# Demand-Responsive Transport for Students in Rural Areas: A Case Study in Vulkaneifel, Germany

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**Abstract**

In rural areas with a low population density, demand-responsive transport (DRT) is considered a promising alternative to conventional public transport. With a fleet of smaller vehicles, DRT provides a much more flexible and convenient service. This characteristic makes the DRT also a potential mode of transport to serve the school children in rural areas. If the DRT vehicles are used to serve the school children, then the funding for conventional school buses (or adapted public transport schedules) can be reinvested in the DRT system. This may help to relieve the financial burden experienced by the DRT operators and enable the operation of a large-scale DRT service in rural areas. In this study, a demand model for school commutes based on real-world, open-source data for Landkreis Vulkaneifel, a rural region in Germany, is built. Then a feasibility study is carried out using an agent-based transport simulation. In the feasibility study, various setups and operational schemes are explored, which is followed by a systematic cost analysis. Results from the simulations show that an annual budget of 1617 Euro per student is sufficient to maintain and operate a fleet of DRT vehicles that can transport all the students in the region from home to school on time in the morning. During the remaining time of the day and on school holidays, the vehicles can be used for conventional DRT service for the public.

**Keywords:** Demand-responsive transport (DRT), School transport, Mobility service in rural area, Vehicle routing problem

## 1 Introduction

In rural areas, the population density is usually low. The operation of public transport service in such areas faces a dilemma between service quality and efficiency. Because of the low population density, long intervals and tortuous routes are necessary to ensure an acceptable occupancy of the vehicles. On the passenger side, however, this leads to long waiting time and extended traveling time on the public transport system, which discourages people from using public transport in the area and makes it even more difficult to justify a denser timetable or network. In the end, a vicious cycle as proposed by Bar-Yosef et al. (2013) will be formed, and most of the residents in the rural area will choose to use other modes of transport for their daily commutes when possible (Mohring, 1972).

In Germany, the public bus services in some rural areas are operated in conjunction with the local education authority (Zoellmer, 1991; Verband Deutscher Verkehrsunternehmen, n.d.). Some buses run on bus routes specially designed to serve the school commutes during the morning and evening. During the other time of the day, those buses operate on normal bus routes. As the vehicles are partially utilized by the students, the economic burden of the operation of the bus line during the day is relatively low because the funding from the local education authority covers part of the costs. Nevertheless, the overall service quality and the efficiency of the bus service are still not satisfying.

The demand-responsive transport (DRT) is an emerging mode of transport. DRT services of different types, such as taxi, ride-hailing service, and on-demand bus, are now commonly available in cities and places all over the world. Recently, a growing number of pilot projects on the experimental operation of DRT in rural or remote areas are also rolling out, such as the KelRide project in Kelheim, Germany (Bundesministerium für Digitales und Verkehr, 2021) and the on-demand mobility service in Rendsburg, Germany (Landesportal Schleswig-Holstein, 2021). In most of those experimental projects, however, the cost of the fleet and its maintenance significantly limits the scale of the DRT service. In the KelRide project, for example, only three vehicles will be put into service[1]. In fact, even in large cities, it is also

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[1] https://kelride.com/en/vehicles-utilized/

challenging to operate a large DRT fleet. In Berlin, BerlKönig, a DRT service operated by the Berlin public transport company (BVG), is experiencing financial difficulties, and its operation heavily relies on funding from the authority (Rundfunk Berlin-Brandenburg, 2020; Schwär and Kaleta, 2020).

As a result, transport authorities in some rural areas have begun considering merging the funding for school transport with the funding for DRT projects. Instead of purchasing buses, a fleet of smaller vehicles, such as minivans or cars, can be used to serve the school commutes in the morning and evening. During the rest of the day, those vehicles can be operated within a DRT service for the general public. The benefit of this novel combination is that smaller vehicles are more flexible, and they are more suitable for rural areas. Rather than operating on a fixed and thin schedule, the vehicles provide an on-demand service. Residents can simply request a ride during the operation hours from any places within the service area via a mobile phone app, online platform, or telephone call. This provides a good service quality while maintaining a relatively high utilization of vehicles and thus a higher cost efficiency. With a merged funding, the fleet size can be significantly larger, which means the DRT service will be more reliable and attractive. Evidently, such an approach would become particularly attractive if vehicles could be operated without drivers and thus without the cost of drivers, which is often about 80% of the operating costs (Hörl, Becker, et al., 2019).

In this study, we examine the feasibility of using a DRT fleet to serve the school commutes, which is the fundamental prerequisite for the novel idea mentioned above. First, the demand model of school commutes for the Landkreis Vulkaneifel, a rural area in Rhineland-Palatinate, Germany, is built based on open-source, real-world data. Next, we define a vehicle routing problem for school transport and solve it with two different approaches. Both approaches are assessed by simulating the operation of the DRT service in an agent-based traffic simulator. Various factors that may impact operational costs and performance are taken into account. Finally, a comprehensive cost analysis is performed to determine whether it is feasible to serve the school children in the region with a DRT service.

## 2 Literature Review

Operating a DRT service is a popular research topic, and various studies can be found in the literature. In the studies from Yang et al. (2000) and Anderson (2014), the operations of taxi, which is one of the most commonly available DRT services, are explored. In addition to the taxi service, the on-demand bus service is also a form of the DRT. For example, a scheduling algorithm of the on-demand bus is presented in the study from Tsubouchi et al. (2009). More recently, with the rise of the autonomous driving technology, there is more and more research focusing specifically on large-scale DRT systems. A hypothetical scenario of replacing all the private cars in Berlin with autonomous DRT vehicles is explored in the work from Bischoff and Maciejewski (2016). Similar studies with a large autonomous DRT fleet have also been carried out in Zurich (Hörl, Ruch, et al., 2019), Paris (Hörl, Balac, et al., 2019) and San Francisco (Ruch et al., 2018). Given a large fleet of vehicles, the operational strategy opens up new research topics. Alonso-Mora et al. (2017) proposes an online optimization approach to the operation of the autonomous mobility-on-demand system. This approach has demonstrated a superior performance in another study (Ruch et al., 2021), where multiple DRT dispatching strategies were compared. In addition to the dispatching strategies, also relocation of empty vehicles (i.e., fleet rebalancing) plays an important role, which has been proven in the study from Pavone et al. (2012). This topic was further explored by various studies (Ruch et al., 2020; Bischoff and Maciejewski, 2020; Lu et al., 2020), where various new rebalancing strategies have been proposed and evaluated.

Most of these studies were carried out in areas with a relatively high population density (mainly urban areas). If the DRT is to be operated in a rural area, longer waiting time is expected given a limited fleet size (Kaddoura et al., 2020). Nevertheless, previous studies from Kaddoura et al. (2021) and Lu et al. (2020) suggest that it is technically possible to provide a DRT service in rural areas with a relatively good service quality when an appropriate vehicle operational strategy is used. As the conventional public transport in rural areas is very limited, a DRT system with a good service quality may become a better alternative. For example, the possibility of replacing a train line operating in a rural area in Switzerland with an autonomous DRT system was investigated by Sieber et al. (2020). Moreover, given a good DRT service quality, not only the existing public transport users can benefit, as some residents who currently use other modes of transport, such as private cars, may also switch to DRT. The prerequisite for a good service quality, however, is an adequately large DRT fleet. For instance, in the study from Kaddoura et al. (2021), 914 vehicles are used in order to provide a satisfying service across the Vulkaneifel region. Such a large fleet can be a practical challenge for many transport authorities.

The transport service for the school children can be treated as a vehicle routing problem (VRP). There are multiple methods to solve the problems, and each approach has its strength and weakness (Park and Kim, 2010; Li and Fu, 2002). For small to medium size problems, integer linear programming may be used to solve for the exact solutions (Schittekat et al., 2006; Bektas and Elmastas, 2007). For larger and more complex problems, heuristic methods are more commonly used (Schittekat et al., 2013; Schrimpf et al., 2000). The methods mentioned above usually optimize the routes of the vehicles offline, and vehicles will simply follow the schedule during the day. Nevertheless, the service based on the offline optimization approach can still be considered as demand-responsive, as the routing of the vehicles is calculated based on the travel demands of the students. On the other hand, the school transport can also be viewed as a reactive DRT problem. With a reactive DRT fleet, the users can enjoy higher flexibility, as the vehicle routing problem is solved online. The rebalancing operation may still maintain the system with a certain level of efficiency. To the knowledge of the authors of this article, there are currently not many studies that tackle the school transport problem with the online DRT approach. In this study, we will include both the offline optimization approach and the online optimization approach to tackle the school transport problem in a realistic setup, and compare the results.

**Contributions:** In this study, two different DRT operational strategies, designed for school transport in rural areas, are implemented and integrated into an agent-based transport simulator (MATSim). A detailed case study based on the real-world demand model of school commutes in a rural area is performed with the newly implemented strategies. The results of this study provide insights on the replacement of traditional school bus service with DRT service.

# 3 Methodology

## 3.1 School transport model for Vulkaneifel

### 3.1.1 Generating a detailed agent-based school transport model based on open data

The Vulkaneifel county (Landkreis) is located in the Rhineland-Palatinate, Germany. The region is one of the least densely populated areas in Germany. There are several small cities and villages loosely scattered across the area. Due to its geographical characteristics, the public transport service is very limited.

The travel demand of the school commutes for the Vulkaneifel region is extracted from the open-source agent-based transport model for Landkreis Vulkaneifel and its surrounding area.[2] The transport model is constructed based on mobile phone and survey data (Neumann and Balmer, 2020). The model consists of agents who have at least one activity within the relevant region, among which 59,998 are residents of Landkreis Vulkaneifel. This makes a good representation of the Vulkaneifel population of 60.5 thousand (by the end of 2020) (Statistisches Landesamt Rheinland-Pfalz, 2021). The model includes 106,932 trips that are made on an average weekday by the residents. As the trips are generated from the mobile phone data, some short trips which cannot be properly identified are excluded (e.g., trips within the same mobile phone signal zone). As in many large-scale transport simulations, the detailed population input, consisting of personal attributes and daily plans, is created by sampling 25% of the population extracted from the original full model. This gives a good balance between the computational workload and the accuracy of the simulation. The spatial distribution of the modelled activities is shown in Figure 1.

