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Demand-responsive transport for students in rural areas: A case study in Vulkaneifel, Germany

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ABSTRACT

In rural areas with low population density, demand-responsive transport (DRT) is considered a promising alternative to conventional public transport (PT). With a fleet of smaller vehicles, DRT provides a much more flexible and convenient service. This characteristic makes DRT also a potential mode of transport to serve students in rural areas. If DRT vehicles are used to serve students, 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 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 framework. In the feasibility study, various setups and operational schemes are explored, which are followed by a systematic cost analysis. Based on a conservative estimation, an annual budget of around 1600 Euro per student will be needed 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.

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). 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

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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 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 et al., 2019b).

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 et al., 2019c), Paris (Hörl et al., 2019a) 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, where multiple DRT dispatching strategies were compared (Ruch et al., 2021). 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, where various new rebalancing strategies have been proposed and evaluated (Ruch et al., 2020; Bischoff and Maciejewski, 2020; Lu et al., 2020).

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,

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

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 modeled activities is shown in Fig. 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. In the afternoon, some students may leave the school right after the classes finish, while others may stay at the school longer (e.g., having extra curriculum activities). That means the demand is less concentrated, and there will be less pressure on the school transport service. 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. In other words, the minimum required fleet size is determined by the school trips in the morning. Therefore, it is reasonable to reduce the problem and focus only on the morning trips.

The modeled 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 Fig. 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 the corresponding residential areas. In the end, a school trip model consisting of 928 morning school trips is created. The resulting school trips are illustrated in Fig. 2, where students travel from homes to schools (represented by yellow lines connecting red dots with green stars). Fig. 2(b) is a zoomed-in view of the area within the white dotted rectangle in Fig. 2(a). It shows that the locations of students' homes are disaggregated from the grid and re-distributed within residential areas (marked with orange).

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

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

[3] http://download.geofabrik.de/

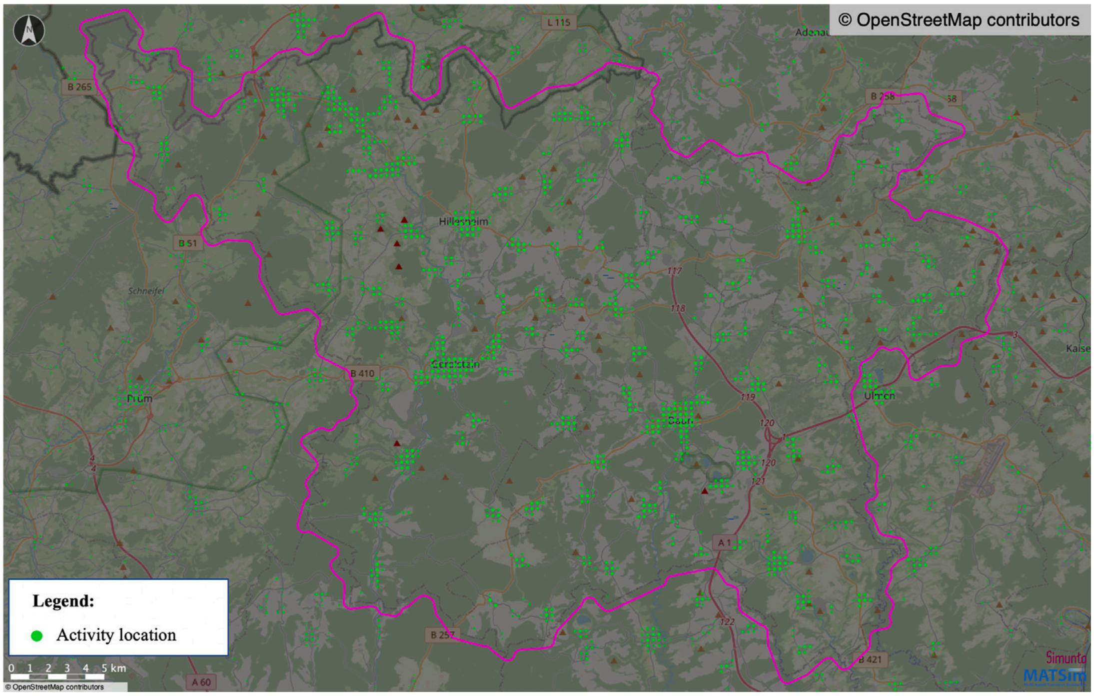
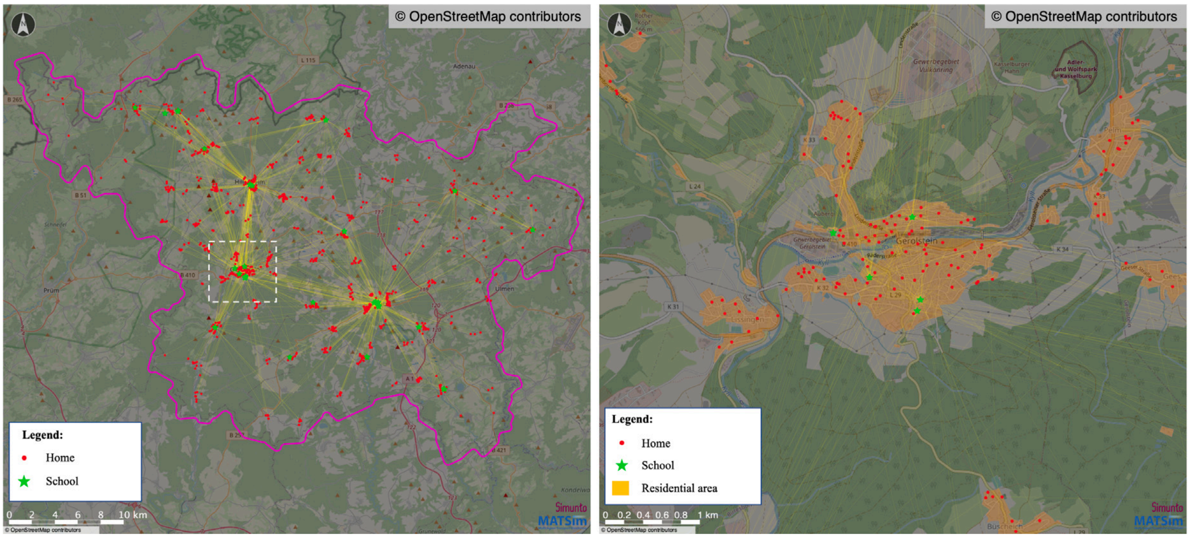


