

Assessing the potential of demand-responsive transportation for sustainable rural mobility through macroscopic travel demand modeling

vorgelegt von

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1 Introduction and motivation

The private car is the dominant mode of transportation for everyday mobility, including trips to work, shopping, education, leisure activities, and social participation. Its widespread availability has expanded individual activity spaces and encouraged daily routines and spatial structures based on car accessibility. However, the private car requires individual financial investment, is not accessible to everyone, and cannot be used by all population groups. It also contributes substantially to transportation-related emissions, land consumption, accidents, and other negative externalities. The transformation of the transportation sector therefore aims to reduce these impacts while maintaining accessibility to increase sustainability. Public transportation plays a central role in this context, as it provides an alternative to private car use and can reduce traffic volumes, energy use, and emissions per passenger trip through higher capacities and pooling. It does however require certain levels of density to achieve efficiency.

This poses a challenge in rural and low-density areas, which, as a result, are often characterized by incomplete public transportation services. In combination with long travel distances, dispersed settlement structures, many residents depend on private cars. At the same time, demographic change is increasing the share of elderly residents in many rural regions, raising the importance of mobility alternatives for people who are less able or no longer able to drive. Improving mobility in such regions is therefore a central policy objective, as it enhances access to essential infrastructure such as healthcare, education, and employment, supports social participation, and improves regional attractiveness. However, adequate public transportation provision in these areas is associated with substantial economic challenges due to low demand densities and occupancy rates. This creates a fundamental goal conflict between comprehensive mobility provision and financial feasibility.

In this context, technological and organizational innovations in the transportation sector are gaining increasing attention. Against the background of automation and digitalization, Demand-Responsive Transportation (DRT), in particular, is considered a promising approach to complement traditional fixed-route public transportation. By dynamically adapting routes and schedules to user demand and enabling ride pooling, DRT has the potential to combine the flexibility of private car use with the resource efficiency of bundled collective transport. Consequently, DRT is increasingly discussed as a means to improve and extend public transportation supply.

Before introducing DRT into the mobility system, central questions regarding service design and evaluation need answering. From a planning and decision-making perspective, the key question is to what extent DRT can contribute to sustainable mobility provision and under which conditions its implementation is effective. While DRT offers opportunities to enhance accessibility and complement existing public transportation systems, particularly in low-demand areas, it also entails risks. These include potential competition with, and cannibalization of, conventional public transportation, uncertain user acceptance, and unclear impacts on overall traffic volumes. Furthermore, low demand density may create challenges regarding financing and subsidy requirements. The trade-off between high-quality mobility provision and economic viability often results in rural public transportation providing only a limited level of basic mobility. Addressing these uncertainties and trade-offs requires robust analytical tools, such as travel demand models, which allow for the systematic evaluation of different service designs and policy interventions. However, the availability and applicability of such models, ranging from macroscopic approaches to agent-based simulations, vary considerably, further complicating evidence-based decision-making.

Against this background, this thesis is motivated by the need to better understand the role of DRT in addressing the mobility challenges of low-density areas and to support informed planning decisions through appropriate modeling and evaluation approaches. The central question in this context is how a DRT system for rural areas should be designed to contribute to attractive rural public transportation.

2 DRT in rural areas

This section defines the scope and research object of this thesis. First, the service DRT is defined in the thesis' context. Second, the characteristics of rural areas and their challenges and requirements regarding mobility are described. The chapter concludes with an overview of the prospects of DRT in a rural context.

2.1 Demand Responsive Transportation (DRT)

Public transportation describes forms of transportation that are publicly available, such as buses, trams, trains, but also shared systems like bike-sharing, car-sharing, or on-demand mobility. In the context of this thesis, traditional public transportation includes scheduled mobility services that follow a pre-defined timetable and route and that are operated by a private or public service provider. In contrast to traditional public transportation services, DRT is only dispatched if there is a ride request: The passengers have to actively book the transportation service in advance.

The German passenger transportation law (Personenbeförderungsgesetz – PBefG) includes DRT services since 2021 as demand-controlled, pooled transportation of passengers without fixed schedules (PBefG, 2021). Similarly, the UK Department for Transport defines them as flexible services with no fixed routes or timetables, responding to user demand, which uses smaller vehicles than traditional bus services (Department for Transport, 2025). The US American Code of Federal Regulations defines demand-responsive services as “any non-fixed route system of transporting individuals that requires advanced scheduling by the customer, including services provided by public entities, nonprofits, and private providers” (49 CFR § 604.3, 2025). Figure 1 illustrates DRT operations: A user requests a ride, which is then processed in a dispatch center to dispatch a vehicle to the user's pick-up location. Then, the vehicle transports the user to their destination or drop-off location and is available for the next request. Potentially matching rides of other users are identified in the dispatch center and can be picked up along the way.

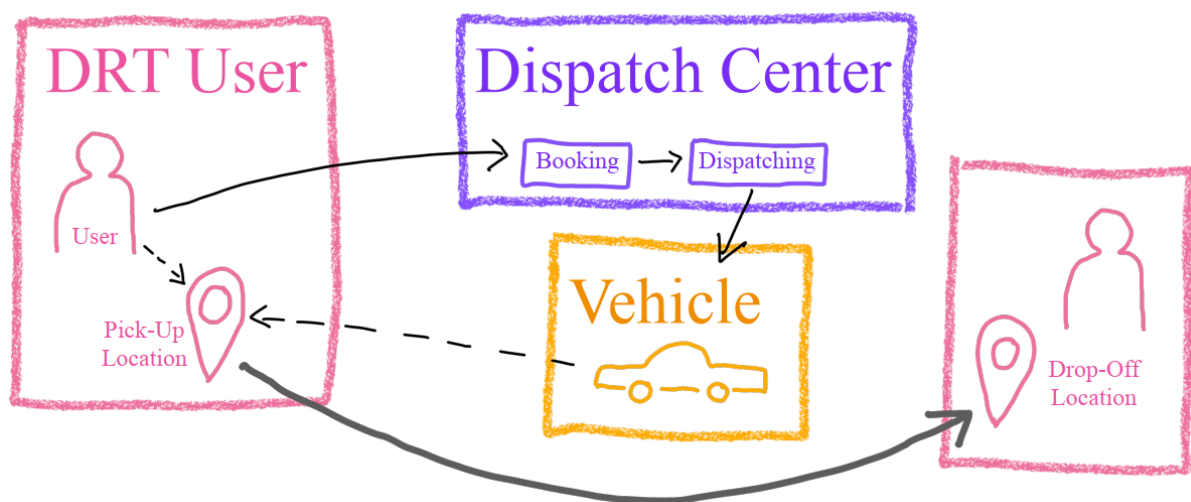


Figure 1: Schematic overview of basic DRT operations (own illustration)

Agora Verkehrswende (2023) provides a conclusive definition of demand-responsive transportation (DRT) in Germany. It is characterized by public availability, a high number of pick-up and drop-off (PUDO) locations where users enter and exit the vehicles, and trips that are not bound to fixed routes or schedules but are defined by passenger demand and allocated by automated disposition operations.

Within this umbrella, there is a differentiation between commercial and non-commercial services. Commercial DRT services, where vehicles and drivers are provided by an operator, include the following:

- Ride-hailing: Denotes single-request, commercially booked trips
- Ride-pooling: Refers to commercially operated vehicles in which passengers with similar trajectories and departure times are bundled together

Non-commercial DRT offers include ride-sharing, which is defined by private drivers picking up additional passengers with comparable trips. In contrast to commercial services, there is no vehicle fleet specifically for the DRT service, and the supply depends on the trip of the car driver. This thesis will focus on commercial DRT services.

There are several concepts for DRT that have been established. The most prominent examples are ride-hailing companies, such as Uber and Lyft, who have popularized ride-hailing, especially in the North American market where public transportation supply is low. These services are typically independent of public-transportation providers. Traditional flexible public transportation services include call-bus schemes or on-demand shared taxis (AST) in low-density or night-time contexts. However, they remain tied to specific lines and schedules and do not provide door-to-door service.

In the context of this thesis, DRT is defined as app-based, ride-pooling services for trips with similar origins, destinations and departure times. Services are either door-to-door or PUDO-based and operate without a predefined schedule or line. Additionally, they complement public transportation spatially as feeder, and pricing can be either integrated into the public transportation tariff or offered as a separate fare.

2.2 Characteristics of rural areas and rural mobility

Rural regions are characterized by heterogeneous spatial and functional structures, ranging from small and medium-sized central towns to dispersed villages and peripheral settlements with low settlement and building densities (Figure 2). Central towns often serve as local supply and service hubs, concentrating infrastructure such as retail, healthcare, education, administrative services, and other public facilities, whereas smaller villages frequently have limited or no direct access to such amenities. These structural differences shape accessibility conditions and mobility needs.

In line with territorial classifications such as RegioStaR and the EU TERCET typology (BMDV, 2018, Eurostat, 2024b), rural regions can be described as areas with low population density, limited proximity to urban centers, and spatial structures in which central towns play a key role in providing infrastructure for surrounding villages and settlements. They are also often associated with a stronger role of agriculture and forestry, reflected in employment structures and in the high share of agricultural and forested land. Furthermore, rurality is linked to weaker functional integration with major urban centers, for instance through longer travel times to metropolitan areas, lower shares of outbound commuters, and varying degrees of workplace centrality or commuter balances between central towns and peripheral municipalities. This leads to longer distances for everyday travel outside of the central towns, which often require motorized transportation.

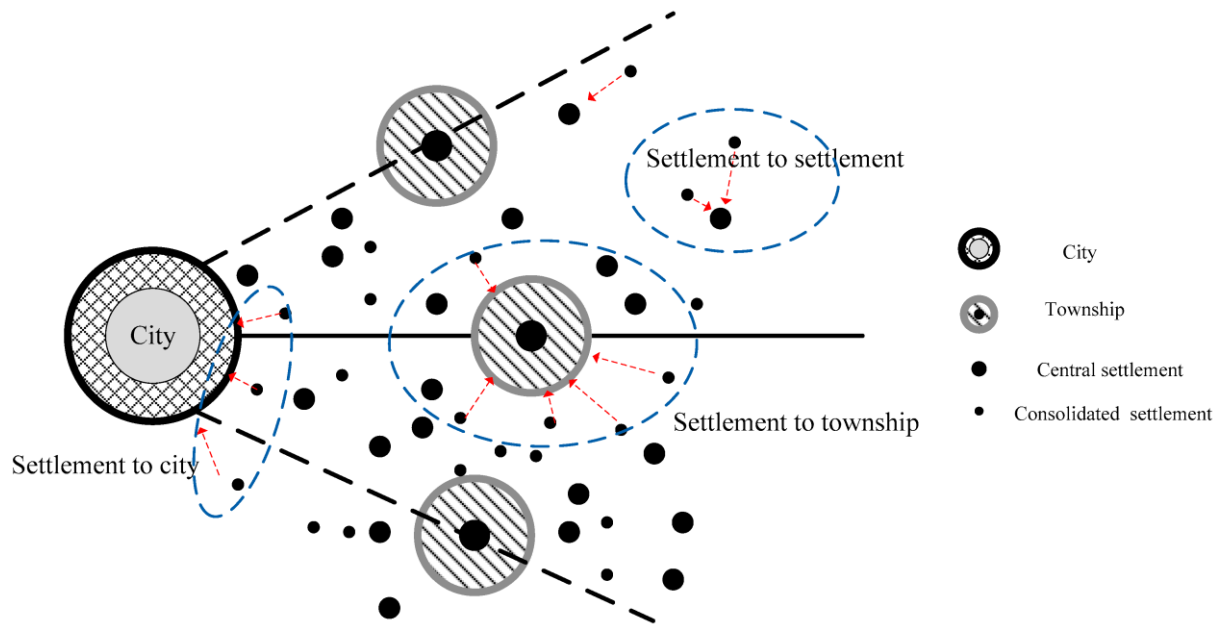


Figure 2: Spatial structure of rural regions and their development axes (Source: Mao et al., 2017)

According to the federal report on rural development (Bundesministerium für Ernährung und Landwirtschaft, 2024), demographic change leads to a higher share of senior residents throughout Germany, and the effect is particularly strong in rural regions that experienced a decline in overall population and economic activity. But even wealthy rural areas are predicted to see a steep increase in average population age. With this, the requirements for basic infrastructure and mobility needs change as well, as especially in areas with high car-dependency the number of elderly people who are less able to drive is rising. Rural mobility is predominantly characterized by a high reliance on private car use, driven by long travel distances, limited walking and cycling infrastructure, and an incomplete public transportation supply. Consequently, user satisfaction with public transportation tends to be lower than in urban areas. Nevertheless, public transportation remains a central component of the provision of essential public services, as it enables societal participation and supports regional economic development. In this context, innovative approaches such as flexible DRT and the implementation of mobility stations are increasingly seen as promising solutions to improve service provision in low-demand regions.

Conventional public transportation provision in rural areas is frequently oriented towards school transportation, since low and disperse demand often prevent economically feasible operations (Bundesministerium für Ernährung und Landwirtschaft, 2024). This results in schedules and routes that are not well aligned with other trip purposes, such as commuting, shopping, or leisure activities. This mismatch is further exacerbated by the diverse requirements of different user groups. For instance, elderly populations often have distinct mobility patterns compared to students or working-age individuals, including different preferred travel times and destinations, as well as a greater need for accessibility and convenience.

Empirical evidence from the German Mobility in Germany (MiD) survey further highlights the extent of car dependency in rural areas (infas et al., 2025). The majority of trips (up to 65% in the most rural parts) are conducted by private car, reflecting both limited alternatives and structural necessity. Outside of central towns, more than 50% of rural residents can be assigned to a user segment oriented towards daily car use. Trip distances are, on average, longer than in urban regions. Car ownership is correspondingly high, especially in remote regions, where less than 10% of households do not own a car. Nevertheless, these households still need access to option for fulfilling their mobility needs, underscoring the importance of alternative mobility options.

Overall, rural mobility systems face the dual challenge of addressing diverse and often dispersed demand patterns while maintaining economic feasibility. Improving accessibility and reducing car dependency, particularly for vulnerable populations, remains a central objective in the development of sustainable rural transportation solutions.

2.3 Prospects of using DRT in rural areas

To address the challenges in rural mobility and mobility planning, DRT is increasingly discussed as a promising approach for improving public transportation in rural areas. A key advantage of DRT is its ability to adapt public transportation to dispersed rural structures. Instead of operating large vehicles along fixed routes and schedules with low occupancy, DRT can use smaller, flexible vehicles dispatched according to actual demand. These services may operate as line-based DRT, feeder services to railway stations or central towns, or area-wide door-to-door or stop-to-stop systems. In this way, DRT should not be understood as a replacement for the entire public transportation network, but as a complementary element that fills spatial and temporal gaps.

The integration of DRT with fixed-route services is especially relevant. Where demand is high and predictable, such as school transportation, commuter flows, or connections to central towns and stations, conventional bus services remain more efficient due to higher pooling rates. DRT is more suitable for areas and times with low or dispersed demand. This enables a differentiated system in which fast regional bus lines connect central towns, railway stations, and major service locations, while DRT functions as a flexible distributor in the rural periphery, where local bus routes would no longer need to serve multiple settlements through indirect trajectories. DRT would cover first- and last-mile access in peripheral settlements. Since vehicles can be routed dynamically and detours can be limited within predefined thresholds, travel times may become more competitive with private car use than traditional rural bus services.

DRT may also support sustainable rural mobility. The definition of sustainability is understood as “needs of the present are met without compromising the ability of future generations to meet their own needs” (World Commission on Environment and Development [WCED], 1987, 27), which includes economic, ecological and societal dimensions. In the United Nations’ Sustainable Development Goals (SDG), SDG target 11.2 “Sustainable transport” explicitly requires “[providing] access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons” (High-level Advisory Group on Sustainable Transport, 2016, p. 12). Additionally, minimizing emissions and environmental impact is a critical objective. This underscores the role of transportation not only for climate action, but also for social inclusion. In rural areas, as described in the previous chapter, this requires special attention: car dependency can exclude people who cannot drive or afford to own a car and can increase emissions from driving; accessibility to basic infrastructure for societal participation, health, and education facilities is low; and an aging population demands tailored mobility services. Consequently, DRT can contribute to a more sustainable rural transportation system by improving public transportation and accessibility. Unlike dense urban areas, additional DRT vehicles are less likely to exacerbate congestion or disrupt traffic flow because traffic volumes are generally lower. However, environmental benefits depend on sufficient pooling rates, vehicle occupancy, fleet size, and whether DRT replaces private car trips rather than existing public transport, walking, or cycling, as well as drivetrain technologies employed by the DRT fleet.

Overall, DRT has considerable potential in rural areas when used as a targeted complement to conventional public transportation. Its main contribution lies in improving accessibility in dispersed settlement structures, supporting mobility for people without regular car access, strengthening feeder connections, and enabling faster fixed-route services between central towns. DRT is therefore most promising as part of an integrated rural mobility system that combines conventional buses on high-demand corridors with flexible services in peripheral areas and during low-demand periods.

3 State of the art

In the following sections, key contributions from the literature on DRT are summarized to describe the current state of knowledge, to assess successful implementation strategies, and to identify existing barriers and limitations. Therefore, three categories of sources are considered. First, evaluations of deployed real-world DRT services provide empirical data on usage and operations; however, they do not enable experiments on different level of service, scaling options, or user behavior under different configurations. This is addressed with the second category of literature, which focuses on user-centric research on DRT. Finally, results from transportation models and simulation studies enable forecasting and analysis of potential future service designs.

3.1 Ex-Post assessment: Empirical evaluation of pilot studies

In less densely populated urban, suburban or rural areas, DRT services are often introduced as pilot projects within model regions for mobility innovations. Many of these pilots have been studied scientifically, producing publications that evaluate their performance. The following section presents findings from a selection of ex-post assessments.

Wisser et al. (2024) identified more than 100 model regions throughout Europe with different innovations tested and varying scopes from city districts to larger municipalities, cities and countries. The majority of these model regions are urban, only 8% are within rural areas. In two thirds of these regions, on-demand or shared mobility is introduced as a pilot project. However, a lot of these pilot projects face the issue that the implementation of innovations is only possible through public funding, which leaves a limited time frame to develop a business case, which requires sustainable long-term solutions that are accepted by users and scalable. Reported success factors include strong regional demand, involvement of regional partners, reaching a critical mass of users, user-centered service design, and continuous evaluation with flexible adjustments.

Nelson and Caulfield (2022) highlight the role of flexible and demand-responsive services for sustainable rural transportation developments, especially for accessibility beyond the main transportation axes. According to a survey among rural microtransit providers in the US (McKeeman et al., 2025), rural DRT helps improve quality of life, and that demand for the services was often higher than the supply. However, especially in very large, low-density areas with high travel distances, providers faced the challenge of meeting high demand without pre-booking, demonstrating the goal conflict between high pooling rates and flexibility. Several agencies were also able to implement rural microtransit due to federal grants and funds, similar to European pilots.

Early evidence from rural Mobility-as-a-Service (MaaS) pilots in Finland (Eckhardt et al., 2020) indicates that the integration of DRT into MaaS ecosystems can enhance accessibility and resource efficiency while reducing public sector costs. The case study analysis reports generally positive user perceptions, particularly regarding modal shift and perceived accessibility. Notably, at least one of the investigated pilots continued operation beyond the trial phase, suggesting a degree of institutional and operational viability.

In addition, findings from Austin (Zuniga-Garcia et al., 2022) highlight the importance of service design and contextual factors. Using comparative demand data from areas with and without DRT services, the study shows that door-to-door services achieve higher user uptake than feeder solutions. However, level of service is low and public transportation supply consists of bus lines only, which might influence the low usage of feeder services. Furthermore, usage patterns are significantly influenced by external variables such as socio-demographic characteristics, app usability, and marketing strategies, indicating that service performance cannot be evaluated independently of its deployment context.

Insights from the urban and suburban pilot “Loop Münster” (Hartz et al., 2024) further emphasize operational constraints. The evaluation reveals that the provided service level was insufficient to meet potential demand, as evidenced by high cancellation rates due to excessive waiting times. Although increasing user fares reduced cancellations by dampening demand, this simultaneously demonstrated that the existing fleet capacity was inadequate under more attractive pricing conditions. Despite positive user reception, low cost recovery and reliance on public funding ultimately led to the discontinuation of the service after the funding period (Stadtwerke Münster, 2024). Conversely, the “Sprinti” service in the Hanover region demonstrates a successful example of DRT implementation. Operating in peripheral areas of the region, it supplements the local public transportation network and recorded continually increasing demand, leading to further expansions and continuation after the federally funded pilot phase (Schrills et al., 2026). Key success factors include strong integration into the public transportation system, with the inclusion in tariffs, booking and navigation platforms, and an effective governance structure. This particularly refers to the regional cooperation in the provision of public transportation, where funding and planning is effectively pooled over several municipalities. Empirical observations from Bensler et al. (2025) suggest that Sprinti is used for both leisure and commuting purposes and improves social participation, especially for vulnerable groups such as elderly or impaired people and people without a car.

Analyzing DRT systems in more than 100 service areas throughout Germany, Ramboll Management Consulting GmbH (2026) derive success factors from a systemic perspective. They state that DRT has a higher impact if the base public transportation supply quality is low, which is often the case in low-density regions. In rural areas, it is used to ensure base mobility, and most value is added with the creation of new connections. Furthermore, DRT is usually observed to have a higher cost per km than traditional public transportation, but is more cost efficient in areas where public transportation demand is low.

3.2 User-centered research

User-centric perspectives are further explored by Diebold and Gertz (2025), who conducted household surveys in a suburban area near Hamburg, including both users and non-users of DRT. Their results indicate a high level of awareness and a usage rate of approximately 30% of households. Spontaneous booking emerges as a critical service attribute, and respondents express a willingness to accept surcharges in addition to standard public transportation tickets. Overall, there is clear public support for maintaining the service. Targeted applications, such as the “Silverbus” pilot in Genoa (Burlando et al., 2025), demonstrate the relevance of DRT for specific user groups. Focusing on elderly populations, the study employs pre- and post-trial surveys combined with logistic regression analysis to assess adoption behavior. The results show strong and consistent usage, high satisfaction levels, and the role of DRT as an enabler of independent mobility for seniors. These findings underline the importance of aligning transportation policy with demographic trends, particularly population aging. From a system performance perspective, Yen et al. (2025) analyze DRT services in Taiwan, where they operate primarily in low-density areas where conventional public transportation is not economically viable. Their findings indicate that service performance is closely linked to connectivity with urban centers and access to key destinations and amenities, reinforcing the importance of network integration.

Recent stated-preference studies provide additional insights into the potential role of DRT as part of integrated transportation systems. Klinkhardt et al. (2024) employ a stated choice experiment with a nested logit model to analyze autonomous DRT buses as feeders within public transportation and intermodal travel chains. Their results indicate a particular suitability of such services for low-demand-density areas and medium-distance trips. Notably, users show a willingness to accept longer waiting times at home in exchange for avoiding walking to fixed public transportation stops, highlighting the value of doorstep accessibility. Complementing this, Tordai et al. (2025) investigate user preferences in a rural town in Hungary through a stated-preference experiment and identify a substantial potential for

high uptake of DRT services. These findings suggest that DRT can address specific user needs in rural and low-density contexts and may achieve significant adoption under appropriate service designs.

Overall, the literature suggests that DRT services are generally well received by users and can contribute positively to accessibility and modal shift. However, a recurring challenge lies in the transition from pilot to permanent operation. Financial sustainability and cost recovery remain critical barriers, with many services depending on temporary funding schemes and struggling to maintain operations beyond the pilot phase.

3.3 Model-Based ex-ante assessment

The challenges faced for practical implementation when it comes to establishing DRT as a competitive mobility option for the broader public highlights the importance of transportation models for adequate planning. Models enable the forecast and prediction of demand, as well as the simulation of DRT operations and thus, play an important part in developing concepts for scalability.

The calculation of travel demand follows the four-step modeling approach, where (1) trips are generated, (2) those trips are distributed between origin and destination locations, (3) mode choice is performed for the trips and (4) the demand is assigned on the transportation network (Ortúzar S., 2011), all of which can be impacted by the introduction of DRT. Depending on model type, these steps are performed sequentially, iterative with feedback loops or simultaneous. Macroscopic travel demand models depict average traffic flows between traffic analysis zones (TAZ), which function as origins and destinations, for a reference time period (e.g., one day or one hour). In contrast to that, agent-based models or microscopic simulations depict movement spatially and temporally disaggregated for individual agents.

3.3.1 Methods for DRT supply modeling

First, the focus is on key methodological contributions that enable transportation models and simulations to represent DRT services. An essential aspect is the supply-side implementation: How can a model depict DRT operations (vehicle dispatching and pooling) for a given demand? This representation permits evaluation of economic efficiency and service quality, for example by determining fleet size, mileage, passenger waiting time, and empty-vehicle kilometers. Moreover, different boundary conditions apply to various model types, requiring algorithms and methods to be tailored to either microscopic or macroscopic scales.