In this study, we focus only on the school trips during the morning. This is because the morning and afternoon school trips are more or less similar. Besides that, the trips in the morning are more concentrated, and the time pressure is higher, as the students need to arrive at schools on time. If the school trips in the morning can be served properly, it is very likely that the trips in the afternoon can also be served. Therefore, it is reasonable to reduce the problem and focus only on the morning trips.

The modelled school trips are made by persons aged between 6 and 18. Because of the privacy protection laws, the open-source traffic model is aggregated into a grid (see figure 1). To increase the accuracy of the school trip model, we map the destination of the trips to the actual locations of schools, according to the age of the students and the educational activity types. In addition, the departure locations, which are mostly homes of the students, are diffused within their residential areas. In the end, a school trip model consisting of 928 morning school trips is created. The resulting school trips are illustrated in figure 2, where students travel from homes to schools (represented by yellow lines connecting red dots with green stars). Figure 2b is a zoomed-in view of the area within the white dotted rectangle in Figure 2a. It shows that the locations of students' homes are disaggregated from the grid and re-distributed within residential areas (marked with orange).

[2] https://github.com/matsim-scenarios/matsim-vulkaneifel

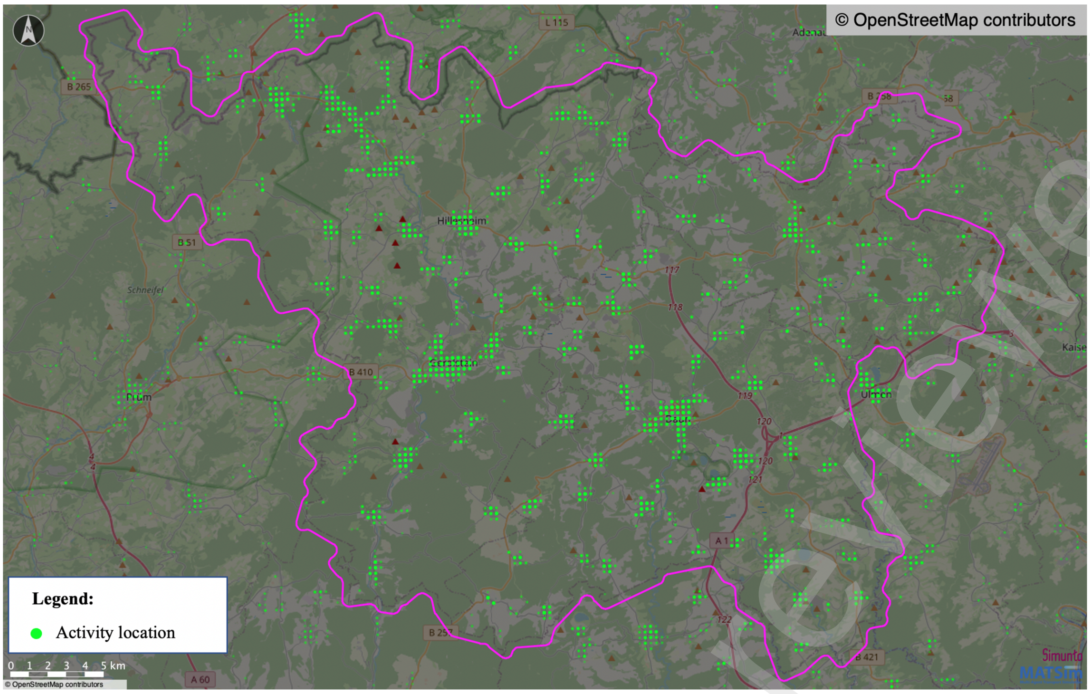



Figure 1: Illustration of the open-source agent-based transport model data based on cell phone data

### 3.1.2 Generation and validation of the network

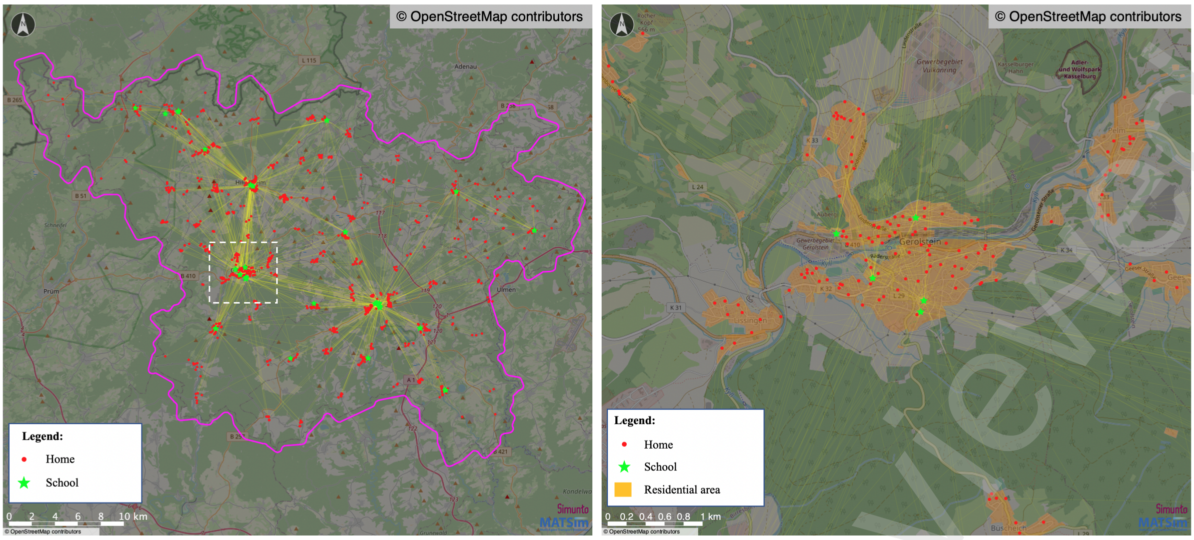
The road network for the study area is generated from Open Street Map (OSM) and calibrated using online map/routing services. The network for the Vulkaneifel region is cut out from the OSM network data available on GeoFabrik[3]. The free speeds of the road segments are then adjusted based on multiple factors. When the speed limit for a road segment is available, the free speed is defined as 0.9 of the speed limit. If the speed limit is not available, then the free speed is determined based on the road type and the land use data around the road. If the road segment is located in an urban area (i.e., the land use type equals "residential", "commercial", "retail" or "industrial"), the free speed is further reduced to accommodate for the effect of the general speed limit within the city (e.g., 50 km/h in Germany) and the traffic signals. Finally, the estimated free speeds are validated and calibrated against the travel time data from the Google Maps API[4] and HERE Routing API[5]. In the calibration process, for randomly selected trips, we compare their duration computed in the created network with the duration obtained from the external APIs. Calibration consists in adjusting the network free-flow speeds to match the travel time obtained from the online APIs. The validation plots of the calibrated network are shown in figure 3, where each data point corresponds to one trip. The x-axis value is the obtained travel time, and the y-axis value is the calculated travel time. Both figures show that the data points are closely distributed around the target line ($y = x$), which indicates the network is well calibrated. The resulting network is illustrated in figure 4, where the free speeds of the roads are indicated by different colors.

### 3.1.3 Adapting the school transport model to the agent-based transport simulation framework

We use the Multi-Agent Transport Simulation (MATSim) as the simulation platform in this study. MATSim is an open-source framework[6] for large-scale agent-based transport simulations (Horni et al., 2016). It is capable of simulating very large networks and populations while maintaining a relatively high level of detail. MATSim also offers several extensions which enhance its functionality with additional features. One of them, the Demand-Responsive Transport (DRT) extension, enables the simulation of ride-sharing services, including the investigated problem of school transport.

In MATSim, agents perform activities during the simulated time horizon, which is usually a day, based on their plans. If two consecutive activities happen at different places, then a trip is needed to connect the two activities. The departure time of the trip is the end time of the former activity.

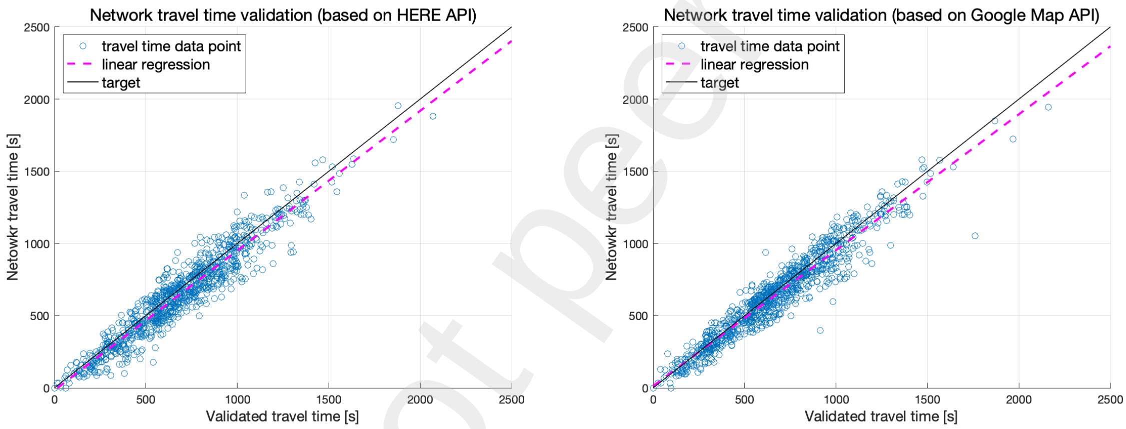
[3] http://download.geofabrik.de/
[4] https://developers.google.com/maps
[5] https://developer.here.com/
[6] https://matsim.org/




(a) Pre-processed school trips in the morning

(b) A closer look at the trips: home locations are re-distributed in the residential areas and school locations are updated based on actual coordinates of schools

Figure 2: School trips in the morning




(a) Validation based on HERE API

(b) Validation based on Google Map API

Figure 3: Travel time validation against data obtained from public routing APIs

To transform the school transport model into the MATSim input plans, we map the coordinate of the trip origin and destination to the closest link in the network. The original open data contains the trip departure time and transport modes. In this study, however, we explore the potential of serving all school trips with a DRT service. Therefore, we switch all the transport modes for the school trips to DRT, and accordingly, we adjust the original departure time by subtracting the maximum allowed DRT trip duration from the time the school starts. The maximum allowed DRT trip duration, $t_{max}$ is defined as a linear function of the direct car trip duration $t_{direct}$, i.e.,

$$t_{max} = \alpha \cdot t_{direct} + \beta, \tag{1}$$

where $\alpha \geq 1$ and $\beta \geq 0$ are used to add a time buffer due to potential waiting or detours. In this study, we use $\alpha = 2$ and $\beta = 1200$ s as the base values. For example, if it takes 10 minutes to travel from home to school in a private car, then the student can be picked up at most 40 minutes before school starts. Given the school starts at 8:00 am, the earliest departure time is 7:20 am, which is the time the student is ready to leave home, while the actual pickup usually occurs later.

