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Identifying Alternative Stops for First and Last Mile Urban Travel Planning

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Abstract As we move into an increasingly connected world for urban travel planning, we need to expand our concept of itinerary planning to meet the multimodal and diverse needs of today's traveler. Often, urban itinerary planning applications seek to minimize route travel time between two specific places at a certain time. Our approach provides travelers with a set of optimal nearby stops that presents a number of traveler preferences in an easily comprehensible and quickly calculable manner. We display first and last mile stops that fall on a Pareto front based on multiple criteria such as travel time, number of transfers, and frequency of service. Our algorithm combines stop and route-based information to quickly present the traveler with numerous nearby quality options for their itinerary decision-making. We expand this algorithm to include multimodal itineraries with the incorporation of free-floating scooters to investigate the change in stop and itinerary characteristics. We then analyze the results on the star-shaped urban transit network of Göttingen, Germany, to show what advantages stops on the Pareto front have as well as demonstrate the increased effect on frequency and service lines when incorporating a broadened multimodal approach.

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1 Introduction

Modern transit travelers expect a high quality of service and have varying priorities when creating their individual itineraries. Currently, urban itinerary planning is focused on using time-dependent, route-based optimization to minimize the traveler's travel time. However, while this itinerary may be optimal at a given moment, this may change with the time of day or with traveler itinerary preferences. While applications like GoogleMaps, City Mapper, and others have made large strides in recent years of developing their navigation tools to be traveler-friendly, there still needs to be a way to make information about relevant nearby stops for the first and last mile more transparent to the traveler considering a multitude of traveler preferences. Studies like Sharples (2017) focus qualitatively on what is needed to educate travelers in order to increase "traveler competence" to be able to make better use of available transport options. Our stop-based optimization (SBO) aggregates detailed information from transit timetables to give the traveler a simplified overview of multiple criteria for their itinerary planning.

Our SBO approach incorporates a mixture of route and stop-based information to provide a Pareto-optimal set of nearby stops for the first and last mile of the traveler's itinerary. The identification of these stops gets more complex as multiple innovative mobility services, such as scooter-sharing, have emerged recently. Therefore, the number of available nearby stops, in particular for the first and the last mile, increases greatly. This implies higher complexity of identifying a Pareto-optimal set of request-specific relevant initial and final stops, but it also gives the traveler additional options. The complexity increases further as travelers have varying individual preferences. For instance, besides travel time, price, and number of transfers, travelers care about frequency and number of transit lines. Additionally, the overall walking distance can be of high importance for the traveler. Presenting diversified solutions in a multimodal setting to the traveler is important as it broadens a traveler's decision making according to personal preferences and context, like personal mobility or time of day.

We choose to complement standard route-based parameters with stop-based information to enrich our SBO approach, which uses both quickly calculable route information as well pre-computed stop information. Therefore, the computational time for a specific request can be reduced significantly and the most relevant nearby stops can be presented to the traveler to refine itinerary planning. Figure 1 shows an illustrative example. Here, we assume for simplicity that a traveler has three stops available in walking distance with two traveler preferences considered (travel time and number of transfers for example). The comparison of stop characteristics is made transparent to the traveler using bubbles. Stop $S3$ would not be displayed to the traveler in this fictitious

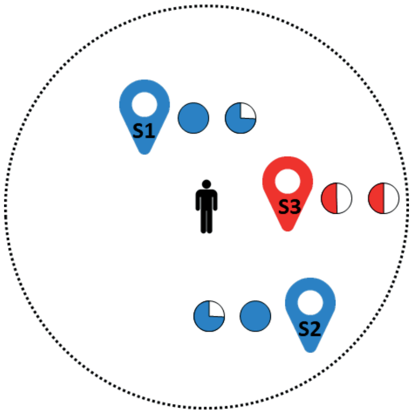

Fig. 1: Generic Example For Identifying Alternative Stops

example as is it dominated by at least one other stop. While Stop $S1$ is best for the first preference, and Stop $S2$ is best for the second considered preference. This simplified approach can incorporate multiple preferences while giving the most relevant, non-dominated nearby stops and their characteristics to the traveler.

