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An activity chain optimization method with comparison of test cases for different transportation modes

Domokos Esztergár-Kiss , Zoltán Rózsa and Tamás Tettamanti

Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Budapest, Hungary

ABSTRACT
In order to provide optimal choice of activity locations and travel time reduction, a daily activity chain optimization method has been elaborated, which includes temporal and spatial flexibility of the activities. In the course of the optimization process, possible alternatives are searched using a modified version of the Traveling Salesman Problem with Time Window. The method is extended with a genetic algorithm to provide an optimal order of activities as the minimum of the predefined cost function (i.e. travel time). The multi-objective optimization can efficiently mitigate the travel time of the users. In order to provide some insight regarding the performance of the optimization algorithm, application-oriented simulations were performed on a real-world transportation network using real travel time information. Three transportation modes were considered: car, public transport, and combined (public transport with car-sharing). The simulation results demonstrate that the optimization is able to reduce travel time by 20–30%.

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KEYWORDS
Activity chain; mobility patterns; optimization; flexible activities

1. Introduction

The growing mobility demands are an increasing challenge for passenger transport systems, which requires the creation of innovative solutions in transportation research. The journey times of passengers should be decreased, while the quality of transportation services should be increased, and transportation-related processes should be optimized.

One efficient way to optimize processes is the introduction of information systems for travelers. Keynon and Lyons (2013) worked on the concept of integrated multimodal traveler information, which is a key ingredient in the optimization of journeys. With suitable information about journeys, travel patterns can be defined and predictions for the optimization can be applied. Timmermans et al. (2003) reported an international comparison of travel patterns. The aim of their research was to understand the connection of urban structure and travel habits of individuals. They used data from various data collection methods and compared them by applying a unified methodology. The results indicated that, in general, travel patterns are independent from the urban structure, thus a well elaborated methodology can be used in a scalable way in an urban environment. Song et al. (2010)

CONTACT Domokos Esztergár-Kiss esztergar@mail.bme.hu

analyzed the limits of predictability in human behavior. They calculated routes based on mobile phone information and were able to predict journeys. They claim that there may be many different travel patterns for passengers, but these are easily predicted and independent from the distance. Thus, the optimization of travel patterns may probably provide beneficial results in various circumstances.

In order to give an overview, activity chain related optimization efforts were collected. Hafezi et al. (2018) developed a methodology for modeling the daily activity engagement patterns of individuals. The dependencies between activity type, frequency, and socio-demographic characteristics were taken into account while employing a Random Forest model. Zhang et al. (2018) proposed a multi-day activity definition method, which uses single-day household travel survey data. Some multiday parameters can be estimated from the data generated by a group of people in a single day. The proposed method is based on activity-travel pattern type clustering, travel distance, and variability distribution. Sharmeen et al. (2016) analyzed the effects of activities on long term changes (life-cycle events) and dynamics of time allocation in activities. According to their research, the effects vary depending on the type of event and the activity, and their method helps in the prediction of long-term changes, in addition to day-to-day dynamics. Javamnardi et al. (2016) provided solutions for activity conflicts. They simulate the process of activity scheduling and resolve the conflicts with a set of linear optimization sub-models. Hilgert et al. (2016) developed a mobility assistance system, which gathers information from timetables of public transportation, and is connected to mobility services (e.g. car-sharing). The solution is aware of the user's schedule and can reorganize weekly activity schedules according to personal preferences. Predictions and evaluations of activity patterns are possible. However, in order to perform these operations, a suitable dataset should be present.

In order to collect data from activities and user preferences, traditional survey methods and automatic data collection methods can be applied by Juhász et al. (2014). In case of using survey-based methods, the answers of the questionnaires can be analyzed by the AHP (Analytic Hierarchical Method), in order to determine the preferences of user groups by Duleba, Mishina, and Shimazaki (2012). As an example, for the latter case, Prelipcean et al. (2015) used a smartphone-based system and compared it to a web-based survey. The results showed that both systems capture the same number of trips, however, they did not collect all trips. Applications can not only be used to collect data, but also to plan journeys and provide suggestions for travel-related decisions. A current application is GTPlanner by Sierpiński, Staniek, and Celiński (2016), which takes into account personal preferences, when planning routes for users, and provides value added information about their trips (e.g. environmental impacts). This information enables users to optimize their routes according to their actual requirements. These systems usually provide information between two locations, but an efficient optimization can be presented, if the whole activity chain of each user during the day is considered.

The objective of the paper is to introduce an innovative solution in the field of urban transportation and to optimize travels of passengers by decreasing the total travel time of a journey during the day. This will be achieved by developing an optimization method with a genetic algorithm based framework providing multiobjective optimal solutions to the activity chain problem.

This paper is organized into 7 sections. In section 2, relevant research contributions are analyzed. In section 3, the optimization method is described, and implementation issues are discussed regarding priorities and transport modes. In section 4, the results of test activity chains are illustrated. Then in section 5, results of simulations for different transportation modes are discussed. Conclusions and future research are presented at the end of the paper in section 6 and 7.

2. Literature review

Transportation is considered to be one of the main contributors to climate change and energy consumption, but these may be mitigated by introducing transport policy measures. Inturri et al. (2017) claimed that mobility can be influenced by using more sustainable transportation modes and by promoting smart solutions. For example, activity travel diary data were used by Ahmed et al. (2018) to change the attitudes of travelers and reduce the negative impact of mobility. The analysis of travel-related information and optimization of mobility patterns could be considered as efficient tools in reducing travel time, travel distance, and therefore, mobility needs in the long term.

The organization of daily activity chains has been analyzed in several articles and books by Timmermans (2005). Hägerstrand (1970) already considered the issue that the opening time of the facilities can influence the daily program of the travelers. This useful theoretical approach was later applied in several solutions. By analyzing the regularity of chains, some periodically repeated activity cycles can be revealed (e.g. commuting to work), which may depend on demographics, spatial circumstances, and the personal characteristics of the user. Several measurements were conducted in order to define the visited points, the average travel distance and time, and in general, the way of organizing the chains. Many transportation related optimization was considered by Tarantilis, Anagnostopoulou, and Repoussis (2013), such as vehicle routing and scheduling problems, but the TSP (Travelling Salesman Problem) has the widest literature and range of applications related to travel chains. Numerous articles deal with the problems and solutions of the TSP-TW (Travelling Salesman Problem with Time Window) method, where typical heuristic applications to this kind of optimization problem are genetic algorithms. Therefore, the algorithm we propose in this paper is based on the TSP-TW version using a genetic algorithm.

We have collected several relevant papers, which handled the issue of activity chain optimization (Table 1). The papers were grouped by the goal of the contribution, the characteristics of the network, the flexibility used in the calculations, the type of the fitness function, and included constraints.

