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Procedia Computer Science 238 (2024) 352–360

Procedia Computer Science

www.elsevier.com/locate/procedia

The 15th International Conference on Ambient Systems, Networks and Technologies (ANT)
April 23-25, 2023, Hasselt, Belgium

Personalized Day-Trip Planning: A TSP-TW-Based Multimodal Multicriteria Optimisation Approach

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Abstract

In this paper, we present a novel approach for computing personalized itineraries for individual travel plans throughout one day, considering the wide variety of mobility preferences individuals consider when making itinerary choices. We extend the Traveling Salesman Problem with Time Windows (TSP-TW) by integrating multi-criteria optimization techniques, flexible activities, park-and-ride options, and various transport modes to provide a more comprehensive representation of transportation options. We assess travelers' mobility preferences, selecting a relevant subset for a real-world itinerary optimization scenario, and employ choice experiments to identify the importance of these preferences for individual decision-makers. The utility functions derived from these experiments are then used for itinerary optimization. We validated our method through simulations in a medium-sized German city, which demonstrated a significant improvement of 16.19% in travel utility when incorporating a utility function into itinerary optimization compared to plans based solely on travel time.

Keywords: Activity chain; Optimisation; Traveling Salesman Problem; Multimodal networks; Travel preferences

1. Introduction and Related Work

Facilitating individual mobility is crucial for the prosperity of a society. Reconciling parental duties, professional and voluntary commitments, and leisure activities leads to complex travel patterns. Multimodal transportation, including public transport, walking, cycling, and driving, can provide better time, cost, and environmental efficiency compared to relying solely on a single transport mode, such as a car. Itinerary planners can simplify the planning of daily activities and associated travel plans by arranging transportation options, thereby improving the accessibil-

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10.1016/j.procs.2024.06.035

ity of multimodal transportation. Moreover, they can potentially increase the attractiveness of alternative modes of transportation by suggesting personalized travel plans. However, contemporary itinerary planners primarily focus on optimizing routes based only on travel time and cost and tend to optimize for only one mode of transport at a time, neglecting the potential for simultaneous optimization across multiple modes of transport. This constraint underscores the necessity for a more flexible and comprehensive approach to daily travel planning that can accommodate the diverse and interconnected nature of modern transportation systems.

To address this issue, we propose a new approach for generating personalized travel plans that optimizes the sequencing and timing of daily activities by minimizing the disutility of travel. This entails planning both the activities and the routes between them. The optimization process considers multiple transport modes simultaneously and integrates various mobility preferences, thereby providing a holistic representation of transportation options. We extend the Traveling Salesman Problem with Time Windows (TSP-TW) to model and solve our problem by incorporating multi-criteria optimization techniques, flexible activities, park-and-ride options, and various transport modes. We use utility functions to model the individual mobility preferences of users. Our approach utilizes statistically efficient designs for discrete choice experiments and repeated most and least preferred choice questions to estimate these functions. This utility-based optimization approach is derived from the frameworks introduced in [14] and [5]. In these works, researchers have introduced a utility-based approach for path suggestions that considers individual mobility preferences, improving path advice performance over using average preferences. Nevertheless, this methodology has not yet been applied to activity chain optimization problems.

Multiple TSP-based approaches have been introduced to address the activity chain optimization problem, which involves optimizing the sequence and timing of activities while minimizing the travel disutility, often measured in terms of travel time, as addressed in prior works [3, 7, 13, 18]. Most existing approaches focus on optimizing activity chains by considering activity preferences and only a few mobility preferences, such as travel time and cost. In contrast, our approach integrates a wide variety of mobility preferences into the optimization process without taking activity preferences into account. However, it can be extended to include activity preferences as well. In particular, a method introduced in [10] does not consider individual mobility preferences and multimodal scenarios. The methods introduced in [7, 13] are multi-criteria optimization approaches, focusing primarily on activity preferences. These methods currently only consider mobility preferences such as travel time and cost. In addition, the optimization approach outlined in [13] considers the simultaneous use of multiple transport modes. However, as it relies solely on travel time and cost as route optimization criteria, the modeling of the problem differs significantly from that proposed in our approach. Furthermore, an optimization approach for electric car drivers based on TSP was proposed in [17]. It does not, however, take into account individual preferences. The approach presented in [3] integrates multiple mobility preferences and transport modes but lacks the ability to define flexible activities. Regarding the optimization methods employed in the field, the Genetic Algorithm (GA) is a commonly utilized technique. In our approach, we have integrated GLKH solver [9], a top-performing state-of-the-art algorithm for solving Generalized TSP [15]. Furthermore, our approach offers a comprehensive representation of available transportation choices by incorporating park-and-ride options and various combinations of transport modes, such as bike/folding bike, car, public transport, and walking. This extension promotes higher flexibility and efficiency in planning, surpassing the conventional evaluation of monomodal options or combinations of public transport with walking or driving, as observed in current approaches.

