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

Statements and Declarations

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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 1.

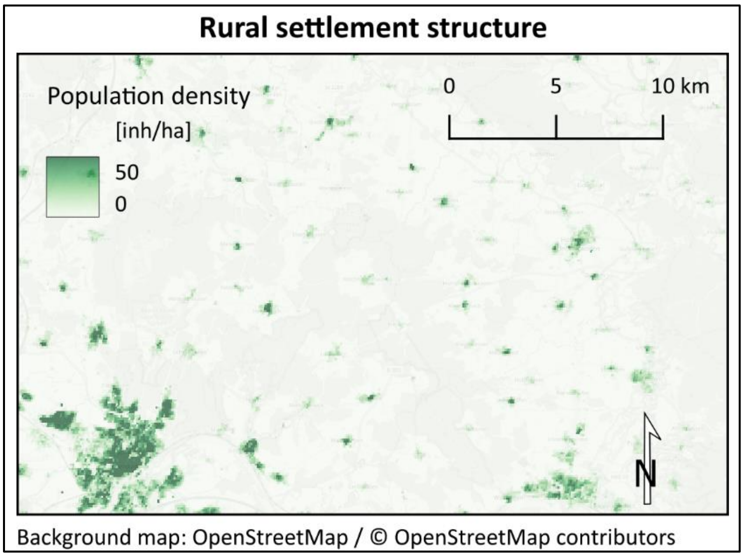


Figure 1: Population density in a typical rural region in Europe

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.

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 and 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 and 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 und 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 nontechnical 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 and 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.

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.

3.1 Reference region

The Main-Rhön-Region in Bavaria, Germany, was selected as the reference region (Figure 2). The region covers approximately 4,000 km^2 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 an der 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.