- Paper: The main author and the topic are listed in order to identify the contribution.
- Goal: The aim of the paper is grouped as considering mainly analysis, as dealing with modeling the problem, and as developing optimization algorithms. The most advanced option is when an algorithm is being developed.
- Network: The main distinction is whether the results are based on a theoretical network or performed on a real network. In addition, the appearance of POIs (Points of Interest) and the capability of calculating with different transportation modes are listed.
- Flexibility: Defines whether temporal or spatial flexibility is taken into account during the calculations, where temporal means changing the time of activities or routes and spatial means changing the location of activities or routes.

Table 1. Comparison of related literature.

Paper		Goal			Network				Flexibility		Fitness function		Constraints	
Author	Topic	Analysis	Modeling	Algorithm	Theoretical	Real transport	Including POIs	Multimodal	Temporal	Spatial	Single criterion	Utility function	Opening times	Demanded times
Buliung et al. (2008)	spatial variety of activity patterns	x				x			x	x				
Artenze (2013)	personalized advice based on travel choices	x				x		x						
Kamruzzaman (2011)	indicators to measure personal mobility	x				x								
Nijland et al. (2012)	effects of planned activities on the activity schedule		x		x				x					
Miller, Rooda (2003)	activity schedules and travel patterns		x			x					x			
Nuzzolo and Comi (2016)	route suggestions based on individual utility function		x			x		x				x		
Dib et al. (2015)	route planning using genetic algorithm			x	x			x			x			
Ghiani et al. (2011)	Traveling Salesman Problem with heuristic algorithm			x	x						x			
Dumas et al. (1995)	TSP-TW with dynamic programming			x	x				x		x		x	
Charypar and Nagel (2005)	scheduling with multi-agent simulation model			x	x				x	x		x	x	
proposed	daily activity chain optimization with genetic algorithm			x		x	x	x	x	x		x	x	x

- Fitness function: The fitness (or cost) function is one of the main elements of an optimization. The papers were distinguished whether they use only one criterion (e.g. time) or use multiple criteria during the optimization process.
- Constraints: Additional constraints of the optimization were identified, as opening times of the activity locations and possibility to set the demanded arrival time by the user.

The first set of related papers analyzed travel patterns. Buliung et al. (2008) explored the spatial variety of activity patterns. They were mostly interested in weekend time behavior, where from weekday activities spatially and temporally different patterns were observed using panel data (trips conducted on real transportation networks). This means that the importance of flexibility arises, which is the basis of our idea. However, no algorithm was developed to provide solutions to the travelers.

Another issue is the analysis of the travel choice of users. Artenze (2013) put emphasis on providing personalized advice for travelers. The main idea is to learn preference parameters based on travel choices. Here travel choice between different transportation modes is introduced, and therefore this paper can be recognized as multimodal. The empirical testing was performed based on a travel choice experiment, and thus it can be said that a real network was used. However, no optimization was performed. The idea of preferences is used in our approach, where we introduce different types of activities, where users can set the 'importance'.

In the paper of Kamruzzaman (2011), travel behaviour was analyzed as well, where the number of unique locations visited, average daily distance traveled, and average daily activity duration were used to measure the size of activity spaces. These indicators reflect levels of personal mobility and were used to assess transport service coverage. This paper helps to determine the most important parameters of an activity chain optimization algorithm, which data were utilized in our approach.

The next set of relevant papers provided models for activity scheduling and route planning problems. Nijland et al. (2012) developed a dynamic activity-based model, where daily agendas were modeled based on a web survey with reported activities. The research analyzed the effects of planned activities on the decision to schedule an activity on a day. In the model the flexibility idea arises, as an activity might be postponed until the day some other activity is planned in order to save time. This idea was utilized in our approach, at the phase of defining the flexibility labels. Another activity travel scheduling model was created by Miller and Rooda (2003), who generated activity schedules based on travel diaries. Their aim was to understand the process how travelers schedule and reschedule activities with a utility maximization approach. However, several features were lacking, such as flexibility and multimodality. Still this paper is a good example of creating schedules of activities for travelers, which was useful for generating activity chain scenarios in our case.

Routing problem is a subtask of activity scheduling, which has an effect on the final results of the optimization process. Nuzzolo and Comi (2016) created a new method of providing advice to choose paths in multimodal travel networks. The method uses an individual traveler utility function, which allows personal preferences to be included. This paper introduced the concept of a utility function for route planning between two points, although daily activity chains were not considered. The utility function was extended to an activity location choice-based utility function in our proposed algorithm.

The last set of papers describes algorithms, which perform optimization and provide solutions related to route planning or activity scheduling problems. Dib et al. (2015) worked on a route planning problem in a practical way. They developed route planning methods in multimodal transportation networks using genetic algorithms and variable neighborhood search methods. They compared their approach with a modified shortest path algorithm and the results converged to the optimal solution. Moreover, in contrast to traditional algorithms like Dijkstra, this approach was fast enough for practical routing applications. The approach is presented on a theoretical network and provides results for different transportation modes, although it uses only time as the utility function and calculates only routes between two points. Therefore, it does not consider daily activities. Based on the promising results of using a genetic algorithm, we have implemented the idea to solve the activity chain optimization problem.

Finally, TSP solutions with different constraints have the most connection to our paper, as we also intend to solve a complex TSP problem in order to generate optimal activity chains. Ghiani et al. (2011) solved the Traveling Salesman Problem with heuristic algorithms. Two approaches are compared, a sample-scenario planning and an anticipatory insertion version. The first one provides exact and optimal results, but it has a higher computational effort, while the second one approaches the optimal solution, but provides quicker solutions. This is much appreciated, especially in case of activity scheduling problems. Here the implementation of daily activities solved the TSP, and this was the main contribution. However, neither flexibility nor a complex utility function were elaborated. The idea of heuristic algorithms and the application of TSP to solve activity chain optimization were used in our approach.

In the paper of Dumas et al. (1995) the constrain of opening times is present as they discuss an optimization algorithm for the Traveling Salesman Problem with Time Windows. A dynamic programming approach is suggested, where time windows are calculated as constraints, which helps the performance of the algorithm. The main strength of the paper is that it includes daily activities and time windows of the locations, although the solutions are provided only on artificial test sets to minimize the cost of total travel time. The most comprehensive solution is provided by Charypar and Nagel (2005). They developed daily activity plans using a multi-agent simulation, in which they focused on activity-based transport demand generation. They solved both the location selection and time allocation problems, and thus temporal and spatial flexibility is present. Furthermore, priorities of the activities and opening times of the shops appeared in the calculations. A genetic algorithm was applied to provide the activity plans, and a complex utility function was created, taking into account the preferences of the users. This utility function includes the time of the activity, the allocated time for the activity, the location of the activity, and the location of the last activity. Several ideas also appear in our solution. Furthermore, in our model a real transport network is used, where optimization for several transportation modes is available. Additionally, POIs and user-specified time slots are present in our solution.

