# Implementing a Ride-Sharing Algorithm in the German National Transport Model (DEMO)

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**Keywords:** macroscopic travel demand model, ride-sharing, mobility as a service, national transport model

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**Data Accessibility**
The data used in this paper is the result of model calculations for the macroscopic travel demand model of Weimar and the German national transport model. The use of both models is restricted to the declared project purposes and thus, they cannot be published in the context of this study. The analyzed model results for the case study are available from the corresponding author upon reasonable request.

# ABSTRACT

As macroscopic travel demand models are widespread among regional modelers, it is crucial to develop extensions for new mobility services such as ride-sharing services in order to assess their effects on the transport system. In a feasible approach that was introduced with previous research, origin-destination network-based paths are transformed to a series of crossed traffic analysis zones (TAZ). These series are compared to find overlapping trajectories to derive ride-sharing potential. However, in national transport models the TAZ sizes are larger than in regional models, which can lead to unrealistically high matching rates due to imprecise path trajectories. This paper presents a modified approach for the implementation in the German national transport model DEMO. The main adjustment is to use population centers as pick-up locations instead of TAZ. Each TAZ includes multiple points. This way, the trajectories of paths can be better differentiated. Another advantage of this method is that intra-zonal trips can be distributed between the centers and thus be included in the algorithm. With the successful implementation in DEMO, the effects of new mobility tools in German cities can be evaluated within the same model.


**Keywords:** macroscopic travel demand model, ride-sharing, mobility as a service, national transport model

# INTRODUCTION

With technology advancements and digitalization, mobility as a service (MaaS) in the form of on-demand car- and ride-sharing is expected to gain importance in the transport sector (e.g. 1). In order to support policy makers and planners, assessing the effects of MaaS is an important research issue. Therefore, transport models play a key role in forecasting its trends and effects. Generally speaking, the first step for including MaaS services is to develop algorithms for the technical implementation of matching ride-sharing trips. This is needed to generate relevant utility components like travel times, costs and occupancies. In a second step, the aspect of forecasting demand and individual choices based on utilities for new modes is regarded. This is however not covered in this paper, as it focuses only on the technical implementation of the service in the network model.

Using a model of national scope enables the nation-wide assessment of diffusion of MaaS services and of fleet sizes, mileages and occupancies. It also offers the possibility of analyzing the effects in different regional types, especially in less dense rural and suburban areas that are not commonly in the focus of regional modelling. The larger scope of a national assessment however leads to differences in requirements compared to modelling frameworks for regions and cities. Due to the large area that is covered, national models often are static macroscopic travel demand models with a coarse granularity. As a consequence, traffic analysis zones (TAZ) are larger and the road network is less dense than in regional models of the same type. This leads to high intrazonal traffic as well as less detailed origins and destinations of trips. These differences have to be addressed when transferring methods for depicting ride-sharing in macroscopic models from regional to national models.

This paper presents the necessary adjustments to implement an existing ride-sharing algorithm successfully in a network model of higher scope. It gives an overview of the applied algorithm and points out its flaws when it comes to a higher model scope. After describing the adjusted methodology, a case study for the German national transport model is performed to show the effects on indicators of the ride-sharing algorithm. As the focus is on the development of the method, the algorithm is applied to a smaller regional model that was extracted from the national model.

## State of the Art

Methods for modelling on-demand ride-sharing services are often developed in the context of automated vehicles, as shown in Soteropoulos et al. (2) where current literature in this field is reviewed. Previous research shows different approaches for simulating on-demand ride-sharing services, predominantly on a microscopic scale in agent-based models. Maciejewski (3) for example implemented an extension for the dynamic routing of vehicles for MATSim simulations. The algorithm was applied for several research cases, such as a study about large-scale autonomous taxi-cabs in Berlin (4). Other important research was conducted with the implementation of on-demand ride-sharing using MATSim for the city of Austin (5), including economical analyses and fleet sizing. Wilkes et al. (6) used an agent-based travel demand model to analyze the effects of new mobility services like ride-sharing for the city of Stuttgart. The successful application of these algorithms in microscopic simulations gives great insight into the requirements for modelling MaaS, transferring these methods to macroscopic models is however not a trivial task.