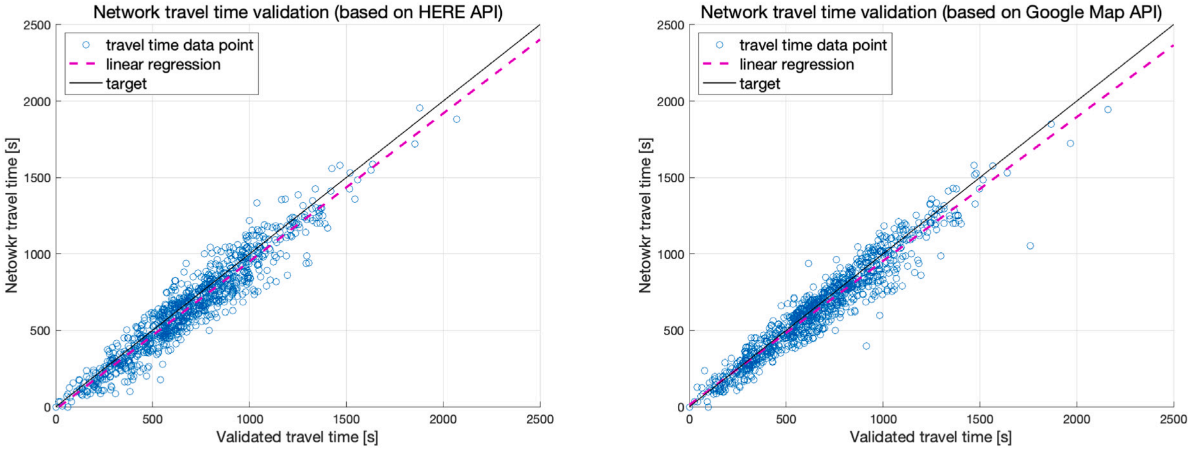
Fig. 1. Illustration of the open-source agent-based transport model data based on cell phone data.



(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

Fig. 2. School trips in the morning. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Validation based on HERE API

(b) Validation based on Google Map API

Fig. 3. Travel time validation against data obtained from public routing APIs.

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. According to the online APIs, the travel time of the trips in the area varies only slightly during the day, therefore, the base travel time (i.e., time-invariant) from the online APIs is used in the calibration process. The validation plots of the calibrated network are shown in Fig. 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 Fig. 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.

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 obtain the 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 min to travel from home to school in a private car, then the student can be picked up at most 40 min 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 DRT 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 is to find minimum cost routes that serve all the school children

[4] https://developers.google.com/maps
[5] https://developer.here.com/
[6] https://matsim.org/

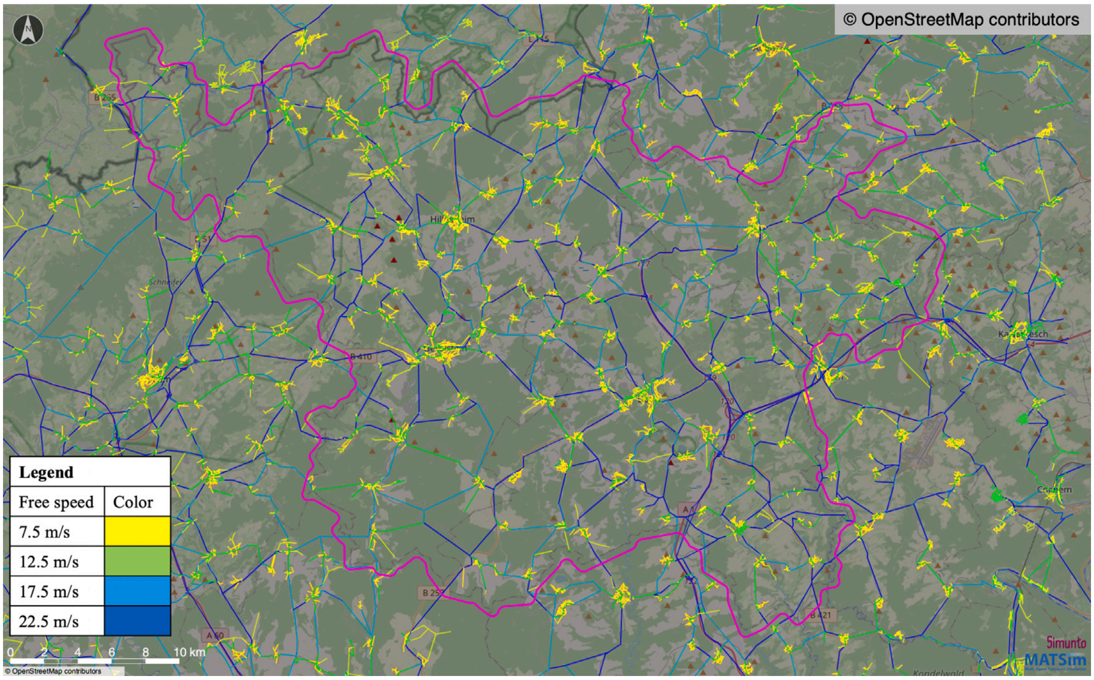


Fig. 4. Modeled road network: the free speeds of road segments are indicated by the color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

without violating the time and capacity constraints. The students should be picked up not earlier than their 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 — this serves as an indicator that the vehicle fleet is too small. 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 of adding a support for trip pre-booking to the DRT extension.

In this study, a fleet of minivans with 8 passenger seats will be used to provide the school transport service. There are several reasons for using this setup. First, as an initial study on the feasibility of this new concept, a uniform fleet is used to avoid the complex optimization process associated with heterogeneous fleets. At the same time, a uniform fleet also reduces the administrative and maintenance cost compared to a heterogeneous fleet. Second, according to the German traffic rules, a driver with a normal car license is allowed to drive a vehicle with up to 9 seats (including driver's seat), and that means the minivan with 8 passenger seats can be driven with a normal driver's license. Furthermore, based on the previous study (Kaddoura et al., 2021) and the preliminary experiments, using minivans with 8 passenger seats will reduce the number of vehicles and drivers required by around 30% compared to a fleet of regular cars with 4 passenger seats. Since hiring a large group of drivers in the rural area is challenging and will increase the operational costs, therefore, using vehicles with 8 passenger seats is a more suitable choice.

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 tours 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. Simulations 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 Eq. (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. This means that access and egress times are zero — or more precisely, MATSim assumes that synthetic persons have to walk to the network, but those times are the same for all considered means of transport.