As compared to the papers above, the new contributions of our research are given below:

- the algorithm is applied to a real transportation network by using timetable data,
- the activity locations are real POIs with opening times,
- optimization for several transportation modes is available,

- flexible points are introduced, providing spatial and temporal variability,
- a heuristic approach is applied, combining two genetic algorithm functions,
- personalized parameters of demanded times are taken into account,
- optimal solution is provided, aiming for total travel time reduction.

3. Elaboration of the optimization algorithm

The nowadays available TSP methods are usually working on a predefined set of activity locations and are based on a transportation network, where activities have to be explored. The optimum is calculated with a cost function (e.g. travel time) that provides the values among these activities. The TSP method is considered flexible, when according to preferences of travelers, the location of activities can be arbitrarily replaced by another activity with the same function.

The added values of the proposed method are (1) the extension of TSP-TW with flexible activities that may vary in time and space, (2) the implementation of the algorithm in a MATLAB environment, (3) and the application of a genetic algorithm for efficient calculation. The workflow of the implementation is depicted in Figure 1 with the basic steps, which are explained in the following subsections.

3.1. Definition of activity chains and constraints

The activity chains are defined in the first step of the optimization algorithm. This is followed by the description of the basic structure of the graph model and the specification of the most important constraints.

The optimization algorithm for daily activity chains relies on the solution of the Traveling Salesman Problem, a problem that can be defined as an undirected weighted graph (G). Its vertices (V) are the activity locations, and the edges (E) are the trips between the activities. The cost matrix (C) is defined on E, and its elements are travel times between the activity locations (i,j,k). This can also be represented as a utility function with an abstract measure.

$$G = (V, E) \tag{1}$$

$$V = \{1, \ldots, n\} \tag{2}$$

$$E = \{(i,j), \quad \text{where } i,j \in V \text{ and } i \neq j\} \tag{3}$$

$$C = C(i,j) \tag{4}$$

The goal of the optimization with TSP is to minimize the cost of the entire set of trips, where x_{ij} is a binary variable with the value 1, if the trip is part of the optimal activity chain and the value 0, if it is not.

$$\min \sum c_{ij} * x_{ij} \tag{5}$$

The following constraints were defined when solving the basic TSP problem:

- the traveler leaves each activity,

$$\sum_{j=1}^{n} x_{ij} = 1, \quad \text{where } i \in V \text{ and } i \neq j \tag{6}$$

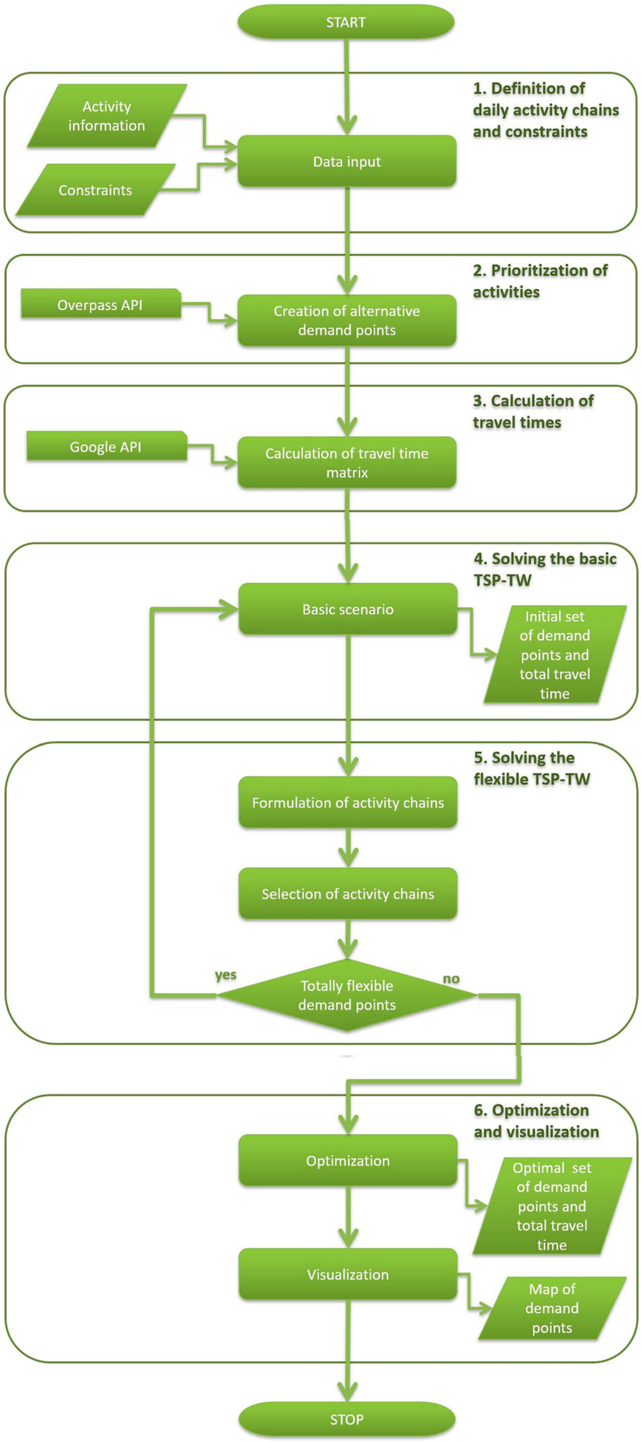

Figure 1. Workflow of the activity chain optimization.

- the traveler arrives to each activity,

$$\sum_{i=1}^{n} x_{ij} = 1, \quad \text{where } j \in V \text{ and } i \neq j \tag{7}$$

- disjunctive partial activity chains are not allowed, and therefore the traveler must always visit an activity, which was not visited before,
- the elements of the cost matrix satisfy the inequality,

$$c_{ij} \leq c_{ik} + c_{kj}, \quad \text{for } \forall i, j, k \tag{8}$$

- and the elements of the cost matrix are not negative.

$$c_{ij} \geq 0, \quad \text{for } \forall i, \quad j \text{ and } i \neq j \tag{9}$$

Furthermore, the following constrains have to be fulfilled when using the graph model with Time Windows (Figure 2):

- real time window (TR) is defined as a difference of the time window (TW) and the processing times (TP),

$$TR = TW - TP \tag{10}$$

  where *TW* means the time interval available for the given activity. *TP* is the time needed for travelers to execute operations and use the provided services (e.g. shopping). The processing times are static, and therefore queues or delayed services are not considered.
- each time window (*TW*) lasts at least as long as the processing time (*TP*),

$$TW \geq TP \tag{11}$$

- an activity is valid, if the real time window (*TR*) and the processing time (*TP*) suits in the demand time window (*TD*) of the traveler,
- each activity has to be reachable during the travel time (*TT*) between activities,
- the total travel time (*T*) is the sum of all travel times (*TT*) and potential waiting times (T_{wait}), which can occur when arriving earlier to an activity.