The challenge for macroscopic models is that demand is represented by non-discrete origin destination matrices (OD-matrices) for a certain time period (e.g. a day or an hour). This makes it difficult to find trip requests with similar directions and departure times. In Heilig et al. (7), the applied agent-based model uses a macroscopic assignment to model person and car movement between TAZ. To depict ride-sharing, the demand is split into 15-min timeslots and all agents with the same origin and destination TAZ are pooled. Given the nature of an agent-based model, the demand is still discrete in this study and questions regarding the possible pick-up of passengers along the route remain. A solution for this is suggested in Friedrich et al. (8), with an approach that was developed specifically for macroscopic models. It regards non-discrete demand and matches trip trajectories based on crossed TAZ with the trips' network-based paths. This approach has been successfully implemented for regional modelling studies in the context of automated driving (9,10). Applying the scheduling algorithm by Hartleb et al. (11), it is possible to determine relocation trips and fleet sizes.

A nation-wide assessment of MaaS services and the optimization of fleet sizes and user prices was done in Kröger et al. (12) with an aspatial model of Germany. However, this model only distinguishes between different regional types and there is no spatial distribution. A classic macroscopic travel demand model with a road network and cell structure provides more possibilities regarding spatially distinct effects on road capacity. It is also possible to model potential use cases and implement the service in specific areas and cities. The interaction between different regional types can be regarded as well. To the author's knowledge, there has not been a comparable study modelling ride-sharing on a national level using a sophisticated macroscopic travel demand model so far.

To summarize, the approach by Friedrich et al. (8) provides a framework which stands out with its straightforward implementation into existing macroscopic travel demand models and produces good results with reasonable computational effort. For these reasons, the approach was already applied and further developed in different research works (9,10). It suggests itself that this approach is suitable for a large-scale implementation, too.

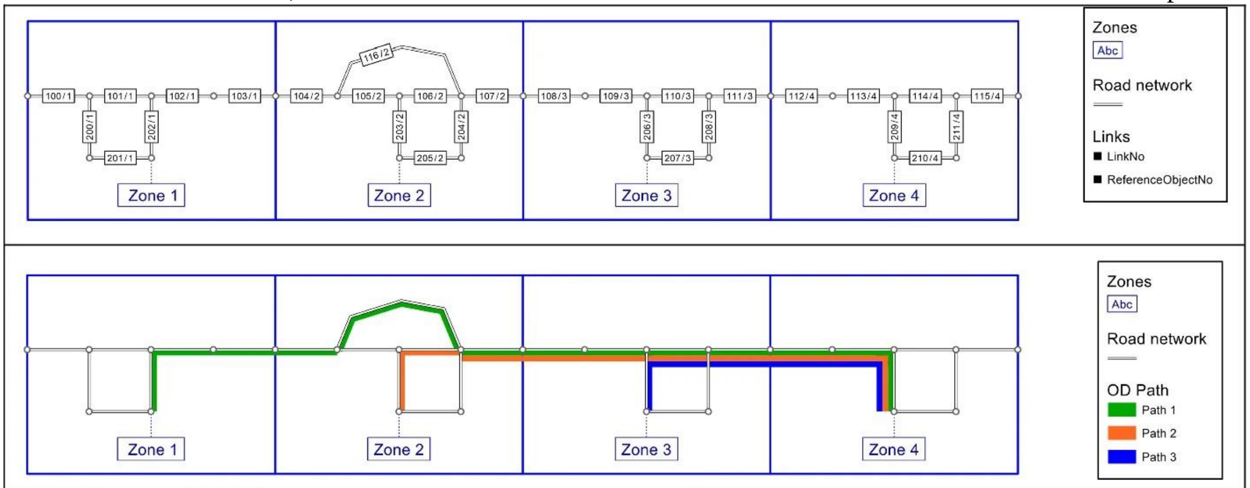
**Overview of the Base Ride-Sharing Algorithm**

The goal of the algorithm is to find origin-destination relations (OD-relations) with matching trajectories and departure times and pool their demand. Friedrich et al. (8) initially developed it in the context of car drivers (suppliers) offering empty seats in their vehicles for travelers with similar trip directions (demanders). Therefore, the daily demand of suppliers and demanders is first divided into short time intervals (e.g. 10 min). This ensures realistic waiting times, as it is assumed that all trips within the same interval can be pooled. With a network assignment of both groups' demand, shortest paths are generated. These paths are used as the base for the trips' trajectories.

In order to match the supplier and demander paths, there is an iteration over all demander paths where the current path is compared to longer supplier paths. The algorithm follows the following steps, based on Friedrich et al. (8) and Richter et al. (10):

1. Assign TAZ to the links in the road network.
2. Determine the demand matrices for the current time interval.
3. Assign trips to the road network and convert the resulting network-based paths from a series of links to a series of TAZ crossed by these links (Figure 1).
4. Find paths with matching trajectories by checking whether origin and destination of the current path are among the crossed TAZ of the supplier path. In Figure 1, route 1 (green) can act as a supplier path to the matching route 2 (orange).
5. Pool the demand on matched paths by placing the demand from the current path into the supplier's vehicle.

