

Improved public transportation in rural areas with self-driving cars: A study on the operation of Swiss train lines

L. Sieber^{a,1}, C. Ruch^{a,*,1}, S. Hörl^b, K.W. Axhausen^b, E. Frazzoli^a

^a Institute for Dynamic Systems and Control, ETH Zurich, Switzerland

^b Institute for Transport Planning and Systems, ETH Zurich, Switzerland

ARTICLE INFO

Keywords:

Autonomous mobility
Mobility-on-demand
Taxi
Rural transportation
Train substitution
Fleet control
Agent-based simulation

ABSTRACT

Public transport lines, especially train lines, have historically played an important role as economic lifelines of rural areas. They are one of the most important factors contributing to economic prosperity as they provide access to mobility for all the inhabitants of these regions. Maintaining such rural public transport lines can be a challenge due to the low utilization inherent to rural areas. Today, with the emergence of fully self-driving cars, on-demand mobility schemes in which autonomous robotic taxis transport passengers, are becoming possible. In this work, we analyze if rural public transport lines with low utilization can be replaced with autonomous mobility-on-demand systems. More specifically, we compare the existing public transportation infrastructure to hypothetical mobility-on-demand systems both in terms of cost and service level. We perform our analysis, which focuses on the operational aspects, using a simulation approach in which unit-capacity robotic taxis are operated in a street network taking into account congestion effects and state-of-the-art control (dispatching and rebalancing) strategies. Our study considers the case of four rural train lines in Switzerland that operate at low utilization and cost coverage. We show that a unit-capacity mobility-on-demand service with self-driving cars reduces both travel times and operational cost in three out of four cases. In one case, even a service with human driven vehicles would provide higher service levels at lower cost. The results suggest that centrally coordinated mobility-on-demand schemes could be a very attractive option for rural areas.

1. Introduction

In rural regions, the population density is low and distances to the cities and their available services are large. To ensure economic prosperity and social connection to the surrounding cities and within the region itself, access to a suitable mobility system is one of the most important factors (Starkey et al., 2002). Today, in rural regions the preferred mode of transportation is the privately owned car (Pucher and Renne, 2005). Cars are the ideal means of transport to serve the diverse travel demand patterns in a rural region as they are highly flexible.

Yet, there are people who are not able to own and drive a car and thus often lack adequate access to mobility. For this and other reasons, schedule- and line-based public transportation (PT) services, e.g., buses or trains, are implemented by governments to

* Corresponding author.

E-mail addresses: lsieber@ethz.ch (L. Sieber), claudio.ruch@idsc.mavt.ethz.ch, clruch@ethz.ch (C. Ruch), sebastian.hoerl@ivt.baug.ethz.ch (S. Hörl), axhausen@ivt.baug.ethz.ch (K.W. Axhausen), emilio.frazzoli@idsc.mavt.ethz.ch (E. Frazzoli).

¹ Shared first co-authorship.

provide a viable alternative. Due to the low population density in rural regions, these public transportation services differ substantially from the ones available in major cities: the frequencies are much lower, the operating hours are reduced, and the travel times are longer as routes are less direct. In addition to these drawbacks for users, the operators also face challenges. For a public transportation operator, an urban environment is more attractive than a rural area, as it is often more profitable to run a service in a densely populated region. In rural areas, the vehicles have to drive large distances while only carrying a few customers. For this reason, rural public transportation lines are under a constant economic pressure and operators often search for more cost-efficient services to ensure access to mobility. For example, existing train lines have been substituted with bus lines (Gray and Crichton, 2014) or bus lines with dial-a-bus services (Velaga et al., 2012).

Even in densely populated Switzerland, there are a number of regional train lines with an average cost recovery of less than 30%, i.e., more than 70% of the costs are subsidized by the government. In 2013, there were 13 such lines (Eidgenössisches Departement für Umwelt, 2013).² For many of them, there are continued public debates in which attempts to close the operations are countered by public votes.³ Such questions also are subject to active research in Zurich, where attempts to replace conventional unprofitable public transport lines with on-demand services are investigated regarding their impact on welfare and energy consumption (Becker et al., 2020).

Interestingly, a solution to these challenges of rural mobility could be provided by novel technologies. Automation of vehicles is advancing at a rapid pace; over recent years it advanced to a point where self-driving cars are now tested on streets around the globe (Fagnant and Kockelman, 2015; Wadud et al., 2016). In combination with the possibilities enabled by smartphones and communication technologies in general, a new type of mobility could emerge from the combination: in a so-called autonomous mobility-on-demand (AMoD) system, self-driving cars operating in a fleet serve transportation requests in an on-demand manner. This combination of self-driving vehicles and the taxi service model can be seen as one of the dominant modes of future mobility (Litman, 2017). AMoD will enable a more affordable mobility with less upfront cost, while offering a high spatial and temporal flexibility of the service. The costs are assumed to be lower compared to conventional mobility-on-demand (CMoD), mainly because no wages for the drivers have to be paid. In this work, we assess the potential impact of both coordinated AMoD and coordinated CMoD systems on rural mobility. We limit our study to fully coordinated CMoD systems in which the drivers do not take independent or strategic decisions but only execute the commands given by the coordinator. Therefore, the term CMoD in the work at hand refers only to fully coordinated CMoD systems; it does not include conventional ride-hailing schemes in which drivers may make strategic decisions in order to optimize their individual profit.

Specifically, our objective is to analyze if mobility-on-demand could replace an existing rural public transportation line, i.e., if it could provide higher service levels at lower cost than the mobility systems which are in operation today.

The work focuses on public transportation lines with the characteristics that are illustrated in Fig. 1. The line operates between the two cities A and B and the villages in the rural region between the two cities A and B are served by it. The cities A and B are connected to the rest of the transportation network of the country. In the examples that we assess, no other perpendicularly oriented public transportation line exists, i.e., it is not a setting in a mesh network. One could imagine such a public transportation line to be situated in a valley without any possibility of crossing the hills. The hypothetical mobility-on-demand service which we assess transports customers directly from their origin *O* to the final destination *D*. The taxis are single-passenger and thus no ride sharing is considered.

The paper is organized as follows: we summarize related work in Section 2. We then present the assessed scenarios in Section 3 and present the chosen methods in Section 4. Detailed results are presented in Section 5 and our conclusions in Section 6.

2. Related work

Consensus has emerged that the availability of fully self-driving cars will fundamentally change transportation systems. Self-driving cars will enable large-scale one-way on-demand mobility as they resolve several of the shortcomings of today's mobility-on-demand systems, most importantly the difficulty or impossibility of repositioning empty vehicles in a cost-efficient manner as well as the availability and cost of drivers. The impact of autonomous mobility-on-demand systems was assessed in several studies focusing on urban mobility, e.g., for Austin, Texas (Fagnant et al., 2015; Gurumurthy et al., 2019; Simoni et al., 2019), Berlin (Bischoff and Maciejewski, 2016), Lisbon (Martinez and Viegas, 2017), New Jersey (Zachariah et al., 2014), Paris (Hörl et al., 2019), Singapore (Spieser et al., 2014), and Zurich (Hörl et al., 2019). The studies agree that several privately owned cars can be replaced with one robotic taxi, that overall vehicle distance traveled will increase compared to today, and that the service level and price of such transportation systems would be very competitive in comparison to other transportation modes.