In the following, we will analyze the potential of combining route-based and stop-based information to better inform the traveler of the characteristics of their first and last mile decisions. Our experiments are based on the public urban bus network of Göttingen, Germany. In addition to the bus network with walking edges, we will consider unscheduled, innovative modes of transportation, such as electric scooters. The novelty of this approach differs from route-based planning to focus more on the choice of stops for the first and last mile of the itinerary by including stop-based information into the decision-making process. We incorporate multiple traveler preferences and allow for various modes of transportation within our model to build upon recent work in travel planning.

Section 2 focuses on how our work contributes and builds upon current urban itinerary planning literature. Section 3 highlights the problem structure, our stop-based methodology, and the algorithm we use to identify the Pareto-optimal stops. Section 4 outlines our experiments that analyze the quality of stops on the urban transit network of Göttingen, Germany, and also incorporates scooters as a comparative example of how our approach can expand to multimodal networks. Finally, Section 5 summarizes our approach and its impact on multimodal urban transit as well as offering further research avenues for expansion of this approach.

2 Related Work

Urban itinerary planning research has markedly expanded in recent years as it becomes easier to incorporate into travelers' decision-making. In this section, we review how traveler preferences can help expand classic route-based optimization to help multi-preference travelers navigate complex multimodal networks. Section 2.1 highlights various multi-criteria and multimodal optimization research that motivated the development of our algorithm for finding high quality, Pareto-optimal first and last mile stops. Section 2.2 explores current work on incorporation of traveler preferences on itinerary decision-making.

2.1 Multimodal Routing

Traditional route-based optimization typically requires a fixed origin, destination, and start time. However, recent research has expanded this route-based optimization view. Delling et al. (2013a,b) use public transit route planning techniques to propose a bi-criteria journey planning algortihm. The authors use optimization rounds of the multimodal network to produce a Pareto-optimal set while limiting the computational time. Dib et al. (2017) introduce a label-based multi-criteria routing algorithm considering travel time, number of transfers and the total walking time as traveler preferences. Nasibov et al. (2016) examine route planning from a perspective of stop-based preference degrees. The authors develop a fuzzy preference model that factors in the stop's activity, the count of the transit lines that run through that stop and the walking distance to the stop. Our approach introduces a user-oriented aggregation of detailed route-based search into more comprehensible stop-based information.

Redmond et al. (2020) limit the computational time of multimodal driving and flight networks by focusing on a set of nearby first and last mile airports for the traveler's decision. This focus on selecting nearby airports showed that always myopically choosing the closest or largest nearby airport can result in less reliable itineraries. Bucher et al. (2017) propose to pre-compute candidate stops for the first and the last mile in a pre-processing step of the actual routing. Based on the candidate solutions, the routing algorithm focuses primarily on these. Therefore, the computational effort can be significantly reduced by considering a select set of nearby first and last mile stops.

Nykl et al. (2015) integrate these multiple traveler preferences using a meta-graph that is able to incorporate multimodal journeys. They also use a multi-criteria approach with time, distance, emissions, physical effort, and price as their parameters. Their approach is defined by a two-stage algorithm that capitalizes on using existing journey planning meta-data to set the weights on their graph. McKenzie (2019) examines scooter and bike-share usage in the United States capital of Washington, D.C. The author focuses on the spatial and temporal distributions of scooter-sharing itineraries in the area, and the similarities and distinctions around the city highlight itinerary purpose and regional differences. Our research integrates multimodal networks with traveler preferences for an easily-to-understand and quickly computed tool for itinerary planning.

2.2 Traveler Preferences

Understanding what is important to a traveler while navigating an urban transit network is key to developing itinerary planning tools. A considerable amount of literature has been published to identify traveler preferences for multimodal mobility by mainly analyzing traveler surveys (Willing et al. (2017); Ehmke et al. (2016); Spickermann et al. (2014); Stopka (2014); Esztergár-Kiss and Csiszár (2015); Clauss and Döppe (2016)). Besides the preferences of travel time, price and number of transfers, which are already considered by the majority of mobility apps, further relevant traveler preferences can be identified such as walking distance and waiting time.

