Creating a Baseline Scenario for Simulating Travel Demand: A Case Study for Preparing the Region Test Bed Lower Saxony, Germany

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***Abstract*—Agent-based travel demand models can be used to estimate the impact of possible transportation planning measures and to forecast future development of human mobility. Related transport models and associated simulation results are described often in detail, but explanations of the creation of the required baseline scenario including the necessary data preparation are rarely available and often not shown. Therefore, this paper gives general data requirements for creating a needed virtual representation of a study area. Furthermore, it shows a real example based on the preparation of the region covering the Test Bed Lower Saxony in Germany. Special focus is laid on population, location, and accessibility data within the area. The presented approach can also be used to prepare a different study area. Therefore, possible data sources and recommendations for preparing the data are given.**

Keywords*—*travel demand; synthetic population; locations for activities; accessibility measures.

I. INTRODUCTION

How, when, where, and why do people move from one location to another? Agent-based travel demand models can give answers to those questions. These models are important tools in transportation planning. They are used to estimate the impact of possible measures, such as the installation of a new public transportation infrastructure. Furthermore, they can provide important insights on various possible future developments in travel demand, like due to an aging population, the use of innovative vehicles, changing fuel prices or new mobility trends.

For simulating the travel demand with agent-based models a baseline scenario is required. It represents the current state and is used as reference. Therefore, a virtual representation of the related study area is an essential input for these models. Recently, recommendations for input data regarding spatial structure and transport offer have been provided [1]. The spatially related structural data often include information about the population and the locations where activities can be performed, whereas accessibility measures and transport network for different modes describe the transport offer. In addition, these models require usually information about travel behavior. Such required detailed information is often not available. Instead, it has to be created from a variety of data sources. In particular, these data are very heterogeneous in terms of format, spatial resolution, and time frame. Such challenges of agent-based models are discussed in [2].

The purpose of this paper is to highlight general data requirements, possible data sources, and appropriate approaches for creating a virtual representation of a study area. It also gives a real example based on the preparation of the region covering the Test Bed Lower Saxony in Germany. Special focus is laid on population, location, and accessibility data within the area.

The paper is organized as follows: Section II gives information on related work and contains an overview about essential input data. The data preparation of the selected study area is outlined in Section III. The results of the virtual representation are presented in Section IV. Finally, Section V includes the conclusions and gives an outlook on future work.

II. RELATED WORK AND ESSENTIAL INPUT DATA

Travel demand models are often based on the common four-step model [3], which consists of trip generation, trip distribution, mode choice, and traffic assignment. The trip generation includes the estimation of how many trips are generated within a zone whereas the trip distribution covers their destinations. Afterwards, a suitable transport mode is chosen. The exact routes to be selected are determined in the last step. In the case of agent-based models, this traditional approach has been strongly expanded [4]. There is usually no isolated consideration of a single step, but also interactions within and between these steps. Rather than modeling aggregate Origin-Destination (OD) matrices for each zone, these models rely on a non-aggregated approach, where activities are the starting point for representing daily mobility [5].

Detailed descriptions of agent-based models and associated simulation results can be found often, but descriptions about creating the underlying baseline scenario and the data preparation are rarely available. Such models require a variety of different input data for each step. Current research shows that the level of detail of the required input data may differ [6] [7] [8]. This can depend on both the transport model used or the specific research question. In the following, essentially required input data, possible data sources, and further related work for each discussed approach to generate the specific data are given in the subsections below.

A. Spatial reference units

A subdivision of the study area into smaller units is necessary to reflect spatial differences in travel demand. In travel demand modeling these spatial units are called Traffic Analysis Zones (TAZ). Usually they are homogeneous, for example, containing the same number of households but they can also correspond to administrative boundaries. The spatial reference units are needed within the model, but they are also used for the analysis and visualization of the simulation results [9].