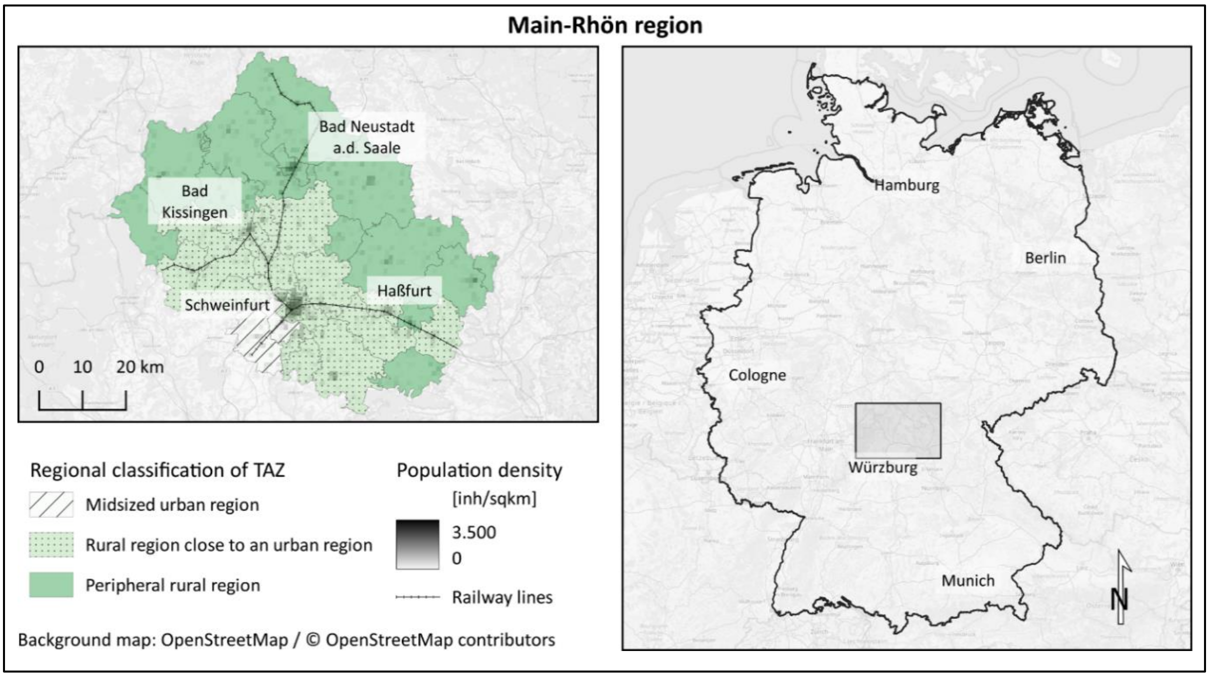


Figure 2: Location of reference region and regional classification

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 2 shows the classification of the region, from the midsized 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 2024).

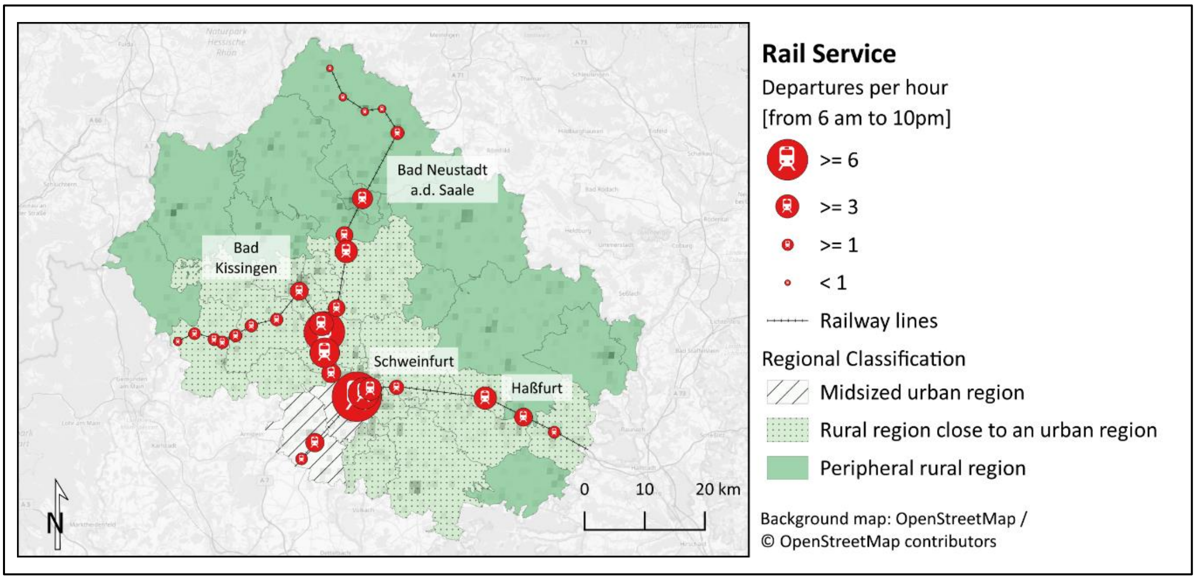


Figure 3: Railway service in the reference region (size of station symbol represents hourly departures during service times, from more than six in Schweinfurt main station to less than one in the periphery)

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 3).

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.

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 3. 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.

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 2), 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.

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.

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-MOdell), which is a calibrated and validated model (Winkler and 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, Axausen 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 2. 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.

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 4. 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.