$$T = \sum TT + \sum T_{\text{wait}} \tag{12}$$

3.2. *Prioritization of activities*

Activity chains consist of all regular (e.g. school, workplace) and irregular (e.g. eating out at a restaurant) activities of a traveler. The spatial and temporal parameters of regular activities are usually fix, while in many cases non-regular activities are flexible. A label value is assigned to each activity, representing its importance. Regarding flexibility we assume that the travelers create their daily schedule in a logical way, still they may be not aware of all possibilities (e.g. opening times, locations of services), and therefore the aim of our solution is to support the finding of the optimal chain of activities. On the other hand, prioritization

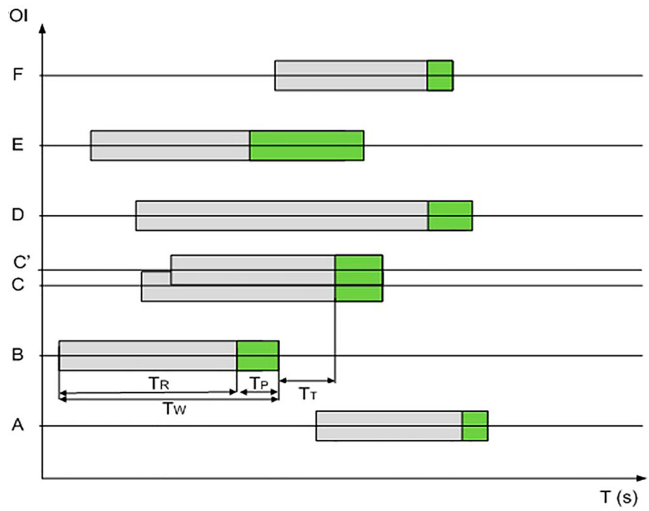

Figure 2. Temporal reachability of the activity locations, where gray areas mean real time window (TR) and green areas depict the processing time (TP).

Table 2. Flexibility of priorities.

Label value	Label name	Temporal flexibility	Spatial flexibility
1	fix	–	–
2	spatially flexible	–	x
3	temporally flexible	x	–
4	totally flexible	xx	–

is realized according to the personal decisions of the traveler, and therefore any activities can be set as fix.

Labels can take the following values (Table 2):

- 1: fix, when the activity has to be arranged in a predefined location and demand time window,
- 2: spatially flexible, meaning that the demand time window is fix, but the location is not predetermined,
- 3: temporally flexible, when only the location is fix (i.e. the activity location can be visited anytime during the day),
- 4: totally flexible, meaning that the activity could be even shifted to another day if necessary (e.g. if reaching the activity would take more than a predefined value of travel time).

In the case of label 1, the location, earliest start time, and latest end time are set. The activity is fix and has to be visited according the choice of the traveler.

In the case of label 2, all nearby activities are searched by the algorithm, which are within a predefined radius (e.g. 1000 m) and have the same POI (Point of Interest) type (e.g. bar). The alternative locations of activities are searched by an Overpass API (Application Programming Interface) based on OSM (Open Street Map). The Overpass API provides location coordinates of nearby alternative activities of the same POI type. These alternative activities are searched around every fix activity. In the case of closely located fix activities, identical alternatives are filtered out. From the examined alternative activities, those are considered, where average distance from the fix activity is minimal. This measure is implemented because the chosen alternative activity would more likely be close to routes among other activities. The number of chosen alternative activities can be set in the algorithm. Having more activities with label 2, all alternative combinations are calculated.

In the case of label 3, only temporal flexibility is considered, when the end time is left blank by the traveler. This parameter is then set by the algorithm to 23:59 of the chosen day. After that from the algorithmic point of view, the activity is handled as a fix activity of label 1.

In the case of label 4, the algorithm considers traveler preferences (e.g. the traveler would like to arrive home before a certain time). If the preference is not fulfilled, the algorithm skips the totally flexible activity (this activity drops out from the actual daily activity schedule and is postponed for another day) and recalculates the whole daily activity chain. Iteratively, totally flexible activities can be skipped until the preference is fulfilled or until the remaining totally flexible activities run out.

3.3. Travel time calculation

In order to model the realization of activities in different locations with feasible trips between them, we have defined travel time matrices between activity locations. The change of activity can be realized by three different transportation modes: car, public transport, and combined (public transport with car-sharing).

- Car mode:

Car travel time is provided by Google API (using communication with Google Maps services integrated in the program code), and only an average walking time to and from the parking spot has been added (5 min). Also, the search time for a parking spot is fix (5 min). As arbitrary departure time cannot be set through Google API, a dynamic traffic situation was not applied to the travel time calculation process. A possible solution for this could be the usage of time dependent additions (or multiplications) to the calculated travel time matrices. However, this would present only an average value for each addition, which would not be specific for the chosen route.

- Public transport mode:

In the case of the public transport mode, travel time calculation is also performed by a Google API using actual departure time. The data source for this mode is the GTFS (General Transit Feed Specification), for which input is provided by local transport authorities. This information is usually available and regularly updated in major cities. However, GTFS-RT (GTFS-Real-Time) data, which would allow calculation with real-time schedules, are not always available. The criterion of the chosen route is the minimal travel time. Currently no other criteria, such as walking distance or number of transfers, are taken into account.

- Combined mode:

For the combined mode, travel times for each route between two activity locations are requested through Google API, both for public transport and for car-sharing modes. Then, the better option is chosen for each route (the transportation mode with less travel time). In the case of the car-sharing mode, an extra walking time of accessing the closest free usable car is added to the travel time. If there is no available car in a predefined distance, the algorithm calculates with public transport mode only.

3.4. Solving the basic TSP-TW

The originally chosen activities of the activity chain are the inputs for the basic TSP-TW method. During the optimization process, all possible combinations are considered, and the objective function is the minimum of the total travel time function. The algorithm calculates the order of the activities and the associated total travel time. This basic scenario is the reference for comparisons with the proposed method with flexible activities.

3.5. Solving the flexible TSP-TW

In case of flexible activities, the activities can be reached at multiple locations. A new set of alternative activities of the same activity type can be considered, which results in new versions of the daily activity chain.

Due to the high complexity and long processing time of solving a TSP-TW problem with many flexible points, a genetic algorithm (GA) is applied to speed up the calculation process. A genetic algorithm is an evolutionary algorithm producing heuristic solutions presented by Mitchell (1998). Thus, it does not necessarily provide the optimal solution, but it produces useful results that are close enough to the optimal one. The closeness can be defined by setting the parameters of the algorithm.