B. Spatial structure data

For each TAZ, non-aggregated population data are required. Each person of a synthetic population is described by a set of socio-demographic information. In addition, information about available mobility options is required. Household information comprises for example the number of persons, the total household income, and the number of cars that belong to the household. Within the simulation, each tour usually starts and ends at the home location of the person. Therefore, a spatial reference of the address for each household is required. Based on the address, each household can also be assigned to the corresponding TAZ. Such detailed population data are usually not available, but have to be generated on the basis of empirical data and by suitable mathematical methods. The consolidation of all information often remains difficult, as various and heterogeneous data sources have to be used. Therefore, a variety of different approaches have been established for creating a synthetic population. Most of these approaches are sample-based [10]. In order to correspond to both a desired household and person distribution, several methods can be used, for example household weight updating [11], hierarchical fitting [12], or Bayesian networks [13]. Due to limited data availability, alternative approaches that do not require a sample have been developed as well [14]. The synthetic population has a direct impact on the resulting traffic volume, but also on the simulated travel behavior.

Apart from the synthetic population, possible locations where activities can take place at are needed. Location choice depends not only on individuals, but also on location specific characteristics. Frequently used attributes in location and destination choice include type of activity, spatial distribution, accessibility, maximum capacity, as well as destination attractiveness. The main activity types used in agent-based travel demand models are often related to work, education, shopping, and leisure, but further types, such as personal business or accompanying, may be also regarded depending on the model [15] [16]. Information about activity locations usually has to be collected from a variety of sources (e.g., public authorities, surveys, commercial data). Since this process can be time-consuming and expensive, open data is another option, especially OpenStreetMap (OSM). Its suitability and accuracy as a data source for travel demand modeling has been subject of study, with different results depending on the region or activity type, with a possible improvement in data quality over the years [17]. Another possibility is to generate activity locations randomly using complementary data, such as land use [18] or commuter flows [16]. Information about the numbers of workers, students, etc. is used by travel demand models as a capacity constraint to avoid exceeding the location's capacity and is only provided by some data sources. If not available, it can be generated synthetically, for example using building area and number of floors. Another attribute used by some models for destination choice is attractiveness, for example based on store size [18] or using data from a location-based social network [19].

C. Transport offer data

In an agent-based demand model, each person from the synthetic population acts as an agent. An agent has its own daily plan of activities which need to be simulated. These plans are commonly represented as tours. A tour starts and respectively ends at home and contains a set of trips which connect subsequent activities. Trips are entities that represent the movement between two locations, including the time they should start at, as well as the required time to accomplish them. In order to complete a trip, an agent has to make several choices, such as which location to head to and which mode to use. Since the duration of a trip is known in advance, the choice for a potential destination is, among other things, dependent on mode specific travel times that are structured in OD matrices. To reduce the dimension of these matrices, travel time data between every location is aggregated on TAZ level. There are several possibilities to generate disaggregated travel time data. In the context of motorized individual transport, one can use a graph-based routing algorithm like Dijkstra [20] or A* [21] or acquire raw data from external sources with further processing. In the context of public transport, time table-based data like the General Transit Feed Specification (GTFS) could be used. These accessibility measures play an important role in computing both, destination and mode choice.

D. Travel behavior data

Information about travel behavior within a study area is required in several steps of the modeling process. Such data can be usually obtained from travel or time-use surveys. Mobility options for the synthetic population can be estimated by related logit models. However, the fundamentals of these microscopic travel demand models are based on activities of each individual. Besides the type of activity, the reported diaries typically include both the start time and the duration of the activity, but also the activity sequence. During a simulation run, the prepared standardized diaries from the survey are used to determine for each person in the synthetic population what activities they undertake, when, and for how long. This also reflects the number of trips to be generated. An appropriate decision model is needed for the choice of the transport mode. For this purpose, a multinomial logit model could be created, for example, based on travel time, trip purpose, and distance obtained from the survey. In addition, the distribution of observed distances per mode, modeshare or trip purpose can be used to calibrate and validate the simulation results.