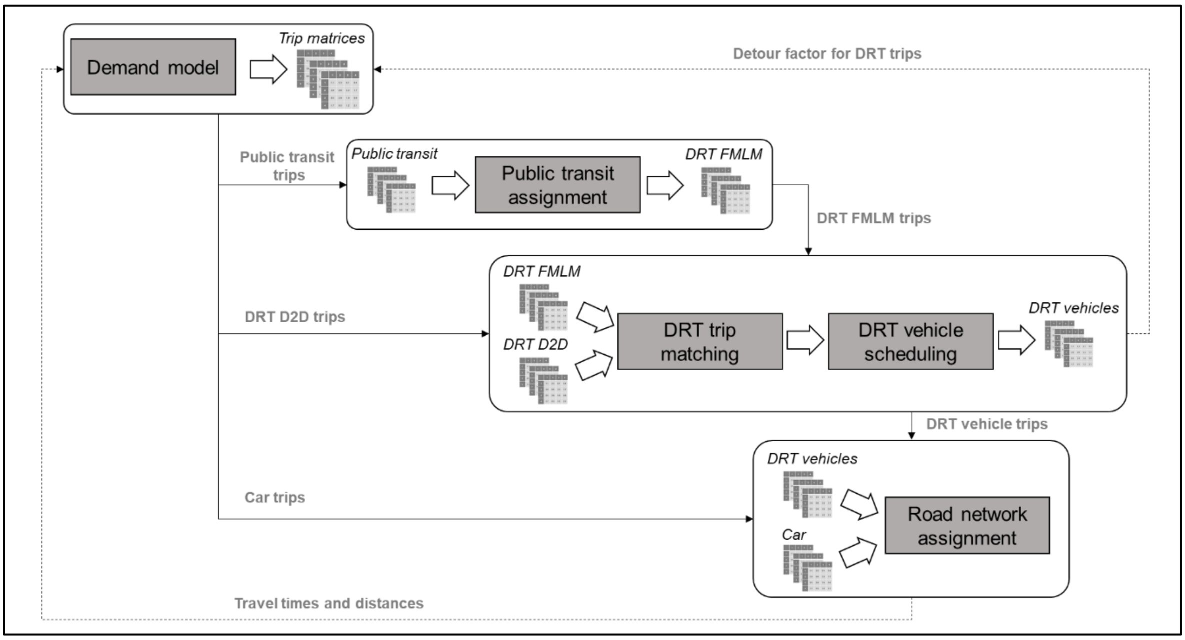


Figure 4: Schematic overview of the model processes

4.2.1 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. (1). 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 1. 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 3.3.

$$(1)\quad V_i = \sum_u \left(\beta_u x_{i,u} + \alpha_u \ln\left(x_{i,u} + \gamma_u\right)\right)$$

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

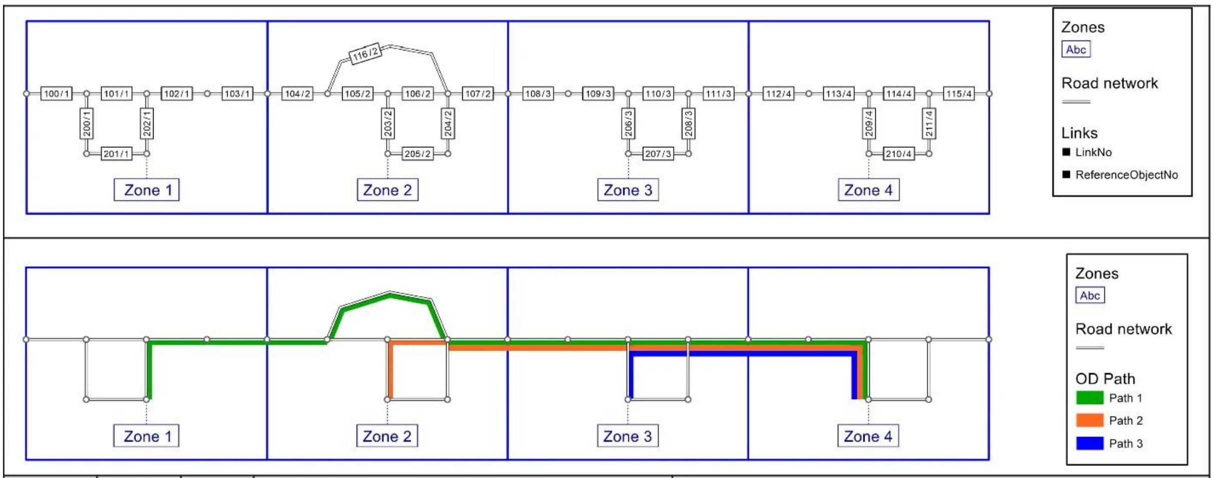
Table 1: Preference parameters for utility calculation in the mode choice model, based on Axhausen et al. (2015)

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.

