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Simulation-based investigation of transport scenarios for Hamburg

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Abstract

This simulation work investigates new means to decrease the modal share of motorized transport in a large urban area in Hamburg, Germany. This was deemed necessary in order to cut down CO_2 emissions. The five scenarios simulated with the MATSim [13] framework including an adapted mode choice model strongly suggest that making public transport more attractive is not sufficient to reach this goal, the results display a meager 3%-point change in the share of motorized transport. With introducing additional means to repel motorized transport, an 8%-point change may be within reach. The results also show that by making bike riding more safe, a considerably higher share of biking is possible (+8%-points).

Keywords: Future mobility; Agent-based Simulation; Impact Assessment; Mobility-On-Demand; Autonomous Vehicles

1. Introduction

Future transport systems may look different from today's. There are at least two noteworthy trends that may shape our future mobility, and this is the quest for a smaller carbon footprint of the transport system, and a strong pull toward more digital services, either in the form of mobility as a service or the development of autonomous vehicles (AV) [11, 18, 19]. Especially the introduction of AVs may change public transport for the better, however, it not done careful, it might also change the whole system into one that consumes more resources [4].

The city of Hamburg has made a huge investment in the modernization of it's transport system, aiming for neutralizing the carbon footprint and creating a more livable city. In the recent past, several pilot projects were conducted that

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included a real technology laboratory [24], banning private cars from neighbourhoods at day time [9] or even entirely from a major road in the city center [8]. In this study, we investigate several future scenarios for the transport system of the Hamburg city and it's surroundings, proposed by Bieker-Walz et al. [2].

The remainder of this text consists of three parts: section 2 describes the simulation setup, in section 3 are the results of this study, and section 4 summarizes and concludes this work.

2. Methodology

With Hamburg being the second largest German city in terms of inhabitants and representing one of the largest transshipment ports in the world, one needs to account for the surrounding areas, commuter flows and freight transports when trying to understand the transport system. In this study, we aim to assess the impact of a large roll-out of future mobility systems such as Mobility-On-Demand (MoD) shuttles, sharing fleets and city-wide major improvements of the bicycle infrastructure. In the past, agent-based transport simulation frameworks have proven an adequate tool to investigate impacts of such large changes without the need of implementing substantial experimental projects in reality. The usage of activity- and agent-based simulation allows us to model the behavior of single travellers and still account for the entire metropolitan region of Hamburg. This section first gives an introduction into the simulation framework used, before the derived model and the scenarios under investigation are described.

2.1. Simulation tool

We decide to use MATSim [13] as simulation framework for this study, as it has been successfully applied to various scenarios for diverse research questions in multiple countries already [17, 25, 1]. MATSim comes with built-in modules that enable the user to model impacts of autonomous vehicles, both privately owned [23] or organized in MoD fleets [20, 3], as well as car- and bike-sharing [1] and environmental impacts of transport such as the carbon footprint [13, chapter 36]. Moreover, MATSim is extensible, allowing to add features such as a mobility budget for travellers, a parking pressure model (see section 2.2) or an accident cost analysis. In this work, the latter is based on cost rates from [22] to be multiplied with the vehicle mileage on each road segment. The cost rate of each road segment depends on infrastructural parameters such as the number of lanes and the intersection type as well as on the location (urban vs. rural areas).

2.1.1. The MATSim framework

In MATSim, the transport demand is modeled by a synthetic population represented by agents, each of which holds an initial plan that describes its course of a typical working day. The plan consists of activities like home, work, errands or leisure and legs in between them, representing changes of location. In a physical mobility simulation, all agents perform their plan. Depending on the traffic state resulting from the interaction of demand and supply, agents might experience congestion or long waiting times, come late to activities or travel smoothly. After the mobility simulation, each plan is assigned to a score depending on its recent performance. For this, time spent while performing an activity is assumed to be perceived positive whereas time spent for traveling is accounted for negatively, leading to the effect that agents try to minimize travel time. Additionally, different transport modes can be assigned different parameters that model prices, comfort, safety perception etc. After the scoring, the simulation enters a re-planning phase, where a certain share of the agents is allowed to mutate their plan. This allows to model mode choice, route choice and departure time choice. By re-iterating over these steps several hundreds of times, a co-evolutionary algorithm is performed, meaning that agents optimize their scores and a stochastic user equilibrium is approximated [13].

