Trip Planner MODE (Multimodal Optimal Dynamic pErsonalized)

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***Abstract*— Current free and subscription-based trip planners have heavily focused on providing available transit options to improve the first- and last-mile connectivity to the destination. However, those trip planners may not truly be multimodal to vulnerable road users (VRU)s since those selected sidewalk routes may not be accessible or feasible for people with disability. Depending on the level of availability of digital twin of travelers behaviors and sidewalk inventory, providing the personalized suggestion about the sidewalk with route features coupled with transit service reliability could be useful and happier transit riders may boost public transit demand/funding and reduce rush hour congestion. In this paper, the adaptive trip planner considers the real-time impact of environment changes on pedestrian route choice preferences (e.g., fatigue, weather conditions, unexpected construction, road congestion) and tolerance level in response to transit service uncertainty. Sidewalk inventory is integrated in directed hypergraph on the General Transit Feed Specification 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 travelers 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 without extra efforts.**

I. INTRODUCTION

89 percent of the U.S. population is projected to live in urban areas by 2050 and more than 300 urban areas having populations above 100,000 spark greater demand for multimodal transit. Recent widespread food insecurity and housing instability have magnified the already extreme income inequities and accessibilities. Vulnerable road users (VRUs) walk and bike to reach transit, food, jobs, and medical services while temperatures dive from record highs to freezing. While one in five North Carolinians will be at least 65 years old needing other accessible alternatives to driving, current free and subscription solutions such as Google Maps and GoTriangle fail to incorporate detailed access information for people with personal preference and mobility limitations. In response to unprecedented climate change, poverty, and inflation, we need a multimodal trip planner more than ever. Happy transit riders play an important role in boosting public transit demand/funding and reducing rush hour congestion.

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North Carolina's GoTriangle planner provides travel options to commuters by referencing Google Transit routes. However, GoTriangle does not provide integrated mobility and accessibility options for NC travelers. The trip planner does not connect transit options to other modal options (bikes, e-scooter, etc.). Each trip option only provides estimated walking time to/from transit stops without considering the accessibility. The Massachusetts Bay Trip planner is the only successful tool to integrate mobility information about sidewalk slope, surface, width, and shade. It takes great effort and time to develop a trip planner tool that reflects local community needs and deliver multimodal transportation safely and equitably. In this paper, unlike other trip planners, Multi-Modal Optimal Dynamic pErsonalized (M^{2}ODE) trip planner recommends the transit options including accessible and feasible sidewalk routes for travelers in the pedestrian modes.

Recent work done by authors of this study developed VRU Personalized Optimized Dynamic (VRUPOD) [1] trip planner to provide personalized sidewalk route guidance for users who save personal information relevant to transportation needs (e.g., stamina and ability to traverse uneven terrain) and publicly-available information about route nodes, elevation changes, weather, and traffic etc. This paper integrates utilities of transit route choices with sidewalk route choices associated with individual needs and capabilities (Figure 1).

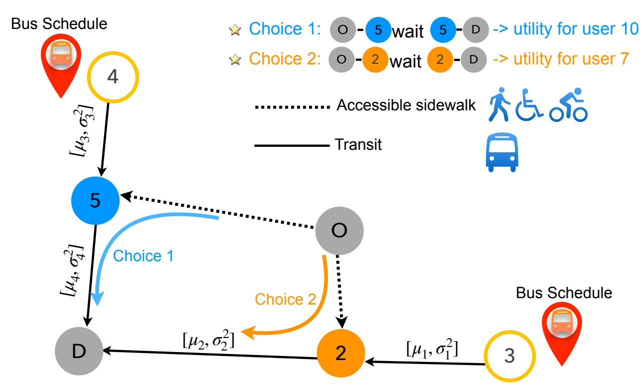


Fig. 1: M^{2}ODE trip planning with best path recommendation:To go from origin **O** to destination **D**, the traveler's multimodal options, including sidewalk (e.g., walk, bike) or transit (bus), depends on availability and anticipated conditions on these modes.

This paper addresses the limitations of existing linear shortest cost algorithms in multimodal trip planning due to dynamic interactions between environmental parameters and user preferences. It introduces an adaptable model that considers various modes of transportation, changing environmental conditions, and user preferences over time. By incorporating travel time uncertainties and travelers' tolerance levels, the proposed multimodal trip planner provides personalized path recommendations. The model combines pedestrian and transit mode decisions using a heuristic approach and utility maximization. The paper utilizes the hypergraph framework [2], [3], [4], [6] to model the transit schedule network and presents a numerical example to estimate anticipated travel-time variability. In conclusion, the paper offers a novel approach for personalized path accessibility considering multimodal transportation and traveler preferences.