We evaluate our approach in a medium-sized German city, where we analyze travelers' mobility preferences and relevant mobility data. We identify a specific subset of mobility preferences suitable for integration into our itinerary planner. These preferences are chosen based on their applicability to a real-world itinerary optimization scenario and the availability of the relevant data in the evaluation region. We propose a choice experiment design to assess the importance of these preferences for individual decision-makers. The utility functions derived from these experiments are then employed to optimize the itineraries. Finally, we conduct simulations on a real-world transportation network using real-time travel information to evaluate the effectiveness of our proposed approach.

2. Method

Our method aims to enhance the overall travel experience by optimizing the sequencing and timing of activities while minimizing the disutility of travel. This includes planning both activities and the routes connecting them. Our

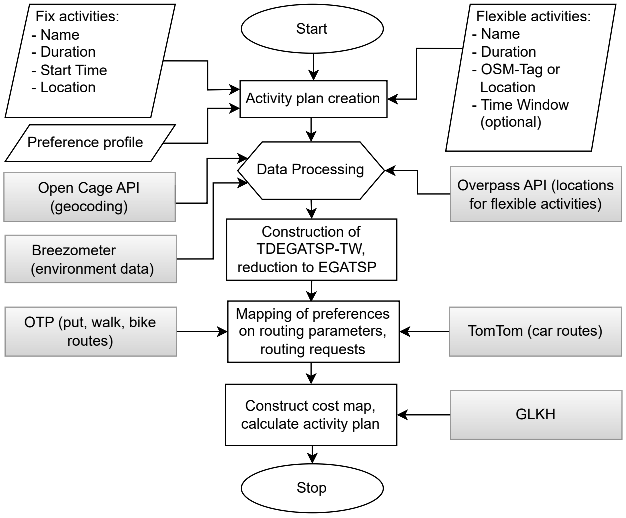

Fig. 1. Activity Plan Creation Flowchart

approach considers a broad spectrum of mobility preferences, addresses time window constraints, and embraces the flexibility of activities in terms of both location and timing. Figure 1 illustrates the process flow for computing personalized activity and mobility plans. In the initial phase, users select a preferences profile and enter their fixed and flexible activities. Users must provide the name, duration, start time, and exact address if it's a fixed activity. Flexible activities require the name, duration, and either the exact location or OpenStreetMap (OSM) tag. When users specify the exact location of a flexible activity, they must also set a time interval for when the activity should take place. Alternatively, if an OSM tag is used instead of an exact location, providing a time interval is optional. If no time interval is specified, the location's opening hours will be considered as the timeframe for conducting the activity. Next, the itinerary planner proceeds to analyze and process the user input. To achieve this, it utilizes various APIs. The addresses of the activities are geocoded using the Open Cage API, while the locations for flexible activities with an OSM tag are searched using the Overpass API. Additionally, the itinerary planner requests relevant environmental data, such as air quality and weather, from the Breezometer API. After processing data and obtaining the necessary information, the itinerary planner generates the Time Dependent Equality Generalized Asymmetric Traveling Salesmen Problem with Time Windows (TDEGATSP-TW) and reduces it to Equality Generalized Asymmetric Traveling Salesmen Problem (EGATSP). This enables the determination of specific routes to be requested, including the departure time, mode of transportation, and locations. Moving to the next step, the itinerary planner maps the user's preferences to routing service parameters. For instance, when a user indicates a preference for a wheelchair, it is mapped to the "wheelchair" parameter of the OpenTripPlanner (OTP). The itinerary planner then uses this mapping to request routes. Bike, public transport (put), and walking routes are requested from OTP, while car routes are requested from TomTom, allowing for more personalization options for car drivers. In the next step, a cost map is generated by considering the attributes of the routes and applying the utility function from the selected preference profile. This cost map is then utilized as an input for the GLKH Solver [9], which aims to identify the most cost-efficient path. After completing its calculations, the solver provides the optimized path, which is mapped to an itinerary and visualized for the user. The itinerary planner thus calculates the routes and schedules for the specified activities while considering user preferences and constraints. The calculated plan ensures that fixed activities are visited on time while flexible activities are arranged to maximize the total utility of the travel plan.