4.2.2 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 5). 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.



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

Figure 5: 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.

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.

5.1 Impact on mobility and traffic flows

Table 2 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 6 (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 2: Travel demand within the region in the scenarios

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

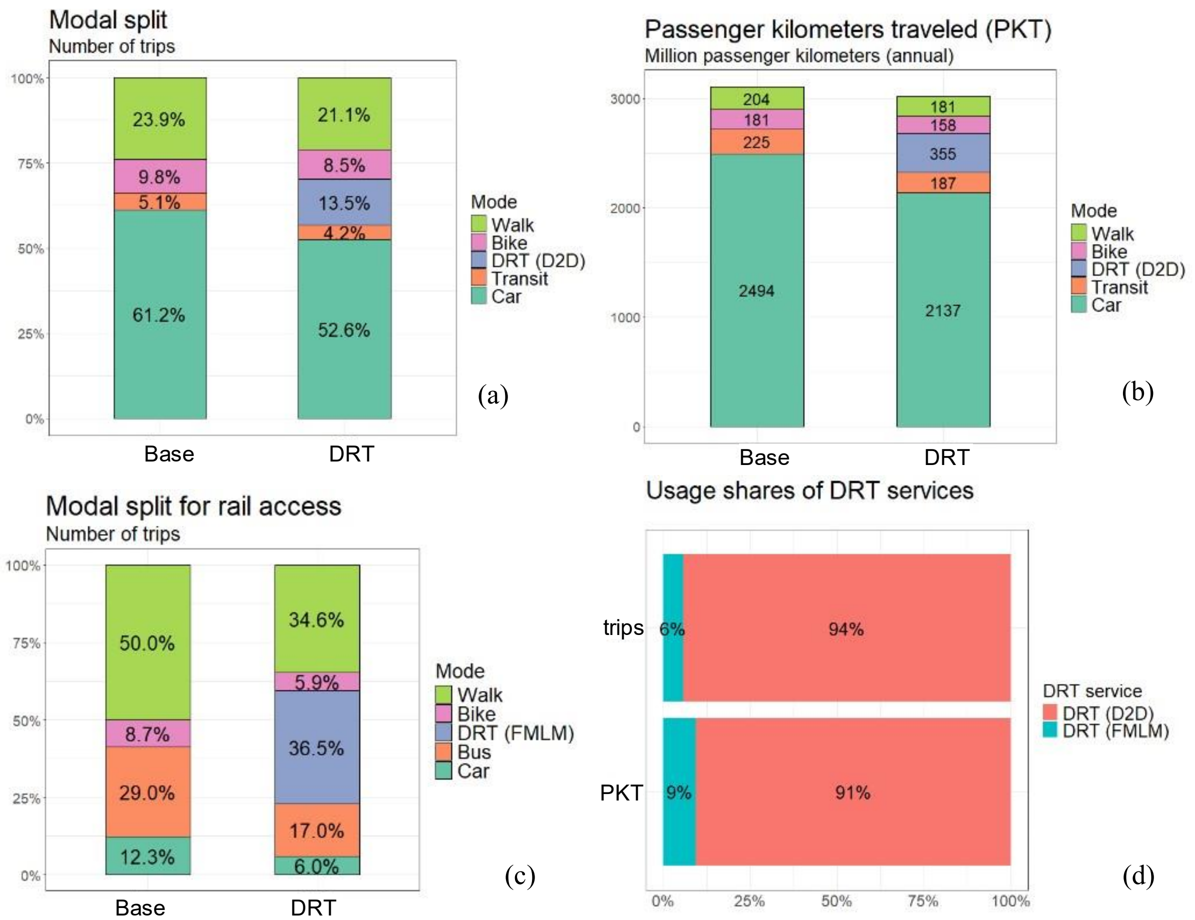


Figure 6: Results of the travel demand model for both scenarios (base and DRT scenario)

Vehicle kilometers in individual traffic decrease by 12% on an average working day (cf. Figure 6 (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 7.

