City-wide Shared Taxis: A Simulation Study in Berlin

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***Abstract*—Recently, ridesharing services have grown rapidly. In future, fleets of shared and pooled autonomous vehicles may transform urban mobility. In this paper, we introduce an approach to dynamically simulate these services within a full-stack transport simulation using an insertion-based algorithm. In a first test case, using a taxi data set from Berlin, the potential for shared rides is evaluated using a fleet of vehicles with a capacity between two and four ride requests. The simulation suggests that the overall vehicle kilometers traveled may be reduced by 15–20 % , while travel time increases can be kept at a relatively low level of less than three minutes per person. Additionally, the simulation results suggest in which areas of the city it may be the most rewarding to offer shared services.**

I. Introduction

In recent years, taxi and taxi-like limousine services have undergone a digital disruption: From radio-based dispatch systems and street hailing towards smartphone-based ordering and dispatch. In the foreseeable future, shared autonomous vehicles (SAVs) may even turn driverless taxi services into a flexible, on-demand mass-transport system. In this context, the question whether trips could be shared among passengers is often raised. This dynamic ridesharing could not only reduce the stress on such systems during peak hours, but also help to reduce the overall impact on the road network and the city in general. In an SAV context, shared rides may mitigate effects of growing traffic that is often feared [1]. In this paper we introduce an open source simulation system that may be used to simulate shared rides in taxi-like or other demand-responsive transport (DRT) systems and, as a first use case, apply it to a real-world taxi dataset for Berlin, Germany. To the best knowledge of the authors, similar studies have not been published in this study area.

In the following section, a brief overview of shared taxi services and their scientific interpretation will be given. This is followed by a description of the simulation software and algorithms used. Finally, the results of our case study will be presented.

II. State of the art and related work

Ridesharing (or *tripsharing*), where multiple passengers share a taxi or limousine at the same time, is nothing new. Systems for shared rides, operating as jitney or taxi services, have been operating for decades in countries all over the world. Usually, there is either a common origin or destination of the vehicle, or both, and maybe even a fixed route [2, ch. 2].

More recently, app-based dynamic ridesharing services started rolling out pooled services. Both Uber and Lyft, as the most known providers, offer these, naming them *uberPool* and *Lyft Line* respectively [3], [4]. When ordering, customers are provided with an arrival time prediction and fixed fare for both pooled and non-pooled options. Depending on a predicted likelihood of sharing a ride with another customer, the price may be significantly lower if choosing the pooled option. Both systems require their users to submit the destination upon ordering a vehicle. In science, ridesharing has been looked at from different perspectives. A formal definition of a spectrum of dynamic ridesharing problems, including their categorization, and an outline of related optimization challenges can be found in [5]. Especially, with regard to classical car trips and carpooling, simulation results show potentials, but also limitations of these services [6], [7], with one main problem being the right timing for both drivers and passengers. A more recent study has introduced a framework and mathematical model for sharing rides. Their study concludes that the demand currently served by 14 000 yellow taxis in New York City could be replaced by 2 000 ten-seat minibuses, with most passengers being served [8]. The potential of shared taxi rides has also been addressed for Singapore [9]. The algorithm used for matching passengers is based on partitioning the road network and matching customers possibly traveling in a similar sub-set of partitions. The results suggest a sharing potential between 15 and 20%, when keeping the detour per customer below 5 minutes. Similar values have also be found for a simulation study in Tokyo's suburbs . Most notably, none of the studies above takes the willingness to share a ride of passengers into account. This may be further reduced by additional walks to main streets or collection points, which for instance Uber suggests to its customers. One study has included a mode choice model between non-pooled and pooled option, however, the pooling algorithm is rather simple and both origins and destinations of customers need to be in close distance to each other [10].

III. Methodology

In order to simulate dynamic ridesharing trips, an existing simulation framework is extended which so far has been mainly used for simulation of non-shared taxi trips. Also a set of performance criteria for shared trips needs to be defined in order to evaluate different simulation outcomes.