In Richter et al. (10), this algorithm is implemented for autonomous ride-sharing where suppliers are vehicles of a commercial service provider. Since the suppliers' tours in this case solely depend on the demanders' trips, the demander paths are matched with themselves following the previously descriped steps. Finally, fleet size and relocation trips of the ride-sharing vehicles are determined with the scheduling method described in Hartleb et al. (11) and Richter et al. (10). It is a heuristic approach at optimizing vehicle usage. Therefore, the vehicle trip matrices for the pre-defined time intervals are processed chronologically. The ride-sharing vehicles are then distributed over the span of a day with new vehicles being added to the pool whenever there are no existing vehicles available for a trip. As a result, vehicle tours are formed, which enables the calculation of the minimum fleet size and relocation trips.




| path | from | to | sequence of links | sequence of reference zones | |
|---|---|---|---|---|---|
| | | | | complete | without duplicates |
| 1 | 1 | 4 | 202,102,103,104,116,107,108,109, 110,111,112,113,209 | 1,1,1,2,2,2,3,3,3,3,4,4,4 | 1,2,3,4 |
| 2 | 2 | 4 | 203,106,107,108,109, 110,111,112,113,209 | 2,2,2,3,3,3,3,4,4,4 | 2,3,4 |
| 3 | 3 | 4 | 206, 110,111,112,113,209 | 3,3,3,4,4,4 | 3,4 |

*Source: Friedrich et al. (7, p. 1644)*

**Figure 1: Identify matching routes with the zone-based algorithm**

The algorithm is straightforward to apply in regional macroscopic travel demand models. However, it is highly dependent on cell and network structure of the model, which could influence the results. For a model of national scope, the granularity is usually lower than in a regional model. This is illustrated by the comparison of TAZ sizes for the German national transport model and a regional model in Figure 2. As a consequence, there is not only a significant difference in the number of OD-relations, leading to a much smaller set of paths to be matched, but the trajectories are also described with less crossed reference objects. Furthermore, OD-relations from a regional model with smaller cell sizes could be happening as intrazonal traffic in a larger model and thus, not be represented as network paths from an assignment. Therefore, adjustments to the base ride-sharing algorithm are necessary so that even with a coarse structure, a national model is able to replicate results from a regional model. The presented methodology addresses these flaws and aims at mitigating the influence of the zoning structure on the ride-sharing results.

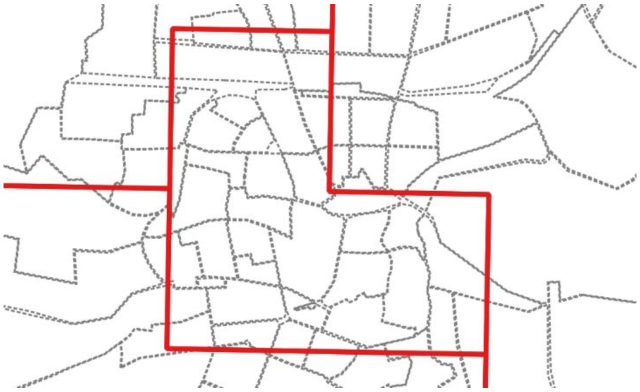


**Figure 2: TAZ sizes in national model (red outline) compared to regional model (grey outline)**

## RIDE-SHARING ALGORITHM FOR NATIONAL MODELS

The new methodology should enable the algorithm to generate results in a national model that match the values from a regional model. Since there is a large discrepancy between those models when it comes to cell size, this is the focus of the adjustments. The main idea of the adjustments is to display more detailed trajectories by defining multiple reference objects per cell, serving as pick-up and drop-off locations. This way, the existing OD-relations can be multiplied and the trajectories of the network paths are far more precise. It also enables the distribution of inner cell demand between these pick-up points and their inclusion in the ride-sharing algorithm.

