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ORIGINAL RESEARCH

Identifying alternative stops for first and last-mile urban travel planning

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Abstract
Urban travelers today are seeking increasingly more information to plan their optimal trip, based on additional factors other than scheduled departure times. Still, some route planning applications provide a simple approach with a few parameter settings (e.g. to minimize travel time between two specific places at a certain time) and without any multimodal solutions. Our approach provides travelers with a set of non-dominated 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 public transportation 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.

Keywords Route planning · Non-dominated solutions · Stop and route optimization · Multimodal

1 Introduction

Modern public transport travelers expect a high quality of service and have varying priorities when creating their individual itineraries. Currently, several widespread urban route planners are focused on using time-dependent, route-based optimization

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to minimize preferences including the traveler's travel time. However, while this itinerary may be preferred 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. Our stop-based optimization (SBO) framework aggregates detailed information from public transport route-based information and stop characteristics to give the traveler a simplified overview of multiple criteria for their route planning.

Current public transportation literature primarily revolves around route-based preferences, such as walking time or total travel time that are calculated in accordance with the traveler's available routes (Mulley et al. 2018). However, there is also research into other important information revolving around a traveler's nearby stops either at the origin or destination (Yang et al. 2020; Nasibov et al. 2016). Currently, only a few researchers propose to integrate both route-based criteria with first and last-mile stop information, like accessibility, number of lines and frequency of transport services at that stop. By focusing on this unique combination of criteria, we can offer a comprehensive decision tool for the traveler for more informed travel planning.

Our SBO approach incorporates a mixture of quickly calculable route and precomputed stop-based information to provide a set of non-dominated nearby stops for the first and last mile of the traveler's itinerary. For instance, besides travel time, price, and number of transfers, travelers care about stop-based information like frequency, accessibility, and the number of public transport lines. Additionally, the overall walking distance can be of high importance for the traveler. When the route and stop-based information is taken into account, several non-dominated stops result due to the conflicting objectives of these preferences. For example, there may be a stop that is operated at a high frequency. This results in backup options for the traveler. On the other hand, the itinerary starting at this stop may be more expensive compared to the itinerary starting at another stop within walking distance from the origin. Presenting these diversified solutions in a multimodal setting to the traveler is important since it broadens a traveler's decision making according to personal preferences and context, like personal mobility or time of day (Lyons et al. 2020).

In the following, we will analyze the potential of combining route-based and stop-based information to better inform the traveler about the characteristics of the first and last-mile decisions. Our experiments are based on the public transport bus network of Göttingen. 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 route planning literature. Section 3 highlights the problem structure, our stop-based methodology, and the algorithm we use to identify the non-dominated stops. Section 4 outlines our experiments that analyze the quality of stops on the public transport network of Göttingen, Germany, and also incorporates scooters as a comparative example of how our approach can expand to multimodal networks. Section 5 discusses limitations of this study, offers further research avenues for expansion of this approach and its contributions on the long term of travel planning policies. Finally, Sect. 6 summarizes our approach and its impact on multimodal public transport.

2 Related work

Urban route 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, non-dominated first and last-mile stops. Section 2.2 explores current work on incorporating 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 (Willing et al. 2017). Delling et al. (2013a, b) use public transport route planning techniques to propose a bi-criteria itinerary planning algorithm. 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. Bozyigit et al. (2017) extend Dijkstra's algorithm to enable taking walking distance as well as number of transfers as additional relevant traveler preferences into account. Therefore, they introduce a penalty rule set integrated into Dijkstra's algorithm. This research utilizes both stop-based information as well as aggregated route data to form a multi-criteria objective. We explore the Pareto front and how travel options change based on this stop and route-based approach.

Redmond et al. (2020) limit the computational time of optimizing on 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. Ge et al. (2021) highlight the importance that multimodal itinerary applications have in integrating all available mobility services and data sources into one framework to support the traveler in their decision-making process. Bucher et al. (2017) propose to precompute candidate stops for the first and the last mile in a preprocessing 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 multiple traveler preferences using a metagraph that is able to incorporate multimodal itineraries. 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 itinerary planning meta-data to set the weights on their graph. Horstmannshoff and Ehmke (2022) propose a sampling framework to approximate the set of non-dominated itineraries. In particular, they focus on the efficient scalability with respect to the number of considered traveler preferences in a large multimodal network. In addition, they present insights into itinerary characteristics which can be embedded into decision tools for the traveler.