The implications on rural mobility are likely to be equally profound but have been studied much less until today. In rural areas, access to mobility is generally more restricted than in urban areas and it is an important factor determining the welfare of the population. In many countries, the demographic decline in rural areas is severe and has been linked to the lack of access to mobility, see, e.g., (Starkey et al., 2002; Osti, 2010). This lack of access to adequate and affordable transportation services “constrains economic and social development and contributes to poverty” (Starkey et al., 2002). Many approaches exist to improve access to mobility in rural areas, including subsidies, policy measures, and technological, e.g., communication-infrastructure-based approaches.

² Approximately 11% of all the lines owned by the Swiss Federal Railways (SBB Open Data, 2018).

³ Switzerland's direct democratic and federal political system allows for broad participation of the citizens in the decision-making progress, including frequent votes on factual issues.

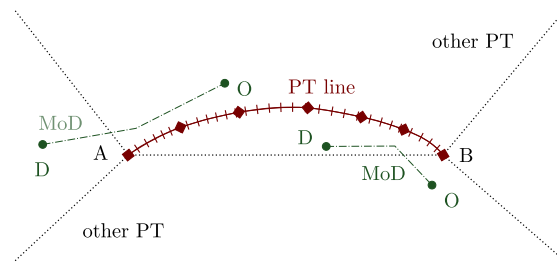


Fig. 1. Abstract sketch of the problem addressed in this study. An existing rural public transportation line between A and B is replaced with a mobility-on-demand service.

Rural areas are characterized by low spatial and temporal demand density; for this reason, one technology-oriented solution is the design and introduction of mobility-on-demand systems which respond “in some manner or form to individualized requests or demand” (Ellis and McCollom, 2009). In comparison to systems with a fixed schedule and fixed lines, such demand-responsive systems can improve service level without increasing costs as they can be operated at higher utilization levels. In the United States, there are currently about 1,500 mobility-on-demand systems in operation in rural areas (Ellis and McCollom, 2009). Such systems are also operating in other countries: (Velaga et al., 2012) presents an overview of the different mobility services in rural Scotland, where many dial-a-bus services are running. A majority operate in a specific area where either no public transport was present before or an existing bus line was replaced. Often, these services are operated by local taxi companies and financially supported by the government. For most of the services, a ride has to be booked a day in advance. Some of the buses run based on a fixed line, while others are fully flexible and can pick up a customer at any location. In the Netherlands, NS Zonetaxi (Zonetaxi and Zonetaxi, 2018) connects local taxi services to the national rail network. It solves the last mile problem with single-passenger taxis with a simple zone-based pricing scheme. A taxi can be booked in advance via a national online platform. The authors of König and Grippenkov (2017) have identified 17 dial-a-ride bus schemes in Germany in a recent study, mostly with small passenger numbers. Most users use these schemes due to the inability to own and drive a car.

In Switzerland the national public transport company Postauto offers around 20 dial-a-ride services in rural regions (Postauto et al., 2018) which connect the area to the rest of the public transport system. These minibuses have to be booked up to an hour in advance and the service is schedule and line based. In some regions the dial-a-ride services were upgraded to a regular public transport line as they proved to be used frequently enough. Furthermore, there exist a number of highly subsidized train lines in rural areas operating with an average cost recovery of less than 30%. We focus our work on these train lines.

Interestingly, many of the existing mobility-on-demand schemes in rural areas exhibit simple operational setups and do not make use of available technologies, e.g., communication technology for efficient booking, optimized fleet operations, and others. As an example, one of the schemes mentioned in König and Grippenkov (2017) is organizing its operation with only the use of spreadsheets. The results of these methods of operation may be reduced service levels; e.g., users have to book well in advance or can board only at designated stations. Also the operational costs are likely to be higher due to undetected inefficiencies. This gives rise to the question of how mobility-on-demand schemes in rural areas would compare to existing public transit lines if all potential technology was exhausted.

In this work, we attempt to make such a comparison by considering the case of train lines in rural areas of Switzerland which operate under very low utilization. A similar question was treated in Mendes et al. (2017) where the authors assess an alternative solution for a projected light rail line in New York City. The study investigated whether the travel demand to be served by the line could be served with a fleet of shared autonomous vehicles (SAV). The authors propose a line- and station-based service which is operated on demand using 12-person capacity SAVs. In an event-based simulation framework, the demand was represented with a stochastic process. Several relevant factors such as congestion were not considered. The study concluded that 39 light train vehicles could be replaced with 150 SAV to serve the customers with the same travel time. An increase of the number of vehicles to 450 would result in the same average wait time as for the light rail service and a 39% reduction in travel time. The authors conclude that SAVs can be a viable alternative to traditional line-based systems, and further studies are encouraged. There are several important differences to our work: (Mendes et al., 2017) focuses only on service level. Instead, in our analysis we consider both service level and cost, using accurate numbers available from the transportation service provider and cost models. In comparison to Mendes et al. (2017), our travel demands are based on actual distributions of travel requests, our simulation environment models the road network in high resolution, and does take into account effects such as congestion.

A second related study is (von Mörner, 2018). This detailed study examines the economic feasibility of mobility-on-demand in rural areas in Germany as an alternative for conventional public transport. The main focus is placed on autonomous vehicles, and the authors conclude that “ride pooling with autonomous vehicles in rural areas replacing classic public transport can be economically feasible” (von Mörner, 2018). In comparison to our study, the author uses a heuristic fleet-control strategy, instead we compare several strategies including globally optimized ones. The operating policies were shown to be a decisive factor determining the performance of mobility-on-demand systems, e.g., in Hörl et al. (2019). This difference may also explain why the author of von Mörner (2018) does not see any potential to operate systems requiring drivers in an economically feasible way whereas we come to different conclusions. Our analysis assumes that there are no stations and all requests are served from origin to destination, while in von Mörner (2018) a station-based system is assessed. A final difference is that the author of von Mörner (2018) considers the case of



Fig. 2. The four case scenarios in Switzerland: Homburgertal (from Olten to Sissach), Thunersee (from Spiez to Interlaken), Boncourt (from Boncourt to Porrentruy) and Tösstal (from Winterthur to Rüti). Map from Google Maps (Google Maps, 2018).

ride-sharing in which multiple passengers may be in a vehicle at the same time. Instead, we focus solely on unit-capacity mobility-on-demand where either one or zero travel parties are in a vehicle at every given time.