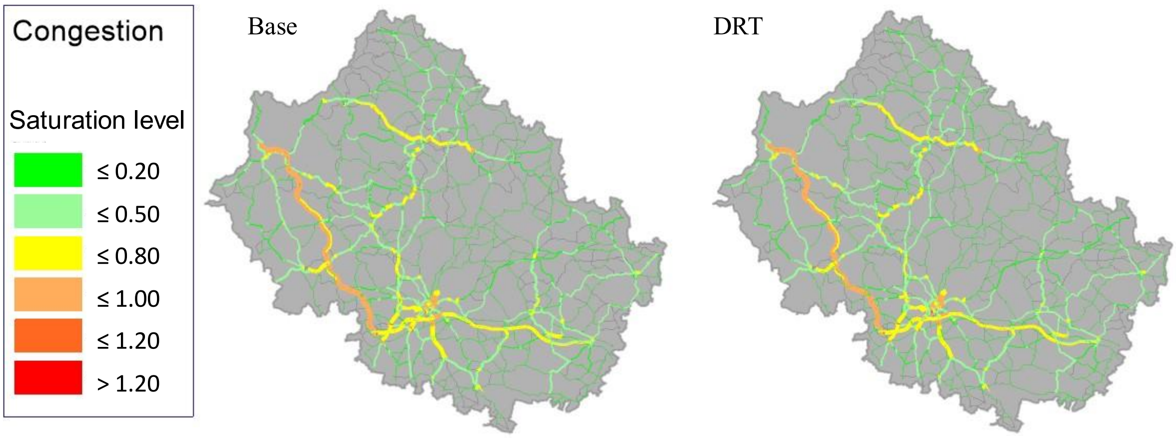


Figure 7: Saturation level of road network in both scenarios

5.2 Indicators of the DRT fleet

The matching and vehicle dispatching algorithms applied generate indicators for DRT operation as shown in Table 3. 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 [9], 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 3: Indicators for DRT operations

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

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%.

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 8, 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.