2.1.2. Mode Choice Model

For the setup of the Hamburg transportation model, we use a mode choice model (ChangeSingleTripMode) that mutates one single trip at a time. In contrast to another mode choice model available in MATSim, that typically changes the transport mode for all trips of a subtour (SubtourModeChoice), ChangeSingleTripMode does not guarantee so-called mass conservation. A subtour is considered a sequence of trips that start and end at the same location, e.g. home-work-leisure-home. Mass conservation is the phenomenon that (non-autonomous) vehicles can not pop up out of the blue, meaning that one can only take a trip with a car when it was parked near the origin before. In the example

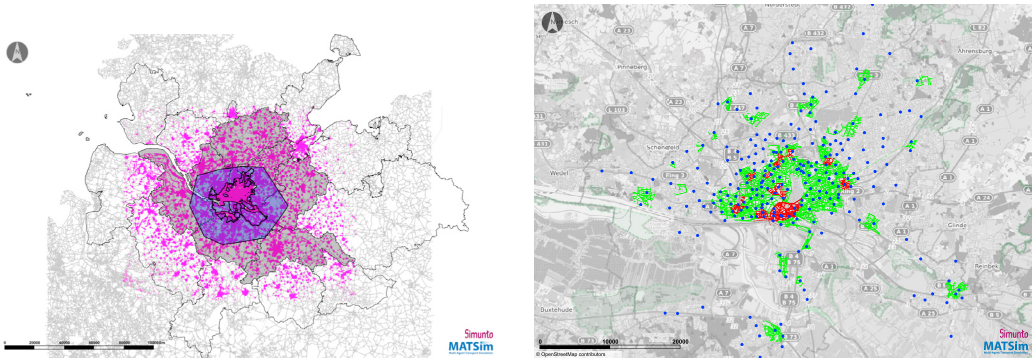

Fig. 1: (a) Spatial scope of the model and the DRT service area; (b) Roads with increased parking pressure and HVV Switch points for 2030

above, that would mean that the corresponding agent can not travel by car from work to leisure if it had not taken the car for going to work. Moreover, the agent had to take the car to get back home as well, as otherwise the car would not be there at the start of the next day. There are two reasons for using ChangeSingleTrip, although it does not respect mass conservation by default: (1) the initial plans, generated based on mobile phone data by an external provider, are not compatible with SubtourModeChoice, as they were produced with ChangeSingleTripMode and roughly 21.5% of the subtours are open, i.e. do not end at the origin activity; (2) in reality, people actually do leave their cars at leisure activities in bars etc. or hand them over to household members. However, in order to account for the fact that in reality, most parts of the population do not have an autonomous car (yet) and do not hand over vehicles with others during the day, we add a scoring penalty of the equivalent of roughly half the daily fixed costs of a car for each subtour that violates mass conservation. This has not been done to the knowledge of the authors, yet. The value of the score penalty results from rough calibration and yields a percentage of less than 7% of subtours violating mass conservation in the Base2019 scenario (see 2.2 for a description and mode-choice calibration results).

2.2. The scenarios

Bieker-Walz et al. [2] define future mobility scenarios for Hamburg that are taken as the basis for this study. The set of scenarios is composed of a base case representing the state of the transportation system in late 2019, before the Corona pandemic, and four scenarios describing possible future states in the year 2030. For all of the modeled scenarios, the overall transport demand stagnates, meaning that we do not account for forecasts on the demographic development for the region. This is done in order to isolate and investigate the impact of future mobility technologies described below, which is the major goal of the present study. The person demand is based on multiple data sources including mobile phone trajectories and represents the private transport demand on a typical working day for the city of Hamburg and a larger surrounding area. Figure 1 (a) displays the locations of the first activities of the day (typically of type home) of all agents as purple dots. Note that for all of the following analysis including the calibration, we filter agents living in the grey and blue colored (and inner city) areas. We also include commercial traffic that is generated from data provided by Hamburg's Authority for Transport and Mobility Change. For this work, we run a 10% sample of the transport demand consisting of 371,998 person agents and 102,372 freight agents.