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. Zou et al. (2020) also look at how e-scooters compete against and complement public transport and bike share in Washington D.C., and show other reasons for choosing included public health priorities and access in underserved areas. Esztergár-Kiss and Lizarraga (2021) utilize surveys across five European cities to discover that their popularity is driven by flexibility and speed, despite safety and road-sharing concerns. Further surveys are done by Jie et al. (2021) to show factors associated with shared mobility usage including gender, employment status, and income. Smith (2020) demonstrates the time saving and accessibility benefits of incorporating scooters into multimodal itineraries in Chicago. Shokouhyar et al. (2021) examine the impact COVID-19 had on shared mobility, and the authors highlight the need to consider social and environmental factors when considering shared mobility implementation. Our research integrates shared mobility in multimodal networks with traveler preferences for an easily comprehensible and quickly computed tool for route planning.

2.2 Traveler preferences

Understanding what is important to a traveler while navigating a public transport network is key to developing route planning tools. Javadian Sabet et al. (2021) highlight that the individual context of the traveler is of high importance to be able to take traveler preferences into account. 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. They present a model (context dimension tree) which allows the real-time integration of traveler requirements, the individual traveler preferences as well as the individual profile into the decision-making progress of the traveler. A considerable amount of literature has been published to identify traveler preferences for multimodal mobility by mainly analyzing traveler surveys. Grotenhuis et al. (2007) outline how integrated multimodal information can affect a traveler's choice. The authors highlight what types of information are necessary and the importance that travelers place on travel time and minimizing effort in route planning. Table 1 gives an overview of the preferences considered in the literature differentiated according to route and stop-based information.

Travel time, price, and number of transfers are the most prevalent preferences for route planning. In addition, the consideration of the overall walking time during an itinerary and the overall waiting time are of high importance as well (Grotenhuis et al. 2007; Spickermann et al. 2014; Stopka 2014; Stopka et al. 2015; Gilibert and Ribas 2019; He and Csiszár, 2020). Please note that further route-based preferences, such as comfort, are not included in this overview as these are rarely mentioned and hard to quantify. We refer to Horstmannshoff (2022) for a detailed overview of relevant traveler preferences in a multimodal setting.

Further works integrate stop-based characteristics into the planning of multimodal itineraries. Yan et al. (2019) show the significance that low-quality last-mile stops have in deterring travelers from using public transport options. Thus, there is a need to incorporate additional preferences about stop-based information into the search to increase the option quality of first and last-mile stops in route planning. Recent research has attempted to model these preferences in traveler decision making. Mulley et al. (2018) demonstrate through stated choice experiments that travelers are generally willing to walk further for a more frequent public transport service as well as to achieve travel time savings. Yang et al. (2020) develop a Markov game to sequence travelers' interactive public transport mode choices based on a set of features. The authors highlight that besides common preferences, such as travel time, price and number of transfers, the number of choices available is of relevance as well. Wu et al. (2018) use a preference-learning algorithm to predict travelers' decisions when evaluating a new public transportation plan. The goal of this paper is to integrate both route-based information and stop-based information into a comprehensive decision tool for travelers trying to navigate a multimodal urban public transportation network. 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 public transport lines that run through that stop, the travel time, the number of transfers and the walking distance to the stop. Fatima and Moridpour (2019) emphasize that due to the aging population further challenges in the planning of multimodal mobility arise. In particular, mobility applications should provide information whether the itinerary can be completed in a handicapped accessible manner. Esztergár-Kiss (2019) compares multiple European route planning applications from a traveler perspective. A differentiation is made between different user groups with individual requirements. In addition to the high relevance of integrating a variety of route-based preferences into the search, the inclusion of handicapped routes especially for elderly people is mentioned. Mandžuka (2021) discusses the challenge of multimodal routing, particularly between different countries. The author highlights that travelers have multiple parameters such as travel time, price, number of transfers, walking distance and waiting time as examples for route-based preferences. Furthermore, accessibility information describing whether the access to the respective mode of transportation is, e.g., step-free and wheelchair-accessibility has to be provided. We abstain from further stop-based information such as safety information and the simplicity to find the right stop into the search in this overview. We envision to embed this information in the future within the proposed framework.