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 quantitative analysis, such as average travel time and total fleet travel distance, is performed for the identified minimum fleet size.

We do not include the conventional waiting time statistics, as the definition of the waiting time is different in this context. For each student, we specify the earliest departure time based on the school starting time and the distance between the home of the student and the school. The student can be picked up at any time after the earliest departure time, as long as the DRT system can transport the student to the school in time. In the conventional DRT service analysis, the waiting time is defined as the difference between the actual pickup time and the earliest departure time. This is, however, not meaningful in this case, as a later pickup time is actually desirable and students can spend more time at home.

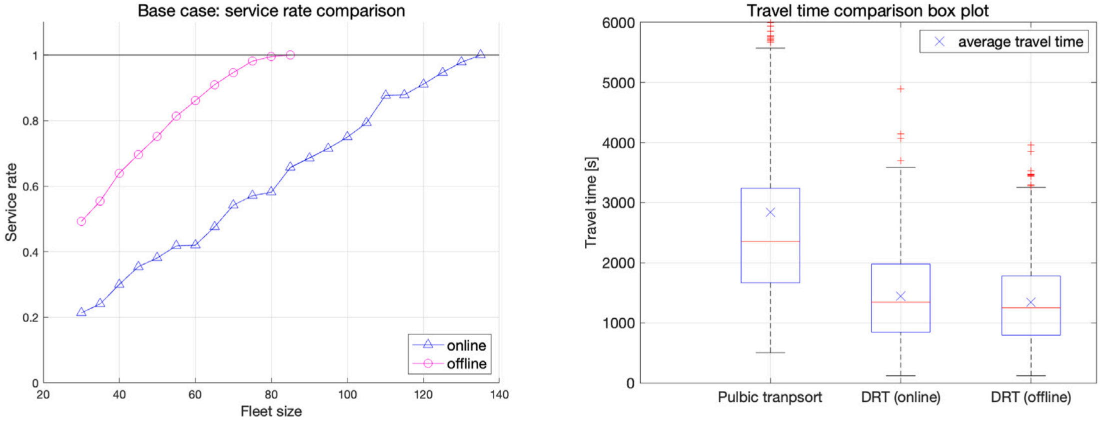
To identify the minimum required fleet size, we increase the fleet size from 30 with increments of 5 vehicles, until all the students can be transported to the schools on time. At the start of the day, the vehicles are located in the following four major towns of the region, namely Daun, Gerolstein, 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 Fig. 5(a). 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 online optimization, and only 85 for the offline optimization.

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 s on their journey. In comparison, if they choose to travel with DRT, the average travel time can be reduced to 1444 s (online approach) or 1346 s (offline approach). The comparison of the travel time distribution of the 628 students is summarized in the box plot in Fig. 5(b). 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.

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 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.

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



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

(b) Travel time comparison between PT and DRT service (note that the statistics in this plot only include students who can find suitable PT connections)

Fig. 5. General results of base case.

Table 1
Summary of the key performance indicators of the online and the offline optimization approaches.

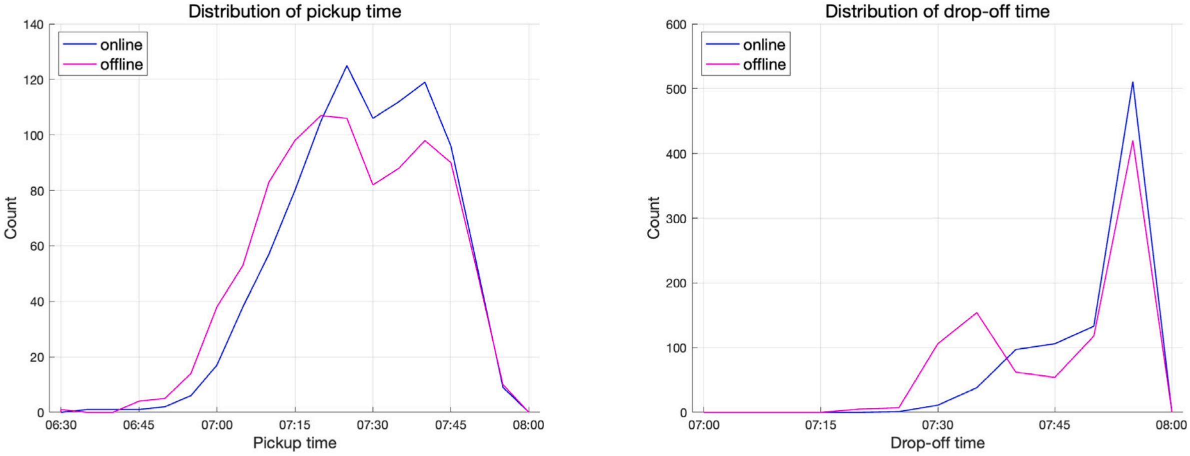
	Minimum fleet size	Total fleet distance [km]	Mean travel time [s]
Online optimization	135	5489	1348
Offline optimization	85	3772	1248

In addition, 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 s (online approach) or 1248 s (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 s. That means around 10 min 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. To quantify the savings in driving distance, we compare the total fleet distance of the DRT system to the sum of single trips by private cars (assuming every student is driven to school by a private car). By switching to DRT, a distance saving of 40% (online approach) or 59% (offline approach) can be achieved. That corresponds to 14,400 or 21,600 vehicle kilometers saved every morning (in the 100% scenario), which can have a substantial positive impact on the environment and the traffic network.

We will now focus on the comparison between the two DRT operational strategies. Table 1 summaries the key performance indicators of the online and the offline optimization approaches mentioned in the previous text. Fig. 6 illustrates the time distribution of the pickups and the drop-offs of the students when the online or offline approach is used. The number of pickups and drop-offs are aggregated to 5-minute time bins. It can be observed that the distribution of the pickups are in similar shape for both approaches, and the overall pickup time of the offline approach is slightly earlier than that of the online approach. In the distribution of the drop-offs, it can be seen that there is a minor peak at around 7:35 am, when the offline approach is used. Subsequently, the peak of the drop-offs near 8:00 am is slightly lower for the offline approach, as more drop-offs have been performed earlier. The average drop-off time of the online approach and the offline approach is 7:53 am and 7:48 am respectively. The median drop-off time of the online approach and the offline approach is 7:56 am and 7:54 am respectively.