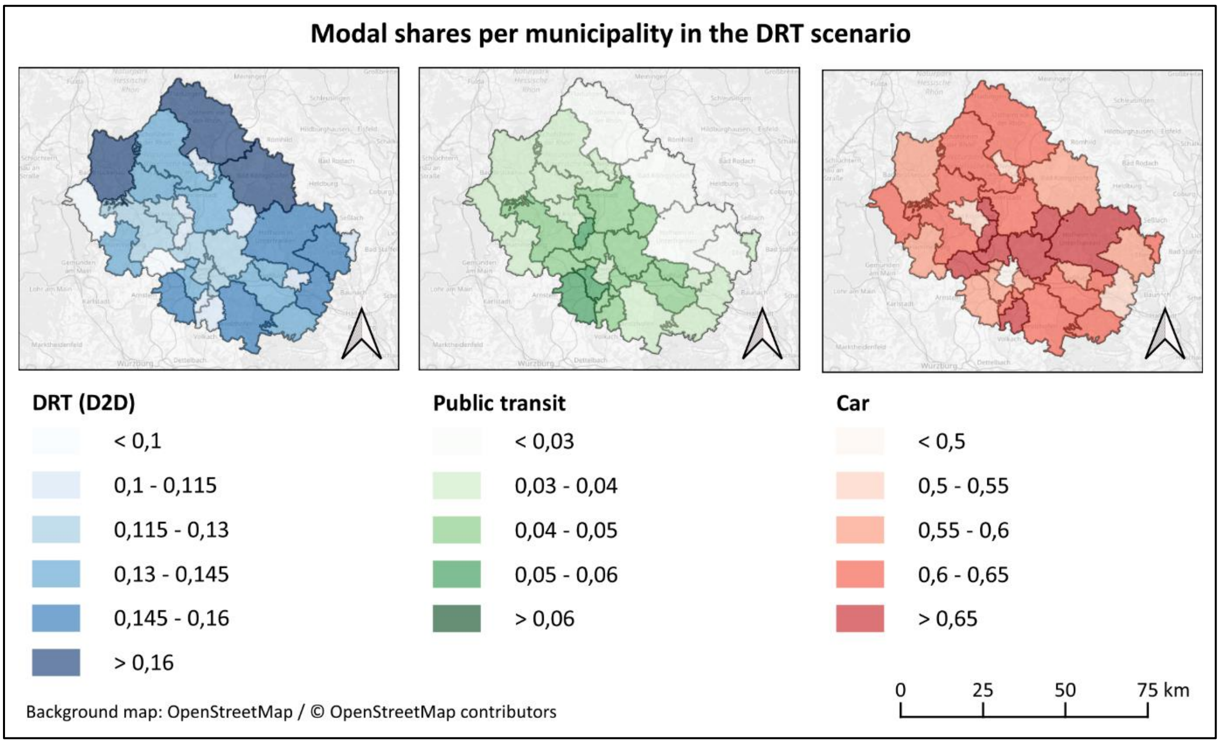


Figure 8: Modal shares for origin trips per municipality for DRT, public transit and car in the DRT scenario

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 9 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.