Grotenhuis et al. (2007) outlines how integrated multimodal information can affect a traveler's choice. The authors highlight what types of information are necessary and the importance travelers place on travel time and minimizing effort in itinerary planning. Mulley et al. (2018) demonstrate through stated choice experiments that travelers are generally willing to walk further for a more frequent transit service. Additionally, Yan et al. (2019) show the significance that low quality last-mile stops have in deterring travelers from using transit options. Thus, there is a need to incorporate additional preferences to increase the option quality of first and last mile stops in itinerary planning. Recent research has attempted to model these preferences in traveler decision-making. Yang et al. (2020) develop a Markov game to sequence travelers' interactive transit mode choices based on a set of features. Wu et al. (2018) use a preference-learning algorithm to predict traveler decisions when evaluating a new transit plan. The goal of this paper is to incorporate these traveler preferences into a comprehensive decision tool for travelers trying to navigate a multimodal urban transit network.

3 Framework for Identifying Relevant First and Last Mile Stops

We propose a new framework to identify request-specific stops for the first and the last mile for travelers. As shown in Section 2.1, enormous progress has been made in multimodal routing in recent years. These approaches neglect evaluating stops to start and end the itinerary and making the stop characteristics transparent to the traveler. Hence, we focus on these in the presented framework.

As mentioned in Section 2, there is extensive research on the benefits of incorporating unscheduled modes into an itinerary that takes advantage of popular trends in bike-sharing and scooter-sharing. We address how this would look in our algorithm by showing how relevant stops for the first and last mile can change based on the availability of these modes. We will model them based on simulated and schedule-based data and see in our experiments how this could affect the traveler's decision criteria and the Pareto-optimal set.

3.1 Stop-based Methodology

Travelers expect quick identification of relevant nearby stops for their individual itinerary from their specific origin O to their destination D. As shown in Section 2, most itinerary planning algorithms merely consider route-based information to enable door-to-door mobility for the traveler. Our approach incorporates stop-based information as additional parameters, and thereby enriches existing route-based information with stop-based information. In the following section, we identify relevant stops for travelers based on their respective requests on an undirected network graph (3.1.1), which has been supplemented by stop-based information (3.1.2). This sets the framework for discussion of our algorithm for identifying and presenting these stops in Section 3.1.3.

3.1.1 Network graph

We define a public urban transit network of an undirected graph $G = (V, A)$ where V represents all possible stops in the transit network. The set of edges A represents legs between these stops. Each leg $a \in A$ is defined by a deterministic travel time, either using the existing bus network or a deterministic walking or scooter time.

By running a standard Dijkstra's algorithm (Dijkstra et al., 1959) on this network optimized by overall travel time, we are able to calculate the following route-based information quickly:

- Overall travel time: This parameter provides information on the travel time to get from O to D. The overall travel time includes the time from origin O to the first transit stop, the cumulatively summed travel times of all modes used in public transit, and from the final transit stop of the itinerary to destination D.
- Overall walking time: This parameter provides information on the required combined walking time for the specific itinerary. Hereby, we assume a predefined walking speed.
- Number of transfers: This parameter provides information on the minimum times the traveler has to transfer from one service to another.

3.1.2 Stop-based information

We enrich the discussed route-based parameters with additional stop-based information for every stop $v \in V$ to have a more sophisticated multi-criteria decision-making approach identifying relevant nearby stops for the traveler.

This stop-based information can be easily precomputed using the timetable for the respective transit network. As additional stop-based parameters, we consider the following:

– Frequency: This parameter provides information on how often a bus is scheduled on average to access a specific stop. This information gives insight into how long a traveler has to wait in case of missing a bus or if a bus fails on short notice. A stop with a smaller frequency in average minutes between bus lines is more ideal for a traveler than a stop with a larger, more infrequent average time between service.
– Number of bus lines: This parameter provides information on how many bus lines service a stop. As more bus lines service a stop, the traveler has more alternatives available. Thus, a higher number of bus lines is advantageous for the traveler in comparison to a lower number of bus lines servicing a bus stop.

For route-based information as well as for stop-based information an extension with further parameters is possible. For instance, additional route-based information can be the overall waiting time. Additional stop-based information network centrality measures, such as closeness and degree centrality, can be integrated in future work.

3.1.3 Framework for identification of relevant nearby stops

Based on the network graph and additional stop-based information, we present the framework for identifying a set $S_{traveler}$ of traveler-oriented nearby stops to achieve door-to-door mobility. Algorithm 1 shows the basic components of the framework. Given O and D, we identify a set of stops nearby the origin S_O^{Choice}, which are in walking distance (line 1). Then, for each $s \in S_O^{Choice}$ (line 2), the overall travel time s_{dijk} as well as the optimal path from s to D is calculated by solving a standard Dijkstra's algorithm minimizing the overall travel time (line 3).

