A practical method for the optimization of daily activity chains including electric vehicles

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Abstract

The focus of this paper is to introduce a methodology for the optimization of daily activity chains of passengers, who use Electric Vehicles (EVs) in order to fully cover their transportation needs and attend activities in their daily life. An approach has been developed using a Genetic Algorithm (GA) framework to optimize the order, the locations of activities, the modes of transport and the travel time between the activities. The priorities of the passenger concerning flexibility were considered, as well as, special constraints that are related to the limited range of the EVs. The methodology consists of the modelling and the solution approach. While the first constitutes the basis of the approach and gives form to the solution space of the problem, the second includes the rules to be followed during the exploration of that solution space according to the GA framework. Our methodology allows to incorporate more parameters of the real-world problem and derive solutions for metropolitan size urban environments within reasonable computation times.

Keywords

activity based modelling, activity chains optimization, genetic algorithm, electric vehicle

1 Introduction

The Daily Activity Chains Optimization (DACO) problem, as it is referred to in the literature, is one of the problems which provide an answer to the commuting challenges of the everyday life of travelers. The objective is to calculate a proper sequence of visits to several locations and an optimal path between them, given a set of the activities that the traveler wants to conduct, their initial indicated locations, the priorities of the traveler, his or her time frame and the opening hours of the locations in which those activities can be carried out. Similarly, the Daily Activity Chains Optimization problem with the use of EVs (DACO-EV) is a problem, where the DACO problem is extended to include EVs as a mode of transport. The DACO and DACO-EV are two modern problems, which fall under the umbrella of the Travelling Salesman Problem (TSP) and its several variants.

For the study of this problem, activity-based modeling of transportation systems has been utilized. The methodologies that are based on this scientific framework are especially useful in real-world cases where the passengers have a wide variety of choices concerning the activities that they can conduct in regard to both the content, the location, and the time of attendance for each available activity. Dense urban environments, such as metropolitan areas, are such kinds of cases where activity-based modelling is mostly useful.

For the optimization of the activity chains of travelers a GA was developed. Especially in the case of transportation problems, the GA framework has been successfully applied to problems such as the TSP, the Travelling Salesman Problem with Time-Windows (TSP-TW) and the Vehicle Routing Problem (VRP), which are classified as NP-hard problems. By utilizing the genetic operators, heuristic solutions can be calculated for such problems in reasonable amounts of time.

The goal of this ongoing research is to provide a realistic modeling and solution approach for the DACO-EV problem by exploiting activity-based analysis and the GA framework. While the incorporation of the EV range constraints is a major part of our work, special focus is also given to mechanisms that enable the implementation of such a system into a real-world application that will serve the travelers.

2 Literature review

The basic instance of DACO was created by Esztergár-Kiss et al.[1], [2]. Not only the definition of the DACO problem is shared, but a modelling and a solution approach for the problem is introduced. Charypar et al.[3] have dealt with a similar problem and introduced a similar solution approach. The authors have considered several simplifications, such as the computation of distances according to geometric distance and not based on the real transportation network. Another similar work is conducted by Abbaspour et al. [4], where the authors tackle the same problem, but have a specific focus on the touristic aspect of the optimization of activity chains.

Useful insights about the incorporation of EVs into generic route planning can be extracted from a series of works in the literature. Extended work on the subject has been conducted by Baum et al. Notably, in the work conducted in 2013 [5], they extend their algorithm, named Customizable Route Planning (CRP) to calculate fast queries on graphs that are suited to Electric Vehicles (EV). Their goal is to provide energy optimal routes including parameters, such as the recuperation of the electric vehicle, the battery capacity constraints and the dynamic behavior in energy consumption of the vehicle. In their work conducted in 2015 [6], they introduce their approach named CHArge which solves the EV routing problem in realistic settings. They discuss the properties of charging functions, which are used to map an initial State of Charge (SoC) and the duration of a charging session with a resulting SoC. They also point out the importance of incorporation of live traffic in future work.

Finally, there is another group of important papers that address the optimization of activity chains considering the use of EVs. The paper by Liao et al. [7] is very close our approach, but does not solve the exact same problem. The authors provide modelling and solutions to the EV shortest travel time path problem and the fixed tour EV touring problem. They consider battery swap system and for the touring problem and two cases are discussed in more depth, the on-site station model, where each city is considered also a swapping station, and the off-site model, where the swapping station is further away than the main city by a distance indicated by a parameter. Although their work can be generalized to work for a case like ours, it cannot be directly applied to real-world cases.