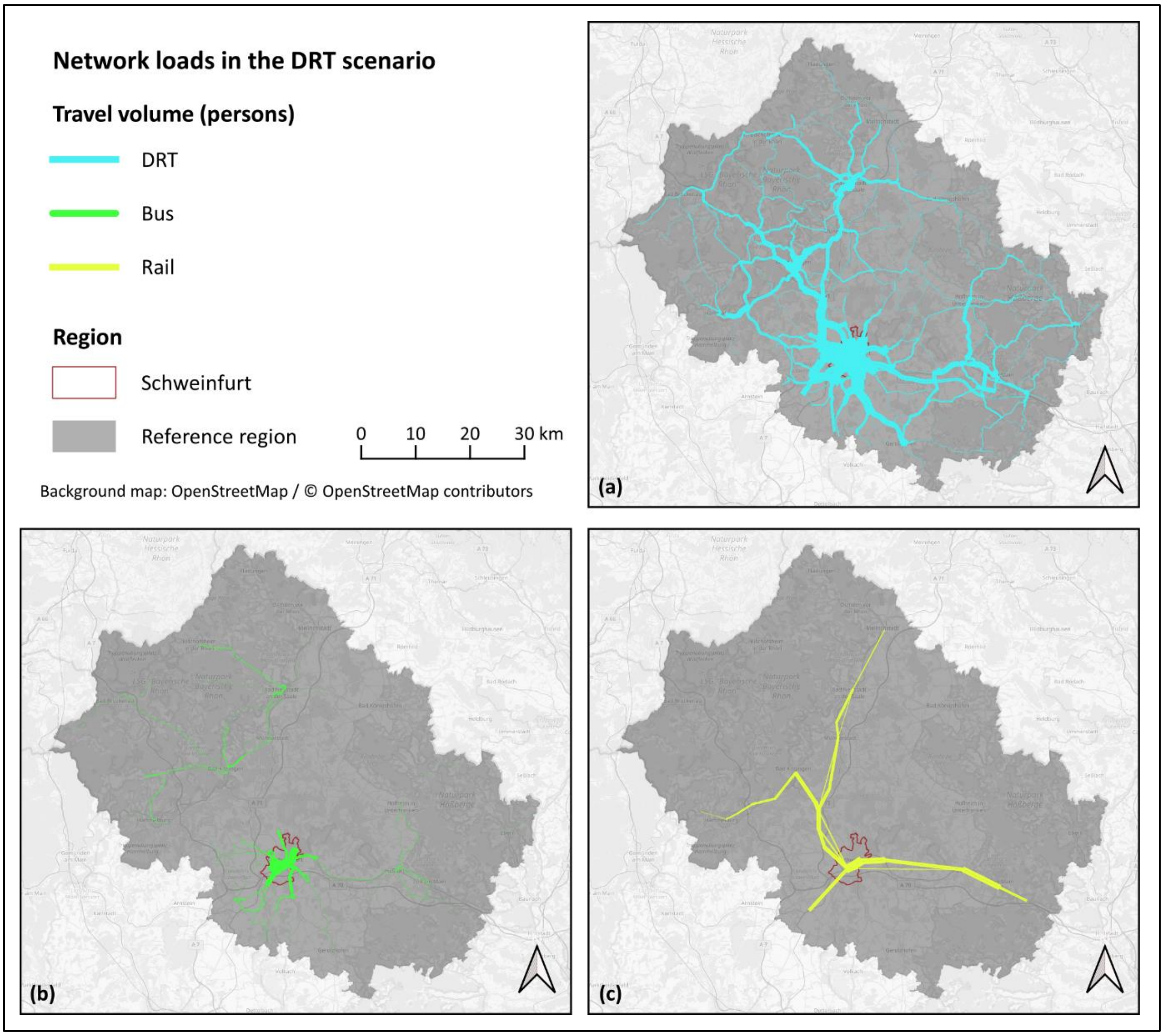


Figure 9: Person volumes on public transit routes and with DRT vehicles

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 10) shows that pooling rates are homogeneous and that there is pooling potential. Looking at all DRT trips (Figure 10 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 10 b) being significantly higher than for all DRT trips (Figure 10 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.

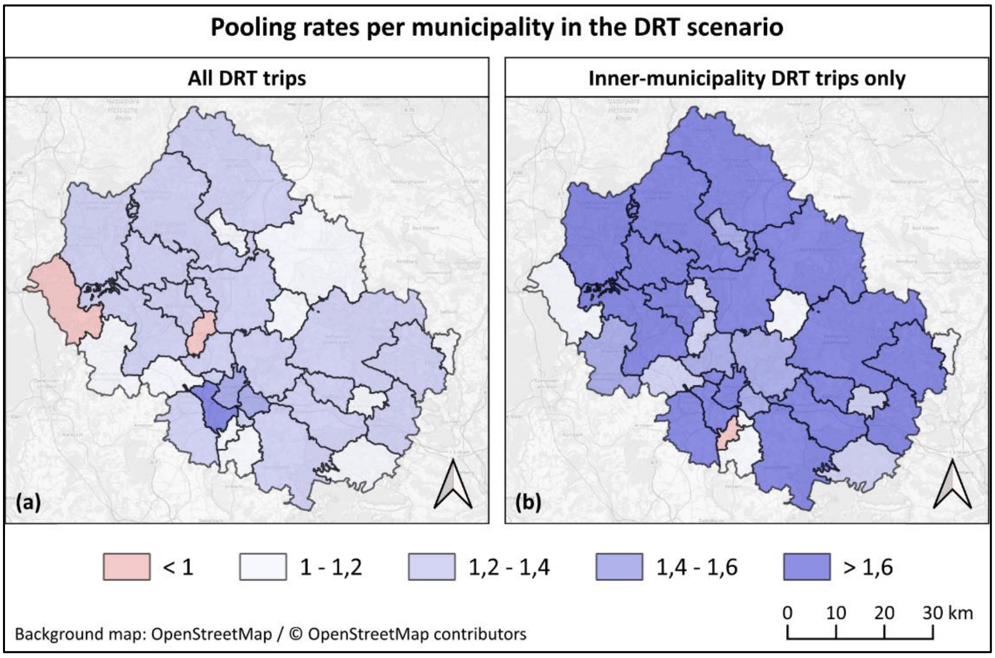


Figure 10: Pooling rates of DRT origin trips per municipality

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.

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.

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.

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