Finally, there are also studies that assess the possibility of substituting or complementing public transportation systems in urban environments with mobility-on-demand. One such study is (Shen et al., 2018), in which first-/last-mile transportation in Singapore is studied. The authors argue that the 16 bus routes with most passengers serve 90% of the demand. Thus, they propose to keep these bus routes while substituting the other bus routes with a mobility-on-demand system. Based on agent-based simulations, and consistent with our own findings, they identify a “potential of enhancing service quality, occupying fewer road resources, being financially sustainable, and utilizing bus services more efficiently.”

In summary, mobility-on-demand as a concept to improve access to mobility in rural areas has been considered in only a few studies. Evidence suggests that it may be a viable alternative to existing fixed-schedule and fixed-line public transit schemes. However, the existing state of the literature is characterized by several shortcomings which we resolve in the work at hand as we consider an actual demand profile to model the transportation scenario in a recognized open-source framework (Horni et al., 2016) on a high-resolution road network. We consider a free-floating on-demand mobility system without stations in which the behavior of the cars is governed by several globally coordinated fleet operational policies. Finally, we rigorously compare cost and service level for both with and without self-driving cars.

3. Four case scenarios

We have selected the train lines with low utilization levels and cost recovery which are illustrated in Fig. 2 for our study. Additionally, the entire framework is created in a generic way and allows assessing additional lines if necessary. We use the travel demand from the IVT baseline scenario (Hörl et al., 2016) for our work, and the characteristics of the train lines are taken from the database of the Swiss Federal Railways (SBB); specifically, we accessed the schedule at (Open Data Platform Swiss Public Transport, 2018) and information on the stations at (SBB Open Data, 2018). The baseline scenario (Hörl et al., 2016) indicates that between 14% and 16% of the trips are done with public transportation in the four scenarios.

3.1. Homburgertal

One train line which had a lot of attention in past years is the S9 (also called “Läufelfingerli”) between Sissach and Olten through the Homburgertal. It is a 18 km long train line with 6 stops in small villages, all of which have a population below 2,000 people. On this line, a single train is operating with a frequency of one train per hour, and it travels 22 min from end to end. The SBB data about passenger frequencies at the stations indicates that 1,000 people are using this line on a regular week day (SBB Open Data, 2018). Most of them travel either to Olten or Sissach or take a connecting train from there onward to larger cities such as Basel, Zürich, or Bern. Between Olten and Sissach, there exists a second train line through a parallel valley with a longer tunnel. This line is the main connection for Intercity trains between the two towns and does not stop in inside the rural area that we consider. In November 2017, the population clearly rejected the plans to replace the train line with a bus service.

3.2. Thunersee

The regional train line between Interlaken and Spiez at the south coast of the lake of Thun (Thunersee) mainly serves the two villages Leissigen and Därligen with a total of 1,500 inhabitants. There is a direct train from Interlaken to Spiez every 30 min. However, these trains do not stop in Leissigen and Därligen which are served by another hourly connection that operates on the 18 km long route. The parliament of Bern has decided in 2017 ([Der Regierungsrat des Kantons Bern, 2017](#)) to replace these services with a bus line. A detailed study ([Lebküchner and Kugelmeier, 2016](#)) pointed out that on an average day only 416 people are transported from and to the two stations. Most of them want to travel to Spiez or from there on further to the larger cities Thun or Bern. Another large user group is the children who go to school in Interlaken.

3.3. Boncourt

Close to the border of France and Switzerland, the 10.5 km long train line between Boncourt and Porrentruy serves 590 people on an average week day. The train is not only operating between the two towns but starts in Delemont and ends in Boncourt. Therefore, within this scenario a reduction of the operating area to the line between Delemont and Porrentruy is considered. The part between Porrentruy and Boncourt is served once an hour and takes around 15 min. The connection to the close French city Delle is only provided by a bus service; a reopening of the train line is in discussion. This is mainly due to the connection to the French high speed rail network which would start in Belfort. It can be assumed that this region will face some changes of the train service supply in the near future. Thus, it is interesting to consider the possibility of mobility-on-demand service as well.

3.4. Tösstal

The S26 through the Tösstal in the east part of the canton of Zürich connects the city of Winterthur with Rüti over a distance of 41 km. 8,500 people are using the train line per day; the close surroundings of Winterthur are especially well frequented. Therefore only the rural part of the line between Winterthur Seen and Rüti ZH is considered within this study. In this part of the line, the S26 is the only train which uses the track. Every hour, one train serves all 14 stations along the valley. Additionally, one train per hour runs between Winterthur Seen and Bauma to give this part of the line a connection towards Winterthur with a frequency of 30 min.

4. Simulation methods

The goal of this work is to analyze if a hypothetical mobility-on-demand system is able to provide better service levels at lower cost than existing public transit lines in rural areas. To answer this question, simulations are carried out in the MATSim ([Horni et al., 2016](#)) simulation environment. One important methodological decision is that the assessment was done under static demand, i.e., both the train lines and the mobility-on-demand system process the exact same transportation requests which do not change in response to the chosen method. We consider this approach sensible for different reasons. On one hand, even under the consideration of static demand, it is not well understood if mobility-on-demand systems could provide better service levels than the existing conventional public transit lines. There are good reasons to believe so as a mobility-on-demand system does, for instance, allow for almost infinite hours of operation without additional cost, it transports passengers directly from their origin to their destination, and it could operate without a schedule. Additionally, there would be almost no operating costs and emissions when no requests occur. A bus or train with low utilization on the other hand has very large costs and emissions per passenger. Using state-of-the-art fleet control strategies, an actual demand profile, a high-resolution road network, an accurate and open-source simulation environment, and detailed cost models, we can provide new insights into these questions.

However, we do provide an outlook of what consequences induced demand could have in Section 5.5 of our Results Section. At this point, we first focus on a thorough comparison of the different transportation systems from an operational point of view.

The general simulation approach is shown in [Fig. 3](#). Based on the input data two simulations are carried out. One simulation models the existing PT line service. The current cost and service levels are evaluated based on the demand and the PT line properties. The second simulation provides data to compare a potential MoD service, namely the service level and cost for a given scenario which depends on the MoD fleet configuration, a street network, and the same travel demand as the PT line. The input data, the two simulations, and output data are discussed in more detail in the following paragraphs.

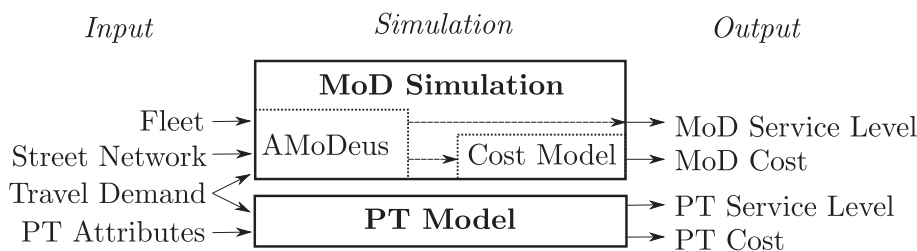


Fig. 3. Workflow of the simulation approach.

