Performance evaluation of heuristic algorithms for the activity chain optimization problem

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1. Introduction

Integrated transport policies, analysis of travel related information and optimization of mobility patterns could to be considered as efficient tools of reducing travel time, travel distance and mobility needs of citizens. This can be realized by introducing intelligent activity planning methods, especially the organization of daily activity chains. One basic work in this field originates from Timmermans et al. [1], who described and analyzed travel patterns. In the paper of Liao et al. [2] activity travel scheduling was handled as a modeling problem. Their aim was to provide a model to predict short-term effects of travel information systems and travel demand management. Sharmeen et al. [3] analyzed the effects of activities on long term changes and dynamics of time allocation in activities. Nuzzolo and Comi [4] created a new method for generating path advice for multimodal travel networks. The method uses individual traveller utility function, which allows personal preferences to be included. Hafezi et al. [5] developed a methodology for modeling the daily activity engagement patterns of individuals. The dependencies between activity type, activity frequency and socio-demographic characteristics are taken into account while employing a Random Forest model. Hilgert et al. [6] developed a mobility assistance system, which gathers information from timetables and real time information systems in public transportation, and is also connected to mobility services (e.g. car sharing). Furthermore it knows the user's schedule and can reorganize weekly activity schedule according to personal preferences. The organization of the daily activity chains has been analyzed in several articles [7] and books [8]. Many optimizing algorithms were considered, but TSP has the widest literature and range of applications [9]. Therefore we propose to use a TSP-TW (Traveling Salesman Problem-Time Window) based algorithm. The main aim of this research is to compare and evaluate the exhaustive search method and the genetic algorithm based solution for activity chain optimization.

2. Method description

The methods available nowadays are based on a transportation network with activities that have to be explored, and cost functions that describe the values (e.g. travel times) among the activities. A TSP method is considered flexible (Fig 1), when according the subjective preferences of travelers, location of activities can be arbitrarily replaced with another activity with the same function. The added values of the proposed method are:

(1) extension of TSP-TW with flexible activities that may vary in time and space,
(2) application of heuristic algorithms to solve the activity chain optimization problem,
(3) comparison of the algorithms based on their performance.

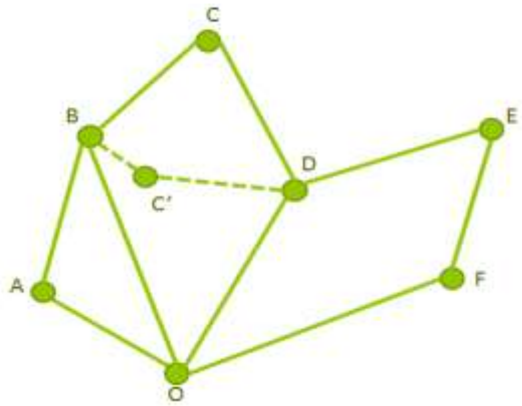

Fig 1 Schematic representation of the flexible TSP method

The functioning of the method can be summarized in the following steps:

1. Definition of daily activity chains and constraints:

During establishing activity chains it is assumed that the traveler is already aware of the activities, which he/she would like to realize on the given day. Therefore the list of activities, time windows and processing times (time spent at the demand points) are defined.

2. Prioritization of activities:

To each activity a value is assigned by each traveler, which represents its priority. Regular activities get usually higher priorities, because they are spatially and temporally bounded, while the non-regular activities get lower priorities.

3. Creation of alternative demand points:

In the case of flexible activities the same service (e.g. post office) may be reachable in more spatial locations. The search for new demand points is conducted according to a predefined distance. The results represent alternative activity chains.

4. Calculation of travel time matrix:

The calculation of travel time matrix for cars and public transport is performed in advance, as for running the algorithms general values for travel times are needed, but the real travel times are not crucial.

5. Optimization algorithm with fixed demand points:

The algorithm calculates an order of the originally defined fixed activities, which result is the basis for comparison with results of the proposed method (basic scenario).

6. Optimization algorithm with flexible demand point:

The algorithms optimize the generated activity chains. The activity chain with the lowest cost function is chosen. Finally the result of the basic scenario is compared to the optimal solutions.

3. Evaluation

With the increasing number of total activities and flexible activities the complexity of the algorithm and the processing time expands enormously. Therefore it was clear at the early stage of the research, that exploring all possible combinations with exhaustive search is not possible for a general daily activity chain scenario for a typical user.

We have introduced several heuristic algorithms, which may be useful decreasing the processing time of calculating optimal activity chains. Three typed of heuristic algorithms were considered, such as genetic algorithm, ant colony algorithm and neural networks.

In this abstract we provide some results of comparing the exhaustive search (original) algorithm and genetic (optimization) algorithm, where processing times of the original and optimization algorithms were compared (Fig 2). The basic scenario (when all activities are fixed) and the optimal scenario (when there are flexible activities) were calculated with both algorithms. The difference is obvious, in general the optimization algorithm over performs the original algorithm by 90% (resulting in 10% processing time).

In case of fix activities the difference is smaller for public transport (original algorithm: 96 s; optimization algorithm: 19 s) and combined transportation mode (147 s; 29 s). The performance of the optimization algorithm is even worse for cars (7 s; 16 s). This is because the genetic algorithm generates huge populations, which requires computing time, while in the original case only a few combinations were present. In case of flexible activities for cars the difference is already quite big in favour of the optimization algorithm (71 s; 23 s), but for the other transportation modes (public transport and combined) it is remarkable (556 s; 34 s and 861 s; 41 s).

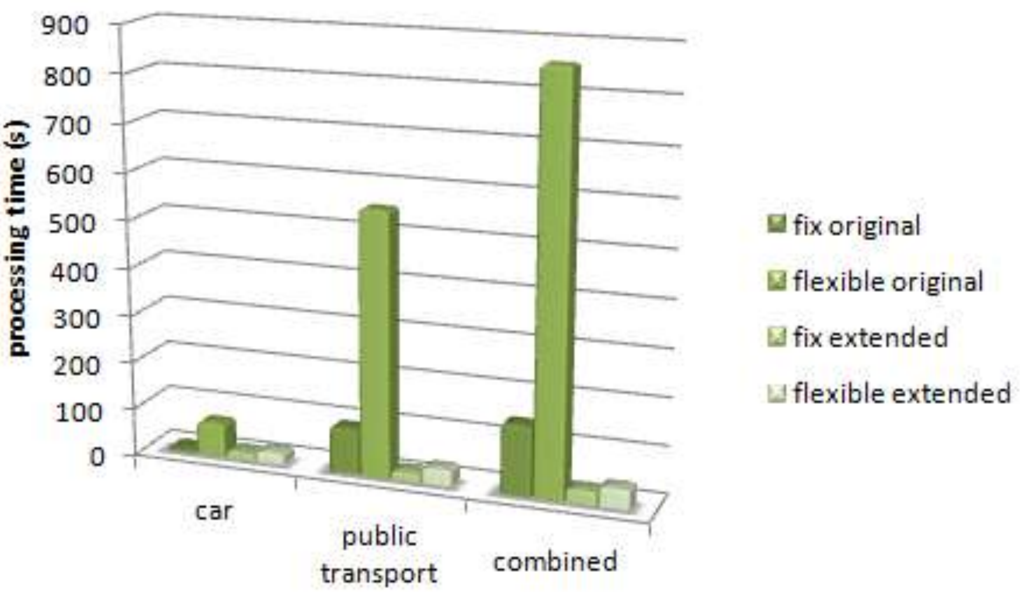

Fig 2 Comparison of processing times of the original and the extended optimization algorithm

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