### Identifying Pick-Up Points

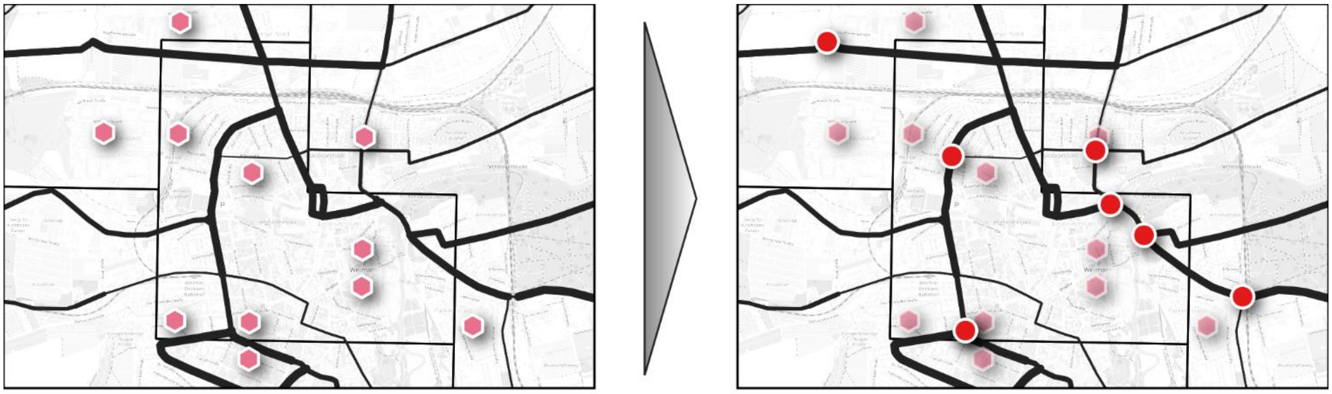
The pick-up locations should represent possible origins and destinations within a cell. This could be residences or workplaces for example. For practical reasons, population density was chosen as base for defining these points, as this data provides accessible spatial information. There will be multiple population centers per TAZ that function as the base for pick-up locations. These will then be moved to the nearest network node to ensure the pick-up points are accessible by a network-based path from an assignment. For a wider range of possible detours, each point gets assigned a buffer area.

#### *Population Centers*

The population centers are defined by intersecting a 250x250 m population grid with the zone boundaries. Each grid cell is assigned the ID of the zone it lies within. Afterwards, the population of each cell is clustered and the cluster's centers are defined (e.g. with kmeans[1] algorithm in R). The cluster's population is used to assign a weight to each center.

With a wide variety of cell sizes, making the number of cluster centers per cell dependent on the cell's area is advisable. After clustering the zones' population, each center will be moved to the nearest network node, so that it is possible to cross them in a shortest path network assignment, as shown in Figure 3. This is especially necessary because of the network structure of national models. Usually, minor roads like collector streets are not included (e.g. in the German national model, Matthias et al., 2020). This is why the centers of the population clusters are not necessarily near the road network, as settlements are often accessed with smaller streets.

[1]For documentation see: https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/kmeans



Background map: Open Street Map / © OpenStreetMap Contributors

**Figure 3: Moving pick-up points from population centers (left) to the nearest node in the road network (right)**

***Create Pick-Up Points***

The ride-sharing algorithm checks whether the origin and destination of a path are among the crossed reference objects of another path. Therefore, it is important that there are unique origin and destination pick-up points for each network path. This is why in addition to the previously defined population centers, all connector points from the network model will be added to the list of pick-up points. A connector point is a node in the road network that connects the zone to the network, marking the points at which outgoing and incoming traffic starts or ends. All trips in the road network start and end at connector points.

Following the addition of connector nodes, some pick-up points will be removed if they meet the following conditions:

- They are identical to a connector node.
- They are identical to another pick-up point.

To improve performance of the ride-sharing algorithm, pick-up points that are too close to each other can be merged. It is however necessary to define a feasible minimum distance between points. In the end, at least two points per TAZ have to remain so that inner cell demand distribution is still possible. The remaining set of points represents the final pick-up locations in the road network. Finally, a buffer will be determined for each pick-up point. This buffer will be used in the matching algorithm for assigning network links to pick-up points that are accessible from this link. This ensures that detours from the shortest path are possible. The buffer sizes can vary depending on cell sizes.

**Applying the Ride-Sharing Algorithm**

The base ride-sharing algorithm is implemented with a few adjustments, starting with the intersection of reference objects and the road network. Instead of TAZ, the pick-up points and their respective buffer area will be assigned to the network links. Using buffers enables the possibility of detours from the shortest path to collect other passengers. The network-based paths can then be described as a sequence of crossed pick-up points, and a matching path's origin and destination connectors have to be a part of this sequence.

Considering the cell size in national transport models, intrazonal trips should be part of the algorithm, too. However, there are no network paths for these trips and thus no trajectories. This problem is comparable to the challenges Kröger et al. (12) faced when implementing autonomous ride-sharing in an aspatial model. They decided to create virtual grid cells of one square kilometer, where the demand would be evenly spread as vectors in multiple directions. A modified version of this method is applied to distribute inner cell demand. The directions in each TAZ are the linear distances between the pick-up points (Figure 4). The inner cell demand $vol_{cell}$ is then distributed on these directions ($vol_{dir}$), weighted by the population weights of origin ($w_o$) and destination ($w_d$) pick-up point with (1). The sum of all population weights is one.

$$vol_{dir} = vol_{cell} \cdot w_o \cdot w_d \qquad (1)$$

The population weights act like attraction factors in a gravity model, yielding consistent results. The sequence of points for intrazonal trips consists of the origin and destination pick-up point, and they can be matched with and replaced by network paths.