4.1. Inputs

The following input data is used in the simulations:

- The **PT line attributes** are required to simulate the PT journeys and to evaluate the costs of the PT line. The location of all the stations along the PT line are used to calculate trip distances and the total length l of the PT line (A to B in Fig. 1). Furthermore, a schedule of the PT line which includes the drive times between stations as well as the number of PT vehicles per day (N_{day}) is used for the simulation.
- The **taxi fleet** contains information about the vehicles and organization of the MoD service. The two most important parameters are the number of vehicles N (fleet size) and the control strategy. These two values will be varied to find an optimal fleet setting for a given scenario; more information on this process is provided in Section 4.4. As we consider coordinated MoD systems and not MoD systems with strategic and independent agents, these control strategies can be applied equally to AMoD and CMoD systems.
- The **street network** is an abstract representation of the real streets in the region surrounding the PT line. The links in the network represent the streets and have a length and a free speed associated to them. Additional attributes can be added such as the traffic flow capacity or the number of lanes. For the four case studies, Open Street Map (OSM) data (OpenStreetMap, 2018) is used and then calibrated with the Google Maps Distance Matrix API data (Google, 2018).
- the **travel demand** used for the study should only contain trips of the PT line under consideration. This data is typically not directly available. If surveys are made in a train, the primary origin and the final destination in street-level precision are often not part of the survey, which considers only the PT stops at the beginning and at the end of the journey. Therefore, a method was developed in this work to extract the travel demand of the train line from the demand of a larger enclosing region. Such data is often available from surveys recording daily mobility behavior, e.g., for the United States of America (Santos et al., 2011) or for the United Kingdom (Stillwell et al., 2016). Typically, it contains the daily plans of participants including their activities and journey legs. In order to produce a suitable demand profile, all legs need to be identified for which the PT line of interest is used as a means of transportation.

We have developed and applied a procedure for this task which is illustrated in Fig. 4. First, we observe that the line serves a specific area between city A and city B which is called *train area*. For trips starting or ending in this area, the PT line is the dominant public transportation service. Travelers who travel directly between A and B would rather use a faster and direct connection without stops as the PT line under consideration is a slow, regional line serving the rural area between A and B . The end stations of the line are not inside the train area because often A and B are stations which belong to a larger city. There, other public transport systems such as bus or tram lines exist, these services would be maintained in the event of a replacement of the considered PT line, thus the demand served by them is not considered. If such a station was included in the train area, a lot of travelers who use the bus or tram according to the travel data would have to be served by the MoD service. As the new service is only a possible substitution of the rural PT line and not the bus and tram service in the cities A and B , this would not be a suitable modeling approach. However, in certain cases, it could make sense to include one (or both) of the final stations A and B in the train area, for example, if one of the stations is located at an isolated area without other external network connections, e.g., at the end of a valley. For all the scenarios evaluated in this work, this is not the case.

Apart from the *train area*, we define the *access area* as the set of locations with access to the new MoD service. The access area encloses the PT line of interest. We consider all trips which have at least one end point in the train area as trips served by the PT line of interest. The other end point can be inside or outside the access area. In the first case, e.g., from O_1 to D_1 , the MoD service can reach the second location and transport the traveler directly to this place. Such a leg would be served exclusively by the MoD system. In the second case, the destination is outside the access area of the MoD service, e.g., D_2 . Then, it is assumed that the traveler will travel with both the MoD and PT service. The traveler will change between the two modes at one of the two large stations A or B . The choice of the station depends on the location of D_2 . In this work, we would always choose the station which is faster to reach from D_2 by public transport. A trip from the original travel demand from O_2 to D_2 would thus be decomposed into a MoD trip from O_2 to A and a public transport trip from A to D_2 . If the origin is outside the access area and the destination inside the train area, the analogous procedure is applied. After this process yields a set of trips representing the travel demand, two final

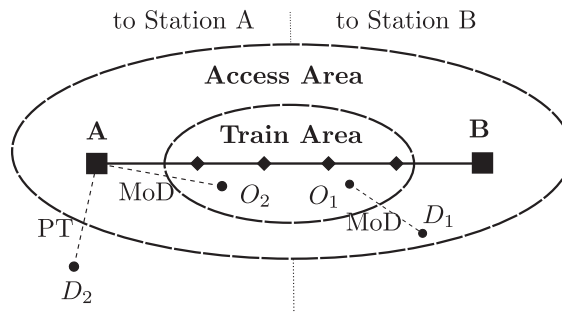


Fig. 4. The access area defines the region where the new MoD service operates and the train area in which region travelers use the PT line. Dependent on the location of the destination D a trip is split (2) or kept as it is (1).

steps are carried out. First, if a person had to walk further to the closest train station than going directly to the final destination, this person is removed. Second, the remaining population is scaled to the number of passengers R which use the PT line according to the information of the operator. Operators typically provide such aggregate data. The data used in this study is available at ([SBB Open Data, 2018](#)).

4.2. Simulation models

The input data is used in the two simulations to calculate the service level and the cost of both the existing PT line and the new MoD service.

- The **MoD Simulation** is carried out with AMoDeus, which was used previously for similar tasks, e.g., in [Hörl et al. \(2019\)](#). AMoDeus is an extension of the agent-based transportation simulation framework MATSim ([Horni et al., 2016](#)) specifically designed to evaluate mobility-on-demand systems operating with different control strategies. MATSim uses waiting queues to model roads instead of modeling each vehicle as a continuous time dynamic system. Its traffic simulation engine is well tested and validated. By default, the activities of the agents (population) over one day are considered. Agents have specified activities at certain locations in the road network which are connected by travel legs, for which various modes of transportation are modeled. Often, the agents' selfish behavior is modeled using MATSim's outer loop with a co-evolutionary algorithm. If suitable cost functions are defined, this approach allows finding the Wardrop equilibrium for a given transportation scenario. In this work, these functions are not used as we focus on the comparison of operations and consider a static demand profile (see the beginning of Section 4 for a detailed explanation).

AMoDeus contains all the necessary code to extract the metrics which define the service level of the mobility-on-demand system. The most important metrics considered in this work are the wait time t_w and the in-vehicle time t_v . The first is the time from request submission to the pick up of the passenger. The second is the time from pick up to drop off. The sum of the two values is then the (total) travel time $t_t = t_w + t_v$. Apart from the service level, the efficiency of the operation is also measured. The principal metrics used for this in this work are the vehicles distance traveled and their composition into different types, the states of the taxis at every time step, and the distance ratio which is defined as the fraction of vehicle distance traveled with a customer and the total vehicle distance traveled.