Base2019 For the base scenario, we consider the transport modes car, bike, pt, walk and ride, which represents private car passengers and is not included in mode choice, as no detailed household model is established which would be necessary to account for vehicle availability in ridership. The modal split and the modal distance distribution is calibrated against survey data from [6]. Figure 2 shows the results. Moreover, we validated car travel times and distances with the help of data from a navigation service provider. The road network is based on OpenStreetMap [21] while the pt schedule is generated from GTFS data. We model parking pressure with generalized costs representing monetary and time efforts based on data from Hamburg's larges pt operator Hamburger Hochbahn AG. Figure 1 (b) displays roads with high parking pressure in red, modeled by a score deduction of 1.0 for each parking procedure, and roads with medium parking pressure (score deduction of 0.7)

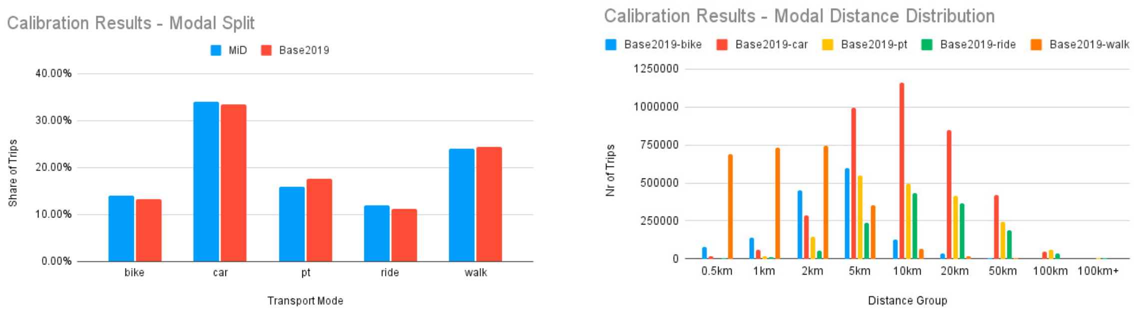

Fig. 2: (a) Modal Split: reference data [6] vs. simulation; (b) Modal distance distribution in the simulation

in green. The medium parking pressure is equivalent to a travel time saving of 2.5 minutes in pt, 6 minutes walking or 7 minutes car driving.

RealLab2030 In this scenario, we model the implementation of several technologies tested in the RealLabHH project [24], project them into the year 2030 and apply them to the entire city. Specifically we include the following measurements in this future scenario:

- A monetary incentive to abandon private cars, called mobility budget within the project. Agents receive €2.50 (per day) if they used car in the base case, but never do so in the policy case.
- City-wide bike and car sharing, both modeled as free-floating services. Fleet sizes and user prices are based on available services in 2021. Additionally to the current fleet, we place 5 vehicles at each of 249 fixed stations (a projection of HVV Switch Points [10] for 2030, see blue dots in Figure 1 (b)) at the start of the day.
- An MoD pooling shuttle service, also called DRT for demand-responsive-transport, to and from pt. The service area is shown in blue in Figure 1 (a) and does not cover the city center. The shuttle must not be used for direct transport, i.e. it exclusively operates as a feeder to and from pt, and costs roughly €1.00 per ride.
- We model scenario-wide bike infrastructure improvements based on stated-preference data [12], which suggests that a change from no bike lane to bike lane as well as the change from a bike lane to a protected bike lane increase the safety perception of users. This effect is modeled by adjusting the alternative-specific constant (ASC) for the mode choice model.

RealLab2030plus In addition to the measurements implemented in RealLab2030, we insert a projected pt schedule for 2030, provided by the current operator. The schedule represents a significant improvement of the current public transport system in terms of frequencies, network expansion and density. The city has started with its implementation, but will not finish before 2025 [2].

ProClimate2030 In addition to RealLab2030plus, we implement the following measures to reduce the attractiveness of private motorized transport:

- City-wide increase of the parking pressure (i.e. reduction of parking space and increase of fees), modeled by a deduction of 0.7 score points, which is interpreted as medium parking pressure in the base model.
- City-wide speed limit of 30 kilometers per hour on all roads except for primary roads and for motorways.
- On primary roads where two or more lanes were in place, capacity is reduced by one lane.

DRT2030 This scenario is the same as RealLab2030plus except that the DRT shuttle service covers also the city center and allows for direct passenger transport in the entire service area. The user price is €0.40 per kilometer with a minimum of €2.00 per ride. Intermodal trips receive a refund of €1.00.

