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Research Article

An Activity-Based Travel Personalization Tool Driven by the Genetic Algorithm

Ali Enes Dingil[1] and Domokos Esztergár-Kiss[2]

[1]*LAMbDA Lab (λ), Faculty of Transportation Sciences, Czech Technical University in Prague, Prague, Czech Republic*
[2]*Faculty of Transportation and Vehicle Engineering, Budapest University of Technology and Economics, Budapest, Hungary*

Correspondence should be addressed to Domokos Esztergár-Kiss; esztergar@mail.bme.hu

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The necessity for an external control mechanism that optimizes daily urban trips becomes evident when considering numerous factors at play within a complex environment. This research introduces an activity-based travel personalization tool that incorporates 10 travel decision-making factors driven by the genetic algorithm. To evaluate the framework, a complex artificial scenario is created comprising six activities in a daily plan. Afterwards, the scenario is simulated for predefined user profiles, and the results of the simulation are compared based on the users' characteristics. The simulations of the scenario successfully demonstrate the appropriate utilization of activity constraints and the efficient implementation of users' spatiotemporal priorities. In comparison to the base case, significant time savings ranging from 31.2% to 70.2% are observed in the daily activity chains of the simulations. These results indicate that the magnitude of time savings in daily activity simulations depends on how users assign values to the travel decision-making parameters, reflecting the attitudinal differences among the predefined users in this study. This tool holds promise for advancing longitudinal travel behavior research, particularly in gaining a more profound understanding of travel patterns.

1. Introduction

An average individual spends approximately 2.65 years, spanning from 12 to 65 years old, engaged in urban mobility [1, 2]. The rapid growth of the global population coupled with car-centric mobility planning has led to a significant disparity between the travel demand and the availability of transportation infrastructure in urban areas [3]. In addition, this situation is exacerbated by the swift pace of urbanization, posing a challenge meeting escalating travel demands within cities. To address these issues, the concepts of mobility management (MM) and transport demand management (TDM) have emerged aiming to alleviate the inefficient utilization of transportation capacity [4, 5]. MM focuses on the reallocating space to favor sustainable modes of transportation, while TDM is centered around modifying the travel behavior to manage the car demand and encourage users to transition to sustainable modes [6]. The advent of the digital age has witnessed the rise of information and communication technology (ICT) in the management of travel demand aligning with transport-related concepts. Consequently, over the past two decades, travel information, planning, and routing services have evolved significantly. Prominent examples include Google Maps, Moovit (i.e., specializing in public transport (PT) planning), and Bike-Citizens (i.e., focusing on cycling planning). These services provide comprehensive layouts of the transportation infrastructure and furnish users with pertinent information regarding locations within urban areas, thus facilitating efficient trip planning processes.

Moreover, the impact of preinformation on travel behavior is examined, highlighting the capacity of ICTs to guide and influence individuals' travel choices [7]. In relation to this, another concept of the consideration in travel information, planning, and routing services is the behavior change support system [8]. The primary objective of integrating the behavior change concept into travel planning services is to shape, manipulate, and transform users' behavior towards more sustainable patterns [9]. Such ICT services can serve as strategic tools across various stages of travel decision-making by providing information and recommendations. An exemplary application, i.e., UbiGo, offers mobility as a service, enabling the testing of novel travel solutions. Based on users' reports, the UbiGo application has successfully reduced the users' reliance on private car usage by 50% through a transition from trial to adoption [10].

On the other hand, modern travel apps come with more advanced personalization features that allow users to tailor their experiences based on preferences, such as avoiding toll roads, choosing specific bike paths, and prioritizing public transportation options. Given the intricate set of variables that characterize today's urban environments, the necessity for an external system to optimize travel is increasingly evident. This study aims to address this need by introducing an activity-based travel personalization tool. The tool considers the ten travel decision-making factors outlined in the subsequent section, while it employs the genetic algorithm (GA) to optimize daily activity sequences.

Following the introduction, the next section provides a thorough literature overview of travel personalization, considering an activity-based approach and examining the key factors influencing travel decision-making. Section 3 elucidates the methodological rationale and outlines the application of the GA in this study. Subsequently, the travel optimization formulation is expounded, encompassing the fitness function for the GA. Section 4 presents the case scenario considering built environment dynamics along with the requisite data requirements and processing steps. In Section 5, the effectiveness of the algorithm is evaluated by simulating an artificial scenario that encompasses three predefined users' profiles. The simulation results are compared and assessed based on these distinct user profiles. Section 6 deals with the main limitations of the study and directions with future work, while in the concluding section, a brief synthesis of the study's key findings is presented.

2. Literature Review

Each individual lives in a distinct built environment and possesses unique needs and preferences, leading to variations in the perceived importance of decision-making factors [11]. Consequently, everyone employs a cognitive control mechanism to optimize their daily trips. However, the need for an external control mechanism to optimize daily urban trips becomes apparent due to the multitude of factors at play within a complex environment. Therefore, travel personalization must be in focus. A travel personalization tool can be defined as a means of adjusting and tailoring travel services to incorporate contextual information and specific preferences, as well as to generate user-centric outputs [12]. Several application trials have attempted to support personalization in urban travel planning by considering certain user's mobility preferences and inputs, such as location, age, and gender [9], thus providing customized travel plans. However, these services have not attained the desired level of comprehensive consideration of factors and resultant measures yet. The literature identifies numerous urban travel decision-making factors that should be taken into account during the decision-making process. Primary factors influencing travel decision-making include travel time, travel time reliability (TTR), and travel cost, as highlighted by numerous studies [13–16]. Additional persuasive factors influencing travel decision-making encompass travel comfort [17–19], travel safety [19, 20], travel quality [21–23], ownership [24–26], weather conditions [27–30], environmental friendliness [17, 31], and healthcare [32, 33], with the latter two assuming greater significance in the light of recent changes in travel behavior due to the COVID-19 pandemic [34].

The literature offers numerous mathematical models that support rational travel planning, among which activity-based travel demand models (ABMs) are particularly a compatible approach with travel personalization tools. In addition, the longitudinal data generated by these tools can play a crucial role in enhancing the realism and accuracy of ABMs. ABMs take into account decision-making processes that underlie participation in a variety of daily activities, including work, education, leisure, errands, and shopping. This comprehensive lens makes ABMs a standard in transportation modeling, offering a more holistic understanding of urban travel behavior [35]. One recent article [36] critically reviews the evolution and gaps in ABMs, assesses the strengths and weaknesses of various modeling techniques, and traces the integration of spatial-temporal and behavioral factors into ABMs. The study emphasizes that current frameworks often neglect to model implicit activity participation decisions and focus mainly on activity scheduling, while there is the need for standardizing activity categories and balancing data requirements with behavioral realism. As stated above, decision-making parameters play a pivotal role in enhancing the modeling of travel behavior. Accordingly, we offer a detailed examination of these decision-making processes presented in the next section, providing a more advanced perspective on the subject.