2.1. *Integration of preferences*

The itinerary planner enables users to create multiple preference profiles representing distinct travel contexts. For instance, individuals can create a profile for leisure trips, specifying a preference for scenic routes and another for work trips, favouring shorter and more comfortable routes. We have analyzed literature and studies on mobility preferences to select preferences for integration into the itinerary planner. The literature describes a broad range of mobility preferences integrated into existing mobility platforms, trip planners, and routing services. Including a preference in the itinerary planner is only meaningful if it can be evaluated in a real-case optimization scenario. The study [4] found that older pedestrians (women and men, 70 years and above) perceive walking as dangerous when sharing the road with cyclists or roller skaters. However, it is not possible to evaluate this preference at present due to a lack of relevant data in the evaluation region. To address this issue, we analyzed and selected the mobility preferences based on the availability of relevant data in the evaluation region. We chose to exclude preferences such as traffic and elevation despite the availability of data. The inclusion of real-time traffic data would complicate the analysis of simulation results. The elevation is disregarded as the evaluation region exhibits minimal changes in elevation. Nonetheless, the preferences included in the profile can be modified for other regions. Table 1 presents the selected and integrated preferences, which can be directly or indirectly (through choice experiment results) specified in the preference profile.

Table 1. Preferences integrated in preferences profiles

Preference	Integration Type	Data Source
Length of the trip	Cost calculation	OTP
Air quality	RBC	Breezometer
Weather	RBC	Breezometer
Preferred and excluded modes	RBC	User
Mobility impairment	RBC, Routing	OTP
Abonnements	Cost calculation	User
Travel time	Cost calculation	OTP
Travel cost	Cost calculation	Mobility provider [8]
Number of transfers	Cost calculation, Routing	OTP
Distance (walking/cycling)	Cost calculation, Routing	OTP
Access/egress walk time	Cost calculation	OTP
Baggage	RBC, Routing	OTP
Speed	Routing	OTP
Existence of a cycling path	Routing	OTP
Barriers (e.g. stairs)	Routing	OTP
Existence of a sideway	Routing	OTP
Waiting time	Cost calculation	OTP

The itinerary planner enables various integration types of mobility preferences. One integration option is to use rule-based constraints (RBC), which eliminate specific travel options before computing the itinerary. For example, users may avoid walking or cycling in particular weather conditions, and these transport modes will not be considered. Another option is to utilize routing services such as OTP. OTP allows the personalization of routing parameters, such as setting customized cycling and walking speeds. By mapping the preferences onto the routing parameters, the itinerary planner can produce routes tailored to meet different mobility preferences. Furthermore, users' preferences are considered when evaluating the costs of the routes. The cost of a route is the negation of its utility. The utility of the route is calculated as a sum of the weighted route attributes. These weights are determined for each user and preference profile through choice experiments, as described in the next section. Additionally, users may create preference profiles that reflect their specific wishes and needs, such as environmental friendliness, by prioritizing non-motorized transportation options in the corresponding profile. This allows for greater customization of itineraries. By combining these approaches, the itinerary planner enhances personalization and integrates various mobility preferences.