A. Simulation framework

In this study, MATSim [11] is used as the simulation software. Its basic concept is the simulation of agents and their daily plans that consists of activities (such as home or work) and trips in between these activity locations. These may be of varying modes, including car, public transport or taxi. At the end of a day, each executed plan is scored depending on its performance and may be altered before the next iteration. MATSim uses a fast queue-based model to simulate traffic flow, which is detailed enough for most transport-related questions. The software is open-source, written in JAVA and capable of handling millions of agents.

For simulation of on-demand transport modes, such as taxi, DRT or SAVs, a set of MATSim extensions have been created [12], [13]. These allow dynamic dispatching of vehicle fleets during simulation in response to incoming requests and other events by means of pluggable algorithms that differ in terms of objectives and constraints. This way, different aspects of real-life taxi and ridesharing operations, as well as applications for SAVs have been simulated for many urban areas [10], [14]–[17].

B. Model

In order to dispatch customers in a shared taxi system, we assume the following prerequisites which are taken from various real-life applications.

Let $N = 1, \ldots, n$ be the set of immediate requests (pre-booking is not allowed). Taxi request $r \in N$ is submitted at the moment of departure τ_r^{dep} and specifies the exact pickup and dropoff locations (door-to-door service). The amount of time the customer is willing to wait for departure (i.e. waiting and boarding) is fixed to t^{wait}. The overall time spent on traveling (waiting, boarding and riding) must not exceed $t_r = \alpha t_r^{direct} + \beta$, where t_r^{direct} is the direct ride time between the origin and destination of request i, while $\alpha \geq 1$ and $\beta \geq 0$ are used to model the maximal amount of time loss due to waiting, boarding and possible detours. A request can be rejected (e.g. due to constraints violation) only immediately after submission. Once scheduled, the request is guaranteed to be served (i.e. cannot be rejected later) even if there are delays on the way causing violation of some constraints.

Let $M = 1, \ldots, m$ be the set of shared taxis. Initially, each vehicle $k \in M$ has a capacity c_k, current location l_k and time window $[a_k, b_k)$, in which it may operate. Vehicles are managed by a central dispatch system that is responsible for scheduling or rejecting incoming requests. Each vehicle has a route that leads through a sequence of stops $S_k = \langle 1, \ldots, s_k \rangle$. Two sets of requests: pickups P_{ki} and dropoffs D_{ki} are defined for all stops $i \in S_k$ on the route of vehicle $k \in M$. At least one passenger gets in or out at each stop, i.e. $|P_{ki}| + |D_{ki}| > 0, \forall k \in M, i \in S_k$. Each stop is of a fixed duration t^{stop}. Arrival at the last stop, s_k, must be scheduled at latest for time $b_k - t^{stop}$, so that the time window is not violated. The capacity of a vehicle cannot be exceeded when driving between stops, i.e. $o_{ki} \leq c_k, \forall k \in M, i \in S_k$, where o_{ki} is the occupancy of vehicle k on the way to stop i and is defined recursively backwards from the last stop:

$$o_{ks_k} = |D_{ks_k}|,$$
$$o_{ki} = o_{k,i+1} - |P_{ki}| + |D_{ki}|, \qquad \forall k \in M, i \in S_k - \{s_k\}.$$

Vehicles are monitored as they move and their location is being updated. On arrival at a stop, the stop is removed from the route. Boarding and alighting are modeled in a simplified way: All the passengers who have reached their destination get out immediately at the beginning of the stop, while new passengers get in at its end. Insertion of a stop at the first position in the route results in an immediate diversion of a vehicle towards that location. After all scheduled stops have been visited, the list of stops is empty and the vehicle remains idle until a new dispatch or the end of its time window. Cruising and/or relocation of idle vehicles is possible in the implemented model, though not analyzed in this study.