II. Literature Review

While there is a rich history of trip planner for the transit mode, the pedestrian mode with preference has received less attention, thus there is an absence of full integration of both pedestrian and transit modes. This is critical since individuals with mobility issues such as elderly persons or wheelchair users are more sensitive to uncertainties in services.

A. Trip Planner for Pedestrian Mode

Undoubtedly, navigation systems that integrate user preferences find routes that are more suitable for VRUs than the shortest routes [5], [8], [9]. VRUs encounter a range of obstacles impeding easy navigation in the sidewalk network [10]. Existing designs of public transportation systems do not entirely fulfill the needs of people with disabilities in terms of mobility and accessibility though they are user centered [7], [9], [11]. Though exisiting desgin may offer personalized routing, it lacks in multimodality [12]. Identifying and avoiding inaccessible places in the current pavement network as a short-term solution instead of redesigning urban transportation and sidewalk networks as a long-term solution can accelerate helping VRUs [13]. Applications such as the OpenRouteService provides a single American Disability Association (ADA)-compliant path for a baselinelevel of accessibility. Such "one-size-fits-all" approaches to different pedestrian mobility needonly ensurethat pedestrians fulfilling a particular description (e.g., wheelchair user) can use the path specified. However, the path for many mobility-impaired people requires consideration of their specific needs and capabilities.

This paper develops the pedestrian model with the following contributions. First, the pedestrian model accommodates the various sidewalk factors: width, slope, surface type, and length, identified to influence users' path choice significantly [8], [14], [15], to improve the safety and mobility for people with mobility impairments who walk and use transit in urban and suburban environments. Second, the pedestrian model accommodates changing preferences and the interaction effect between sidewalk variables and weather conditions contributing to a path choice.

B. Trip Planner for Transit Mode

The majority of studies on transit accessibility and route choice decisions for flexible/fixed transit have focused on travel time as the only measure for planning route choice, though some have accounted for attributes such as monetary fare [16], [17]. Consequently, minimizing the expected travel time has been widely developed for evaluating transit route choice [18]. For transit trip planning purposes, the most common method of estimating the expected travel time is to use the schedule-based data in a standard format known as the General Transit Feed Specification (GTFS) [19].OpenTripPlanner utilizes GTFS data and pedestrian networks (e.g., OpenStreetMap) for route planning. However, relying solely on schedules has limitations, such as under/overestimating travel time and disregarding congestion and variability. Traditional route choices prioritize minimizing schedule travel time, neglecting real-time delays and urban peak-hour variations.

The availability of automatic vehicle location (AVL) data allows transit system managers to measure day-to-day travel-time variability on transit links. This data can be used to improve traveler's accessibility and route choice decisions by considering anticipated variability. Previous studies have shown the impact of travel-time variability on transit route choices [20], [21], but integrating traveler's perception of this variability is lacking. This research contributes to personalized path accessibility models by incorporating traveler's perception of variability, even if it doesn't result in the lowest expected schedule travel time.

The widespread collection and availability of AVL data can support characterizing the reliability of transit networks. AVL data can estimate the anticipated travel-time variability on transit links for a given period and day before making route choice decisions. Anticipating and integrating the travel-time variability as a measure of reliability for planning route choice can provide more rational routes according to the traveler's perception of the anticipated variability, even if such route is not one with the minimum schedule travel time. Even for driving, the inclusion of reliability in route choice and accessibility modeling is still at an exploratory stage [22].

C. Integrated Multimodal Networks

Studies on integrating first/last mile connections with flexible/fixed transit in multimodal networks are popular in literature [23]. The emphasis has been on integrating modes such as electric scooters, bike-sharing, and car-sharing with fixed transit in a decentralized problem with less attention on pedestrian modes (e.g., sidewalk) [24], [25], [26], [27]. Still, those considering pedestrian modes are limited to recommending the shortest sidewalk path to users in getting to/from transit stops and other destinations in the pedestrian network. In addition, the existing framework for integrating pedestrian connections is based on each mode's local routing [24], [25]. However, there are several concerns on the benefit of the current multimodal framework. First, rather than the shortest path, considering the accessibility of VRUs in the path model will improve the mobility of VRUs. Second, building pedestrian connections to the fixed transit in multimodal networks needs to guarantee a smooth transfer between the modes.