The occupancy profile of the fleet is summarized in Fig. 7. Figs. 7(a) and 7(b) show the occupancy of the vehicle throughout the morning for the both approaches. The plots are also aggregated to 5-minute time bins. For both approaches, the vehicles are well occupied during the operation, and up to around 25% of the vehicles are fully occupied at some time. When the online approach is used, some of the vehicles are still empty even during the peak hour (i.e., 7:30 am to 8:00 am). This is mainly due to the empty vehicle relocation process (mentioned in Section 3.2.1), which is necessary to maintain a good service quality. For the offline approach, such operation is not necessary, and thus all the vehicles are at some point occupied by students. Besides, a double peaks pattern can also be observed in the vehicle occupancy plot (Fig. 7(b)). Together with Fig. 6(b), it can be concluded that some of the vehicles will perform multiple pickup and drop-off rounds during the morning, when the offline optimization approach is used. This is also part of the reason why a smaller fleet can fulfill the same transport demand.

Fig. 7(c) shows the distribution of the maximum occupancy of the vehicle during the service. It can be seen from this plot that a significant number of vehicles have reached their full capacity at some points during the operation. In particular, when the offline



(a) Comparison of the distribution of pickup time (b) Comparison of the distribution of drop-off time

Fig. 6. Departure and arrival analysis.

approach is used, 71 out of the 85 vehicles will be fully occupied at least once. This indicates that the seats in the vehicles are well utilized, and the extra seats of the minivan compared to a regular car play an active role in reducing the fleet size. When the online optimization approach is used, some of the vehicles are not occupied throughout the operation, this is again due to the rebalancing operation of the online strategy. In other word, those vehicles still participate in the operation despite not serving any students. This is apparently a drawback of applying the online optimization approach to the school transport problem.

Fig. 7(d) shows the distribution of the number of students alighting at each drop-off stop that indicates the offline approach plans fewer drop-off stops than the online one. The proportion of the drop-off stops with multiple alighting students is higher. This figure also reveals that most of the vehicles perform a sequence of drop-offs rather than drop off 8 students all at once. This is because of the geographic characteristics of the scenario (see Fig. 2). In each major town or city, there are several schools of different types (i.e., primary school, junior and senior high school, tertiary school). Meanwhile, the home locations of the students are scattered throughout the villages and residential areas in the region. It makes sense to group the students who live in the same village and go to different schools in the same town/city, and transport them with one vehicle. When reaching the destination area, the vehicle drop-offs the students at several schools.

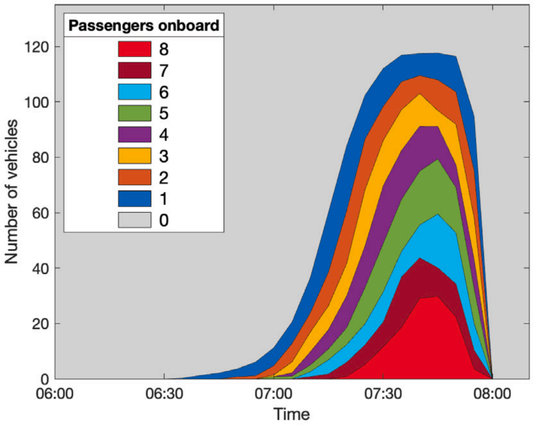
In addition to the reduced fleet size, the offline approach also provides a key advantage over the online one: the pickup time is fixed in the former one, whereas in the latter one, they are subject to change as new requests are inserted into the existing schedules, potentially delaying subsequent pickups. 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 an additional 102 s before he/she is actually picked up. In contrast, in the offline approach, the students are picked up at the scheduled time and no extra waiting occurs if the traffic condition is stable, which is a reasonable assumption for the rural area.

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

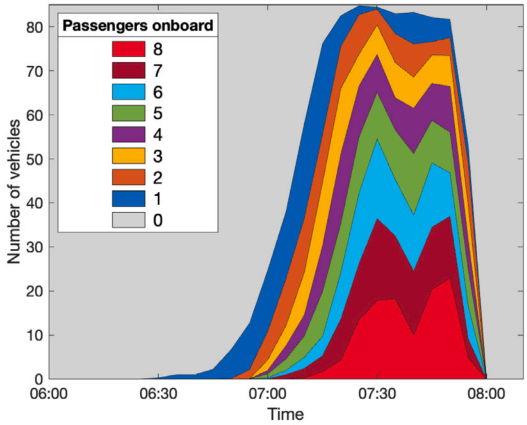
In addition to the DRT operational strategy, there are other factors that may impact the fleet size required for a satisfying service quality and operational costs. This part of the study explores the impact of three different factors of the DRT operational scheme: the maximum travel time, the school starting times, 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

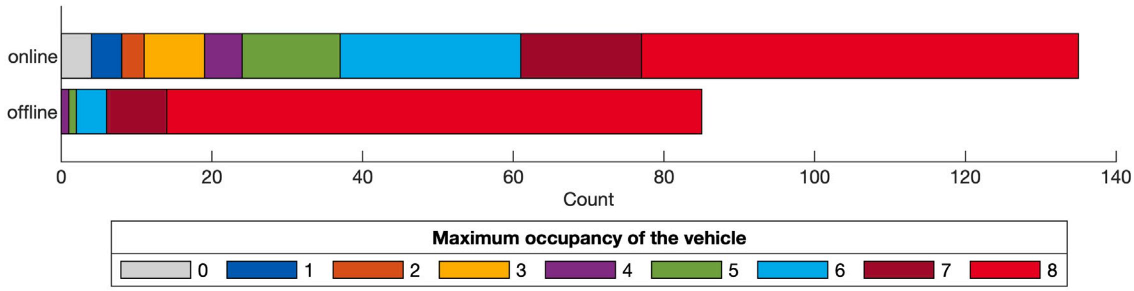
In this experiment, we study the impact of the maximum allowed travel time. We quantify the minimum required fleet size when students allocate different amounts of time for school trips. By modifying the value of α and β in Eq. (1), we investigate



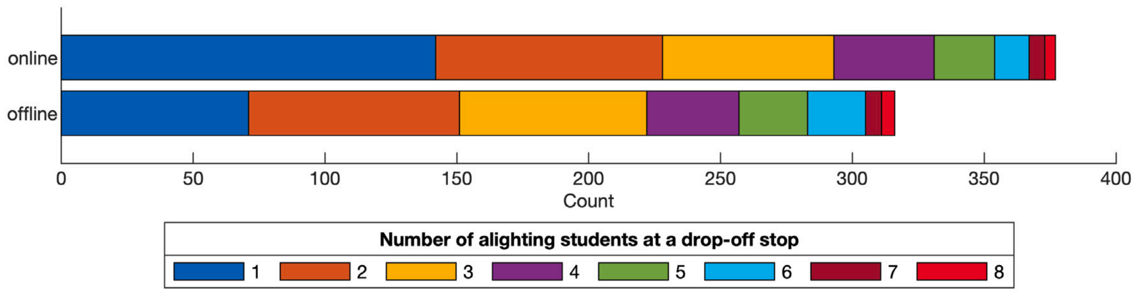
(a) Vehicles occupancy plot for online optimization