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III. Preparing the Region Test Bed Lower Saxony

In this section, the study area will be outlined. First, an overview of the data sources is given. Then, the spatial representation of the area. Afterwards, the generation of the synthetic population, followed by the locations including their capacities. Finally, the preparation of accessibility measures for different modes of transport are described. The presented study area will be used within the agent-based travel demand model TAPAS [22] [23]. The software was recently made available as open source and can be found at: https://github.com/DLR-VF/TAPAS.

A. Overview of data sources

For preparing the study area, various data sets from freely accessible data portals, administrative authorities but also a commercial data provider have been used. The data sources on which the study area are based are listed in Table I and described in more detail in the following subsections B to E.

B. Study Area

With the Test Bed Lower Saxony [24], a research infrastructure for automated and connected vehicles is currently being created. The test field includes sections of various highways, but also parts of federal and country roads. Furthermore, it also integrates the roads of the Application Platform for Intelligent Mobility (AIM) [25], which is in operation within the city center of Brunswick. In total, the test field will cover more than 280 road kilometers after completion. This road network is located in the federal state of Lower Saxony within the districts of Gifhorn, Helmstedt, Hildesheim, Peine, Hanover region, and Wolfenbüttel, as well as the district-free cities of Brunswick, Salzgitter, and Wolfsburg. Population data for forecast periods are often available at the district level rather than at the municipality level. For this reason, these 6 districts and the 3 independent cities represent the study area which is used in this paper. As mentioned in Section II, it is necessary to subdivide the area into traffic zones. Unfortunately, no small-scale uniform subdivision covering this area was available for free. Therefore, a suitable division by neighborhoods containing approximately 500 households was obtained from Nexiga [26]. As a result, the area is divided into 2807 zones. The region is mainly characterized as urban. Fig. 1 shows the spatial coverage of the study area including the road network of the Test Bed Lower Saxony and the division into traffic zones. The geographical position within Germany is given in the overview image, highlighted in dark gray.

TABLE I. Data sources

Data provider	Study area	Synthetic population	Locations for activities	Accessibility measures
Connect Fahrplanauskunft GmbH (Connect)				x
Federal Agency for Cartography and Geodesy (BKG)		x	x	
Federal and State Statistical Offices		x		
Kraftfahrt-Bundesamt (KBA)		x		
Mobility in Germany (MiD2017)		x		
Nexiga	x	x	x	
OpenStreetMap (OSM)			x	x
Statistics Office of Lower Saxony (LSN)		x		

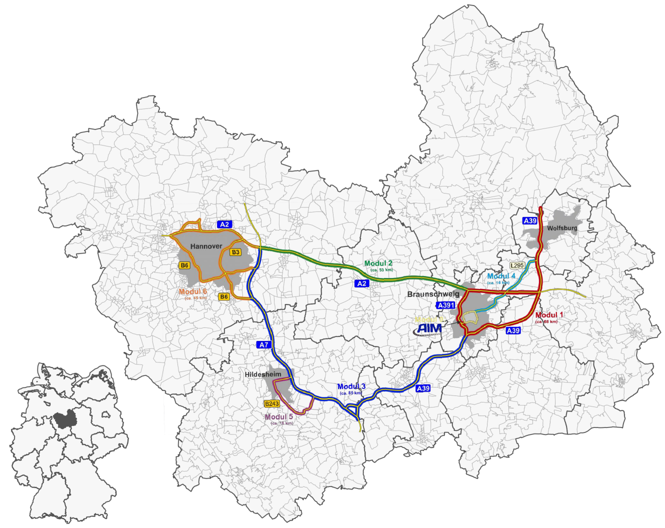

Figure 1. Spatial coverage of the study area including the road network of the Test Bed Lower Saxony and the division into traffic zones. The geographic location within Germany is highlighted in the overview image.