C. Routing algorithm

Shared taxis are dynamically routed using an insertion heuristic that aims at minimizing the total taxi workload measured as the total time spent on handling requests (i.e. excluding idle time). Whenever a new request is submitted, the algorithm searches the routes of all vehicles for optimal insertions. A request insertion $(k, i, j), k \in M, i, j \in 0 \cup S_k, i \leq j$ means the request is inserted into k-th vehicle's stop list at position $i+1$ (pickup stop) and $j+1$ (dropoff stop), assuming the list elements are indexed from 1. If $i = j$, the pickup is followed directly by the dropoff. If a newly inserted stop has the same location as either of the adjacent stops, both stops are consolidated. By a feasible insertion we mean an insertion that satisfies the following conditions: (i) the wait and travel duration constraints are satisfied for both the new and already inserted requests, (ii) the vehicle time window is satisfied. All feasible insertions are evaluated by calculating an increase of kth vehicle work time. The first insertion that offers the smallest increase is selected. If no feasible insertion exists, the request gets rejected.

During simulation, as in real life, vehicles may encounter some delays while driving. This may lead to violation of some wait and travel time constraints. This, however, impacts only scheduling of new requests, while the already accepted ones cannot be rejected or re-scheduled.

The sole use of insertion, without re-ordering of stops or moving requests between vehicles, is justified by the tight maximum waiting and travel time constraints and no pre-booking. Although this heuristic algorithm does not guarantee optimality, it offers good results (see comparison between non-shared and shared taxi services in Section V) at a low computational cost. For instance, the 24-hour city-wide simulation runs presented in Section V took roughly 20 minutes on a standard modern laptop with an Intel i7 core processor. This allows its use for real-time dispatching of large fleets of shared taxis.

D. Performance criteria

In both non-shared and shared taxi services, the average customer wait (including boarding) time T^W and the 95th percentile T^W_{95}, the average ride (i.e. on board or in-vehicle travel) time T^R, the fleet-wide ratio of empty-to-total mileage e^D, the rate of request rejection ρ are key performance indicators.

In addition to that, the revenue kilometers d^U per overall driven distance d^T, $U^D = d^U/d^T$, is of relevance. This value may be interpreted as an indicator for fleet utilization, with a higher value indicating a higher vehicle occupancy. However, it needs to be taken with care, since also extreme detours result in a high utilization, as long as there are passengers on board the vehicle. This may not be necessarily beneficial for operators, who tend to charge flat fees based on direct trip distances.

To accommodate for this, we introduce another fleet-wide indicator which takes into account the overall driven distance to the total mileage requested by customers:

$$\lambda = \frac{d^T}{\sum_{r \in N} d_r^{direct}},$$

where d_r^{direct} is the direct distance between the origin and destination of request r.

For non-shared taxi, $1/\lambda = 1 - e^D$ and thus λ is always greater than 1 as vehicles have empty drives between requests. It can be 1 for a single-person private car trip, as long as no detours are made, e.g. for parking search (which may account to 20% of additional traffic in residential city areas [18]).

For shared rides, however, $\lambda < 1$ is feasible and should be targeted, especially when focusing on providing sustainable transport services. This allows operators to claim their service to be more efficient than private cars.

IV. Taxi traffic in Berlin and base case generation

For a real-world demonstration, we are applying the proposed shared taxi algorithm to a real-world dataset of taxi requests in Berlin, which has been analyzed in [19] and used in several simulation studies [14], [20]. It depicts a typical workday (Tuesday) in 2013 and resembles the majority requests of the taxi fleet handled by Taxi Berlin, the largest local taxi dispatch company. An estimated 5 000 vehicles of the city's overall 8 000 vehicle fleet are (partly) dispatched by them. The taxi business in Berlin is very fragmented, with many small companies owning only one or two vehicles. Monitored vehicle occupancy is rather low and in tendency there is an oversupply of vehicles. Generally, vehicles are busy handling customers for less than 30% of their time. The demand for taxis is characterized by a strong morning peak and a longer lasting afternoon peak. Demand at night times grows constantly during weekdays, with demand surging at Saturday nights. This pattern is rather typical and can be observed similarly in other cities around the globe [21]. Spatially, most taxi trips either start or end within the inner city. The biggest single origin and destination is Tegel Airport. There are first attempts to offer shared taxi-like services in the city. These currently have very limited operation times and areas.

