Integration of MaaS into macroscopic demand models

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Abstract
The mode MaaS (means here 'ride-pooling') is quite new in demand modelling. Because of its microscopic nature, many researchers conclude microscopic demand models like activity-or agent-based models (ABM) to be unavoidable.
This paper discusses a hybrid approach to integrate MaaS into a macroscopic demand model. It preserves the microscopic characteristics of MaaS but remains in a macroscopic framework and keeps thereby the desirable convergence properties of macroscopic models. In the second section of the paper, we report about an application of the approach with the transport planning software PTV Visum.
Even though the current trend is going away from macroscopic towards microscopic demand modelling, the topic discussed here is still highly demanded. The majority of existing and running models is based on the traditional four-step approach (or on derivates of it) and many of them need a MaaS update rather than a complete re-construction towards ABM. This paper shows that MaaS can be integrated appropriately into these models preserving most of their original convergence qualities.

Keywords*:* Mobility as a Service (MaaS), ride-pooling, travel demand modelling, macroscopic demand modelling, microsimulation of MaaS, stability of demand models, unserved demand.

1. Problem description

1.1 Definition of MaaS

The transport system we call "MaaS" in this paper has different names in the transport community. In this paper, MaaS means a taxi system, which can take additional passengers during its rides (ride-pooling or ride-sharing). The system has one dispatcher, planning the tours of all taxi vehicles in real-time. The MaaS system works under some fixed constraints like fleet size and maximum passenger waiting time.
The experiments of this paper are carried out with the tour planning procedure of the transport planning software PTV Visum.

1.2 Literature research

The current publications can be divided into two groups: one group like Friedrich (2018) integrates MaaS into the framework of a macroscopic demand model. Typically, these papers don't consider the full microscopic nature of MaaS. The MaaS simulation is typically not based

on a sound dispatching algorithm, the discrete localisations of trip starts and ends don't play an appropriate role. These papers serve well as studies of potential but are not suited to fully understand the impact of all aspects of MaaS on the demand.
The other group stresses the microscopic nature of MaaS and concludes the necessity of microscopic demand modelling, agent- or activity-based. The papers which deal with agent-based models like Ciari (2009) focus on the implementation of a detailed and realistic MaaS system rather than on stability problems. The activity-based papers like Jittrapirom (2017) mainly focus on the precise modelling of human decision-making referring to all aspects of MaaS. There is no doubt, ABM (both activity- and agent-based) may be an appropriate approach, but it is not mandatory.
The open question is how to keep the microscopic characteristics of MaaS within a macroscopic demand model and at the same time produce stable results and consequently convergent demand models. The importance of convergence cannot be overestimated, since it is crucial for the modeller's ability to separate the true impact of MaaS from random fluctuations.

1.3 Research objectives

Macroscopic models are based on zones, whereas MaaS simulations need a much higher resolution. Different from the traditional modes, the performance of MaaS depends highly on concrete locations and times of the trip requests. Shifting the start point of a MaaS trip by 50 metres or by a few minutes can be crucial for the possibility to be picked up by another MaaS vehicle having a similar destination.
Therefore, modelling MaaS requires the dis-aggregation of the demand, otherwise the model ignores the MaaS specific characteristics. Since the macroscopic modeller does not know anything below the zone level (and nothing about the temporal distribution), such a dis-aggregation is necessarily random. In addition, it changes a fractional demand randomly to an integer one. Among simulations, that leads to a highly variable demand what determines highly variable and hence unstable skims what hides the correlation between supply and demand and worsens convergence.
This paper presents a hybrid approach which dis-aggregates the demand to feed the MaaS simulation and re-aggregates the observed skims to continue macroscopically. It focusses on the problem of instability and discusses an aggregation approach.
The MaaS implementation we used for our experiments refuses trip requests, if they cannot be served with at least a certain user-defined quality. Thus, we were faced with the existence of unserved demand. This paper discusses an approach, how to reduce the mode utility due to unserved demand.