First a random population of predefined size is created as in Gen and Cheng (2000), in which each member of the population represents a possible solution for the TSP-TW problem. This population is evolved by creating new possible solutions. The direction of evolution is determined by the fitness function. Those solutions are chosen, which are closest to the minimum of the cost function. The process is iterative, and each step is called a generation. For the creation of new solutions, GA uses mutation, crossover, and selection. In the selection phase, those solutions are chosen with higher probability, which are closer to the minimum of the cost function. For creating new solutions, two existing solutions are chosen, and their parameters are mixed together. The algorithm terminates when it either reaches the maximal number of generations (generation limit) or reaches the predefined fitness level.

The optimization algorithm consists of 2 GAs: inner GA and multiobjective GA. The inner GA optimizes a scenario with flexible activities for total travel time. If the scenario does not fit the predefined criteria, an infinite penalty in the cost function for the total travel time is set, and therefore this scenario will never be optimal. The multiobjective GA is introduced in order to minimize two competitive objectives. One objective is the number of totally flexible activities. If an activity can be postponed to another day, its value is 0, and if not, its value is 1. The other objective for the multiobjective GA is the result of the inner GA. The cost function is therefore a combination of the number of postponed activities and total travel time, since the aim is to minimize both parameters.

The outer (multiobjective) GA has to decide among a few options, and thus low valued parameters in terms of iteration proved to be enough (population size: 10, stall generations limit: 10, generations: 10). It should be noted that currently the algorithm has quasi-real time operation on a laptop configuration. If the problem size is growing, it is possible to increase the parameter values in the case of enhanced hardware resources or offline operation. The inner GA has the following parameters: population size, 60; stall generations limit, 10; generations, 100. The built-in permutation Matlab functions were used for population generation, mutation, and crossover.

The activity chains with flexible activities are formulated for all possible alternatives. Regarding the car mode, the travel time matrix is calculated between all activity locations for all possible activity chains. For the public transport mode, there is no need to create travel matrices, because the actual travel times are requested during the activity chain generation. Regarding the combined mode, travel time and scheduling values of both transportation modes are calculated and compared. All combinations are tested for predefined constraints (e.g. opening time), and those activity chains are selected that are valid for these constraints. In this step, all trips of the travelers (demanded time windows) are assigned to the activities (e.g. opening times). Arriving by a predefined time interval (e.g. 15 min) earlier than the requested start time of the activity is acceptable. If this time interval is longer, the solution will not be considered. In the case of totally flexible activities, which may be shifted to another day, the traveler preferences are checked. If the preference is not fulfilled, the calculation of possible activity chains is repeated with skipping of totally flexible activities. For each valid version (where a flexible activity was chosen), the TSP-TW problem is solved, and the total travel time is calculated.

3.6. Optimization and visualization

After creating all feasible activity chains, the one with the least total travel time will be selected as optimal. Finally, the set of optimal activities and total travel times are presented as the output. This is calculated for all transportation modes. Additionally, visualization of the optimal daily activity chain is realized using Google Maps. Thus, the result of the basic scenario can be compared to the best version of flexible TSP-TW.

4. Example activity chains

The simulations were performed on arbitrarily chosen test networks using MATLAB, where the GPS positions and the time windows (e.g. opening times of the shops) of the activities were given. In order to simulate a typical daily activity chain, four activities were used in the test network. A practical limitation for the algorithm was set by Google API, as it provides no more than 2500 queries per day.

4.1. Data generation for simulating activity chains

The GPS coordinates of the locations of activity chains were randomly generated within the area of Budapest (bounded by the corner points of (47.385740, 18.963384) and (47.581563, 19.206457)). This was done by a random coordinate generator in case of home and by random selection from a POI (Points of Interest) database in case of other activities. The population of Budapest is about 1.75 million (2016), and its area is 525.2 km. The number of vertices (activity types) of the network is 5 in all the example cases (thanks to the heuristic solution, the processing time does not increase radically by increasing this value). However, the number of examined activity locations is much higher in each example because of our selection rules for the possible locations (resulting in numerous possible edges). We have created edges connecting all the vertices including the possible locations, so the cost of traveling depends on the transportation mode and departure time. Theoretically all the flexible activities can be replaced by at least 400 alternative activity locations. in the literature, e.g. compared to the networks of Charypar and Nagel (2005), where a similar problem was solved with 5 vertices in the network, but only 2 alternative locations were considered for each activity.

In our case, first the GPS coordinates of the home location were generated and considered fix. In the second step, we stored information about work related locations (school, office, workplace) from a POI database by Certicky et al. (2005) containing the coordinates and opening times of the POIs of Budapest. After random selection from a total of 4545 options, the coordinates were fix. This was considered to be the traveler's workplace, to which an eight-hour duration was applied.

Originally ca. 1000 types of activities were included in the POI database, but we narrowed it down to the types of activities, which have at least 400 specific locations in the city and can be considered as activity with flexible location. This resulted in 14 activity types. Then the durations that a traveler would spend at the locations of the activities were determined by assumptions from the authors experience. The following activity types have been chosen (with the defined processing times in minutes): bakery (10 min), bank (25 min), bar (120 min), cafe (25 min), pharmacy shop (20 min), dentist (30 min), doctor (30 min), electronics store (40 min), grocery store (15 min), health center (30 min), monument (20 min), pub (120 min), restaurant (40 min), hairdresser (35 min). The next step was to select 3 activity types out of 14 possibilities for each scenario, this was done again by random selection.

The daily average distance traveled is about 20 km based on Kerr et al. (2007), most of which is spent commuting to and from the workplace. Therefore, we have calculated with a commuting distance to and from the workplace on average 7.5 km each way and reaching other activity locations with an average of 5 km per day. When we generated the coordinates of the activities, we searched in the region of a circle with a 7.5 km radius with the home location coordinates as its center, so that we could create realistic cases. Additional constraints in the framework (e.g. the time period in which the traveler wants to perform the activity) have been set up.

The input data of the activity chain (Table 3) contains the type of activity, the processing time, the label, the opening and closing times of the activity (which defines the time window), and the earliest start and latest end time (which defines the demanded time window of the traveler).

In the next subsections the results of arbitrarily chosen activity chains are presented considering different transportation modes: car, public transport, combined. The example activity chains aim to represent typical cases of real-world travel patterns. This means that the measure of achievable results by the optimization considering different scenarios is

Table 3. Example daily activity chain input data.

Type of activity	Processing time	Label	Opening time	Closing time	Earliest start time	Latest end time
Workplace	480 min	1	07:00	17:00	00:00	23:59
Restaurant	40 min	2	08:00	23:00	00:00	23:59
Pub	120 min	2	10:00	23:59	00:00	23:59
Grocery Store	15 min	2	07:00	22:00	00:00	23:59

Table 4. Example of a daily activity chain with fix and flexible activities using car (numerical results), flexibility noted with*.