Boesch and Ciari (2015) emphasize that agent-based models or microscopic simulations are best suited for modeling automated mobility services, including DRT, by simulating traffic at an individual level, both spatially and temporally. This microscopic focus can also be observed by looking at important contributions in the methodological area, where algorithms were developed for observed trips with high spatio-temporal resolution and for agent-based models. Santi et al. (2014) used GPS tracks of NYC taxi trips in order to develop a matching and pooling algorithm, where they defined rules for pooling and distribution mechanisms. Similarly using an observed trip data set, Agatz et al. (2011) applied a bipartite matching model to match and pool car drivers with possible riders, where they optimized by minimizing system vehicle kilometers traveled, total travel cost and maximizing revenue. Based on this method, Stiglic et al. (2015) included the option to include pre-defined PUDOs, which yields better matching results than strictly door-to-door trips. This ride-sharing framework was applied for a case study in a fictional city, where non-commercial ride-sharing was integrated with public transportation, which leads to even higher matching rates (Stiglic et al., 2018). They did however not consider a commercially operated fleet and relied on given car driver trips. Maciejewski (2016) focused on commercial services by an operator and developed the dynamic transportation service extension of the simulation tool MATsim for the dynamic distribution of DRT fleets, which was applied in Bischoff and Maciejewski (2016) and Maciejewski et al. (2016), among others, for the simulation of autonomous taxi fleets in urban areas. The focus is predominantly on dispatching algorithms of a dedicated commercial vehicle

fleet for given demand, which is an essential feature required for the depiction of DRT as it determines empty relocation trips and pick-up times. The second important feature in DRT modeling is the matching and pooling of trips with similar trajectories. Thus, the MATSim dynamic transportation algorithm was extended in other research contributions, for example by a method from Fagnant and Kockelman (2018), to also cover the rule-based bundling of ride requests. This enables the simulation of a DRT service in the sense of this thesis with a fixed vehicle fleet and its mileage to determine waiting times and detour factors for a set demand in agent-based models. Another example of DRT implementation in agent-based modeling frameworks is demonstrated in Heilig et al. (2018) and Wilkes et al. (2021), where they include the service in their MobiTopp tool. They perform an integrated demand and supply simulation.

Against the background of the use in established models for transportation planning or national models, however, the stronger aggregation of data and thus the use of macroscopic models makes sense. Despite the aforementioned advantages of agent-based models, Boesch and Ciari (2015) also emphasize the use of macroscopic models for large-scale applications in an established phase. Exemplary applications use pre-defined aggregated demand as an input for microscopic simulations to model DRT operations (Agora Verkehrswende, 2023). However, this requires several simulations to achieve stable results, which contradicts the premise of faster and stable computations. As an alternative that does not require microscopic simulations, Friedrich et al. (2018) developed a matching algorithm for macroscopic travel demand models. This algorithm enables the matching of trajectories of trips and simultaneously obtains the aggregated level of macroscopic modeling. This approach was initially developed to model classic ride-sharing by car drivers and was also applied in further research to analyze commercial DRT services in a macroscopic model for the Stuttgart region (Richter et al., 2019). Further research in this area includes the development of a fleet scheduling algorithm, which can be used to simulate the distribution of vehicles to the next point of use and thus also determine the required fleet sizes (Hartleb et al., 2022). In contrast to the agent-based and microscopic applications, the scheduling is performed on a pre-defined set of occupied vehicle trips, thus after matching and pooling of DRT demand.

To summarize, many studies focus on mathematically solving optimization problems related to DRT operations and dispatching strategies. The dominant model types are microscopic simulations and agent-based models, because macroscopic models lack the required spatio-temporal resolution. The method proposed by Friedrich et al. (2018) provides an initial solution for macroscopic applicability, which would expand the scope of practical applications in existing models.

3.3.2 Model applications and DRT demand modeling

The methodological contributions presented in the previous section have in common that they usually operate on a given demand. When applied in case studies using existing urban models to demonstrate applicability (e.g., Maciejewski et al., 2016; Richter et al., 2019; Fagnant & Kockelman, 2018), these scenarios typically replace existing demand, e.g., all car trips, with DRT to assess implications for overall vehicle fleet sizes and traffic conditions. Similar questions have been examined in modeling case studies for rural contexts. In a simulation based on observed public transportation demand data for a low-demand district of Canberra, Mortazavi et al. (2024) replaced local bus lines with DRT to evaluate DRT performance from different policy perspectives. They concluded that DRT can be more cost efficient than traditional public transportation in low-demand areas, with the benefit of much improved travel times. DRT was also more effective with regard to travel times and travel experience. This suggests that DRT might reap more benefits in lower density areas. In another rural simulation, Martí et al. (2024) simulated PUDO-based DRT with a focus on operational aspects. They varied demand, fleet size and vehicle capacities to analyze the impact on service quality, which was highest with larger fleets. Sieber et al. (2020) replaced low usage rail in rural Switzerland with autonomous DRT in a simulation, concluding that such a service has the potential to be more economically feasible with the right configuration. They did however not consider ride-pooling or demand changes.

Simulating the impact of the DRT service on travel demand is however required for DRT planning, as forecasting potential usage is one of the most important needs for information. Demand effects are to be expected that are influenced by the design of the service and the resulting service quality. With the indicator for the potential of ride-sharing in cities, Tachet et al. (2017) provided a transferable method based on characteristics such as population and area. Zwick and Axhausen (2022) estimated a regression model for DRT demand based on spatial characteristics using observed DRT data, however, they found the method more suited for first estimations of spatial demand patterns and potentials. Thus, there is a need for methods to synthetically generate demand as a result of a given service.

For case studies, complete travel demand models have been employed to analyze DRT implementation strategies and their impacts. Consequently, simulating both supply and demand response is essential. The following paragraph presents a selection of significant contributions in this area.

A full simulation of DRT in a city including demand response was performed with an agent-based model for Aachen in Höing et al. (2025). They applied scoring parameters from public transportation for DRT in mode choice and DRT as feeder with door-to-door function as well as replacement of local buses using their stops as PUDOs. While they achieved high modal shares for DRT, they observed a shift from public transportation, walking and cycling, leading to increased motorized road traffic. Applying DRT implementation methods in MATSim, Schlenther et al. (2023) analyze the demand response to service quality depending on the distribution strategy in Berlin. The influence of the size of the distribution zones on waiting times was examined, with increased demand being observed in small zones and low waiting times. In another agent-based modeling example, Huang et al. (2021) combine a nested logit mode choice model for generating trips with a microscopic simulation of vehicle trips of the DRT service for simulating flexible feeder services to rail transport. They show that the modal share of feeder services increases with higher frequency of the associated public transportation system and higher fleet size, but did not consider ride-pooling. The simulation by Wilkes et al. (2021) included a demand model which was integrated with the distribution model, where they applied preference parameters from public transportation to the DRT service. The demand in this case study reacted sensitively to parameters such as fleet size and costs.

Overall, modeling studies are often limited by the unknown specification of utility for DRT in the mode choice model. Thus, they often operate on fixed demand sets. For studies with synthetic demand, public transportation preferences were predominantly used to simulate DRT demand. Again, agent-based simulations are the dominating modeling method.

3.4 Recapitulation and research gap

The literature review shows that DRT and shared mobility services have received increasing attention in recent years. Empirical evidence from surveys and ex-post assessments of implemented services suggests that DRT and shared mobility services are often well received by users. However, many services are designed for specific user groups or travel purposes and therefore lack the scope required to represent a competitive alternative to private car use. At the same time, these studies highlight the relevance of such services for rural and low-density areas from an accessibility perspective. Due to limited demand and high operating costs, many services strongly depend on public funding or are discontinued after the pilot phase.

Modeling studies provide a way to analyze key service parameters and demand responses, which can support the design of scalable services. Early studies often focused on mathematical models for operational questions, such as vehicle rebalancing and trip matching. These approaches were later extended and applied in the context of microscopic simulation and agent-based modeling. However, many studies focus on urban regions and build on existing travel demand models. In addition, most case studies rely on fixed demand assumptions, as user preferences regarding DRT services remain uncertain.

Overall, the literature shows that DRT services have been analyzed from both user-centered and operational perspectives, identifying success factors, user requirements, and operational constraints. Nevertheless, knowledge gaps remain regarding large-scale service design and implementation, because empirical evaluations are often based on small-scale deployments that do not reflect the fleet sizes or operational parameters, such as waiting times, assumed in larger-scale simulation studies. Conversely, larger simulations are frequently conducted without incorporating demand reactions and are often situated in urban contexts.

Table 1 summarizes the relevant literature identified in this chapter, differentiated by study scope, spatial context, investigated aspects of shared mobility, and, for transportation modeling studies, model type and demand generation approach. The scope of the studies includes empirical analyses, the introduction of modeling methods, and model-based case studies.

Table 1: Overview of studies with a focus on shared mobility and DRT

REFERENCE	SCOPE	SPA-TIAL TYPE	SHARED MOBILITY				TRANSPORTATION MODELS				
			Type	Pooling	Service	Focus					
			<i>DRT</i>	<i>Ride-sharing</i>	<i>Ride-hailing</i>	<i>Ride-pooling</i>	<i>Feeder</i>	<i>Door-to-door</i>	<i>Operations</i>	<i>Demand</i>	<i>Model type</i>
AGATZ ET AL. (2011)	x	urban	x		x		x	x		microscopic	fixed
BENSLER ET AL. (2025)	x	urban	x		x	x	x		x	-	-
BISCHOFF AND MACIEJEWSKI (2016)	x	urban	x	x			x	x		agent-based	fixed
BURLANDO ET AL. (2025)	x	urban	x		x		x		x	-	-
DIEBOLD AND GERTZ (2025)	x	urban	x		x		x		x	-	-
ECKHARDT ET AL. (2020)	x	rural	x				x	x	x	-	-
FAGNANT AND KOCKELMAN (2018)	x	urban	x		x		x	x		agent-based	fixed
FRIEDRICH ET AL. (2018)	x	urban	x		x		x	x		macroscopic	fixed
HARTLEB ET AL. (2022)	x	-	x						x	macroscopic	-
HARTZ ET AL. (2024)	x	urban	x		x	x	x	x	x	-	-
HEILIG ET AL. (2018)	x	urban	x		x		x	x	x	agent-based	generated
HÔNG ET AL. (2025)	x	urban	x		x	x	x	x	x	agent-based	generated
HUANG ET AL. (2021)	x	urban	x		x	x		x	x	microscopic	generated
KLINKHARDT ET AL. (2024)	x	all	x		x	x	x		x	-	-
MACIEJEWSKI ET AL. (2016)	x	urban	x	x			x	x		agent-based	fixed

REFERENCE	SCOPE	SPA-TIAL TYPE	SHARED MOBILITY							TRANSPORTATION MODELS	
			Type	Pooling	Service	Focus					
			<i>DRT</i>	<i>Ride-sharing</i>	<i>Ride-hailing</i>	<i>Ride-pooling</i>	<i>Feeder</i>	<i>Door-to-door</i>	<i>Operations</i>	<i>Demand</i>	<i>Model type</i>
MACIEJEWSKI (2016)	x	-	x	x			x	x		agent-based	-
MARTÍ ET AL. (2024)	x	rural	x		x		x	x		microscopic	fixed
MCKEEMAN ET AL. (2025)	x	rural	x		x		x	x	x	-	-
MORTAZAVI ET AL. (2024)	x	urban	x		x	x	x	x		microscopic	fixed
NELSON AND CAULFIELD (2022)	x	rural	x						x	-	-
RICHTER ET AL. (2019)	x	x	urban	x		x	x	x	x	macroscopic	generated
SANTI ET AL. (2014)	x		urban	x		x		x	x	microscopic	fixed
SCHLENTHER ET AL. (2023)		x	urban	x		x		x	x	agent-based	generated
SIEBER ET AL. (2020)		x	rural	x		x		x	x	agent-based	fixed
STIGLIC ET AL. (2015)	x		urban	x		x		x	x	microscopic	fixed
STIGLIC ET AL. (2018)		x	urban	x		x	x	x	x	microscopic	fixed
TACHET ET AL. (2017)	x		urban	x		x		x	x	-	-
TORDAI ET AL. (2025)	x		rural	x		x		x	x	-	-
WILKES ET AL. (2021)		x	urban	x		x		x	x	agent-based	generated
YEN ET AL. (2025)	x		rural	x		x	x	x	x	-	-
ZUNIGA-GARCIA ET AL. (2022)	x		urban	x		x	x	x	x	-	-
ZWICK AND AXHAUSEN (2022)	x		urban	x		x	x	x	x	-	-

Table 1 shows that there is a broad range of literature on DRT, encompassing both empirical and modeling scopes across various spatial contexts. Empirical analyses typically concentrate on the demand side, examining DRT usage as well as user behavior and acceptance. Modeling studies – focusing on methods or case-study applications – primarily address the operational aspects of DRT, and the predominance of agent-based and microscopic simulations is evident. A gap exists in integrating empirical, demand-oriented research with operationally focused modeling studies: few investigations combine DRT simulation with synthetically generated demand that responds to the provided service. Moreover, most modeling studies target urban applications, leaving a gap in analyses of rural impacts and economic implications using synthetically generated demand. This reveals a research gap regarding the design and assessment of sustainable DRT systems in rural areas.

4 Focus of the thesis and research questions

This thesis examines the potential of DRT to support the development of sustainable public transportation systems in rural regions. The focus is on improving accessibility, reducing car dependency, and contributing to the broader transformation of the transportation sector. Building on the findings of the preceding chapters, the following main research question guides the thesis:

MRQ: *How can an area-wide rural DRT system be designed and evaluated as a contribution to sustainable rural mobility, and what demand response can be expected under a high level of service?*

The literature review identified several research gaps concerning the design, scalability, economic feasibility, and demand effects of rural DRT. These gaps are addressed through the following detailed research questions:

DRQ1: *What constitutes a consistent DRT supply in rural areas?*

DRQ2: *What is the demand response to a rural DRT system without the restrictions of real-world pilots?*

DRQ3: *Under which spatial and operational conditions does DRT have advantages over traditional public transportation in providing an alternative to private car use?*

DRQ4: *What are the economic implications of introducing DRT, and how could a consistent system be financially viable in low-demand areas?*

To answer these questions, the thesis develops and applies a macroscopic transportation modeling approach. This approach forms the methodological core of the thesis and must meet four central requirements:

R1: *Representation of DRT operations, including trip matching, pooling, and vehicle dispatching.*

R2: *Simulation of demand responses to DRT service provision.*

R3: *Integration of supply and demand interfaces, including the incorporation of demand responses into operations modeling and the derivation of service attributes for demand modeling.*

R4: *Applicability to low-demand and low-density rural areas.*

5 Short summary and publication status of papers

This thesis contains three journal articles, where methods for depicting DRT in macroscopic travel demand models and applications for rural areas are centered. According to the requirements listed in chapter 4, methods that work for low-density regions within macroscopic travel demand models were developed and applied. The combination of these studies provides a working modeling framework for rural DRT in existing macroscopic models. First, the development of a pooling-algorithm enables the technical implementation of DRT in macroscopic models. Second, the aspect of spatial granularity in macroscopic models and its influence on matching and pooling results for DRT systems is addressed. Third, the developed algorithms are applied in a case study for a rural reference region. All three studies were submitted to or published in a peer-reviewed scientific journal. Based on the results from these studies, the two main research questions MRQ1 and MRQ2 will be answered.

The studies will be presented in the following chapters, with the structure as follows:

I. From Aggregate Requests to Shared Rides: A Method for Quantifying Vehicle Trips and Occupancies for Demand Responsive Transport in Macroscopic Transport Models

This study addresses the question of how to integrate shared-mobility services, specifically ride-pooling, into large-scale, macroscopic travel demand models that are typically limited by their temporal granularity and aggregated demand. By developing a fast and reliable disaggregation method that pools matching trip trajectories directly from aggregated demand, we demonstrate that it is possible to obtain reproducible, validated results without resorting to computationally intensive microsimulation. The new approach not only enables the realistic modeling of DRT with ride-pooling across larger regions, but also does so within a computational budget compatible with contemporary state-of-the-practice travel demand modeling tools, thereby opening a practical pathway for evaluating shared-mobility impacts in regional and national transportation scenarios. Thus, this article provides a methodological base to fulfill requirements R1, R3 and R4.

Submitted to IEEE Transactions on Intelligent Transportation Systems on 12th June 2026. Currently under Review

II. Implementing a Ride-sharing Algorithm in the German National Transport Model (DEMO)

This study tackles the broader research question of how to extend DRT modeling to travel demand frameworks that rely on large traffic analysis zones (TAZ), where coarse spatial granularity, particularly in rural areas, is limiting the fidelity of shared mobility analyses. The authors present a novel algorithm that uses population center points as synthetic pick-up locations to spatially disaggregate aggregated OD demand and to represent inner-cell traffic flows, thereby preserving fine-grained travel patterns without redefining the existing TAZ structure. The method is tested and validated by reproducing the results of a detailed regional model within a corresponding national-scale model, demonstrating consistent outputs across differing spatial resolutions. Consequently, the approach enables reliable computation of DRT services for models of any spatial granularity and can be embedded directly into current travel demand models without any need for extensive model restructuring. This addresses the transferability of the methods provided in I, and fulfills requirements R3 and R4.

Published in Transportation Research Records:

Thomsen, N (2023): Implementing a Ride-sharing Algorithm in the German National Transport Model (DEMO). Transportation Research Record: Journal of the Transportation Research Board, 2677(5). SAGE Publications. doi: 10.1177/03611981221127015. ISSN 0361-1981.

III. Reimagining rural transit: Model-based insights into demand-responsive transportation

This study applies the methods developed in the first two articles to answer the wider research question of whether DRT can realistically complement public-transportation provision in sparsely populated areas. Using a representative rural region in Germany as a case study, we combine the fast aggregated ride-pooling algorithm and the spatial disaggregation technique with additional operational models for fleet sizing, dispatching, pooling and detour-factor estimation as well as a fully synthetic demand calculation. The DRT demand is determined by relying on the similarities to public transportation, and thus, applying public transportation preference parameters. The analysis assumes that DRT is offered for every trip but is limited by two service constraints, maximum waiting time and a cost-per-kilometer ceiling, while the detour factor is derived endogenously from the simulated operations. Results demonstrate that, when DRT is integrated into the public transportation supply mix, overall ridership increases and DRT becomes a viable alternative to private car travel, highlighting its potential as a complementary mobility solution for rural communities. This article constitutes the core of the thesis, as it answers the research questions DRQ1, DRQ2, DRQ3 and DRQ4, as well as presenting a solution to requirement R2.

Published in Transportation:

Thomsen, N and Liedtke, G (2026): Reimagining rural transit: model-based insights into demand-responsive transportation. Transportation. Springer. doi: 10.1007/s11116-026-10746-6. ISSN 0049-4488.

6 From Aggregate Requests to Shared Rides: A Method for Quantifying Vehicle Trips and Occupancies for Demand Responsive Transport in Macroscopic Transport Models

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Abstract

Emerging mobility-on-demand services, such as demand responsive transport (DRT) with ride-sharing, are promoted to increase accessibility and to complement conventional public-transport networks. Planning and performance assessment of these services typically rely on agent-based, microscopic simulations that provide detailed outputs, such as pooling factors, occupancy rates, vehicle trips, or fleet sizes. While macroscopic models enable region-wide evaluations with substantially lower computational effort, their reliance on aggregated spatio-temporal demand and the absence of discrete request information hinder a realistic representation of pooling mechanisms.

This paper introduces a pooling algorithm capable of operating on aggregated demand while still generating concrete vehicle-trip counts. The method embeds a model using a simplified probability distribution to derive a discrete representation of individual trip requests from the aggregate demand matrix. These probabilities drive the formation of shared rides and the computation of resulting vehicle trips, fleet size, and occupancy.

An illustrative case study demonstrates the integration of the algorithm into a macroscopic transport model and quantifies the impacts of DRT and ride-pooling fleets on vehicle-kilometers traveled, load factors, and fleet requirements. Results show that the proposed approach bridges the gap between detailed microsimulations and efficient macroscopic evaluations, offering a pragmatic tool for strategic planning and policy analysis of future DRT systems.

Keywords: demand-responsive transport, ride-pooling, macroscopic modelling, pooling algorithm

6.1 Introduction

6.1.1 Background

Demand responsive transport (DRT) as a taxi-like service with small buses or regular cars is an emerging mode that gains in importance with the ongoing digitalization of transport services and vehicle automation. Rather than following a pre-defined schedule and route like conventional public transportation, the travelers themselves define the start and end point, as well as departure time for their ride. The implementation of DRT is accompanied by expectations of improving the mobility of the general population while at the same time reducing the demand for private car trips. To achieve an overall net reduction in road traffic, it is necessary to pool DRT trips with similar directions and departure times into shared vehicles, which also increases the overall system efficiency. One of the main challenges in designing an efficient and attractive DRT service is finding the optimal system parameters. These include, among others, the number of DRT vehicles required to service a given region, but also the pooling strategies. These system parameters directly influence the user experience in terms of waiting times and detours, but also the overall efficiency and the total vehicle kilometers travelled (VKT).

The potential benefits of DRT and its best implementation strategies can be identified via simulation using transport models. Such simulations can reveal the relevant level of service indicators, operational indicators and the overall impact on road traffic. To do so, it is necessary to calculate the required vehicle trips and their respective occupancy from a given demand in the form of passenger trips.

While matching algorithms are relatively straightforward to implement in agent-based transport simulations with discrete demand and a high spatial and temporal resolution, such models might not be available for every region where a DRT service is being considered. In particular, low density rural areas – where DRT with ride-sharing can complement traditional line-based public transport in places where such mass transport services are not economically feasible – are often represented only as part of larger regional or national models. These models are more often than not macroscopic with a higher level of aggregation, which in turn poses particular challenges to the simulation of DRT and ride-sharing. Therefore, methods and algorithms for matching and pooling trips need to be developed for various transport models, including macroscopic ones.

6.1.2 Previous work on implementing ridesharing in transport models

The starting point for the simulation of DRT are the algorithms that match or pool individual trips. Early work used recorded trip data: For example, Agatz et al. (2011) applied a bipartite-matching model to an Atlanta dataset to maximize matches and optimize system VKT. Santi et al. (2014) built a shareability network from New York taxi GPS traces to match trips or optimize travel time. Tachet et al. (2017) extended this approach to other cities, creating a shareability index of taxi trips based on attributes like trip volume and area. These studies demonstrate the mechanics of trip matching, but converting them to transport-model implementations requires adapting the algorithms to each model's structure and data format.

Modeling methods for ride-sharing have often been developed in the context of vehicle automation, especially shared autonomous vehicles (SAV). Soteropoulos et al. (2019) summarize several studies that assess SAV-based ride-sharing, usually focusing on private-car replacement and VKT impacts via microscopic simulations or agent-based demand models. This is consistent with the findings of Boesch and Ciari (2015), who determine agent-based models as most suitable for the depiction of SAV fleets due to the spatiotemporal level of detail, while also noting that macroscopic models become valuable once the technology is mature – highlighting a need for aggregated-scale ride-sharing methods.

Following the assumption that agent-based models are most appropriate, much effort has gone into extending the modeling software MATSim (Horni et al., 2016) for ride-sharing. The core requirement

of such an extension is dynamic spatial-temporal matching, together with fleet-management (vehicle distribution and relocation). Early extensions (Maciejewski, 2016) addressed vehicle distribution for given fleet sizes and demand with dynamic routing, enabling DRT-only scenarios in Berlin and Barcelona (Bischoff & Maciejewski, 2016; Maciejewski et al., 2016). However, ride-sharing was not yet considered. This was made possible with the dynamic ride-sharing (DRS) extension (Fagnant & Kockelman, 2018), which adds passenger-trip matching: every five minutes the nearest request is linked to an empty or occupied vehicle in the network via Dijkstra shortest-path searches, respecting pre-set detour-time limits. This yields indicators such as waiting time, occupancy rates, and VKT, and has been employed in studies by Schlenther et al. (2023) and Sieber et al. (2020).

Besides MATSim, other agent-based modeling and microscopic simulation software also support ride-sharing. The tool *mobiTopp* (Mallig et al., 2013) was applied to match trips with identical origins and destinations in the form of traffic analysis zones (TAZ) in 15-minute windows, but ignored en-route pick-ups in Heilig et al. (2018). Wilkes et al. (2021) therefore added an online matching and relocation algorithm integrated into the mode-choice step, allowing idle and occupied vehicles to serve requests within detour and waiting-time thresholds. This algorithm is able to work with a fixed fleet size and determine detours and waiting times. With POLARIS (Auld et al., 2016), another agent-based model is applied for ride-sharing by Gurumurthy and Kockelman (2022). They use Euclidean trajectories between TAZs for trip matching, where the angle between the trajectories of the vehicle and passenger trip as well as detour time constraints determine if a match is successful.

Far fewer authors have considered the implementation of ride-sharing in macroscopic models, even though such models are wide-spread and appeal with reduced computing times and data requirements for larger study areas. Their main drawback in simulating ride-sharing is the low level of spatial and temporal detail, which prevents the straight-forward implementation of trip matching and pooling. In particular, travel demand is represented by origin-destination trip matrices (OD matrices) that include the average demand for a longer time period (e.g. an hour or even a day), and the spatial resolution depends on the size of the model's TAZ.

A solution to the spatial and temporal matching of trips within a macroscopic model was proposed by Friedrich et al. (2018). Their algorithm was developed for conventional ride-sharing, where car drivers offer their remaining seats to other passengers. First, they divide the daily demand matrices into shorter time intervals (e.g. 15 minutes) and assume that all trips within the same time interval can be temporally matched. Then, they determine trip trajectories in the form of crossed TAZ based on shortest network paths. A match between two trips occurs if the origin and destination of a passenger are both within the list of the crossed TAZ of a driver. Friedrich et al. (2018) also suggest that commercial ride-sharing by a service provider could be implemented in the model by adapting the algorithm to match the passenger trips with other passenger trips. Furthermore, Hartleb et al. (2022) propose a scheduling algorithm with which the required fleet sizes and the necessary relocation trips can be determined for a commercial service on the basis of pooled passenger trips from a macroscopic model.

6.1.3 Research gap and objectives

As shown above, research has mainly focused on the implementation of ride-sharing in agent-based models so far. In the context of matching and pooling trips in macroscopic transport models, three issues arise regarding the implementation: There are no exact departure times, no exact start and end locations and non-integer demand. While the methodology proposed by Friedrich et al. (2018) addresses the first two by considering time bins and spatial matching using zone-based network paths, it relies on pre-defined vehicle trips stemming from the car drivers in the conventional ride-sharing scenario.