C. Synthetic population

The required detailed population data are not available in Germany, or if they are, they are not available without charge. Usually, population data for the base year are only available in aggregated form at municipal level. But, this spatial resolution is much too low. For example, a city like Berlin with 3.7 million inhabitants would be a municipality. In order to take spatial differences within the study area into account, the data must, on the one hand, be on a higher spatial resolution and be available in a non-aggregated form. The synthetic population was created using SYNTHESIZER [27]. This in-house application is often used within projects to generate the required non-aggregated population data for TAPAS. Beside the spatial subdivision into traffic zones, aggregated socio-demographic data as marginal totals, and a non-aggregated data set for duplicating the respective households and persons are needed as input. Therefore, aggregated population data on TAZ level from Nexiga were used. This data set includes the number of persons subdivided into various age groups, gender, and labor force. The latter are further subdivided into employed and unemployed persons. In addition, household size and income, as well as number of private cars are

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included. A person within a synthetic population for TAPAS is mainly described by age, gender, and a status classification like children under 6 years, pupil, trainee, student, both full time and part time employed, unemployed or retired. To get the total number of children under 6 years of age, the corresponding age groups were added. Number of pupils and students in formal education schools, type of employment (part-time or full-time), and number of pensioners come from the LSN [28]. Data on students in higher education were used from the municipal education database [29]. In addition, the scientific use file of the Microcensus [30] was used as non-aggregated sample. Both data sets are taken from the Federal and State Statistical Offices. Since the aggregated data were partly available on different spatial scales, they were proportionally allocated to the corresponding traffic zone in advance. In the SYNTHESIZER application, the respective distributions at household and person level are generated for each TAZ. To ensure that both distributions are included in the target population, a new household weight is generated and used when copying the entries from the sample. The result is a non-aggregated base population.

Section II mentions that an address is needed for each household. So far, only a spatial reference to the associated TAZ is given. Instead of distributing the corresponding households evenly among the associated addresses within a TAZ, the distribution was done by using a weight for each address. This weight is composed of land use, building height, and building area. Depending on the land use in which an address is located, a corresponding factor was assigned to this address, with addresses in residential areas having a higher value. The weight of an address (A) is calculated by the product of the land use factor (LU), the building height (BH), and the building area (BA) as shown in (1).

$$Weight_A = LU_A * BH_A * BA_A \tag{1}$$

Finally, the weighted number of inhabitants was added to each address. It is composed by the product of inhabitants living in a TAZ and the weight of the address (A) divided by the sum of all related address weights located in this TAZ, see (2).

$$Inhabitants_A = \frac{Inhabitants_{TAZ} * Weight_A}{\sum_{A' \in TAZ} Weight_{A'}} \tag{2}$$

Addresses, a digital landscape model, and a three-dimensional building data set with the LoD1 level of detail from the BKG [31] were used to distribute the inhabitants on buildings.

In addition to socio-demographic data, information on available mobility options for each person or, respectively, household are important for the upcoming simulation. The availability of various mobility options was reported in the nationwide household travel behavior survey MiD2017 [32]. Based on the survey data, logit models could be estimated for owning a driver license, a public transport ticket, as well as the ownership and number of cars in the household, and their subdivision into three different size classes. No significant model could be estimated for bicycle ownership. Instead, the respective proportion by gender and age group were used for this purpose. The total number of private cars for each traffic zone from Nexiga was used as the vehicle fleet. Whereas data from the KBA [33] was used for the distribution of the vehicle fleet in regard to the corresponding engine types and their size classes.

D. Locations for activities

Activity locations from different sources were gathered and their format was harmonized for its use in TAPAS. Activity locations in TAPAS can serve different activities and need exact coordinates, activity type, and total capacity as attributes for destination choice. An example for a location serving multiple activities is a school, which can serve for educational and working purposes. All data sets contained spatial information, even if the coordinate reference system may vary. On the contrary, type of activity and capacity were not always available and even if they were, they had to be converted and manually classified.

TAPAS has its own classification of activities with three levels. The first level is based on the main activities work, education, shopping, leisure, and personal matters. Within each category there is a more detailed subdivision with one or two subcategories. This is to address different kinds of locations, especially in matters of size and special use. An example with three levels would be *education-school-primary school*.