The works of Cuchý et al. [8], [9] the authors model the problem as a graph and apply a label-setting algorithm for each solution. The definition of the problem is identical to ours, but the authors in the latest iteration of their work, include fewer parameters than the ones that are included in our definition. Also, they possibly ignore the overall weight of the vehicle including the passengers' weight and they do not include as an option to have a final desired amount of energy in the battery when the tour ends. Finally, the availability of the chargers is not included in the designing of the routes.

3 Presentation of the methodology

The method introduced in this paper for the solution of the DACO-EV is based on three different sets of parameters. The first set contains the parameters whose values are defined by the traveler and refer to his or her schedule and preferences (e.g. start and end time of the tour, start and end location of the traveler, activities and their type, processing time at the activity, priority of the activity, used EV model, number of passengers, start and end status of battery). The second group includes all of the parameters that are related to the EV and its use (e.g. capacity of the battery, plug type, consumption, charging rate, energy recuperation). Since the traveler specifies the EV model in the first parameter group, the parameters of this second group can be considered as sub-parameters to the first group and the EV that is in use by the traveler. Finally, the third group of parameters is needed to fully describe the problem. Those parameters are not defined for each passenger, but rather they are specified for the network, the modes of transport and the types of activities available (e.g. network topology, POI locations and opening times, charging point locations and types of chargers and availability).

The methodology that has been developed for the solution of the problem is presented in two parts: the modelling and the solution approach. While the first constitutes the basis of the approach and gives form to the solution space of the problem, the second includes the rules to be followed during the exploration of that solution space according to the GA framework.

3.1 Modelling of the DACO-EV

The most important part of the modeling is connected with the proper representation of the variables of the problem in the solution encoding (i.e. individual). Those variables are included as chromosomes of the encoding and are fully described by a two-dimensional matrix. A set of chromosomes for each location has been defined in order to describe the variables of the problem and the final quantities that need to be calculated for the optimized tours of the travelers. Of course, not all chromosomes of the solution encoding are of the same importance for the solution approach (Table 1). They can be separated into two groups, a prioritized one, whose chromosomes are subject to stochastically change, and a second group, whose chromosomes are deterministic variables and whose values depend on the first group.

Group	Priority information	Description of the chromosomes of the group
First prioritized group	The chromosomes in this group are subject to mutation.	Location of the activity, Starting and ending time of the activity, Mode of transport used to get to the location, Duration of charging time
Second non-prioritized group	Chromosomes that are not subjected to mutation and values are deterministic.	Order of the activities, Ability to charge the EV at location, Energy left in reserve in the EV battery, Cost of charging if charging took place

Table 1: Groups of chromosomes according to mutation priority

Another important aspect of the modelling is the consideration of two scenarios that are related to the size of solution matrix and the specified order of the activities. Those scenarios were introduced in order to make the solution process either faster or more flexible. The first modelling scenario is called *Fixed size matrix calculation scenario*, where it is considered that the solution matrix can include up to *2*(N+1)* activities (i.e. columns of the solution matrix), where *N* is the number of desired activities to be conducted by the traveler. This first modelling assumption is based on the idea that in an urban environment the driver of an EV does not need to stop at more than one charging stations between two activities. A similar assumption was made in the work of Cuchý et al. [9]. For the second modeling scenario we consider a *Dynamic size matrix allocation* case, where the solution matrix size and the order of the activities are not predefined. A great differentiation point for those two scenarios is the way that the genetic operators of the GA framework are utilized in order to properly exploit the advantages of each scenario.

Other important aspects of the modelling are the constraints imposed on the chromosomes and the fitness function which is used for giving direction to the search of the solution space and the successful solution of the problem. The optimization criteria of the fitness function are:

1. Duration of the whole tour;
2. Arrival time at the final destination;
3. Duration of charging time;
4. Overall cost of charging.

3.2 The solution approach to the problem

On the one hand, the solution approach is based on a GA algorithm that iterates through steps and utilizes well-established search techniques to explore the solution space and derive solutions in reasonable times. On the other hand, in order to be able to speed-up the solution phase the solution approach was broken into two parts, the pre-optimization phase and the main optimization phase. The steps of the algorithm to derive a heuristic solution are the following.