When considering a commercial DRT or ride-sharing scenario, there are only car passengers and no pre-defined vehicle trips. Thus, the first (pooled) passenger would yield one vehicle trip and additional passengers can share this same vehicle up until its capacity is reached. However, since a macroscopic

travel demand model works with aggregated data, non-integer demand and even demand between zero and one is possible. Pooling non-integer and sub-unit demand and dividing it by the vehicle (seat) capacity to obtain the required number of vehicle trips is not as straightforward as with discrete and integer demand and can possibly over- or underestimate the vehicle trips.

This paper presents an approach that enables trip matching and pooling based on (non-integer) demand from an OD matrix of passengers by disaggregating said demand with a simplified probability distribution. This enables macroscopic travel demand models to derive vehicle trips and pooling rates. In the following section, the suggested disaggregation methodology is described. Then, the method is validated by comparing it to a simulation approach and then applied to a test region to demonstrate its functionality for macroscopic travel demand models, and compare the results to indicators from other modelling studies.

6.2 Methodology

In this section, we present a new methodology for pooling trips on matching paths for non-integer demand. The method disaggregates macroscopic demand by applying probability distributions and creating a discrete environment for the matching process. To keep the process streamlined, reduce resource requirements, and generate reproducible results, a simple transformation to discrete values at the level of pooling passengers with matching trajectories is proposed. Subsequently, the bundled passenger flows and vehicle trips can be re-aggregated for further processing in the macroscopic model.

6.2.1 Overview

Trips can be spatially matched by comparing their trajectories (e.g., their network paths, as suggested by Friedrich et al., 2018). The proposed matching algorithm can be applied independently of the spatial-matching technique. In the following, the trips' trajectories are referred to as paths.

A ride-sharing algorithm incorporating the new disaggregation method is described in Figure 3. It is recommended to perform matching and pooling of trips as an iterative process in order to identify all possible matches: The outer loop iterates over all trips and their respective paths (matching object P), while the inner loop iterates over all matching paths M for the current path. Pooling of passengers is then carried out on this level for pairs of matching paths.

Input: Matching object P with a list of all paths, their demand, their origins and destinations and their trajectories

Output: Vehicle trips and pooled demand per path

Initialization: A priori demand conversion and sorting for Matching object P with given data.

```
# Process all paths in the matching object P in the pre-defined order
For  $path \in P$  do
    Search  $P$  to find matching paths  $M$ 
    For  $match \in M$  do
        Create discrete pooling environment and calculate the matching
        between  $path$  and  $match$ .
        Update the demand of  $path$  and  $match$  by aggregating the discrete
        matching result.
Return  $P$  with updated demand after matching
```

Figure 3: Overview of the disaggregation method within a ride-pooling algorithm

Demand disaggregation occurs whenever two matching relations are identified. In the following methodological description, one matching relation – the longer one – is referred to as supplier (the

vehicle trip that starts and ends at its origin and destination), and the other one is referred to as demander, as it can be completely supplemented by the supplier route. This terminology facilitates differentiation between the paths during the pooling process. Table 2 presents the definitions of the terms used in the method description and their abbreviations.

Table 2: Glossary and abbreviations

Glossary

<i>Path</i>	Spatial reference object for matching
<i>Match</i>	Path that spatially matches another path
<i>Supplier</i>	Path in the matching process that can replace a matching path
<i>Demander</i>	Path in the matching process that can be replaced by a matching path
<i>Discrete demand cases</i>	Cases that can occur when transforming the OD demand into discrete demand
<i>Discrete demand combinations</i>	Combination of discrete demand cases for supplier and demander paths in the matching process

Abbreviations

P	List of all available paths (matching object)
M	List of all spatially matching paths (matches) for a selected path
$P(v)$	Probability of at least one vehicle trip on a path
$P(v_{i, new})$	Updated probability of vehicle trips on path i
$P(v_{i, final})$	Remaining probability of vehicle trips on path i after matching
x	Mean demand on a path
$x_{i, new}$	Updated mean demand on path i
$x_{i, final}$	Bundled mean demand on path i after matching
$comb_i$	Subset of discrete demand combinations where a vehicle trip is needed on path i
$P(comb_i)$	Discrete demand combination's probability of occurrence
$x'_{comb, i}$	Cumulated discrete demand of a discrete demand combination
$trips_i$	Vehicle trips on path i
$capacity$	Vehicle capacity

6.2.2 Preparation and conversion of demand

Initially, the foundation for the later disaggregation is established by converting the OD-demand into a priori probabilities and mean demand. In preparation for that, the OD-demand is allocated to the paths used as spatial reference objects, thereby assigning each path a specific initial demand that serves as the primary input value to the algorithm.

In the second step, two values are derived from the initial demand on each path:

- a) *A priori probability of at least one vehicle trip*: What is the probability that a vehicle trip is needed to satisfy demand on a certain path in a given time interval?
- b) *A priori mean demand*: What is the demand in case at least one vehicle trip is needed?

These values define the minimum number of vehicles required to fulfil the demand on each path in the absence of matching, when trips are pooled on the same path. The matching algorithm then seeks paths whose demand can be combined within the same vehicle while respecting this minimum-trip requirement. To obtain the a priori values, the given demand is interpreted as the probability that at least one passenger requires a vehicle trip. If the demand is higher than one, there is more than one person

with a ride request. Accordingly, the probability of a vehicle trip is calculated as the minimum of the demand and one, $\min(demand_{path}, 1)$. The mean demand in case of a vehicle trip then is defined as the maximum between the demand and one, $\max(demand_{path}, 1)$, reflecting the assumption that at least one passenger is on board if a vehicle trip is realized. Consequently, the a priori values for each path are the initial demand and one. These values constitute the basis for constructing a discrete environment for the passenger and vehicle disaggregation per path.

6.2.3 Matching paths and pooling demand in a discrete environment

After the initial preparation is completed and the a priori values for probability and mean demand are derived, the network path trajectories can be spatially matched. When a match is found, the demand is disaggregated and pooled for exactly one demander and one supplier. Generally, the supplier corresponds to the longer path, whose vehicle trips can replace those of the shorter demander path.

Theory

The disaggregation steps are executed each time two path trajectories are matched. Since paths may be matched multiple times, the a priori probabilities and mean demand are continuously updated within an iterative process. Although at least one of the a priori values is initially integer-valued, they may become non-integer after matching and pooling. Consequently, during the iteration, both the mean demand and the probability of a vehicle trip for a given path can assume non-integer values.

Thus, a total of three discrete demand cases can be derived for each path:

- 1) C: A vehicle trip is needed for the ceiling value of the mean demand.
- 2) F: A vehicle trip is needed for the floor value of the mean demand.
- 3) N: There is no demand, and no vehicle trip is needed.

Figure 4 illustrates the cases and also contains the formulas to calculate their probabilities.

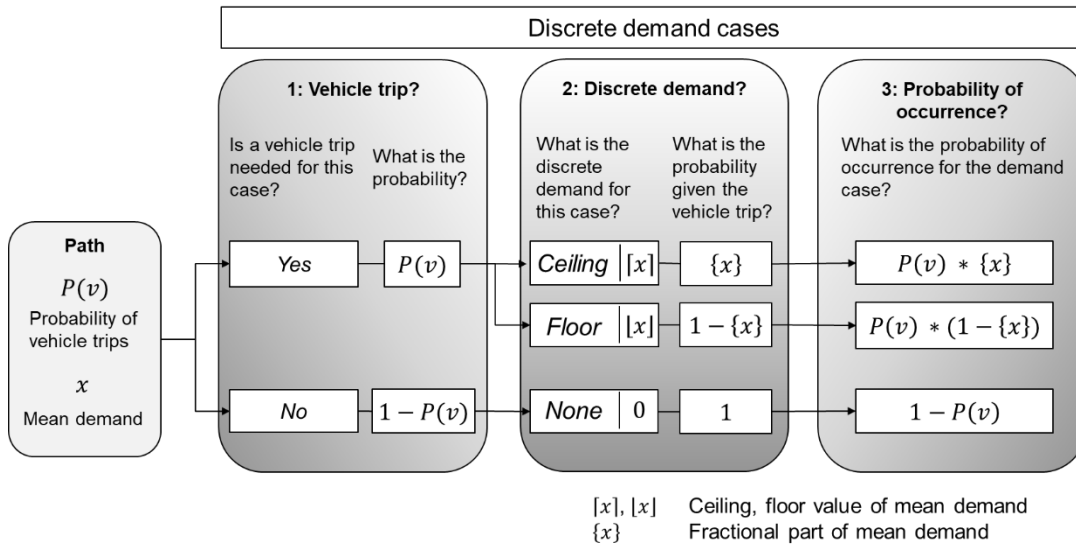


Figure 4: Discrete demand cases of a path given the (a priori) probability of vehicle trips and mean demand

Based on these cases, up to nine pooling combinations with discrete demand can be derived, as shown in the tree diagram in Figure 5. A combination may induce

- a) no vehicle trip at all,
- b) a vehicle trip on the supplier path (red) and
- c) an additional vehicle trip on the demander path (blue), which is only needed if there is either no demand for the supplier or the total discrete demand of a combination (x'_{comb}) exceeds the seat capacity of the supplier vehicle.

The possible subsets of combinations are highlighted in Figure 5. To summarize this step, the (a priori) probabilities and mean demand of matching paths are disaggregated into a set of possible pooling combinations with discrete demand x'_{comb} . Each combination is assigned a probability of occurrence $P(comb)$, defined as the conditional probability of a case on the demander path given a case on the supplier path.

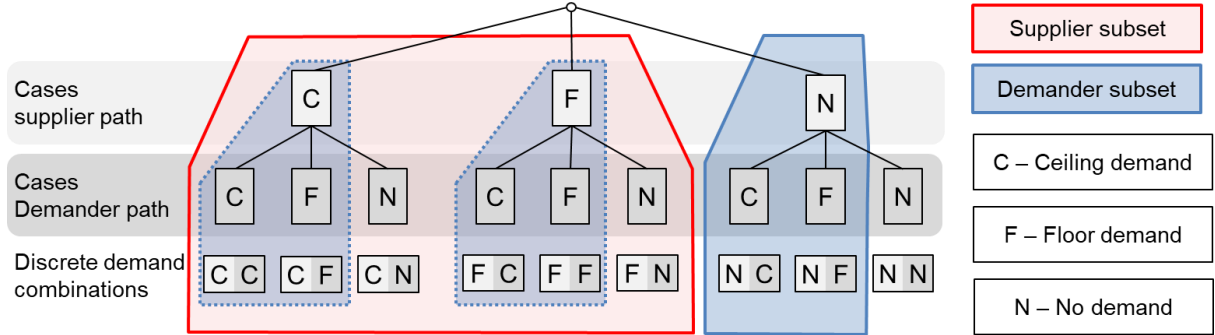


Figure 5: Discrete demand combinations and resulting subsets for vehicle trips

The updated values for probability and mean demand are calculated in the next step using equations (1) and (2). The updated probability of a vehicle trip on a path is the sum of the respective subset's probabilities of occurrence. This equals the initial (a priori) value for the supplier, because demand cases on matched paths do not affect its need for a vehicle trip. This is not the case for the demander, since part of the demand can be served with a vehicle trip on the supplier's path. Thus, the new probability of vehicle trips for the demander represents the residual need for a vehicle trip on this path. The updated mean demand is obtained by computing the probability-weighted mean of the discrete demand values for the combinations. The algorithm does not distinguish vehicle occupancy by legs of the route.

$$P(v_{i,new}) = \sum P(comb_i) \quad (1)$$

$$x_{i,new} = \sum \frac{P(comb_i)}{\sum P(comb_i)} * x'_{comb,i} \quad (2)$$

with

$comb_i$ subset of combinations where a vehicle trip is needed on path i

$P(v_{i,new})$ updated probability of vehicle trips on path i

$P(comb_i)$ combination's probability of occurrence

$x_{i,new}$ updated mean demand on path i (replaces a priori mean demand)

$x'_{comb,i}$ combination's discrete demand (on path i)

Example

The previously described disaggregation process during the passenger pooling is best illustrated by a simple example. In this example, the initial demand on one path (supplier) is 0.5, whereas the demand on the matching demander is 1.3. Following the preparation steps, the a priori probabilities and mean demand are presented in Table 3.

Table 3: Convert initial demand to a priori probabilities and mean demand for an example case

Path	Demand	A priori probabilities of at least one vehicle trip $P(v)$	A priori mean demand x
Supplier	0.5	$\min(0.5, 1) = 0.5$	$\max(0.5, 1) = 1$
Demander	1.3	$\min(1.3, 1) = 1$	$\max(1.5, 1) = 1.3$

Building on the a priori values, demand is disaggregated by rounding the mean demand to create discrete demand. The resulting fractions indicate the probabilities of the ceiling and floor demand levels. In the supplier case of this example, the mean demand is already discrete. However, regarding vehicle-trip probability, there is a 50 % chance of zero demand. For the demander, there is a 30 % chance that two passengers request a vehicle trip and a 70 % chance that one passenger requests a trip. Thus, both paths in this example comprise two discrete demand cases. The discrete demand and the corresponding probabilities of occurrence are used to create discrete demand combinations, as shown in Figure 6. These discrete demand combinations allow exact determination of the required vehicle trips per combination and their occupancies.

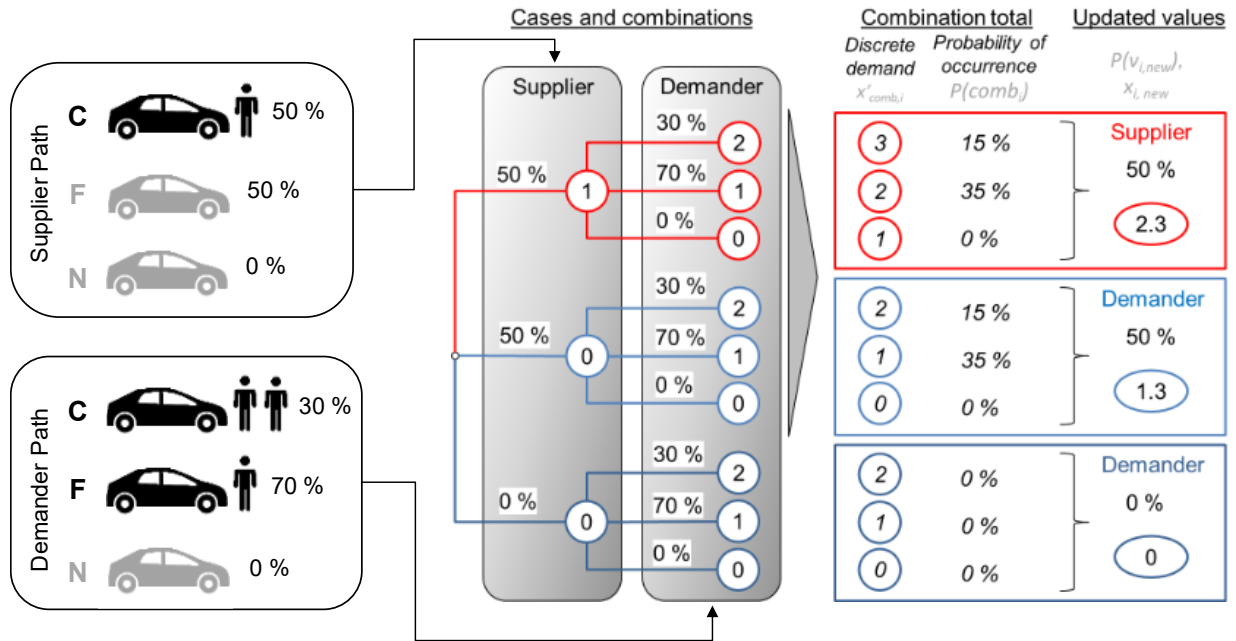


Figure 6: Discrete pooling environment for an example

In this example, the supplier cannot fully satisfy the demand of the demander, because there is a 50 % probability that no vehicle trip occurs on the supplier side while demand exists on the demander side. Consequently, the search for additional matching suppliers continues. The resulting demand combinations are then aggregated to update the a priori values for mean demand and trip probability, thereby constituting the matching outcome. For this purpose, the discrete demand combinations are partitioned into subsets that contain all combinations featuring a vehicle trip on either path. Figure 6 shows the combinations with a vehicle trip on the supplier path in red and those with a vehicle trip on the demander path in blue.

The probabilities of occurrence $P(comb_j)$ are summarized, and a weighted mean demand $x_{i,new}$ is calculated for each subset to replace the a priori path values. The results indicate that the vehicle on the supplier path does not operate at full capacity, and the demander path retains unsatisfied demand after this match. Consequently, this matching result is used in subsequent iterations.

6.2.4 Calculate vehicle trips and generate outputs

The results of the matching iteration are network paths with bundled passenger flows that contain the remaining probability of vehicle trips and the bundled mean demand per path. These values serve as inputs for calculating aggregated vehicle trips for these flows. The calculation begins after the matching process is completed, using the final values in equation (3). In the case of a vehicle trip, the number of required vehicles is determined using the bundled mean demand and the vehicle's seat capacity, yielding an integer value (e.g., a mean demand of 7.5 with a 6-seat capacity requires exactly two vehicles). Combined with the remaining probability of vehicle trips, the aggregated vehicle trips are obtained (e.g., a 30 % probability of two vehicles on a path results in an expected 0.6 vehicle trips). Transforming the paths' vehicle trips into an OD-matrix allows their inclusion in the model's network assignment.

$$trips_i = P(v_{i,final}) * \left\lceil \frac{x_{i,final}}{capacity} \right\rceil \quad (3)$$

with

$trips_i$ vehicle trips on path i

$P(v_{i,final})$ remaining probability of vehicle trips on path i

$x_{i,final}$ bundled mean demand on path i

$capacity$ vehicle capacity

$\lceil \cdot \rceil$ ceiling value

6.2.5 Result validation

The proposed algorithm assumes a simple probability distribution that only uses either the ceiling or floor value of the initial demand. This simplification masks a more complex issue which resides at the core of (macroscopic) travel demand models. The results of such models, for instance passenger trips between an OD pair, are always provided in terms of probabilities and expected values from the aggregation of probabilities at an individual choice level. There is a wide variety of probability distribution functions that can result in the same mean or expected value.

For example, using our algorithm we discretize the demander's mean demand of 1.3 trips into a demand of 1 with a probability of 70 percent and a demand of 2 with a probability of 30 percent. However, the same mean demand could also be discretized using e.g. a Poisson distribution with $\lambda = 1.3$ leading to the following (different) probabilities for 0, 1, 2 or more trips (Figure 7).

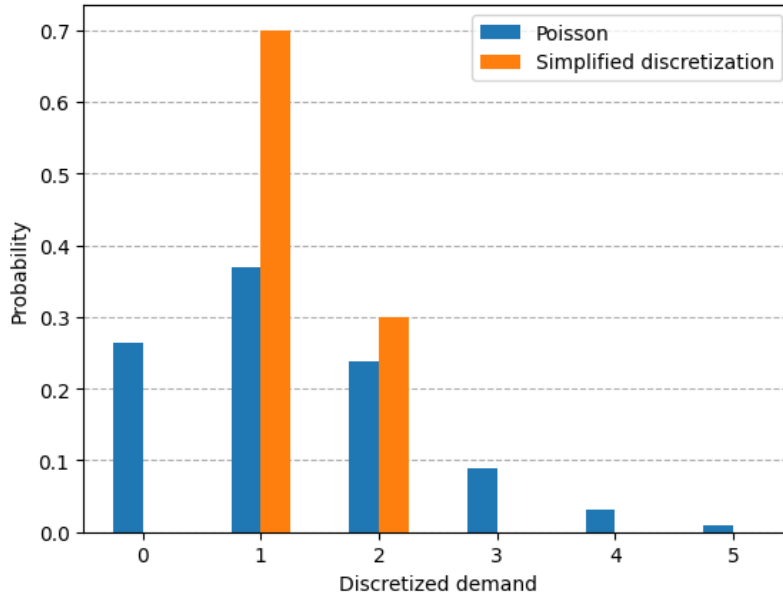


Figure 7: Comparison of simplified discretization with Poisson distribution with $\lambda=1.3$

Thus, in our simplified approach cases with much higher or lower demand are disregarded, which could affect the end result. In order to validate the algorithm's results and identify potential weaknesses, a simple experiment comparing the proposed method to a microsimulation using a Poisson distribution is performed. The main questions this answer are as follows:

- How does the proposed method perform compared to other disaggregation methods?
- With two paths matched per iteration, how does the sorting impact the results?

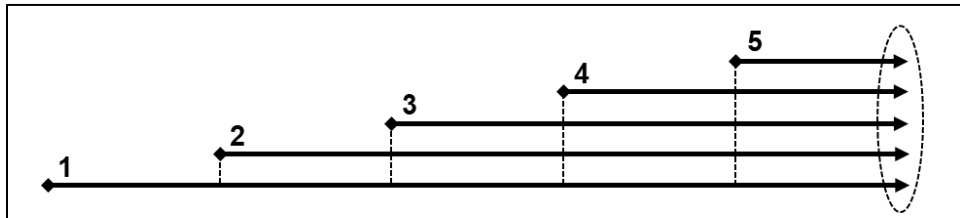


Figure 8: Path set for validity tests

For the tests, we assume a set of five matching paths with randomly generated demand. It is assumed that the first path is the longest, with each following path being shorter. All shorter paths match with the next longer path (Figure 8). For the randomly generated demand, both the proposed algorithm as well as a Monte Carlo simulation are performed. The Monte Carlo simulation consists of 1,000 runs with the following steps:

1. Draw an integer number of passengers for each path, based on their demand and using a Poisson distribution.
2. Iterate over all paths.
3. Iterate over all matching paths for the current path if the number of passengers is larger than zero.
4. Place as many passengers from the matching path in the vehicle on the current path as vehicle capacity allows.
5. Update the number of remaining passengers on the matching path.
6. After the iteration from step 2 has finished, calculate vehicle trips based on the matched demand.

After all runs are finished, the mean value for matched demand and vehicle trips is calculated to generate the final result. This result is compared to the result from the proposed method. Overall, this test is repeated 1,000 times with new random demand to compare the resulting vehicle trips between the two methods. The path order is defined by demand in ascending order, so that low-demand trips get pooled (and replaced) first. Thus, it is more likely that paths with high demand will yield a vehicle trip without detours.

Comparing the results of the validity test, there is a small difference in cumulated vehicle trips between both approaches. In general, the proposed method generates more vehicle trips (as shown in Figure 9). However, there is no apparent pattern that suggests that there is a systematic deviation. Overall, the results of both approaches are more similar for higher demand.

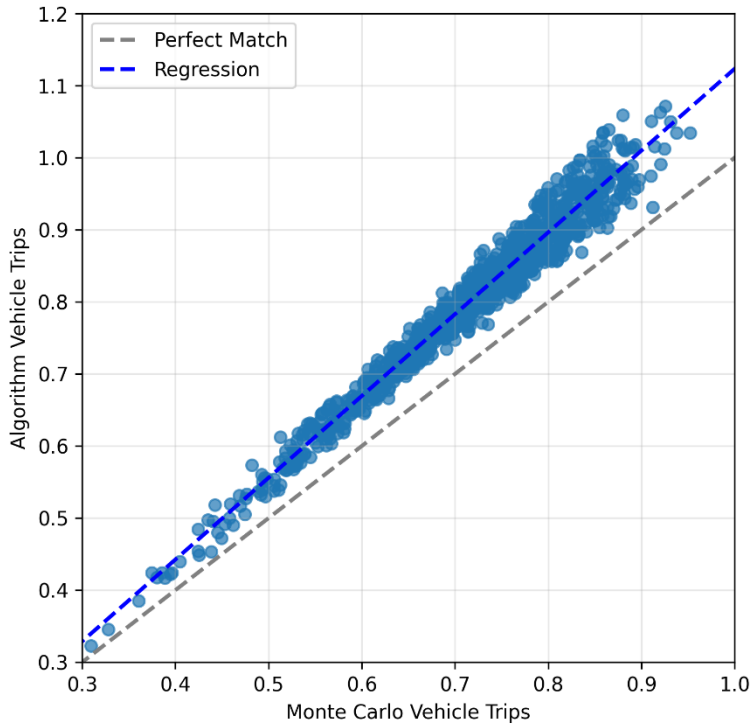


Figure 9: Vehicle trip results for proposed algorithm against Monte Carlo simulation

Considering performance, there is a large difference in computing times between the tested methods. Calculating results with the Monte Carlo simulation was on average 30 times longer than the proposed method. Similar runtimes could only be achieved by reducing the number of runs in the simulation to 30, where the fluctuation in the final result is quite high and reproducible results cannot be reached.

All in all, the differences in results are very small, with a major advantage of the proposed method when it comes to computation times. This suggests that the presented simplified approach is able to sufficiently reproduce simulation results with less computational effort, making it especially suitable for large-scale applications.

6.3 Application example

To demonstrate the applicability of the proposed algorithm for transport modeling, it is applied to a regional macroscopic travel demand model. This exemplary application shows the impact of trip density as well as the impact of the picked time intervals in a realistic setting, producing results that are comparable to other modeling studies.

6.3.1 Model region and assumptions

The developed method was tested with the macroscopic travel demand model of the city of Weimar in Thuringia, Germany in combination with the matching algorithm in Friedrich et al. (2018). The model is implemented in the software PTV Visum (2022). Approximately 70,000 inhabitants from the city area and its surroundings are represented, generating around 230,000 trips per day. The model is a 4-step-model with an activity chain approach and consists of 168 TAZ. It is well-suited for testing and implementing new approaches with its low computing times. The smaller scale of the model also allows for in-depth analyses of the mechanisms of the ride-sharing algorithm. An overview of the model region, traffic loads and modal split are given in Figure 10. The picture is typical for a medium-sized German city, with most road-based traffic on the primary road network. The network model includes the federal motorway BAB A4 (in the bottom of Figure 10), where the traffic loads are the highest, as well as external transit movements.