From Nexiga came most of work and shopping locations and to a lesser extent locations of other categories. From the BKG forest-related data from the Digital Landscape Model (DLM) and Points of Interest (POI), such as universities, schools, hospitals or embassies, were used. Lastly, different leisure locations, including parks, allotments, playgrounds or places of worship were extracted from OSM. Most of the TAPAS activity categories were mapped onto economic activity codes, which are available for most of the companies in the Nexiga data set. These codes correspond to the German Classification of Economic Activities, which is based on the Statistical Classification of Economic Activities in the European Community. Categories without a link to economic activity codes had to be classified by string-matching or manually, which was the case for the BKG and OSM data, as well as for part of the Nexiga data.

In order to calculate capacities for activity locations, a system based on relating location area to the number of potential users/customers and workers was used and adapted to our needs. These factors can be obtained by planing engineering offices like [34] or from the Trip Generation Handbook [35]. Our system consists of an employee factor as well as a user factor for each activity category. Both factors are interconnected, allowing to determine the number of users per employee and vice versa. We also included a default value (used in case of unavailable capacities), extracted from available data or determined after some visual analysis. Those factors were used to calculate missing capacities for all Nexiga locations as well as for schools and hospitals from BKG, since the number of employees for the former and the number of

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pupils and beds for the latter were available. For example, for the Nexiga locations the number of users/customers was calculated using the number of employees and the corresponding user factor. From the forest-data the area was used to subtract a possible number of visitors, whereas default values were assign to all OSM locations.

E. Accessibility measures

Since an agent inside a TAPAS simulation has a predefined time frame for a trip, the location choice model is, among other things, based on travel time matrices. Over the course of a simulated day, these matrices have to change because travel time is dependent on factors like current situation on roads and the roads' capacities in the context of individual transport or time table changes when it comes to public transportation systems. As stated in Section II, several techniques exist to compute these for each available mode. Average travel times and travel distances between each TAZ for every mode have been computed using the UrMoAC [36], which is a Dijkstra-based, in-house, and open-source application. Based on the fact that computing all routes between every location in the study area will require a lot of computation time, five location representatives for every TAZ have been chosen at random in advance for all modes. In the context of public transportation, these computations have been done for multiple time frames over three days (Tuesday, Wednesday, and Thursday) in an average week with no special events. Time frames from 7am to 10am and 5pm to 7pm cover the morning and evening rush hour travel times. 10am to 5pm and 7pm to 11pm represent average utilisation. The last time frame from 11pm to 7am contains average travel times for night traffic. A common problem with this approach refers to untrustworthy travel times for trips that start and end in the same zone. The matrix diagonal for the whole area is computed separately, calculating every distance between every location inside the same TAZ and using the median as average travel time [37].

IV. Results

The study area was prepared for the base year 2017 and the forecast year 2030. The following results refer to the base year.

The synthetic population for this area contains a total of 2.4 million persons grouped into 1.3 million households. Fig. 2 presents the spatial distribution of the population density. The district cities appear quite prominently here. On average, 1.9 people live in each household. The population distribution according to age and gender is shown in Fig. 3. About 51% of all people are female and the remaining are male. Approximately 16% of the inhabitants are younger than 18 years, 62% are of working age and 22% are older than 65 years. 88% people of age 18 or older have a driver license. In addition, about 84% of all people have a bicycle and 23% have a ticket for public transport. 21% of all households do not have a car, whereas 79% own at least one car. All added mobility options correspond almost exactly to the values reported in the MiD2017. Only the value for the public transport ticket is 2% higher than in the survey. This is due to the fact that when adding the public transport ticket, both school as well as semester tickets for students were assumed in the entire study area. The overall level of motorization is about 537 vehicles per 1,000 inhabitants. Fig. 4 shows the spatial distribution of the motorization level. It can be noticed that the level of motorization is lower in the cities of the district. However, if the number of vehicle per km² is taken into account, the vehicle density in the cities is higher than in the surrounding communities.