Fix activity chain			1 flexible activity			2 flexible activities		
Activity types	Start time	End time	Activity types	Start time	End time	Activity types	Start time	End time
0. Home	–	7:25	0. Home	–	7:25	0. Home	–	7:25
1. Grocery Store *	08:01	08:16	1. Grocery Store *	07:57	08:12	1. Work	07:59	15:59
2. Work	08:37	16:37	2. Work	08:29	16:29	2. Grocery Store *	16:14	16:29
3. Res-taurant *	16:55	17:35	3. Res-taurant *	16:47	17:27	3. Res-taurant *	16:47	17:27
4. Bar *	18:00	20:00	4. Bar *	17:52	19:52	4. Bar *	17:44	19:44
5. Home	20:14	–	5. Home	20:06	–	5. Home	20:01	–
Total travel time	1 h 54 min		Total travel time	1 h 46 min		Total travel time	1 h 41 min	

average. Nevertheless, the relative improvements represent the effectiveness of our activity chain optimization.

4.2. Car

In the case of car mode, it was assumed that the traveler uses a private car during the whole day without any serious traffic jams. In the basic scenario with a fix schedule, the total travel time is 1 h 54 min, which decreases in the optimized scenario by 8 min, if there is one flexible point, and by 13 min if there are two flexible points (Table 4). However, it is noted that this value strongly depends on the chosen example. Furthermore, if the distance between the two activities is close enough, there is no need to use the car, and more time saving can be achieved by walking between the specific locations.

In the most flexible schedule, a closer grocery store was found, but since a fix walking time of 5 min between the parking spot and the location of the activity is added, only a moderate gain was obtained. In this case, the flexibility did not cause any major changes in the daily schedule in the afternoon, but time saving was still achieved. Although a restaurant was also flexible, it was close to the previous activities, and thus, a change in its location was not necessary. A bar is spatially flexible, and therefore a new location for this activity was found, which is closer to the restaurant. Therefore, the pub and home were both reached sooner.

Concerning the visualization (Figure 3) of the daily activities (car travel colored with magenta), it can be observed that shorter trips were performed and the locations of the activities are closer to each other.

4.3. Public transport

In the case of public transport, the activity types, as well as the start and end times are summarized in Table 5. It was assumed that only public transportation and walking is used

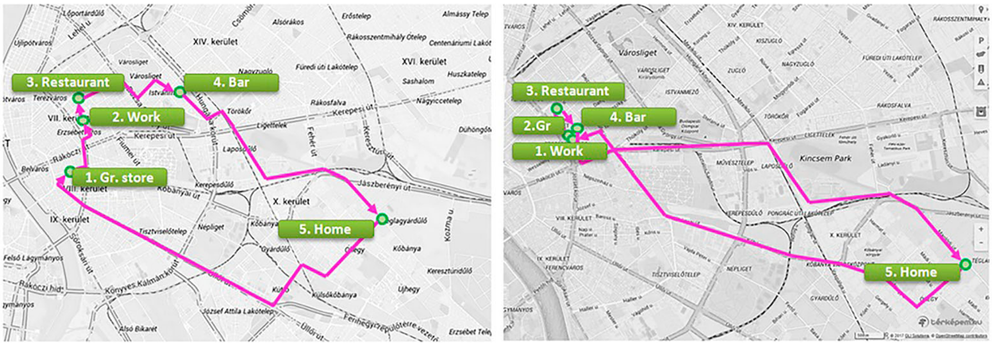

Figure 3. Example of a daily activity chain with fix and flexible activities using car (visualization).

Table 5. Example of a daily activity chain with fix and flexible activities using public transport (numerical results), flexibility noted with*.

Fix activity chain			1 flexible activity			2 flexible activities		
Activity types	Start time	End time	Activity types	Start time	End time	Activity types	Start time	End time
0. Home	–	7:25	0. Home	–	7:25	0. Home	–	7:25
1. Work	08:06	16:06	1. Work	08:06	16:06	1. Res-taurant *	08:09	08:49
2. Res-taurant *	16:12	16:52	2. Res-taurant *	16:02	16:52	2. Work	08:55	16:55
3. Grocery Store *	17:06	17:21	3. Grocery Store *	16:58	17:13	3. Grocery Store *	16:56	17:11
4. Bar *	17:40	19:40	4. Bar *	17:30	19:30	4. Bar *	17:13	19:13
5. Home	20:07	–	5. Home	19:57	–	5. Home	19:46	–
Total travel time	1 h 47 min		Total travel time	1 h 37 min		Total travel time	1 h 26 min	

during the trips. Here the difference was more significant (i.e. 20% decrease in total travel time was realized). In the basic scenario with a fix activity chain, the total travel time is 1 h 47 min, which decreases in the optimized scenario with 1 flexible activity by 10 min. With 2 flexible activities, the total reduction is 21 min. Considering the differences in the optimized scenario with flexible activities, the locations of the grocery store and bar have changed. This implies that the algorithm found the same activity type closer to the workplace. Thus, unnecessary travel was not performed, and the total travel time could be decreased.

The order of the activities was changed, thus the restaurant became the first activity. This was possible, because of the relaxed earliest start time and latest end time constraints. However, if the restaurant refers to a dinner in the evening, the earliest start time can be set to late afternoon, and then the algorithm will not schedule it in the morning. After work, a grocery store and a bar were found practically next to the workplace, and therefore a high gain in the saving of travel time could be achieved.

In Figure 4 the routes of the public transportation mode can be seen. Regarding transportation modes after the optimization, more walking was chosen, because the new locations of the activities were close to each other. The colors in these plots represent the following transportation modes: walking (black), bus (blue), tram (yellow).

4.4. Combined modes

In the case of combined modes, it is allowed to use public transportation, and a free-floating car-sharing system is assumed. The algorithm now works with an idealized case of always

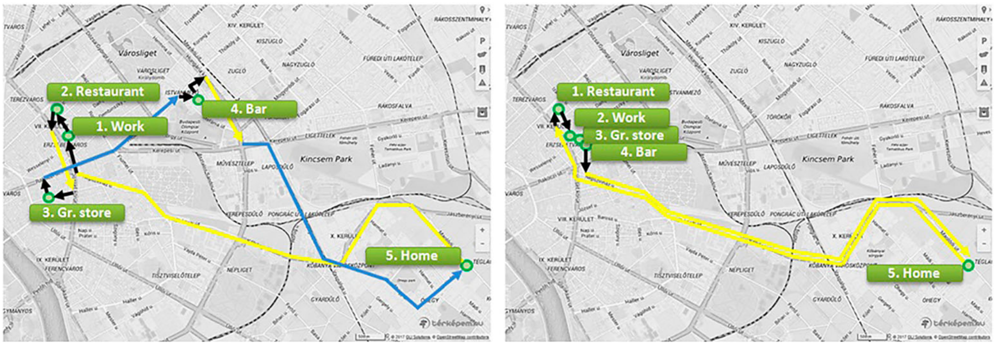

Figure 4. Example of a daily activity chain with fix and flexible activities using public transport (visualization).

