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Computation of mode-dependent travel time matrices for an agent-based demand model computed using a standalone accessibility tool

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Abstract

Agent-based demand models often rely on pre-computed matrices that describe travel times and distances per transport mode as one of the inputs for computing the mode's utility within the embedded mode choice model. These matrices have to consider the available infrastructure, mainly the road network, as well as public transport schedules and the modes' individual characteristics. Thereby, the computation of such matrices can be relatively complex and requires different types of data. This report presents a lean solution for computing such matrices based on an existing open-source tool for accessibility measures computation. A comparison of the results against matrices obtained from an earlier approach, which involved several manual steps, shows a high conformity.

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Keywords: Agent-based demand modelling; travel time matrices; accessibilities; multi-modality.

1. Introduction

Macroscopic demand models look at the population of an area in an aggregated way [1]. The individual characteristics of each person or household within a regarded area are thereby usually averaged. [2] states that "[a]lthough this approach has been moderately successful in the aggregate, it has failed to perform in most relevant

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policy tests, whether on the demand or supply side". For this reason, agent-based demand models (ABM) are increasingly regarded to be a replacement for conventional, macroscopic traffic demand models. The ABM we use is named TAPAS [3][4], a development of the Institute of Transport Research at the German Aerospace Center (DLR). Within TAPAS, each single individual the population consists of is modelled explicitly using attributes that describe her/him, including the person's age, sex, employment status, mobility budget, etc. TAPAS groups these individuals additionally into households for regarding constraints when using shared resources, such as a vehicle that is used by different household members over a day [5].

ABMs compute the mobility behavior of each person within the regarded area individually. The needed prerequisites in terms of data include daily activity plans for different person groups, the locations of activity places, as well as information about distances and travel times between locations for the regarded modes of transport. The major task of the demand model is to compute which locations within the described area will be visited by a person over the day as well as the mode of transport used to get to the respective place. The result of the model thereby consists of so-called trip chains: rides over a day for all persons within the modelled population.

The selection of the mode of transport usually uses a discrete choice model derived from empirical data, e.g. mobility surveys. Such models compute the utility of each of the regarded modes based on a set of attributes that describe the person as well as the ride from the person's current location to the chosen destination. These attributes usually include information about the travel time and the distances between a trip's origin and its destination, as well as the access and egress times to get to / from the mode's transport vehicle. In our prior work, these travel time and distance matrices were computed using the commercial application PTV VISUM. Within this process, some steps could not be automated. The resulting effort is high as the process of computing travel time matrices usually requires several iteration steps, until the simulated traffic state matches the travel time matrices used by the demand model [6]. Herein, an attempt to achieve a workflow for generating travel time matrices that is more lightweight and can be fully automated is discussed. It uses an open source tool that was originally developed for computing accessibility measures named UrMoAC [7].

The remainder of this report is structured as follows. At first, the mode choice used in TAPAS is shown in Section 2. Section 3 then describes the computation of the travel time and distance matrices, which is needed by this mode selection, using UrMoAC. In Section 4, a comparison between the matrices obtained using the initial and the new approach is given. The article closes with a discussion in Section 5.

2. Mode Choice in TAPAS

The ABM TAPAS uses data from the German national mobility survey "Mobilität in Deutschland" (MiD) as the base for the multinomial mode choice model. Herein, the mode-dependent travel time between a trip's source and destination location is one of the major variables. It is hardly possible to store this information for each relationship between an origin and a destination at the level of single addresses, which are used to describe locations in TAPAS. For the city of Berlin, each of such data tables would contain 351290^2 entries – about 1 TB of data for each mode. Yet, it is as well hardly applicable to have these data being computed on-line as TAPAS chooses and weights different destinations for each person, his/her activity, and mode. Performing a routing for each investigated combination would yield in a too high execution time of the model.

For this reason, the mode-dependent travel times and distances are currently stored as values between so-called "Teilverkehrszellen" ("sub traffic analysis zones", TVZ). The TVZ used for replicating Berlin are shown in Fig. 1. The initial approach for computing travel time and distance matrices did not involve the computation of all ways between all buildings in a region. Instead, each TVZ has five selected addresses that act as its representants. All pairs of a region's representants are used as sources / destinations and the travel times and distances obtained for a cell's representants are averaged to obtain the travel times and distances for the cell.