On the other hand, travel planning tools can supply robust and reliable longitudinal travel behavior datasets, which serve as the cornerstone for developing accurate ABMs. One study [37] introduces a dynamic structural equation model (SEM) focusing on longitudinal data from the Puget Sound transportation panel to explore complex causal connections between sociodemographics, activity engagement, and travel behavior. The study findings offer valuable insights into the activity-based approach, enhancing its utility in transportation planning and policy development. Also, the authors in [38] using longitudinal data from the transportation tomorrow surveys conducted an analysis of activity generation behavior in the Greater Toronto and Hamilton Area (GTHA) with year-specific and joint models to investigate study area dynamics and activity types. Leveraging social media platforms as data collection tools for activity behavior presents an alternative yet promising avenue. For example, the authors in [39] used geotagged tweets as longitudinal observations for the activity pattern estimation. Similarly, another study conducted by

[40] emphasizes the importance of utilizing longitudinal geolocation data obtained from social media platforms, where users freely share their activity-related preferences. The study illuminates how these emerging data sources substantially enhance our understanding of human activity patterns, providing insights for the realms of transportation planning and policy. Moreover, the study demonstrates the potential for augmenting conventional activity-based diaries by integrating them with the wealth of longitudinal geospatial information available through social media tools.

A recent study [41] discusses the present status of activity-based travel demand modeling. Global researchers are investigating how to optimally leverage the growing abundance of passive location data, such as cellphone and GPS traces or transit smartcard data to model activity patterns. The study highlights that while these large, dynamic datasets are promising, their anonymized nature and varying spatial-temporal accuracy present hurdles for activity-based modeling. In addition, most traditional household travel surveys lack comprehensive data for all members, complicating the shift towards a household-centric approach in an era of individualized, anonymous tracking data. As information and communication technology (ICT)-based tools proliferate, they contribute a rich content of mobility data that plays a pivotal role in understanding activity patterns and shaping sustainable transport planning. However, these tools are generally not designed to capture activity-based travel patterns, which is the focal point of our current study. Our work presents and tests an activity-based travel personalization tool, driven by the genetic algorithm (GA) considering built environment dynamics. The subsequent section will elaborate on the methodological framework and demonstrate how the GA can optimize activity chains within the context of travel personalization.

3. Methodology

This section provides a detailed explanation of the methodological framework, specifically focusing on the application of the genetic algorithm (GA) in our study. It then elaborates on the travel optimization formulation, including the design of the GA's fitness function.

3.1. The Applied Algorithm. In this section, we present the employment of the genetic algorithm (GA) framework for orchestrating daily travel activities. The GA's optimization capabilities make it a preferred choice for tackling complex issues in transportation planning. Its strengths lie in its ability to efficiently navigate expansive solution spaces, manage nonlinear objective functions, accommodate a range of goals, and flexibly integrate constraints. The versatility of the GA in transportation planning is well-documented across many academic reviews, and the GA is the most typically used optimization algorithm for optimal route recommendations [42–45]. For example, one study [46] utilized the GA to fine-tune the arrival and departure times of trains to better align with passenger schedules, while another application of the GA [47] was used to optimize the establishment of cordon sanitaire for controlling epidemics, taking intricate transportation systems into account. In the context of our current research, we employ the GA framework to streamline daily travel sequences based on predetermined activities. Prior studies have validated the efficacy of the GA in solving similar transportation planning problems rooted in an activity-based approach. For example, one such research effort [48] explored the optimization of individualistic daily activity chains in relation to the built environment, while another investigation [49] used a co-evolutionary approach to optimize daily activity sequences for large populations. These preceding studies not only underscore the broad applicability of the GA framework but also highlight its proven effectiveness in addressing the complex challenges found in activity-based transportation planning optimization. Primarily, adopting the methodology outlined in [48], the present GA concentrates on individualized planning, while it aims to closely mirror the dynamics of the built environment.

Figure 1 depicts the GA framework applied in current study. The GA comprises five distinct phases aimed at identifying the most optimal solution from the population of daily plan solutions. These phases involve the initial population, fitness function, selection, crossover, and mutation. The initial population includes a collection of individual daily plan solutions, i.e., referred to as chromosomes. These chromosomes are generated by mutating a set of activity variables, a.k.a. genes, which are derived from the user inputs. The initial genes encompass the user's location, the type of activities used to filter the locations in the facility database, the sequence of daily activities, and the designated time windows for each activity in the sequence (i.e., arrival and departure times).

In certain situations, the location or timing of our activities, such as work, education, or errands, can be fixed, whereas other activities such as shopping and leisure offer more flexibility. To account for these variations, we incorporate predefined constraints within the GA. Prior to the execution of the GA, a preconstraint phase is implemented to establish the initial pool of daily plan solutions, considering personal preferences.

This process also aims to reduce the high number of chromosomes in the solution pool, thereby enhancing the efficiency of the GA and expediting the processing time of the application. The preoptimization procedure relies on the spatiotemporal priorities specified by the users. Four spatiotemporal priority options are defined based on the user-provided information for each daily activity in the chain. The first option is spatiotemporally fixed; thus, it is ensured that the selected facility and the requested time windows remain unaltered. The second option allows spatial flexibility, meaning that the selected activity locations can vary, while the demanded time windows remain fixed. The third option provides temporal flexibility, allowing changes in demanded time windows while maintaining fixed activity locations. Lastly, the fourth option, i.e., spatiotemporally flexible, permits adjustments to both the locations of the selected activities and the demanded time windows within the chain.