To calculate the operational cost of the fleet, the model presented in [Bösch et al. \(2018\)](#) is used. It contains detailed cost parameters for rural regions and is calibrated for a setting in Switzerland. Assuming that the fleet is operating with only midsize and nonelectric vehicles, the model allows extracting the cost parameters for AMoD and CMoD which are shown in [Table 1](#). The costs per trip for AMoD are related to cleaning, whereas for CMoD the cleaning costs are included in the costs per year as presented in [Bösch et al. \(2018\)](#). The costs for buying a vehicle are depreciated over a vehicle lifetime of 300,000 km ([Bösch et al., 2018](#)). The total yearly fleet costs $C_{\text{fleet,year}}$ are then calculated as shown in Eq. (1):

$$C_{\text{fleet,year}} = C_v \cdot N_v + C_{km} \cdot d_{\text{total}} + C_{\text{trip}} \cdot N_{\text{trips}} + C_{\text{hour}} \cdot t_{\text{working}} \quad (1)$$

where N_v is the number of vehicles, d_{total} is the distance traveled by the fleet in one year, N_{trips} is the number of trips per year and t_{working} are the working hours by all drivers in a year. These yearly values are extrapolated from the simulations for one day as the data contains trips on an average day. The average cost per vehicle kilometer CV_{km} can then be calculated using Eq. (2):

Table 1
Cost parameters for the AMoD and CMoD services. All values are adapted from [Bösch et al. \(2018\)](#).

| | Value | AMoD [CHF] | CMoD [CHF] |
|----------------------|--------------------------------|------------|------------|
| Per year and vehicle | Insurance | 400 | 800 |
| | Tax | 250 | 250 |
| | Parking | 3495 | 3495 |
| | Toll | 40 | 40 |
| | Overhead | 5110 | 5110 |
| | Vehicle Management | 3650 | 3650 |
| | Cleaning | 0 | 2745 |
| | Total (C_v) | 12945 | 16090 |
| Per vehicle km | Maintenance | 0.045 | 0.045 |
| | Tires | 0.014 | 0.015 |
| | Fuel | 0.068 | 0.076 |
| | Acquisition | 0.098 | 0.082 |
| | Total (C_{km}) | 0.225 | 0.218 |
| Per trip | Cleaning (C_{trip}) | 0.375 | 0 |
| per hour | Driver (C_{hour}) | 0 | 35 |

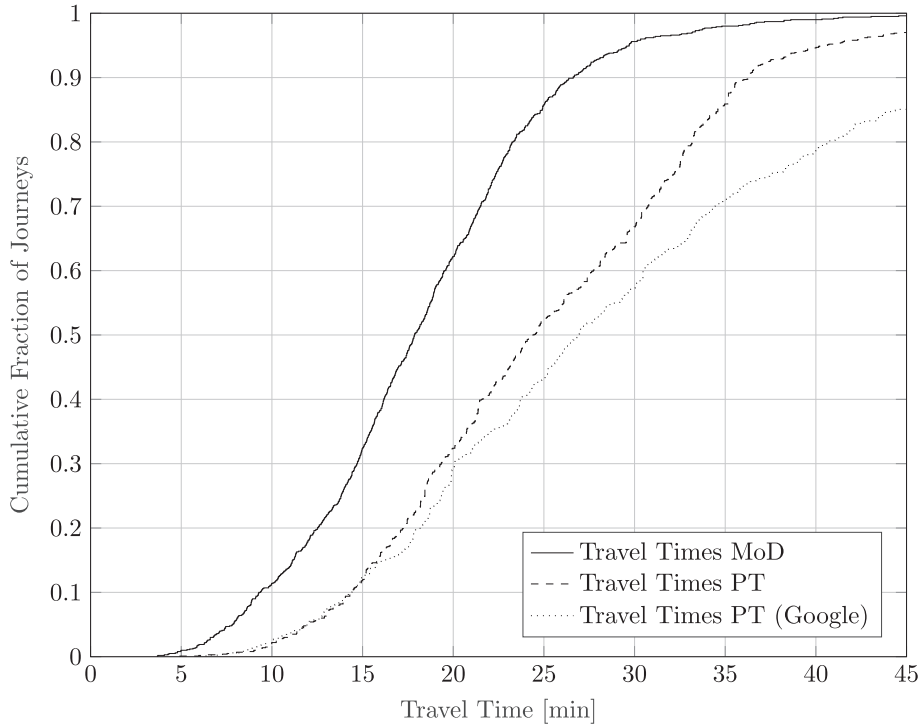


Fig. 5. Comparison of the cumulative distribution of PT travel times (access/egress time plus in-vehicle time) and MoD travel times (wait time plus in-vehicle time).

$$CV_{km} = \frac{C_{fleet,year}}{d_{total}} \quad (2)$$

Because all the taxis are used by only one person at a time, the total cost per passenger kilometer CP_{km} is

$$CP_{km} = \frac{C_{fleet,year}}{d_{customer}} \quad (3)$$

where $d_{customer}$ is the vehicle distance traveled with customers on board.

- The **PT model** is necessary to enable a realistic comparison of the MoD service to today's operation of the PT lines. In accordance with the procedure presented in [Salonen and Toivonen \(2013\)](#), a PT journey is modeled with three legs: (1) accessing a PT station, (2) driving with the PT to another station and finally (3) accessing the journey destination. The two relevant stations are found by searching for the closest station to the origin and the closest station to the destination of the journey. For the legs to and from the stations, it is assumed that the person would walk with an average velocity of 1.34 m/s ([Weidmann, 1992](#)). Distances above 2 km are assumed to be covered by bicycle (or another PT) with an average velocity of 5 m/s ([Allen et al., 1998](#)). The duration with the PT (2) is according to the PT schedule which is part of the input data. This method of calculation covers the most important characteristics of a journey. Furthermore, it is a conservative approach in line with our objective of not depicting the novel technology of AMoD with several unknowns excessively well. The approach can also be interpreted as follows: a person would orient his or her daily plan according to the PT schedule and be capable of arriving exactly at the departure time at the station. To be sure the PT travel times are in the right order of magnitude, each ride is compared to the result for a public transit ride in the Google Maps Distance API ([Google, 2018](#)). This comparison reveals that the presented model leads to a slightly lower travel time than the Google data would indicate ([Fig. 5](#)).

The operational costs of a PT line are calculated with Eq. (4) which is for an average day and neglects the small differences in schedule frequency on weekdays and weekends.

$$C_{pt,year} = CV_{km,pt} \cdot l \cdot N_{day} \cdot 365 \quad (4)$$

where l is the length of the PT line, N_{day} the number of PT vehicles per day on this line and $CV_{km,pt}$ the average vehicle cost per km of the public transport service. In this work, a value of 15 CHF/km ([SBB Personenverkehr, 2018](#)) is used for $CV_{km,pt}$ according to the recommendation of the railway operator. This value contains all running costs such as the wages, vehicles, cleaning costs, and overhead. Additionally, it includes a part of the infrastructure costs associated with the railway and stations. It can be seen as the cost savings which would be possible if the operation of the passenger train line was stopped but the rail tracks would be preserved for other purposes, e.g., to relieve network congestion, to bypass other lines under maintenance or to transport cargo. If the rail tracks were decommissioned, the cost savings would be higher.