The preparation of the activity locations resulted in a total of around 220,000 locations, taking into account that some of them correspond to the same location but have different types. For example, a hospital belongs to the categories *work*, but also

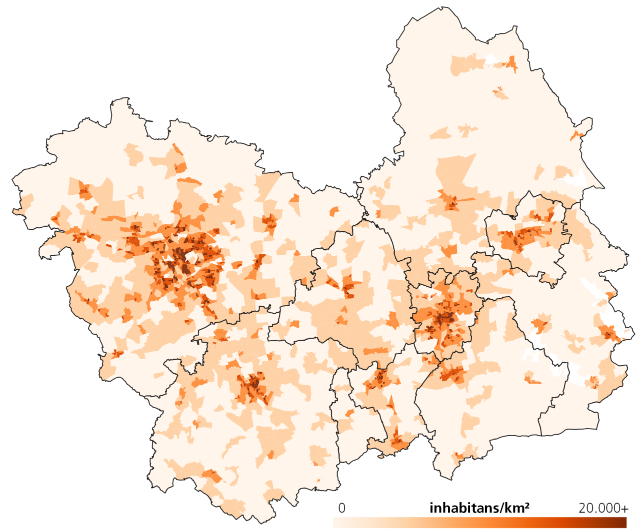

Figure 2. Spatial distribution of the population density.

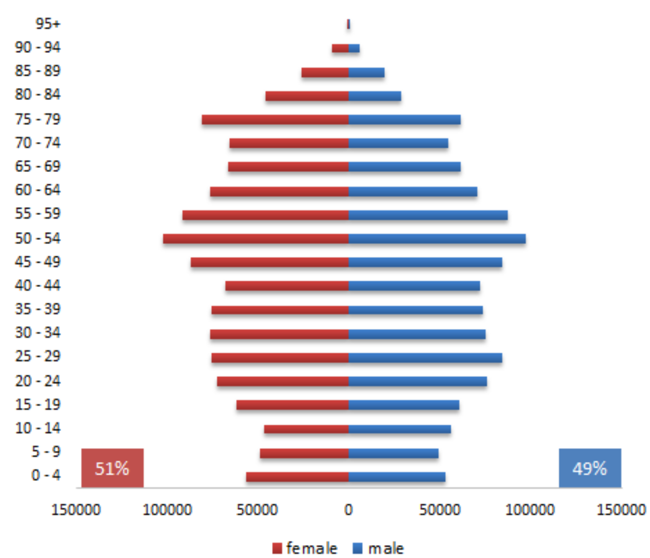

Figure 3. Distribution of individuals by age and gender.

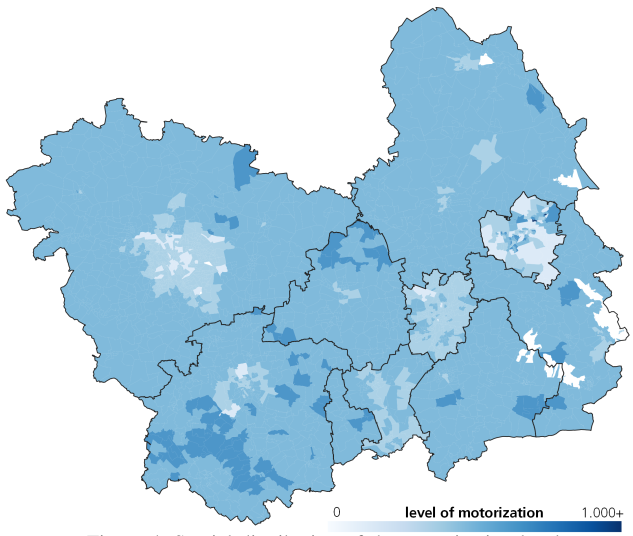

Figure 4. Spatial distribution of the motorization level.