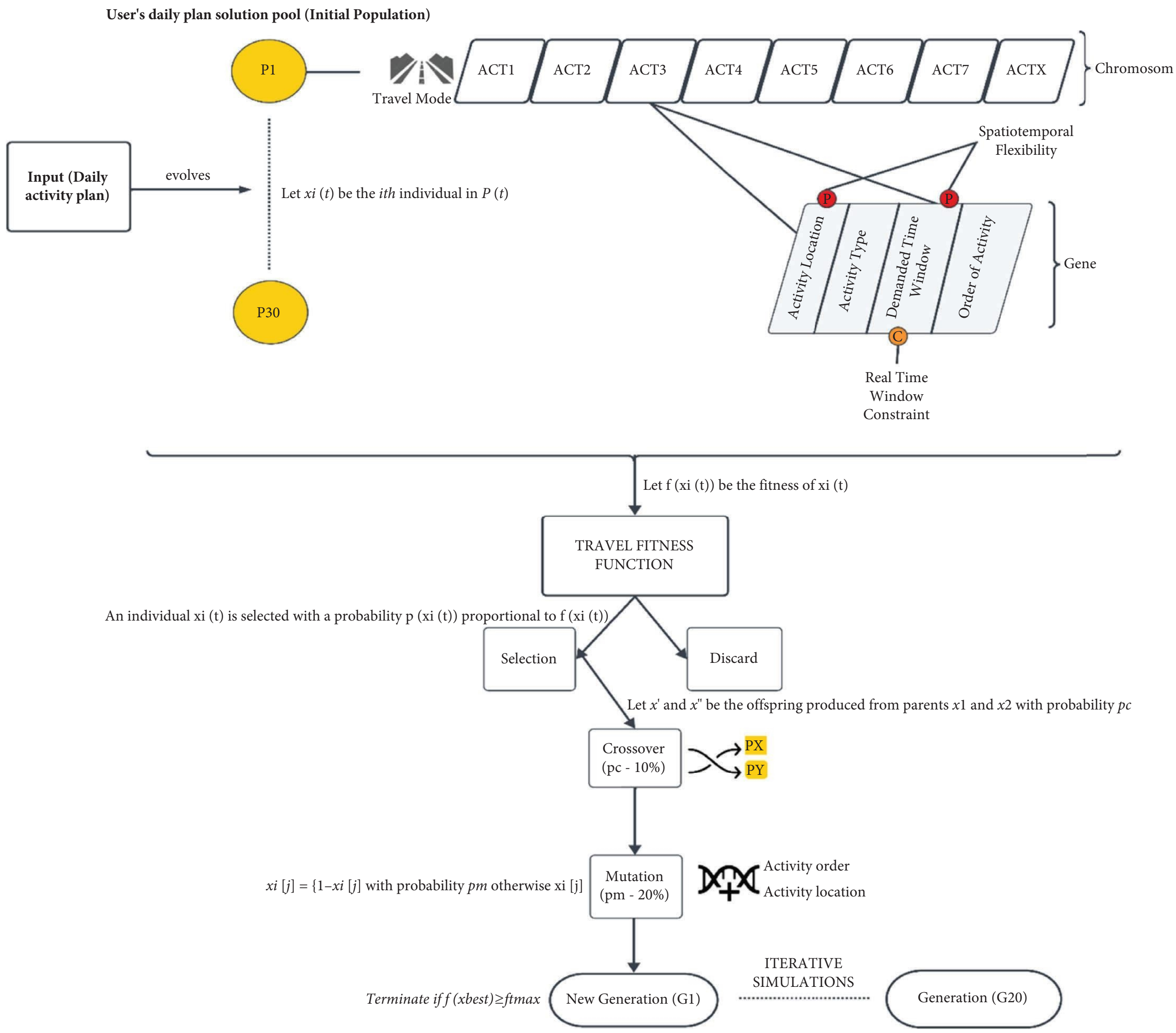

Figure 1: Genetic framework for the organization of daily plans.

For instance, if a user sets the third priority option for any activity in the chain, all other spatial options in the facility database for that activity are disregarded. However, users may not possess accurate real-time information regarding the time windows of facilities. Therefore, all chromosomes are subjected to certain constraints, such as verifying the validity of the selected facilities based on real-time information. The demanded time windows are compared with the real-time information stored in the facility database, and the algorithm generates an error message if demanded time windows do not align with the actual time windows of the facilities.

Once the initial phase is completed, the initial daily plan solution pool undergoes evolution to generate a new population comprising additional potential plans. The fitness function plays a crucial role in determining the direction of this evolution by serving as a metric for assessing the fitness level of each individual daily plan solution. The fitness function utilizes the travel optimization formula, discussed in the subsequent subsection, to evaluate different daily trip chains for evolutionary purposes. Each plan solution is assigned a fitness score calculated by the algorithm taking the 10 parameters introduced in the optimization function into account. These parameters, involving both minimization and maximization objectives, guide the evolution of the solutions. The weights assigned to these parameters are predetermined by the users prior to the execution of the algorithm. The algorithm defines the recognition and calculation methods for these parameters, which are elucidated in the subsequent subsection. While certain technical values and user experience valuations are incorporated as default values in the algorithm, as explained in the next section, users have the flexibility to customize these parameters based on their individual experiences.

Following the evaluation of the plan fitness by using travel utility scores, the algorithm proceeds to generate a new generation of daily plan solutions. Selection is performed in the selection phase, thus favoring the individual plan solutions with higher fitness scores for reproduction. Two pairs of parents consisting of daily plan solutions are randomly selected for reproduction, while some plan solutions in the population are discarded during this process. The selected parents serve as the basis for the new generation, and the crossover phase involves the mating process between each pair of parents. Offspring are created in the same positions as their respective parents, enhancing the mating process. The recombination of the chromosomes from the parent pool involves the exchange of genes between each pair of parents potentially altering the sequence of daily activities within the chain based on the initially set spatiotemporal priority. The mutation phase aims to introduce diversity among candidate daily plan solutions. A low random probability triggers gene changes in some newly formed offspring. This process randomly swaps the facilities with their alternatives and modifies the order of the activities according to the spatiotemporal priority. For the simulation, the following parameters are set: an initial population size of 30 daily plans, a 10% crossover probability, a 20% mutation probability, and 20 generations. Upon the completion of all phases, the algorithm terminates yielding the best-fit solution from the final generation as the output.

3.2. Fitness Function. Section 2 highlights the factors influencing the travel decision-making process. Building upon this, the formulation of the fitness function based on 10 identified travel decision-making parameters is conducted. Prior to initiating any daily activity chains, individuals engage in self-cognitive evaluation based on utility factors. This evaluation takes the specific needs, desires, and benefits associated with transportation modes within a given built environment and at a particular time into account. When selecting from the available alternatives, individuals make decisions that aim to maximize their daily travel utility. To achieve the maximum overall travel utility, certain parameters must be maximized while considering the weight of an individual's attitude; at the same time, other parameters need to be minimized. The general travel utility function, a.k.a. the fitness function, is formulated for use in the GA as follows:

$$V_{i\sigma} = \sum X_{\mathrm{ij}}\beta_{\mathrm{ij}} - \sum Z_{\mathrm{ik}}\mu_{\mathrm{ik}}. \tag{1}$$

The dependent variable $V_{i\sigma}$ is the utility value of mode choice "σ" for trip maker "i". The independent variable X_{ij} presents the maximization attribute of trip maker "i" for parameter "j", while Z_{ik} is the minimization attribute of trip maker "i" for parameter "k". β_{ij} and μ_{ik} are independent parameter weights for trip maker "i". To harmonize with the travel decision-making factors, the utility function of mode choice "σ" for trip maker "i" is formulated as follows:

$$\begin{aligned} V_{i\sigma} &= \beta_{\mathrm{ai}} * A_i + \beta_{\mathrm{hi}} * H_i + \beta_{\mathrm{cmi}} * \mathrm{CM}_i + \beta_{\mathrm{si}} * S_i + \beta_{\mathrm{wi}} * W_i + \beta_{\mathrm{qi}} * Q_i + \beta_{\mathrm{ci}} * \mathrm{PP}_i \\ &\quad - \mu_{\mathrm{tri}} * \mathrm{TTR}_i - \mu_{\mathrm{ei}} * E_i - \mu_{\mathrm{ti}} * T_{\mathrm{vi}} \\ V_{i\sigma} &= \beta_{\mathrm{ai}} * A_i + \beta_{\mathrm{hi}} * \ln\ (\mathrm{Calorie}_i) + \beta_{\mathrm{cmi}} * \mathrm{CM}_i + \beta_{\mathrm{si}} * S_i + (\beta_{\mathrm{wt}} * W_t + \beta_{\mathrm{wh}} * W_h + \beta_{\mathrm{aa}} * W_w + \beta_{\mathrm{ww}} * W_r + \beta_{\mathrm{ws}} * W_s) \\ &\quad + \beta_{\mathrm{qi}} * Q_i + \beta_{\mathrm{ci}} * \ln\left(\frac{(\mathrm{Income}/30)}{C_t}\right)_i - \mu_{\mathrm{tri}} * \left(\frac{T_t}{T_v}\right)_i - \mu_{\mathrm{ei}} * \ln\ (\mathrm{CO2}_i) - \mu_{\mathrm{ti}} * T_{\mathrm{vi}}. \end{aligned} \tag{2}$$