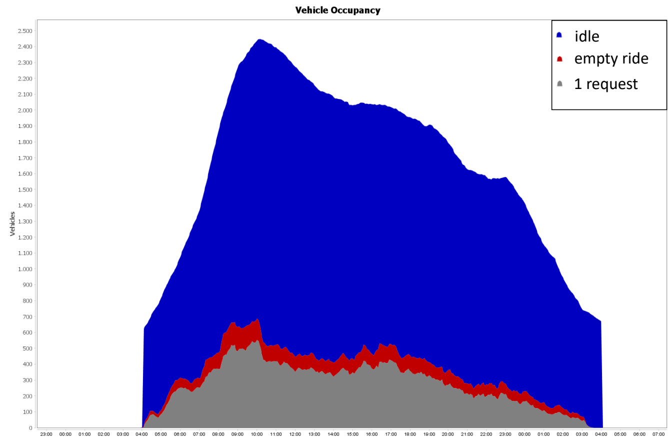

Fig. 1. Fleet occupancy of an unshared fleet

For comparison purposes, a base case, where all vehicles are non-shared, was also simulated. A total of 27 336 requests are handled by 4 212 vehicles (all of them have different service times). The simulation runs from 4 am to 4 am, because this is the hour of smallest demand. On average, the waiting time for a taxi is 4:32 minutes, and the mean waiting time 3:31 minutes. In the city center, the value is usually lower, whereas it is considerably higher in suburban areas (which is reflected by the 95th percentile of roughly 12 minutes). Fig. 1 shows the vehicle occupancy over the day in stacked chart. According to this figure, there is a maximum of 2 500 vehicles available during the morning peak hour, of which only roughly one third is busy serving requests. During other times, the number of available vehicles is lower, though their occupancy remains more or less at the same, low level. The average distance of a trip is 7.6 km. This would translate into an average revenue of 19 EUR per trip.

V. Application

In order to estimate the potential for shared taxi rides, we assume that each customer ordering a vehicle is potentially willing to share a ride. Obviously, this may work better for some customers than for others, as some requests may already serve a group of persons. However, we assume a big share of requests consists of people traveling either alone or in a group of two, so sharing a vehicle would be a theoretical option. This is in line with real world sharing services, where requests often may serve up to two customers. All vehicles have the same capacity c_k that was set to 2, 3 or 4 in computational experiments. Assuming a maximum of two passengers per request, a capacity of 2 could be served by a standard-size car, a capacity of 3 by a minivan, whereas, in order to

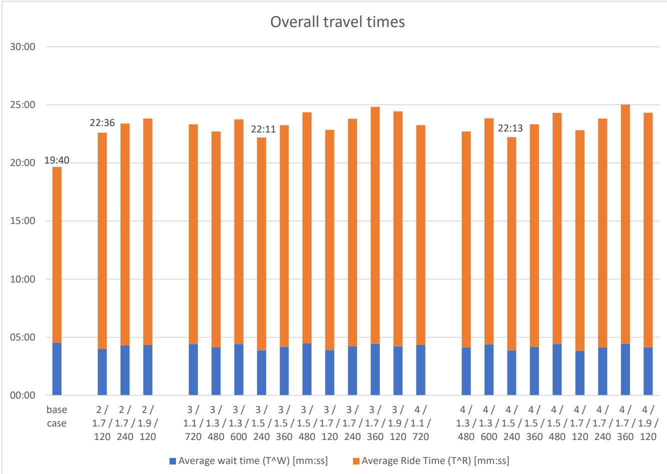

Fig. 2. Comparison of overall travel times (wait + ride time)

serve 4 requests at the same time, a minibus is required. The first two vehicle types are both commonly used in taxi fleets, whereas minibuses are still rather uncommon. A further capacity increase would require a bus driving license.

An overall of 180 simulation runs were conducted: 60 runs per capacity (2, 3 or 4) with the maximum travel time defined by α ranging between 1.1 and 2.1 and β between 0 and 1080 seconds. Furthermore, we set the maximum wait time t^{wait} to 15 minutes. The duration of stop to pick up and/or drop off passengers t^{stop} was assumed to be 60 seconds. All these values were also used in the non-shared base case.

In order to achieve a high level of service for the shared taxi service, we assume that the overall service quality indicators, namely T^W, T^W_{95} and ρ, should not be worse than in the non-shared one. Furthermore, only simulation runs where $\lambda < 1$ were evaluated.