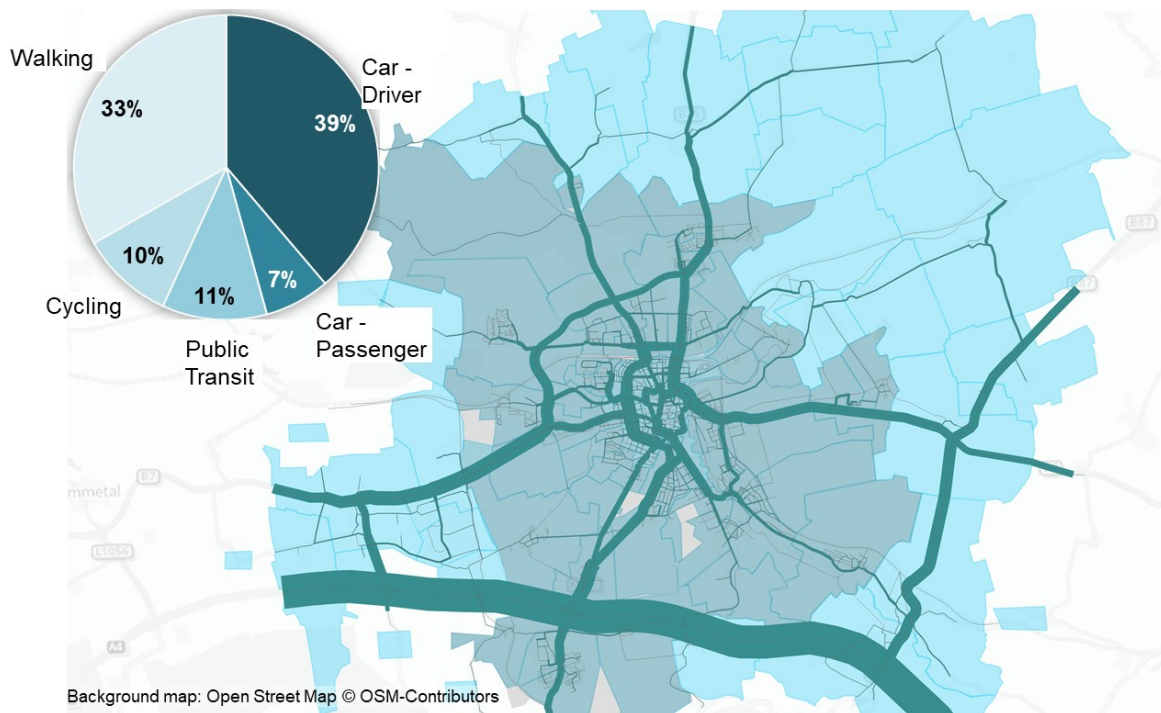


Figure 10: Model region with traffic loads and modal split

For the implementation, the following assumptions were made:

- The demand for ride-sharing is fixed.
- The entire demand is served, i.e. there are no trips left unserved and there is no unsatisfied demand. Paths without a match will yield vehicle trips.
- The vehicle seat capacity is 6.
- The matching of trajectories is based on the TAZ that the network paths cross. Passengers can board at all links that are accessible by foot (no motorways and non-urban roads); each of these links is assigned to the TAZ they are within and those within a 100 m buffer to allow for detours.

- An iteration over paths is performed to find matching paths, starting with the longest. As suggested in Richter et al. (2019), this ensures that the paths with the longest common route match first.

Empty trips from relocation and fleet size were determined based on the occupied vehicle trips from the algorithm using the vehicle scheduling algorithm described in Hartleb et al. (2022). From the scheduling results, vehicle mileage and operation hours can be derived.

6.3.2 Impact of demand magnitude

In the first part, the algorithm is applied for three different demand scenarios:

1. All car passengers switch to ride-sharing (7 % modal share)
2. All public transport users switch to ride-sharing (11 % modal share)
3. All car drivers and passengers switch to ride-sharing (47 % modal share)

The daily demand for ride-sharing in these scenarios is disaggregated into time intervals of 10 min. The size of the required vehicle fleet, vehicles per inhabitant and vehicle operation hours resulting from the new approach are summarized in Table 4. The mean occupancy per day was calculated as the quotient of total person trip mileage and vehicle mileage in order to include empty trips.

Table 4: Comparison of model results for Weimar

Modal share	Demand (number of trips)	Fleet per 1000 inhabitants	km per vehicle per day	vehicle operation hours per day	Mean occupancy per day	Served person trips per vehicle per day
7 %	~ 16,100	3.8	268.98	6.97	1.12	58.1
11 %	~ 25,300	5.22	260.85	6.77	1.35	66.6
46 %	~ 104,300	12.43	297.94	7.39	2.03	115.1

In general, the results indicate that the algorithm and disaggregation method produce plausible results. The fleet size increases with a higher modal share, as more trips have to be served. In addition to that, the mean occupancy per day also increases with the demand. This shows that with higher demand, the probability to find a matching path in the same timeframe is higher, which is a logical conclusion. Furthermore, higher occupancy rates and less relocation with higher demand results in a higher usage rate per vehicle, which is reflected by the number of served trips per day. Finally, the daily mileage per vehicle and the operation hours are within a reasonable range with the mean speed of approximately 40 km/h. Stops and waiting times for picking up passengers are not included in the operation hours.

6.3.3 Impact of temporal resolution

To assess the impact of the temporal resolution on the algorithm's results, different time intervals for matching were tested for ride-sharing with public transit demand (11% of all trips). Table 5 shows the relative changes in fleet size in reference to the results for the 10-minute time interval. It is visible that the time interval selected for the pooling of passengers influences the resulting fleet, with a 20 % decrease for the 5-minute interval to more than double the fleet size with 30 minutes. While the number of vehicle trips per time interval could be reduced with larger intervals due to higher pooling factors with higher demand, more relocation trips per hour are possible with smaller intervals in the applied scheduling algorithm, leading to a smaller fleet. For instance, one vehicle can pick up three different requests in 15 minutes when a 5-minute interval is used, while it is only possible to perform one trip if the interval is 15 minutes. This is due to the algorithm matching and pooling all trips within the same interval, independent from the actual trip length and time of departure within the interval.

Table 5: Relative changes in fleet size for public transit demand depending on temporal resolution

Time interval	Change in fleet size to 10 min interval
5	0.81
15	1.19
20	1.46
30	2.17

It follows that the temporal resolution for the algorithm has to be picked carefully to generate realistic results. Ideally, the interval could be selected based on the mean trip duration for the demand. Furthermore, the time interval for matching, pooling and vehicle relocation indicates expected waiting times, which can influence the demand in a demand model. With an average trip duration of 8 min in the Weimar model, the applied 10-minute interval seems reasonable.

6.3.4 Comparison to other modelling studies

Key values from the Weimar model can be compared to other study results for further classification of the algorithm results. Fagnant et al. (2016) for example determined a fleet size of 2,118 vehicles serving 26.6 person trips per vehicle per day (1.2 % modal share) in a simulation of central Austin, Texas. Maciejewski et al. (2016) used a fleet of approximately 0.5 vehicles per 1,000 inhabitants to serve 28,000 trips in a model of Berlin (16.6 served trips per vehicle). The fleet density is lower than in the Weimar model, which can be expected with lower modal shares. Furthermore, the usage rates in these studies are lower than in the Weimar model. That does not necessarily discredit either result, as the base conditions are rather different. The regions of Austin or Berlin are much larger than Weimar, where the mean travel time is 8 min. Shorter trips allow for more trips to be served per vehicle. Another factor is that the fleet was optimized to serve every trip request without waiting time and there was no limit for relocation trip length.

The fleet density can also be compared to the results of Lars Kröger et al. (2018), who assessed the effect of automation on the German transport system, including optimization of fleets and prices of autonomous ride-sharing services. Their scenario with market equilibrium determines a fleet density between 2.7 and 3.6 vehicles per 1,000 inhabitants for a modal share of 11.2 %, which is lower than in the model run for 11 % modal share. Again, this can be due to the fact that all demand was served without waiting time in the Weimar model, whereas there were balancing operations to find a market equilibrium in the approach of Lars Kröger et al. (2018) as well as demand calculation. Still, using the values as orientation, the results from the Weimar model are within a reasonable range. With average occupancy rates for a day between 1.12 and 1.35 for the 7 % and 11 % scenarios, our model results match the results from Lars Kröger et al. (2018) for comparable modal shares.

6.4 Discussion and limitations

With the proposed disaggregation method, it is possible to calculate operational indicators and vehicle trips for a commercial DRT service with pooling in macroscopic travel demand models. This feasible solution works without adding microscopic simulations and generates reproducible results in the form of bundled passenger flows and vehicle trips. The upsides of this approach include:

- **Straightforward implementation:** The algorithm can easily be implemented into existing macroscopic travel demand models.
- **Transferability:** Although the approach was developed and tested using macroscopic models in PTV Visum (2022), the methodology can be transferred to other software.
- **Compatibility with other algorithms:** The proposed algorithm can be included in various other algorithms for trip matching and vehicle scheduling.
- **Detour analyses:** Using the stop probability for and the distance or travel time within a TAZ, the detours for each path with a vehicle trip can be calculated. They can be used as a parameter in the demand model.
- **Reproducible results:** Due to the simplified probability distribution, results from the proposed algorithm are reproducible and thus, only require one iteration. This provides a strong advantage compared to micro simulations with regard to performance and enables the calculation of multiple scenarios.

Further research aims at improving some current limitations, including the following:

- **Limited fleet size:** The current approach is suitable for answering the question of how many vehicles are required to fulfill a given demand. However, the question of how much demand can be satisfied with a given vehicle fleet requires further research.
- **Differentiation for legs of the route:** When a route is separated in legs, occupancies can be calculated for each leg instead of a potential maximum. This mostly affects the initialization of the algorithm in the form of matching trips.
- **More efficient computing:** While faster than a simulation approach, future work should focus on reducing computing times and improving performance, especially for application in larger models. Currently, the computing time increases by a factor of 1.75 when doubling the number of paths.
- **Situations with very high or low demand:** Due to the simple distribution between the ceiling and floor value, situations with higher or lower demand are not regarded in the calculation. However, since the final result is again an aggregation representing a mean value over a time span, this limitation is acceptable. The validity tests using a Monte Carlo simulation showed that the deviation levels of the final result to a microsimulation are low.

Furthermore, the algorithm currently underlies certain assumptions, such as that all trips in the given demand are eligible for matching and that all trips are served, and there is no limitation in fleet size. The number of assumptions could be reduced with the integration of matching and dispatching algorithms in future work, where vehicle availability and resulting waiting times could influence the number of ride requests and cancellations.

6.5 Conclusion

Macroscopic travel demand models are the prevalent tool for practitioners, and they require methods to include new mobility options like commercial ride-sharing in a DRT system. However, the format of the demand – mean values over a time span in an OD matrix – complicates the implementation and the calculation of resulting vehicle trips. While solutions for the problem of spatial and temporal resolution exist, this paper addresses the non-integer demand with a new disaggregation method. The method uses a simplified probability distribution that transforms the demand of matching trips into ceiling and floor values, and derives the probability that spatiotemporally matching trips can be actually pooled. This enables the accurate calculation of DRT vehicle trips to fulfill a given demand and results in OD-matrices with DRT vehicle trips and their pooling rates. The proposed method produces reproducible results in feasible computation times, since it does not require microscopic simulations. The validity of the results was confirmed with an experiment comparing the resulting vehicle trips to those from a Monte Carlo simulation using a Poisson distribution, as well as comparing results from an exemplary application to literature.

The presented approach can be integrated in existing macroscopic travel demand models, in combination with other ride-sharing algorithms enabling spatial matching and vehicle scheduling. Questions regarding the impact of DRT vehicles for a given – or calculated – demand can now be answered with macroscopic models. Besides regional applications, large-scale analysis of DRT with ride-sharing (e.g., on a national level) are possible now with feasible computational effort. Further research can expand the existing ride-sharing algorithms by methods that determine the satisfiable demand with a fixed fleet.

7 Implementing a Ride-sharing Algorithm in the German National Transport Model (DEMO)

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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

7.1 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., Zmud, 2018). 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.

7.1.1 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. (2019) 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 (2016) 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 (Bischoff & Maciejewski, 2016). Other important research was conducted with the implementation of on-demand ride-sharing using MATSim for the city of Austin (Fagnant & Kockelman, 2018), including economical analyses and fleet sizing. Wilkes et al. (2021) 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. (2017), 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. (2018), 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 (Friedrich et al., 2019, Richter et al., 2019). Applying the scheduling algorithm by Hartleb et al. (2022), 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. (2018) 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. (2018) 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 (Friedrich et al., 2019, Richter et al., 2019). It suggests itself that this approach is suitable for a large-scale implementation, too.

7.1.2 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. (2018) 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. (2018) and Richter et al. (2019):

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 11).
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 11, 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. (2019), 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 described steps. Finally, fleet size and relocation trips of the ride-sharing vehicles are determined with the scheduling method described in Hartleb et al. (2022) and Richter et al. (2019). 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.

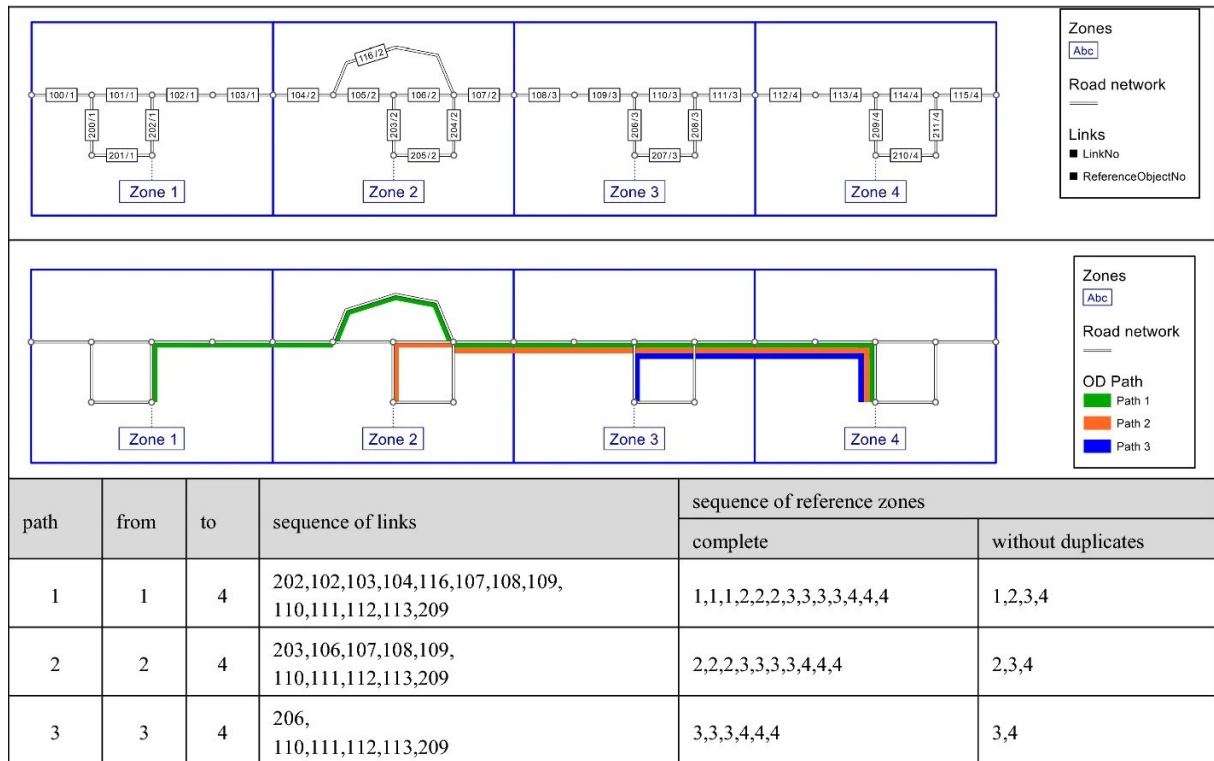


Figure 11: Identify matching routes with the zone-based algorithm (Source: Friedrich et al. (7, p. 1644))

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 12. 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.

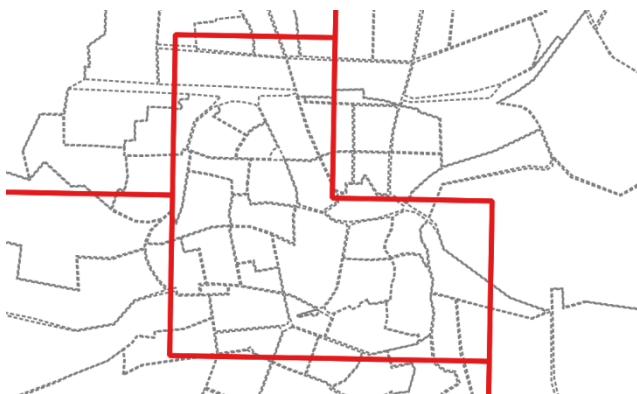


Figure 12: TAZ sizes in national model (red outline) compared to regional model (grey outline)

7.2 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.

7.2.1 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 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 13. 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.

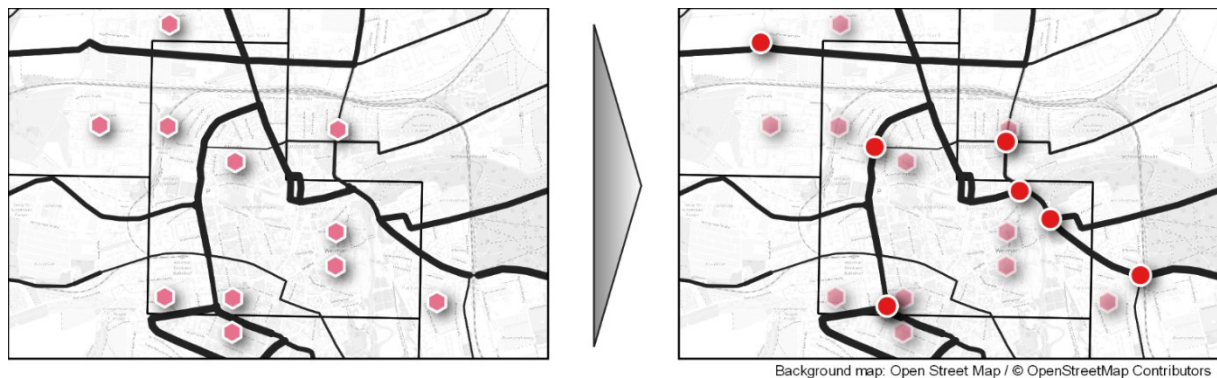


Figure 13: Moving pick-up points from population centers (left) to the nearest node in the road network (right)

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.

7.2.2 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. (2018) 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 14). 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 (4). The sum of all population weights is one.

$$vol_{dir} = vol_{cell} \cdot w_o \cdot w_d \quad (4)$$

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.

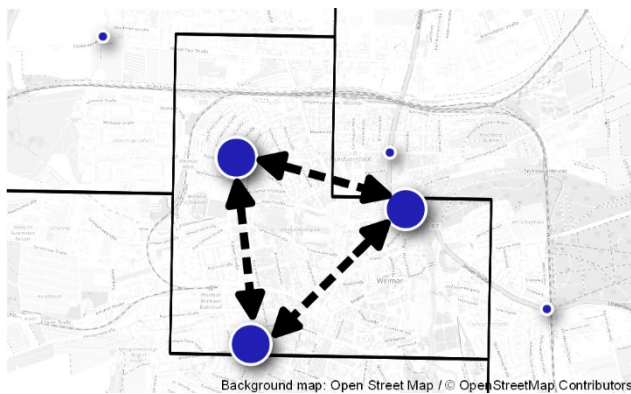


Figure 14: Exemplary directions for intrazonal trips between pick-up points

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 15 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.

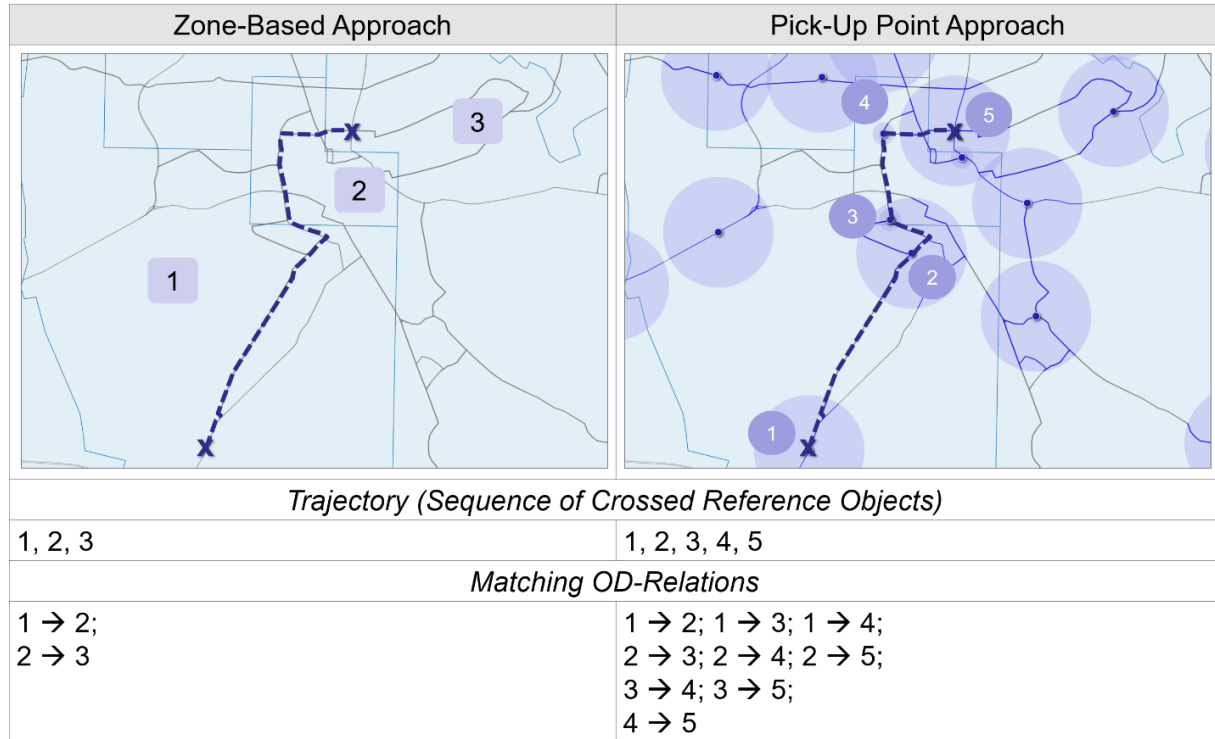


Figure 15: Comparing trajectories and possible matching OD-relations for the zone-based and the pick-up point approach

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.

7.3 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 MOdel) 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.

7.3.1 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 and Mocanu (2017). 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 16 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 and Mocanu (2017) 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.

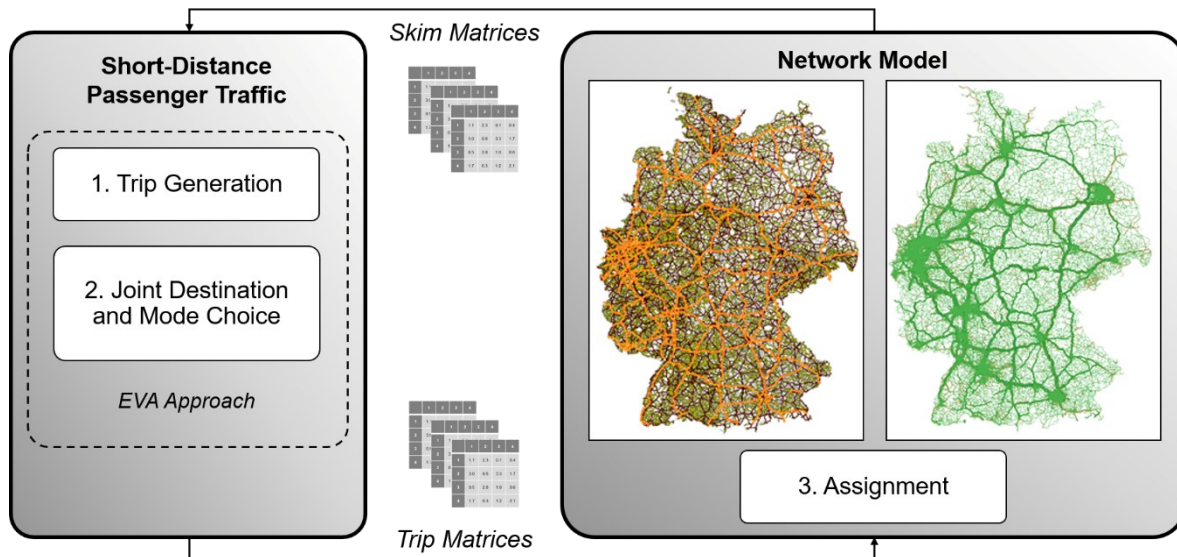


Figure 16: DEMO short-distance passenger traffic model

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. (2019). 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 17).

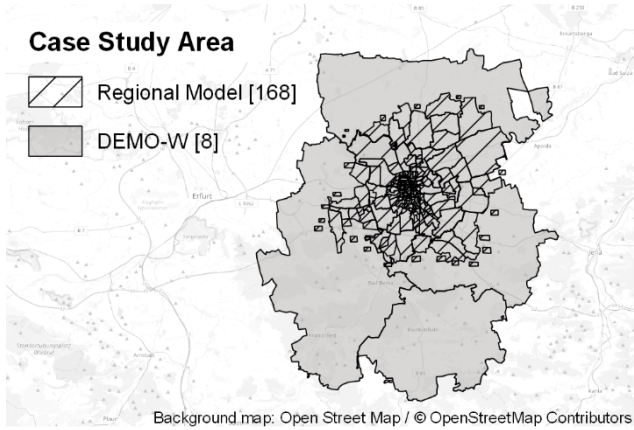


Figure 17: Case study area and TAZ for regional model and DEMO-W

7.3.2 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*, 2022. Table 6 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 6: 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 6. 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 and Kockelman (2018) 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 6 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.