## 3.2 Optimization of DRT vehicle routes

The school trips are served by a fleet of 8-seat minivan vehicles, initially located at depots. The vehicles perform a sequence of tasks such as picking up and dropping off students, driving, and waiting. The goal

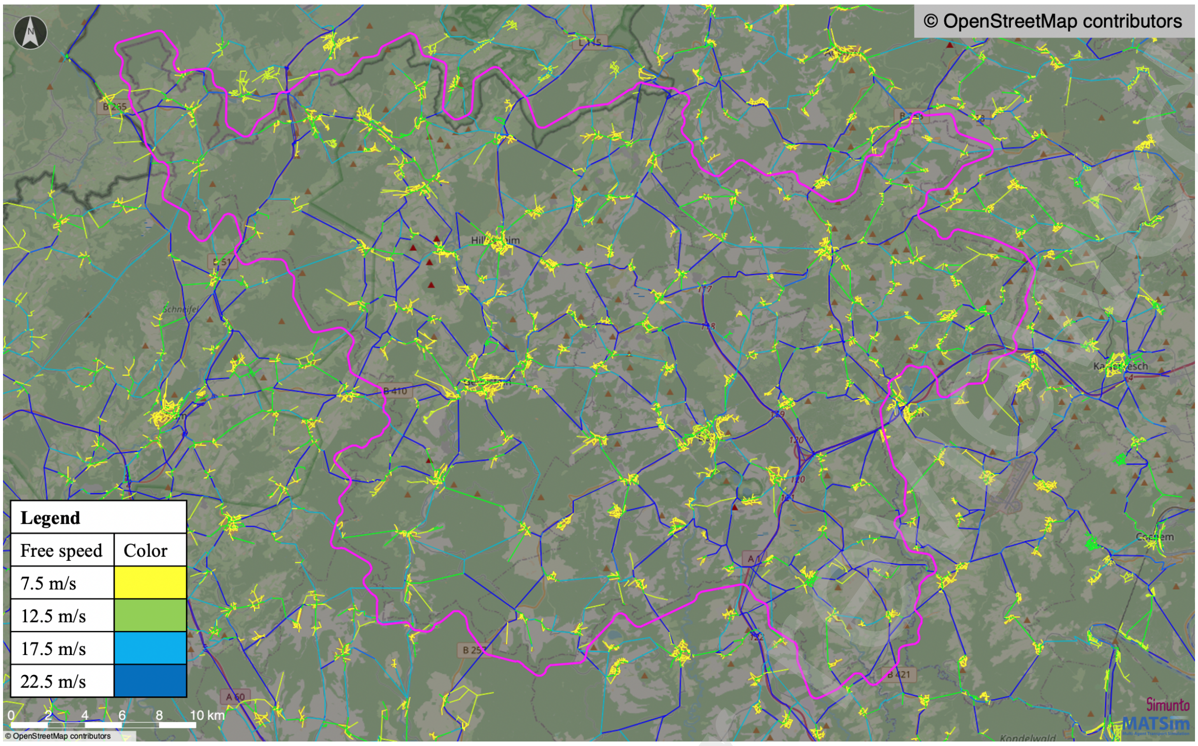



Figure 4: Modelled road network: the free speeds of road segments are indicated by the color

is to find minimum cost routes that serve all the school children without violating the time and capacity constraints. The students should be picked up not earlier than the earliest departure time, and they should arrive at the school before it starts. If the request cannot be scheduled without violating any of the constraints, it gets rejected. In addition, the vehicles should never be overloaded. In this study, we investigate and compare two approaches: online (real-time, no pre-booking) and offline (next-day) optimization. By comparing both approaches, we want to assess the potential behind adding a support for trip pre-booking to the DRT extension.

### 3.2.1 Online optimization

In the online optimization case, school trips are submitted as immediate requests at the moment of the earliest departure time (i.e., no pre-booking occurs), and the optimization algorithm dispatches vehicles without any knowledge of the future requests. The actual dispatch decisions are based on an insertion heuristic, where for each new incoming request all feasible insertion points are assessed and the minimum cost one is chosen. A detailed mathematical formulation of the problem and the insertion heuristic can be found in Bischoff et al., 2017.

The insertion heuristic has proved to provide meaningful and efficient solutions reasonably fast. However, the reactive dispatching without knowing the upcoming requests may lead to some myopic decisions. To improve its performance, we enable fleet rebalancing so that idle vehicles are periodically relocated towards areas where the near-future requests are expected to occur (Pavone et al., 2012; Bischoff and Maciejewski, 2020). For the present investigation, a simple rebalancing strategy is used where vehicles are sent to the areas where school trips originate. To achieve this, we partition the network into small squares (1 km × 1 km) and discretize time into 15-minute bins. Whenever a DRT request is expected to be submitted for a given zone and time bin, one vehicle is sent to this region shortly before the start of that time bin. Because of the relatively high sharing rates of school trips, this simple rebalancing strategy outperforms many of the more advanced rebalancing strategies implemented in the MATSim DRT extension (Lu et al., 2020). Because school trips are highly repeatable daily routines, the assumption that we know the expected aggregated travel demand of school trips is reasonable.

### 3.2.2 Offline optimization

Since school trips are highly repetitive, we can assume that we know all the demand and pre-calculate the vehicle routes offline before the day starts and then execute them the next day morning. In this case, we can model the offline optimization problem as the Capacitated Vehicle Routing Problem with Pickups and Deliveries and Time Windows (CVRPPDTW). There are many available solvers that support this problem. In this study, we use jsprit[7], an open-source vehicle routing problem solver. This specific solver uses the Ruin and Recreate meta-heuristics proposed by Schrimpf et al. (2000) that belongs to the family of adaptive large-neighborhood search methods. Like the insertion algorithm, jsprit respects the capacity and time window constraints.

The offline optimization procedure is run before the day starts, and it takes all school trips as the input data. Knowing all the requests a priori is advantageous, however, the computation time is significantly higher compared to the insertion heuristics. The computed routes are then converted to DRT vehicle schedules and simulated inside MATSim. As a result, for both online and offline optimization, we obtain the same set of output data. The offline method is not part of MATSim, the both-way translation between MATSim and jsprit is one of the contributions of this study, and it is available online[8].

# 4 Results and Analysis

## 4.1 The base case

In the base case, we assume the default parameter values for calculating the maximum allowed travel time (see equation 1, where $\alpha = 2$ and $\beta = 1200$). We also assume that all schools in the area start at 8:00 am, and the DRT service operates in door-to-door mode. Since the resolution of MATSim traffic simulation is limited to whole road segments (network links), the students will be picked up/dropped off at the DRT-accessible road segment that is closest to their origin/destination.

Because the DRT fleet serves school trips, arriving on time is one of the most important criteria to consider. Meanwhile, a smaller fleet is desirable, as vehicles and drivers are the main cost component of the service and are of utmost importance when accessing its feasibility. In this study, we run a sequence of simulations with different fleet sizes to determine the minimum fleet size required for transporting all the students to schools on time. Additional qualitative analysis, such as average travel time and total fleet travel distance, is performed for the identified minimum fleet size. We also determine the minimum required fleet size to reach a service rate of 95%. This serves as an additional reference for the DRT operator. It is comparable to the 95-percentile values commonly used in the analysis of DRT service quality (e.g., 95-percentile waiting time). By excluding the extreme values, the comparison between different setups can become more reliable.

In the experiments, we vary fleet size from 30 to 200 with increments of 5 vehicles. At the start of the day, the vehicles are located in the following four major towns of the region, namely Daun, Gerolstein, Hillesheim and Kelberg. A large parking lot in each town is chosen as the exact location of the depot. The vehicles are evenly distributed across the depots before the service starts.

The simulation results obtained for online and offline approaches are summarized in figure 5a. In the base case, when all the students need to arrive at school on time, the minimum fleet size of 135 vehicles is required when using the offline optimization, and only 85 for the offline optimization. When the service rate of 95% is used as the criterion (indicated by the red horizontal lines in the figure 5a), then the fleet size can be reduced to 130 vehicles and 75 vehicles, respectively.