VI. Results

Of the 180 simulation runs conducted, a majority can be filtered out, because at least one of the criteria described in the previous section was not fulfilled. An overall set of 24 simulation runs remain. Their key output indicators are listed in Table I and discussed in the following sections.

A. Passenger statistics

The average waiting time for vehicles remains lower than in the base case for all runs observed. This goes in line with the expectations that a shared system has a higher number of potential vehicles available to dispatch. For vehicle capacities of 2 and 4, the combination of $\alpha = 1.7$ and $\beta = 120$ s scores the lowest waiting times, both in average and in the P95 value, while for a capacity of 3, $\alpha = 1.5$ and $\beta = 240$ s performs slightly better.

While waiting times are one important factor, the overall travel time, defined as the sum of wait and ride times, is just as important. The values found to have the lowest wait times also tend to score a low overall travel time, as depicted in Fig. 2. For a capacity of 2, $\alpha = 1.7$ and $\beta = 120$ s also score the lowest average overall travel time in all valid solutions. For higher capacities, the simulation indicates that the value set of $\alpha = 1.5$ and $\beta = 240$ s provides better results. Notably, the average detour is also lower in this case. Together with slightly higher average wait times, this indicates fewer shared rides, which can also be observed in higher λ values. For a capacity of 2, the $\lambda < 1$ criterion was not fulfilled for this set of parameters and the solution was therefore not taken into account. The rejection rate ρ is generally lower than in the base case.

Overall, both parameter sets provide sufficiently good results for passengers. The decision which set to chose should therefore depend mainly on the passenger's evaluation of wait vs. ride time. Literature suggests that waiting time for buses at stops is generally more negatively evaluated than riding time [22], but for taxi rides the opposite may apply.

B. Fleet usage

In all simulation runs evaluated, the vehicle kilometers traveled d^T by the fleet is considerably lower than in the base case. The actual savings vary between 15 and 22%, with less rejected requests than in the base case.

Consequently, the λ value is considerably lower than in the non-shared base case for all scenario runs. With increasing fleet capacity, λ is generally lower. For all capacities, the lowest λ may be observed for simulations, where α values are high. In these cases, the additional fixed β is of a lower weight. However, while these values may be preferable from an operators perspective, they tend to create longer overall travel times. This indicates once more the need for an operator to weight out between passenger comfort and fleet performance.

The distances traveled by empty vehicles are considerably lower in all policy cases.

C. Vehicle occupancy

Based on the overall vehicle kilometers traveled and the λ value, higher capacity vehicles may be favorable to use. However, it needs to be weighed out, whether the usage of high-capacity vehicles really pays off, since they generally come along with higher fixed and variable operational costs. As the values in Table I already suggest, the differences between capacity 3 and 4 are not very high. As Fig. 3 reveals, vehicles are occupied with two requests at the same time for up to 50% of all the time they are busy and for roughly 10% of the time with three requests on board. However, the chance of carrying four requests at the same time are slim, mostly due to tight time constraints, as the right part of the figure reveals. This leads to the conclusion that vehicles do not require the ability to serve four requests at the same time.

D. Network effects

In the current simulation model, shared taxi trips are offered city-wide. However, taxi operations are focused towards the city-center and Tegel airport. Fig. 4 shows the average occupancy of taxis traveling on links in the network. It is generally in the range of 1.0–1.5 in the city center or on ways leading to and from the airport, whereas outside is often below 1.

TABLE I
SHARED TAXI STATISTICS FOR DIFFERENT VEHICLE CAPACITIES, α AND β VALUES. IF APPLICABLE, THE MOST FAVORABLE VALUES PER COLUMN AND FLEET CAPACITY ARE INDICATED IN BOLD LETTERS