7.4 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 and Kockelman (2018) or Bischoff and Maciejewski (2016) 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. (2018) 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. (2022) 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. 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.

8 Reimagining rural transit: Model-based insights into demand-responsive transportation

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Abstract

Public transit in rural areas faces the challenge of providing an adequate level of service at a reasonable cost, given very low demand density and long average travel distances. There is an expectation to reduce costs and improve service quality by introducing demand-responsive transportation (DRT). This paper uses a model-based analysis to explore the potential of a high-quality and comprehensive DRT system to substitute individual car journeys in a typical rural region. The reference region – surrounding Schweinfurt in Germany – covers 4,000 km², has 432,000 inhabitants, and is characterized by low population density and low-quality public transit offer. The model consists of a trip pooling component and a mode choice model. We compare a baseline scenario for 2025 with a scenario where DRT functions as a door-to-door service and for first and last mile connections to railway stations. The model predicts a DRT modal trip share of 14%, with higher shares in peripheral areas where it connects neighboring settlements. Although DRT leads to a significant modal shift from car use, it may increase road traffic in certain areas due to a shift from non-car modes. First economic estimates indicate that the service can achieve a similar cost coverage to the existing public transit system with a pricing scheme that is roughly twice as expensive as the current public transit single ticket. Overall, the findings suggest that DRT can play a crucial role in enhancing rural mobility by improving accessibility and connectivity, especially in regions with limited traditional public transit, and offers a viable alternative to private car use in peripheral areas.

Keywords: Public Transit, Demand-Responsive Transportation, Travel Demand Model, Rural Transportation

8.1 Introduction

Providing public transit is crucial to ensure basic mobility and social inclusion for the whole population, including disabled, young and old people. It also consumes relatively few resources and causes few environmental externalities compared to the private car. In metropolitan areas, the public transit offer consists of a dense network of subways, commuter trains, trams and buses that operate at high frequencies and bundle people onto large vehicles. These systems enable accessibility throughout their service area, and achieve competitive travel times compared to congested roadways. As a result, public transit in cities can attract user groups that would be almost entirely mobile by car outside of urban areas. In rural areas, the bus typically runs once an hour and often even less frequently, with bus lines often following the spatial development axes and connecting rural areas with sub-centers and sub-centers with main centers. With the help of this service structure, public transit lines can serve certain niches and also fill larger vehicles, for example, school traffic and Saturday shopping trips. Except for these niche markets, however, little potential is seen for pooling people in larger vehicles on regular public transit lines, and even less so for a comprehensive network. This is illustrated by the low service quality of public transit in rural regions compared to urban areas: According to data on public transit quality from the latest German national household travel survey (MiD 2023, (infas et al., 2025)), around 50% of the urban population has access to public transit with good quality, whereas this applies for less than 10% of the rural inhabitants.

However, there are some aspects that suggest that there might be a higher potential for pooling trips and improving public transit quality, even in low-density regions. First, rural space is typically well structured: population is concentrated in villages and small towns that are arranged in hierarchical spatial structures in the form of hexagons (Christaller, 1933, Lösch, 1940) From the hierarchical structures of spatial planning, one can also identify axes along which preferred transactions and traffic occur. The concept of development axes is used to provide a framework for spatial planning and infrastructure measures and contributes to the structuring of land use and transportation networks. These spatial patterns suggest that there is some concentration and clustering after all, as illustrated by the population density map in Figure 18.

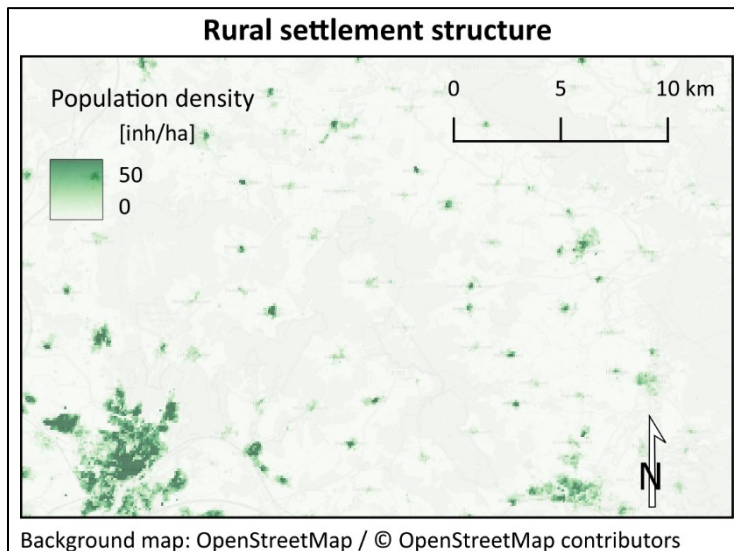


Figure 18: Population density in a typical rural region in Europe

Secondly, it is important to remember that it is not always necessary to fill entire buses with more than 50 seats. These small buses have been in use for decades in rural public transit on low-demand routes and as call buses, and in the future, they could also run autonomously. Thirdly, digitalization opens up the possibility of flexibly bundling individual journeys, which is even easier when there are only a

limited number of people on the bus. This describes a demand-responsive transportation (DRT) system. In contrast, a high-quality DRT system would not be perceived by customers as too similar to a conventional scheduled bus, because the access to the stops as well as waiting and travel times would be comparable to those of a private car. This could make public transit attractive for people who currently only drive their own private car, opening the potential to generate additional demand and revenue. Furthermore, a public transit offer with traffic connections in all spatial directions could be possible and financially viable with a realization complementing existing public transit lines.

And these are precisely the questions that this paper addresses: How big is the market potential of a high-quality DRT in rural areas as a supplement to the existing public transit system and as a real alternative to the car? And what would be the financial implications for the public sector, which typically organizes and subsidizes public transit in rural areas? To answer these questions, a simulation-based ex-ante assessment is carried out for a rural reference region in Germany.

After summarizing the current research state of the art, the case study including the reference region and modeled scenarios is introduced. In the following section, the applied methodology is described. The paper ends with the presentation of the results, a first approximation of economic aspects as well as plausibility checks and a discussion of model limitations and policy implications.

8.2 State of the art

In recent years, there has been an increase in research and practical implementations of DRT. This was motivated by the introduction of digital booking platforms (“mobility apps”) and the potential employing autonomous vehicles. Most ex-ante studies rely on microscopic simulations and agent-based travel demand models, as dispatching strategies, vehicle routing, and ride-pooling algorithms are most naturally represented at the individual traveler and vehicle level. Prominent methodological studies conducting a comprehensive assessment of DRT systems are, among others, e.g., Bischoff and Maciejewski (2016); Fagnant and Kockelman (2018). Key findings confirm a correlation between trip density, operational performance and pooling rates, which could present an issue for low-density regions (Fagnant & Kockelman, 2018). Stiglic et al. (2018) modelled the integration of DRT into public transit by assuming that people offer conventional ride-sharing to bring people to rail stations in a fictional city. Complementary to these predominantly operational approaches, methods to represent ride-sharing and DRT within macroscopic travel demand models have been developed, enabling larger-scale assessments (Friedrich et al., 2018; Richter et al., 2019).

The described methodological work in transportation models enables applications for regional use cases with modeling studies, which provide further insights relevant to transferability and rural service design. For rural transit, Sieber et al. (2020) have explored whether DRT could replace lightly used rail services under specific levels of service with a simulation study. Results suggest that, under very high service quality (e.g., short peak waiting times of under 5 minutes), autonomous DRT may be cost-effective relative to rail in several cases, though behavioral change and pooling were not considered. In an optimization study, Mortazavi et al. (2024) determined trade-offs between different policy goals for a low-demand urban area. They concluded that DRT is much more effective with regard to travel time and experience, and can be more cost-efficient compared to traditional public transit given the same demand. An operationally focused simulation for rural regions by Martí et al. (2024) concludes that DRT is a suitable public transit option with the potential to provide better service quality more efficiently for rural residents; however, demand was imposed synthetically rather than generated through mode choice, limiting conclusions on realized uptake and network-wide impacts. A common limitation in many studies is the assumption of exogenous and fixed demand for DRT and little differentiation of user groups and trip purposes. Statements about changes in the modal split and the improvement of mobility for people with mobility impairments are hardly possible.

Other studies explicitly study the implications of DRT on modal share: For instance, Heilig et al. (2017) apply a mode choice model to analyze whether travelers would switch to DRT or to other, conventional modes if all private cars were replaced, assuming similar preferences to the mode car as a passenger and reporting potentially reduced VKT. Wilkes et al. (2021) integrate mode choice and vehicle dispatching within their simulation. They adapt the general cost parameters of the mode public transit accordingly to the characteristics of DRT, but still emphasize remaining uncertainties in the choice model. Similarly, a nested logit approach has been applied for DRT-as-feeder scenarios using public-transit-based value-of-time assumptions, finding that supplier car trips can be reduced while total VKT may increase under low pooling rates (Huang et al., 2021). In a more recent study, Höing et al. (2025) simulated a DRT service replacing local bus lines in the city of Aachen by applying public transit preferences as well, resulting in a high modal share for DRT and increased VKT. Gurumurthy and Kockelman (2022) estimate DRT preference parameters from ride-hailing observations and employ these in their simulation for DRT with virtual stops. In a data-driven approach based on existing Services, Zwick and Axhausen (2022) evaluated data of MOIA, one of the largest DRT operators in Germany. They analyze spatial data (e.g., population, workplaces, retail, rail access) in relation to usage behavior for the cities Hamburg and Hannover. It is demonstrated that data-driven models can reproduce mobility patterns in the context of new DRT services at an aggregate level. When the model is applied to different regions and population layers, the predictive accuracy is rather poor. Thus, local conditions such as urban structures play a significant role (Zwick & Axhausen, 2022). Taken together, these studies indicate that behavioral responses substantially influence both demand and operational indicators and should be considered when evaluating system-level impacts.

Besides simulation studies and model developments, there are also a number of evaluations of real-world implementations of DRT in practice. Predominantly, the focus is on urban regions, where higher trip density supports pooling and where ride-sharing services have often been introduced as complements and/or competitors to public transit. Empirical evidence from rural pilots suggests that flexible services can be perceived positively and may continue beyond trial phases under favorable conditions (Eckhardt et al., 2020). This is supported by findings from a household survey in a DRT-served suburban area near Hamburg, where 23% of the respondents were regular users and there was strong support for its continuation throughout the population (Diebold and Gertz, 2025). They highlighted spontaneous booking (less than 30 min in advance) as the main advantage of DRT from user perspective. Real-world data analyses in low public transit demand areas in Austin/Texas further indicate that the success of DRT services is shaped by socio-demographic characteristics as well as non-technical factors such as user experience and marketing, while direct connections were more popular than feeders (Zuniga-Garcia et al., 2022). More generally, flexible public transit is discussed as an important component of sustainable rural mobility, potentially providing area-wide coverage in combination with high-speed connections on main corridors (Nelson & Caulfield, 2022). German pilot projects in suburban and rural areas also illustrate typical implementation challenges: service quality constraints can lead to high cancellation rates due to unacceptable waiting times, while improving operational feasibility (e.g., by adjusting pricing) may reduce demand; moreover, long-term operation is frequently tied to temporary funding and cost coverage remains low, underlining the importance of robust service design for sustained deployment (Hartz et al., 2024; Stadtwerke Münster, 2024).

Overall, despite increasing methodological sophistication, there remains limited evidence from large-scale assessments of rural DRT systems that jointly account for endogenous demand, modal shift, and operational performance indicators for realistic service designs. Against this background, the present paper addresses this gap by integrating a spatially unlimited DRT service into a mode choice framework and simultaneously deriving key operational indicators for a rural reference region in Germany, explicitly considering travelers' potential to change modes.

8.3 Case study

In the study at hand, large-scale DRT is implemented in an existing travel demand model and analyzed for a representative reference region. The goal is to assess the potential demand for a high-quality DRT service in the periphery and to analyze operational aspects of the service, such as required fleet size and economic feasibility. The impact of DRT is determined by comparing the results of a baseline scenario, which refers to the status quo, with a scenario that includes DRT services.

8.3.1 Reference region

The Main-Rhön-Region in Bavaria, Germany, was selected as the reference region (Figure 19). The region covers approximately 4,000 km² and 432,000 inhabitants and includes the mid-sized city Schweinfurt (approx. 55,000 inhabitants), as well as smaller cities such as Bad Kissingen, Bad Neustadt a.d. Saale and Haßfurt (between 13,000 and 23,000 inhabitants). Most areas are sparsely populated, with higher local population densities in Schweinfurt and the smaller towns.

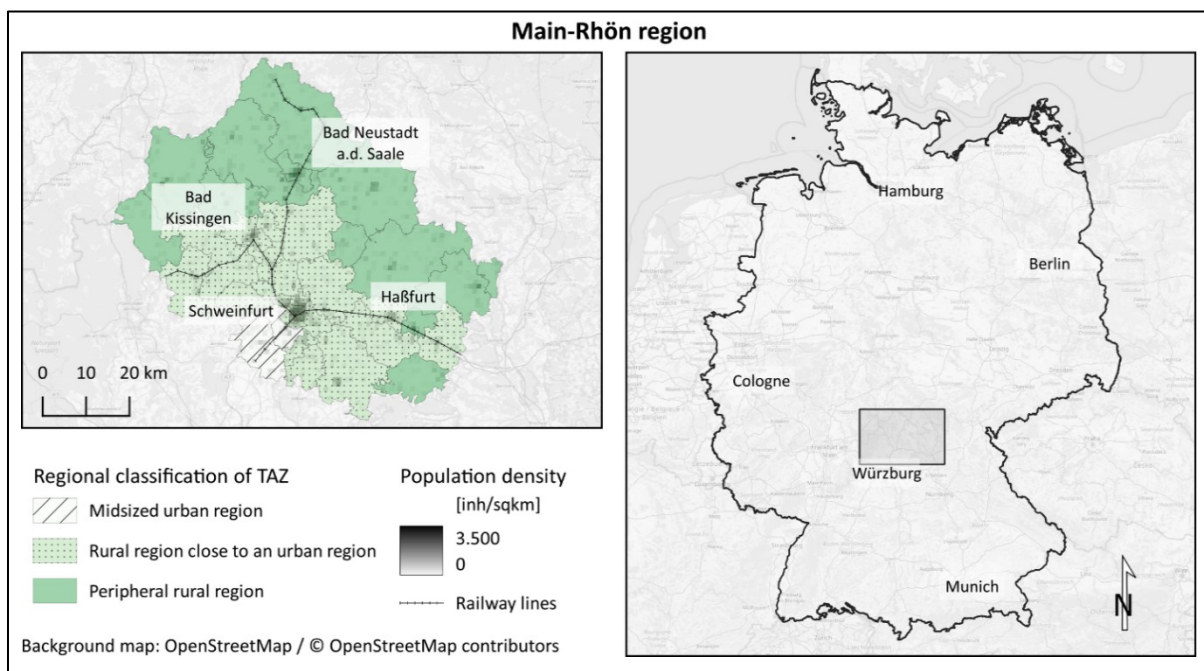


Figure 19: Location of reference region and regional classification

The region is suitable as a reference region for rural areas because it fulfills several typical characteristics. According to the German regional statistical spatial typology for mobility and transportation research (RegioStaR), most of the area can be classified as rural, with Schweinfurt as the central city (BMDV, 2021). Figure 19 shows the classification of the region, from the mid-sized urban region around the next largest city Würzburg to gradually more rural area types. Rural areas do not include the areas around metropolitan areas, which are characterized by high interdependencies with metropolitan areas (BMDV, 2018). They are characterized by low population and building density, as well as a high proportion of agricultural and forestry land. Those characteristics are also used as indicators in the rurality index of the Thünen-Landatlas (Thünen-Institut Forschungsbereich ländliche Räume, Braunschweig, 2023), where 1 indicates the most rural area. The reference region is characterized by high rurality indices between 0.76 and 0.97 for all municipalities except Schweinfurt, which has an index of 0.52. The urban-rural typology of the European Union also classifies the region as predominantly rural, with Schweinfurt and the surrounding area being identified as intermediate region (Eurostat, 2024a).

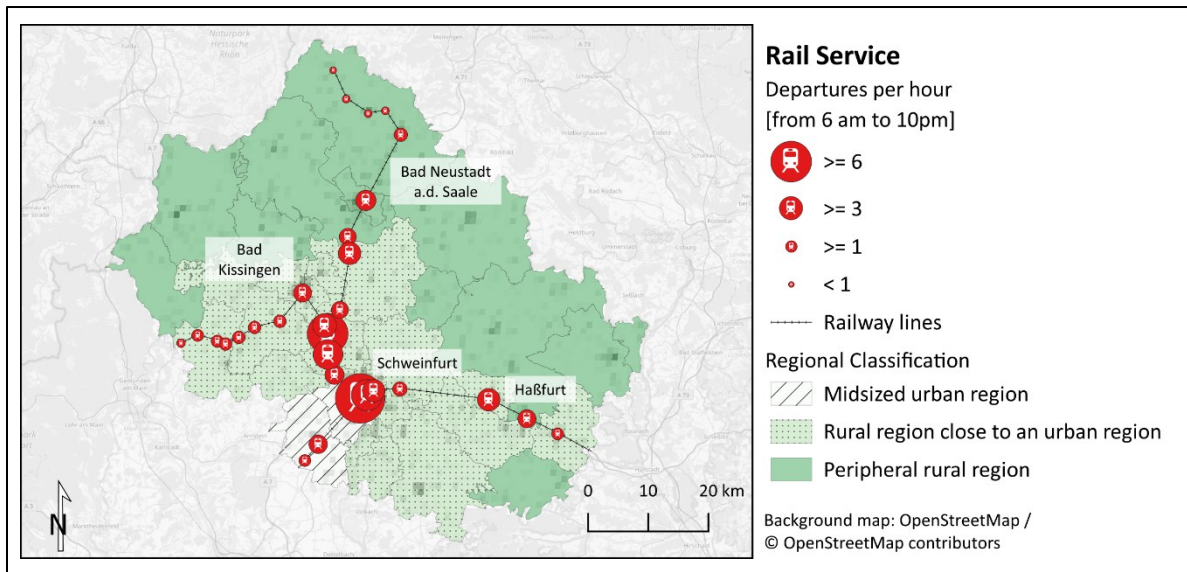


Figure 20: Railway service in the reference region (size of station symbol represents hourly departures during service times, from more than six in Schweinfurt main station to less than one in the periphery)

In the context of DRT, it is particularly interesting that the overall quality of public transit in the region is poor. In large parts of the region, there are practically no public transit services (Agora Verkehrswende, 2022), considering the frequency of departures in the settlement area. The only exception is the city of Schweinfurt with an overall good public transit quality. Regional rail service is available to the next larger towns, with frequent departures mostly in Schweinfurt (Figure 20).

On this basis, the DRT service can be considered as a supplement to traditional public transit in the region around Schweinfurt and as a substitute in the peripheral rural regions. In fact, a DRT service was introduced in the region between Schweinfurt and Würzburg in May 2023, covering a small part of this study's reference region, and has been further expanded since then (Nahverkehr Mainfranken (NVM) GmbH, 2025). The service operates between 5 a.m. and 11 p.m., with virtual stops within the covered area, and requires booking up to 30 minutes in advance. This demonstrates that there is a demand for new public transit solutions in the area.

8.3.2 Description of the DRT service

It is assumed that a region-wide DRT service will be introduced, which serves door-to-door connections (D2D), as well as first and last mile trips from and to railway stations (FMLM). Railway stops for regional trains are in the central towns along the railway lines, as shown in Figure 20. A welfare-oriented pricing is assumed. The operator can therefore be either a subsidized and (price-)regulated private company or a public company. It is also assumed that the service provides a predefined level of service, measured in terms of waiting times and costs, and that there are no restrictions in terms of vehicle fleet. The vehicles travel together with passenger cars in the road network.

The design of the DRT service is subject to the following conditions and assumptions: A day is divided into time bins of 10 minutes. Once a DRT vehicle is dispatched, all customers who wish to take a ride on a particular run of the vehicle within the corresponding time bin can be picked up by the vehicle. Implicit in this determination is that no customer will have more than a 10-minute difference between ride request and pick-up, representing a high level of service. Beyond service quality considerations, the choice of 10-minute time bins is further supported by operational findings. Sensitivity tests conducted during method development with the applied matching and dispatching algorithms showed that fleet size and vehicle utilization are optimized when the temporal resolution of the model is aligned with mean travel times.

The DRT demand is pooled for each time bin using a heuristic optimization. Therefore, trips that follow a common trajectory are matched and bundled along the main axes connecting the settlements. It is assumed that every request can be served, and thus, the fleet size is not defined a priori, but determined based on the demand. Furthermore, it is assumed that there are no transfers between DRT vehicles, as the whole regarded area is covered by the service.

8.3.3 Scenarios

To quantify the impact of DRT, two scenarios are analyzed with a macroscopic travel demand model. The first is a baseline scenario for the year 2025. The model was parameterized and calibrated for the year 2017 using population data from that year and the national household travel survey MiD 2017 (infas et al., 2019). Population figures for 2025 were derived from a federal population projection for Germany, supplemented by regionally differentiated development trends (Destatis, 2022; Eltges, 2021). The public transit supply was implemented based on timetable data from 2023. The analysis is restricted to everyday trips, excluding long-distance and touristic travel.

In the second scenario the DRT service is introduced (DRT scenario). All assumptions regarding socio-demographic development as well as road, rail, and local public transit infrastructure are adopted from the baseline scenario. The key modification is the introduction of the described DRT service as an additional public transit offer. It is assumed that all DRT trips are operated by the same provider and that all requests are eligible for ride pooling.

FMLM trips are included in the public transit ticket, whereas door-to-door (D2D) trips are priced based on distance traveled, with a base fare of €3.00 and a distance-dependent fee of €0.40 per kilometer. This pricing scheme follows several considerations: it should remain affordable for lower-income groups; be more expensive than conventional public transit to limit parallel traffic; include a base fare to reflect boarding and alighting costs and discourage very short trips; remain close to the perceived cost of car use to attract new users; and feature a distance-based component in the same order of magnitude of full-cost mileage-based pricing of a (private) car to prevent unnecessary overuse by people who own a private car.

The guaranteed maximum waiting time is set to 5 min, except in peripheral rural regions (Figure 19), where the waiting time is 10 min. The level of service is intended to be similar to that of a private car and thus represent an upper bound of potential demand. The required fleet size to achieve this level of service is calculated endogenously based on the demand, including a 5% reserve. Vehicles are assumed to have four seats, allowing the use of standard passenger cars. The service is implemented across the entire region without adjustments to the existing public transit network. While this may result in overlapping services, the approach is intended to identify the potential of a high-quality DRT system and to highlight locations where flexible services could substitute low-quality fixed-route public transit.

8.4 Methodology

The impact of DRT is analyzed by comparing the results of the described scenarios, which are simulated in a travel demand model. The aim of this study is to combine the technical implementation of DRT with a mode choice model for the rural reference region. In this way, the effects on travel behavior as well as on transportation infrastructure are included and further analyzed.

8.4.1 Base travel demand model – the German national transportation model DEMO

The base for the model calculations is the German national transportation model DEMO (DEutschland-MOdel), which is a calibrated and validated model (Winkler & Mocanu, 2017). DEMO is a macroscopic travel demand model consisting of modules for local and long-distance passenger transportation and network models for road and rail transportation. For public transit, General Transit Feed Specification (GTFS) data is used to derive level of service indicators, such as in-vehicle time, waiting times or number of interchanges. Using a macroscopic model enables the calculation of travel demand for a large region with feasible computation times, while also demonstrating the applicability in commercial models. In this study, only short-distance journeys of less than 100 km are considered. DEMO follows the steps of the 4-step model, starting with trip generation based on mobility rates, population and structural data. This step is followed by a joint destination and mode choice, with origin-destination trip matrices being generated for different modes and trip purposes. The preference parameters for mode choice are derived from a value of time study conducted for Germany (Ehreke et al., 2015; Axhausen et al., 2015); the mobility rates and travel purposes are based on the national household travel survey for Germany, MiD 2017 (infas et al., 2019). These travel matrices are then used to make network allocations in the road and rail supply models. Based on these assignment results, skim matrices for travel times, distances and costs are derived and form new input values for the demand model. This iterative process is continued until equilibrium is reached, i.e. travel times do not change significantly compared to the previous iteration. For more information on the structure of DEMO, see Winkler and Mocanu (2017). DEMO is able to depict regional differences within Germany due to the accurate depiction of transport supply, structural and population data throughout the country, as well as differentiating car availability on the level of TAZ.

For the scenario calculations, DEMO was supplemented by the DRT service in the rural reference region, whose indicators are also derived from a network assignment and thus change with each iteration. The detailed implementation of the service is described in the following chapter 4.2. The reference region is divided into 41 traffic analysis zones (TAZ) as depicted in Figure 19. The TAZ in DEMO are based on population and workplace density, as well as administrative borders. Due to their size in the low-density regions, there are multiple settlements per TAZ in the reference region. In order to accurately depict travel demand between these settlements, inner-cell travel times and costs are estimated based on the values for the closest trips to other TAZ. In the context of DRT, this could lead to very high pooling rates if the inner-cell trajectories are not considered. Therefore, inner-cell DRT demand is distributed between pick-up locations weighted by population density, as described in Thomsen (2022) and in the following chapter. The model further includes a superordinate road network, as well as 30 stops of regional rail services and local bus lines for the reference region. For the purpose of showing the accumulation of FMLM trip requests to arrive at the platform just in time for train departure and vice versa, the time bins for matching these trips are set to 20 min instead of 10 min. In order to correctly account for congestion effects in the network assignment, external traffic and freight transportation are included via external origin-destination matrices.