Our approach calculates the most accessible sidewalk path for pedestrians based on an ADA [28] standard measure. We narrow down the sidewalk network to a spatial region centered around the traveler's location, using the shortest distance between relevant points. This reduces the search space and avoids impractical solutions. The personalized path recommendation considers schedule travel time, anticipated travel-time variability, and pedestrian accessibility in a utility maximization model. We also account for the inconvenience that travelers may tolerate due to variability in transit travel times and waiting times. This is done by incorporating risk-tolerance to anticipated variability. Our model considers personalized sidewalk preferences, sidewalk factors interacting with weather conditions, and the traveler's perception of reliability and variability in route choices [29].

- Incorporate the travelers' personalized-preference to sidewalk accessibility to/from transit stops and to other destinations
- Accommodate the interaction between sidewalk factors and weather conditions for each sidewalk segment contributing to a path choice.
- In addition to expected schedule travel time, the travelers' perception of reliability on the schedule is incorporated as the risk-tolerance on the anticipated travel-time variability, modeled as a function of the mean and variance of link/route travel time.

III. Methodology

The travelers' preferences on the transit and pedestrian mode decisions are evaluated and combined in a heuristic for the personalized path search. We describe the transit network through nodes representing the origin stop, destination stop, and transit stops along a route, and edges representing the travel time conditions of the road between the nodes (Figure 2)

A. Transit Network Description

This study characterizes the anticipated day-to-day travel-time variability for a vehicle run on each link/route in the transit network using historical time at each location from archived AVL data, also known as retrospective GTFS data. Vehicle run refers to the daily assignments for an individual bus. $i \in I$ is the set of transit stops along the route and the set of vehicle runs $r \in R$ allocated to the route. AAT_i^r is the actual arrival time of vehicle run $r \in R$ at stop $i \in I$. The in-vehicle travel time ($IVTT$) and the number of days/periods N is given by:

$$IVTT^r_{i,i+1} = AAT^r_{i+1} - AAT^r_i. \tag{1}$$

The anticipated mean (μ) and variance (σ^2) for $IVTT$ is estimated as:

$$\mu^{(r)}_{(i,i+1)} = \frac{\sum_{n=1}^{N} IVTT^r_{(i,i+1),n}}{N}, \tag{2}$$

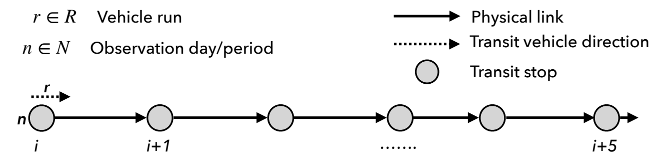


Fig. 2: A transit route with multiple stops showing how the experienced travel time for vehicle run r is aggregated over several observation periods or days N and used to estimate link and route level travel-time variability. Different times of the day are associated with different degrees of variability in link travel time.

and the variance for $IVTT$ is estimated as:

$$\sigma^{2(r)}_{(i,i+1)} = \frac{\sum_{n=1}^{N} \left(IVTT^r_{(i,i+1),n} - \mu^r_{(i,i+1)} \right)^2}{N}. \tag{3}$$

For cases of a normally distributed $IVTT$ for link l, $v(\mu_l, \sigma_l^2)$, this study assumes link travel-time variability can be treated as normally distributed random variables. Therefore, the total anticipated $IVTT$ of path $\mathscr{P}$ is defined as the sum of each links anticipated mean and variances of travel time as $\mu_{\mathscr{P}=\sum_{\mathscr{P}} \mu}$ and $\sigma_{\mathscr{P}=\sum_{\mathscr{P}} \sigma}$. In selecting a transit route, our goal is to evaluate and incorporate the anticipated mean and variance of travel time for feasible alternative routes that satisfy a traveler's PAT at the destination.

1) Transit schedule network: A route service graph for the transit network is expanded to a node-based time graph to capture the temporal information provided through the schedule data (Figure 3). The links connect these nodes to indicate the vehicle run trajectory between consecutive stops. In-vehicle travel time and walking time links are used to indicate movement from one node/stop to another node/stop. The anticipated in-vehicle travel-time variability for each link/route is represented through the mean and variance of travel time for the link/route. Given the traveler's origin-destination pair $(O-D)$, a PAT, the first of our two-phase solution search procedure, utilizes the node-based time expanded graph in the personalized path accessibility framework.