2. Hybrid approach

2.1 Model

We apply the hybrid approach to a PTV Visum model of the city of Halle an der Saale in Germany.

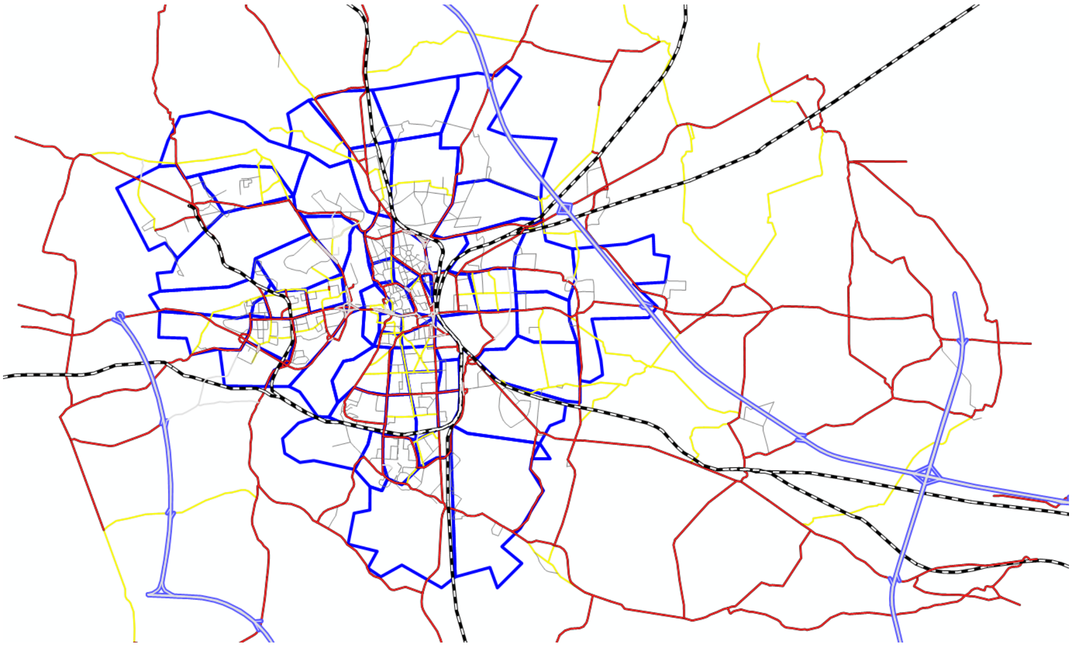

Figure 1: The PTV Visum model of Halle an der Saale with zones drawn in blue.

The Model consists of 81 Zones, 8 main zones, and a reduced network (without pure residential streets, about 5000 links). The tour-based demand model comprises 7 person groups, 7 activities and 6 modes. The MaaS system operates in 61 zones (only city) with 451 stops for MaaS vehicles. The MaaS fleet comprises 200 vehicles with 4 seats each.

2.2 Model Structure

The hybrid approach fits perfectly in a traditional 4-step demand model. Within the demand loop, the MaaS demand is discretised which feeds a MaaS simulation. The observed travel characteristics are aggregated on zone level and serve as skims for the demand model.

1. Initial skims
2. Calculation of demand
3. Discretising MaaS demand
4. Performing a microscopic MaaS simulation
5. Aggregating characteristics of MaaS trips on zone relation level
6. Assignment PrT including MaaS vehicles
7. Re-calculation of PrT skims
8. Back to Step 2, until demand converges

The mode utilities for MaaS, which are used within the demand calculation, are based on the aggregated results of the microscopic MaaS simulation. The utility components of the mode MaaS are, among others, mean and standard deviation of travel and wait time.

2.3 Results

The following table shows the number of converged OD-relations per mode in each iteration of the demand loop. An OD-relation is called converged, if the change Δ of demand (with respect to the previous iteration) meets the condition

$$|\Delta| \leq \min\{5, \max\{\text{Old}, \text{New}\} \cdot 0.01 + 1\}.$$

Table 1. Results of the iterative demand loop.