Algorithm 1 Stop-based optimization framework

1: $S_O^{Choice} \leftarrow$ IdentificationOfStopsInWalkingDistance(O, D)
2: **for** $s \in S_O^{Choice}$ **do**
3: $\quad s_{dijk}, path \leftarrow$ Dijkstra(s, D)
4: $\quad s_{\#transfers}, s_{walkingTime} \leftarrow$ FurtherRouteBasedInformation$(s, path)$
5: $\quad s_{freq}, s_{\#lines} \leftarrow$ StopBasedInformation(s)
6: **end for**
7: $S_{traveler} \leftarrow$ RemovalOfDominatedStops(S_O^{Choice})

The parameters for number of transfers $s_{\#transfers}$ as well as walking time $s_{walkingTime}$ are derived easily in a subsequent step after solving Dijkstra's algorithm using *path* information retrieved in the preceding step (line 4).

In the next step, based on available scheduled network data, pre-computed information about the frequency s_{freq} and number of bus lines $s_{\#lines}$ are added as additional stop-based information for each stop $s \in S_O^{Choice}$ (line 5). This stop-based data needs to be pre-computed based on the transit network details to ensure a quick runtime of the algorithm.

Finally, after all parameters for each stop $s \in S_O^{Choice}$ have been quickly calculated, dominated stops are removed. This results in a set of Pareto-optimal stops $S_{traveler}$, which can then be presented to the traveler with all relevant information. A stop s_1 dominates a stop s_2 if s_1 is superior to s_2 according to at least one parameter and not inferior regarding all other parameters (Delling et al., 2013a). It is worth mentioning that we apply a minimization objective in this multi-criteria decision-making setting. Therefore, $s_{\#lines}$ has to be transformed for a minimization setting before it is considered in any domination rules. Remaining stops build up the Pareto front and give the traveler their set of high quality first and last mile stops.

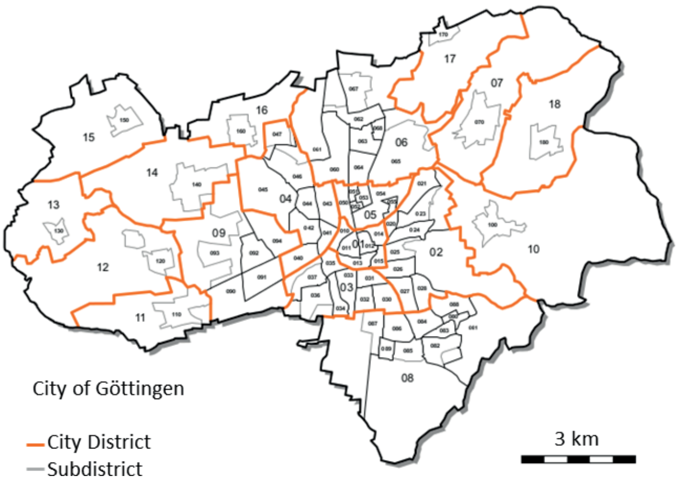

Fig. 2: Districts for Experiments
Adapted by Klatt and Walter (2011)

4 Experimental Results

This section implements Algorithm 1 from Section 3.1.3 in a medium-sized transit network in the city of Göttingen, Germany. This is a university town with a star-shaped structure with the downtown and train station at the center, similar to many other European cities. Section 4.1 outlines the experiments run with our dataset to provide varied results from different areas of the city. We demonstrate in Section 4.2 the benefit and effect that considering stop and route information simultaneously can have in expanding the traveler's options. Sections 4.3 and 4.4 detail the differences that arise when scooters are added to the network.

4.1 Design of Experiment

To discover the effects that our stop-based algorithm has on transit networks, we consider all 18 districts of the city of Göttingen as shown in Figure 2. Our experiments run Algorithm 1 from each of the 18 districts to every other district for a total of 306 Origin-Destination combinations. The origin and destination for each experiment is located at the center of the district, and nearby stops (within 0.5 kilometers) are potential relevant stops for the first and last mile.

The bus network is based on the real-world schedule of Göttingen, Germany, reduced to one day of scheduled operations. We limit the maximum walking distance between two stops to 500 meters, but this could be expanded later to see the effect on experimental results. We assume a walking speed of $5km/h$.