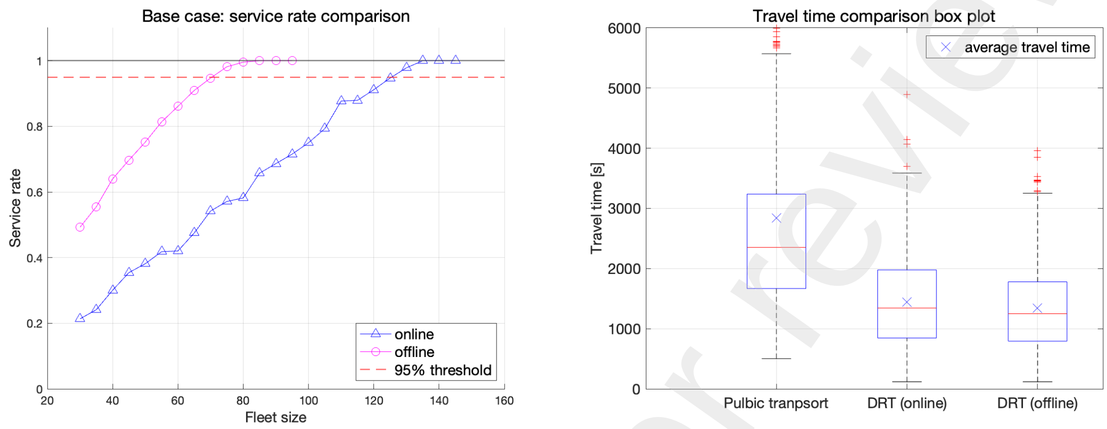
In addition to the reduced fleet size, the offline approach also provides another advantage over the online one: the pickup time is fixed in the former one, whereas in the latter one they are subject to change as new requests are inserted into the existing schedules, potentially delaying subsequent pickups. That means the students need to be ready to be picked up at the initially scheduled time, but they may need to wait for some time until they are actually picked up. In this study, we provide a relatively large time window for pickup, such that the DRT fleet can be well utilized. On average, when a fleet of 135 vehicles is operated with the online approach, a student needs to wait for 102 seconds before he/she is actually picked up. In contrast, in the offline approach, the students will be picked up at the scheduled time and no extra waiting occurs.

As mentioned in the introduction, the public transport systems in many rural areas in Germany are adapted to the school commutes in the morning and afternoon. To quantify the benefit of serving the school trips with DRT, we carry out a comparison between DRT service and conventional public transport in Vulkaneifel. Of the 928 students to be served by DRT, 628 students can use the conventional public transport service. The remaining 300 students cannot find a suitable public transport connection (e.g., no bus stop near the home location, no suitable connection during the morning). If those 628 students, who can use public transport, all choose to use public transport, they will spend on average 2839 seconds on their journey. In comparison, if they choose to travel with DRT, the average travel time can be reduced to 1444 seconds (online approach) or 1346 seconds (offline approach). That is, the DRT approach reduces the average travel time compared to PT from about 45 to about 25 minutes, and the offline approach is

[7] https://jsprit.github.io/index.html
[8] https://github.com/matsim-scenarios/matsim-vulkaneifel/tree/master/src/main/java/drtSchoolTransportStudy

able to deliver this service quality with considerably fewer vehicles. At the same time, the DRT provides service for a considerable number of students where a public transport connection currently does not exist. In practice, such students are either delivered by their parents to a suitable bus stop or to the school, or the community pays for a taxi service.

The travel time statistics for those 628 students who can take conventional public transport are then analyzed. The comparison of the travel time distribution of the 628 students is summarized in the box plot in figure 5b. The whisker length of 1.5 of the interquartile range is used. The boxes indicate the upper and lower quartile values in each setup, and the red horizontal lines correspond to the median values. Outliers are indicted by red crossing marks. The average values for each setup are also included in the box plot, which are indicated by the blue crossing marks.




(a) Comparison of service rate under various fleet sizes between online and offline approach

(b) Travel time comparison between public transport and DRT service

Figure 5: Base case results

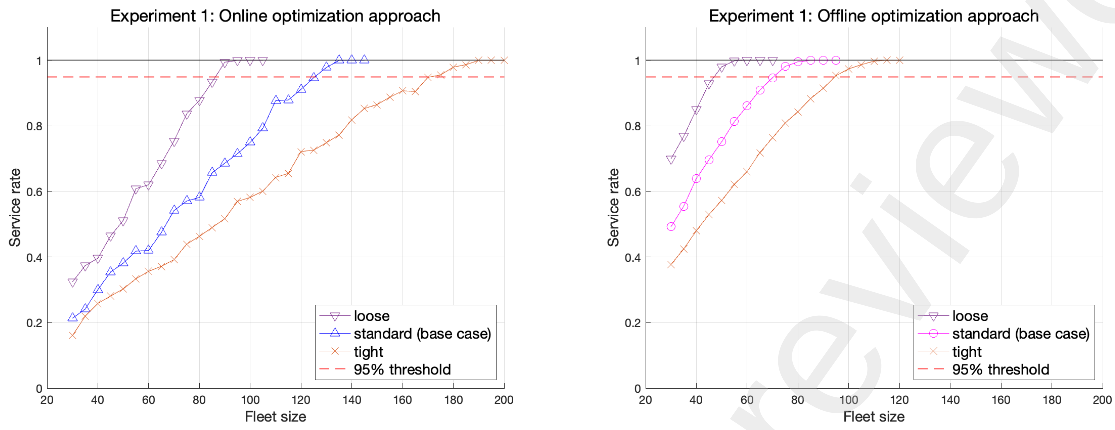
Finally, it is also worth comparing the DRT to private cars. As the DRT in this scenario is a ride-pooling service, the average in-vehicle travel time is inevitably longer than private car trips. On average, students spend 1348 seconds (online approach) or 1248 seconds (offline approach) in the DRT vehicles. Note that these values are based on all the 928 students. If all students choose to travel in private cars, then the average in-vehicle travel time will be 670 seconds. That means around 10 minutes of extra in-vehicle travel time should be expected when switching from private cars to DRT. On the other hand, the pooling service increases the vehicle utilization rate and the total fleet distance is significantly shorter than in the case where private vehicles are used. If all students switch from private cars to DRT, then a distance saving of 40% (online approach) or 59% (offline approach) can be achieved. That corresponds to 14400 or 21600 vehicle kilometers saved every morning (in the 100% scenario), which can have a substantial positive impact on the environment and the traffic network.

## 4.2 Factors that may impact the fleet size and operational costs

In addition to the DRT operational strategy, there are other factors that may impact the fleet size required for a satisfying service quality and operational costs. This part of the study explores the impact of three different factors of the DRT operational scheme: the maximum travel time, the school start time, and switching from the door-to-door mode to a stop-based service. To quantify the impact of each factor independently, we modify only one parameter in each experiment. We deliberately avoid performing an exhaustive set of experiments on combinations of different parameters and setups, through which the minimum operational cost can be identified. This is because of two reasons: firstly, that requires a lot of simulations (for each parameter combination, we need to run multiple simulations for different fleet sizes); secondly, detailed parametric tuning only makes sense for very accurate and detailed data (e.g., the exact cost of the vehicles, the exact number of students to serve, laws, and regulations), which we do not have. Instead, we focus on providing general insights into how operational costs can be influenced by different DRT operational setups.

### 4.2.1 Experiment 1: maximum travel time

In this experiment, we study the impact of the maximum allowed travel time. We quantify the minimum required fleet size when students allocate different amounts of time for school trips. By modifying the value of $\alpha$ and $\beta$ in equation 1, we investigate three different levels of this time constraint, namely "tight"($\alpha = 1.5$, $\beta = 900$), "standard" ($\alpha = 2$, $\beta = 1200$) and "loose" ($\alpha = 3$, $\beta = 1800$). In the "tight" setup, students allocate shorter travel time for their school trip, which means that they can leave home later, which adds more pressure to the system. On the other hand, in the "loose" case, students accept longer travel time, which means earlier departures, but smaller peak in demand. The "standard" case is equal to the base case. The results for both online and offline approaches are shown in figure 6.




(a) Online optimization

(b) Offline optimization

Figure 6: Impact of maximum travel time

As expected, the higher the maximum time, the fewer vehicles are required to provide a good service quality. To quantify the impact on the DRT system, we summarize the key results in table 1. In the minimum fleet size column, there are two values in each data entry. The first value corresponds to the minimum required fleet to reach 100% service rate. The second value (in the brackets) refers to the number of vehicles needed such that at least 95% of the students can be served and transported to school on time.

| | Minimum fleet size | Total fleet distance [km] | Mean travel time [s] |
|---|---|---|---|
| Online optimization | | | |
| Tight ($\alpha = 1.5$, $\beta = 900$) | 190 (175) | 5782 | 1114 |
| Standard ($\alpha = 2$, $\beta = 1200$) | 135 (130) | 5489 | 1348 |
| Loose ($\alpha = 3$, $\beta = 1800$) | 95 (90) | 5390 | 1747 |
| Offline optimization | | | |
| Tight ($\alpha = 1.5$, $\beta = 900$) | 115 (95) | 4320 | 1157 |
| Standard ($\alpha = 2$, $\beta = 1200$) | 85 (75) | 3772 | 1248 |
| Loose ($\alpha = 3$, $\beta = 1800$) | 60 (50) | 3587 | 1363 |

Table 1: Summary of the experiment 1

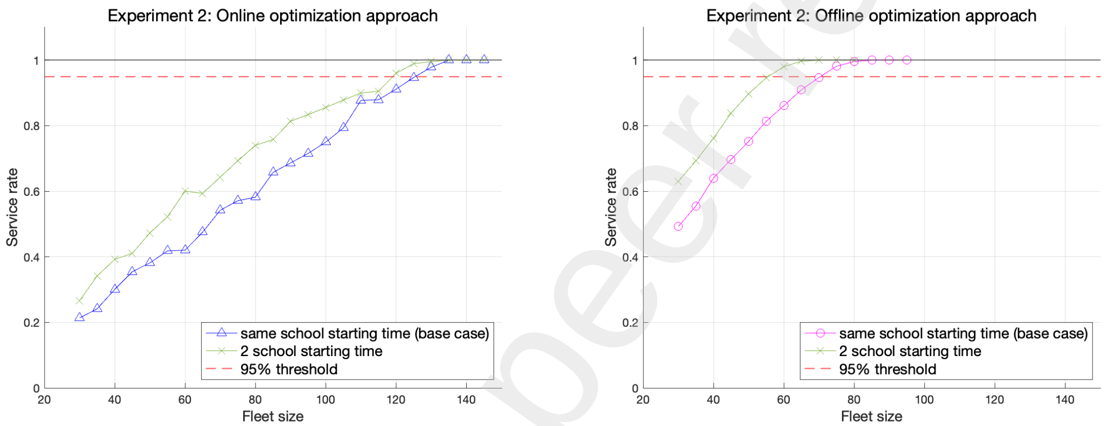
#### 4.2.2 Experiment 2: varying school start time

In the Vulkaneifel region, schools have different starting time. Some schools start at 7:30 am, while the others start at 8:00 am. By doing so, some buses may carry students multiple times in the morning and therefore fewer buses are needed. In this experiment, we also split the schools in the region into two groups with different school starting time, which are 30 minutes apart from each other (i.e., 7:30 am and 8:00 am). For simplicity, we divide the schools in the region based on their geographical locations. A division line is drawn on the map where there are similar numbers of schools on both sides. The schools in the eastern half of the Vulkaneifel region start at 7:30 am, and the schools in the western half of the region start at 8:00 am. Students allocate a standard amount of time for travel (as defined in section 4.1), however, since the starting time of school for some students is now earlier, they need to adjust their earliest departure time.