8.4.2 Implementing DRT into the travel demand model

The implementation of DRT services in the travel demand model requires several additional model steps, as shown in Figure 21. First, travel demand is calculated in the demand model in the form of origin-

destination matrices. In the next step, the public transit demand is assigned to the public transit network to derive the DRT trips to and from train stations. These FMLM trips from public transit and the D2D trips generated by the demand model are then processed with a “matching algorithm” to determine the DRT vehicle trips. These trips are assigned to the road network together with the rest of the road traffic, including the car trips from the demand model, to determine the traffic load. Travel times and distances are drawn from the loaded network after the assignment step. These values are then fed back into the demand model for the next iteration, and so on. This process continues until there are no more significant changes. Similarly, the detour factors, summarizing the relation between the direct trip and the trip with ride pooling, are fed back to the demand model.

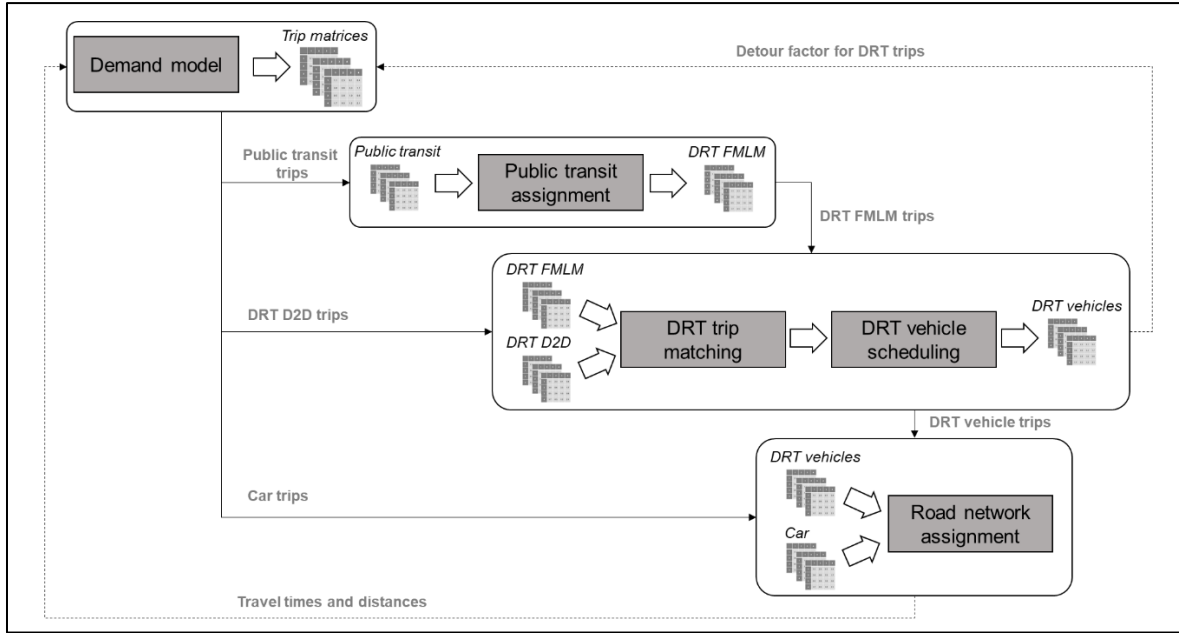


Figure 21: Schematic overview of the model processes

Demand model

In the model, DRT is introduced in two conceptually distinct ways: as an access mode to rail-based public transit (FMLM) and as a stand-alone door-to-door (D2D) mode. Behind this approach is the assumption that a DRT system is more similar to public transit than to private car traffic. In the FMLM service, the characteristics 'scheduled service' and 'trip chain with possible transfers' are inherited from public transit.

FMLM-DRT is implemented within the existing public transit model, where railway access is modeled using a dedicated supply model. In the base case, access modes include car, cycling, walking, and bus. This set is extended by DRT by adjusting access and egress travel times, waiting times, and costs according to FMLM-specific assumptions. To compute DRT travel times, car travel times are multiplied by a detour factor derived from network assignment, and an average DRT waiting time is applied. As a result, generalized access costs to rail stations are reduced, particularly in areas with weak fixed-route feeder services. From a behavioral perspective, this is equivalent to introducing a substantially improved public transit access option.

DRT can also be used as a door-to-door option (D2D-DRT). For these trips, DRT is introduced as a new, independent alternative in the multinomial logit (MNL) mode choice model alongside the independent alternatives car, public transit, walking, and cycling. The choice probability of DRT, P_{DRT} , is thus determined within the standard MNL framework as $P_{DRT} = \exp(V_{DRT}) / \sum_{m \in M} \exp(V_m)$ with V_{DRT} being the utility of the alternative DRT and V_m representing the utility of the alternative $m \in M$. M represents all alternatives in the choice model.

This representation reflects the assumption that DRT, although sharing some characteristics with private car use (e.g. short access times and direct routing), is perceived closer to public transit due to the absence of driving, vehicle sharing, and waiting times. Consequently, DRT as a D2D service is treated as a new public-transport-like option with shifts occurring from all existing modes. Alternatively, D2D-DRT could be introduced as an additional public transit alternative within a nested logit framework. This option was not pursued in the present study for two reasons. First, there are currently no sufficiently robust revealed- or stated-preference datasets available to reliably estimate such a model. Second, spatial and temporal overlaps between existing public transit services and D2D-DRT are limited in the study region, suggesting that the expected differences in results would be small.

The formulation of utility functions follows the structure of the base model. For all modes, utility consists of time-related components with mode-specific preference parameters and a cost component whose valuation depends on trip purpose, as specified in Eq. (5). For DRT, the utility formulation includes in-vehicle travel time, waiting time, and monetary cost. Preference parameters for travel time and waiting time are adopted from public transit, based on the assumption that travelers can perform other activities during the trip and experience similar waiting disutility. This is in line with the procedure in other studies, as mentioned in the State of the Art section (e.g., Wilkes et al., 2021). Parameter values are taken from a German value-of-time study (Axhausen et al., 2015, pp. 73–75) and are listed in Table 7. Travel times and costs are derived from network assignment results, including detours caused by ride pooling, while waiting times are specified exogenously as described in chapter 8.3.3.

$$V_i = \sum_u (\beta_u x_{i,u} + \alpha_u \ln(x_{i,u} + \gamma_u)) \quad (5)$$

with

- V_i Utility of the alternative i
- $x_{i,u}$ Value of utility component u for alternative i
- α_u Logarithmic preference parameter
- β_u Linear preference parameter
- γ_u Logarithmic displacement parameter

Table 7: Preference parameters for utility calculation in the mode choice model, based on Axhausen et al. (2015)

Component	Mode	Parameter value		
		β	α	γ
Travel time	Car	-0.0006	-0.9910	30
	Public transit	0	-0.9850	
	Walk	-0.0111	-1.5100	
	Bike	-0.0443	-0.6790	
	DRT (D2D)	0	-0.9850	
Access & Egress Time	Car	-0.0138	0	-
	Public transit	-0.0122	0	-
Waiting time	Public transit	-0.0072	0	-
	DRT (D2D)	-0.0072	0	-
Frequency	Public transit	-0.1130	0	-
Costs	Work, Education	0	-0.6330	0.5
	Shopping	0	-0.4920	
	Other	-0.0016	-0.6220	

To summarize, for D2D trips, DRT is included as a new, independent mode using the public transit preference parameters, with a level of uncertainty regarding error terms remaining. FMLM trips are

integrated as part of the already existing public transit model, where DRT changes the accessibility of stations.

DRT operations

In the network model, DRT vehicles are added as a new car-like mode of transportation. The mode choice indicators are calculated using a ride-sharing algorithm for macroscopic models as described in Friedrich et al. (2018) and Thomsen (2022). In this algorithm, the origin-destination matrix for trip requests from the demand model is first spatially and temporally matched to determine the necessary vehicle trips for each relation. This is done by comparing crossed reference objects for the respective network paths of the trip trajectories (Figure 22). It follows that the vehicle routes are determined by the longest trips, looking for pick-ups along the way. The reference objects for this study are pick-up points based on population density, as described in Thomsen (2022). For the reference region, 281 pick-up and drop-off locations have been identified, with 3 to 6 points per TAZ depending on their area. In the very rural parts of the reference region, this means that a service connecting the central places and settlements is modeled, since there is often a maximum of one pick-up point per settlement.

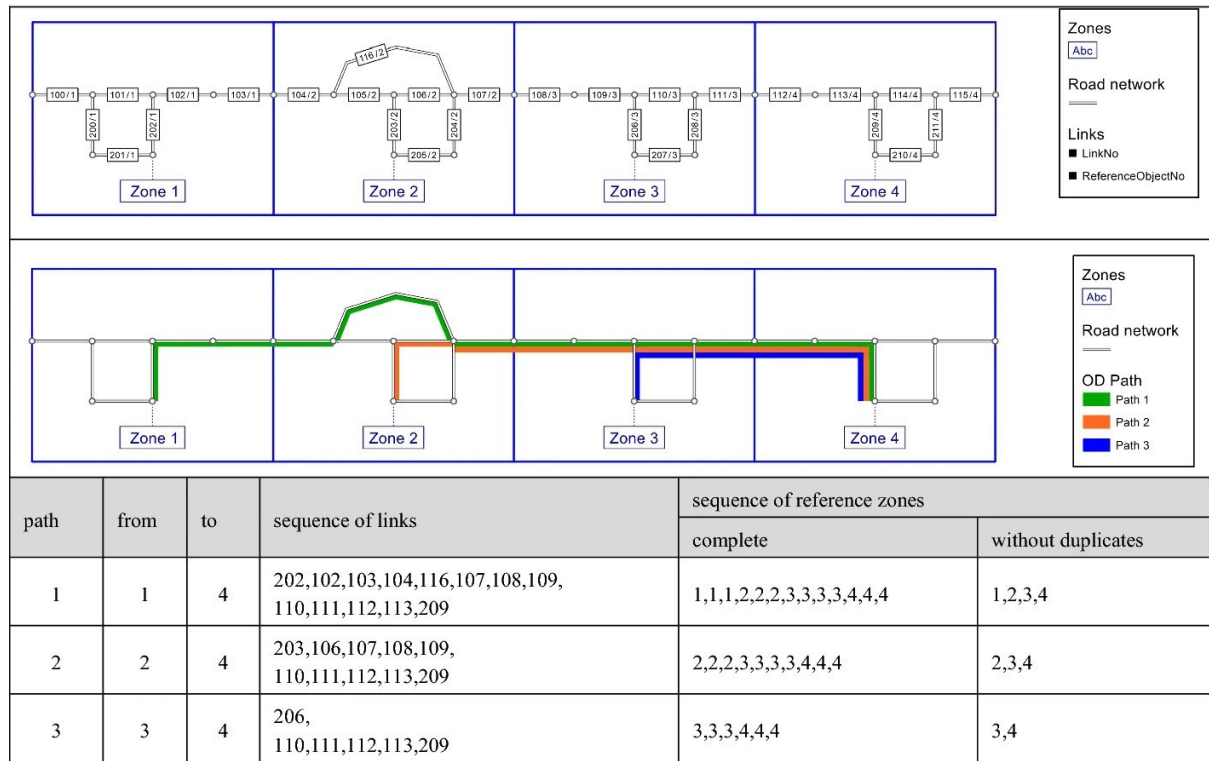


Figure 22: Matching algorithm for DRT trips (Source: Friedrich et al., 2018, (7, p. 1644))

In the temporal dimension, daily trip demand from the demand model is distributed into 10-minute time bins. Within each bin, requests are pooled if a spatial match exists, and the vehicle trips required to serve this pooled demand are determined. Once all DRT vehicle trips for the full day have been identified, a scheduling algorithm is applied to determine vehicle relocations and the required fleet size (Hartleb et al., 2022). The algorithm tracks the locations of occupied DRT vehicles over successive time bins, relocates empty vehicles as needed, and adds vehicles to the fleet if demand cannot otherwise be served.

With these results, the DRT vehicles can be included in the road network assignment and thus influence the traffic situation and travel times of other road users. The applied method calculates average detour factors for each relation, which are used to determine DRT travel times by multiplying them by car travel times. In addition to mode choice indicators, operational indicators such as daily mileage, operating times or pooling rates can also be determined.

8.5 Results and discussion

The travel demand model calculates trip matrices for each mode and performs a road network assignment for private cars. In addition, the carpooling algorithm is run for DRT trips. On this basis, all essential indicators for the comparison of the baseline and the DRT scenario can be determined, such as travel times, transportation performance and modal split. Operational indicators for the DRT system can also be derived, in particular fleet size and vehicle utilization. Certain traffic relations can also be looked at in detail.

8.5.1 Impact on mobility and traffic flows

Table 8 gives an overview of the modal split, the passenger kilometers traveled (PKT) and the average travel times and distances in the scenarios. DRT as D2D option is listed as a separate mode, while the FMLM service is included in public transit, following the demand model set-up. Looking at the modal split of all trips within the region in the baseline scenario, the car was the dominant mode of transportation with 61%. Public transit was used for only 5% of all trips within the region. The introduction of DRT, especially the D2D service, has a strong impact in the model. At 14%, it is the third most popular mode after the private car (53%) and walking (21%). The car share decreases by 8 percentage points, while the number of trips decreases by 14%. Although DRT also acts as a feeder to the existing rail network with the FMLM service, public transit did not benefit from DRT; its number of trips even decreased by 17% (see Figure 23 (a)). The change in trips in the traditional modes is between -11% and -17%, with the strongest losses for car and public transit. This shows that within the MNL, DRT as D2D service is causing a shift from all modes, mainly public transit and private car and the weakest shift from walking. Looking at absolute numbers, the largest shift comes from car trips, which is a logical consequence given the high share of motorized traffic and the model structure. The shares of the trip shifts from car (63.8%) and public transit (6.5%) are slightly higher than their baseline modal shares, which suggests a stronger effect of DRT on these modes. Induced traffic due to the new mobility option was not calculated.

Table 8: Travel demand within the region in the scenarios

Mode	Baseline	DRT	Relative Impact	Absolute Shift
<i>Modal split (trips)</i>				<i>Mio trips (annual)</i>
Car	61%	53%	-14%	-42
Walk	24%	21%	-11%	-13
Bike	10%	9%	-13%	-6
Transit	5%	4%	-17%	-4
DRT (D2D)	0%	14%	--	
<i>Mio. person kilometers traveled (PKT), annual</i>				
Car	2494	2137	-14%	-357
Walk	204	181	-11%	-22
Bike	181	158	-13%	-23
Transit	225	187	-17%	-38
DRT (D2D)	0	355	--	--
<i>Thousand vehicle kilometers traveled (VKT), daily</i>				
Car	6460	5671	-12%	-789
DRT (D2D)	0	1057	--	--
Total	6460	6728	+4%	+268

Regarding the travel volume in PKT in both scenarios, there was a slight decrease in total passenger kilometers of 3% with the introduction of the DRT service (see Figure 23 (b)). This is due to the fact that the average trip length by D2D DRT is 5.4 km, which is shorter than the average car trip (8.4 km). This is why the average trip length has also changed by -3% in the DRT scenario. Due to the implemented pricing scheme, trips shorter than 7.5 km are more attractive for DRT users, as well as the potential detours increasing with the duration of the trip. It has to be noted that induced trips due to a higher number of mobility options were not included. The average travel time per trip also decreased with DRT, by 8% for all trips, which is due to the shorter and faster trips with the DRT. As expected, all modes show lower PKT in the DRT scenario than in the baseline scenario, as all modes lost trips to the D2D-DRT service. The change in PKT for all modes ranges from -11% to -17% compared to the baseline scenario, with the highest overall loss being for the car mode with 350 million fewer annual PKT (-14%). The D2D service accounts for 12% of the total PKT in the DRT scenario. Within the DRT service, most trips are made as D2D trips.

FMLM trips to the stations account for only 6% of all DRT trips and 9% of DRT passenger kilometers (see Figure 23 (d)). The reason is that line-based public transit only plays a minor role in that region. There is, however, a significant shift from persons using Park & Ride to DRT FMLM, as well as from walking and cycling. Looking at the changes in bus trips for railway access, there is a strong decline from 29% to 17%. This seems logical since the bus lines from and to stations have not been redesigned after the introduction of DRT, and the FMLM service and bus lines might operate in parallel.

The results suggest that for shorter connections, DRT is the preferred public transit mode due to its enhanced level of service. Considering both DRT and line-based public transit as public transit options, the transport volume increased drastically, reaching 2.4 times the PKT compared to the baseline scenario.

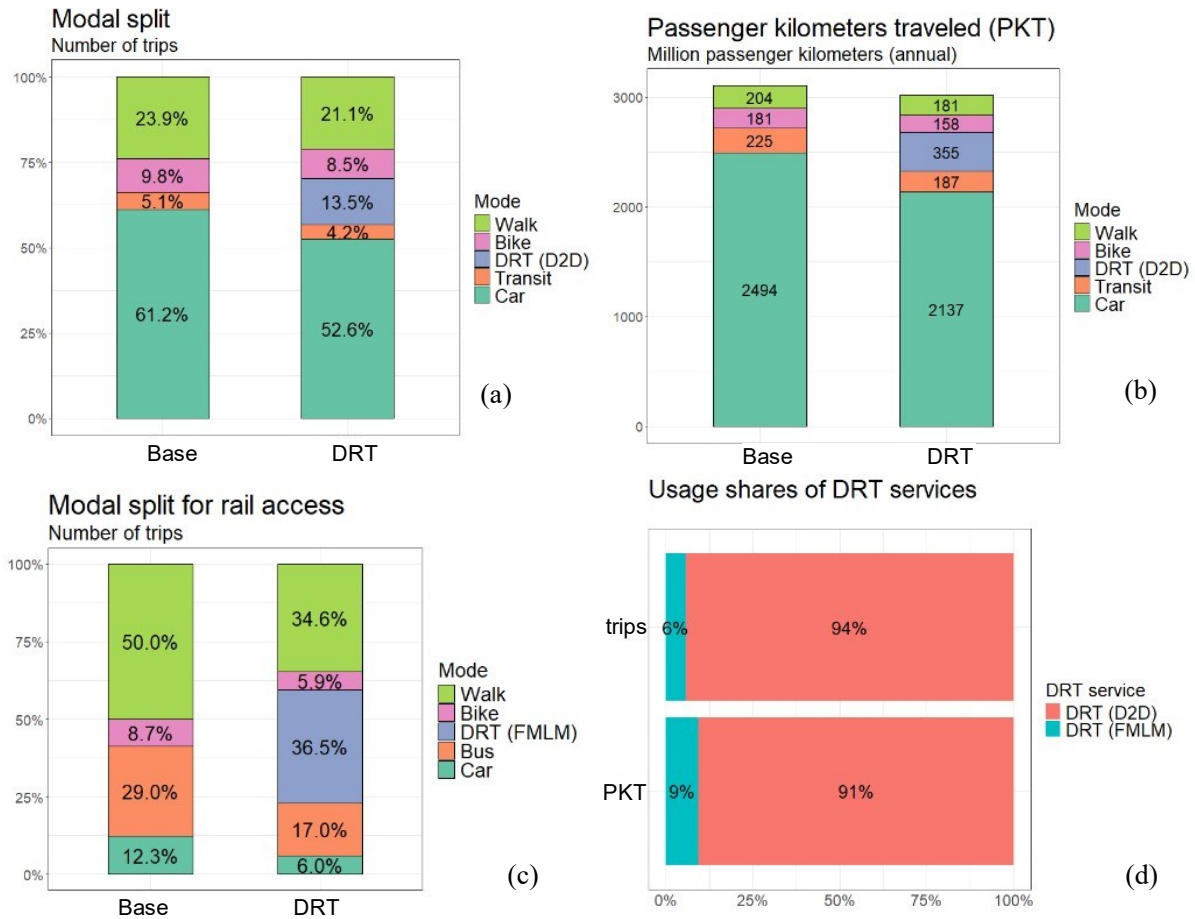


Figure 23: Results of the travel demand model for both scenarios (base and DRT scenario)

Vehicle kilometers in individual traffic decrease by 12% on an average working day (cf. Figure 23 (c)). However, if the kilometers traveled by DRT vehicles are added, the total VKT in the region increases by 4%. Since empty trips for relocating vehicles only account for 5.4% of daily DRT kilometers, this increase is mainly due to the change in transportation demand and the resulting modal shift from modes other than the car (walking, cycling and public transit) to DRT, as detours are not included in the network assignment. Despite the increase in VKT, there are no new infrastructural capacity bottlenecks ("congestion") in the DRT scenario as highlighted in Figure 24.

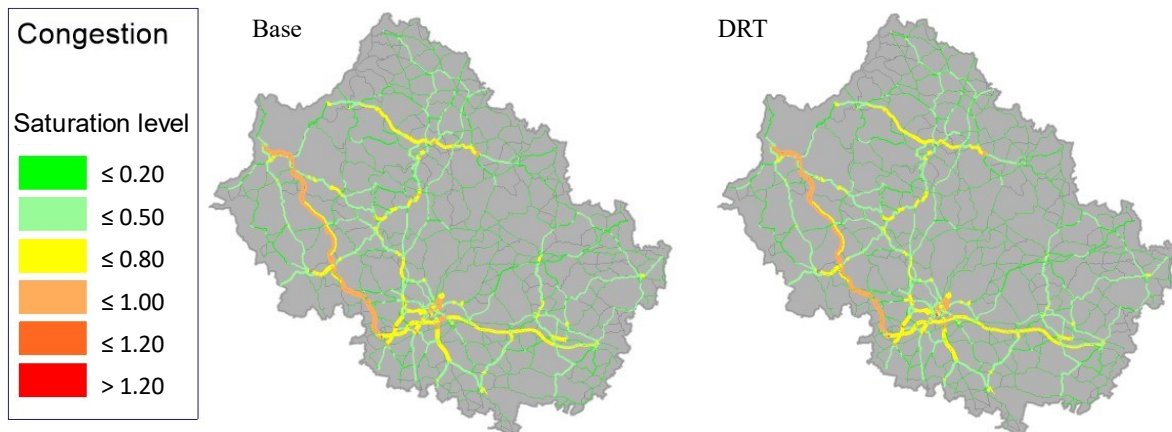


Figure 24: Saturation level of road network in both scenarios

8.5.2 Indicators of the DRT fleet

The matching and vehicle dispatching algorithms applied generate indicators for DRT operation as shown in Table 9. In order to fulfil all travel requests in the region within the 10-minute time windows, 3,287 vehicles are needed, including a reserve of 5%. Each vehicle covers approximately 320 km per day in ~7 h of operation. This means that on average, a vehicle is idle for about 17 h per day, which is consistent with the results from Gurumurthy and Kockelman (2022), where vehicles were idle about 66% of the time. The main influence on fleet size is therefore the demand at peak times and ensuring the required level of service (i.e. maximum waiting time) there. One could therefore reduce the fleet size significantly, but at the price of longer maximum waiting times. The proportion of total kilometers required to relocate vehicles is quite low at 5.4%. This indicates that vehicles remain within quite small sub-zones in the region (these are individual villages and their neighbors) instead of crossing the whole region. The average occupancy rate for all DRT trips in the region on a given day is 1.4. Due to the bundling of trips, detours are to be expected, resulting in a 15% increase in travel time during peak hours. As mentioned above, the D2D DRT service is used for shorter trips, with an average trip duration of 6.7 min for an average distance of 5.4 km. With the implemented pricing scheme, this means that the average user cost per trip is the base fare of 3.00 €, as the additional cost per kilometer would only apply for trips longer than 7.5 km.

Table 9: Indicators for DRT operations

<i>Fleet operations</i>	
<i>Fleet size [total vehicles]</i>	3286.6
<i>Daily mileage per vehicle</i>	321.5 km
<i>Daily operation hours per vehicle</i>	7.2 h
<i>Share of empty mileage</i>	5.4%
<i>Bookings per vehicle per day</i>	112.4
<i>User</i>	
<i>Occupancy rate (all DRT trips)</i>	1.4
<i>Additional travel time in peak hour (detours)</i>	+15%
<i>Average travel time per trip</i>	6.7 min
<i>Average trip distance</i>	5.4 km

8.5.3 Sensitivity analyses

The indicators for mobility and vehicle use in DRT shown in the last two chapters are based on a parameterized model, whose parameters were determined in an exploratory approach with regard to the pricing system, service quality and vehicles, in order to build a logical and functional system. In this section, it will be shown that alternative parameter settings are not suitable to improve the system. The service quality of DRT in this study is defined by waiting times below 10 minutes, and a cost of 0.40€ per kilometer. Increasing waiting times in the mode choice model by the factor 2 leads to a reduction in DRT trips by 4%, and increasing cost per kilometer to 1.00€ reduces DRT trips by 13% to a modal share of 12%. This indicates that even with higher waiting times, DRT is still a popular alternative and lower service quality could be accepted, while the higher costs lead to a stronger reaction in the model. Changing the vehicle size, e.g., to 10 available seats per vehicle, would result in a reduced fleet size (-12%), but ultimately not improve pooling rates significantly (+5%). Using 20 min time bins instead of 10 min would increase the fleet size by 18% due to less frequent vehicle relocation. The pooling rates in turn, increase by only 15%.