C	α	β [s]	T^W [mm:ss]	T^W_{95} [mm:ss]	T^R [mm:ss]	Avg. travel dist. [km]	Avg. direct dist. [km]	Avg. de-tour [km]	ρ	d^T [km]	e^D	d^U [km]	U^D	λ
1	*base case*		*04:32*	*11:51*	*15:08*	*7.58*	*7.58*	*0.00*	*0.04*	*233 040*	*0.15*	*198 899*	*0.85*	*1.17*
2	1.7	120	**04:00**	**10:54**	**18:36**	**8.82**	7.65	**1.17**	0.04	197 943	0.09	229 542	1.16	0.99
2	1.7	240	04:19	11:34	19:04	8.92	7.54	1.39	**0.02**	198 897	0.09	237 885	1.2	0.99
2	1.9	120	04:20	11:54	19:29	9.07	7.59	1.48	0.03	197 333	0.09	239 542	**1.21**	**0.98**
3	1.1	720	04:25	11:33	18:54	8.83	7.48	1.35	**0.01**	197 367	0.09	237 664	1.2	0.98
3	1.3	480	04:09	10:39	18:33	8.74	7.50	1.24	0.02	197 245	0.09	234 322	1.19	0.98
3	1.3	600	04:25	11:39	19:20	8.99	7.48	1.50	**0.01**	194 775	0.09	241 762	1.24	0.97
3	1.5	240	**03:53**	**10:06**	**18:18**	**8.70**	7.56	**1.14**	0.03	196 232	0.09	229 220	1.17	0.98
3	1.5	360	04:11	10:56	19:03	8.93	7.51	1.42	0.02	194 995	0.09	239 144	1.23	0.97
3	1.5	480	04:28	11:46	19:54	9.17	7.49	1.68	**0.01**	192 620	**0.08**	246 977	1.28	0.96
3	1.7	120	03:54	10:36	18:57	8.92	7.64	1.28	0.04	193 122	0.09	232 174	1.2	0.97
3	1.7	240	04:13	11:16	19:35	9.10	7.53	1.57	0.02	193 081	0.09	242 972	1.26	0.96
3	1.7	360	04:27	11:54	20:23	9.33	7.50	1.83	**0.01**	**190 864**	**0.08**	250 674	**1.31**	**0.95**
3	1.9	120	04:14	11:31	20:13	9.31	7.58	1.74	0.03	191 276	**0.08**	246 509	1.29	**0.95**
4	1.1	720	04:21	11:28	18:54	8.85	7.48	1.37	**0.01**	196 180	0.09	238 143	1.21	0.97
4	1.3	480	04:09	10:37	18:33	8.73	7.49	1.23	0.02	196 729	0.09	233 954	1.19	0.98
4	1.3	600	04:25	11:40	19:26	9.03	7.48	1.55	**0.01**	194 062	0.09	243 265	1.25	0.96
4	1.5	240	03:52	**10:08**	**18:21**	**8.70**	7.56	**1.14**	0.03	195 764	0.09	229 676	1.17	0.98
4	1.5	360	04:11	11:03	19:08	8.93	7.51	1.41	0.02	193 402	0.09	238 993	1.24	0.96
4	1.5	480	04:25	11:40	19:54	9.18	7.49	1.70	**0.01**	191 094	**0.08**	247 194	1.29	0.95
4	1.7	120	**03:51**	10:29	18:58	8.95	7.64	1.31	0.04	192 988	0.09	233 242	1.21	0.97
4	1.7	240	04:09	11:11	19:40	9.12	7.53	1.59	0.02	191 723	**0.08**	243 544	1.27	0.95
4	1.7	360	04:27	11:55	20:35	9.39	7.50	1.89	**0.01**	**190 082**	**0.08**	252 603	**1.33**	**0.94**
4	1.9	120	04:09	11:29	20:11	9.31	7.57	1.73	0.03	189 162	**0.08**	246 340	1.3	**0.94**