2) Weighting functions on hyperedge: The directed hypergraph on the transit schedule network associates each hyperedge ω with a real weight vector $\mathbf{w}(\omega)$. Without loss of generality, the component of the weight vector is expected schedule travel time (including walking and waiting time) on the hyperedge. For each feasible path Π that satisfies the travelers PAT at the destination, the weighting function defines a node function $\mathbf{W}_\Pi$ which assigns weights to all its nodes (time expanded stops) depending on the weights of its hyperedges. Given the destination D, $\mathbf{W}_\Pi(D)$ is the weight of the path Π under the chosen weighting function. In this study, we define an additive weight function on each time expanded stop S^n as a function of both the weights of the

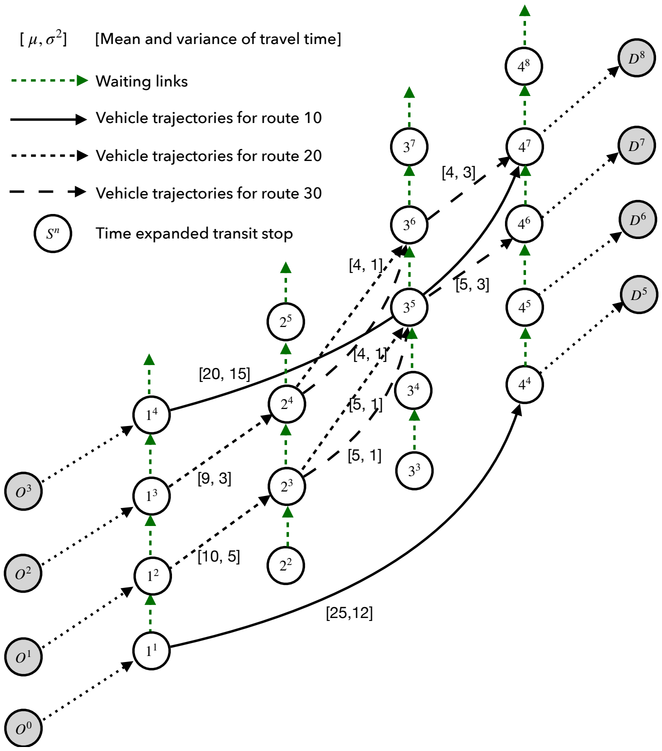


Fig. 3: A Node-based representation of a transit network showing the time expanded transit stops. The nodes have space-time coordinates representing the different times of transit vehicle availability according to the schedule. Specifically, every stop is (a) expanded based on points in time when a vehicle from a route will visit, and (b) the time points are connected and expanded spatially by each vehicle run (or route).

hyperedges entering into S^n and that of the nodes in their tail (for simplicity, let $y = S^n$):

$$\mathbf{W}_\Pi(y) = \min\{\mathbf{w}(\omega) + \mathrm{F}_\Pi(\mathrm{T}(\omega)) : \omega \in \mathrm{E}_\Pi \cap \mathrm{BS(y)}\}, \quad y \in V_\Pi \setminus \{s\}, \tag{4}$$

where $\mathrm{F}_\Pi(\mathrm{T}(\omega))$ is a function of the weights of the nodes in $\mathrm{T}(\omega)$, and $\mathrm{BS(y)} = \{\omega \in \mathrm{E} : \mathrm{y} \in \mathrm{H}(\omega)\}$ is the backward star of node y representing the incoming edge at node y. F is a nondecreasing function of $\mathbf{W}_\Pi(x)$ for each $x \in T(\omega)$

$$\mathrm{F}_\Pi(\mathrm{T}(\omega)) = \mathrm{F}\left(\{\mathrm{W}_\Pi(\mathrm{x}) : \mathrm{x} \in \mathrm{T(y)}\}\right), \omega \in \mathrm{E}_\Pi. \tag{5}$$

3) Cost of anticipated travel-time variability: We integrate the travelers' risk-tolerance level concerning the anticipated variability for the best route recommendation, even if such a route is not with the lowest expected schedule travel time. We propose the exponential utility function $u(\Pi) = -(\mathbf{sgn}(\lambda))e^{-\lambda\Pi}$, to characterize the traveler's preference to the anticipated travel-time variability for transit links on feasible path Π. The local measure of risk-tolerance, known as the *Arrow-pratt measure of absolute risk-aversion* at Π, is $\frac{-u''(\Pi)}{u'(\Pi)} = \lambda$. The representations $u'(\Pi)$ and $u''(\Pi)$ are the first and second derivative of $u(\Pi)$. The values of $\lambda \neq 0$ represents the risk-tolerance coefficient with the sign of λ (**sgn**). The mean-variance approximation is the sum of the anticipated mean travel time (μ) and the risk ($\frac{\sigma^2}{2}$) multiplied by the risk-tolerance coefficient (λ), representing $\mathrm{MV}_\Pi = \mu_\Pi + \frac{\lambda\sigma_\Pi^2}{2}$ as the balance between mean and variance of $IVTT$ on feasible path Π. The generalized cost function in the transit route choice is defined to find the strategy that minimizes the sum of traveler's cost on (1) expected schedule travel time and (2) the anticipated travel-time variability adjusted for the traveler's risk tolerance.