Figure 3 demonstrates an example output of Algorithm 1 of nearby stops in Göttingen. Here, the traveler's origin is marked in gray. The stops that are dominated are displayed in red and would not be shown to the traveler. Each stop on the Pareto front is shown in blue, and its characteristics are displayed with bubbles to represent how each stop compares to others on the Pareto front. For example, the optimal travel time would be displayed as a full circle with "best" while an alternative stop choice may be partially shaded and have +1.2 minutes in the label. This algorithm output gives the traveler a complete picture of the benefits and drawbacks of all nearby stops.

4.2 Stop-relevant Results

To investigate the impact that Algorithm 1 had on identifying relevant stops, we performed experiments between Origin-Destination (OD) centroids of each district only considering walking and bus edges for $v \in V$. We found that there were on average 10 stops within walking distance of both the origin or destination. However, when using Algorithm 1, there were only a quarter (2.4) of these stops on the Pareto front. Additionally, the average travel time between origin and destination was approximately 23 minutes with buses that frequent the chosen stops coming every 24.5 minutes.

Table 1 presents a comparison between relevant stops on the Pareto front to dominated stops. While on average around 2% overall travel time savings and 4% walking time can be seen, relevant stops have a 21% more frequent schedule in comparison to stops not presented to the traveler. Thus, the largest savings for travelers using this method arise in the frequency, number of lines, and number of transfers.

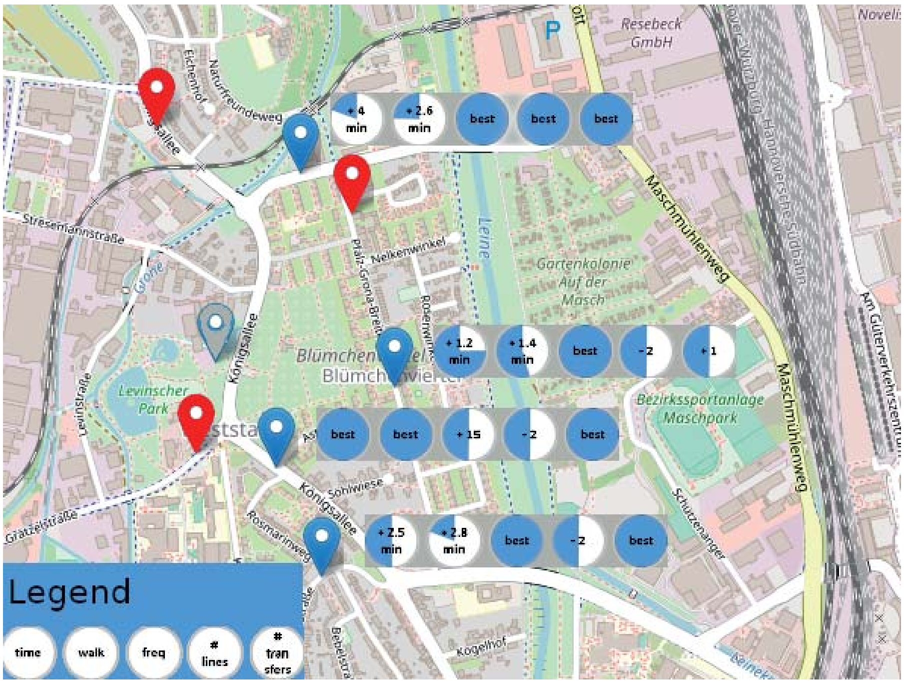

Fig. 3: Example Identification of Nearby Stops for a Traveler

Table 1: Savings Potential with respect to different Parameters

	Time (min)	Walk (min)	Freq (min)	Lines	Transfers
Relevant Stops	22.7	6.6	24.5	2.6	1.4
Dominated Stops	23.1	6.9	31.0	2.1	1.5
Savings Potential	2%	4%	21%	20%	12%

Further examining the non-dominated stops yields the closeness to optimality for stops on the Pareto front in each category as shown in Figure 4. Here, we can see that 75% of the stops on the Pareto front add an additional 2-3 minutes of overall time and walking time to the traveler's itinerary. Thus, most stops on the Pareto front reveal first and last mile stops that do not add unreasonable amounts of time to the itinerary.