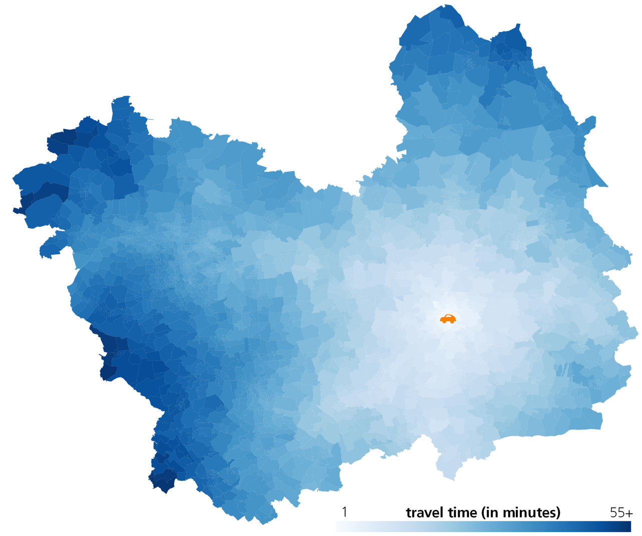

Figure 6. Travel times by car from Brunswick to all traffic analysis zones in the study area.

to *personal matters - health - hospital*, and *personal matters - family - visit*. Approximately half of the locations correspond to workplaces, 4,000 to education, 13,000 to shopping, and 33,000 to personal matters. More than 20% are leisure locations, but this number is misleading, because forests are divided into small areas, of which the centroid represents a location. Furthermore, as with the spatial distribution of the population, most workplaces are concentrated in the main cities, shown in Fig. 5.

Fig. 6 shows the temporal accessibility from the center of Brunswick to all other traffic analysis zones inside the area using a car. One can see that an agent can reach farther regions that are located along highways in a certain amount of time. The main transport network is included in Fig. 1.

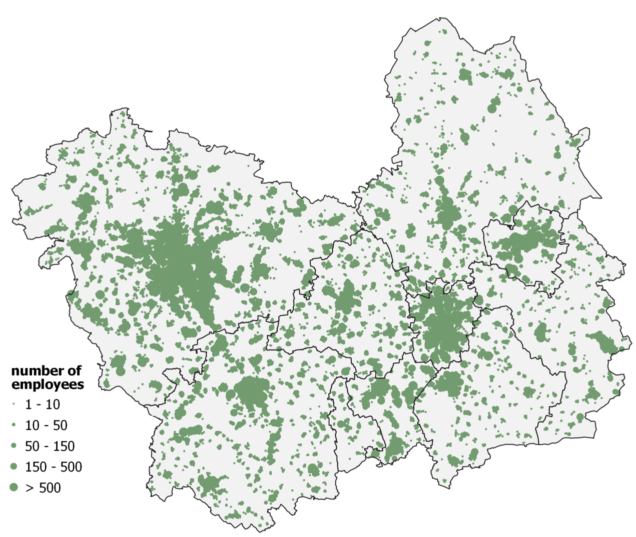

Figure 5. Spatial distribution of workplaces as well as number of employees represented by the symbol size.

V. Conclusion and Future Work

Agent-based travel demand models are important tools to estimate the impact of possible transportation planning measures and to forecast future development of human mobility. A virtual representation of the related study area is an essential input for these models. This paper gives a real example based on the preparation of the region covering the Test Bed Lower Saxony in Germany for the year 2017. The presented approach can be used to prepare a different study area. Therefore, several recommendations, possible data sources, and approaches to generate the needed data are given. The method for generating the synthetic population could also be used within a different research domain. For this purpose, data on mobility options could be replaced by relevant other information or additional ones could be added.

It should be noted that the quality of the input data has a strong influence on the quality of the simulation results. Therefore, special attention should be paid to the correctness of the data and, if necessary, plausibility checks should be carried out. This ensures that realistic findings and useful conclusions can be derived from the simulation results. Furthermore, data preparation and maintenance can be very time-consuming and expensive, depending on the level of detail and the availability of data for the study area.

Upcoming work will focus on the simulation of different scenarios in the field of autonomous driving. For this purpose, the study area presented in this paper will be used in the travel demand model TAPAS.

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