2.2. *Quantification of Preferences using Choice Experiments*

Choice experiments are used to make it easier to quantify user preferences while minimizing cognitive effort. Comparative assessments prove less demanding for users as compared to quantitative judgments [6]. The primary aim of choice analysis is to estimate the utility function, a quantitative method of measuring a user's perceived value of the itinerary. The itinerary's total utility is calculated as a sum of the weighted utilities for each mobility preference. We use the method introduced in [11] to estimate individual user preferences. This approach enables gathering and modelling individual choices using statistically efficient designs for discrete choice experiments and repeated most and least preferred choice questions about choice options in the choice sets. Applying the software NGENE, we use Fedorov Algorithm to generate statistically efficient designs comprising 16 choice sets and 4 alternatives for short-distance routes and 16 choice sets and 3 alternatives for medium-distance routes. The parameters and levels analyzed in the proposed choice experiments are displayed in Table 2. Since users' preferences can vary depending on the route distance [2], the proposed method allows users to execute distinct choice experiments for short and medium-distance ranges: 0-5 km and 5-10 km. We do not consider longer distances to evaluate our method in a medium-sized German city, but they may be included in future studies.

Table 2. Choice Experiments Parameters

Attribute	Description	Experiment	Values
s_{ttcar}	Travel time car	Short distance	4, 6, 8, 10, 12, 14 (min)
$s_{car.cost}$	Travel cost car	Short distance	0.9, 1.8, 2.7, 3.6, 4.5, 5.4, 6.3, 7.2, 8.1 (euro)
s_{ttbike}	Travel time bike	Short distance	7, 10, 13, 16, 19, 22 (min)
s_{ttwalk}	Travel time walk	Short distance	10, 15, 20, 25, 30, 35 (min)
s_{ttpt}	Travel time put	Short distance	5, 7, 9, 11, 13, 15 (min)
s_{ptcost}	Travel cost put	Short distance	0, 1.5, 3, 4.5, 6, 7.5 (euro)
m_{ttcar}	Travel time car	Medium distance	15, 17, 19, 21, 23, 25 (min)
$m_{car.cost}$	Travel cost car	Medium distance	0.9, 4.5, 8.1, 11.7, 15.3 (euro)
m_{ttbike}	Travel time bike	Medium distance	30, 36, 42, 48, 54, 60 (min)
m_{ttpt}	Travel time put	Medium distance	17, 20, 23, 26, 29, 32 (min)
$m_{pt.cost}$	Travel cost put	Medium distance	0, 4.5, 9, 13.5 (euro)
$m_{transfer}$	Number of transfers	Medium distance	0, 1, 2, 3, 4, 5
a_{ttwait}	Waiting time	Short, medium distance	3, 7, 11, 15, 19, 23, 27, 31 (min)
$a_{car.ttaewalk}$	Access/egress walk time to/from car	Short, Medium distance	3, 7, 11, 15, 19, 23, 27 (min)
$a_{pt.ttaewalk}$	Access/egress walk time to/from put	Short, Medium distance	7, 12, 17, 22, 27, 32 (min)

The default utility function, which corresponds to the shortest path profile, initializes each user preference profile. To personalize the utility functions, users are given the option to participate in choice experiments generated in the previous step. The results of these experiments are analyzed using weighted least squares regression, based on the procedure described in [11]. The computed utility function for the short-distance experiment is defined as follows:

$$\begin{aligned} U_s = \beta + s_{ttbike} * \beta_{s\_ttbike} * bike + s_{ttcar} * \beta_{s\_ttcar} * car + s_{ttput} * \beta_{s\_ttput} * put + s_{ttaewalk} * \beta_{s\_ttaewalk} * walk \\ + s_{car.cost} * \beta_{s\_car.cost} * car + s_{pt.cost} * \beta_{s\_pt.cost} * put + a_{ttwait} * \beta_{a\_ttwait} \end{aligned} \tag{1}$$

where β is a base utility and β_i defines the weight of the associated route attribute i. The variables *bike*, *car*, *walk*, and *put* are binary variables, taking a value of 1 when the route involves the corresponding travel mode. The utility function for medium-distance routes is defined analogously to the short-distance function, based on table 2. The mode of transportation determines the travel costs. The costs for public transportation routes are based on the prices set by the regional mobility provider, available abonnements, and the distance traveled. The cost of car routes is based on the average fuel price [8] and distance traveled. Our plans include a vehicle type parameter and a differentiated cost calculation.