These results indicate that by evaluating multiple preferences when considering nearby stops, we can identify high quality stops with a number of advantages. The Pareto front stops give much more frequent service and number of lines while displaying options that are usually adding only a few minutes to travel and walking time. This approach can help travelers focus on these non-dominated stops and evaluate the preferences that are important in their itinerary planning.

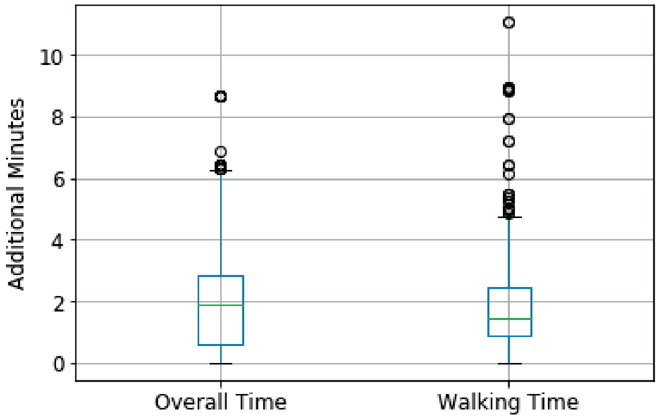

Fig. 4: Additional Time for Stops in the Pareto Set

4.3 Results from Scooter Implementation

Following the initial experiments that tracked how stops were chosen based on the parameters, we investigated the effect that incorporating an additional mode of transportation had on the results. Specifically, we focused on how positioning scooter nodes close to bus stops in each region of the city would expand and alter the Pareto-optimal stops shown to the traveler.

To achieve this, in each region we assume there are scooter nodes located near the region center and also scooter edges that connect any two bus nodes within 1.5 kilometers of each other. If the two bus nodes are within 0.5 kilometers of each other, then a walking edge supersedes this scooter edge and is added to the network instead. The results of these added free-floating scooter edges are displayed in Table 2.

Table 2 demonstrates that by adding scooters as first and last mile modes to the network, the options for travelers are expanded to more than twice that of the original network. While the average time of the shortest path slightly increases, the traveler is presented with stops that have a number of attractive qualities. In addition, slightly less walking is required in case scooters are considered. The stops considered have more frequent service, are serviced by two more bus lines on average, and have less transfers on the traveler's itinerary. This demonstrates the benefits that increasing the range of nearby stops by adding scooters can provide more options that may more closely suit travelers' preferences.

This benefit is further illustrated in Figure 5. Here, the average number of transfers as well as the average frequency between buses in seconds is shown for each of the 18 districts. The relationship intuitively indicates an increasing number of minimum transfers as the stop becomes less frequent. The blue marks and line show that on average implementing scooter access to the trav-

Table 2: Average differences between Scooter and Non-Scooter Experiments

Mode	Stops on Pareto Front	Time (min)	Walk (min)	Freq (min)	Lines	Transfers
No Scooters	2.4 (29.6%)	22.7	6.6	24.5	2.6	1.4
Scooters	5.4 (16%)	23.2	6.3	18	4.4	0.9

eler results in use of bus stops that have more frequent service as well as less transfers for the traveler.