In this study, regarding minimization, the focus is on the following three main attributes: absolute travel time, relative ratio of total travel time, and environmental impact. The absolute travel time T_{vi} represents the expected in-vehicle travel time without considering congestion delays, while congestion delays are separately accounted for as T_{ci}. The metric for travel time reliability is quantified by the relative ratio of total travel time to absolute travel time, denoted as TTR_i. This measure serves as an indicator of reliability, with a lower ratio yielding utility gains in the context of mode choice, represented by the variable "σ." The total travel time variable T_{ti} is calculated as the sum of the absolute in-vehicle travel time, delay time, out-vehicle travel time (i.e., including waiting and transfer time), and parking time. The out-vehicle travel time is calculated for the PT mode, while parking time is considered for the car mode. In addition, the environmental impact parameter E_i, which represents CO_2 emissions per passenger-kilometer in logarithmic form for both car and PT travel modes, is incorporated. Logarithmic transformation was employed during the computation of certain variables exhibiting diminishing returns as depicted in the equation.

The maximization attributes in this study encompass various factors that contribute to the travel decision-making process. These factors include the purchasing power PP_i, travel comfort C_t, travel quality Q_i, travel safety S_i, availability A_i, travel mode performance under weather conditions W_i, and health contribution H_i. The purchasing power is determined by the relative ratio of the daily income to the total trip costs C_t in the logarithmic form. The trip costs for the different modes can be calculated based on the running costs per kilometer. For the car mode, this includes such expenses as gasoline, maintenance, tires, cleaning, congestion, parking, and road toll costs. The costs of PT are represented by the ticket costs or the equivalent cost of a monthly pass per day. The costs of cycling are based on the maintenance costs per kilometer, while the costs of walking can be estimated by using the lifetime cost of shoes per kilometer walked. The health contribution reflects how many calories in the logarithmic form are burned during the travel time in the case of mode choice "σ." The availability parameter indicates whether the individual owns or holds a monthly pass for the chosen mode. The travel comfort, travel safety, and travel quality parameters represent the average performance ranking of mode choice "σ" in a given city. In addition, the parameter W_i captures the transportation mode performance under specific weather conditions. It considers the average performance ranking of the mode choice "σ" under various weather conditions including rain, snow, temperature, humidity, and wind. These factors collectively contribute to the assessment of the travel decision-making process and aid in selecting the optimal mode of transportation.

4. Case Study

In this section, we present the case scenario, primarily detailing the necessary datasets required and also various processing steps involved to prepare and integrate the data into the algorithm. Following this, we elaborate on a simulation scenario featuring three predefined user profiles, each with unique characteristics, to further illustrate the study's applications.

4.1. Data Requirements and Processing. In this study, for the simulation, the built environment of Budapest serves as the test environment. To ensure the functionality of the GA, several data requirements need to be fulfilled including the real transportation infrastructure map, the spatiotemporal data of the facilities, and the spatiotemporal information of the PT network. To obtain data on the real transportation infrastructure and the spatiotemporal information of the facilities in Budapest, OpenStreetMap (OSM) is applied. OSM relies on volunteer contributions for geocoding, which can lead to some potential errors, particularly concerning PT stops and routes. To mitigate these errors, the spatiotemporal data of the PT system are sourced from the local authority BKK (Centre for Budapest Transport) in the general transit feed specification (GTFS) format. The GTFS provides comprehensive information on the time schedules and associated geographical data. In order to simplify the location search and facilitate the identification of the facility locations, the spatiotemporal data of the facilities are clustered based on the similarity of facilities. The resulted spatiotemporal database comprises 57,350 locations encompassing 935 types of facilities. Following the simplification process, the database is streamlined to include 84 main types of facilities. Some examples of these clusters include bar and pub, beauty and cosmetics, cinema and theater, fast food, shopping center, and baby care. By leveraging these data sources and applying appropriate clustering techniques, the study ensures a comprehensive representation of the transportation infrastructure, facilities, and their spatiotemporal characteristics in Budapest, thus facilitating simulations and analyses within the GA framework.

To provide default travel parameter values specific to Budapest for the tool, a travel survey conducted by the Budapest University of Technology is utilized in this study. The survey consists of 285 samples and focuses on participants who reside in Budapest. The survey data were collected within a specific timeline, from October 15 to November 15, 2020. The survey employs a Likert-7 scale to inquire about transportation mode parameters. Participants are asked to rate various factors related to travel modes, such as travel comfort, travel safety, travel quality, and travel mode performance under different weather conditions (i.e., rainy, snowy, hot, cold, windy, and humid). In addition, the survey collects information on the average time spent by the participants on finding a car parking place and the average out-vehicle travel time when using PT. The mean values obtained from the survey responses for each transportation mode are used as default values within the algorithm. These values include travel comfort, travel safety, travel quality parameters, travel mode performance under weather conditions, out-vehicle travel time (i.e., for PT-related planning solutions), and parking time (i.e., for car-related planning solutions). Utilizing average values from the survey data for these parameters does not pose any challenges in testing the algorithm. Furthermore, the algorithm calculates the TTR parameter incorporating data from the survey. With these parameter values derived from the travel survey, the algorithm is set to the default mode for the daily travel planning solutions, ensuring better reflection of the representation of the travel preferences and experiences in the city.

The ownership parameter, which indicates whether the user owns a monthly pass for a particular transportation mode, is determined by the user and can be set as either 0 or 1 depending on the mode of transportation. The algorithm calculates the purchasing power based on the user's income inputs, which are specified at the beginning of the process. Furthermore, travel costs are calculated by the algorithm, taking the chosen transportation mode into account as outlined in the formulation. For such modes as car, bike, and walking, running costs are computed based on the distance covered during the activity chain. In contrast, the costs associated with PT remain constant and are determined by the ticket or monthly pass prices. To determine the average running costs per kilometer for different transportation modes, a comparative study [50] provides reliable information for the algorithm.