The simulation results of the setup with two school start time and the comparison to the base case are shown in figure 7. The key data is summarized in table 2. Same as in table 1, the value in the bracket refers to the number of vehicles needed such that at least 95% of the students can be served and transported to school on time. According to the results, offline optimization benefits more from varying the school start time. The minimum fleet required to serve all students on time is reduced from 85 to 70, which suggests a substantial reduction in the cost of the DRT fleet. For online optimization, on the other hand, the reduction in the minimum fleet size is not so significant. With both approaches, a noticeable increase in the total fleet distance can be observed when the schools in the region adopt two different start time. This is to some extent expected, as some vehicles need to perform additional tours and extra travel distance between the tours needs to be covered.

| | Minimum fleet size | Total fleet distance [km] | Mean travel time [s] |
|---|---|---|---|
| Online optimization | | | |
| Single starting time | 135 (130) | 5489 | 1348 |
| Two starting time | 135 (120) | 6504 | 1347 |
| Offline optimization | | | |
| Single starting time | 85 (75) | 3772 | 1248 |
| Two starting time | 70 (60) | 4465 | 1207 |

Table 2: Summary of the experiment 2




(a) Online optimization

(b) Offline optimization

Figure 7: Impact of different school starting time

#### 4.2.3 Experiment 3: door-to-door vs stop-based

Another way to improve the efficiency of the DRT system is to introduce DRT stops or meeting points. In the literature, there are various studies demonstrating the advantage of utilizing DRT stops, such as Stiglic et al., 2015 and Aissat and Oulamara, 2014. In most of those studies, the focus is mainly given to route optimization and the reduction of operational costs, rather than the on-time arrival of passengers. In this experiment, we explore and quantify the benefits of introducing DRT stops.

To perform this experiment, DRT stops need to be created for the whole region. Since the public transport network in the Vulkaneifel is very sparse, it does not constitute a good base for generating DRT stops, so instead, we use a simple algorithm to generate them. Let $H$ be a set of home locations for all students, and $S$ be a set of all potential stop locations. We want to compute a set of selected stop locations, $D$. For each home location, $h \in H$, and potential stop location, $s \in S$, we specify the walking distance, $d_{hs}$. We consider a given home location covered if there is at least one selected DRT stop within the maximum walking radius, $l_{max}$. In order to select good stop locations that may cover possibly many home locations, for each potential stop location, $s \in S$, we define its significance (weight), $f(s)$, which is calculated based on Equations 2 and 3 given the set of currently uncovered home locations, $U$.

The algorithm for generating DRT stops (Algorithm 1) work in the following way: at the beginning, all home locations are uncovered ($H = U$) and no stop is selected ($D = \emptyset$). The algorithm iteratively finds a new best stop location, $s^*$, and adds it to $D$. By doing so, all home location covered by $s^*$, $H(s^*)$ are removed from $U$. The algorithm stops when all home locations are covered, i.e. $U = \emptyset$.

In addition to the DRT stops that cover the home locations, we also generate one stop for each school location. In this experiment, we set the maximum walking distance $l_{max}$ to 500 meters. By running the DRT stop generation process with this setup, we obtain 199 stops distributed across the region.

$$f(s) = \sum_{h \in U} \sigma_{hs}, \qquad \forall s \in S \setminus D \tag{2}$$

$$\sigma_{hs} = \begin{cases} 2 - (d_{hs}/l_{max})^2, & \text{if } d_{hs} \leq l_{max} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

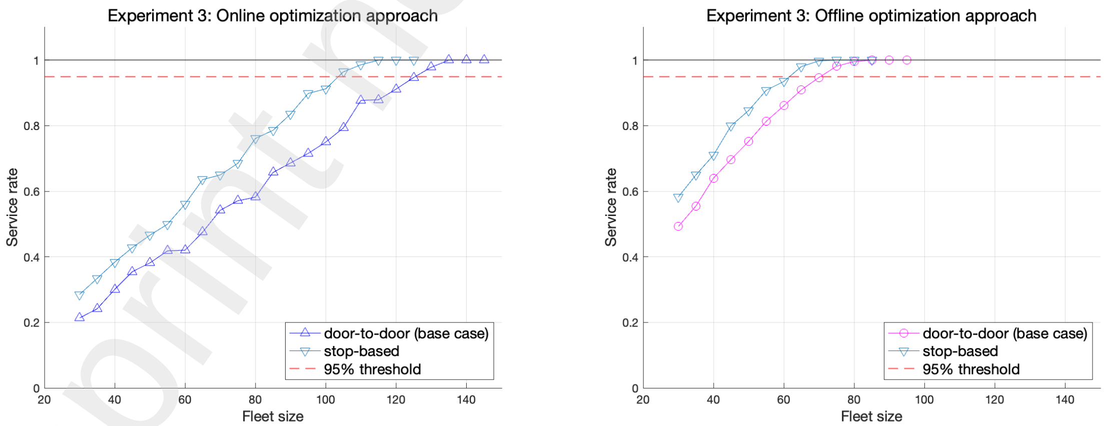
**Algorithm 1:** Generation of DRT stops

**Data:** Home locations of all students $H$, potential locations for DRT stops $S$
**Result:** DRT stop locations $D$
**Initialization:** $D \leftarrow \emptyset$, $U \leftarrow H$;
**while** $U \neq \emptyset$ **do**
  $s^* \leftarrow \underset{s \in S \setminus D}{\operatorname{argmax}} f(s)$;
  $D \leftarrow D \cup \{s^*\}$;
  $U \leftarrow U \setminus \{h | h \in U \land d_{hs^*} \leq l_{max}\}$;
**end**

After DRT stops are introduced to the system, we need to adjust the time students leave their homes. Firstly, the maximum travel time is calculated according to (1), but this time the direct travel duration (i.e., $t_{direct}$) is now calculated from the stop location. Secondly, we need to include the walk time from home to the stop location into the calculated earliest departure time (i.e. the time when a student leaves home).

The results of the stop-based DRT service and the comparison to the door-to-door service are shown in figure 8 and the key output values are summarized in table 3. Same as in table 1, the values in brackets refer to the number of vehicles needed such that at least 95% of the students are served. It needs to be pointed out that the travel time for the stop-based service consists of two parts: walking time and in-vehicle travel time. Therefore, in table 3, we express the average travel time of the stop-based service in the format of "in-vehicle travel time + walking time". In this experiment, the average walking time for the stop-based service is 251 seconds, regardless of which DRT optimization approach is used.

From the results, it can be observed that implementing a stop-based DRT service can also reduce the required fleet size. Furthermore, the total fleet distance and the average in-vehicle travel time are reduced when DRT stops are introduced. Apparently, this is because vehicles make fewer detours when several passengers gather at the same boarding location. With savings in both fleet size and total fleet distance, the introduction of DRT stops is another potential way to reduce operational costs.




(a) Online optimization (b) Offline optimization

Figure 8: Comparison between door-to-door service and stop-based service

On the other hand, we also need to be cautious when interpreting the results of this experiment. If we compare the average total travel time of the students between the stop-based service and the door-to-door service (i.e., base case), we can observe that students actually spend more time on the journey with the stop-based service (with walking time included). That means students need to depart from home earlier. In experiment 1, we have demonstrated that if students can depart earlier (i.e., the loose case),

| | Minimum fleet size | Total fleet distance [km] | Mean travel time [s] |
|---|---|---|---|
| Online optimization | | | |
| Door-to-door | 135 (130) | 5489 | 1348 |
| Stop-based | 115 (105) | 4865 | 1235 + 251 |
| Offline Optimization | | | |
| Door-to-door | 85 (75) | 3772 | 1248 |
| Stop-based | 75 (65) | 3495 | 1126 + 251 |

Table 3: Summary of the experiment 3

then the minimum fleet size, as well as the total fleet distance, can be reduced. Therefore, the benefits of adopting a stop-based service scheme may be a result of multiple factors.

To quantify the "pure" benefits of the stop-based service scheme, we have also carried out another group of simulations, where students do not adapt their earliest departure time (i.e., they can only leave home as early as in the base case). Under that setup, both the reduction in the minimum required fleet size and the total fleet distance are less significant, no matter which optimization approach is used. The detailed results can be found in the Appendix B. In practice, however, it is more reasonable to assume that students, as well as DRT users in general, will adapt their departure time when the extra walking time to the DRT stop is needed. As a result, the reduction in the minimum required fleet size can still be, at least partially, accredited to the introduction of DRT stops.