(b) Vehicles occupancy plot for offline optimization



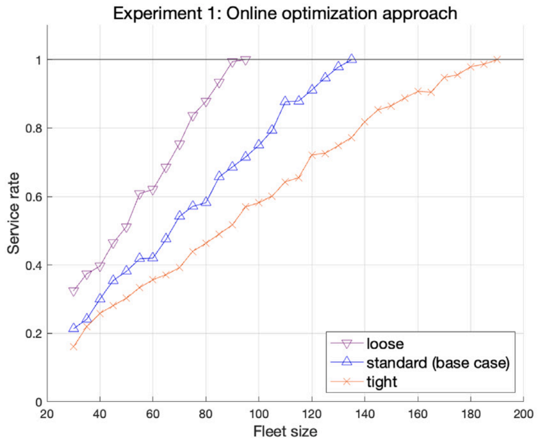
(c) Distribution of the maximum occupancy of the vehicles



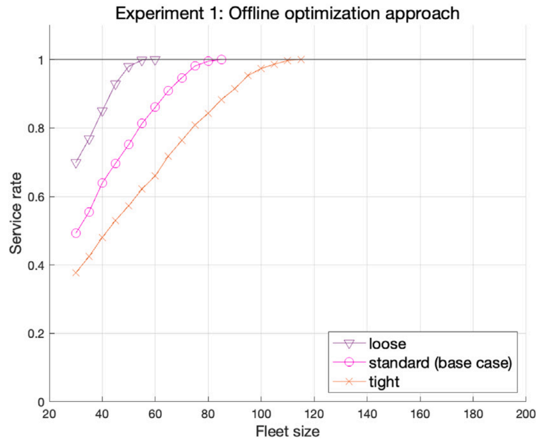
(d) Distribution of the number of alighting students at drop-off stops

Fig. 7. Comparison of the vehicle occupancy profile.

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 Fig. 8. As expected, the higher the maximum allowed travel time, the fewer vehicles are required to provide a good service quality. To quantify the overall impact of the maximum allowed travel time on the DRT system, we summarize the key results in Table 2.



(a) Online optimization



(b) Offline optimization

Fig. 8. Impact of maximum travel time.

Table 2
Summary of the experiment 1.

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

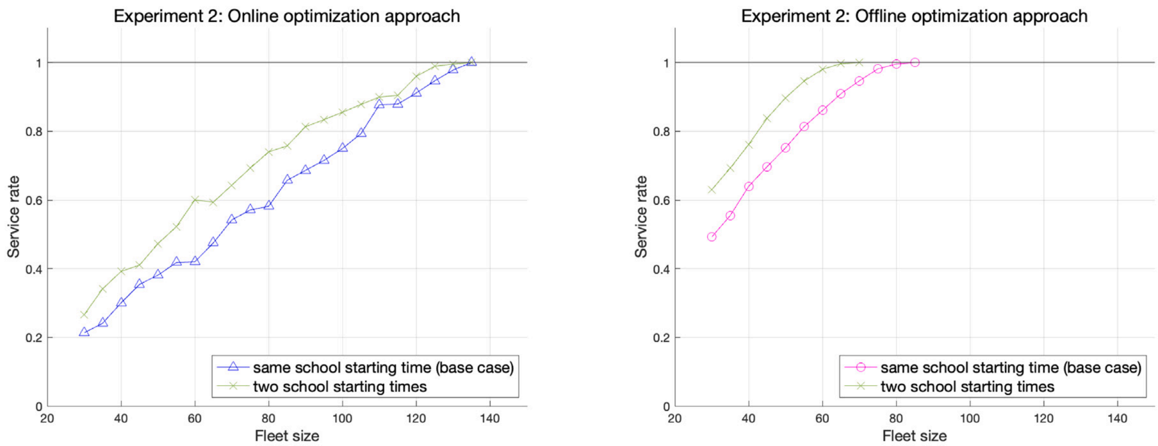
Table 3
Summary of the experiment 2.

	Minimum fleet size	Total fleet distance [km]	Mean travel time [s]
	Online optimization		
Single starting time	135	5489	1348
Two starting times	135	6504	1347
	Offline optimization		
Single starting time	85	3772	1248
Two starting times	70	4465	1207

4.2.2. *Experiment 2: varying school starting times*

In the Vulkaneifel region, schools have different starting times. 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 times, which are 30 min 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 starting times and the comparison to the base case are shown in Fig. 9. The key data is summarized in Table 3. According to the results, offline optimization benefits more from varying the school starting times. 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, setting up two different school starting times does not help to reduce the minimum fleet size required. With both approaches, a noticeable increase in the total fleet distance can be observed when the schools in the region adopt two different starting times. This is because vehicles need to cover extra distance between pickups, as the demands are more sparsely distributed in time when schools start at different times.



(a) Online optimization
(b) Offline optimization

Fig. 9. Impact of different school starting times.

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 Eqs. (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. $U = \emptyset$.