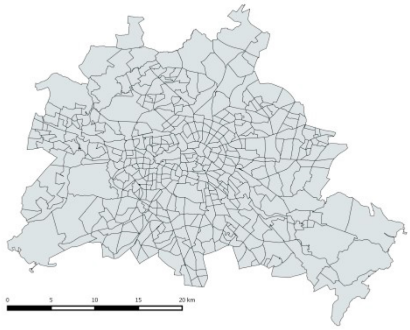

Fig. 1. Zoning used for the city of Berlin.

Given aggregated travel times and distances for TVZ, TAPAS retrieves the travel time and distances between the origin and the destination TVZ, first. In a second step, the offset of these locations to the respective TVZs' center is applied.

3. Computing Matrices Using the UrMoAC Tool

The proposed approach for computing travel time and distance matrices employs a tool named "Urban Mobility Accessibility Computer", or UrMoAC for short, which is available as open source [8]. UrMoAC reads sets of origins and destinations, a road network, optionally a public transport network with schedules from a GTFS data set, and computes different accessibility measures, regarding different limits. While the computation is performed on a most fine-grained level of single buildings and mode-dependent paths between them, the tool can load additional areas for aggregating the results. For the application described herein, the inputs consist of the following data: i) **Sources**: the representants of the TVZs; ii) **Destinations**: the representants of the TVZs; iii) a **road network**; iv) **Public transport schedule** from GTFS; v) **Source aggregation areas**: TVZs; vi) **Destination aggregation areas**: TVZs.

For the investigations described herein, we use a network from the commercial supplier NavTeq, now Here, as it was used in the original computation as well. In case of computing measures for motorized individual transport (MIT), additional travel times are loaded. Usually, we use travel time information obtained from the microscopic traffic flow simulation "SUMO" [9]. When computing measures for public transport (PT), a GTFS-based description of the PT offer within the regarded area is used, together with the NavTeq network which is used to compute the access/egress from/to PT.

Given these data, the tool is started for each mode of transport and is set up to compute the travel times and distances between all sources and all destinations and to aggregate them by the loaded TVZs – both for the sources and the destinations. After computing the O/D distances and travel times between the used TVZ using this way, they have to be imported into TAPAS' matrix map structure what can be accomplished using a single SQL command or a simple script.

4. Comparison

In the following, a comparison between the results of the initially used computation and the one employing UrMoAC are given. Both describe the matrices for the city of Berlin.

4.1. Walking

At first, a look at the results for walking is taken. Fig. 2 shows the comparison between the initial and the new matrices for distances and travel times when walking, respectively. In fact, the distance matrix is the same as the travel time matrix due to using a walking speed of 3.6 m/s. Here, only small and neglectable differences can be seen.

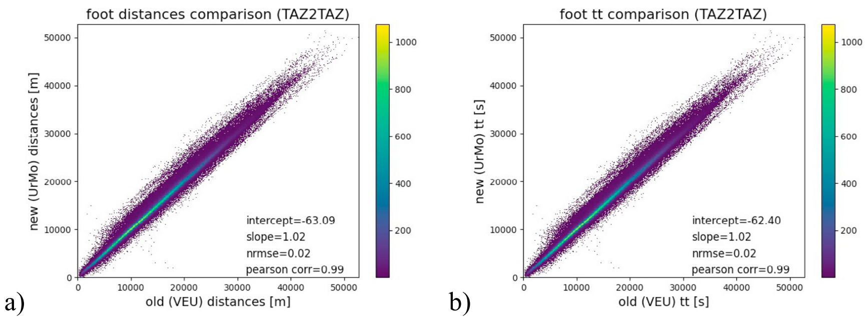

Fig. 2. Comparisons between the initial (x-axis) and the new (y-axis) measures for walking; a) distances, b) travel times.