2.3. Itinerary optimization

The described problem of day activity chain optimization based on utility functions is modeled as an extension of TSP, which is one of the most researched combinatorial optimization problems [15]. More precisely, we model the problem as TDEGATSP-TW, which can be defined as a Graph $G = (V, E)$, where $V = \{v_1, ...v_n\}$ is a vertex set and $E = \{(v_i, v_j) : v_i, v_j \in V\}$ is the set of directed edges with $i \neq j$. The vertex v_0 is the depot. All vertices V are partitioned into m mutually exclusive clusters $V_1...V_m$ with $V = V_1 \cup V_2...V_m$ and $V_i \cap V_j = \emptyset, \forall i, j, i \neq j$. Each vertex $v_i \in V$ has a Time Window $[a_i, b_i]$, with $[a_i, b_i] \in [a_0, b_0]$, where $[a_0, b_0]$ is a time windows of a depot vertex

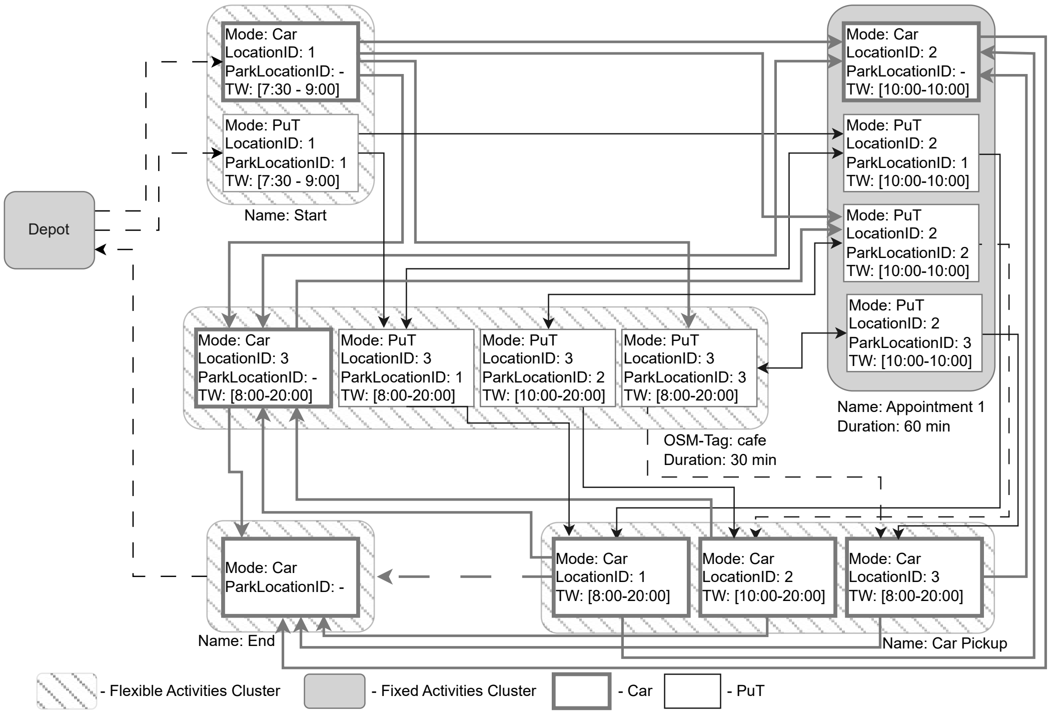

Fig. 2. Graph Example

v_0. Every time window $[a_i, b_i]$ has associated instants of time $t_i^k = a_i + k - 1$, where $k \in [1; b_i - a_i + 1]$. Each vertex also has a service time s_i, and each edge has a duration t_{ij} and a non-negative cost c_{ij}. The cost (disutility) c_{ij} of a route (v_i, v_j) is determined by the negation of its utility $c_{ij} = -1 * u_{ij}$. The utility is calculated as outlined in section 2.2. To ensure that the costs of the routes have positive values if the cost matrix contains negative costs, a constant c is added. This constant is determined as the absolute value of the minimum cost value $|min(c_{ij})|$. An edge (v_i, v_j) is considered feasible if $a_i + s_i + t_{ij} \leq b_j$. The time and the cost of traversing an edge $(v_i, v_j) \in V$ depend on the instance of time t_i^k at which it is traversed. We expand upon the definition provided by Albiach et al. [1] to incorporate details regarding the transport mode and the specific car parking location. Since we consider various factors for calculating the route costs as specified in the section 2.2, it is possible for routes with longer travel times (e.g. scenic walking routes) to have lower costs compared to other transport modes. However, selecting the route with the lowest cost between two activities without considering its impact on the overall travel plan can ultimately reduce the plan's overall utility. To address this issue, we model each transport mode as a separate vertex. This approach allows for a more comprehensive analysis of transport options. Each vertex v_i is assigned a mode of transportation $m_i \in \{car, bike, public\ transportation(put), walk\}$, specifying that the edges (routes) leaving that vertex must be of the mode m_i. Additionally, each vertex is associated with geocoordinates, indicating the location of the corresponding activity, denoted as l_i, and a separate set of geocoordinates to indicate the location of the car parking facility, denoted as p_i. An additional constraint is introduced: $\forall(v_i, v_j) \in E$ the parking locations of both vertices must be identical, i.e., $p_i = p_j$, or in the case where the source vertex