4.3. Outputs

In the work at hand, the objective is to understand if the service level currently provided by the PT line can be reached with a MoD service as well and how the costs would compare in such a case. Thus, we must be able to evaluate both the cost and the service level of both alternatives.

- The main **MoD service level** measure is the travel time. It shows how long the whole trip takes from the time when a person calls a taxi to the time when the person leaves the vehicle. Yet, it is not sufficient to consider only the travel time as the reliability and predictability of the service is heavily influenced by the wait time. When a passenger customer calls a taxi and needs to wait a long time, this would render the service useless for many types of trips; e.g., the ones which depend on the connection to a fast train at one of the end points. The scenarios considered in this work reveal the most severe congestion and the highest demand in the time periods from 6 to 8:30 am and from 4 to 6:30 pm. During these peak hours, approximately 50% of the requests are observed. To ensure a reliable MoD service, we specify that the mean wait time in these peak periods should be below 5 min. With this assumption, the maximal wait times also stay within an acceptable range (see Section A.1.2 for details).
- The **MoD fleet cost** is according to the model presented above in the MoD simulation model in Section 4.2 (Eq. (1)). Depending on the fleet type (CMoD or AMoD), the cost function slightly differs; the largest difference is that the CMoD contains wages for drivers while the AMoD service does not.
- For the **PT service level** the travel time as outlined above is used. It contains the in-vehicle time and the time it takes to access stations at the origin and at the destination. Wait times at the PT station are neglected.
- The **PT cost** includes the operational costs of the PT line. As presented in Eq. (4) the cost is mainly a function of the line length and the number of operating vehicles.

4.4. Evaluation of fleet properties

We summarize the size of the MoD fleet and the control strategy used under the term fleet properties. The cost and service level of an MoD system is strongly influenced by the fleet properties as several previous studies, including (Hörl et al., 2019; Spieser et al., 2014), have shown. Therefore, a suitable procedure has to be found which allows determining the fleet properties which are used for comparison with the PT line.

In order to find the best fleet properties for the assessed cases, we carried out several simulations with different fleet sizes and all of the five control strategies assessed. Then, for each control strategy we searched for the minimum fleet size which resulted in a maximum peak wait time of less than 5 min, which is the predefined criterion for reliability defined in the previous paragraphs. In Appendix A.1, more information about this criterion is provided.

Finally, the control strategy which can fulfill the service level criteria with the lowest number of vehicles was chosen. In total, five control strategies were assessed: (1) demand supply balancing strategy (Maciejewski and Bischoff, 2015), (2) global bipartite matching, (3) feed forward fluidic control strategy (Pavone et al., 2012), (4) adaptive real time control strategy (Pavone et al., 2012) and (5) scenario adapted strategy. The last control strategy is a heuristic strategy developed specifically for the special characteristics of the assessed scenarios. Further details about the control strategies can be found in Appendix A.1.1.

5. Results and discussion

This section presents the simulation results in two steps: first, the influence of the control strategies on the two simulation outputs, service level and operational costs, is presented for an example scenario. Then, in Section 5.2, the results of the four case scenarios will be compared.

5.1. Influence of control strategies

This subsection provides an overview of how the wait time, the vehicle distance traveled, and the annual MoD fleet costs are influenced by the chosen control strategy for the Homburgertal scenario with a fleet size of 50 vehicles.

5.1.1. Travel times

Fig. 5 shows the cumulative distributions of the travel times for both the PT line and the MoD service using the global bipartite matching strategy. It shows that, despite of the conservative approach chosen for the comparison, the travel times are generally faster for a MoD service than the travel times with the PT. On average, the times are 7 min faster. The principal reason for this is that the door-to-door transport of the MoD fleet eliminates the access time to a PT station. This access time accounts for almost 65% of the average travel time with PT. Hence, only when the start and end of the trip are close to a station the travel time with PT is shorter than with MoD. That is the reason why only 17 percent of the journeys will last longer with MoD than with PT in this example. Only for three percent of requests more than 5 min of additional travel time have to be accepted if the PT is substituted with an MoD service. At least in this example, it was possible to obtain improved service levels when MoD instead of the PT line was used to satisfy the travel demand. As a next step, the costs of the proposed service have to be analyzed.

Table 2

Vehicle distances traveled per day for different control strategies for the example scenario with 50 vehicles.

| Control Strategy | Vehicle distances traveled per day [km] | | | |
|---------------------------|---|----------|--------|-------------|
| | Total | Customer | Pickup | Rebalancing |
| Demand Supply Balancing | 11286 | 9370 | 1916 | 0 |
| Global Bipartite Matching | 10955 | 9363 | 1578 | 14 |
| Adaptive Real Time | 13715 | 9366 | 1751 | 2598 |
| Feed Forward Fluidic | 11806 | 9367 | 1408 | 1031 |
| Scenario Adapted | 11658 | 9362 | 1427 | 869 |

5.1.2. Vehicle distance traveled

To understand the operational cost of a mobility-on-demand system, the vehicle distance traveled must be assessed. For the five control strategies, an overview of the vehicle distances traveled at a fleet size of 50 vehicles can be found in Table 2. Vehicle distances traveled with a customer on board are similar for all control strategies as all serve the same demand and use the same routing algorithm in the network (shortest travel time path). The small differences are due to the randomness present in the simulation and would disappear with a substantially higher number of simulations. The data also reveals that only three out of the five control strategies perform any rebalancing of vehicles. Total vehicle distances traveled are least for the global bipartite matching strategy which globally optimizes this metric. Of course, this reduces overall costs as the vehicle distances traveled are an important contributing factor (see Eq. (1)). In order to have reduced wait times, the pickup distance is relevant. Shorter pickup distances correlate with shorter pickup drive times, which are identical to the wait times customers experience. The vehicle distances traveled for pickup are shortest for the scenario adapted and the feed forward fluidic control strategy which is consistent with the results shown in Fig. A.8b showing that these strategies have also the lowest wait times.