Table 6. Example of a daily activity chain with fix and flexible activities using combined modes (numerical results), flexibility noted with*.

Fix activity chain			1 flexible activity			2 flexible activities		
Activity types	Start time	End time	Activity types	Start time	End time	Activity types	Start time	End time
0. Home	–	7:25	0. Home	–	7:25	0. Home	–	7:25
1. Work	07:59	15:59	1. Work	08:02	08:42	1. Work	07:59	15:59
2. Res-taurant *	16:05	16:45	2. Res-taurant *	08:48	16:48	2. Grocery Store *	16:00	16:15
3. Grocery Store *	16:59	17:14	3. Grocery Store *	16:51	17:06	3. Bar *	16:16	18:16
4. Bar *	17:33	19:33	4. Bar *	17:23	19:23	4. Res-taurant *	18:21	19:01
5. Home	19:47	–	5. Home	19:37	–	5. Home	19:19	–
Total travel time	1 h 27 min		Total travel time	1 h 17 min		Total travel time	0 h 59 min	

having a car available within the predefined distance, and it calculates with an average of 5 min walking time to any car. The basic scenario without flexible activities resulted in a total travel time of 1 h and 27 min, which could be decreased by almost half an hour, or by more than 30% (Table 6). The best combinations can usually be achieved when long distance trips are performed by car-sharing and short trips by public transport, or even walking.

In the example, the first trip to work was fulfilled by car-sharing, as the fastest mode available. In the fix schedule, the grocery store is placed after the restaurant, while in the flexible schedule, it is directly after work. In the optimized scenario, the locations of the activities are so close to each other that they can be reached by walking. The last trip was again made by car-sharing, as it is more distant, and no direct public transport connection is available.

Concerning transportation modes (Figure 5) for longer trips, car (magenta) was chosen, which is reasonable. In the basic scenario, tram (yellow), bus (blue), and walking (black) were used, and the optimized case consisted mostly of walking.

Comparing the simulation results (Table 7), combined modes provided the best choice with 0 h 59 min of total travel time, which was 42 min better than the car mode, and 27 min better than public transport. In relative terms the biggest reduction was also observed for combined modes, with a 32.2% reduction, while the car mode obtained 11.4% and the public transport 19.6% in the best scenario of two flexible activities.

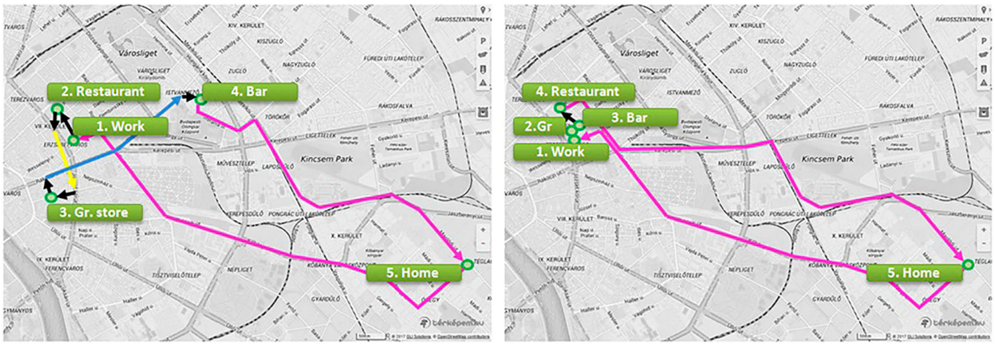

Figure 5. Example of a daily activity chain with fix and flexible activities using combined modes (visualization).

Table 7. Comparison of the simulation results.

Transportation mode	Total travel time with fix schedule	Total travel time with flexible schedule	Relative total travel time reduction
car	1 h 54 min	1 h 41 min	11.4%
public transport	1 h 47 min	1 h 26 min	19.6%
combined	1 h 27 min	0 h 59 min	32.2%

5. Simulation results of test cases

In order to provide an insight into the general usability of the optimization algorithm, 30 randomly generated test cases were run for all considered modes (car, public transport, combined). First the GPS coordinates of the home location were randomly generated within the area of Budapest, and they are always considered fix. In the second step, the location of the school or workplace was selected from the POI database. Next, the locations of the other activities were randomly selected using the POI types (well represented in Budapest). Finally, three different scenarios were generated, where 0, 1, or 2 out of 3 unfix activity locations was flexible. The optimization was run using these scenarios for different settings as defined in section 3.

The simulation results of the test cases for these modes are summarized in Table 8. Column 'fix' means activity chains without flexible activities, while '1flex' and '2flex' labels refer to activity chains with 1 and 2 flexible activities, respectively. In the last two rows, the average total travel time and the percentage of total travel time decrease are shown compared to the fix schedule. The table presents the average values of 30 randomly generated test cases. Some test cases show very moderate benefits with the optimization (e.g. test case nr 30: car, 8.6%; test case nr 7: public transport, 5.1%; test case nr 12: combined, 8.1%), while in other cases significant changes were measured (e.g. test case nr 11: car, 30.0%; test case 19: public transport, 48.0%; test case nr 4: combined, 44.4%). The wide variety of results shows how different activity chains can be, and it clearly reflects the importance of conscious decisions regarding activities, locations, and transportation modes.

In order to provide a better comparison of the test case simulation results, the average total travel times are visualized in Figure 6. It can be observed that the total travel time highly depends on the chosen transportation mode. The longest travel times are realized

Table 8. Average total travel times for different transportation modes with flexibilities (numerical results).