To facilitate the functioning of the mechanism, a routing algorithm is essential. In this case, OpenTripPlanner 1.4 (OTP), i.e., an open-source multimodal routing algorithm, is employed. OTP utilizes OSM infrastructure and GTFS data [51] to generate routes and calculate travel distances and times. The OTP router is responsible for determining the absolute in-vehicle travel time and travel distance to facilities within the activity chain. By utilizing travel routes obtained from OTP, these metrics are accurately computed. It is important to note that the OTP router calculates the travel time without considering the impact of road congestion, which is particularly significant for car and bus users who rely on TTR. To address this concern and incorporate the influence of road congestion, the algorithm integrates

TomTom API, and to the best of our knowledge, this is the first attempt of its kind. The TomTom traffic-monitoring service leverages data from millions of mobile phones, government-owned cameras, road sensors, and millions of connected GPS devices to monitor traffic conditions [3]. By utilizing TomTom API, the algorithm estimates the traffic conditions and incorporates the date-based travel time increase, thus offering insights into traffic conditions relevant to activity chains. The historical database provided by TomTom API includes the percentage increase in travel time on an hourly basis for each day of the year. In addition, the algorithm has the capability to provide real-time traffic information by using TomTom API. However, for predicting the percentage increase in travel time for activity chains, the historical database is utilized. By utilizing both OTP and TomTom API, the algorithm ensures accurate routing calculations and incorporates real-time and historical traffic information to enhance better precision of the travel time estimates for users' activity chains.

The framework is integrated with OpenWeatherMap API to retrieve real-time weather information. OpenWeatherMap is an open-source online service that offers comprehensive data on current weather conditions, such as precipitation, humidity, wind, and temperature. In the algorithm, provisions are made to automatically identify the type of precipitation, whether it is rain or snow, if any is expected prior to commencing the journey. To enable the algorithm to interpret the weather conditions, specific thresholds have been defined. These thresholds include categorizing temperatures above 29°C as hot, temperatures below 15°C as cold, humidity levels above 49% as humid, and wind speeds exceeding 10 m/s as windy. By incorporating OpenWeatherMap API and utilizing these defined thresholds, the algorithm can accurately assess the prevailing weather situation.

The framework utilizes the Harris–Benedict equation to calculate the health contribution, which is determined by the total number of calories burned during the in-vehicle time. This calculation takes the basal metabolic rate (BMR), travel time, and activity level into account. The BMR is calculated by using the personal inputs provided by users including age, gender, weight, and height, which are collected prior to running the algorithm. The activity level is determined by the transportation mode; with each level (i.e., light, moderate, and heavy), different weights are assigned. The default activity levels are set to light for driving and PT, moderate for walking, and heavy for biking. These activity levels play a role in estimating calories burned during the travel time. To assess environmental friendliness, the framework calculates total CO_2 emissions associated with the transportation mode and travel distance throughout the activity chain. This calculation relies on an average value of CO_2 emissions per kilometer per passenger extracted from a dataset [52]. By incorporating these data, the environmental impacts of transportation modes can be evaluated in terms of CO_2 emissions.

4.2. Simulation Scenario. In this section, an overview of the simulation scenario is provided. To observe how the algorithm output varies under different conditions, three predefined user profiles with distinct characteristics are created. Table 1 presents the predefined users' attitudes towards the travel decision parameters along with their sociodemographic information and urban weather conditions. The users share the same age (29), weight (72 kg), and height (1.74 m). However, several assumptions about the urban weather conditions are made for each user as follows:

(i) User A plans daily activities under favorable weather conditions, i.e., a temperature of around 20°C, dry conditions (i.e., humidity below 45%), low wind speed (i.e., below 10 m/s), and no precipitation expected.

(ii) User B plans daily activities under cold, snowy, and windy weather conditions. The temperature is approximately −5°C with dry conditions (i.e., humidity below 45%) and a wind speed of 13 m/s.

(iii) User C plans daily activities under hot weather conditions with a temperature of around 35°C, high humidity (i.e., 70%), low wind speed (i.e., below 10 m/s), and no precipitation expected.

Table 2 illustrates a detailed input of a complex daily activity scenario. The initial activity chain, which remains the same for all predefined users, is presented. The table provides information about the six activities in the chain and the corresponding seven travel routes required to complete them. For each daily activity, the table includes the activity ID, geographic location, type of activity, processing time, the time windows of the selected activity locations (i.e., indicating the opening and closing time), the spatiotemporal priority of each activity in the chain, and the desired time windows for each activity (i.e., indicating the starting and closing time). In addition, Figure 2 visually represents the geographic locations of the input activities, where each activity is labeled by its corresponding activity ID (i.e., the order ID). The map serves as a visual aid for better understanding activity locations and their arrangement. The subsequent section focuses on presenting and evaluating the results of the simulation derived from these input data.

5. Simulation Results

In this section, the daily activity chain presented above is simulated by using the GA framework. This simulation incorporates predefined user inputs and takes into account the influence of the built environment dynamics. The optimization results, including the order of the activities based on the transportation modes, are displayed for each predefined user in Tables 3–5. Furthermore, the optimized activity locations for each best-fit solution along with their corresponding order numbers are visualized in Figures 3–5. Please note that the numbers displayed in the figures do not represent the ID of the activity. Instead, they indicate the order of the activities in the chain for the respective solutions.

Table 3 presents the results of the optimization for user A's daily activity chain, showcasing the best-fit solution based on alternative modes. User A prioritizes factors such

Table 1: Predefined user profiles.

Users	Attitude
User A	User A is a male from the low middle class with a monthly income of 900€. He owns a bike, a car, and a PT monthly pass. When it comes to his attitude towards the optimization parameters, he assigns a high importance degree to the following factors: travel costs, TTR, CO_2 emissions, burnt calories, and specific weather conditions such as cold and rainy. For the parameters of travel time, travel safety, ownership, and other weather conditions such as snowy, humid, and windy, he has a moderate importance degree. Lastly, he assigns a low importance degree to travel comfort, travel quality, and the weather condition of hot weather
User B	User B is a female from the middle class with a monthly income of 1300€. She owns a bike and a PT monthly pass. When considering her attitude towards the optimization parameters, she assigns a high importance degree to specific weather conditions such as hot and humid. For the parameters of travel time, travel costs, TTR, ownership, travel comfort, travel quality, travel safety, and other weather conditions such as rainy and windy, she has a moderate importance degree. Lastly, she assigns a low importance degree to the parameters of CO_2 emissions, burnt calories, and weather conditions of cold and snowy weather
User C	User C is a male from the upper middle class with a monthly income of 1750€. He owns a bike, a car, and a PT monthly pass. When considering his attitude towards the optimization parameters, he assigns a high importance degree to travel comfort, travel quality, travel safety, and specific weather conditions such as cold, snowy, and windy. For the parameters of travel time, TTR, ownership, and the weather condition of rainy weather, he has a moderate importance degree. Lastly, he assigns a low importance degree to the parameters of CO_2 emissions, burnt calories, travel costs, and weather conditions of hot and humid weather

Table 2: The input information of the daily activities.