Table 1 Traveler preferences

	Route-based preferences					Stop-based preferences		
	Travel time	Price	# transfers	Walking time	Waiting time	freq	# lines	Accessibility
Grotenhuis et al. (2007)	x	x	x	x	x	–	–	–
Spickermann et al. (2014)	x	x	x	–	x	–	–	–
Stopka (2014)	x	x	x	x	–	–	–	–
Stopka et al. (2015)	x	x	x	–	–	–	–	–
Gilibert and Ribas (2019)	x	x	–	x	–	–	–	–
He and Csiszár (2020)	x	x	x	x	x	–	–	–
Mulley et al. (2018)	x	–	–	x	–	x	–	–
Yang et al. (2020)	x	x	x	–	–	–	x	–
Wu et al. (2018)	x	x	x	–	–	–	x	–
Nasibov et al. (2016)	x	–	x	x	–	–	x	–
Fatima and Moridpour (2019)	x	x	x	x	–	x	–	x
Esztergár-Kiss (2019)	x	x	x	x	x	–	–	x
Mandžuka (2021)	x	x	x	x	x	–	–	x
SBO approach	x	–	x	x	–	x	x	x

In this paper, we utilize both route and stop-based information to enhance the quality of the set of non-dominated relevant stops and respective itineraries, which can be presented to the traveler and form the choice set for the traveler. In our SBO approach, we use travel time, number of transfers and walking distance as route-based information. As we do not have real price data for all integrated mobility services, we do not consider prices in our proof-of-concept study. For stop-based preferences, we integrate accessibility for disabled and handicapped travelers, the frequency as well as the number of lines. The set of considered preferences can be extended beyond this proof-of-concept study.

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 Sect. 2.1, enormous progress has been made in multimodal routing in recent years. These approaches focus mainly on route-based information, often neglecting deterministic information about relevant nearby stops in their multimodal routing formula. We integrate both route and stop-based information into the search while forming the choice set for the traveler.

As mentioned in Sect. 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 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 set of non-dominated stops. In this context, we assume that the current location and availability of the unscheduled services are provided in real-time in an integrated mobility platform. This mobility platform also includes the data of the scheduled network. Therefore, we can model the environment as a static network at the time of a traveler request. Aggregating all mobility service data into one platform enables traveler-oriented multimodal transportation planning.

3.1 Stop-based methodology

Travelers expect a quick identification of relevant nearby stops for their individual itinerary from their specific origin O to their destination D. As shown in Sect. 2, most route 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 (Sect. 3.1.1), which has been supplemented by stop-based information (Sect. 3.1.2). This sets the framework for discussion of our algorithm for identifying and presenting these stops in Sect. 3.1.3.

3.1.1 Network graph

We define a public transportation network of an undirected graph $G=(V, A)$ where V represents all possible stops in the transportation 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 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 transfer stop, the cumulatively summed travel times of all modes used in public transport, and from the final transfer 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. Walked distances, which occur during the transfer at the same stop, are not taken into account.
- 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 each 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 public transportation network. As additional stop-based parameters, we consider the following:

- Frequency (headway): 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 usually better for a traveler than a stop with a larger, more infrequent average time between service units. Thus, for example, a higher frequency of 20 min is worse in comparison to a lower frequency of 10 min.
- Number of bus lines: This parameter provides information on how many bus lines serve a stop. As more bus lines serve a stop, the more alternatives the traveler has available. Thus, a higher number of bus lines is advantageous for the traveler in comparison to a lower number of bus lines serving a bus stop.
- Accessibility: This parameter is a binary variable indicating if a stop is handicap-accessible for the traveler. This can be of importance for travelers and can be extended to include sheltered stops or well-lit areas for nighttime travel.

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. As additional stop-based information safety information and the simplicity to find the right stop 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. As several conflicting objectives have to be addressed while identifying this set, we are dealing with a multi-criteria decision-making problem. In general, we aim at minimizing a vector ${S_O}^{Choice}$ of n objectives such as $min_{s \in S_O^{Choice}}(f_1(s), f_2(s), \ldots, f_n(s))$ (Ehrgott 2005). ${S_O}^{Choice}$ describes the set of nearby stops and n the set of considered route and stop-based information. The components $s \in {S_O}^{Choice}$ are mostly competing against each other.