8.5.4 Regional impacts of DRT

The reference region covers a large area with different spatial structures, resulting in different impacts of DRT provision within the region. A first way to investigate this is to compare the share of D2D DRT trips in the different municipalities with the share of public transit and private cars. The shares are calculated based on all trips within the administrative boundaries of the municipality, as well as origin and destination trips. As shown in Figure 25, DRT as a D2D service is most popular in areas with low public transit demand. These areas also correspond to those where there is virtually no public transit. The car share is highest in areas without direct rail access and lowest in central settlements. Across the entire region, DRT can therefore make a noticeable contribution to reducing car journeys.

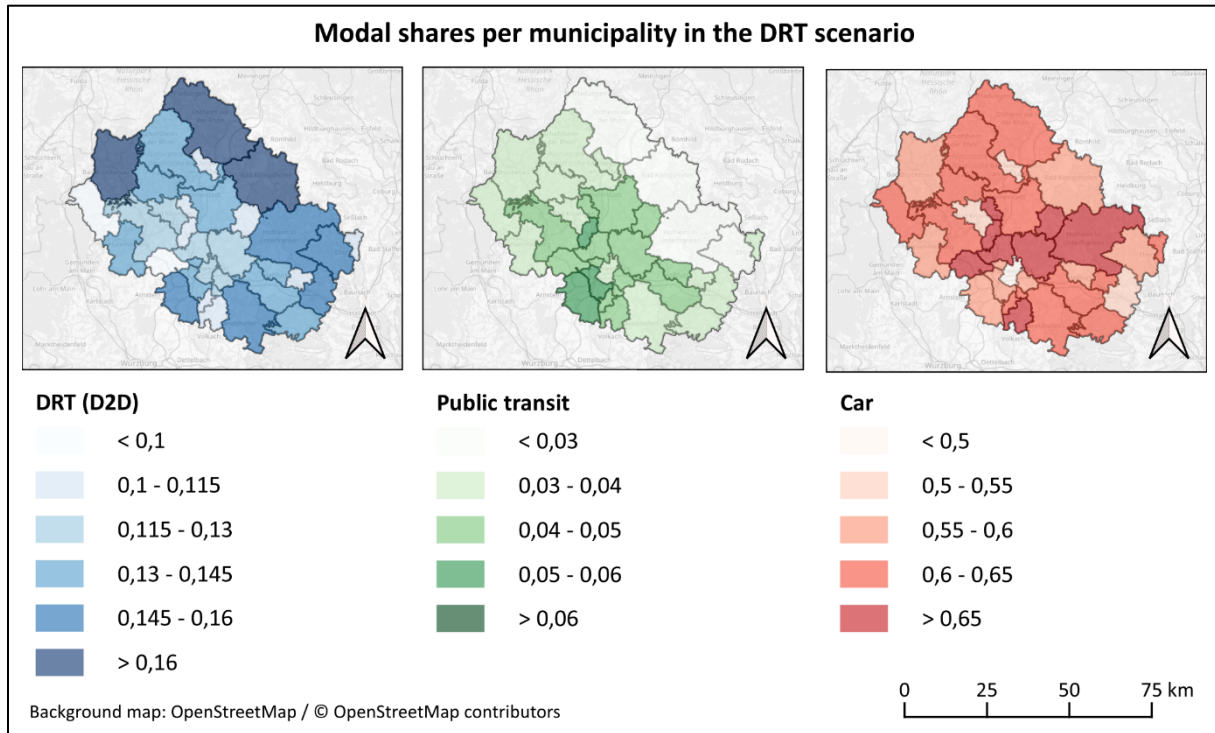


Figure 25: Modal shares for origin trips per municipality for DRT, public transit and car in the DRT scenario

As a car-like mode of transport, DRT is a more area-based service compared to traditional scheduled public transit. This could lead to new routes being frequented and areas with poor rail access being better connected. Figure 26 shows the network assignment results for DRT and public transit demand, highlighting the axes frequented by bus, rail and D2D DRT. Given the similarity with the car, it is logical that DRT has a high volume along major roads. It is also clear that rail services in the region are geared towards connecting the centers of settlement in the region and to the nearest major towns. The quality of public transit in Schweinfurt is reflected in the use of bus routes, while other bus services are not frequently used. It is also evident that the bus infrastructure is concentrated on transportation within the sub-centers.

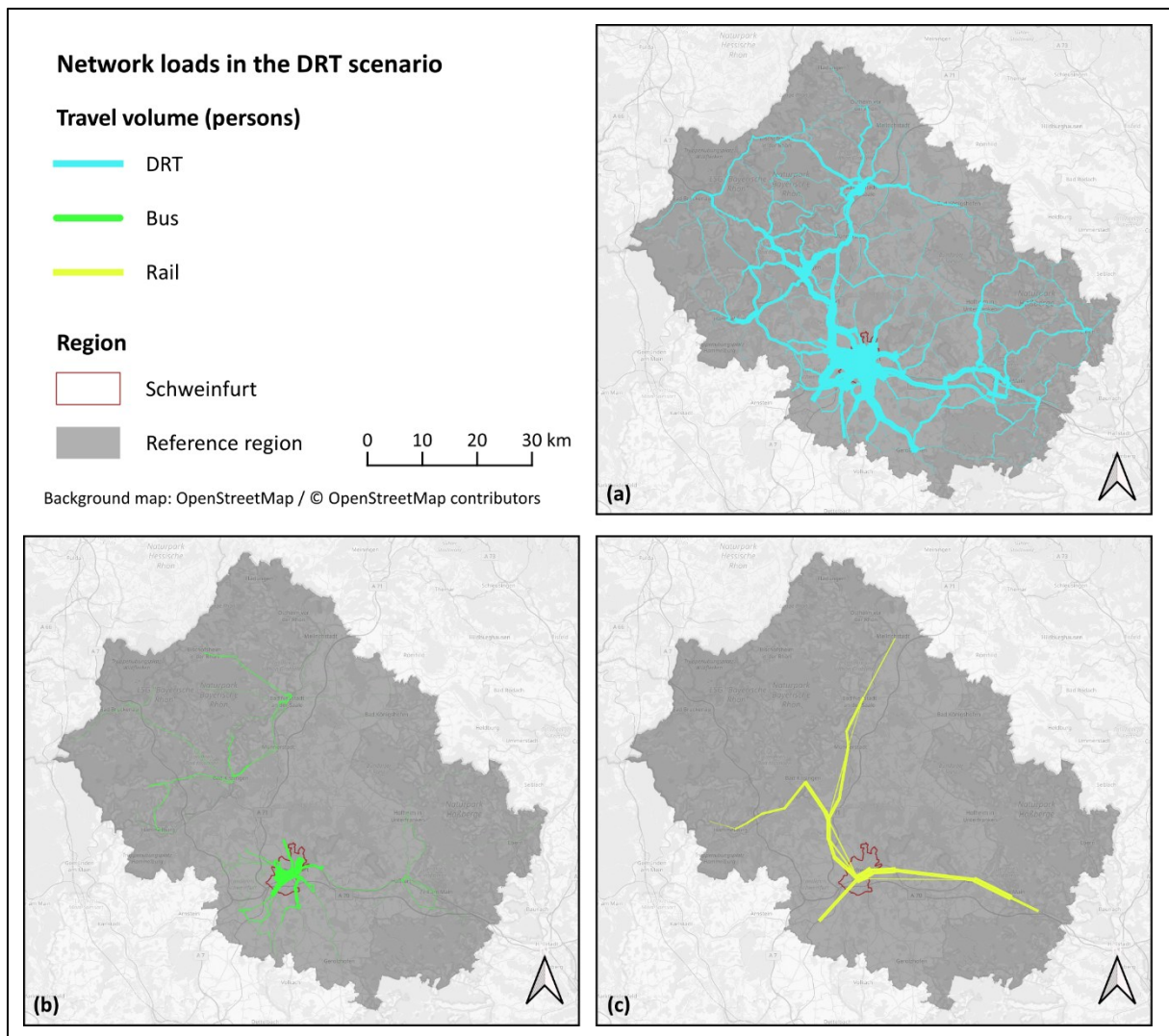


Figure 26: Person volumes on public transit routes and with DRT vehicles

Looking at the volume of DRT trips along the road network, it reflects the spatial structure of the region. There is a high number of trips on the roads between the regional centers and a concentration of trips on the roads in Schweinfurt. It appears that DRT also complements the rail infrastructure, especially in areas with low bus use in the east and north of the reference region. This is another indication that DRT is used as a link between the centers and larger settlements and the surrounding villages. Overall, the traffic volume in DRT is higher than in regional public transit, which is a logical consequence of the higher modal share. However, it should be noted that trips within the TAZ are not included in the network assignment. Especially in the lowest density areas, a TAZ may cover several settlements. It follows that the traffic volumes for DRT in these areas may be even higher.

A look at the mean pooling rates in the region's municipalities (Figure 27) shows that pooling rates are homogeneous and that there is pooling potential. Looking at all DRT trips (Figure 27 a), it is visible that there are higher pooling rates surrounding the central city Schweinfurt, suggesting that there is a high pooling potential for trips into the more urban areas. In the periphery, DRT seems to be more effective for smaller service areas within the municipalities, which is illustrated by the pooling rates for inner-municipality trips (Figure 27 b) being significantly higher than for all DRT trips (Figure 27 a). This can be explained with the shorter relocation distances, as well as the higher modal share. The results suggest that DRT seems particularly effective for connecting settlements within a 5 to 6 km range. Overall, the

pooling rates in the majority of the region are higher than one, which suggests that the service is more efficient than private cars.

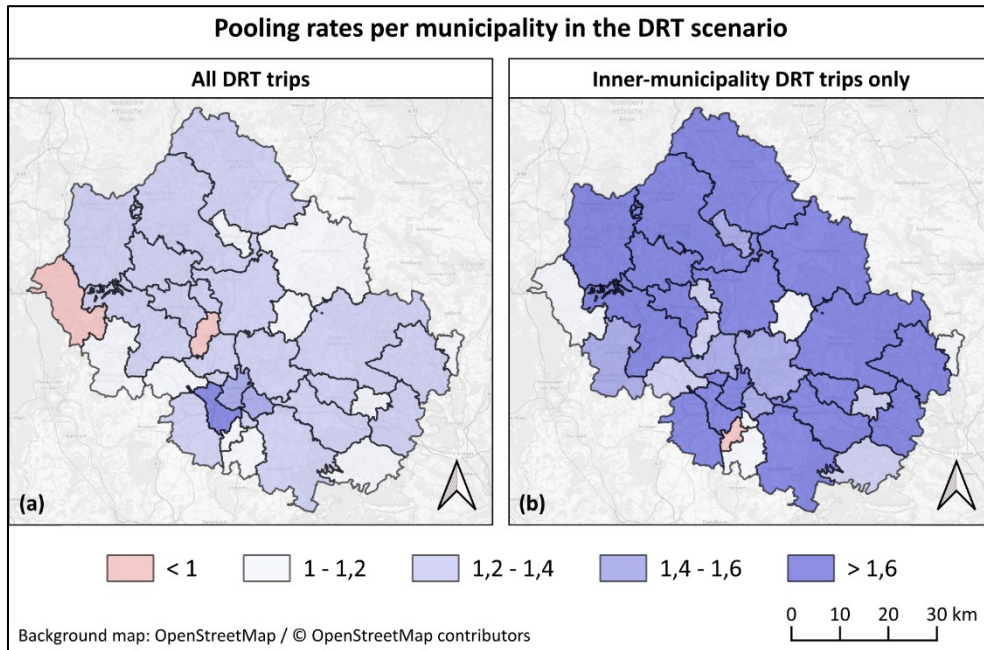


Figure 27: Pooling rates of DRT origin trips per municipality

8.5.4 Economic analysis

The model results suggest that DRT can provide high-quality public transit for low-density areas. While the improvement of public transit service in itself is desirable, decision-makers might also hope for a more favorable cost-benefit ratio. While this paper mainly focuses on potential usage and impact on the transportation system, a coarse approximation of cost coverage can indicate the feasibility of the applied service.

For example, using the operating cost of a standard electric taxi vehicle (e.g., Citroen e-Berlingo M Plus or Kia EV6, see ADAC e.V., 2024) and the generated fleet mileage, the revenue from the DRT service would cover fleet operations almost completely, with a range between 90 and 105%. However, financing driving personnel and overhead would require subsidies. Assuming wages similar to bus drivers in Bavaria (e.g., Landesverband Bayerischer Omnibusunternehmen e.V., München 2023), the total cost coverage could lie between 55 and 65%. In comparison, public transit operators in Germany could cover approximately 60% of their operating cost with ticket revenue in 2018 (Deutscher Bundestag – 19. Wahlperiode, 2021). The degree of cost coverage was even higher for local operators with around 75% (Deutscher Bundestag – 19. Wahlperiode, 2021). There have been major disruptions in public transit operations in Germany since 2018 (e.g., the Covid 19 pandemic, new ticket prices or rise of energy costs, see Verband Deutscher Verkehrsunternehmen [VDV], 2024), which is why using pre-pandemic values from 2018 as reference enables a solid comparison of cost coverage levels.

A simple approximation of transit operation costs in relation to total population (cost per capita) suggests higher costs in the case study than the current level for public transit in Germany, using the value of 31.1B€ in the year 2022 as reference (BMDV, 2023). Even excluding personnel costs, DRT operations exceed the per capita cost for public transit by 35% up to 60%, although this cost would be mostly covered by revenue in the model. The difference in cost per capita including personnel would be even higher. However, the average nationwide expenses as reference point might not represent the costs per capita in rural areas appropriately due to the lower population density. Furthermore, the added revenue due to higher usage cannot be underestimated. To summarize, DRT might lead to a doubling of costs

compared to timetable-based public transit in Germany, with similar cost coverage and thus, the need for subsidies being constant. However, there is a high potential to induce higher demand, with an increase in PKT by a factor of 2.4 in the model (public transit and DRT). The findings of this first approximation can be validated and expanded on in future cost-benefit estimations.

8.5.5 Limitations and plausibility

In order to simulate DRT services in a larger reference region, several model assumptions and simplifications are required. First, due to the macroscopic scale, the demand represents the average mobility of pre-defined person groups and is spatially and temporally aggregated. DEMO provides a validated base model for a rural application, however, due to the low density of rural regions, the spatial granularity is lower than in city-level macroscopic models. Although this limitation is partly addressed through the spatial disaggregation of DRT demand, a considerable share of trips remains internal to single TAZ.

Behavioral responses are modeled in an aggregated manner. Possible disruptions related to demand variability, such as no-shows or user cancellations, are not considered. Similarly, operational side effects, including congestion caused by DRT vehicles during pick-up and drop-off operations as well as the parking of idle vehicles, are not represented. Pick-up and drop-off locations are modeled using reference points in the road network, which can be interpreted as a service using virtual stops rather than a fully door-to-door system. In addition, long-distance trips and trips with destinations outside the reference region are excluded from the analysis. For further planning and implementation of DRT services, the application of a more detailed model with higher spatial and behavioral resolution to selected sub-regions is therefore recommended.

Furthermore, the mode choice model relies on the similarities between DRT and public transit in their value of travel time, but is currently not able to accurately depict preference parameters for DRT due to a lack of observed data. Quick sensitivity analyses using preference parameters for cars for travel times show that demand for DRT decreases by 2%, additionally applying car access time parameters to DRT waiting times yields a decrease by 6%. This shows that even with more negative value of time assumptions, DRT in the modelled form provides a very attractive alternative. Still, there are attributes of DRT services that cannot be quantified as of yet, e.g., sharing a relatively small vehicle with strangers or reliability, and this study does not account for the introductory phase and assumes full acceptance of the service across the population. Further empirical analyses in the form of evaluating pilot services and stated preference experiments are needed to fill this gap.

This also relates to long-term effects of DRT, which might lead to changes in mobility patterns. In the study at hand, these possible effects on trip generation, with different mobility rates or induced trips, are not included. Induced demand due to better mobility option is not necessarily a negative effect, as it indicates higher quality of life with an increase in leisure or shopping trips for example. For quantification in future studies, differences in mobility rates for certain person groups to regions with high-quality public transit could be an indicator for induced demand. Additionally, other long-term effects such as changes in car ownership and spatial structure are not considered. Still, the study at hand shows that DRT might be a suitable mobility service under present-day conditions, given there is a certain quality of service and acceptance.

When it comes to DRT operations, the study at hand does not analyze the impact of changing dispatching algorithms or business models. The applied method assumes that all trip requests are served and there is no calculation of unsatisfied demand. Therefore, the vehicle fleet in the DRT scenario is not limited and calculated in a post-processing step to satisfy the demand. The study results can thus be regarded as a maximum scenario that can be used as a baseline to evaluate efficiency and operational requirements, as well as demand patterns. Real-life operations have more constraints (limited fleet, live matching and distribution), but can be designed according to these findings. For even more insights and design

guidelines, future research could focus on short- and long-term decisions of customers who could not be served due to a limited fleet or compare different dispatching strategies for sparsely populated areas.

In the study at hand, DRT as new mobility option causes a modal shift of trips from private cars as well as from existing fixed-route public transit. Overall, there does not seem to be a strong cannibalization of traditional public transit trips, as the modal share remains stable. At the same time, DRT does not increase the attractiveness of public transit despite the integration with the rail system as feeder service. In practice, a more suitable approach may therefore be a joint service design in which DRT provides area-wide coverage and access to high-speed bus and rail corridors, while the fixed-route network is reorganized to concentrate resources on higher-frequency core lines. This could reduce parallel operations, limit additional subsidy needs, and create a more complementary multimodal system. However, this type of restructuring was beyond the scope of the present study, and future research could focus on integrated network optimization.

The results further indicate that DRT in rural areas can improve the accessibility of railway stations, even though the aggregate effect remains limited due to the small number of rail lines in the study region. This finding nonetheless supports the assumption that DRT may serve as an effective complement to an express bus network and help attract passengers to higher-order public transit services.

Regarding the plausibility of the model results, modal share and operational indicators of the D2D service can be contextualized with findings from other studies. For instance, DRT achieved a modal share of 10% in Gurumurthy and Kockelman (2022), where demand was calculated based on preferences for ride-hailing services and in general public transit demand was very low with only 1%. Applying public transit preferences, Höing et al. (2025) determined a modal share of 29% for DRT when replacing local bus lines in an urban area with similar waiting time constraints, but lower costs and a higher fleet density. In the absence of data for a real-life wide-spread DRT service in rural areas, cities with high quality public transit can be used as benchmark for an upper limit, such as Berlin, Munich or Hamburg with modal shares between 23% and 27% (infas et al. 2025). With a modal share of 14%, the results of this study seem plausible. Furthermore, with approximately 112 bookings per vehicle per day and a daily vehicle mileage of 322 km, the operational indicators of DRT are similar to the results from Wilkes et al. (2021), where DRT demand and vehicle dispatching were simulated for a city area.

8.6 Conclusion

Rural regions are characterized by a low population density and often experience a further decline in population, which exacerbates demographic changes and leads to an aging population. There is also ensuring basic mobility in rural areas, even without reliance on private cars, to facilitate social participation and promote the transformation of the transportation system. Thus, there is a need for a high-quality public transit system also for rural regions.

This study explores the potential of DRT as rural public transit in a representative area with diverse spatial structures, including very rural sub-regions, as well as mid-sized and small towns. The paper demonstrates the demand such a system could generate, given a realistic pricing model, and calculates the required fleet sizes. The impacts were quantified through a modeling study of a reference region, utilizing a macroscopic travel demand model that assumed DRT functions as an alternative to private car use, similar to traditional public transit.

The model results show that DRT achieves three times the modal share (measured in number of trips) of public transit. As a result, the total volume of public transit including DRT more than doubles. The simulations reveal that DRT particularly serves as an alternative to the private car for short trips to neighboring villages and settlements. For passenger flows between central towns, however, DRT was less popular, indicating that routes along development axes should remain served by timetable-based public transit with larger vehicles (e.g., buses or light rail). Therefore, an integrated public transit system

that supplements high-efficiency express lines with flexible DRT services for area-based accessibility in the periphery could offer a feasible solution for rural areas. This study found that, although the overall cost of the public transit system – including DRT – rose with the higher level of service, the subsidy rate remained consistent with current levels and thus stayed within a realistic range. Furthermore, an integrated system can reduce overall system costs by minimizing redundant services.

In conclusion, providing high-quality public transit in rural regions is achievable if the potential of flexible DRT services is effectively integrated with traditional, high-efficiency transit options. However, successful implementation will require public investment in fleets and infrastructure to ensure accessibility and sustainability. Beyond meeting basic mobility needs, improved public transit – especially when incorporating DRT – can strengthen connections to larger economic hubs, improve quality of life, and enhance the appeal of rural areas. In a post-pandemic, digitalized world, where remote work may drive increased urban-to-rural migration, these systems have the potential to significantly enhance the appeal of rural towns as desirable places to live and work.

9 Summary of main results

The selected studies present a functioning method to include DRT in macroscopic travel demand models, and demonstrate the applicability in a rural case study using a German national transportation model as a base. With this case study, the potential impact of rural DRT as public transportation alternative was analyzed for representative region to answer the research questions. In the following chapter, the fulfillment of the requirement will be shown and the answers to the research questions will be extracted and discussed.

9.1 Fulfillment of the model requirements

The requirements introduced in this thesis were defined to ensure that the research questions could be addressed through a modeling study based on a macroscopic travel demand model. Overall, the three studies fulfill the methodological requirements defined for the thesis. Study I provides an algorithm for matching and pooling non-integer demand and deriving DRT vehicle trips within a macroscopic modeling framework. Study II improves the spatial applicability of the approach by introducing pick-up points as reference objects for trajectories in low-density rural areas. Study III integrates DRT into the mode choice model and demonstrates how demand responses can be simulated and linked to operational modeling. This chapter summarizes the main results of the three studies with respect to the four requirements.

Together, these results show that DRT can be represented in a macroscopic travel demand model despite the absence of individual passenger and vehicle movements. The developed approach enables the analysis of operational indicators, demand responses, and service attributes relevant for assessing rural DRT systems. It therefore provides the methodological basis for answering the research questions concerning consistent supply, spatial and operational advantages over traditional public transportation, economic implications, and demand responses to scalable rural DRT provision.

R1: Representation of DRT operations, including trip matching, pooling, and vehicle dispatching

The first requirement concerns the representation of DRT operations, including trip matching, pooling, and vehicle dispatching. This is challenging in macroscopic travel demand models because these models usually operate with aggregated flows between TAZ over defined time periods. They do not represent individual passengers or vehicle movements with exact departure times, locations, and trajectories. As a result, non-integer demand values must be interpreted for operational processes such as trip matching and pooling, particularly when demand is very low.

Study I addresses this challenge by combining existing approaches from the literature with a newly developed procedure for pooling non-integer demand. The matching of potential DRT trips builds on the approach by Friedrich et al. (2018), in which trip trajectories are derived from origin-destination matrices based on shortest paths. Demand is distributed across smaller time intervals, and trajectories are matched according to crossed reference objects, which are the TAZ in their example. If the origin and destination of one trip lie along the trajectory of another trip in the correct order, the two relations can be identified as a potential match. These matching relations are then pooled iteratively.

The missing methodological link was the treatment of non-integer demand and the derivation of required vehicle trips. Study I solves this with a simplified binary choice model approach. For each relation and time interval, the initial demand is interpreted as a probability of occurrence and an occupancy value in the case of a ride request. This allows three demand cases to be distinguished: no ride request, a ride request with the floor value of the occupancy, or a ride request with the ceiling value of the occupancy. Unlike stochastic simulation approaches, this procedure produces deterministic results, which is consistent with the logic of macroscopic modeling. Based on these demand cases, pooling situations are

formed for matching trajectories, and the required vehicle trips and occupancies are determined. The resulting values replace the initial demand values and are used in subsequent matching iterations. After all potential matches have been evaluated, the algorithm produces a three-dimensional vehicle trip matrix with origin, destination, and time interval dimensions. This matrix represents the average (non-integer) vehicle trips required for the DRT service.

For vehicle scheduling, the approach by Hartleb et al. (2022) can be applied as a post-processing step. It uses the vehicle trip matrix to determine fleet size and vehicle relocation trips. Together, the matching, pooling, and scheduling procedures make it possible to derive key operational indicators, including fleet size, empty mileage, total vehicle mileage, operating hours, pooling factors, detour factors, and pick-up time assumptions. A comparison with a Monte Carlo simulation showed that the deterministic approach slightly overestimates the final number of vehicle trips but reduces computing time substantially. The algorithm therefore provides a suitable and efficient method for representing DRT operations in macroscopic models and directly supports the assessment of a consistent DRT supply in rural areas.

R2: Simulation of demand responses to DRT service provision

The second requirement concerns the simulation of demand responses to DRT service provision. This requirement is fulfilled by integrating DRT as an alternative in the mode choice model. A key challenge is the lack of observed data for large-scale DRT systems. Consequently, the definition of utility parameters for DRT cannot rely on extensive empirical evidence from fully established services.

Previous modeling studies have addressed this issue in different ways. Some studies transfer preference structures from public transportation, while others use assumptions derived from taxis or ride-hailing services. In Study III, DRT preferences are modeled based on public transportation parameters. This decision reflects the functional similarities between DRT and public transportation: users do not drive themselves, share the vehicle with others, and are subject to waiting or pick-up times. At the same time, DRT also shares certain characteristics with car passenger trips due to its flexible routing and potentially more direct service. Nevertheless, the public transportation utility formulation was selected as the most consistent basis. Travel time and waiting time parameters are inherited from public transportation, while cost parameters depend on trip purpose rather than mode.

A second methodological question concerns the model structure. The base model is a multinomial logit model, which is widely used in travel demand modeling. Two alternatives for integrating DRT were considered: modeling DRT as an independent alternative in the multinomial logit model or placing DRT and line-based public transportation in a common public transportation nest within a nested logit structure. While the nested logit structure appears conceptually plausible, suitable nesting parameters were not available. Since a nesting parameter of one would collapse the structure into a multinomial logit model, Study III implements DRT as an independent alternative. This has the additional advantage that the approach can be applied in existing travel demand models without requiring substantial changes to the model structure.