Non-converged OD relations						
It	**Bike**	**Car**	**CarP***	**MaaS**	**PT**	**Walk**
0	1650	672	345	2737	1037	645
1	121	296	118	255	147	112
2	183	16	5	886	94	165
3	438	1	130	1733	224	207
4	359	1	249	1893	185	152
5	93	1	105	1263	80	63
6	11	0	15	775	56	29
7	0	0	10	678	44	28
8	1	0	4	768	52	41
9	0	0	1	697	32	24
10	3	0	1	748	45	43

*CarP stands for "Car as Passenger"

The results are quite unstable, especially the number of non-converged MaaS OD-relations stays on a high level. It is seen that the system cannot go beyond a certain level of stability.

3. Aggregation

Assuming a certain utilisation of MaaS, the performance of a MaaS trip depends on the existence of other MaaS trips in the neighbourhood. In this sense, the performance for a certain relation is highly correlated with the performance in the area around the relation, where "area" means here "similar relations". It is the accessibility and the centeredness of the extended areas around the trip start and end which mainly determine the average performance of the trip. These extended areas will be defined as sets of zones, called main zones[1].

For that, assume the MaaS travel times TT_{MaaS} to be the product of the fixed (i.e. non-random) car travel time TT_{act} and a random relation-dependent detour factor D

$$TT_{MaaS} = D \bullet TT_{act}.$$

D can be estimated based on all performed MaaS trips of a relation.
Our studies (see the preceding section) showed that in practical cases estimates of D are too unstable and that many simulations are necessary to get somehow stable results.[2] The idea is now to expand the basis of the estimation to get more stable results.
From the discussion in the paragraph above it follows quite natural to assume all relations within the same main zone relation to behave similarly. They all share the same random mechanism and their detour factors be independent realisations of the same random mechanism. Then, the estimation basis of the mean detour factor expands to all performed MaaS trips of a main zone relation. Our studies show (see the corresponding section below) that this simplification is the decisive thing to get stable results without any repetitions of MaaS assignments inside the demand loop what finally results in moderate model runtimes.
Of course, the assumption of identically distributed detour factors within a main zone relation is quite weak. The error is the larger, the more zones are aggregated to a main zone. In addition, the resolution of the MaaS sub-model worsens to main zones. Obviously, the modeller is faced with a trade-off between precision and stability.

[1] A main zone is a set of traffic analysis zones. For the sake of simplicity, we ignore the temporal aspect here.
[2] By the way: the same problem should occur with activity- and agent-based models.

4. Unserved demand

Unserved demand occurs when trip requests cannot be served with a minimum quality at least. A rejected trip request does not mean that the person cannot perform her trip. The idea is that a passenger can check in advance whether her trip request can be served or not. In case of rejection, a second mode choice (now without the MaaS alternative) is assumed.
This section discusses the penalty which is added to the utility to reflect the utility loss resulting from unserved demand.
The dis-utility due to an unserved trip is quite complicated to estimate and depends on the very concrete specification of the existing MaaS system. Therefore, we propose a quite simple, but intuitive approach.
Assume the typical iterative structure of demand models as in Section 2.2.
Be T_n the number of trips with MaaS in the nth iteration and U_n the number of unserved trip requests. Then we define the penalty for the next iteration of demand calculation as

$$P_{n+1} \approx - f \bullet (U_n / T_n),$$

where f is specific to the concrete MaaS system, expressing the scale of utility loss due to unserved trip requests.

5. Application Example

We apply the hybrid main zone approach to the same model as above with 8 main zones.

Figure 2: PTV Visum model of Halle an der Saale with 8 main zones.

5.1 Results

This section lists the results of some scenarios which show

- that the MaaS demand convergences within the demand loop,
- that the results are independent from the start solution,
- that the approach results in reasonable sensitivities for some selected scenarios.

Convergence

The first results show the degree of convergence of the MaaS demand.