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). For each stop $s \in {S_O}^{Choice}$, route and stop-based information is taken into account. The overall travel time s_{dijk} as well as the optimal path from s to D are calculated by solving a standard Dijkstra's algorithm minimizing the overall travel time (line 3) (Dijkstra 1959). This optimal path contains all the information about the itinerary, the departure and arrival time at which stop, and the respective transfers.

The parameters for the number of transfers, s#transfers, as well as the walking time, swalkingTime, are derived easily in a subsequent step after applying Dijkstra's algorithm using path information retrieved in the preceding step (line 4). The walking time can be calculated by taking into account the individual traveler's origin and destination, the first and last-mile stop of the respective path, as well as the overall walking time at transfer stops.

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: $\quad s_{freq}$, $s_{\#lines}$, $s_{accessibility} \leftarrow$ StopBasedInformation(s)
6: **end for**
7: $S_{traveler} \leftarrow$ RemovalOfDominatedStops(S_O^{Choice})

In the next step, based on available scheduled network data, precomputed information about the frequency s_{freq}, the number of bus lines $s_{\#lines}$ and accessibility information $s_{accessibility}$ is added as a stop-based information for each stop $s \in {S_O}^{Choice}$ (line 5). This stop-based data needs to be precomputed based on the public transportation 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 (line 7). This results in a set of non-dominated 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 set of non-dominated stops.

4 Experimental results

In this section, we present experimental results applying our framework in a medium-sized public transportation network in the city of Göttingen, Germany. This is a university town with a star-shaped structure with the city center and train station at the center, similar to many other European cities. Göttingen's urban area covers approximately 11,699 hectares, in which about 134,000 residents live (Stadt Göttingen 2022). The public transportation network comprises 20 daytime lines, 8 night lines and includes about 500 stops (Göttinger Verkehrsbetriebe GmbH 2022). Section 4.1 outlines the experiments run with our dataset to provide varied results from different areas of the city. We demonstrate in Sect. 4.2 the benefit and effect that considering stop and route-based 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 the experiment

To discover the effects that our SBO approach has on public transportation networks, we consider all 18 districts of the city of Göttingen as shown in Fig. 1. 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 are located at the center of the district, and nearby stops (within 0.5 km) are potential relevant stops for the first and last mile.

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

Figure 2 demonstrates an example output of Algorithm 1 of stops in Göttingen, which are in walking distance. Here, the traveler's origin is marked in gray. The nearby stops that are dominated are displayed in red and would not be shown to the traveler as these do not offer any added value for the traveler. Each non-dominated stop is shown in blue. These are the stops which form the choice set for the traveler. Their characteristics are displayed with bubbles to represent how each stop compares to others, which are non-dominated. For example, the optimal travel time

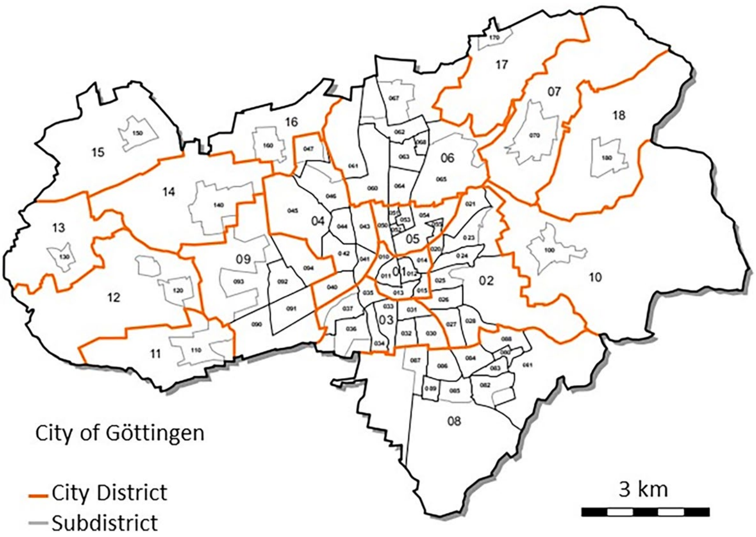


Fig. 1 Districts for experiments: Adapted by Klatt and Walter (2011)