B. *Sidewalk Accessibility Measure*

Relating to previously established research [30], [31], we develop five parameters: width, length, slope, sidewalk surface type, and weather condition to characterize the accessibility of each sidewalk segment. The sidewalk network is represented as a graph $\mathscr{G} = (\mathscr{N}, \mathscr{E})$, where $n \in \mathscr{N}$ is the set of nodes and $e \in \mathscr{E}$ is the set of edges. By assuming a spatial region (Radius ($\mathscr{R}$) equal to the shortest distance between two locations) we reduce the search space and also prevent finding infeasible solutions due to long distances. A traveler can move from node n to node n' if an edge connects the two nodes. The cost of each edge is based on parameters that define sidewalk accessibility for that edge for the traveler [1]. The interaction effect between sidewalk variables can limit the accessibility of sidewalk segments.

This paper considers five surface types based on field survey: concrete (best), asphalt, brick, cobblestone, and gravel (worst). Three levels of weather conditions are considered:sunny (best), rainy, snowy (worst)[1]. With appropriate adjustments to Eq. (4), the sidewalk path considering the travelers sidewalk accessibility preferences is found. Specifically, if we consider the arrival time at a destination n_d (e.g., final destination D satisfying the PAT), the optimal sidewalk path minimizes the total cost for a given origin-destination pair (n_o, n_d):

$$\mathbf{S}_\Pi(n) = \min\{\mathbf{s}(e) + \mathrm{S}_\Pi(\mathrm{T(e)}) : \mathrm{e} \in \mathscr{E} \cap \mathrm{BS(n)}\}, \quad n \in \mathscr{N} \setminus \{\}. \tag{6}$$

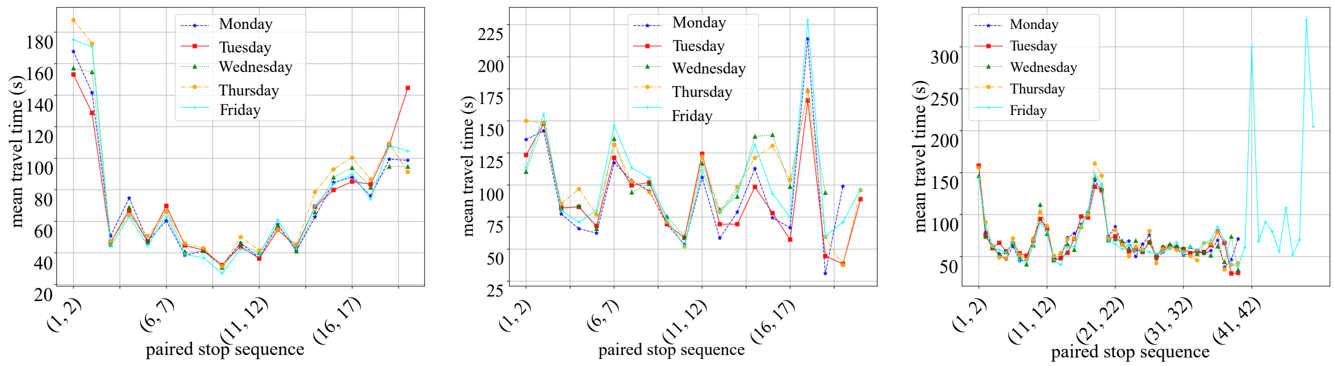
IV. Evaluation

A. *Estimation of in-vehicle travel-time variability*

Using retrospective GTFS data, a temporal aggregation of link-level travel time is used to estimate the anticipated $IVTT$ variability. Retrospective GTFS data capture significant travel-time variations for each vehicle run, providing a more realistic representation of the anticipated travel-time variability. A statistical measure of each link-level variability defined by the mean and standard deviation of travel time is constructed for each day in the weekday as shown in Figure 4.

B. *Impact of risk-tolerance on travelers route selection*

Considering the anticipated travel-time variability for the links/routes, the mean-variance approximation with travelers' risk-tolerance evaluates the inconvenience travelers are willing to experience due to these variability. Figure 5 shows the



(a) Route 43 (b) Route 55 (c) Route 10

(d) Route 43 (e) Route 55 (f) Route 10

Fig. 4: Estimated day-to-day IVTT variability for routes 43, 55, and 10 for the period between 5:00 and 8:00 am from historical AVL data. The estimates show significant travel-time variability for most links. Specifically, we see that several links on routes 43, 55, and 10 have high values of anticipated standard deviations for the period between 5:00 and 8:00 a.m. For example, looking at the link (1, 2) on route 43 (Figure 4a and Figure 4d), the variability profile shows a significantly high standard deviation ($\approx$ 220 s) compared to the mean travel time ($\approx$ 170 s) for Friday. This implies high volatility concerning the anticipated travel time on the link. The link-level travel-time variability is easily extended to multiple consecutive links/routes as described in Section III-A.

impact of the anticipated travel-time variability on the route choice given the traveler's risk-tolerance coefficient.