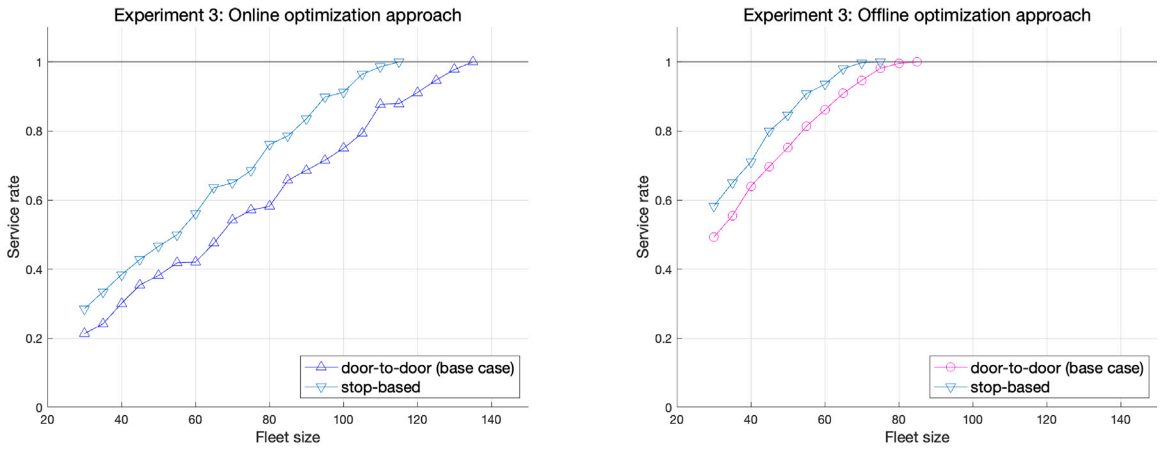
In addition to the DRT stops that cover the home locations, we also generate one stop for each school location. In this experiment, we set the maximum walking distance l_{max} to 500 m. By running the DRT stop generation process with this setup, we obtain 199 stops distributed across the region.

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

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

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**
  $s^* \leftarrow \operatorname{argmax}_{s \in S \setminus D} f(s)$;
  $D \leftarrow D \cup \{s^*\}$;
  $U \leftarrow U \setminus \{h | h \in U \wedge d_{hs^*} \le l_{max}\}$;
end



(a) Online optimization (b) Offline optimization

Fig. 10. Comparison between door-to-door service and stop-based service.

Table 4
Summary of the experiment 3.

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

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 Fig. 10 and the key output values are summarized in Table 4. 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. This is because the values of time spent on walking and sitting in a vehicle are usually perceived differently. Usually, sitting in a car is considered to be more comfortable than walking, and a lower time-based travel disutility is associated with the former mode than the later one. Therefore, in Table 4, 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 s, 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.

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), 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 Appendix A. 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.

Table 5
Framework for the cost analysis based on Planco et al. (2015).

	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**

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). The values are extended and revised based on several other studies in the literature (Tirachini and Antoniou, 2020; Bösch et al., 2018-05-01; 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 Sections 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 h 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 h, 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 5. 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 our school trips are based on the 25% population model, the costs are multiplied by 4 to serve as an estimation for the actual scenario (i.e., 100% population model). 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 6.

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

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

Table 6
Annual costs estimation for the base case (unit: million Euro, except for per capita).

	Fleet	Operational	Personnel	Total	Per capita [Euro]
			Conventional vehicle		
Online approach	2.99	1.05	5.09	9.13	2460
Offline approach	1.88	0.72	3.20	5.81	1565
			Electric vehicle		
Online approach	3.10	1.24	5.09	9.24	2489
Offline approach	1.95	0.85	3.20	6.00	1617
			Autonomous electric vehicle		
Online approach	3.69	1.44	0	5.13	1382
Offline approach	2.32	0.99	0	3.31	892

Table 7
Impacts of operational schemes (Electric vehicles, annual costs, unit: million Euro per year).

	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 times	
Two starting times	9.65 (+2.4%)	5.25 (−12.5%)
	Introduction of DRT stops	
Stop-based	8.07 (−14.4%)	5.33 (−11.1%)

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 7. 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 times, on the other hand, is an interesting case. When an online optimization approach is used, the annual costs actually increase 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 times do not have a significant advantage. When the offline optimization approach is used, however, the result becomes different. With two different school starting times 30 min apart from each other, the total annual costs are reduced by 12.5%.

The results suggest that adopting different school starting times 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 7, 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.

[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

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.

4.4. Robustness of the offline optimization approach

From the simulations and analysis above, it can be seen that the offline optimization approach is more efficient than the online one. With the offline approach, the cost to provide school transport service can be significantly reduced. On the other hand, due to its design, the offline approach may be susceptible to uncertainty and stochasticity with respect to traffic and the boarding process. Despite the fact that the scenario of this study is located in the rural area, there are still day-to-day traffic fluctuation in the network. Furthermore, as pointed out in a recent study (Kucharski et al., 2021), the delays and no-shows of the passenger may have a strong negative impact on the ride-pooling system. Those uncertainties may undermine the punctuality of the service. In this section, we examine the robustness of the offline optimization approach.

To simulate the fluctuation of the traffic in the network, we use the network change events in the MATSim framework. The simulated period is divided into 10-minute time bins. At each time bin, the travel time of each link (i.e., road segment) is updated to a new value based on its initial travel time and a random perturbation. The perturbation is generated based on the Burr type XII distribution, which is a three-parameter variation of the Burr distribution (Tadikamalla, 1980). The probability density function of the distribution is shown in Eq. (4), where $x > 0$, $\alpha > 0$, $c > 0$, $k > 0$. Because of its heavier weight in the upper tail, the Burr type XII distribution can better represent the daily fluctuation of the traffic. The Burr distribution can also be found in many other studies related to travel time estimation, such as Taylor (2017) and Guessous et al. (2014). Based on the characteristic of the scenario, the parameters are set as follows: $\alpha = 0.95$, $c = 20.5$, $k = 0.5$. By multiplying the original travel time to the factor drawn from the above-mentioned Burr distribution, the updated travel time of a link during a 10-minute time bin can be acquired. This process is then repeated for each of the link and each of the time bin throughout the simulation.

$$f(x, \alpha, c, k) = \frac{ck}{\alpha}(\frac{x}{\alpha})^{c-1}(1 + (\frac{x}{\alpha})^{c})^{-(k+1)} \tag{4}$$

To model the uncertainty in the boarding process, normal distribution is used. We assume that the students will be ready to board the vehicle based on a normal distribution around the scheduled pickup time: $t_{ready} = t_{scheduled} + \epsilon$, where $\epsilon \sim \mathcal{N}(0, 120^2)$ (in seconds). If a student is not yet ready for pickup when the vehicle arrives, then the vehicle will wait for the student. The pickup process will be performed when the student is ready. If a student is ready for the pickup before the vehicle arrives, then he/she will wait until the vehicle arrives. As in the previous experiments, the boarding process itself takes 10 s.