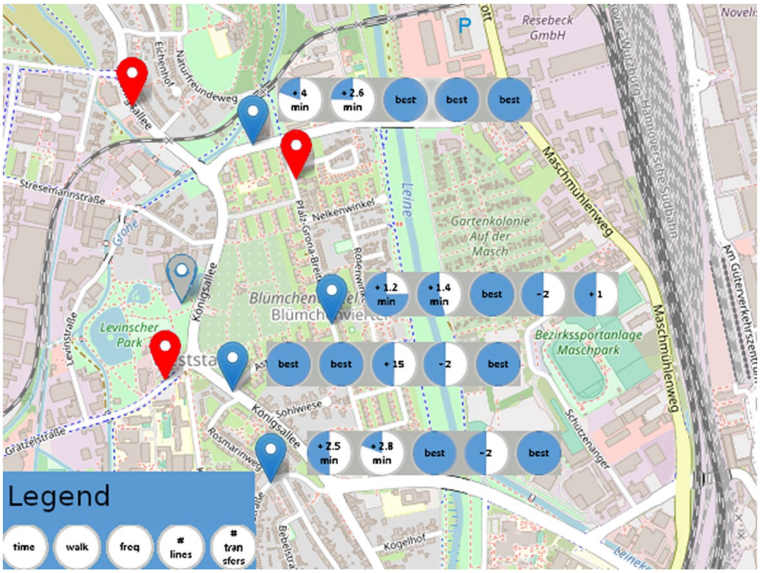


Fig. 2 Example identification of nearby stops for a traveler

would be displayed as a full circle with "best" while an alternative stop choice may be partially shaded and have + 1.2 min in the label. This algorithm output gives the traveler a complete picture of the benefits and drawbacks of all nearby stops. Further information such as the underlying itinerary and the actual values for each respective preference can be presented as more in-depth information for each relevant stop. This supports the travelers in their decision-making process.

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 non-dominated. Additionally, the average travel time between origin and destination was approximately 23 min with average headway between buses of 24.5 min.

Table 2 presents a comparison between relevant non-dominated stops and 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, the number of lines and the number of transfers. These key savings in the frequency, lines, and number of transfers are substantial, given that it shows that the results can yield savings in areas other than traditional route-based optimization, which focuses on time savings. By expanding the definition of optimal beyond fastest transport service, travelers can experience more frequent public transport options, more lines serving the stop, and a lower number of transfers to their destination. This research highlights the expansion of the non-dominated stops to lesser utilized, but important categories that can give the traveler options not displayed by strictly time-optimized techniques.

Further examining the non-dominated stops yields the closeness to optimality in each category as shown in Fig. 3. Here, we can see that 75% of the non-dominated stops add 2–3 min to the overall time and walking time of the traveler's itinerary. Thus, most non-dominated stops 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 non-dominated stops give much more frequent service and the 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 route planning.

Table 2 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%

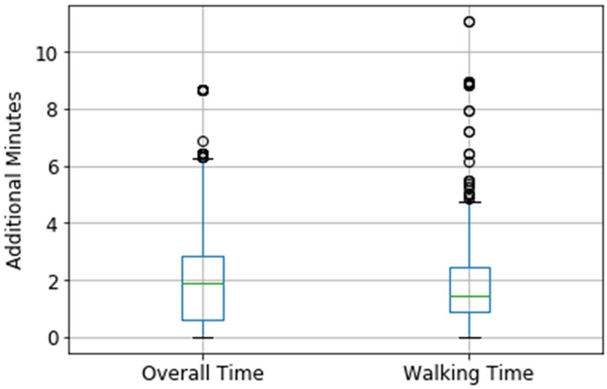


Fig. 3 Additional time for stops in the Pareto set

4.2.1 Accessibility

One additional example of a preference that could be important to travelers is accessibility for disabled and handicapped travelers (Fatima and Moridpour 2019). We have included this additional parameter in Table 3. Here, when comparing results with and without the binary accessibility parameter, the number of non-dominated stops increases on average from 2.4 to 2.9, while the overall travel time decreases by over 80 s. The average frequency of arrivals does not change, but both, the number of lines per stop and the number of transfers per itinerary increase when considering accessible stops. When we examine accessible-only stops, we can see a drastic decrease in the travel time as well as an increase in the number of lines accessed per stop. This type of analysis for parameters that can be of significant importance to certain travelers is essential to provide the traveler with routes and stops that will fit their preferences. We can expand on this with additional parameters or incorporate alternate transportation methods into the model.