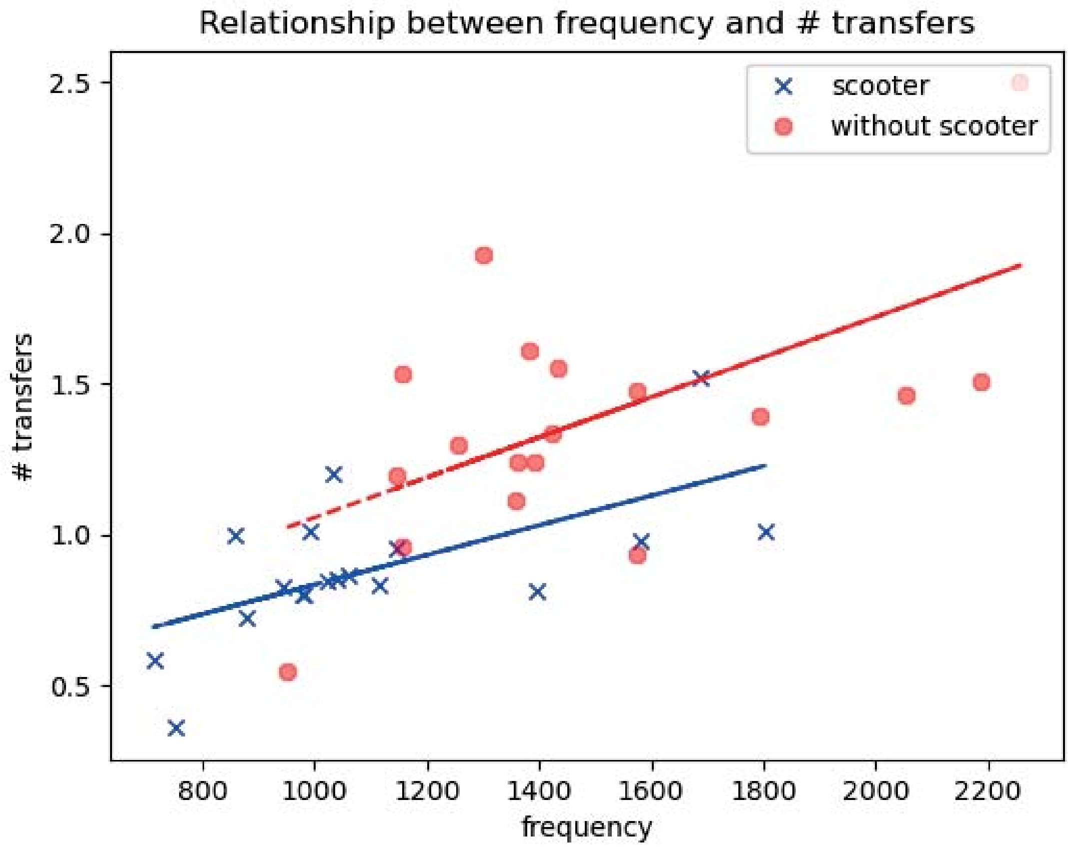

Fig. 5: Comparing Frequency of Service with Number of Transfers

4.4 Visualizing Results of Comparative Scooter Implementation

For a specific comparison of the effect of scooter usage by region, we examine Figure 6. These two regions are Innenstadt, represented in orange and near the city center, and Weststadt, represented in blue and away from downtown. The solid line represents the average across categories when scooters are utilized. While the average travel time is comparable between the modes, slightly longer runtime is necessary if scooters are considered as an additional service. Additionally, buses arrive more frequently for stops accessed by scooters. These expanded stop options also service more bus lines and require fewer transfers. These averages vary across the regions, but the benefit of including scooters into a multimodal network persists throughout. Incorporating a first or last mile on-demand option, such as scooters, can identify stops with more frequent and varied service and less transfers that can expand the traveler's information availability and decision making.

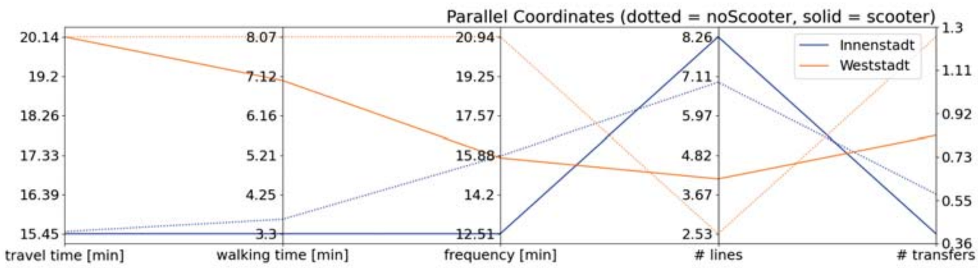

Fig. 6: Parallel Coordinates Plot of Different Pareto Front Parameters

5 Conclusion

In this research, we have demonstrated a framework to improve the overall experience in urban travel planning. We enhance current mobility apps by making relevant first and last mile stops and their characteristics transparent to the traveler. To accomplish this, we combine stop and route-based information in the decision-making progress. This enables travelers to make better-informed decisions. We evaluate the proposed framework for identifying alternative stops for first and last mile urban travel planning using a medium-sized transit network of Göttingen, Germany. We show that the traveler has several non-dominated nearby stops with different characteristics available to choose from. Stops on the Pareto front have on average much more frequent and more transit lines than dominated stops. This trend is also true for incorporation of scooter nodes that expand the traveler's nearby stop options. We envision this technique being implemented in the future as the demand for integrated multimodal transportation information increases.

Conflict of interest

The authors declare that they have no conflict of interest.

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