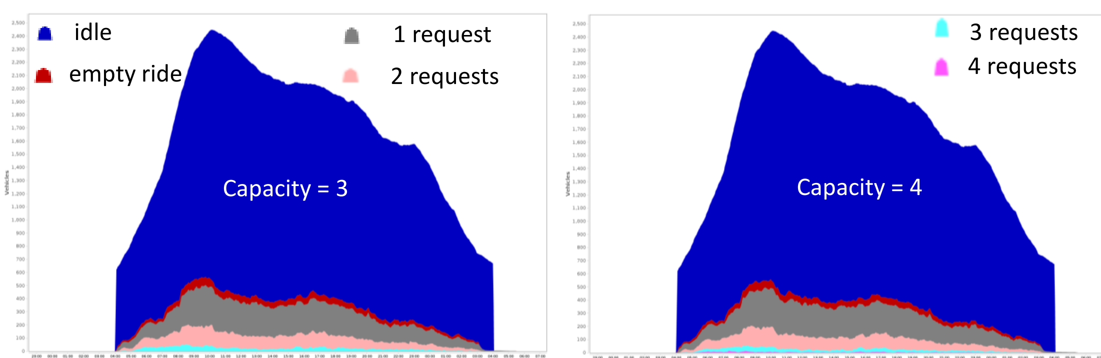

Fig. 3. Vehicle occupancy for capacities 3 (left) and 4 (right) with $\alpha = 1.7$ and $\beta = 240$ s

VII. CONCLUSION

In this paper we demonstrated the integration of shared taxi services into a transport simulation based on insertion heuristics. An application based on the taxi demand for Berlin shows the potential of the proposed approach. An overall reduction of vehicle kilometers traveled by taxi in the region of 15–20% is feasible. The fine tuning of the algorithm parameters demonstrates that sharing of rides will most likely work best in areas of high overall taxi demand. Real-world operators would therefore most likely limit shared operations to these areas. Another obvious issue is the large number of idle vehicles in the city, which is a real-life occurrence and may reduce taxi drivers' willingness to offer shared services. Further research could focus on a simulation scenario with autonomous vehicles, where a drop in prices could attract a higher number of users all over the city. Also other usage forms may be tried out, such as the gathering of people at stops, rather than door-to-door operations or the combination of DRT services with public transport. On the demand side, choice modeling between shared and non-shared taxi options should also looked at.

ADDITIONAL MATERIAL

Additional information about the software package used can be found under http://matsim.org/extension/drt. The software source code, including a runnable example script, is available on https://github.com/matsim-org.

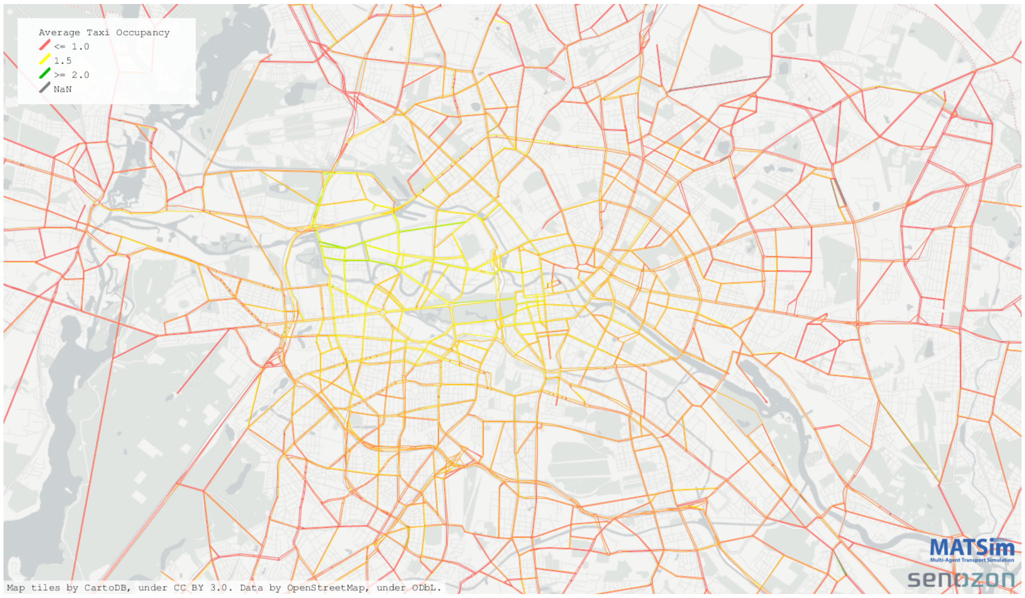

Fig. 4. Average taxi occupancy per link

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