4.2. Bicycling

The comparison of the measures for bicycling shows bigger differences, see Fig. 3. The travel time plot shows a high difference regarding the scale due to an outlier in the original dataset. Here, a connection was marked as being invalid (marked using a red circle in Fig. 3b). Besides this artifact, the results match to a high degree. The outlier with the higher travel times in the new computation (large top ellipsoid in Fig. 3a) are located in a single TVZ in Grunewald, Berlin, an area dominated by a forest. Even though more bike infrastructure is given in the OSM data set used in the second run, its velocity is low, leading to the travel time increase. The outlier with lower travel times when using the new approach (smaller bottom ellipsoid in Fig. 3a) are located in a single TVZ, as well. In this case, the Navteq network contains more bicycle infrastructure what yields in longer ways.

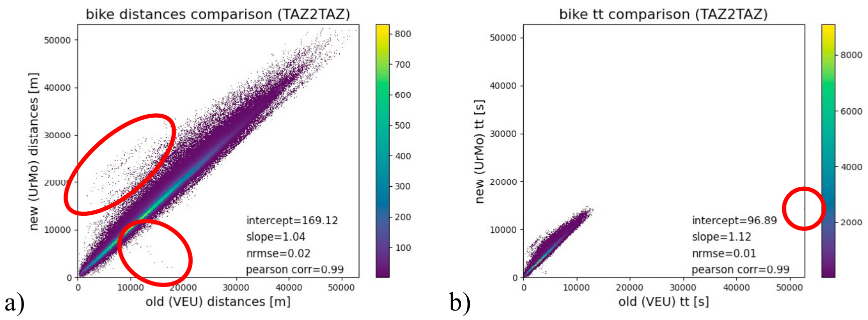

Fig. 3. Comparisons between the initial (x-axis) and the new (y-axis) measures for bicycling; a) distances, b) travel times.

4.3. Motorized Individual Transport

The comparisons of the matrices for using a passenger car are shown in Fig. 4. Here, a difference in the distances is clearly visible (ellipsoid in Fig. 4a), while the travel times match to a high degree. The differences in the distances can be explained by the fact that the latter investigation included the outer highway ring around the city of Berlin, which was missing in the initial computation runs. Vehicles using it to avoid crossing the city need to pass longer distances, yet at a higher speed, what explains why the travel times stay similar. This is supported by the fact that the probability of a TVZ being included in this set as origin or destination increase with an increasing distance from the city center.

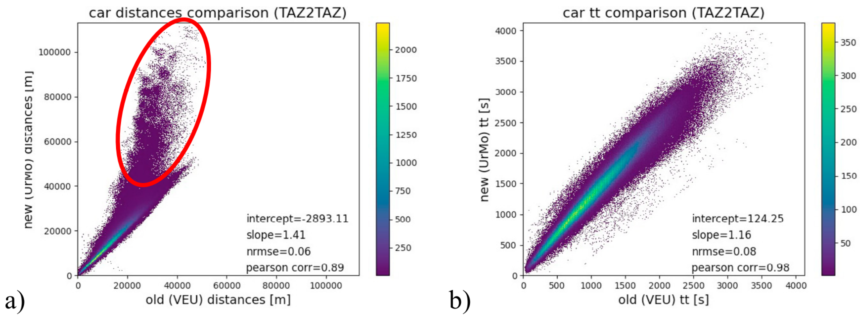

Fig. 4. Comparisons between the initial (x-axis) and the new (y-axis) measures for MIT; a) distances, b) travel times.

4.4. Public Transport

The computation of matrices for public transport is a more complex task than the ones given before. The reason is the higher number of factors that determine a PT ride. Not only the access and the egress times have to be considered when computing "optimal" public transport routes, but as well the waiting times – both, when arriving at the first station as well as when changing the public transport carrier –, the transfer times at stops, and the number of interchanges. It must be noted that the initial approach did not deliver distances for PT. Instead, the walking distances were used. As such, the differences in the old and new distances, shown in Figure 5 a), can be explained by detours some PT lines contain. Regarding travel times, shown in Figure 5 b), one may note that the old computation delivered very high values of almost 6 hours in some few cases, denoted by the red circle. They are not realistic for the city of Berlin. Overall, travel times are lower when using the new approach.