5.1.3. Operational cost MoD

As outlined before, the fleet size and control strategy both have an influence on the cost of the MoD system. For the example scenario, these costs for different peak wait times are shown in Fig. 6. In this case, for five minute mean peak wait time, the total annual fleet costs are in the range from 1.6 to 2.0 million Swiss francs for the example scenario. The two strategies with the lowest cost are the global bipartite matching strategy and the scenario adapted strategy; they outperform the worst strategy significantly. Interestingly, for different strategies, other mechanisms help to reduce costs. While the global bipartite matching results in low costs as it has low vehicle distance traveled, the scenario adapted strategy and the feed forward fluidic strategy can reduce wait times

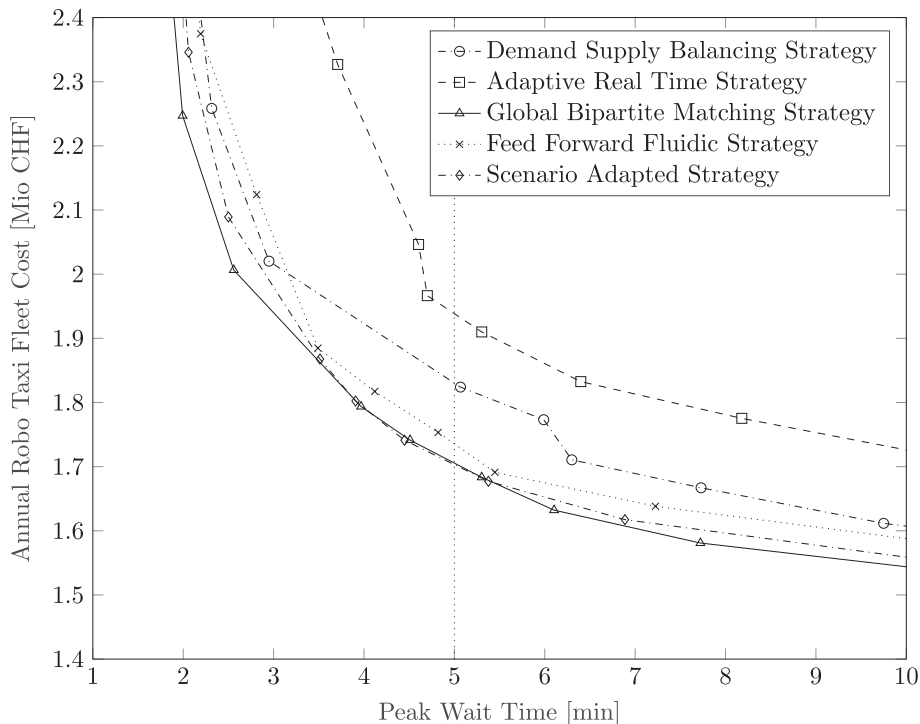


Fig. 6. Annual AMoD fleet costs as a function of the accepted mean peak wait time (from 6 to 8:30 am and from 4 to 6:30 pm) for the five control strategies.

Table 3

Comparison of the results for the four scenarios described in Section 3. The scenario adapted strategy (Section A.1.1 and a minimal fleet size to achieve a 5 min mean peak wait time were used. The distance ratio is the fraction of the vehicle distance traveled with a customer and the total vehicle distance.

| | Scenario | | | |
|---|--------------|-------------|--------------|-------------|
| | Homburgertal | Thunersee | Tösstal | Boncourt |
| General Line Properties: | | | | |
| Train Line Length [km] | 18.2 | 18.1 | 41.4 | 10.5 |
| Drive Time [min] End to End | 22 | 21 | 57 | 15 |
| Passengers per Day R | 1,000 | 416 | 8,300 | 590 |
| Stations | 8 | 5 | 15 | 6 |
| Stations in Train Area | 5 | 2 | 12 | 5 |
| Trains per Day N_{day} | 38 | 38 | 54* | 42 |
| Passengers per Train km [1/km] | 1.4 | 0.6 | 3.7 | 1.3 |
| Simulation Results: | | | | |
| Fleet Size N for Peak Wait Time under 5 min | 47 | 16 | 825 | 22 |
| Share Ratio R/N | 21.3 | 26.0 | 10.1 | 26.8 |
| Mean Peak Wait Time [min] | 4.9 | 4.3 | 4.9 | 4.8 |
| Mean Wait Time [min] | 3.9 | 3.7 | 3.7 | 3.5 |
| Mean In-Vehicle Time [min] | 14.5 | 10.9 | 18.9 | 11.2 |
| Mean Travel Time MoD [min] | 18.4 | 14.5 | 22.6 | 14.7 |
| Mean Travel Time Train [min] | 24.8 | 25.2 | 30.5 | 26.0 |
| Mean Trip Distance [km] | 9.36 | 8.64 | 12.41 | 8.22 |
| Mean Daily Vehicle Distance Traveled [km] | 253.1 | 290.0 | 170.9 | 289.1 |
| Avg. Vehicle Velocity [m/s] | 10.4 | 12.7 | 10.8 | 11.8 |
| Distance Ratio [%] | 80.4 | 77.5 | 73.1 | 76.3 |
| Costs: [MCHF] | | | | |
| Vehicles ($C_v \cdot N_v$) | 0.61 | 0.21 | 10.68 | 0.29 |
| Distance ($C_{km} \cdot d_{total}$) | 0.97 | 0.38 | 11.52 | 0.52 |
| Trips ($C_{trip} \cdot N_{trips}$) | 0.14 | 0.06 | 1.14 | 0.08 |
| Driver ($C_{hour} \cdot t_{working}$) | - | - | - | - |
| Annual Fleet Cost AMoD ($C_{fleet, year}$) | 1.72 | 0.65 | 23.34 | 0.89 |
| Vehicles ($C_v \cdot N_v$) | 0.76 | 0.26 | 13.27 | 0.35 |
| Distance ($C_{km} \cdot d_{total}$) | 0.90 | 0.35 | 10.68 | 0.49 |
| Trips ($C_{trip} \cdot N_{trips}$) | - | - | - | - |
| Driver ($C_{hour} \cdot t_{working}$) | 4.88 | 1.56 | 55.65 | 2.30 |
| Annual Fleet Cost CMoD ($C_{fleet, year}$) | 6.54 | 2.17 | 79.60 | 3.14 |
| Annual Train Costs | 3.78 | 3.77 | 12.2 | 2.41 |

* Including trains from Winterthur to Bauma proportional to the covered distance.

without increasing the vehicle distance traveled.

5.2. Comparison of four case scenarios

In this section, the simulation results of the four chosen scenarios in Section 3 are shown. First, an overview is provided. Then, the applicability of the results for each of the assessed cases is discussed. Finally, the environmental impact is briefly discussed.

5.2.1. Overview

Table 3 gives an overview over the most important results of each scenario. In the first part, the general line properties are listed, and the second part covers the simulation results. The number of vehicles N_v required to guarantee a maximum of 5 min peak wait time differs significantly for the train lines. The fleet size varies from 16 vehicles in the Thunersee scenario to 825 vehicles in the Tösstal scenario. The share ratio is defined as the number of requests divided by this fleet size. It is equal to the average number of customers per day and ranges from 10.1 in the Tösstal scenario to 26.8 in the Boncourt scenario. The small value in the Tösstal scenario can be explained by the larger trip distances and the long in-vehicle times. A closer look at the daily vehicle performance shows that the vehicles in the Boncourt and Thunersee scenarios are driving around 290 km per day. In the Homburgertal and in the Tösstal, 253 km and 171 km, respectively, are driven. Out of the total vehicle distance traveled, only 73–81% percent are covered with a customer on board. The highest value can be found in the Homburgertal scenario which suggests that vehicles can be used more efficiently in smaller scenarios.