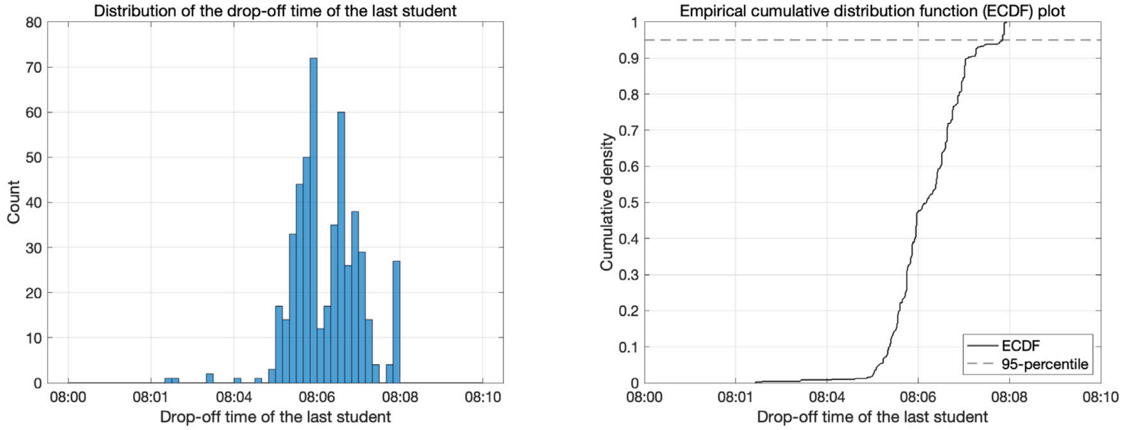
In a conventional school bus service, the bus normally will not wait for the student and depart from the stop according to the schedule. Likewise, in a taxi or DRT service, the driver will either charge a waiting fee or reject the passenger if the passenger arrives too late. Therefore, it is also reasonable to set an upper limit for the acceptable delay. In this experiment, the maximum acceptable delay is set to 3 min. That is to say, a vehicle will wait until at most 3 min after the scheduled pickup time. If the student is still not yet ready for pickup, then the vehicle will move on and continue to perform next tasks according to the schedule. As we are not interested in the number of students who are too late for departure, which is simply determined by the distribution model and the cut-off line, and it is outside the scope of the vehicle operation study, we assume the students who are more than 3 min late will just be ready to be picked up at the latest acceptable pickup time. Note that this simplification will not impact the operation of the vehicles, as vehicles will wait for those students until 3 min after the scheduled pickup times in either case.

Based on this setup, 500 simulations have been carried out with the pre-calculated schedules acquired from the offline optimization approach. In each simulation, a different seed is used to generate the uncertainty in traffic and the boarding process. For each analysis, we extract the drop-off time of the last student in the system. The distribution of the drop-off time of the last student in the 500 simulations are summarized in Fig. 11. Fig. 11(a) shows the histogram of the distribution of the drop-off time of the last student. Fig. 11(b) shows the cumulative density function of the distribution. From the plots, it can be observed that, in the worst case, the last student will be transported to the school at 8:08 am, which is 8 min too late. From the operational perspective, a buffer of 8 min can be added to guarantee the punctual arrivals of the students.

It needs to be pointed out that the schedule is pre-calculated and fixed in this robustness test. In the actual operation, however, the schedule can be updated during the operation, especially when there are heavy delays on one or more vehicles. That means the delay in the arrival time of the last student can be reduced in the actual operation. The outcome of this robustness test can be viewed as a conservative estimation. Alternatively, extra vehicles can be put into service to transport the students who cannot be transported to school on time due to the delays.

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, an estimated annual budget of around 1600 Euro per student will be needed if DRT system is used to 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. The costs can be reduced by adopting



(a) Distribution of the drop-off time of the last student

(b) Empirical cumulative density function of the drop-off time of the last student

Fig. 11. Results of the robustness test.

different operational schemes, such as allowing longer travel time, varying school starting times, switching to a stop-based service. In the long run, the autonomous vehicles can also be introduced to the service to further reduce the costs. 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.

It needs to be pointed out that our cost estimation is on the conservative side. The school trips are extracted from the MATSim open Vulkaneifel scenario based on 25% population model, which is the maximum sample size available. By serving all the school trips in the 25% model, it is equivalent to the case where 25% of the students use the service in the full scenario (i.e., with 100% population model). As the school transport service is supposed to be a public service that is available to all the students, therefore, it is reasonable to assume the system should be able to serve all the feasible school trips within the region, when calculating the total costs. To come up with the total cost estimation for the actual case, we linearly scale up the total costs from the 25% case (i.e., multiply by 4).

Usually, higher demand densities have positive impact on the ride-pooling (Santi et al., 2014; Kaddoura and Schlenther, 2021). With a higher pooling potential, the average cost to serve each passenger will become lower. When doing the linear upscaling, however, the average cost to serve each student remain unchanged. This means, our cost estimation, which is linearly scaled up from the 25% case, tends to overestimate average cost to serve each student and is therefore on the conservative side. In other words, in the actual operation, where much more than 25% of the students use the service, the average cost to serve each student is likely to be lower. Additional experiments have confirmed this speculation and suggest that our cost analysis may slightly overestimate the cost per capita of the proposed DRT school transport service (see Appendix B).

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. 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.

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.

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 include the background traffic (e.g., private cars, freight vehicles) in the simulation. 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 MATSim's default traffic model with background traffic is 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, a simplified traffic model is used instead. Nevertheless, we have examined the robustness of the offline optimization approach by introducing artificial fluctuations in the traffic and the boarding process (see Section 4.4), and the results indicate that some simple measurements will be adequate to counteract the negative impact of the uncertainty on the offline optimization approach.

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 s 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 s 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 board at the same place, the less boarding time per person is expected. If a more sophisticated stop duration model is introduced, the benefits of introducing DRT stops may become more significant.

Based on the results from this study, several potential future research topics can be identified. Given the fact that the budget required to maintain and operate the DRT fleet for school transport in the morning is reasonable compared to the actual budget being spent in the school transport service in the region, it is worth examining the operation of the DRT fleet during the rest of the day. For instance, the students also need to be transported back to home in the afternoon. But as the home-returning trips are less concentrated, the DRT fleet can serve the students while fulfilling additional travel demands from the public. A special dispatching algorithm may be developed for this purpose. In addition, the pricing and operational schemes, as well as how the people in the region will react to the DRT service, also deserve a closer look, such that the fare collected can cover the cost as far as possible. With a suitable vehicle operational strategy and the help of the emerging autonomous driving technology, the outlook of having an integrated DRT system (i.e., serving both the students and the public) in the rural area that requires no extra funding is positive.

CRediT authorship contribution statement

Chengqi Lu: Conceptualization, Methodology, Software, Writing – original draft. **Michal Maciejewski:** Methodology, Software, Writing – review & editing. **Hao Wu:** Methodology, Software, Writing – review & editing. **Kai Nagel:** Supervision, Conceptualization, Writing – review & editing.