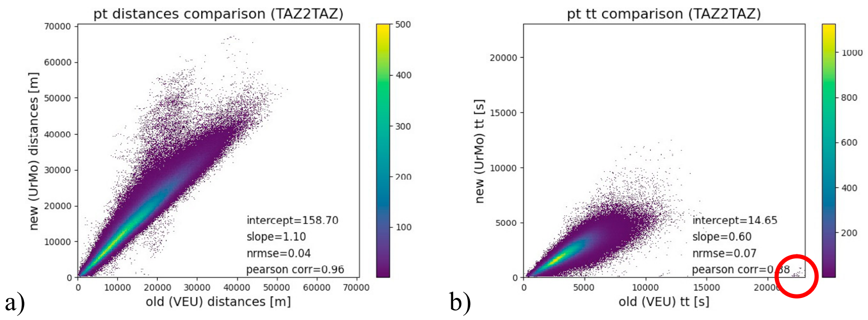

Fig. 5. Comparisons between the initial (x-axis) and the new (y-axis) measures for public transport; a) distances, b) travel times.

Due to being important for weighting public transport, Fig. 6 shows a comparison between number of interchanges computed using the old and new approach.

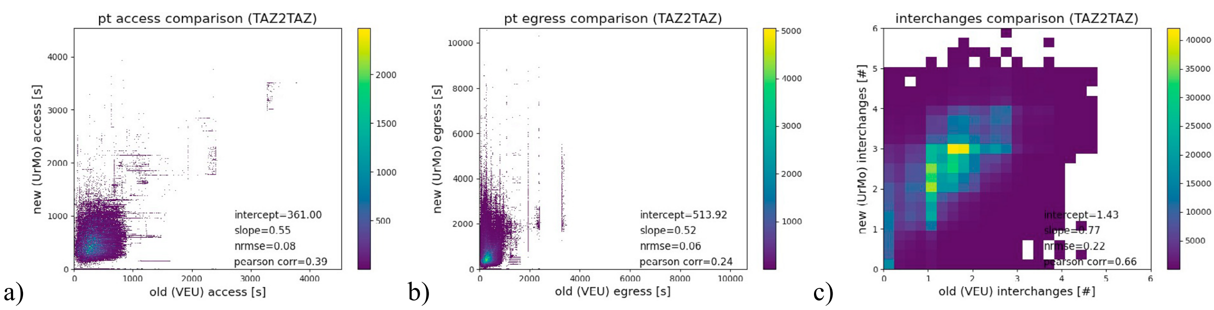

Fig. 6. Comparisons between the initial (x-axis) and the new (y-axis) measures for public transport; a) access, b) egress, c) number of interchanges.

One may note that especially the egress times are getting very high within the new computation method's results. In the meantime, UrMoAC has been extended by the possibility to weight routes by more than the travel time only. Possibilities to use different parameter sets for obtaining more realistic public transport travel times will be investigated in the future.

5. Summary and Outlook

The proposed procedure for computing travel time, distance, and additional public transport matrices for the agent-based demand model TAPAS using a simple accessibility tool shows only few and mostly explainable differences to the initially used system that involved a macroscopic assignment tool and several manual steps. The overall process requires two application calls on the command line and no manual interaction and can be thereby well automated. Yet, the attempt lacks of a possibility to consider the capacity of the respective transport network – may it be the road network or the public transport carriers. One possibility to include capacity constraints would be to run the tool in conjunction with an assignment tool. This is usually done anyway for obtaining traffic measures, such as the MIT speeds, and could be applied for considering capacity constraints as well.

In following steps, one should consider other possibilities to store the information than on the level of TVZs. The current approach introduces errors when using representants for computing the matrices, when aggregating them into the TVZs, and as well when applying a function for adapting the offset between a single location and the TVZ center. UrMoAC has been tested for its capability to compute the complete O/D matrix of all sources/destinations and has proved to accomplish this task in a reasonable time. While [10] presented an attempt to compute travel times within the ABM, we assume that other, error-minimizing partition methods could be employed as well.

In addition, the factors for weighting the subparts of the complex travel time and the number of interchanges when computing accessibilities with public transport should be re-investigated. We hope to present new insights based on literature, real-world data and further tests in the near future.

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