### 4.3 Cost analysis

As this is a case study for a German scenario, we construct the framework for the cost analysis based on the method and data from the German Federal Ministry for Digital and Transport[9]. In specific, our cost analysis framework is adapted from the article in the German federal transport infrastructure plans (Bundesverkehrswegeplanung) project (Planco et al., 2015, based on the value of money in year 2012). The values are extended and revised based on several other studies in the literature (Tirachini and Antoniou, 2020; Bösch et al., 2018; Litman, 2009), as well as the data from several major manufacturers of vehicles (i.e., minivans with 8 passenger seats). Three different types of vehicles: conventional internal combustion engine vehicle (in short, conventional vehicle), electric vehicle, and autonomous electric vehicle (in short, autonomous vehicle) are included in the cost analysis. From the results in section 4.1 and 4.2, the average driving distance of a vehicle to provide school transport is between 40 km to 65 km, depending on the operational scheme. This distance can be covered by most modern electric vehicles with a single charge. Therefore, we do not need to adjust the fleet size for electric vehicles to compensate for the charging process. In this study, we present the cost analysis in the unit of Euro, in terms of the value of money in year 2021. Data from different years is adjusted based on the consumer price index (CPI) in Germany (Statistisches Bundesamt, 2022).

The costs to maintain and operate the DRT fleet mainly consist of three parts: fleet costs, operational costs, and personnel costs. The fleet costs refer to the annual expenses to maintain the fleet. A fleet of vehicles needs to be purchased and this incurs capital costs each year (i.e., time-based depreciation of the vehicle, interest). In addition to that, a fixed cost that covers miscellaneous aspects (e.g., management, documentation, parking) also needs to be covered. As suggested by the name, the fleet costs directly depend on the fleet size. The operational costs cover the cost of energy (e.g, fuel or electricity), distance-based depreciation, vehicle maintenance, and charging facilities (when applicable). The operational costs are determined by the distance covered by the vehicles. The personnel costs contribute to another part of the total costs. Based on the simulation result, the DRT vehicle fleets are active for 2.5 hours when serving the school commutes in the morning (including the time to depart from and return to depots). If the vehicles are to be driven by human drivers, then the same number of drivers, each working for 2.5 hours, is required. On the other hand, if autonomous vehicles are used, then the cost for drivers can be eliminated. In addition to the driver, fleet managers also need to be hired. In this cost analysis framework, the cost for fleet management is already covered by the fixed cost of the vehicle. Therefore, it will not appear in the personnel cost again. The resulting framework for the cost analysis is summarized in table 4. More information on the cost analysis framework can be found in Appendix C.

By feeding the simulation output data to the cost analysis framework, we can estimate the annual costs to provide DRT service to all the students in the Vulkaneifel region. We use Euro per year as the unit for the cost estimation. In the Vulkaneifel region, there are around 190 school days in a school year (Landesrecht Rheinland-Pfalz, 2015). With this, we can convert the operational costs and personnel costs to annual values. In addition, as we used a 25% scenario in our simulation, the costs are multiplied

[9] https://www.bmvi.de/EN/Home/home.html

| | Conventional | Electric | Autonomous |
|---|---|---|---|
| Fleet costs [Euro per vehicle per year] | | | |
| Capital cost | 1754 | 1928 | 2901 |
| Fixed cost | 3176 | 3176 | 3176 |
| Total fixed costs | 4930 | 5104 | 6077 |
| **Values in year 2021** | **5541** | **5737** | **6831** |
| Operational costs [Euro per km] | | | |
| Vehicle utilization cost | 0.1501 | 0.1579 | 0.2019 |
| Energy cost | 0.0735 | 0.0554 | 0.0554 |
| Charging facility cost | 0 | 0.0507 | 0.0507 |
| Total operational costs (2012) | 0.2236 | 0.2640 | 0.3080 |
| **Values in year 2021** | **0.2513** | **0.2967** | **0.3462** |
| Personnel costs [Euro per vehicle-hour] | | | |
| Driver | 17.64 | 17.64 | 0 |
| Total personnel costs (2012) | 17.64 | 17.64 | 0 |
| **Values in year 2021** | **19.83** | **19.83** | **0** |

Table 4: Framework for the cost analysis based on Planco et al., 2015

by 4 to serve as an estimation for the 100% scenario. In the 25% scenario, there are 928 students to be served by the DRT fleet. This corresponds to around 3712 students in the 100% scenario. The estimated annual costs to serve the 3712 students by DRT, under the operational scheme of the base case, are summarized in table 5.

| | Fleet costs | Operational costs | personnel costs | Total costs |
|---|---|---|---|---|
| Conventional vehicle | | | | |
| Online approach | 2.99 | 1.05 | 5.09 | 9.13 |
| Offline approach | 1.88 | 0.72 | 3.20 | 5.81 |
| Electric vehicle | | | | |
| Online approach | 3.10 | 1.24 | 5.09 | 9.24 |
| Offline approach | 1.95 | 0.85 | 3.20 | 6.00 |
| Autonomous electric vehicle | | | | |
| Online approach | 3.69 | 1.44 | 0 | 5.13 |
| Offline approach | 2.32 | 0.99 | 0 | 3.31 |

Table 5: Annual costs estimation for the base case (unit: million Euro per year)

From the results, it can be seen that the autonomous electric vehicle option has the lowest cost. This is largely because of the savings in personnel costs. In the short term, however, it is still challenging to operate a large fleet of autonomous vehicles in a large area. Therefore, it serves as a reference value for future scenarios. Comparing the conventional and electric vehicle options, we can see that the total annual costs of these two options are similar. Meanwhile, electric vehicles are more efficient and environment-friendly. When the offline optimization approach is used, an annual expense of 6.00 million Euro is needed to maintain and operate the DRT fleet.[10] This corresponds to 1617 Euro per student per year or 8.51 Euro per student per school day (i.e., based on 190 school days per year). Among the 6.00 million Euro, 1.95 million Euro, which takes around 33% of the total costs, are the fleet costs. This part of the costs are used to purchase and maintain the DRT fleet, which can be used as the conventional DRT service (i.e., for the public) during the remaining time of the day, as well as on school holidays. Therefore, this 33% of the total annual costs can be viewed as a multipurpose investment. With this investment in place, the operation of the DRT service in the area can take place with significantly reduced costs. As the vehicles are already there, the DRT operator only needs to pay for the operational costs and personnel costs.

Then, we compare the costs to provide DRT service for students under different operational schemes. As the electric vehicle option is the most suitable choice, we use it for comparison. The results are summarized in table 6. From that table, we can observe that a longer travel time allocation and the introduction of the DRT stops can help to reduce the costs, regardless of whether an online approach or offline approach is used. The setup with two different school starting time, on the other hand, is an interesting case. When an online optimization approach is used, the annual costs actually increase

[10] For comparison: The annual budget for school traffic in "Landkreis Vulkaneifel", in the current system that uses large conventional buses, is 6.736 million Euro https://www.vulkaneifel.de/images/pdf/abtZ/Haushalt_2022.pdf.

| | Online approach | Offline approach |
|---|---|---|
| Base case (reference point) | | |
| Base case | 9.42 (0%) | 6.00 (0%) |
| Different maximum travel time | | |
| Tight | 12.82 (+36.1%) | 7.95 (+32.4%) |
| Loose | 6.97 (−26.0%) | 4.45 (−25.9%) |
| Adopting different school starting time | | |
| Two starting time | 9.65 (+2.4%) | 5.25 (−12.5%) |
| Introduction of DRT stops | | |
| Stop-based | 8.07 (−14.4%) | 5.33 (−11.1%) |

Table 6: Impacts of operational schemes (Electric vehicles, annual costs, unit: million Euro per year)

slightly. This is mainly due to the extra travel distance. This result is similar to the findings in the previous study (Kaddoura et al., 2021) and it was concluded that the two different school starting time do not have a significant advantage. When the offline optimization approach is used, however, the result becomes different. With two different school starting time 30 minutes apart from each other, the total annual costs are reduced by 12.5%. The results suggest that adopting different school starting time possesses the potential to reduce the costs of school transport. To exploit this potential, some pre-planning or pre-optimization is required. When schools start at different time, students will adjust their departure time accordingly. This means that the travel demands for the DRT system become more widely spread. This can help to reduce the pressure on the DRT fleet, as the peak of the travel demand becomes lower. Thus, a smaller fleet can serve the same number of students. At the same time, less concentrated travel demands also reduce the potential for ride-sharing. This will lead to extra fleet distance, which will increase the cost to operate the DRT system. To take advantage of the flattened travel demand pattern caused by having different school starting time, we need to minimize the extra travel distance while keeping the fleet size small. As suggested by the results in the table 6, applying the offline optimization approach, which pre-calculates the optimal routes for each vehicle based on knowledge of the demands, can achieve this much better than the online approach.

Apart from the monetary costs, the equivalent costs of travel time should also be considered. In section 4.1, we have shown that by replacing the conventional school transport service (i.e., adapted public transport schedule or conventional school bus) with DRT service, the travel time of the students can be greatly reduced. If we convert the time saving into monetary value based on 5.2 Euro per hour (Tirachini and Antoniou, 2020), then an equivalent benefit of 2.0 Euro or 2.2 Euro per student per day can be achieved, when online optimization or offline optimization is used for the DRT operation respectively. Even though these benefits cannot be used to offset part of the costs directly, they are still an important element in the cost-benefit analysis.

# 5 Discussion and Conclusion

In this study, we have explored the feasibility of providing demand-responsive transport for school children in rural areas. A series of systematic experiments have been carried out. Based on the results, the following answer can be given: with an annual budget of 1617 Euro per student (or 8.51 Euro per student per school day), it is feasible to maintain and operate a fleet of DRT vehicles that can transport all the students in Vulkaneifel region from home to school on time in the morning. This cost estimation is based on a comfortable door-to-door school transport service operated by a fleet of electric vehicles. The costs can be reduced by adopting different operational schemes (e.g., allowing longer travel time, varying school starting time, switching to a stop-based service) or vehicle options (e.g., conventional vehicles, autonomous vehicles). Moreover, using the DRT to serve school children in rural areas also has some major advantages. Compared to the school bus, the DRT offers a superior service quality in terms of convenience, coverage rate, and travel time. Compared to private cars, the DRT provides a comparable convenience and travel time at a much lower mileage, which has a positive impact on the traffic network and environment.