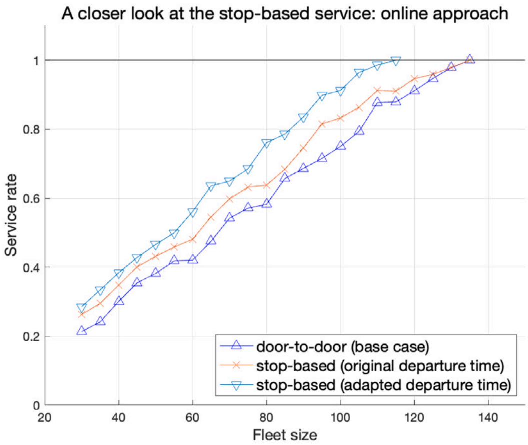
Data availability

Data will be made available on request.

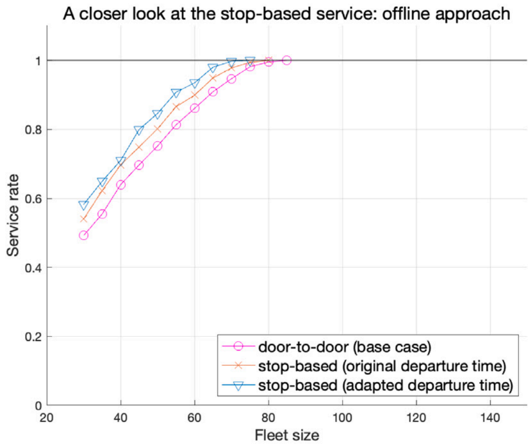
Appendix A. The benefits of introducing DRT stops

As mentioned in 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 s) 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



(a) Online optimization



(b) Offline optimization

Fig. A.1. Stop-based service with and without adaptation of departure time.

Table A.1
The benefits of introducing DRT stops.

	Minimum fleet size	Total fleet distance [km]	Mean travel time [s]
	Online approach		
Door-to-door	135	5489	1348
Stop-based:			
Original max travel time	135	4957	1208 + 251
Extended max travel time	115	4865	1235 + 251
	Offline approach		
Door-to-door	85	3772	1248
Stop-based:			
Original max travel time	80	3723	1140 + 251
Extended max travel time	75	3495	1126 + 251

optimization approach, are summarized in Fig. A.1 and Table A.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 increased maximum allowed travel time and improved efficiency in vehicle utilization.

Appendix B. Impact of number of trips on the cost estimation

As pointed out by several studies, a higher demand density contribute to a higher potential of ride-pooling (Santi et al., 2014; Kaddoura and Schlenther, 2021). With more ride-pooling and everything else the same, the required fleet size and the total fleet mileage can be reduced. This will lead to a lower average costs to serve each customer. This also applies to the school transportation case. In order to acquire a better understanding of the potential overestimation, we have performed a sequence of experiments with different demand densities. Here, the service area remains unchanged, the demand density is proportional to the sample size.

Since it is challenging to generate more trips without additional data, we down-sample the trips from 25% instead. We generate a sequence of subsampled trips, namely 5%, 10%, 15%, 20%. By doing so, we can still observe the relation between the proportion of the trips and the cost per capita. We apply the same approach and setup as in the base case to identify the minimum required fleet size and the fleet distance. Then the cost per capita can be calculated based on the cost structure in Section 4.3. Same as in the main text, we use the cost structure for the electric vehicle to compute the cost estimation.

The results are summarized in Table B.1. Note that the total annual costs in Table B.1 are not scaled up. To better illustrate the relation between the demand density and the cost per capita, we plot the cost per capita against the sample size in Fig. B.1. From the plot, it can be observed that the cost per capita decreases as the percentage of students using the service increases for both online and offline approach.

Table B.1
Impact of demand density.

Sample size	Number of trips	Total cost [Million Euro/year]	Cost per capita [Euro/year]
		Online optimization	
5%	187	0.69	3696
10%	372	1.21	3252
15%	557	1.65	2955
20%	743	2.07	2783
25%	928	2.36	2538
		Offline optimization	
5%	187	0.44	2327
10%	372	0.70	1880
15%	557	0.97	1734
20%	743	1.23	1650
25%	928	1.50	1617

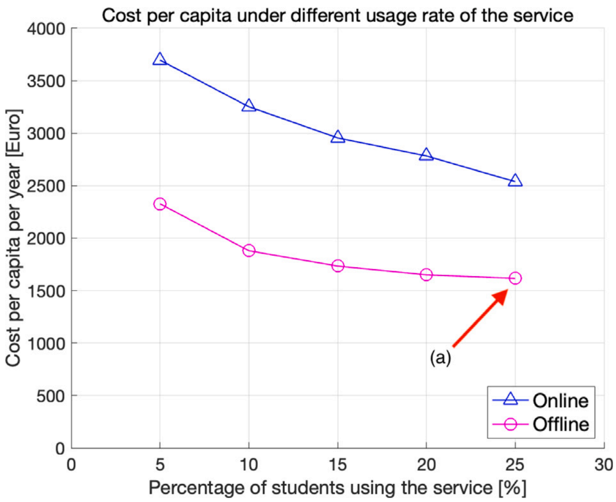


Fig. B.1. Cost per capita when different percentage of students use the service.

As our main results in the cost estimation are based on the offline approach, we now focus on the offline case. Point (a) in Fig. B.1 is the point where our main cost estimating is based on. From the magenta curve (i.e., the offline case), we can make several conclusions and speculations. First, this result is in line with the results from the literature, and the cost per capita is likely to further reduce as more students use the service. This means our cost estimation is on the conservative side. Second, a saturation trend can be observed, which means the cost per capita is likely to remain within a certain range as more students use the service. Finally, point (a) is the largest number of school trips we can acquire from the open-source population model, we use the cost per capita at this point to project the total cost of the actual DRT system (i.e., the system can serve all the students). Based on this plot, it is reasonable to conclude that our cost estimation is on the conservative side, with mild overestimation.

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 18,398 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 35,349 Euro. Half of it, 17,448 Euro, will be lost during the life span

Table C.1
Detailed framework for the cost analysis.

	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),
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),
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)

of 12 years, which corresponds to 1454 Euro per year. The remaining value of 17,448 Euro will be consumed after driving a total distance of 220,776 kilometers (i.e., 18,398 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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