3. Results

To compare the different scenarios on a highly aggregated level, the most important metrics have been compiled into Figure 3. The left graphic (a) displays the resulting modal split for all of the scenarios. Note that the mode ride is

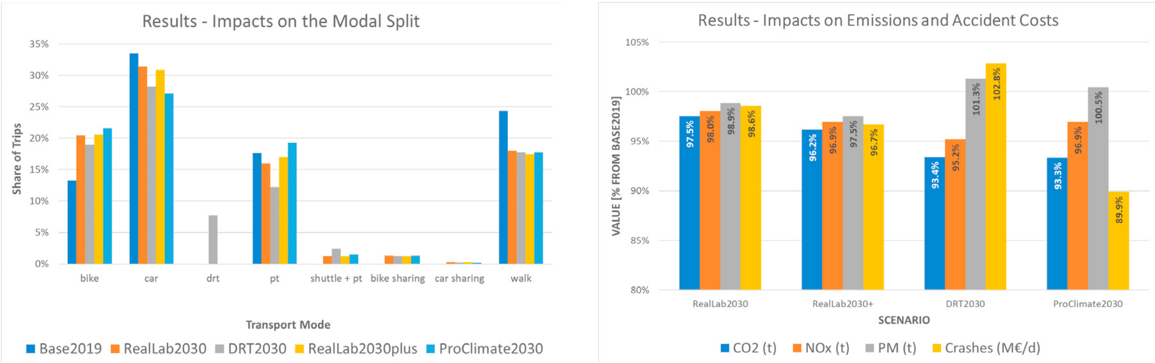

Fig. 3: Results per scenario. (a) Modal Split; (b) Emissions and accident costs, relative to Base2019

spared out, as it is not mutated by the mode choice model. Moreover, note that the bike and car sharing services are only available in Hamburg city, whereas we analyze all trips of people living in the region (see above, colored areas in Figure 1 (a) plus the city center).

The scenario-wide bicycle infrastructure improvement has a strong effect, with the share of bike trips jumping by roughly 7%-points from Base2019 to RealLab2030. However, 70% of the agents switching to bike come from the walk mode and only about 18% from car. Note that modeling the infrastructure improvement via ASC has the effect that the attractiveness of bike is disproportionately increased for short trips. The model derived from [12] does not allow for time- or distance-dependent modeling. However, this would be not only more realistic but also, according to our experience, have the effect that induced bike trips would be longer and substitute more pt and possibly car trips, relatively speaking.

The introduction of an improved pt schedule has no strong effect on the modal split in the simulation, increasing the modal split of pt by 1%-points from RealLab2030 to RealLab2030plus. Kaddoura et al. [14] observed the same effect on the modal split by doubling of the frequencies of all pt lines in a MATSim scenario for the Ruhr area in Germany. The authors state that this might be caused by the fact that the pt has no capacity constraints in the model. Moreover, there are no significant delays in the model.

While a point-to-point DRT service larger than the city boundaries can reduce the share of car trips significantly, the results suggest that it substitutes the same number of pt trips, both former modes representing roughly 42% of the DRT trips in DRT2030. From earlier research in other areas we know that setting a minimum fare helps to obtain low shares of agents transferring from bike and walk to DRT [15]. The ProClimate2030 scenario has the lowest car share of all scenarios and the highest pt share, with 7%-points more than DRT2030, which is roughly equivalent to the share of DRT trips in DRT2030. Note that pt has no capacity constraints in the model.

While demand and supply are typically scaled linearly in transport models (i.e. proportional to the sample size), Kaddoura and Schlenther [16] suggest that for pooling services, the fleet size and mileage should not be scaled linearly. Based on this, we estimate the DRT fleet size for DRT2030 to roughly 20,000 vehicles including a 10% buffer for maintenance, charging etc. This fleet would serve the upscaled demand of 1,106,270 rides with 5.8 million veh-km. The mean of all fares for a ride in the simulation is €2.63.