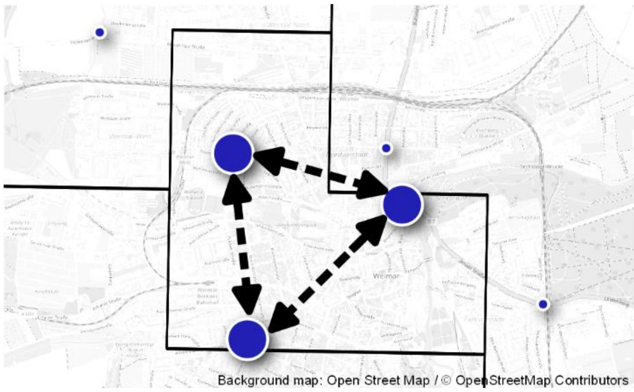
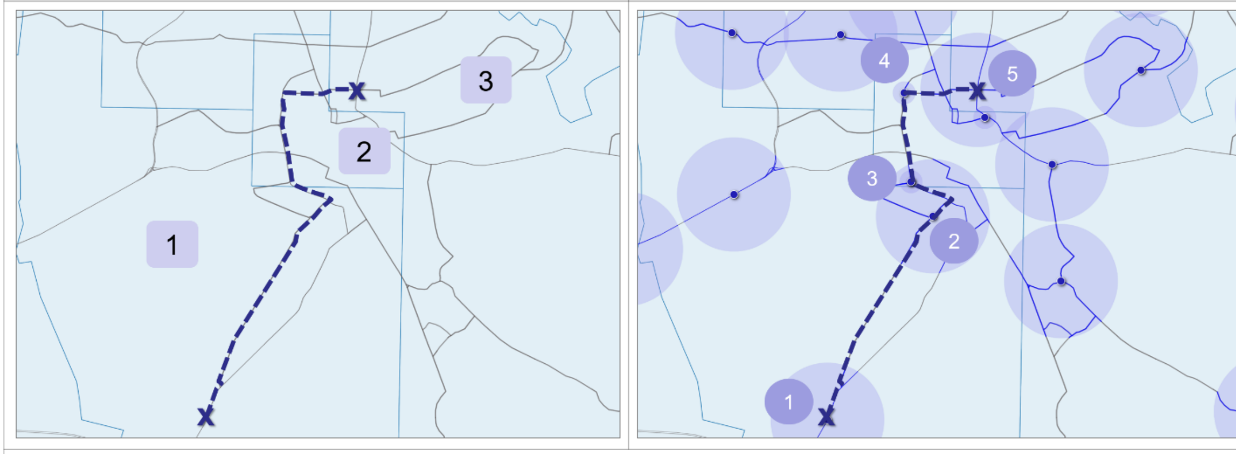



**Figure 4: Examplary directions for intrazonal trips between pick-up points**

The inner cell directions are added to the list of network paths. This supplemented list is used during the matching iterations of the ride-sharing algorithm. Figure 5 illustrates the difference in matching results between the original zone-based and the pick-up point approach. The trajectory of the selected path is described with more crossed reference objects with the ladder and there are far more relations that match, including inner cell trips.

| Zone-Based Approach | Pick-Up Point Approach |
|---|---|




| *Trajectory (Sequence of Crossed Reference Objects)* | |
|---|---|
| 1, 2, 3 | 1, 2, 3, 4, 5 |
| *Matching OD-Relations* | |
| 1 → 2;<br>2 → 3 | 1 → 2; 1 → 3; 1 → 4;<br>2 → 3; 2 → 4; 2 → 5;<br>3 → 4; 3 → 5;<br>4 → 5 |

**Figure 5: Comparing trajectories and possible matching OD-relations for the zone-based and the pick-up point approach**

For the proper scheduling of the resulting vehicle trips, a final adjustment is made. As the network paths and inner cell directions are defined by their origin and destination pick-up points instead of TAZ, the distribution of vehicles will also happen between points, not zones. Therefore, the travel time between each point is determined as the travel time along the network path. For inner cell directions, the travel time for intra-zonal trips is used. These values can then be converted to an origin-destination matrix of pick-up points, which is the main input for relocation and travel times during scheduling.