	Total travel times (min)								
	Car			Public transport			Combined		
	fix	1flex	2flex	fix	1flex	2flex	fix	1flex	2flex
1	114	102	104	93	69	73	76	58	63
2	124	108	105	164	121	114	108	80	74
3	107	106	99	104	87	72	74	66	54
4	130	122	112	142	102	89	115	89	64
5	127	122	113	115	116	105	96	92	76
6	102	102	88	79	75	58	71	70	57
7	105	96	97	137	128	130	81	59	61
8	117	105	92	105	67	76	75	63	62
9	159	147	147	135	132	112	155	132	130
10	108	106	95	80	80	69	79	76	56
11	137	101	96	141	62	49	111	55	41
12	115	113	108	103	99	97	86	85	79
13	126	115	111	154	134	127	101	77	72
14	112	104	104	68	66	59	66	60	58
15	134	126	124	191	174	142	121	108	104
16	128	114	108	107	75	75	95	66	69
17	130	130	104	126	114	89	99	85	65
18	113	109	93	88	84	54	82	76	49
19	101	90	82	102	74	53	77	53	42
20	135	125	112	158	154	121	118	109	86
21	113	113	93	101	97	66	86	77	50
22	114	104	101	115	102	84	85	73	64
23	112	112	101	105	101	89	81	77	62
24	105	96	96	139	119	123	81	59	61
25	117	105	92	105	68	67	83	58	60
26	108	106	95	81	80	73	80	76	59
27	122	107	102	114	92	75	103	77	64
28	114	106	101	107	97	86	87	77	59
29	122	121	107	130	122	88	106	104	72
30	105	96	96	144	121	128	81	59	61
av.	119	110	103	118	100	88	92	77	66
%	–	−6.9%	−13.4%	–	−14.7%	−25.2%	–	−16.8%	−28.5%

by car (119 min). A potential explanation for this is that a uniform 10 min walking time was added to and from the parking lot for each trip, which is realistic in dense urban areas, but less relevant for suburban locations. The results of the optimization are a reduction of 9 min (6.9%) and 16 min (13.4%) on average when introducing 1 and 2 flexible activities, respectively.

Public transport resulted in similar total travel time (118 min) in the case of fix activity chains. However, the optimization was more efficient here, because shortening trips also lead to skipping of transfers and unnecessary waiting times. Thus, travel time savings of 14.7% and 25.2% (18 and 30 min of reduction) were achieved, which is a quite considerable result.

The best results are observed in the case of combined modes. This is in line with the expectations, as this mode combines the benefits of car-sharing and public transport, which provide consistently better options than using a single mode. Even the fix activity chain results are better, with 92 min of total travel time. The optimization outperforms all other modes, with 16.8% and 28.5% total travel time reductions.

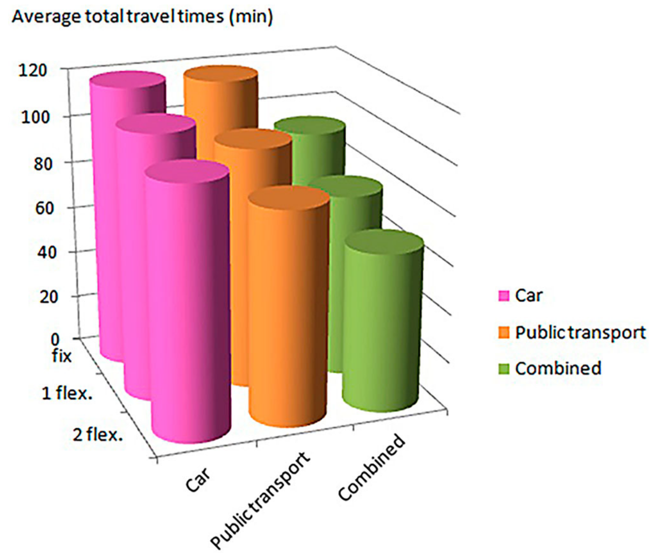

Figure 6. Average total travel times for different transportation modes with flexibilities (visualization).

The results are highly dependent upon the measure of flexibility. In the case of one flexible activity, a 12.8% travel time reduction was observed, while in the case of two flexible activities, 22.3% was achieved. Based on the results, and considering all modes, it can be claimed that on average our optimization provides significant travel time saving.

6. Further development

The theoretical model and the first simulation results will be followed by the elaboration of validation scenarios, using large amounts of real traveler observation data. We would also like to conduct a comprehensive real-world scenario assessment with data collected from passengers.

In our model we assumed that the traveler's start and end point is the same. In most cases this is valid, because usually the daily activity chains start from home, and after finishing all activities, the destination is home again. However, occasionally the destination can be different, which requires the application of another TSP method.

As for daily activity planning, some other optimization aspects may play an important role. The cost function could be interpreted as a more general function, which takes travel time, travel cost, comfort, and personal preferences (e.g. ratings of locations, weather, security in the area) into account. The aspects can be connected to the traveler, to the chosen transportation mode, or to the location type of the activity.

Using mobility analysis on an individual level, the daily activity chains of users can be obtained, and the patterns of their movements can be determined. Predicting the routes of users can be beneficial for transport operators, as they can create timetable schedules for buses and trams that closely represent the real travel demand of the passengers. Understanding and describing mobility patterns aids the simulation of the city life, which can be useful for urban planners and decision makers.

The travel times are now fix values, and therefore, the optimization algorithm always calculates with the same travel times between activity locations. Considering the actual traffic situation, the elements of the travel matrix could be changed, or even predicted. Also, the calculation of processing times could be extended by defining an average TP value, which can be modified to be a minimal TP value, if a delay occurs. The minimal TP value would be the minimum time that has to be spent at the given activity.

By introducing predictive TSP, the latent demands of the passengers could be served. These latent demands of the passengers could be derived from the demands of passengers with similar characteristics.

To enhance the dynamics and actuality of the model, changes in the activity plan during the day could be taken into consideration. These could include the appearance of a new demand (with a corresponding new activity) or the occurrence of a delay in an activity. Thus, the daily activity plan has to be re-planned and recalculated according to the new situation.

7. Conclusion

According to the discovered research gap in the activity chain planning, the research focused on the viability of daily activity chain optimization by considering flexibility in both time and space. The aim was to optimize travels of passengers by decreasing the total travel time of a journey during the day. A complete method was introduced proposing the TSP-TW optimization method within a genetic algorithm based framework providing multiobjective optimal solutions to the activity chain problem. The reason for the choice of GA was to reduce processing time and make the method practically usable. The proposed technique was tested on a real-world transportation network with public transport timetable data, and assuming a free-floating car-sharing system. Realistic simulations were carried out to justify the applicability and the efficiency of the proposed technique via various activity chain examples. The obtained numerical and visual results are promising, demonstrating the practical viability of the method. Furthermore, the performance of the optimization algorithm was evaluated through randomly generated test cases considering transportation modes and the number of flexible activities. In all, by replacing the original activities with alternative ones of the same type but in different locations, the total travel time of urban travelers can be decreased. The simulations proved that significant travel time savings can be achieved via activity chain optimization with temporal and spatial flexibility. As a future work, the extension of the optimization method is planned, i.e. the activity chains will be optimized over longer time horizons (e.g. for a week) and other factors will be included in the cost function (e.g. cost, comfort).

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ORCID

Domokos Esztergár-Kiss http://orcid.org/0000-0002-7424-4214
Zoltán Rózsa http://orcid.org/0000-0002-3699-6669
Tamás Tettamanti http://orcid.org/0000-0002-8934-3653

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