The indifference curves shown in Figure 6 provide a 2-D contour representation of the travelers' perceived cost to the anticipated travel-time variability.

C. Accessible sidewalk path compared to shortest path

To evaluate the proposed pedestrian accessibility model independently, we conduct two experiments for different origin-destination pairs in an 8 $\times$ 8 sidewalk grid network (data from Boston sidewalk inventory) and then compute the total score for sidewalk surface type and slope.

The preferences of two users utilized in the experiment is summarized as: User1: High rating for surface type compared to slope, width, and distance (the lower the sidewalk surface type score, the better the sidewalk path), and User2: High rating for slope compared to width, surface type, and distance (the lower the sidewalk slope score, the better the sidewalk path).

Figure 7 shows the comparison bar graphs for surface type and slope scenarios. While we have presented an elementary evaluation, the pedestrian accessibility model is adaptable to a wide range of sidewalk and weather conditions [1].

D. Results of path recommendations considering degree of risk-tolerance

The simulation-based evaluation for a typical day of the week (i.e., Tuesday) shows the best path recommendation with the normalized cost of each feasible path alternative, and the weights β on the cost ($\beta_1 = -2, \beta_2 = -1, \beta_3 = -2$). In effect, our simulation assumes the expected schedule travel time and the cost of the pedestrian accessibility model are twice as important as the cost of anticipated travel-time variability. As described above, the following components are considered for each feasible path; (1) sidewalk cost estimated from the pedestrian accessibility model, (2) transit cost estimated from the mean-variance function due to anticipated travel-time variability, and (3) total expected schedule travel time (including waiting and walking time). The users preference concerning the sidewalk factors is set as: High rating for slope compared to width, length, and surface type.

Figure 8 shows the results for trips from all stops (origins)

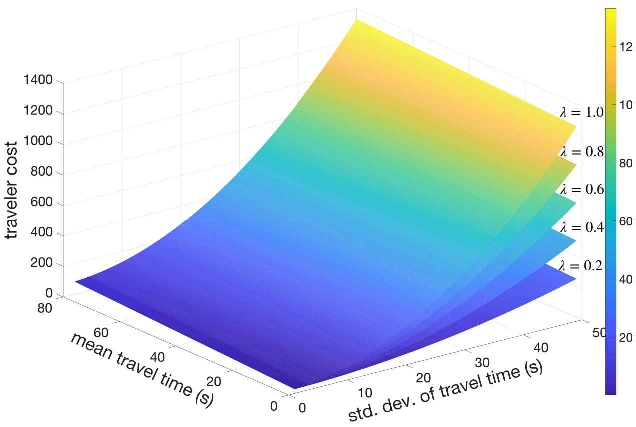


Fig. 5: Variation of travelers' cost for different risk-toleranc The traveler's cost decreases with decreasing uncertain (i.e., standard deviation) in travel time, indicating that tl traveler will prefer a route with less volatility. We al: see that the higher the risk-tolerance coefficient, the high the traveler's sensitivity to anticipated travel-time variabilit Therefore, travelers with high risk-tolerance coefficient a less likely to select options with high standard deviation For example, for the same variability profile (e.g., μ = σ = 50), the traveler with a risk-tolerance coefficient of 0 has a lower travel cost ($\approx$ 250) than the traveler with a ris. tolerance coefficient of 0.4 (cost $\approx$ 500). This implies th the traveler ($\lambda = 0.4$) perceives this route option as too cost compared to the other traveler ($\lambda = 0.2$)