represents the car mode, $m_i = car$, the parking location of the target vertex p_j must match its activity location l_j. This constraint ensures the car is available at each vertex v_i with $m_i = car$. The extended TDEGATSP-TW is the problem of finding a minimum cost cycle that includes exactly one vertex from each cluster while fulfilling the following constraints: the circuit must start at time $t_i^k \geq a_0$, end at time $t_j^k \leq b_0$, leave each vertex $v_i \in V$ inside its assigned time window $[a_i; b_i]$ and all edges $(v_i; v_j) \in E$ must satisfy the property: $p_i = p_j$ or $m_i = car$. To solve the TDEGATSP-TW, we reduce it to the Equality Generalized Asymmetric Traveling Salesmen Problem (EGATSP) based on the procedure described in [1]. We construct an auxiliary graph $G' = (V', E')$ as described in the first transformation step in [1] and extend it by adding parking vertices v_{p_i} and a corresponding cluster $V_p = \{v_{p_1}, ...v_{p_n}\}$. These vertices represent a car pickup activity and allow for a car pickup later in the day if the user travels a part of the trip using alternative modes of transportation. The following reduction steps are omitted in this paper due to space limitations. GLKH Solver [9], implemented by Keld Helsgaun, solves the resulting EGATSP. An example of an auxiliary graph is illustrated in Figure 2. To simplify the representation, the figure depicts an auxiliary graph before the time expansion and considering only two modes of transportation: car and put. Each vertex still has a time window that must be expanded in the next transformation step by creating a vertex for each possible time instance t_i^k. This auxiliary graph is calculated for the following input scenario: one fixed activity "Appointment 1", with a start time of 9 a.m. and a duration of 60 minutes; one flexible activity "Cafe", with no specified start time and a duration of 30 minutes. The vertices from clusters "Cafe", "Appointment 1", and "Car pickup" represent activities, while the vertices from clusters "Depot", "Start", and "End" are dummy vertices added to ensure that the itinerary starts and ends at the same location "LocationID 1". The edges are the routes connecting these activities. The dashed edges are dummy routes, added for modeling purposes only, and have a cost of 0. To simplify the illustration, a bidirectional edge is used to represent edges that exist in both directions. Each vertex contains information about its mode of transportation, its address as indicated by LocationIDs, and its parking location as indicated by ParkLocationIDs, as well as a time window. Time windows are calculated based on duration intervals within which the activities must be completed. These time windows determine the time interval when the user must depart from the activity location. The costs of the edges in the graph are calculated using the attributes of the corresponding routes and the individual utility functions from the selected preference profile.

