run) at each stop considering the traveler's risk-tolerance coefficient of 0.2 is the path with the maximum utility. For example, traveling from origin location one to destination ten has a recommended departure time of 6:12 AM using vehicle run 5502, same as location five to ten. However, due to the optimal sidewalk path required to get to stop four to board bus 5502, the recommended departure time is 6:07 a.m.

Conclusion This study develops a multimodal trip planner for VRUs on the pedestrian mode and on-transit travel time, which has been neglected in commercial trip planners. The anticipated variability profile of the links and routes is computed from retrospective GTFS data. The exponential utility approximated by a function of mean-variance of travel time is used to evaluate travelers' risk-tolerance choice to the anticipated in-vehicle travel-time variability. A case study is carried out on a simulated test network constructed on a section of the Boston transit network. Depending on the travelers' preferences, including their risk-tolerance to anticipated travel-time variability, we find the best path recommendation through a utility maximization approach.

Acknowledgments

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