Activity types	The ID of the activity	Latitude	Longitude	Activity processing time	Spatiotemporal priority	Activity location TW open	Activity location TW close	Demanded starting time	Demanded closing time
Start (home)	0	47,50243	19,05297	0	1	00:00	23:59	08:00	19:30
College	1	47,48147	19,05563	300	1	07:00	22:00	09:00	14:00
Asian restaurant	2	47,48829	19,05813	45	2	12:00	23:00	14:30	15:15
Hair salon	3	47,50774	19,05468	30	4	09:00	19:00	15:45	16:15
Bookshop	4	47,49606	19,05629	30	3	08:00	21:00	16:45	17:15
Pharmacy and health	5	47,50682	19,05230	20	4	08:00	20:00	17:45	18:05
Electronics store	6	47,51398	19,05925	20	4	08:00	20:00	18:30	18:50
End (home)	7	47,5024	19,05297	0	1	00:00	23:59	08:00	19:30

as travel costs, environmental friendliness, burnt calories, cold and rainy weather conditions, and TTR. The other travel decision-making factors are considered moderately important by user A, except for the following parameters which are given low importance: travel comfort, travel quality, and hot weather conditions. Taking these preferences into account, the algorithm suggests a cycling-based daily activity chain as the best-fit solution for user A, as shown in Table 3. As depicted in Figure 3, the algorithm aims to increase the burnt calories throughout the day while moderately considering a reduction in travel time. The total absolute travel time for user A is 42 minutes, which is 31.2% less than the base scenario when cycling is chosen. To optimize the activity chain, the algorithm creates two clusters of nearby activities for user A by leveraging priority options to minimize the travel time and maximize burnt calories by increasing the distance between the activity zones. Initially, the user is directed to activity ID 1, which is the farthest point from the home location. Subsequently, the user is guided to a cluster of nearby activities near the home location comprising activity IDs 2, 6, and 5. Afterwards, the user is advised to proceed with another activity cluster consisting of activity IDs 3 and 4.

The algorithm offers a midfit daily activity scheduling solution for user A, which is based on PT and walking. In this case, the total absolute travel time is reduced to 24.2 minutes, representing a 68% reduction compared to the base case of using PT alone. The algorithm guides the user to take the metro line for activity ID 6 and continue using the same mode for the spatiotemporally fixed activity (i.e., ID 1). A cluster of nearby activities is formed consisting of activity IDs 5, 2, and 4, which are all within a few

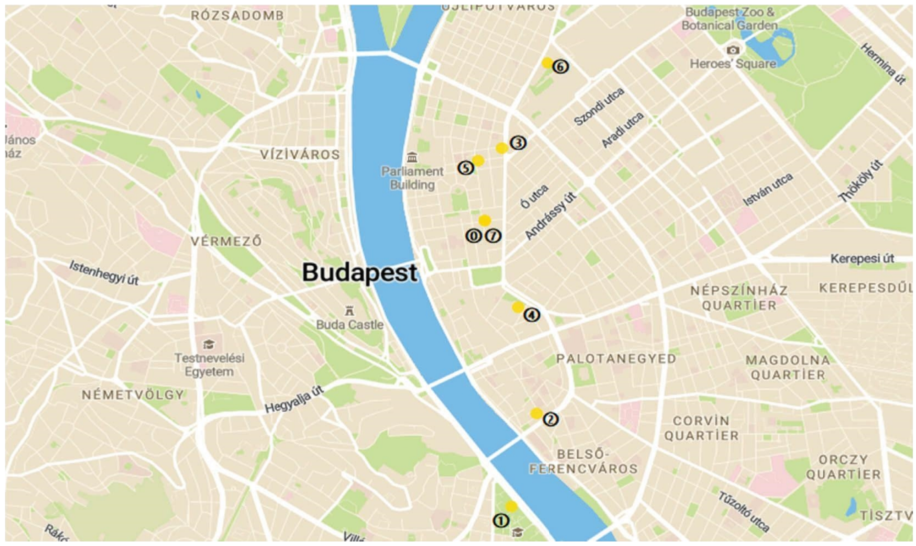

Figure 2: The input locations and their sequence in the daily activity chain.

Table 3: The results of user A's daily activity chain optimization.

User A								
The best-fit solution offered			The best-fit solution of the alternative modes					
Cycling			PT + walking			Car		
The IDs of the activities in an order	Start time	End time	The IDs of the activities in an order	Start time	End time	The IDs of the activities in an order	Start time	End time
0		08:45	0 M		08:00	0		08:00
1	09:00	14:00	6* T	08:03	08:23	6*	08:01	08:21
2*	14:30	15:15	1 T	09:00	14:00	1	09:00	14:00
6*	15:17	15:37	5* W	14:05	14:25	2*	14:30	15:15
5*	15:37	15:57	2* W	14:30	15:15	4	15:16	15:46
3*	16:02	16:32	4 M	15:16	15:46	3*	15:46	16:16
4	16:32	17:02	3* W	15:48	16:18	5*	16:18	16:38
7	17:09		7	16:19		7	16:41	
Total absolute travel time: 42 minutes Estimated congestion delay: 0 minute Estimated out-vehicle time: 0 minute Utility score: 4038.2			Total absolute travel time: 24.2 minutes Estimated congestion delay: 0 minute Estimated out-vehicle time: 15 minutes Utility score: 1559.9			Total absolute travel time: 31.7 minutes Estimated congestion delay: 17.52 minutes Estimated out-vehicle time: 0 minute Utility score: 893.3		

M = metro, T = tram, W = walking; * = flexible location priority.

minutes of walking distance. Finally, the last activity (i.e., ID 3) is located near the home to complete the activity chain. On the other hand, for the low-fit daily activity chain solution, the algorithm suggests a car-based approach for user A. The algorithm aims to minimize the travel time of the car mode by clustering nearby activities in the order of activity IDs 2, 4, and 3. This clustering helps reduce CO_2 emissions and enhance TTR. In addition, the algorithm identifies nearby home activity locations for the first and last activities (i.e., IDs 5 and 6).

Table 4 presents the results of the daily activity chain optimization for user B including the best-fit solution by using alternative modes. The algorithm suggests a PT and walking-based solution for user B. User B's main concerns revolve around adverse weather conditions, specifically hot and humid conditions. Other travel decision-making factors are considered at a moderate level, except for CO_2 emissions, cold and snowy weather conditions, and burnt calories. The total absolute travel time for user B is 23.3 minutes, which is a significant 70.2% reduction compared to the base scenario when using PT alone. This reduction is slightly higher than in the case of user A, demonstrating the effectiveness of the algorithm in minimizing the travel time for user B. In the recommended solution, the algorithm utilizes the metro mode for reaching activity locations with IDs 1, 2, 5, and 6. Activities 3 and 6, which serve as the first and last activities in the chain, are conveniently located near the user's home. In addition, the algorithm clusters nearby activities with IDs 2, 4, and 5.