## CASE STUDY FOR THE GERMAN NATIONAL TRANSPORT MODEL

In order to illustrate the effects of the presented methodology, a case study for a reference region in the German national transport model DEMO (DEutschland MOdell) is performed. The goal is to compare the results of a regional macroscopic model to a submodel of DEMO for the same region (further referred to as DEMO-W). The base approach was developed for regional models, which produce reasonable ride-sharing results and indicators for utility components. A model of national scope should thus be able to recreate these to a degree, so that the quality of results does not suffer with a different granularity. For comparison, the area around Weimar, Thuringia, was chosen as there is a well calibrated regional reference model available to the author. In the case study, it is assumed that all public transport trips will be realized with shared MaaS vehicles with a capacity of six seats. This includes ~ 25,000 daily trips in the regional model. In order to have comparative results, the demand matrices from the regional model were aggregated and imported to DEMO-W.

### The German National Transport Model DEMO

DEMO is a macroscopic model landscape designed to forecast transport developments considering socio-demographic, technological and policy changes, as described in Winkler et al. (13). It includes different demand modules for passenger and commercial transport, forecasting road-based and rail transport. These modules produce demand in the form of OD-matrices, which are imported to network models for road and rail assignment. Afterwards, the network model produces traffic loads and skim matrices for important utility components like travel times. In an iterative process, these skim matrices are then used as new input for the demand modules up until there are no significant travel time changes compared to the previous iteration or a maximum number of iterations is reached.

The demand model for passenger traffic is divided into long- and short-distance modules. To illustrate the procedures in these modules, Figure 6 shows an overview of the short-distance module. It follows the steps of a classic four-step model, starting with trip generation based on structural data (1). Destination and mode choice (2) are followed by a network assignment (3). The model is static. Winkler et al. (13) further describe the utility functions and calibration of both passenger traffic modules. The adjustments to include ride-sharing in the demand modules are however not addressed in this paper.

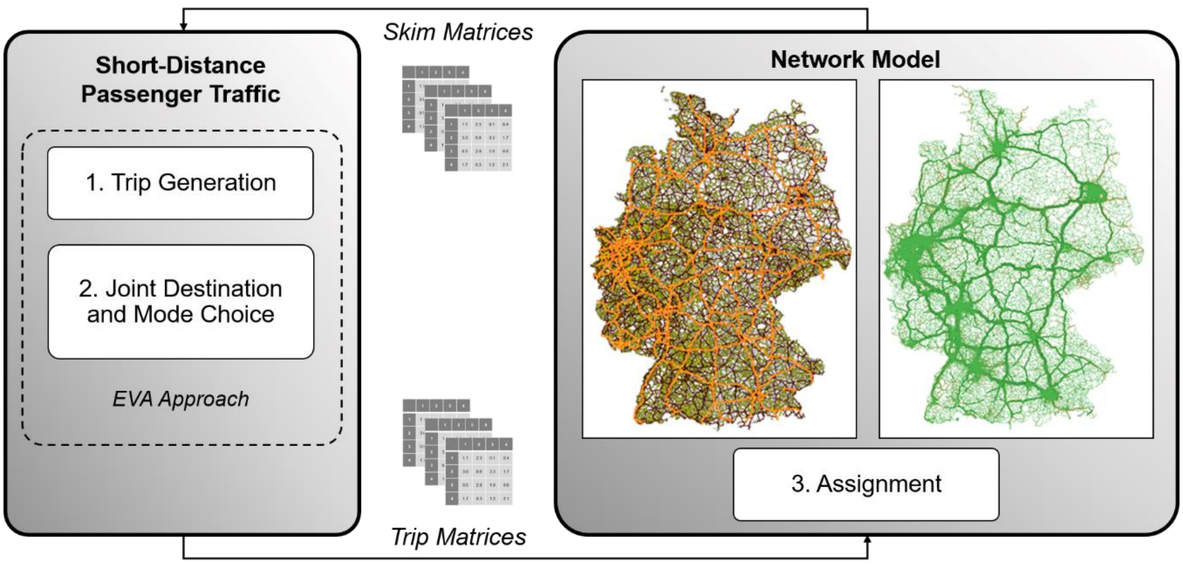



**Figure 6: DEMO short-distance passenger traffic model**

The biggest difference to macroscopic regional models is the zoning in the DEMO network model, which was developed with the method described by Nordenholz et al. (14). They use a 1x1 km population grid as base cells for TAZ and disaggregate other spatial land use data that is given on an administrative level on the grid cells. It follows that each grid cell carries information about population and attraction factors like workplaces. Grid cells within the same municipality are then aggregated again until a population and workplace threshold of 20,000 is reached. As a result, there are small TAZ in high-density areas of 1 km² and larger TAZ in rural areas, with the largest TAZ even matching municipality borders. Germany in the DEMO network model is divided in 6,633 TAZ. For the case study, the covered area consists of 168 TAZ in the regional model, whereas the region in the DEMO network is covered by only 8 TAZ (Figure 7).