4.3 Results from scooter implementation

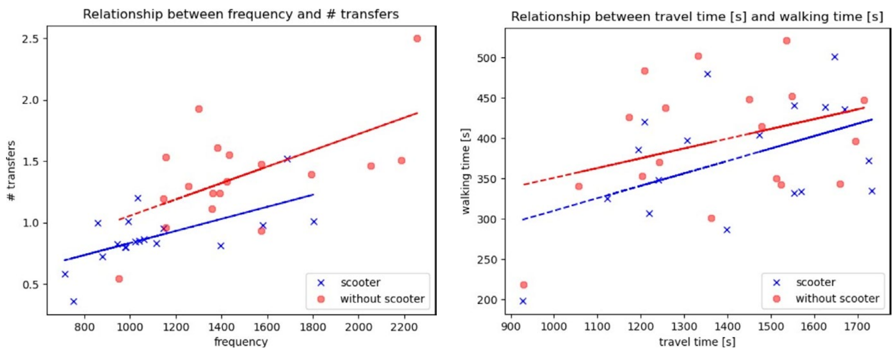
Following the initial experiments that tracked how stops were chosen based on the parameters, we investigated the effect that incorporating an additional mode

Table 3 Advantages for accessible stops when implementing new accessibility parameter

	Non-dominated stops	Time (min)	Freq. (min)	Lines	Transfers
Without accessibility	2.4	22.7	24.5	2.6	1.4
Accessible stops	2.9	21.5	24.4	3.0	1.2
% Improvement	22%	5%	0%	18%	9%

Table 4 Average differences between Scooter and Non-Scooter Experiments

Mode	Non-dominated stops	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



(a) Frequency of Service with Number of Transfers

(b) Travel Time with Walking Time

Fig. 4 Relationship between preferences

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 non-dominated 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 km of each other. If the two bus nodes are within 0.5 km 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 4.

Table 4 demonstrates that by adding scooters as first and last-mile modes to the network, the options for travelers are expanded to more than twice of those 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 served by two more bus lines on average, and have less transfers on the traveler's itinerary. This demonstrates that increasing the range of nearby stops by adding scooters can provide more options that may more closely suit travelers' preferences.

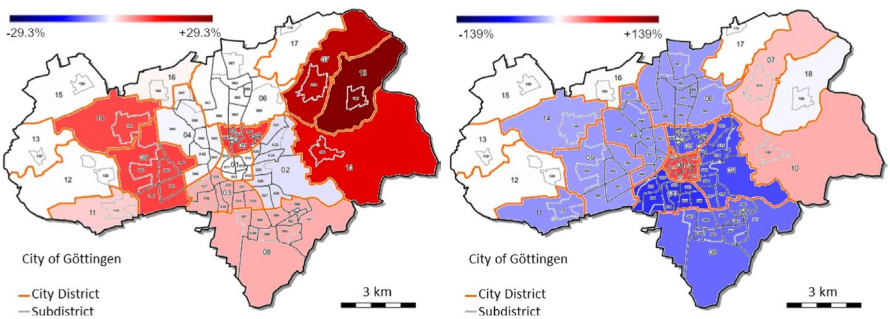
This benefit is further illustrated in Fig. 4a. Here, the average number of transfers as well as the average frequency between buses in seconds is shown for each of the 18 districts. The relationship intuitively indicates an increasing number of minimum transfers as the stop becomes less frequent. It can be seen that considering scooters (blue crosses) yields a lower number of transfers in comparison to merely considering buses as an available mobility service (red circles). Figure 4b compares the average travel time and the average walking time in seconds for scooters against non-scooter integration for each of the 18 districts. The figure shows that a higher travel time results in a higher walking time as well. The required walking time can be reduced by adding scooters into the network as a first and last-mile sharing service (blue crosses).

The blue marks and line show that on average implementing scooter access results in the usage of bus stops that have a more frequent service as well as less transfers for the traveler.

Figure 5 shows the average percent change of the experiments with scooter integration against the non-scooter experiments by districts for each respective route and stop-based preference. The non-scooter experiments serve as a baseline. Following, districts highlighted in red indicate that, on average, the value of the respective preference has worsened in that district. Districts marked in blue indicate that the value of the respective preference has improved, whereas white highlighted districts mean no significant difference in comparison to the non-scooter results. Please note that the percent change indicated by dark blue and dark red, respectively, is determined by the respective maximum change, and therefore differs for each preference.