The results from the case study of the Vulkaneifel region serve as a good reference point for regions with similar geographical characteristics. The whole study is based on an open-source traffic simulation framework and data. This means the same study can be replicated for different scenarios with simple adaptations. It is worth pointing out that if a fleet of DRT vehicles is introduced to the region for school transport, then those vehicles can also be operated as the normal DRT service (i.e., for the general public) during the rest of the day and on school holidays. This enables the operation of a large-scale DRT service in the region with a limited extra budget, as the cost of maintaining the DRT fleet is already covered by the budget for school transport. Because a large fleet of DRT vehicles is considered a promising alternative to the conventional public transport service in areas with lower population density (Sieber et al., 2020; Kaddoura et al., 2021), the results of this study, along with future works in this direction, may bring us closer to providing a comprehensive mobility service in rural areas.

Another key message from this study is that offline optimization plays an important role in bringing down the fleet size when the travel demand arises from highly repeatable daily routines. Even with the help of past data and active rebalancing, the online DRT operational strategy (i.e., online optimization approach) still cannot compete with the offline optimization approach as the latter does not know future requests. Not only a smaller fleet size is required when the offline optimization approach is used, but the total fleet distance is also reduced, which is an indication of higher service efficiency and environmental friendliness. With a significant reduction in the fleet size and total driving distance, the cost to maintain and operate the DRT system is reduced. This may alter the answer of whether it is feasible to operate the DRT service under a certain setup.

When it comes to the driving distance of the vehicles, an interesting phenomenon can be observed. As we have seen in the experiments, the total fleet distance is shorter when the offline optimization approach is used. But if we look at the average driving distance per vehicle, then we can find out that each vehicle actually covers more distance. This can be observed in all the experiments we have carried out. For example, in the base case, if we switch from the online optimization approach to the offline optimization approach, then the average driving distance of a vehicle rises from 40.7 km to 44.4 km, while the total fleet distance reduces from 5489 km to 3772 km. This means that the average workload for each vehicle is higher when the offline optimization approach is used. It can be viewed as another indication of a higher vehicle utilization rate.

Finally, the simplifications, assumptions, and limitations of this study are summarized and explained. When possible, we will also identify potential improvements that can be made to overcome the limitations.

In this study, we did not use a realistic traffic model. This is because the traffic congestion problem is less significant in rural areas. Based on the online travel time services (Google Maps, HERE), we can conclude the travel time of trips in the Vulkaneifel region only slightly varies throughout the day. In addition, if a more detailed traffic model was used, some congestion could occur near schools, as many DRT vehicles will be dropping off school children at the same time. Apparently, if the DRT service for school commutes is to be adopted, some special measures need to be taken to optimize the traffic flow around schools (e.g., setting up a dedicated drop-off zone, traffic restrictions for private vehicles around the school, assigning higher priority to DRT vehicles). Analyzing the traffic near schools is a research topic itself. Therefore, we have simplified our model by simplifying the traffic model. We have examined the robustness of the offline optimization approach by introducing artificial fluctuations in the free speed throughout the network (see Appendix A). Results indicate that the offline optimization approach can handle uncertainty reasonably well.

In the experiments, we adopted a simple linear model to determine the stop duration when a DRT vehicle picks up or drops off a student. We assume every student needs 10 seconds to board or alight the vehicle. This value is determined by referring to various studies (Su et al., 2020; Neumann et al., 2014). The boarding/alighting time of the DRT vehicles for the school transport should be longer than of the bus, as the DRT vehicles used in this study are minivans, which have smaller doors and the space in the vehicle is tighter. Meanwhile, it should also be shorter than the stopping time for the conventional taxi. As the school commute is a daily routine, the boarding/alighting process is simpler and faster. When multiple students board or alight at the same stop, the total stop duration will be set to the sum of all the boarding and alighting activities. For example, if 3 persons board the vehicle together at the same place, then the vehicle will allocate 30 seconds of stopping time for them to board the vehicle. This assumption is made because of the underlying VRP model in jsprit (offline VRP optimization) and the DRT extension (online DRT optimization). In reality, the stop duration may vary. Usually, the more people boarding at the same place, the less boarding time per person is expected. As a result, when a more sophisticated stop duration model is introduced, the benefits of introducing DRT stops may become more significant.

For the offline optimization approach, the students are assumed to show up on time. In reality, however, delays and no-shows may happen. In those cases, DRT vehicles may need to wait for a certain amount of time before the system decides to continue without the students who do not show up at the pickup location on time. This may have a negative impact on the system when the offline optimization approach is used. As everything is pre-calculated, a delay at one stop may lead to delays in all the subsequent stops. In comparison, when the online optimization approach is used, the impact of delays in departure or no-shows is smaller, as new requests are processed in real-time as they arrive based on the current status of the DRT fleet. This is one of the greatest limitations of the offline optimization approach. The construction of a more advanced DRT operational strategy that combines the advantages of both approaches calls for future research.

# Appendix A Robustness of the offline optimization approach

In the study, we have shown that the offline optimization approach provides a significantly better result than the online one. Due to its design, the offline optimization approach may be susceptible to uncertainty in the traffic network. If we want to apply this approach in the actual operation, a certain level of robustness is required. In order to examine the robustness of the offline optimization approach, artificial fluctuation of traffic speed is introduced throughout the space and time of the DRT operation. We divide the simulated period into 10-minute time bins. At each time bin, the free speed of a link (i.e., road segment) is updated to a new value based on a Gaussian distribution around its original speed ($v(l,t) = v_0(l) \cdot \alpha$, where $\alpha \sim \mathcal{N}(1,\, 0.05^2)$ and $\alpha$ is strictly positive). At the same time, the vehicle routes are calculated using the original free speeds.

We then simulated the offline optimization approach 5 times with different random seeds. The results are summarized in figure A.1. As we can see, the offline optimization approach still provides a good performance. When the same fleet size (i.e., 85 vehicles) is used as in the base case in the experiments, almost all the students can still arrive at school on time, even with the fluctuation in the traffic. As a result, it can be concluded that the offline optimization approach is adequately robust given the potential uncertainty of travel time in rural areas, where traffic congestion is not severe. Furthermore, a buffer in the latest arrival time can be used (e.g., set the latest arrival time to 5 minutes earlier), when pre-calculating the route offline, such that the system can become even more robust and transport all the students to school on time despite uncertainty in the traffic network.

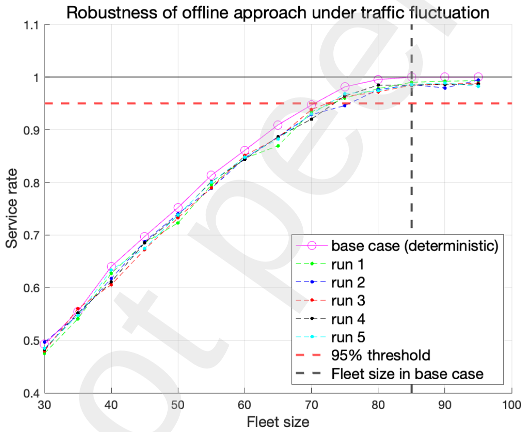
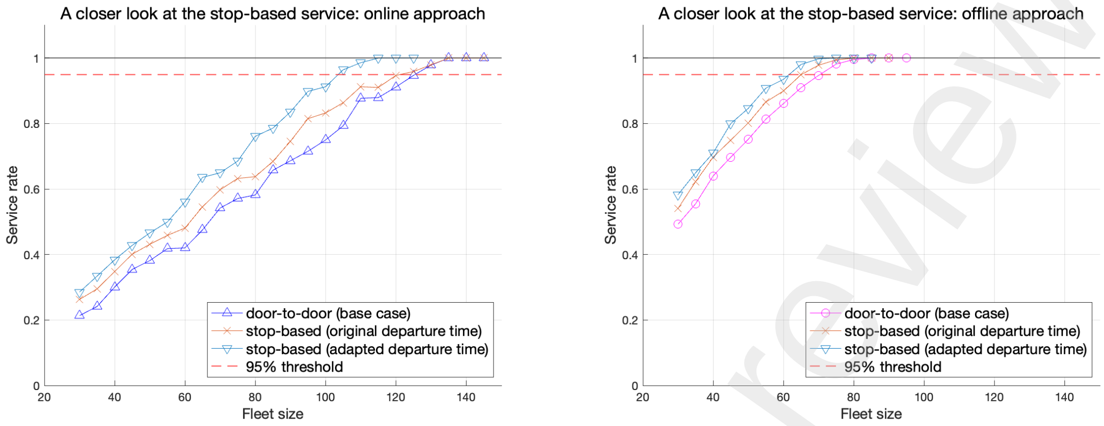



Figure A.1: Robustness of the offline approach under traffic fluctuation

# Appendix B The benefits of introducing DRT stops

As mentioned in the section 4.2.3, when we switch from door-to-door service to stop-based service, we assume that the users will consider the walking time from home to the closest DRT stop and adjust their departure time from home. That means students will allocate more time (on average, 251 seconds) for the school commutes. In the experiment 1, we have demonstrated that a larger maximum travel time allocated by the students has a major impact on the minimum required fleet size, as well as the travel distance. Therefore, it may be argued that part of the benefits we have shown in experiment 3 (i.e., introducing DRT stops) is achieved by the extra travel time allocation. In practice, it is reasonable to assume that the DRT users, not only limited to the students in this study, will adapt their departure time accordingly, when they need to walk to the DRT stops to be picked up by the vehicle. Therefore, we accredited all the benefits in experiment 3 to the stop-based service.