As an alternative solution, cycling is considered for user B, resulting in an expected total absolute travel time of 34.6 minutes. This represents a 43.3% reduction compared to the base scenario where using cycling alone. In comparison to user A, the algorithm achieves a greater reduction in the

Table 4: The results of user B's daily activity chain optimization.

User B					
The best-fit solution offered			The best-fit solution with the alternative mode		
PT + walking			Cycling		
The IDs of the activities in an order	Start time	End time	The IDs of the activities in an order	Start time	End time
0 M		08:00	0		08:00
6* M	08:03	08:23	6*	08:05	08:25
1 M	09:00	14:00	1	09:00	14:00
2* W	14:30	15:15	2*	14:30	15:15
4 W	15:16	15:46	4	15:17	15:47
5* M	15:46	16:06	3*	15:47	16:17
3* W	16:08	16:38	5*	16:19	16:39
7	16:39		7	16:43	
Total absolute travel time: 23.3 minutes Estimated congestion delay 0 minute Estimated out-vehicle time: 20 minutes Utility score: 868.7			Total absolute travel time: 34.6 minutes Estimated congestion delay: 0 minute Estimated out-vehicle time: 0 minute Utility score: 195.8		

M = metro, T = tram, W = walking; * = flexible location priority.

Table 5: The results of user C's daily activity chain optimization.

User C								
The best-fit solution offered			The best-fit solution of the alternative modes					
Car			PT + walking			Cycling		
The IDs of the activities in an order	Start time	End time	The IDs of the activities in an order	Start time	End time	The IDs of the activities in an order	Start time	End time
0		08:00	0 T***		08:42	0		08:00
3*	08:02	08:32	1 T	09:00	14:00	4	08:06	08:36
1	09:00	14:00	2* W	14:30	15:15	1	09:00	14:00
2*	14:30	15:15	4 W	15:16	15:46	2*	14:30	15:15
4	15:16	15:46	6* W	15:46	16:06	5*	15:15	15:35
6*	15:47	16:07	3* M	16:06	16:36	3*	15:38	16:08
5*	16:07	16:27	5* W	16:38	16:58	6*	16:09	16:29
7	16:32		7	16:59		7	16:30	
Total absolute travel time: 31.5 minutes Estimated congestion delay: 16.72 minutes Estimated out-vehicle time: 0 minute Utility score: 5624.2			Total absolute travel time: 27.8 minutes Estimated congestion delay: 0 minute Estimated out-vehicle time: 15 minutes Utility score: 4602.2			Total absolute travel time: 32.4 minutes Estimated congestion delay: 0 minute Estimated out-vehicle time: 0 minute Utility score: 3710		

M = metro, T = tram, W = walking; ∗ = flexible location priority.

travel time of cycling for user B. This difference is mainly due to user B assigning a lower importance level to burnt calories during daily activities. Furthermore, the algorithm optimizes the cycling mode by prioritizing other parameters that user B considers moderately important. The algorithm guides the user to a location between the home and the spatiotemporally fixed activity location (i.e., ID 1) for the first activity. After completing the first activity, the user proceeds to activity location ID 1. Considering priority options, the algorithm creates a cluster of nearby activities, which include activities with IDs 2, 4, 3, and 5.

Table 5 presents the results of the daily activity chain optimization for user C, demonstrating the best-fit solution when using alternative modes. The algorithm suggests a car-based planning solution as the optimal choice for user C. User C's primary concerns revolve around travel comfort, travel quality, travel safety, and adverse weather conditions such as cold, snowy, and windy. Other optimization factors are considered at a moderate level, except for travel costs, CO_2 emissions, hot and humid weather conditions, and burnt calories. The total absolute travel time for user C is 31.5 minutes, representing a significant 48% reduction compared to the base car scenario. To minimize the travel time of car and enhance TTR, the algorithm creates a cluster of nearby activities in the following order: activity IDs 6, 5, 3, and 4. The midfit solution for user C involves the PT and walking modes. The total absolute travel time is 27.8 minutes, which is a substantial 64.4% reduction compared to the base scenario of using PT and walking alone. The algorithm identifies a cluster of nearby activities, including activity IDs 2,

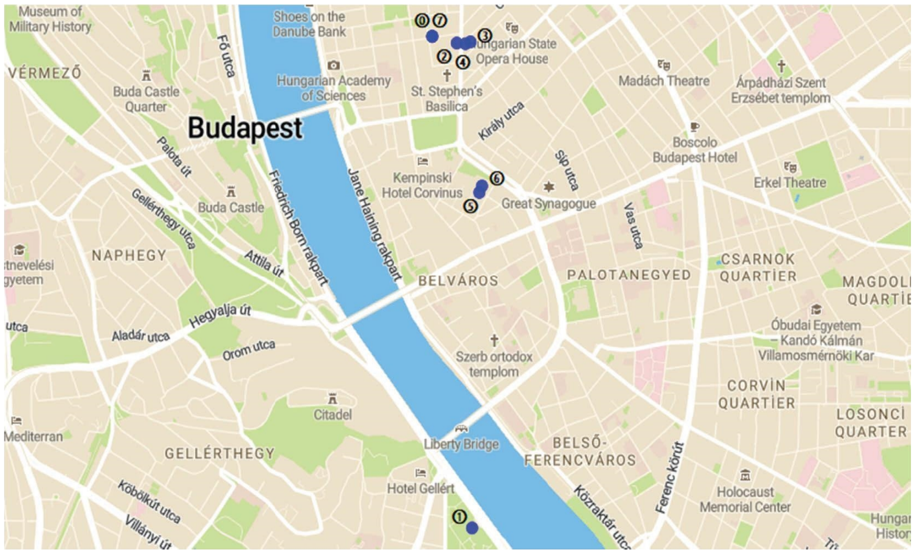

Figure 3: Best-fit solution for the activity locations and their sequence in user A's daily activity chain.

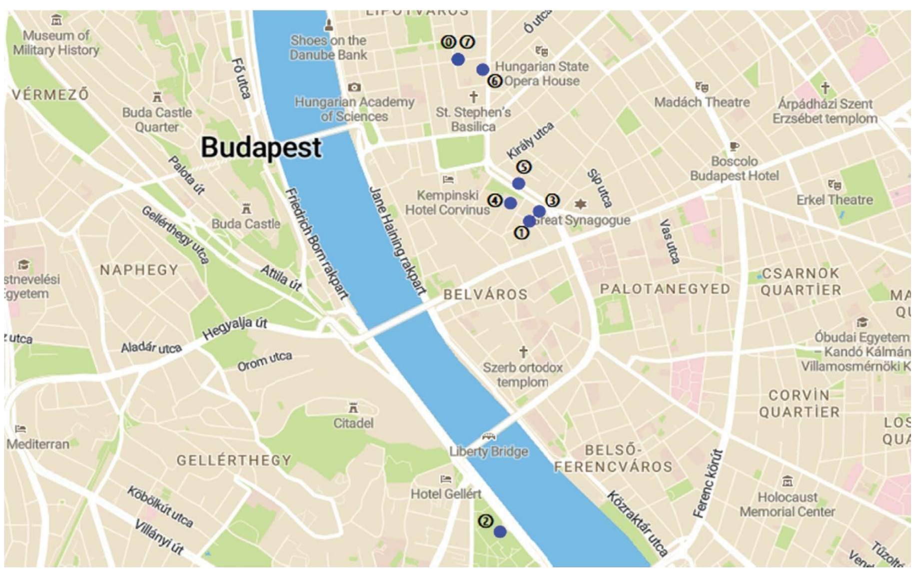

Figure 4: Best-fit solution for the activity locations and their sequence in user B's daily activity chain.