3. Results

The itinerary planner has been implemented in Kotlin. For the evaluation, we use a self-hosted instance of OTP (version 2.2). The OSM data and daily updated GTFS data from the regional mobility provider have been utilized. We conducted two-stage real-world simulations on a transportation network in a medium-sized German city to evaluate the itinerary planner. In the first stage, we created an efficient choice experiment design for short and medium-distance routes, as explained in section 2.2. Subsequently, we generated 1000 utility functions U_s and U_m as defined in section 2.2. Each attribute of the function was randomly weighted. The ranges for the random values are as follows: [-0.5;0.1] for β_{ttbike}, β_{ttcar}, β_{ttput}, and β_{ttbike}; and [-0.5;0] for all other variables. The chosen ranges are based on the results of a survey conducted in [2]. Due to the study design, which involved an artificial simulation without real participants, the base utility was set to zero for all utility functions. Within this simulation, each pair of utility functions, U_s and U_m, represented a hypothetical user, each with their own distinct "true" mobility preferences as defined by these functions. Choice experiments were conducted programmatically for short and medium routes and for each of the hypothetical users. The option choice was determined based on "true" user utilities and the accumulated probability function. This function assigns a higher probability to an option choice that covers a greater proportion of the definition span between 0 and 1. Subsequently, the option choice is determined based on a random draw between 0 and 1 (see [16]). Next, we used the method described in [11] to estimate users' utility functions based on the results of these experiments. The estimated expected choice totals for each choice set were calculated as described in [11]. The parameters of the implied indirect utility function of the CLM (conditional logit model) were calculated using WLS (weighted least squares) [12]. We have used these model estimates to predict the utilities of a hypothetical user. The average correlation (from 1000 simulated utility functions) between the "true" utility functions U_s and U_m and the predicted utility functions U'_s and U'_m was 0.78 and 0.65 respectively.

In the second stage, we conducted 1000 simulations for each of the hypothetical users and their respective estimated utility functions U'_s and U'_m to evaluate their effectiveness in optimizing activity chains and itineraries. Each simulation involved creating an activity list and generating two activity plans: one optimized plan by utility functions U'_s and U'_m and the other by travel time. To define the activities, we have selected 50 points of interest (POI) within the evaluation region. We have implemented an iterative process to generate a set of 5 activities for each simulation run. For each activity, we randomly selected a geocoordinate from the 50 previously defined POIs, picked a duration between 15 and 60 minutes, and determined whether it should be fixed or flexible. We randomly chose an OSM tag from cafe, restaurant, retail, or bank options for flexible activities. A start time between 8 a.m. and 8 p.m. was randomly selected for the fixed activities. We then checked if the activity could be scheduled with the previously generated activities. If any overlaps were found, the fixed activity was discarded, and a new one was generated until a total of 5 activities were defined for each simulation run. To evaluate the utility function's effectiveness, we used the "true" utility functions

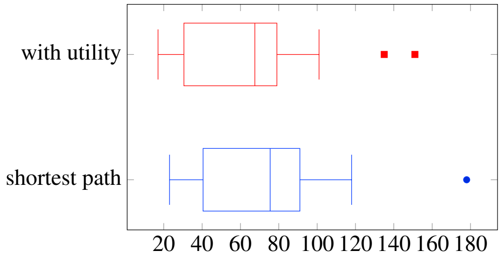

Fig. 3. Average cost distributions of activity plans with and without integration of utilities

U_s and U_m to compare the utility values of both activity plans. Figure 3 illustrates the distributions of the costs of activity plans, calculated with utility functions and using the shortest path. The paired t-test results demonstrate strong evidence of a significant difference in costs (disutility) between the plans. The p-value of 1.028e-10 indicates that the observed difference cannot be attributed to random fluctuations. The simulation shows that integrating the utility function into the activity chain and itinerary optimization results in an average increase of 16.19% in travel utility. This outcome underscores the benefit of considering mobility preferences in the optimization process.

4. Conclusions

This paper proposes a new approach to address the complexities of daily travel planning. The approach optimizes the sequencing and timing of daily activities, incorporates various transport modes, park-and-ride options, and individual mobility preferences. The aim is to provide personalized and efficient travel plans that enhance the accessibility and attractiveness of multimodal transport. The simulation using real-world transport data in a medium-sized German city demonstrated that our approach, on average, enhances the utility of travel by 16.19%. The proposed method could be extended to include additional preferences, particularly when integrated into a travel app with a user base. This would allow for transfer learning and continuous refinement of preference profiles based on user interaction, as suggested in [5]. The mobility preferences, initially estimated through choice experiments, can be more accurately estimated, resulting in an improved travel experience. Additionally, one challenge that must be addressed is the quality of the external data. For example, it can be frustrating for a wheelchair user to encounter a non-working lift during their trip. Real-time data from reliable sources or crowdsourcing could be integrated to address this issue. Furthermore, future studies must evaluate the scalability of the approach.

Acknowledgements

The content of this paper is the result of the project “MobAPlan - Mobility and Activity-based Planing Assistant”. Vector Stiftung (Vector Foundation) funds this research and development project.

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