Figure 5a shows the change for the overall travel time. A slightly worse average travel time can be observed in particular for the eastern districts (7, 10 and 18) as well as for the southwest districts. For district 18 (Roringen) the average travel time decreases by 29%. Conversely, if the traveler's origin is in district 2 (Oststadt), minor improvements of approximately 2% with respect to the average overall travel time can be observed. As can be seen in Fig. 5b, integrating scooters for the first and last mile enables the traveler to reach additional stops, which have a more traveler-oriented frequency in comparison to stops more accessible by walking. A significant deterioration in terms of frequency can be observed in the city center (district 1). It can be assumed that scooter integration also leads to the consideration of less frequented stops outside the city center, which are non-dominated with regard to one of the preferences taken into account.

Further analysis for percent changes by district for the preferences walking time, number of lines and number of transfers can be found in Fig. 7 in the Appendix.



(a) Travel Time

(b) Frequency

Fig. 5 Percent change by district

4.4 Visualizing results of a comparative scooter implementation

For a specific comparison of the effect of scooter usage by region, we examine Fig. 6. These two regions are Innenstadt, represented in blue and near the city center, and Weststadt, represented in orange and away from the city center. 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. The expanded stop options also serve 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.

5 Discussion

While this work contributes to the existing literature through a stop-based optimization that takes into account multiple stop and route-based preferences for the traveler, there are some areas that could expand the reach of this work. For example, additional important parameters, such as safety of a stop's area and ease of access to other public transport modes could be included. In addition to not including these parameters that may be important, this work does not explore the potential large amount of options that may show up on the set of non-dominated solutions for large-scale country or regional multimodal networks.

For multimodal networks, travelers expect dynamic, updated results to know the availability and updated schedule of travel options. In reality, an additional dynamic map—updated each minute or more frequently—could be integrated to refresh the scooter nodes and availability for the traveler. This would give even more additional non-dominated stops for the traveler and knowledge if scooter nodes would be a viable option to begin or end their itinerary. The traveler would need the ability to make a reservation a priori as well since those scooter nodes could disappear when they reach their destination stop.

In future work, further stop and route-based information can be integrated into the search. For instance, the price can be integrated as an additional route-based

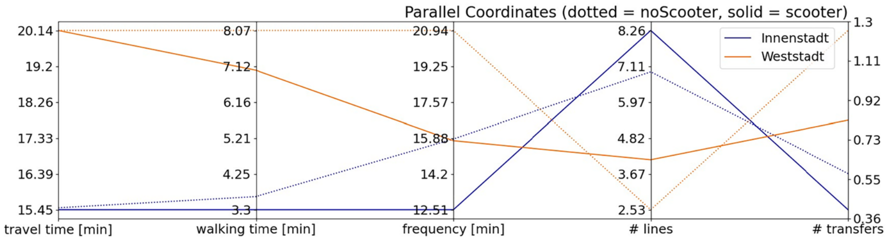


Fig. 6 Parallel coordinates plot of different parameters

preference in case price information is available. Further preferences that are difficult to quantify, such as comfort, can be added, which provide additional value for the traveler. As further stop-based information, we can envision, for example, the integration of safety information and the simplicity to find the right stop within the search. The integration of further preferences leads to a larger set of non-dominated stops. Thus, techniques to limit the set of non-dominated stops for the first and last mile of the traveler's itinerary are required. One way would be to enable the traveler to set weights for individual preferences in an expert menu within a mobility platform to allow travelers to prioritise their preferences individually. This should be aided by advanced visualization techniques to support the travelers in their decision-making process. In addition, further experiments applying the proposed SBO approach to more cities with different characteristics ensures a generalization of the results.

In real-world settings, travelers want to use one multimodal application that integrates all available mobility services. Our framework can easily be adapted to an extended multimodal setting. The integration of additional mobility services can increase the number of relevant nearby stops, which is an exciting potential for future research.

To adequately assist the traveler in selecting the most appropriate nearby stop, a simple presentation of the non-dominated options is necessary. In this work, we have focused on the technical perspective of identifying the set of non-dominated nearby stops and presented a first approach to present this information to the traveler. Further work can additionally present this information into an integrated multimodal routing application in a traveler-oriented way.