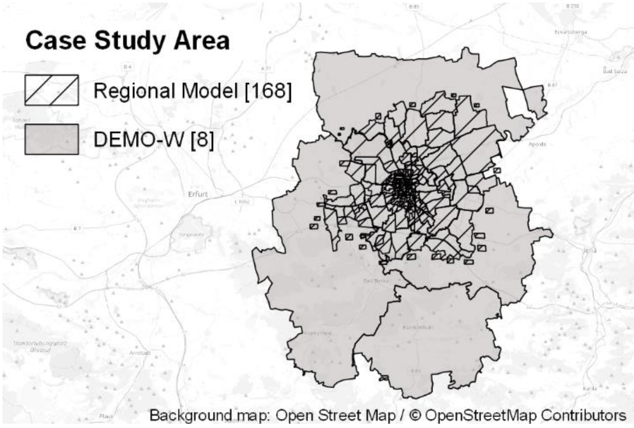



**Figure 7: Case study area and TAZ for regional model and DEMO-W**

**Results of the Case Study**

The presented ride-sharing approach with pick-up points and intrazonal demand distribution was applied to the case study region in DEMO-W with the following additional assumptions:

- For the smallest TAZ with an area of 1 km² there will be three population centers, five for zones of 2 km² and six for all zones larger than that.
- Pick-up points within the same zone and a distance lower than 500 m were combined to one pick-up point.
- TAZ with an area larger than 10 km² were assigned up to three additional connectors at the pick-up points with the highest population weight. This number is chosen heuristically in order to increase the number of network paths per OD-relation without negatively impacting performance.
- Buffer radii for pick-up points depend on the cell's area and are set to 150 m for TAZ smaller than 10 km², 500 m for TAZ smaller than 20 km² and 750 m for TAZ larger than 20 km².

The calculations were performed using PTV Visum (15). Table 1 shows key indicators from model runs for the regional model and DEMO-W. In the regional model, the base algorithm using zones was applied. For DEMO-W, both the base algorithm with zones as reference objects as well as the presented approach with pick-up points were applied to illustrate the effects of the new methodology.

**Table 1: Comparison of Ride-Sharing Results in the Regional Model and DEMO-W**

| **Model** | **Regional** | **DEMO-W** | |
|---|---|---|---|
| **Reference** | *Zones* | *Zones* | *Pick-Up Points* |
| **Travel time with detours (peak hour)** | + 18 % | + 75 % | + 24 % |
| **Fleet** | ~380 | ~140 | ~283 |
| **Fleet density per 1,000 inhabitants** | 5.2 vehicles | 1.9 vehicles | 3.9 vehicles |
| **Occupancy** | 1.35 | 3.71 | 1.95 |
| **Served person trips per vehicle per day** | ~65.8 | ~178.6 | ~88.3 |
| **Mileage per vehicle per day** | 260.85 km | 304.16 km | 347.86 km |
| **Vehicle operation hours per day** | 6.77 h | 6.57 h | 7.91 h |
| **Travel speed** | 38.53 km/h | 46.30 km/h | 43.97 km/h |

There are two major takeaways when the results of the regional model are compared to those of DEMO-W using zones as reference objects, as shown in Table 1. First, the fleet size is lower than in the regional model with higher occupancy levels. This can be attributed to the fact that broad trajectories allow for higher matching rates as well as that with less network trip relations, the demand per path is higher. This leads to high occupancies even without matching. The second takeaway is that the broad directions that are matched would result in the possibility of high detours with cell sizes up to 200 km². The detours were determined based on the intrazonal travel times of TAZ where a vehicle would stop to pick up new passengers, as the pick-up could happen anywhere in the respective area. As Fagnant et al. (5) suggested when they developed their search method for dynamic ridesharing in a microscopic simulation, the travel time should not increase by more than 20 % with picking up new passengers, or else this passenger cannot be transported in the same vehicle. Following this benchmark, the feasibility of the fleet size and the utility for the users can be assessed. In the regional model, where the average detour increases travel times by ~18%, the fleet seems effective in satisfying demand while maintaining a reasonable level of service. In contrast to this, the strong increase in travel times in the peak hour by ~75 % in DEMO-W indicates that the fleet is not sufficient and high detours might negatively affect demand for the mode.