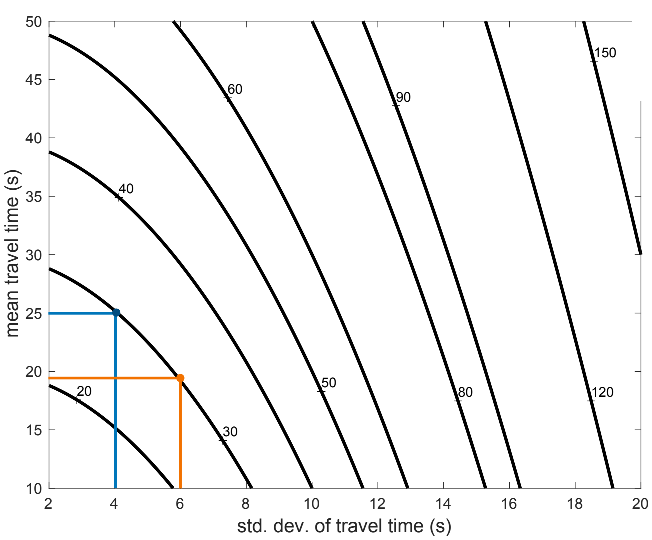


Fig. 6: Indifference curves considering risk-tolerance coefficient ($\lambda = 0.6$). Points on the curves represent different mean and standard deviation combinations of travel time. For routes whose variability profiles result in the same cost, the traveler is indifferent to choosing among the routes. Such alternatives present the same level of inconvenience willing to be experienced by the traveler. For example, looking at the points (representing link/route options) with variability profiles $\mu = 25, \sigma = 4$ and $\mu = 19, \sigma = 6$, the traveler will be indifferent to selecting among these options since both result in the same cost.

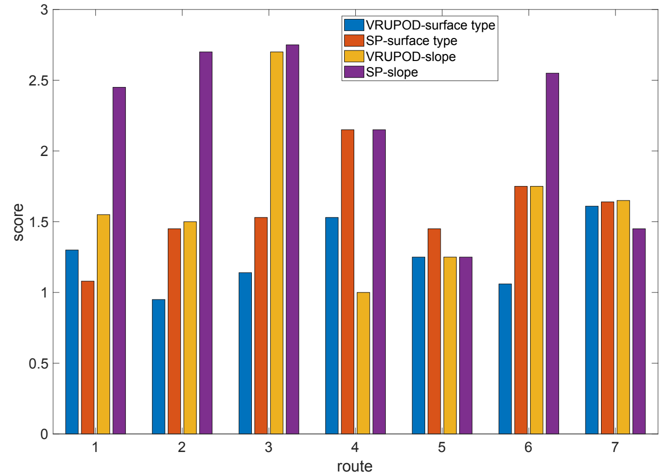


Fig. 7: Surface type and slope score comparison between VRUPOD and Shortest Path (SP). 85.71 percent of sidewalk paths recommended by the VRUPOD method have the lowest average sidewalk surface type score. In the second test, as shown in Figure 7, 71.42 percent of sidewalk paths recommended by VRUPOD have the lowest average sidewalk slope score. This implies that VRUPOD path suggestions are affected by the users' preferences. This interaction effect allows VRUPOD to select the appropriate sidewalk segments for the optimal path.

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 schedule departure time and the expected arrival time.

In special cases, the static waiting time estimation can be extended to a more generalized waiting time as a function of bus punctuality. For example, when vehicles are instructed to wait at stops when vehicle arrival time is less than 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. In other words, the distribution for departure time delay for the vehicle runs at the stops is potentially right-skewed. The anticipated travel-time variability defined by the mean and variance for $IVTT$ for each physical path in a feasible path are computed from the results of the retrospective GTFS data, equal to the sum of mean and variances of travel time of links forming the path. As seen in Figure 8, 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 a.m 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.