Table 2A. Results of the iterative demand loop, applying the main zone approach.

				Demand			
It	**Bike**	**Car**	**CarP**	**MaaS**	**(Uns*)**	**PT**	**Walk**
0	78812	170674	35310	179	(0)	68083	104935
1	77450	172687	36340	884	(1)	66902	103729
2	76182	173526	36543	3142	(8)	66027	102573
3	74679	173755	35928	7030	(113)	65092	101509
4	73277	173735	34979	10996	(408)	64303	100703
5	72420	173603	34246	13662	(508)	63806	100257
6	71889	173509	33709	15309	(670)	63569	100007
7	71645	173418	33480	16101	(648)	63456	99892
8	71513	173506	33322	16404	(1042)	63390	99860
9	71572	173485	33301	16188	(1019)	63496	99950
10	71660	173470	33373	16072	(861)	63454	99965

* Unserved: demand, which was originally assigned to MaaS, but could not be served; has been divided among the remaining modes.

Table 2B. Results of the iterative demand loop, applying the main zone approach.

			Non-converged OD relations			
It	**Bike**	**Car**	**CarP**	**MaaS**	**PT**	**Walk**
0	0	71	23	0	15	9
1	61	196	68	195	111	85
2	65	10	0	617	53	75
3	120	0	58	1107	98	71
4	126	1	81	1216	88	47
5	32	0	40	784	39	18
6	8	1	26	459	11	11
7	0	0	1	120	1	4
8	0	0	0	95	1	1
9	0	0	0	48	8	6
10	0	0	0	68	1	1

The reached level of stability is high, although the MaaS demand has the worst convergence behaviour. However, considering the microscopic simulation nature of this mode, the shown convergence is remarkably good.

Independence of start solution

For the first iteration of the demand loop, the utility of the mode MaaS must be set to a certain initial value. For the base model, we set the journey travel time to a multiple of the car travel time. To proof that the initial value does not influence the results, we changed the initial factor from originally 20 to 5.

Table 3. Result after changing the initial travel time for MaaS.

				Demand			
Scenario	**Bike**	**Car**	**CarP**	**MaaS**	**(Uns)**	**PT**	**Walk**
5	71683	173458	33385	16001	(803)	63460	100006
20	71660	173470	33373	16072	(861)	63454	99965

The results after ten iterations differ only very slightly from those of the base model.

Fleet size
This scenario shows that the system reacts reasonably on fleet size changes. The following results are based on a fleet size of 100 vehicles instead of 200.

Table 4. Result after changing the fleet size.

				Demand			
Scenario	**Bike**	**Car**	**CarP**	**MaaS**	**(Uns)**	**PT**	**Walk**
100	73567	174531	34681	9407	(2299)	64393	101414
200	71660	173470	33373	16072	(861)	63454	99965

The resulting demand is lower than in the base model, but the reduction is, as expected, less than the fleet size reduction of 50%. The considerably increased amount of unserved trip requests (2299 in contrast to 861) is also in line with the expectations.

Reduction of stop points
The base model contains 451 stop points for MaaS vehicles. We reduced them randomly to 266 stop points.

Table 5. Result after reducing the MaaS stop points to pick up and drop of passengers.

				Demand			
Scenario	**Bike**	**Car**	**CarP**	**MaaS**	**(Uns)**	**PT**	**Walk**
266	72324	173674	33888	13961	(829)	63748	100397
451	71660	173470	33373	16072	(861)	63454	99965

The reduction of stop points results in a loss of MaaS passengers, because the walk trips to the stops have become longer. Again, the reaction of the system is within the expected range.

6. Conclusion

Although MaaS has a microscopic nature, which can be represented only based on simulations, we showed that MaaS can be fully integrated into a macroscopic demand model. The hybrid approach discussed here preserves the microscopic characteristics of MaaS while keeping a remarkable good level of convergence. A set of model scenario runs proofed the reasonable sensitivities of the integrated demand model.

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