1. Initialization – Creation of initial candidate solutions and creation of the population based on user input.

2. Feasibility check – Check the feasibility of current solutions according to rules of the problem.
3. Evaluation – Evaluate the solutions provided according to the fitness function and assign a fitness score to each one.
4. Selection – Selection of the fittest solutions, solutions with lower scores are discarded.
5. Crossover – Combination of existing solutions and their chromosomes in order to create new solutions.
6. Mutation – Calculate new solutions based on stochasticity and rules.
7. Go to step 2 until termination criteria are satisfied. If they are satisfied, the algorithm ends.

The crossover and mutation operators are of crucial importance to the performance of the algorithm. The type of crossover that has been used is the ordered crossover, as described in the book by Goldberg et al. [10], and the mutation operation is based on swapping mechanism that swaps the positions of activities within the same individual (i.e. solution instance). Both mechanisms are applied to chromosome B, which can be considered as an indexed list, and from there the rest of the solution attributes are normalized according to the replacement of the activities and corresponding locations.

We used a pre-optimization stage that enables the creation of a personalized network for the preferences of each user. With this technique we aim to reduce the initial solution space. In Table 2 below, we include the combination of parameters that lead to the smaller personalized network.

Parameters of the problem to be combined	**Decision**
“Location of charging points” and “Plug type of the EV “	We can focus on a subset of charging points in the main optimization phase, because charging points with other types of plugs cannot be use in the solution space.
“Locations to be visited”, “Priorities of the user” and “Time windows of operation and POI database”	We can focus on the POIs to be included in the main optimization phase.

Table 2

4 Expected results

In recent experiments on the implementation of our approach we were able to yield meaningful solutions to the problem within reasonable query times that enable its practical usage to support an online web platform that will aid travelers in their daily lives. A crucial point for the smooth development of our approach would be the inclusion of the usage statistics of electric stations into the GA. So that usage statistics are not a deterministic value, but a stochastic entity that is calculated based on previously available data. Overall, we expect our approach to be able to fully address the realistic DACO-EV problem.

References

[1] D. Esztergar-Kiss and Z. Rozsa, "Simulation results for a daily activity chain optimization method," in *2015 International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 2015, no. June, pp. 259–264.

[2] D. Esztergár-Kiss, Z. Rózsa, and T. Tettamanti, "Extensions of the Activity Chain Optimization Method," *J. Urban Technol.*, vol. 25, no. 2, pp. 125–142, Apr. 2018.

[3] D. Charypar and K. Nagel, "Generating complete all-day activity plans with genetic algorithms," *Transportation (Amst).*, vol. 32, no. 4, pp. 369–397, Jul. 2005.

[4] R. A. Abbaspour and F. Samadzadegan, "Time-dependent personal tour planning and scheduling in metropolises," *Expert Syst. Appl.*, vol. 38, no. 10, pp. 12439–12452, Sep. 2011.

[5] M. Baum, J. Dibbelt, T. Pajor, and D. Wagner, "Energy-optimal routes for electric vehicles," in *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - SIGSPATIAL'13*, 2013, pp. 54–63.

[6] M. Baum, J. Dibbelt, A. Gemsa, D. Wagner, and T. Zündorf, "Shortest feasible paths with charging stops for battery electric vehicles," in *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS '15*, 2015, pp. 1–10.

[7] C.-S. Liao, S.-H. Lu, and Z.-J. M. Shen, "The electric vehicle touring problem," *Transp. Res. Part B Methodol.*, vol. 86, pp. 163–180, Apr. 2016.

[8] M. Cuchý, M. Štolba, and M. Jakob, "Whole Day Mobility Planning with Electric Vehicles," in *Proceedings of the 10th International Conference on Agents and Artificial Intelligence*, 2018, pp. 154–164.

[9] M. Cuchý, M. Štolba, and M. Jakob, "Integrated Route, Charging and Activity Planning for Whole Day Mobility with Electric Vehicles," vol. 358, J. Filipe and A. Fred, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2019, pp. 274–289.

[10] D. E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*. Addison-Wesley Publishing Company, Inc, 1989.