With the new approach using pick-up points, the results of DEMO-W are closer to those of the regional model than its zones counterpart. The fleet size is still lower, but was doubled from the value in the zone-based approach. The occupancy is still higher with 1.95, but already closer to the result from the regional model. The higher occupancy is also reflected in the higher number of person trips served per vehicle per day, which could however be drastically decreased with the pick-up approach for DEMO-W. The increase in travel time because of detours has also significantly decreased, although still high with a plus of 24 % in the peak hour. The detours here are determined using the buffer radii of pick-up points where a vehicle would stop. It is assumed that the buffer radius is crossed with a speed of 30 km/h.

Table 1 further includes key indicators like daily mileage and operation hours. Overall, these values indicate that the algorithm itself produces reasonable results for both models in the case study, as the daily operation hours and mileages are within a reasonable range. However, both DEMO-W model runs have much higher travel speeds of the MaaS vehicles than the regional model. This can be due to the network structure. Only higher ranked roads are included, and in the reference region many trips are routed over motorways and major roads with high capacities as well as speed limits higher than 80 km/h.

## CONCLUSION

The presented approach is a first step to enable large-scale models like DEMO to implement dynamic ride-sharing and assess the effects on the transport system. It provides a method for the technical implementation which produces fleet results for assessment and utility components that influence user preferences. Based on this framework, techniques for calculating user preferences and utilities for MaaS can be developed with future research. The focus of this paper is on a case study for a region. By transferring the method to other regions within the national model, quick estimations of ride-sharing services are possible without having to set up new regional models. MaaS can be implemented for cities, as this is the most likely scenario with a business case. However, the scope of the model also allows for more diverse options like feeder services for rail transport, door to door services in less dense areas or scenarios for long-distance travel and even nation-wide ride-sharing services.

Since autonomous dynamic ride-sharing is a future mobility service without observed data, the results should be interpreted carefully. They represent possible trends, but different modelling approaches still yield different results. The microscopic studies by Fagnant et al. (5) or Bischoff et al. (4) were performed for a higher number of trips in larger areas, resulting in much less served person trips per vehicle per day than in the Weimar region (26.6 for Austin and 16.6 for Berlin compared to 65.5-88.3 in Weimar). This could be due to the stricter rules for detours and waiting times as well as a pre-defined fleet size in the microscopic simulations. The results from Kröger et al. (12) yield a fleet density of 2.7 to 3.6 vehicles per 1,000 inhabitants for a comparable modal share and market equilibrium, which are closer to the DEMO-W result with a density of 3.9 than the results from the regional model (5.2 vehicles per

1,000 inhabitants). When comparing these results, it has to be mentioned that there is no reserve included in the fleet as of now. In conclusion, the adjusted ride-sharing algorithm produces reasonable results in a large-scale model like DEMO-W.

Further research following the development of this approach can focus on runtime improvements, as this is heavily influenced by the number of paths. Doubling the number of paths increases runtime by 75 %, which is currently at approximately 90 min for ~30,000 paths. For a nation-wide assessment, computation times still have to be determined, but can be expected to be high due to the number of relations. Other flaws are inherited from the base algorithm, such as the influence of the longest paths on possible vehicle routes and the separation of matching and scheduling, which does not allow for a limited fleet yet.

Building on the network implementation, a key objective is to include MaaS and demand responsive transport in mode choice models. For this study, the demand scenario was that all public transport trips will be served with ride-sharing vehicles, as utility calculation was not a focus. Future applications can also include operational questions like the optimization of vehicle sizes for a given demand. The seat capacity of six in this study is an educated guess at a possible design of purpose-built MaaS vehicles. With the model implementation of on-demand transport being a crucial part of preparing travel demand models for automation, interactions of an automated MaaS fleet within mixed traffic in macroscopic models are another research objective. While studies like Sonnleitner et al. (16) already suggest methods for that, there are still limitations on an individual vehicle level with macroscopic models.

All in all, it is possible to mitigate the strong influence of zoning on the results by using pick-up points and including intrazonal trips into the ride-sharing algorithm by Friedrich et al. (8). The application is not necessarily linked to certain model software, although the methodology was developed using PTV Visum (15). It is transferable to other macroscopic approaches with TAZ and a road network that are able to perform a network assignment.

With the possibility of modelling ride-sharing services in large-scale models like DEMO, a useful tool is provided for planners and policy-makers. The base algorithm's field of application has been enlarged and the effects on MaaS can be evaluated on a higher scope. Using the presented approach, it is possible to achieve similar results regarding the key factors for utility components and the network assignment with models of different scopes. This provides yet another element for preparing transport models to represent and shape mobility of the future.

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**AUTHOR CONTRIBUTION STATEMENT**

NT: Conceptualization, methodology, calculations and analysis, writing, review; The author does not have any conflicts of interest to declare.

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