Travel policy implications of this traveler-centered approach include an analysis of stop location to see if certain stops should be included or excluded for traveler convenience or lack of use. Additionally, timetable policies can use this set of non-dominated stops analysis to see if certain stops should be frequented more or less. With shared mobility policies in a city, the placement and replacement of shared bikes, scooters, and other transportation modes could utilize this tool to maximize the demand for the service along with existing public transportation networks.

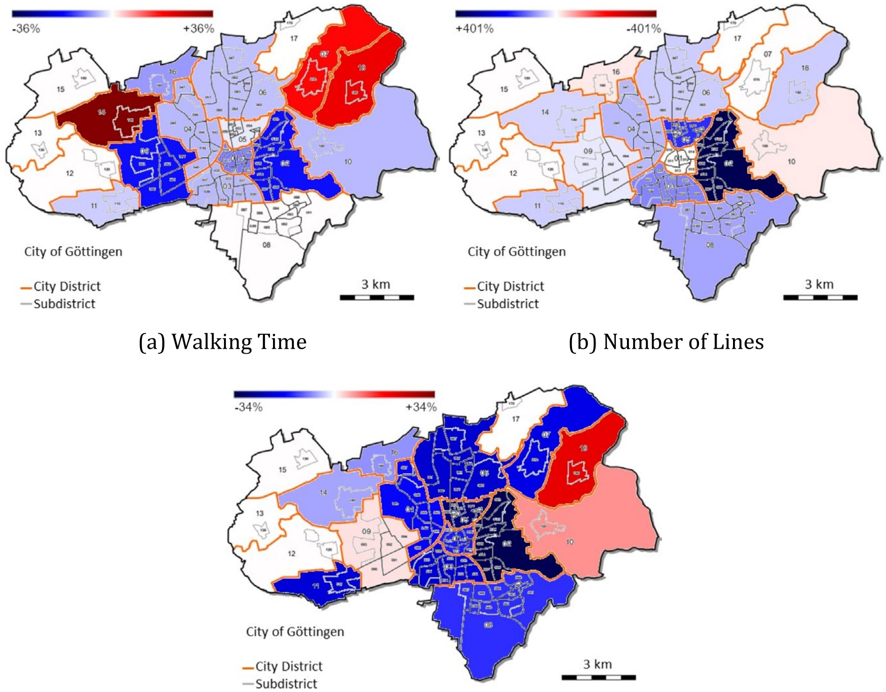
6 Conclusion

In recent years, large strides have been made in creating multimodal door-to-door itineraries. However, significant challenges remain while identifying these options in a traveler-oriented way. Travelers expect information about relevant first and last-mile stops and their characteristics in a transparent way using up-to-date mobility applications. In this work, we combine stop and route-based information in the decision-making progress. In particular, we consider the overall travel time, the overall walking time as well as the number of transfers as route-based preferences, and frequency, accessibility and the number of bus lines as stop-based information into the search. The set of relevant nearby stops considering this information can then be presented to the traveler. This enables travelers to make better-informed decisions.

The proposed framework for identifying alternative stops for first and last-mile urban travel planning has been evaluated using the medium-sized public transportation network of Göttingen, Germany. In addition to the public transport bus network based on real-world data, we integrate unscheduled mobility services such as electric scooters.

We show that the traveler has several non-dominated nearby stops with different characteristics available to choose from. Non-dominated stops have on average more public transport lines and more frequent service than dominated stops. Furthermore, the traveler saves both travel and walking time. This trend is also true for incorporating scooter nodes that expand the traveler's nearby stop options. In addition, we have introduced a novel idea on how to present the non-dominated set of nearby stops to the traveler. We envision this framework of identifying relevant nearby stops being implemented in the future, as the demand for integrated multimodal transportation information increases. Providing this information to the traveler allows for better decision making while planning individual multimodal itineraries.

A Further Percentual Changes by Districts



(a) Walking Time

(b) Number of Lines

(c) Number of Transfers

Fig. 7 Percentual Change by District

Appendix: Further percentual changes by districts

See Fig. 7.

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Declarations

Conflict of interest We declare that we do not have any potential conflicts of interest, nor do we have any involvement of human participants and/or animals in this work.

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