R3: Integration of supply and demand interfaces, including the incorporation of demand responses into operations modeling and the derivation of service attributes for demand modeling

The third requirement concerns the integration of supply and demand. This requires two interfaces. First, relevant service attributes must be derived from the operational model and transferred to the demand model. Second, demand matrices generated by the demand model must be usable as input for the operational algorithms.

The operational algorithm developed in Study I provides the basis for the first interface. It derives detour factors for travel times and distances, which can be applied to car-based travel times and distances to

generate DRT travel times and distances for the demand model. Furthermore, Study II demonstrates how the influence of spatial granularity on detour factors can be reduced. This is particularly important because the representation of DRT trajectories can otherwise be strongly affected by the zoning structure of the underlying travel demand model. Waiting time is represented through the time interval structure of the operational model. The algorithm assumes that each passenger is picked up within the time interval in which the request occurs. Therefore, the waiting time used in the demand model must be consistent with the length and interpretation of these intervals.

The second interface is implemented by using the DRT demand matrices from the mode choice model as input for the operational algorithm. Study III demonstrates this interaction between demand modeling and operational modeling. Together, these interfaces enable an iterative and consistent assessment of DRT supply, service quality, and demand response.

R4: Applicability to low-demand and low-density rural areas

The fourth requirement concerns the applicability of the modeling approach to low-demand and low-density rural areas. This is important because many travel demand models are developed for larger cities or regions with relatively coarse spatial resolution in peripheral areas. National and large regional models also use larger zones to keep the model computationally feasible. For DRT modeling, this creates a problem: if TAZ are used directly as reference objects, trajectories become too broad, detours may be overestimated, and small-scale rural settlement structures are not sufficiently represented.

Study II addresses this limitation by introducing a more detailed reference structure for DRT modeling. Instead of using TAZ as the only reference objects, pick-up points are generated based on population density using a k-means algorithm. Demand from each TAZ is distributed on these pick-up points according to their population-based weights. The number of pick-up points can be selected based on cell size, allowing the spatial resolution to be adapted to the requirements of the DRT analysis. Each pick-up point is assigned a buffer zone that allows for detours and enables more realistic matching and pooling. This approach also makes it possible to include inner-cell trips in the operational algorithm, which would otherwise not be depicted in a macroscopic model.

A comparison with a regional model showed that the pick-up point approach produces results that are more similar to those obtained with a more detailed zoning system. It also reduces the influence of the model's original zoning structure on the outcome of the DRT algorithm. Study II therefore demonstrates that the proposed methodology can be applied to low-demand and low-density rural areas, even when the underlying travel demand model has a relatively coarse spatial resolution.

9.2 Detailed research questions

With the fulfillment of the methodological requirements, particularly through the contributions of Studies I and II, the detailed research questions can be addressed using the modeling case study presented in Study III. Study III applies the developed approach to a rural reference region in Germany, using a travel demand model derived from the national transportation model.

DRQ1: What constitutes a consistent DRT supply in rural areas?

A consistent DRT supply in rural areas can be understood as a service that is reliable, broadly available, and sufficiently attractive to be perceived as part of the public transportation system rather than as a niche service for specific user groups. Ex-post assessments of implemented DRT services show that spontaneous booking, reasonable pick-up times, reliability, and low cancellation rates are central quality dimensions. These aspects are closely interrelated: a service can only be considered available if users can expect that a requested trip will actually be served within an acceptable time frame.

Guidelines for rural DRT from Germany (VDV, 2025) further emphasize that DRT should be integrated into the public transportation system. This includes technical integration and the perception of DRT as

an equivalent component of public transportation rather than as an additional service for selected use cases. A consistent DRT system should also be competitive with private car use, for example by limiting travel times to approximately 1.5 times the corresponding car travel time. The DRT fleet size should be large enough to guarantee waiting times that are below 30 min. At the same time, attractive fixed-route public transportation along main axes remains important, especially for connections between central towns and regional transport nodes. DRT can then function as a flexible distributor in peripheral areas and as a first- and last-mile service.

Study III operationalizes this understanding of consistent supply from a level-of-service perspective. The modeled DRT system is not restricted by fleet size, operating hours, or eligible relations. It is implemented across a large rural region as both a stand-alone door-to-door mobility option and as an integrated first- and last-mile service to railway stations. Waiting times are fixed below ten minutes, depending on remoteness. The first- and last-mile service is included in the public transportation ticket, while the door-to-door service is priced with a base fare of €3 plus €0.40 per kilometer after the base fare distance is reached. Vehicles are modeled with four seats, allowing the use of taxi-like vehicles. This design represents a high-quality rural DRT system that can be evaluated as a potential component of an integrated public transportation network.

DRQ2: What is the demand response to a rural DRT system without the restrictions of real-world pilots?

Study III simulates demand response by integrating DRT into the mode choice model. Because observed preference data for large-scale rural DRT systems are limited, the model applies public transportation utility parameters to DRT. This is justified by the similarities between DRT and public transportation: users do not drive themselves, may share the vehicle with other passengers, and experience waiting or pick-up times. Door-to-door DRT is evaluated as a separate mode, while first- and last-mile DRT is integrated by adjusting access and egress times to and from railway stations.

The results indicate substantial demand for DRT under the modeled level of service. DRT reaches a modal share of 14% across the entire region, making it the third most frequently chosen mode after the private car and walking. It also generates the second-highest passenger kilometers traveled. Although the relative shift is strongest from public transportation, the largest absolute number of shifted trips comes from the private car. DRT also becomes the most frequently used mode for railway access, indicating its relevance for multimodal travel chains.

Most DRT trips are door-to-door trips, suggesting that the flexible direct service is particularly attractive. Overall, the results show that, under the assumption that users evaluate DRT similarly to public transportation, a high-quality rural DRT system can attract substantial demand and become a widely used mode of transportation.

DRQ3: Under which spatial and operational conditions does DRT have advantages over traditional public transportation in providing an alternative to private car use?

Study III implements the DRT system in a large rural region with heterogeneous spatial structures (Figure 28), including the central town of Schweinfurt, the outskirts of a larger city (Würzburg), and extensive peripheral rural areas. This allows the spatial and operational conditions under which DRT performs well to be analyzed.

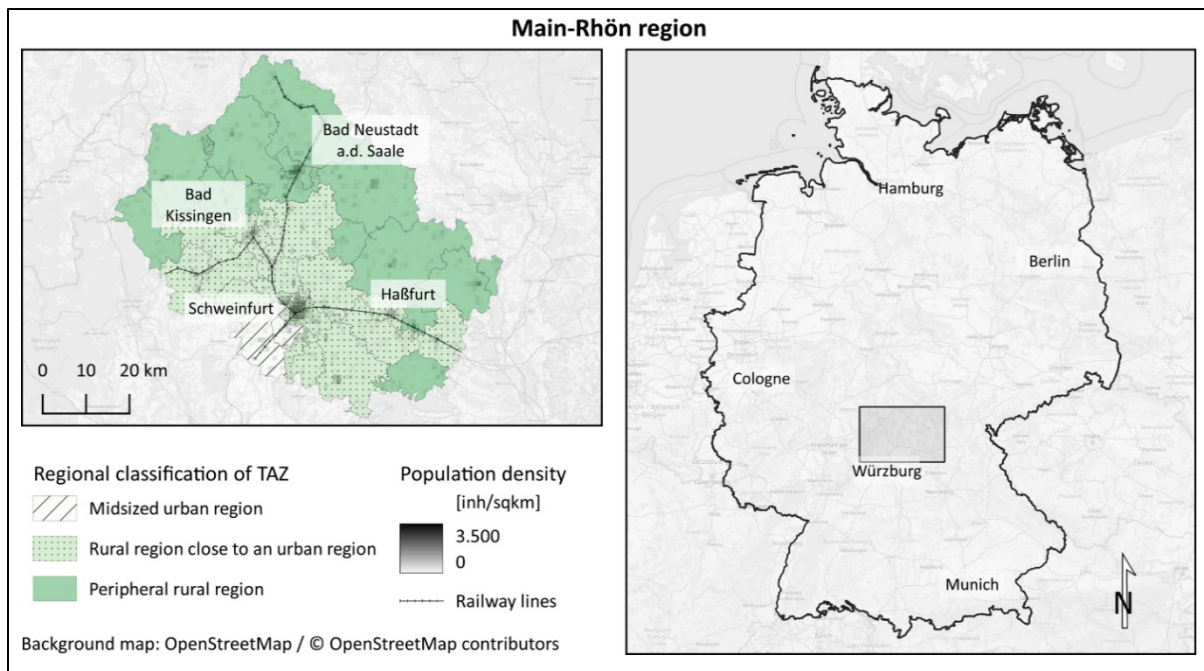


Figure 28: Reference region for the case study in Study III

The results show that DRT is used more frequently than conventional public transportation across the entire region. However, spatial differences emerge, as DRT achieves particularly high shares in peripheral areas and for inner-cell trips, which tend to involve shorter distances. It is especially relevant for trips connecting dispersed settlements, where traditional fixed-route services are often less attractive because routes are indirect, frequencies are low, or access distances are long.

Operational indicators suggest that DRT can provide competitive service quality in these contexts. Average travel times and distances are relatively short, at approximately seven minutes and 5.5 kilometers. The average detour factor is around 15% during peak hours, indicating that pooling can be achieved without excessive additional travel time. The pooling factor for the whole region is 1.4, including empty relocation trips, which is equivalent to average car occupancy rates in Germany. This suggests that DRT does not necessarily generate more vehicle traffic than private car travel. At the same time, total road traffic increases because DRT also attracts trips from non-motorized modes. However, in low-density rural areas with generally low congestion levels, the additional traffic burden is likely to be more tolerable than in dense urban contexts.

Overall, the results suggest that DRT performs particularly well as a connector between dispersed settlements and for shorter-distance trips. Low detour factors and short waiting times allow travel times to be comparable to those of the private car. The connection of towns and surrounding settlements also enables pooling even in low-density areas. Sensitivity tests show that DRT still achieves high modal shares under higher waiting times, indicating that somewhat longer waiting times may be acceptable if they improve pooling factors and reduce fleet requirements. In addition, the spatial distribution of the fleet across the service area contributes to relatively low empty mileage.

DRQ4: What are the economic implications of introducing DRT, and how could a consistent system be financially viable in low-demand areas?

The economic implications of DRT are shaped by several cost components. These include fleet-related costs such as vehicle purchase, refueling or charging, insurance, maintenance, and cleaning; personnel costs for drivers; operations management, including dispatching, IT infrastructure, and potentially telephone booking services; marketing; and stationary infrastructure such as pick-up and drop-off points.

Revenues can be generated through user fares, but higher fares may reduce demand. In low-demand areas, lower pooling rates can also increase the number of vehicles required per passenger trip, which may worsen the cost-revenue ratio compared with higher-density areas.

Study III estimates the cost coverage of a high-quality rural DRT system. Fleet costs are approximated using average cost-per-kilometer values from ADAC (ADAC e.V., 2024) and are covered by the modeled fare revenues. However, once driver wages are added, based on system operating hours and average bus driver wages in Bavaria, total costs exceed fare revenues. Additional cost components, such as dispatching, marketing, and infrastructure, are not included in the estimate and would further increase total operating costs.

The results indicate that, at the modeled level of service, DRT would require public funding with shares that are comparable to current rural public transportation in Germany. While the system is more expensive to operate than conventional low-frequency rural services, it provides a substantially higher level of service and attracts considerably more users. This raises the question of whether DRT, as a complement to public transportation and as part of public service provision, should be expected to operate profitably. Wider welfare effects, such as improved accessibility, increased location attractiveness, and higher living standards, were not quantified but may justify higher service costs. Financial viability could be improved by focusing DRT on area-based services that connect peripheral settlements to central towns and by reducing inefficient or redundant local bus services. Sensitivity tests with higher user costs show that increasing the fare to €1 per kilometer reduces demand by 13%, but DRT still reaches a modal share of 12%. This suggests that the system may remain attractive under higher prices, although the revenue-maximizing fare level would need to be identified carefully to avoid excessive demand losses.

The findings are consistent with recommendations from rural DRT guidelines for Germany (VDV, 2025). They identify integration with public transportation operators, cooperation between public transportation authorities and local taxi companies, and the use of digital booking and dispatching platforms as the main factors to improve service coordination and operational efficiency. At the same time, adjustments in public transportation organization are necessary to balance flexibility, service quality, and cost efficiency. Reducing redundant bus services may help offset part of the additional DRT costs. Overall, they state that DRT can create accessibility and welfare benefits that may justify higher operating costs, particularly if it is implemented as an integrated component of rural public transportation rather than as a stand-alone service.

9.3 Response to the main research question

The results from the three journal articles show that DRT can be represented for low-density rural regions within a macroscopic travel demand model. The methodological developments in Studies I and II make it possible to model DRT operations and supply-demand interfaces, while the rural case study in Study III applies these methods to assess demand responses, operational performance, and economic implications. Based on the answers to the detailed research questions, the main research question can now be addressed.

MRQ: *How can an area-wide rural DRT system be designed and evaluated as a contribution to sustainable rural mobility, and what demand response can be expected under a high level of service?*

The results show that rural DRT can contribute to sustainable rural mobility when it improves accessibility, reduces car dependency, and strengthens public transportation provision. These effects can be evaluated for a large rural region through macroscopic travel demand modeling, enabled by the methodological developments that fulfill requirements R1 to R4.

Based on the answer to DRQ1, DRT should be designed as an integrated component of the public transportation system. This includes two main functions:

- First-mile last-mile access to scheduled public transportation services
- Door-to-door (or PUDO) connections as supplement in low-efficiency areas and service times

Such integration increases the availability of public transportation especially in low-demand areas and enables DRT to complement scheduled services. In particular, feeder services can be integrated into existing public transportation tariff systems, while door-to-door services may require separate pricing.

To contribute to an attractive rural public transportation system, DRT should be designed to ensure:

- Low waiting times
- Low detour factors compared to car travel times

According to German guidelines, pick-up times below 30 minutes and travel times not exceeding approximately 1.5 times the corresponding car travel time are important benchmarks (VDV, 2025). In the modeling case study, considerably lower waiting times were assumed and detour factors below 20 percent were achieved, representing a high-quality service design. These service levels depend primarily on fleet management and fleet size. The results suggest that substantially larger fleets than those used in many current pilot projects are required if DRT is to provide a consistent and reliable level of service. Fleet size should therefore be derived from explicit service quality targets, such as maximum waiting times, detour limits, and spatial coverage.

The rural case study in Study III indicates that DRT can become a viable mobility option when it offers travel times and service availability that are comparable to private car use. DRT is used particularly for shorter trips between settlements and in peripheral areas where conventional public transportation options are limited. The sensitivity analyses further suggest that DRT remains attractive even under higher waiting times, as long as the service is reliably available. This indicates that some flexibility exists for improving pooling factors and reducing fleet requirements without eliminating demand.

The demand response analyzed in DRQ2 confirms the attractiveness of such a system under the assumptions of Study III. DRT achieves substantial demand and becomes competitive with established modes of transportation, including the private car. The modeled modal share indicates that a high-quality DRT system can reach levels of use comparable to cities with high-quality public transportation systems. This supports the conclusion that DRT can contribute to sustainable rural mobility by increasing public transportation use and providing a viable alternative to car travel. The modeled shift from private car trips further indicates a potential reduction in car dependency.

The results also show that an attractive DRT system requires moving beyond the limited service levels typically observed in pilot projects. Many real-world pilots operate with small fleets, restricted service areas, limited operating hours, or narrow target groups. These restrictions reduce service availability and can lead to high rejection or cancellation rates when demand exceeds available capacity (e.g., Münster). Similar to conventional public transportation, DRT requires a sufficiently high level of service before substantial demand can be expected. A reliable and attractive service must therefore be provided in advance, rather than scaled only after demand has already materialized.

The main challenge for implementing a high-quality DRT service at scale is financing. Compared with regional bus lines, DRT requires larger fleets, more driving personnel, and additional resources for dispatching, booking, and operations management. Recognizing DRT as an integral component of the public transportation system would enable integrated planning and allow redundant, low-efficiency bus routes to be reduced in favor of flexible services. It would also support the extension of public transportation funding to DRT. Additional user fees can contribute to cost recovery, but their effects on demand and revenue would need to be examined in more detail. Overall, the accessibility, quality-of-life, and social participation benefits associated with rural DRT provide strong arguments for public investment in high-quality rural mobility services, although the financial implications and optimal funding structure require further analysis.

10 Discussion and future research

The results from this thesis show how DRT can contribute to attractive rural mobility, and how macroscopic travel demand models can be applied to research and plan the service design. The studies presented methodological developments to enable macroscopic simulation of DRT and applied these methods for a rural case study. The following chapter discusses the methods and results with regard to their research contribution and limitations, as well as providing an overview of future research.

10.1 Contribution

The literature review showed that DRT has predominantly been modeled using agent-based models or microscopic simulations (e.g., Fagnant & Kockelman, 2018; Schlenther et al., 2023; Wilkes et al., 2021). This focus is methodologically justified, as DRT operations depend strongly on spatial and temporal detail. Macroscopic travel demand models, by contrast, usually operate with aggregated demand flows and lower spatial and temporal resolution, which makes the representation of flexible services more challenging. However, the reliance on state-of-the-art research models and specialized simulation software may limit the practical consideration of DRT in transportation planning. Such tools often require extensive data, technical expertise, and computational resources, which may not be available to local or regional planning authorities. This is particularly relevant in rural areas, where modeling capacities are often more limited and where detailed synthetic demand data is less frequently available. This thesis contributes by developing and applying an approach that enables DRT to be represented within macroscopic travel demand modeling frameworks, and thus, enables planners to implement DRT in rural areas of large-scale models. This makes it possible to include DRT in long-term mobility strategies, compare it with alternative transportation measures, and identify regions where flexible services may provide accessibility benefits. At the same time, the approach provides a foundation for more detailed operational optimization and practical implementation at later planning stages. The developed approach enables macroscopic models to estimate both demand responses and operational requirements for a given DRT level of service.

The thesis also contributes to the literature on rural DRT by providing a large-scale simulation in a transportation demand model. While DRT in rural regions has gained increasing attention, many previous simulation studies rely on fixed demand assumptions, often based on current low-use public transportation demand (e.g., Martí et al., 2024; Sieber et al., 2020). Such assumptions may underestimate the potential demand for DRT because they do not account for modal shifts resulting from improved service quality. By integrating DRT into the mode choice model, this thesis allows demand to respond to the modeled service level and therefore provides a broader assessment of its potential role in rural mobility systems.

Another contribution lies in the use of a model derived from a larger model, in this case a German national transportation model. Developing a new regional travel demand model for rural areas requires substantial time, data, and expertise, which often limits the feasibility of such analyses. Existing detailed models that can generate synthetic demand data are more commonly available for urban regions and their surroundings, and research on DRT has often been conducted based on these models (e.g., Höing et al., 2025; Richter et al., 2019; Schlenther et al., 2023). By deriving a rural reference model from a national model, this thesis demonstrates how rural DRT can be analyzed even when locally detailed modeling resources are limited. The approach can also be transferred to other large regional or national modeling contexts, making it relevant beyond the specific case study region.

Finally, the thesis contributes by linking modeled service outcomes to economic considerations. The estimation of cost components based on model results provides an initial assessment of future financing needs for high-quality rural DRT systems. While the analysis does not replace a full cost-benefit assessment, it shows how operational indicators such as fleet size, vehicle kilometers, operating hours,

and demand can be translated into approximate cost and revenue implications. This supports a more informed discussion of the financial requirements, funding needs, and possible role of DRT within publicly supported rural transportation systems.

Overall, the contribution of this thesis is both methodological and applied. Methodologically, it extends the applicability of macroscopic travel demand models to flexible DRT services. Empirically, it provides a large-scale rural case study that assesses demand response, operational requirements, and economic implications. From a planning perspective, it offers a transferable approach that enables DRT to be considered in strategic rural transportation planning and prepares the ground for subsequent operational design and implementation.

10.2 Limitations and future research objectives

As with any modeling study, the results of this thesis are subject to uncertainty. The model does not predict an exact future outcome, but rather indicates possible effects under a defined set of assumptions. These assumptions are particularly relevant with regard to user behavior, service perception, and the operational representation of DRT.

One central limitation concerns the demand model. The case study models DRT preferences based on public transportation parameters. This is consistent with parts of the existing literature, but actual preferences for DRT may differ. Users may evaluate reliability, waiting times, sharing a smaller vehicle with strangers, or the comfort of a guaranteed seat differently than in conventional public transportation. These differences may become even more relevant for automated DRT services, where no driver or service personnel are present. The sensitivity test in Study III using car-based parameters for travel and access times resulted in a 6% reduction in DRT trips, indicating that the service remains attractive even when travel time is evaluated more negatively. Nevertheless, the exact magnitude of demand response remains uncertain.

The model structure also remains a limitation. A nested logit structure with DRT and line-based public transportation in a common nest appears plausible, but would require empirical support through revealed preference data or stated-choice experiments. The implemented multinomial logit structure is therefore a practical solution for the case study, but future research should examine whether alternative model structures better reflect user choice behavior for DRT.

Closely linked to user preferences is the question of acceptance. The case study assumes that the DRT service is already widely known and accepted as an everyday mobility option. It does not model the transformation path from a new service to regular use. However, the introduction strategy, marketing, and integration into existing public transportation systems are likely to influence acceptance and demand development. Future research should therefore examine strategies on successful rural DRT introduction with regard to acceptance as an established mobility options.

Further limitations arise from the operational modeling approach. The macroscopic algorithm does not represent online matching, individual trip legs, or fleet restrictions. It is therefore suitable for strategic planning from a user-oriented perspective, as it answers the question of which operational resources are required for the desired demand. In practice, however, planning is often constrained by available budgets and predefined fleet sizes. For this perspective, agent-based models, microscopic simulations, or specialized DRT planning tools are better suited. A useful future direction would be to combine macroscopically generated demand with more detailed operational tools.

Comparative studies between macroscopic and microscopic approaches would also be valuable. Future research could simulate DRT in the same region with both a macroscopic model and a microscopic or agent-based simulation in order to compare results. Such studies could help derive transferable functions for strategic models, for example regarding serviceable demand or waiting times by fleet size, area, population density, or trip density. A comparable agent-based case study in urban context by Höing et

al. (2025) with similar waiting time constraints and fleet density per inhabitant shows partly comparable results in terms of trip length and occupancy, but also clear differences in demand density. This indicates that further comparison across spatial contexts and modeling approaches would be useful.

The results are also sensitive to input assumptions and service specifications. The studies examined sensitivities regarding spatial granularity, time interval size, vehicle capacity, pricing, and waiting times. The demand response to higher costs and longer waiting times suggests that the service remains attractive under less favorable assumptions, but these effects should be analyzed further to define minimum service standards from a user perspective. Vehicle capacity may influence pooling rates and fleet size, making the optimization of fleet composition and vehicle size an important future research topic. Similarly, broader matching conditions can increase pooling but also lead to higher detours, indicating the need to analyze optimal pick-up and drop-off point densities. These trade-offs should be researched in future work to derive the optimum service design under specific viewpoints, while also including demand reactions.

Finally, broader simulations are required before deriving general recommendations for rural DRT implementation. Future research should examine integrated public transportation and DRT networks in which fixed-route services are reorganized, for example by focusing buses on fast connections between central towns while DRT serves dispersed settlements and peripheral areas. Additional studies should also transfer the approach to other rural regions in order to identify spatial patterns and assess the robustness of the findings across different regional contexts.

11 Conclusion

This thesis analyzes the potential of DRT as part of a sustainable rural mobility system using a macroscopic travel demand model. Rural areas are characterized by high car dependency, limited public transportation provision, and demographic change. At the same time, reducing reliance on individual motorized mobility is important for limiting transportation-related externalities while maintaining accessibility. Against this background, the thesis examines whether DRT can contribute to improving rural public transportation and reducing car dependency.

The results show that DRT can become a viable alternative to private car use if it is implemented as a high-quality, integrated, and publicly supported component of rural public transportation. This requires sufficient fleet capacity, reliable service standards, integration with fixed-route services, context-specific service design, and a funding framework that accounts for both operating costs and broader accessibility benefits.

The modeling results indicate that DRT can generate substantial demand when offered at a high level of service. DRT is used frequently as a public transportation option, including in peripheral and low-density areas, and the modeled modal shift from private car trips suggests a potential reduction in car dependency. This implies that DRT can improve public transportation quality not only by complementing existing services, but also by extending access to areas where regular services are deemed unfeasible or inefficient. Instead of operating fixed routes that serve multiple settlements and travel purposes with limited efficiency, DRT can offer connections that are more closely aligned with individual travel needs.

At the same time, the results show that the goal conflict between comprehensive mobility provision and financial feasibility remains. A high-quality DRT system requires larger fleets, more personnel, and higher total operating costs than many current rural public transportation services. However, the case study also indicates that public transportation quality can be significantly improved while maintaining a subsidy rate comparable to existing rural public transportation. DRT may therefore offer a higher-quality service in areas where conventional fixed-route services are inefficient, provided that funding structures recognize not only operating costs but also wider benefits related to accessibility, quality of life, and social participation.

Overall, the thesis demonstrates that DRT can contribute to sustainable rural mobility from multiple perspectives. From an accessibility perspective, it can improve connections to essential services and regional centers. From a social perspective, it can provide mobility options for people with limited access to private cars. From a transportation perspective, it can strengthen public transportation and reduce reliance on individual motorized mobility. By demonstrating how DRT can be represented in a macroscopic travel demand model, the thesis also contributes to the planning and evaluation tools required for assessing flexible mobility services in rural regions.

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