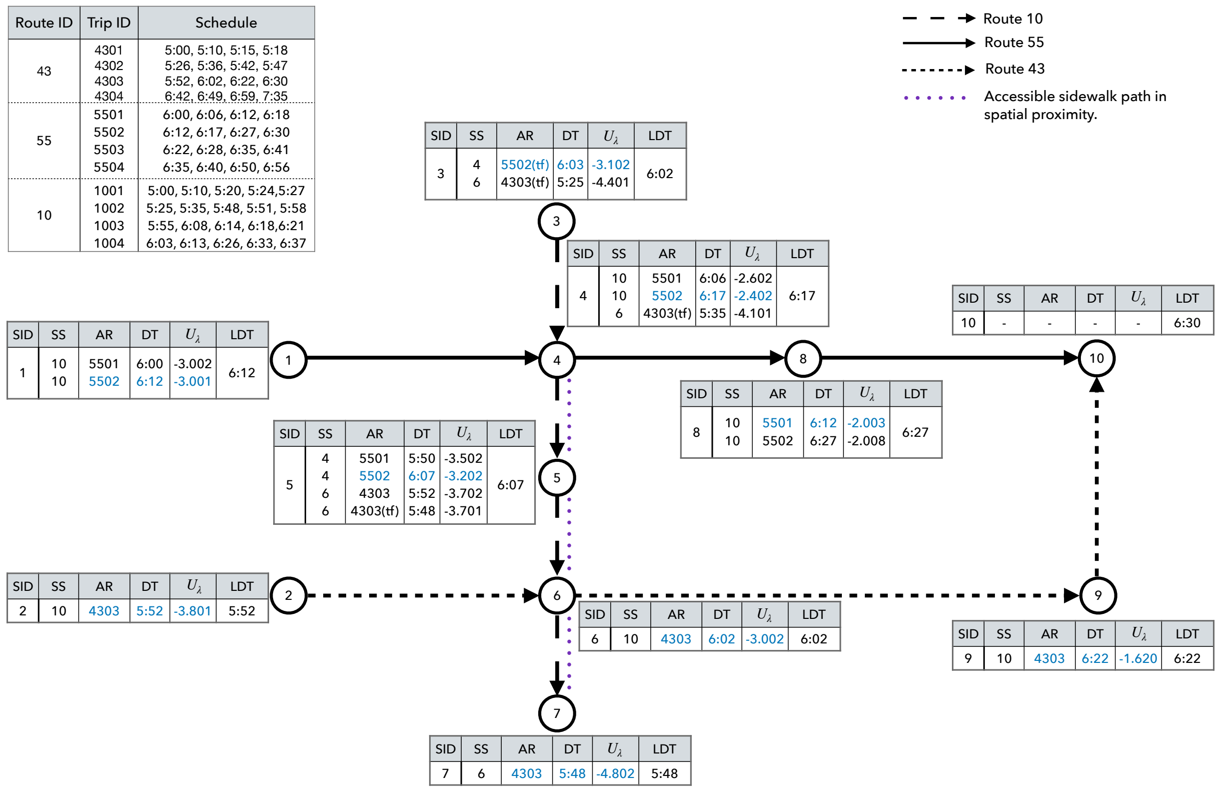


Fig. 8: Modified physical representation of route 10, 43 and 55 from MBTA showing common points. The results of path with utility U_λ for selecting minimum risk path based on the traveler's risk-tolerance at any given stop. SID: Stop ID, SS: Successor Stop, AR: Attractive Run, DT: Departure Time, LDT: Latest Departure Time to ensure arrival within PAT, tf:Transfer. Blue text in the figure shows run (strategy) that will be recommended for a traveler with risk-tolerance coefficient $\lambda = 0.2$.

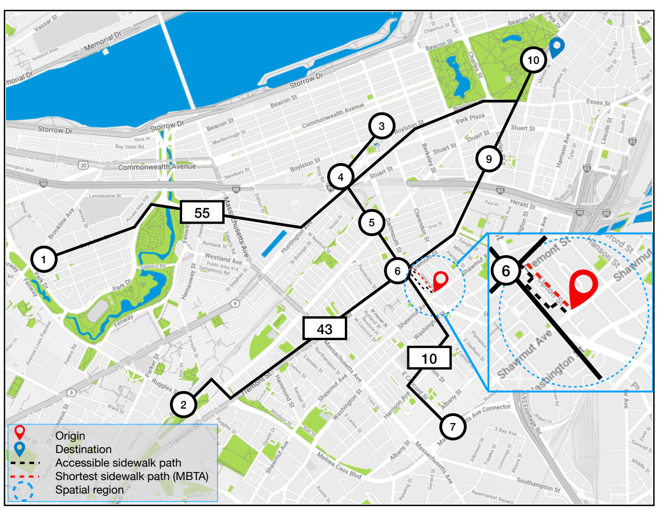


Fig. 9: Paths are evaluated for risk-tolerance coefficients λ = 0.2 and 1.0, with pedestrian mode preferences favoring slope and surface type. Using the MBTA trip planner (PAT: 6:30 a.m), suggested departure time is 6:08 a.m. Optimal path includes a 0.3 mi sidewalk route to stop 6, boarding route 43 outbound to final stop ten. Estimated utilities: λ = 0.2 (-3.010) and 1.0 (-3.033).

For example, looking at the path option from location eight to ten and risk-tolerance coefficients 0.2 and 0.4, we see that the estimated utility for the two path options are simply scaled and so the path recommendation remain the same.

Finally, we compare the path suggestions using the proposed utility function and the trip planner from MBTA for a typical Tuesday (Figure 9).

No definite conclusion can be made about the benefits of using our developed framework over the existing trip planners (e.g., MBTA), mainly because the MBTA trip planner option had a lower estimated schedule travel time of 14 min compared to our models' estimated schedule travel time of 20 min. However, we acknowledge that integrating the personalized sidewalk path option that considers the travelers' PAT at the final destination will serve vulnerable road users who are mostly limited in their social activities due to mobility concerns. In addition, integrating the inconvenience, the travelers are willing to experience will provide a more rational route/path to a traveler's tolerance to on-transit variability.

V. CONCLUSIONS

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

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