4, 6, and 3, utilizing spatiotemporal priorities to minimize the travel time in case of PT and increase TTR.

The low-fit solution recommended by the algorithm is cycling based. The total absolute travel time is 32.4 minutes, thus representing a 47% reduction compared to the base cycling scenario. This reduction is higher than the simulated cycling scenarios for users A and B. User C assigns the least importance to the parameters that give prominence to the bike mode. Therefore, the algorithm focuses on optimizing the travel time to a greater extent. Initially, the algorithm guides the user to activity ID 4 on the way to spatiotemporally fixed activity ID 1. Subsequently, two clusters are suggested to complete the activity chain: the first cluster comprises nearby activities with activity IDs 2 and 5, and the last cluster includes activity IDs 3 and 6, which are conveniently located near the user's home.

The optimization process leads to noticeable changes in the users' initial daily activity plans, as evident in the output tables. These changes encompass the activity sequence, preferred facilities, and demanded time windows for each activity. The extent of these changes is determined by spatiotemporal priorities set prior to running the algorithm. In the output tables, it is observed that when a priority value of four is assigned, the algorithm is granted the flexibility to modify both the spatial and temporal aspects of the activities to achieve a more optimal solution. Conversely, when a spatiotemporally fixed priority (e.g., priority 1) is set, no changes are observed, as seen in the preferred facilities and the demanded time windows for the college activity. Moreover, the algorithm robustly applies other one-dimensional fixed priorities (e.g., priorities 2 and 3) for specific aspects, such as demanded time windows for the

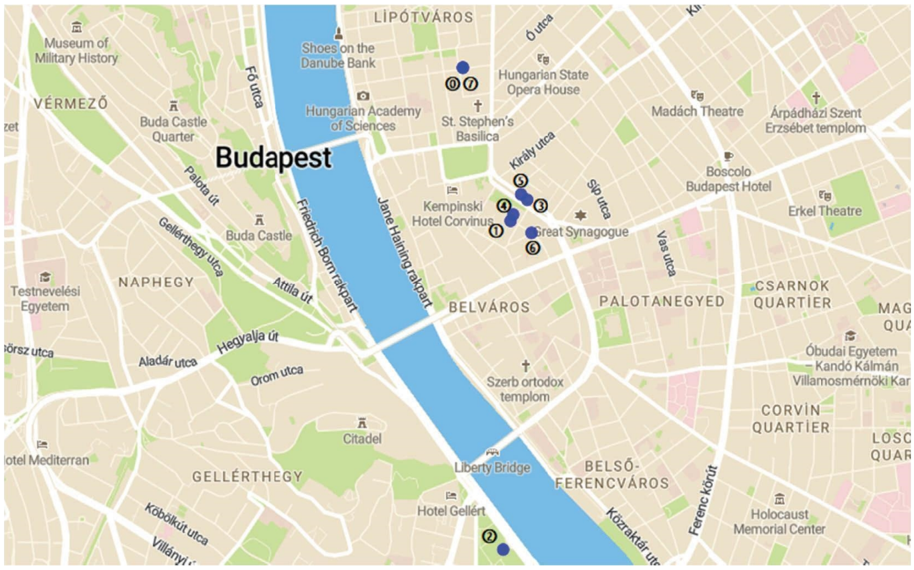

Figure 5: Best-fit solution for the activity locations and their sequence in user C's daily activity chain.

Asian restaurant and preferred location of the bookshop. The algorithm successfully incorporates all spatiotemporal priorities to optimize daily activity chains. During the simulation, different significant travel time savings are observed compared to the base case. These variations in travel time savings highlight how the users' valuation of travel decision-making parameters influences the results reflecting the attitudinal differences among predefined users.

6. Discussion

Overall, the optimization of daily activity chains for users proves to be highly promising. While heuristic algorithms like the GA may not always yield the global optimum, they consistently deliver satisfactory results in terms of travel personalization. Moreover, these algorithms operate within a reasonable timeframe, making them highly beneficial for practical applications.

Although OTP is an open-source router that is actively under development, it has certain limitations that need to be considered. One notable limitation is the incomplete functionality of certain mode options within the OTP router. For instance, when selecting the car option, walking as a mode of transportation is not properly accounted for. This means that even if the optimization algorithm identifies locations in close proximity, the router still treats the scenario as if the car were used. Another issue arises when dealing with PT modes. For instance, when selecting a specific PT option, such as "Bus + Walk" or "Metro + Walk," the router tends to default to the closest available PT option, potentially disregarding the user's preferences. These limitations in the mode options of OTP can impact the accuracy and flexibility of routing calculations. It is important to be aware of these issues when utilizing OTP as part of the optimization algorithm.

The present tool holds potential for longitudinal research offering valuable insights into the in-depth understanding of travel patterns; however, it is important to note that the existing framework does not currently gather users' feedback. As such, future research could concentrate on long-term travel behavior studies, utilizing data collected from users once the web-based version of the tool becomes available. This additional layer of user insight would not only enrich the field of travel behavior research but also facilitate ongoing enhancements to the tool itself.

In terms of real-time implications, the tool can be realized as an application with a user-friendly design to collect real data from real users. Deployment could start with the university staff using the application to provide a longitudinal dataset within a specific timeframe. After that, the collected data could be used for evidence-based transport planning to model activity-based travel behavior of specific user groups, deriving some suggestions related to transport planning and policymaking within the urban context.

7. Conclusion

This study introduces an activity-based travel personalization tool that incorporates 10 travel decision-making factors driven by the GA considering built environment dynamics. To improve both the level of personalization and algorithmic efficiency, the tool takes into account the spatiotemporal priorities of users and the real-time location of facilities, which are served as the constraints within the GA. A complex artificial scenario involving six activities in a specific order and seven route requirements is presented to simulate travel diaries of three predefined users by using the presented framework. The scenario simulations demonstrate the successful application of activity constraints and the efficient implementation of the users' spatiotemporal priorities. Compared to the base case, the simulations show significant travel time savings ranging from 31.2% to 70.2% during daily activity chains. These variations in travel time savings reflect the attitudinal differences among the predefined users, highlighting the influence of individual preferences on travel decision-making parameters.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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