Nevertheless, it may be interesting to assess the direct effect of introducing DRT stops in this school transport scenario without imposing additional travel time on the users due to walking. We carry out another two sets of simulations, where students maintain their original maximum travel time as in the base case ($\alpha = 2.0$, $\beta = 1200$). Under this setup, there is no difference for the users, and the only difference is the service mode (door-to-door service vs stop-based service). The results, for both online and offline optimization approach, are summarized in figure B.1 and table B.1. For comparison purposes, we include the case where adaptation in departure time is assumed (i.e., the stop-based case presented in the experiment 3). To differentiate between the two cases, we denote these two setups as "original max travel time" and "extended max travel time" in the table and plot. The results suggest that without allocating extra time for walking to DRT stops, the benefits of introducing DRT stops are indeed less obvious. While the total fleet distance is still reduced to some extent, the reduction in the minimum required fleet is less significant compared to the case where students extend their maximum travel time. Given the additional experiments, one may say that the benefits of the DRT stops in the experiment 3 is a joint effect of longer travel time allocation and improved efficiency in vehicle utilization.




(a) Online optimization

(b) Offline optimization

Figure B.1: Stop-based service with and without adaptation of departure time

| | Minimum fleet size | Total fleet distance [km] | Mean travel time [s] |
|---|---|---|---|
| Online approach | | | |
| Door-to-door | 135 (130) | 5489 | 1348 |
| Stop-based: | | | |
| original max travel time | 135 (125) | 4957 | 1208 + 251 |
| extended max travel time | 115 (105) | 4865 | 1235 + 251 |
| Offline approach | | | |
| Door-to-door | 85 (75) | 3772 | 1248 |
| Stop-based: | | | |
| original max travel time | 80 (70) | 3723 | 1140 + 251 |
| extended max travel time | 75 (65) | 3495 | 1126 + 251 |

Table B.1: The benefits of introducing DRT stops

# Appendix C Additional information on the cost analysis

The detailed framework for our cost analysis is summarized in table C.1. It is based on the approach of the German national assessment for transport infrastructure, called "Bundesverkehrswegeplan", or BVWP in short (Planco et al., 2015; in particular table 8-37). That approach deprecates only half of the capital value of vehicles over time, and the other half over the driven distance. For this, it divides the second half of the depreciation by the typical annual mileage; any deviation from that mileage in consequence increases or decreases that part of the depreciation. This approach is in line with German used vehicles price lists, which take deviations from the typical mileage into account. Additionally, in Planco et al., 2015 there is interest charged on 1/2 of the initial cost, which is the listed price including tires. The "1/2" is an approximation of the fact that the credit is paid back over time.

According to table 8-37 in Planco et al., 2015, a life span of 12 years and an estimated average annual driving distance of 18398 kilometers are assumed for the vehicle. These estimations are also similar to the values used for the DRT vehicles or taxi in the literature (Tirachini and Antoniou, 2020; Planco et al., 2015; Becker et al., 2020). Note that the estimated annual driving distance is based on the assumption that the vehicles will be used as DRT service during the remaining time of the day and school holidays. With the above-mentioned assumptions, we can calculate the vehicle depreciation for each case. For example, in table C.1, the value of a conventional vehicle, excluding the tires, is 35349 Euro. Half of

| | Conventional | Electric | Autonomous | Source |
|---|---|---|---|---|
| | | Vehicle information | | |
| Vehicle name | Mercedes-Benz Vito Tourer | Citroën E-Spacetourer | Hypothetical | |
| Listed price (Euro, excl. VAT, incl. tires) | 35349 | 38794 | 58192 | Vehicle manufacturer (see text), adjusted to 2012 value |
| Life span (year) | 12 | 12 | 12 | Planco et al., 2015 Tab. 8-37 |
| Annual distance (km) | 18398 | 18398 | 18398 | Planco et al., 2015 Tab. 8-37 |
| Tire distance (km) | 69000 | 69000 | 69000 | Planco et al., 2015 Tab. 8-37 |
| Cost of tires (Euro) | 453 | 453 | 453 | Planco et al., 2015 Tab. 8-37 |
| Energy consumption | Diesel 7.1L/ 100 km | Electricity 25 kWh/100 km | Electricity 25 kWh/100 km | Vehicle manufacturer (see text) |
| | | Fixed costs [Euro per vehicle per year] | | |
| Time-based depreciation | 1454 | 1598 | 2406 | = 1/2 (listed price − tires) / life span (Planco et al., 2015, Tab. 8-37) |
| Interest | 300 | 330 | 495 | = 1/2 listed price × 1.7% (Planco et al., 2015, Tab. 8-37) |
| Parking cost | 530 | 530 | 530 | Planco et al., 2015 Tab. 8-37 |
| General costs (mostly vehicle administration) | 2646 | 2646 | 2646 | = 5291/2 adapted value from Planco et al., 2015 Tab. 8-37 |
| Total fixed costs | 4930 | 5104 | 6077 | |
| **Values in year 2021** | 5541 | 5737 | 6831 | Adjusted based on CPI (Statistisches Bundesamt, 2022) |
| | | Vehicle operational costs [Euro per km] | | |
| Distance-based depreciation | 0.079 | 0.0868 | 0.1308 | = 1/2 (listed price − tires) / life span / annual distance (Planco et al., 2015 Tab. 8-37) |
| Tire replacement | 0.0066 | 0.0066 | 0.0066 | = cost of tires / tire distance (Planco et al., 2015 Tab. 8-37) |
| Repair and maintenance | 0.0645 | 0.0645 | 0.0645 | Planco et al., 2015 Tab. 8-37 |
| Charging infrastr. | 0 | 0.0507 | 0.0507 | Tirachini and Antoniou, 2020, adjusted to 2012 value |
| Energy cost | 0.0735 | 0.0554 | 0.0554 | Online database (see text), adjusted to 2012 value |
| Total operational costs | 0.2236 | 0.264 | 0.308 | |
| **Values in year 2021** | 0.2513 | 0.2967 | 0.3462 | Adjusted based on CPI (Statistisches Bundesamt, 2022) |
| | | Personnel costs [Euro per vehicle-hour] | | |
| Driver | 17.64 | 17.64 | 0 | Planco et al., 2015 Tab. 8-37 |
| Fleet manager | / | / | / | Included in vehicle admin. costs |
| Total personnel costs | 17.64 | 17.64 | 0 | |
| **Values in year 2021** | 19.83 | 19.83 | 0 | Adjusted based on CPI (Statistisches Bundesamt, 2022) |

Table C.1: Detailed framework for the cost analysis

it, 17448 Euro, will be lost during the life span of 12 years, which corresponds to 1454 Euro per year. The remaining value of 17448 Euro will be consumed after driving a total distance of 220776 kilometers (i.e., 18398 kilometers per year, 12 years), and that corresponds to 0.079 Euro per kilometer. We use the same approach to calculate the depreciation of electric vehicles and autonomous vehicles.

BVWP also specifies annual costs for parking the vehicle when it is not in use (530 Euro/year). In addition, there are vehicle administration costs and some general costs related to regular vehicle checking (so-called TÜV and ASU), which are, for small trucks, listed at 5291 Euro/year. In the end, these vehicle administration costs are by far the largest part of the fixed annual costs. For the present study, we assume that these costs can be divided by two, assuming some off-the-shelf approach for the administration of vehicle fleets such as the one considered here, resulting in 2646 Euro/year.

The vehicle operational costs consist of the distance-based depreciation as described earlier, regular tire replacement based on tire costs, repair and maintenance, and energy costs. For electric vehicles, charging facilities that match the total mileage of the fleet are also required. Since BVWP does not include the cost of the charging facility, we adopt the data from Tirachini and Antoniou, 2020. Bischoff and Maciejewski, 2015 had lower costs for the maintenance of electric vehicles, but higher costs for battery replacement every 100,000 km. The end result – that electric vehicles are similar to fossil vehicles both in fixed and in variable costs – was the same.

The vehicle information is acquired from the websites of the vehicle manufacturers (i.e., Vito Tourer from Mercedes-Benz[11] and E-Spacetourer from Citroën[12]). All the vehicles are configured with 9 seats (i.e., 8 passenger seats + 1 driver seat). As autonomous vehicles are not commercially available, a hypothetical model based on the same type of electric vehicle is used. The values for the hypothetical model are determined similarly as in Tirachini and Antoniou, 2020. The prices are adjusted to year 2012 based on the consumer price index (see next paragraph) in order to fit in the table. The energy cost is based on the price of the corresponding energy type in year 2021 (diesel: 1.164 Euro/liter[13 14], or electricity: 0.2492 Euro/kWh[15 16]). The prices are also adjusted to the year 2012 based on the consumer price index (see next paragraph) before being added to the table. All costs in the table do not include taxes, since BVWP computes economic costs, not financial costs.

According to Statistisches Bundesamt, 2022, the consumer price indices (CPI) for Germany from 2012 to 2021 are as follows: 97.1 (2012), 98.5 (2013), 99.5 (2014), 100.0 (2015), 100.5 (2016), 102.0 (2017), 103.8 (2018), 105.3 (2019), 105.8 (2020), 109.1 (2021). The CPI statistics are used to adjust the monetary values between different years. According to these statistics, 1 Euro in year 2012 is equivalent to 1.084 Euro in year 2019, and 1.124 Euro in year 2021. As our cost analysis framework is based on Planco et al., 2015, which is based on the value of money in year 2012, we adjust all the values from other sources to year 2012 when building the table. To adjust the vehicle prices and energy prices from 2021 to 2012, we divide the 2021 prices by 1.124. The data from Tirachini and Antoniou, 2020 (i.e., charging facility cost) is based on year 2019, and the value is divided by 1.084 before being added to the table. Finally, we multiply the total costs in each segment in the table (i.e., total fixed costs, total operational costs, total personnel costs) by 1.124 to acquire the equivalent values in year 2021.

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[11] https://www.mercedes-benz.de/vans/de/vito/tourer-commercial
[12] https://business.citroen.de/modellpalette/spacetourer.html
[13] https://www.adac.de/verkehr/tanken-kraftstoff-antrieb/deutschland/kraftstoffpreisentwicklung/
[14] excluding the 19% VAT
[15] https://www.destatis.de/EN/Press/2021/10/PE21_466_61243.html
[16] non-household electricity price without VAT and other recoverable taxes, less than 20 MWh

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