The right graphic in Figure 3 displays the outcomes in terms of emissions and accident costs, relative to Base2019. Thus, for the latter, all metrics are valued with 100% and are not displayed here. It could be seen that there is a very heterogeneous picture where some of the metrics cease to decline. Note, that we assume the same distribution of propulsion technologies in all of the scenarios for private cars, while DRT shuttles are assumed to work electrically. By doing so, we separate the effects that are due to the scenario technologies alone from effects that come from future propulsion technology market shares.

The DRT shuttles could in principle be AV, and in this case using the accident cost rates given in [22] is certainly not correct. AV can be expected to have a lower accident rate, meaning that we tend to overestimate the total accident costs in the future scenarios with regard to automation, especially in DRT2030. On the other hand, for the accident cost analysis, the DRT mileage was scaled up linearly.

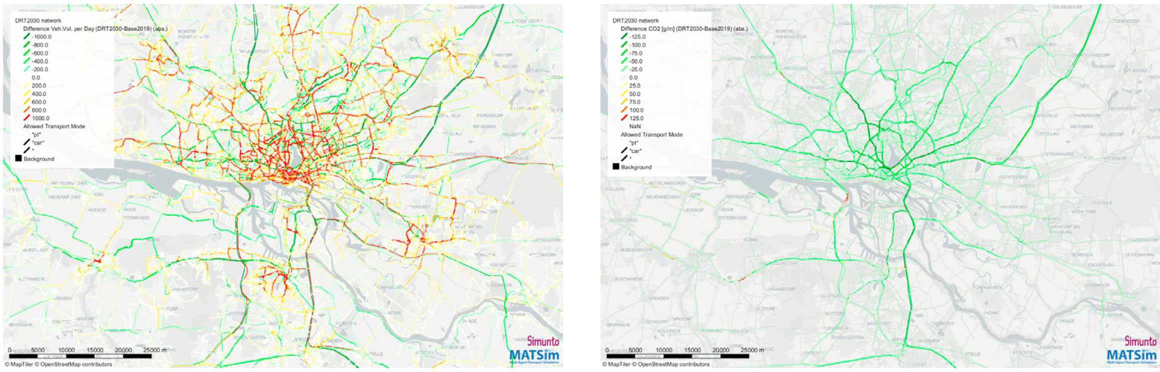

Fig. 4: Changes from Base2019 to DRT2030. Positive values mean an increase in DRT2030 and are displayed in yellow and red, negative values are displayed in green. (a) Daily Vehicle volume per road segment.; (b) CO_2 Emissions; note that the absolute weight of particles is divided through the length of the road segment. See [5] For more plots of spatio-temporal results.

Figure 4 displays changes between Base2019 and DRT2030 regarding the vehicle volumes (left) and CO_2 emissions (right) per road segment. While the DRT vehicles induce a higher mileage in the inner city, they do not emit CO_2 and replace conventional cars (see above). Consequently, a positive effect on CO_2 emissions is observed for the entire city.

4. Conclusion and Outlook

The two RealLab scenarios clearly demonstrate that it is difficult to decrease the modal split of the motorized transport by these technologies alone. The motorized transport just decreases by 3%-points. Only when stronger, but politically much less opportune measures are introduced it seems possible to convince one third of the car drivers to switch to other modes of transport (from 24% to 16% within the city boundaries for the ProClimate2030 scenario). However, the modal shifts might be partially underestimated due to lacking capacity constraints in the pt model. Moreover, the parking pressure increase pushes agents out of their car only if their traveling time with pt is up to 2.5 minutes longer, or if their walking time is up to 6 minutes longer than their travel time with the car. On the one hand side, the measure could be decided to be heavier in other variants of the push scenario. On the other side, the parameterization of the parking pressure model might be reconsidered.

While the sum of carbon and NOx emissions is directly related to the share of private cars, the additional mileage performed by electric DRT shuttles increases the particle emissions and, if operated by a human driver, the accident costs but not the CO_2 emissions.

Many results have been visualized in two interactive dashboards [7, 5]. In the future, it is planned to analyse the results in a more detailed way, looking into spatial and temporal effects of the investigated metrics as well as on additional metrics. For the outlook, one might consider to combine DRT2030 with the pull measures implemented in ProClimate2030 as those scenarios have the strongest impacts. In future investigations, stronger increases in parking pressure for the ProClimate2030 scenario will be investigated. While in this study, the overall transport demand was kept constant, other studies could investigate the interaction of future mobility systems with demographic development forecasts for the region.

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