In three out of four cases, the annual costs of the MoD system are smaller than the annual costs of the train. The cost reductions are 45% in the Homburgertal, 17% in the Thunersee and 37% in the Boncourt scenario. In the Tösstal on the other hand, the costs

would nearly double with an autonomous mobility-on-demand service. Three major influences for this were identified: the high number of passengers both in absolute numbers and also relative to the length of the train line results in large fleet sizes which drives costs. Furthermore, the in-vehicle times in this scenario are substantially longer which again requires more vehicles. Ultimately, the longer trip distance directly translates to higher costs for the fleet operator. Interestingly, in the Thunersee scenario even a service with conventional taxis might be economically beneficial.

5.3. Applicability

In summary, we can conclude that in many cases, AMoD might be a viable alternative to the rural PT lines as it can reduce the costs while maintaining or improving the service level. In some cases, even CMoD could lower the total cost. Compared to MoD and as expected, the rail (and public transportation in general) becomes more efficient if longer distances with more passengers have to be covered. The public transportation services which are most inefficient compared to the AMoD service are expected to have small average trip distances and a relatively low number of customers. These results indicate that for policy makers and operators, it could be beneficial to investigate the presented option and possibly conduct further exploration with pilot projects. However, for such projects, other factors not considered in this study also have to be taken into account. For the sake of completeness, we therefore provide some information about the context of each line in the next paragraphs.

The Homburgertal has rail tracks that are exclusively used by the S9 service and as a network backup. There exists only one other bus line as public transport in this valley. Whether or not the demand currently served by this bus line from Sissach to Wittinsburg is served by the MoD service as well is an important factor that must be considered in the assessment.

In the Thunersee scenario, the costs presented for AMoD are very low compared to the train costs. This is only possible because the customers who travel every two hours directly from Spiez to Interlaken with the train line are neglected. When these customers have to be served additionally, the AMoD service would make less sense. Another possibility would be to use an additional train for these customers as it is suggested in [Lebküchner and Kugelmeier \(2016\)](#). This would increase the costs for the new AMoD service although they could be held below the current train costs. As the number of passengers is very low in this scenario, even a replacement of the train service with CMoD might be a possibility. To make a clearer statement about the economic effects, further investigations on the cost structures of both the current train line and the possible CMoD service are required.

In the Tösstal scenario, a replacement of the train line with an MoD service is not realistic. The large fleet size would generate high costs and at the same time increase road congestion. Additionally, the region has a rather complex and meshed public transportation grid, which requires a more intensive, additional assessment. In the case of Boncourt, an AMoD system could be beneficial from a service level and operational point of view. In this case, the connection to the close French city Delle must also be considered in potential projects and further studies.

5.4. Environmental impact

While operational aspects like travel times and costs can be quantified quite exactly, the impact on the environment is much harder to assess. Especially when considering on-demand mobility with self-driving cars, it is difficult to predict its impact on the environment, which depends on many unknown factors: first, due to vehicle repositioning and the sharing of vehicles between different users, vehicle distance traveled will necessarily increase. Additionally, there are more vehicles on the road, which influences the general traffic impacting average vehicle speeds, emissions, and the service level, see, e.g., ([Maciejewski and Bischoff, 2018](#)). On the other hand, self-driving vehicles could prove to be capable of improving road dynamics, e.g., by reducing clearances between cars, improving intersection throughput, or other metrics, see, e.g., ([Lioris et al., 2016](#); [Lin and Ho, 2019](#)). This influences the overall traffic conditions and emissions as well. The operation of self-driving cars in on-demand mobility might additionally induce and accelerate changes in the vehicle technology itself that could drastically reduce overall emissions. A study has estimated that greenhouse gas emission reductions of light-duty vehicles in the US of up to 94% by 2030 ([Greenblatt and Saxena, 2015](#)) could be achieved. Finally and probably most importantly, there is the question of induced demand. If on-demand mobility gets as convenient and cheap as currently predicted, e.g., in [Hörl et al. \(2019\)](#), it might lead to trips that have not been done before. Such induced additional demand by mobility-on-demand systems again depends on the traffic conditions, the ways the on-demand schemes are operated, and policy boundaries. Also, many subtleties make it harder to draw global conclusions about greenhouse gas emissions of trains. First, it is of relevance if the train line is electrified, which is the case for all train lines in Switzerland. Then, for electric trains, the composition of the electricity used needs to be assessed. In Switzerland, the dominant components are hydro- and nuclear power, and thus, the emissions of the electricity mix in Switzerland are comparatively low ([Bauer et al., 2012](#)). In other countries, the production of power generates significantly more emissions.

For these reasons, the assessment of the environmental impact should be subject of further studies within the upcoming years for each specific case on its own. Nevertheless, we can make some observations with respect to the operation of the mobility-on-demand scheme. The average daily distances per vehicle are provided in [Table 3](#). They are between 171 and 290 km. According to [Nykqvist et al. \(2019\)](#), many battery electric vehicles in the most expensive third price percentile and some vehicles in the mid third price percentile have ranges above 290 km. Thus, it can safely be assumed that even battery electric vehicles designed for the consumer market have a sufficiently large range to allow for the proposed operation to be realized with electric vehicles. Based on this fact, we draw the preliminary conclusion that an environmentally friendly operation of the proposed mobility-on-demand scheme is possible, given that adequate policies to restrict the demand to today's levels are in place.

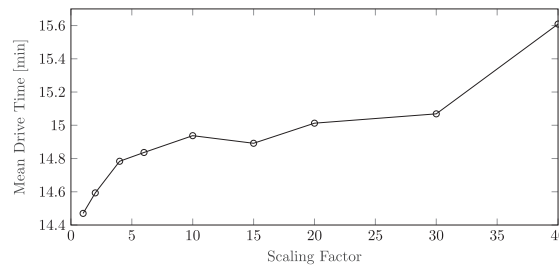


Fig. 7. Mean drive times under increased demand. A scaling factor of 1 corresponds to the demand levels in the regular study. A scaling factor of 40 corresponds to a number of trips increased by a factor of 40.

5.5. Induced demand

This study was carried out under the assumption of fixed demand. However, the results presented in Table 3 suggest that when self-driving cars are available, the service quality that can be provided with the MoD system is better in many aspects compared to the service quality of the existing train lines: the mean travel times are greatly reduced, the service operates door-to-door without the need for walking segments, and it is offered on-demand without a fixed schedule. It is reasonable to expect that this situation would induce additional demand for the new service.

However, these demand dynamics depend on many unknown factors in several time scales: there may be induced demand that occurs immediately and is caused by the ability of the valley's inhabitants to carry out new types of trips, previously not possible, e.g., a public transit user does not have the possibility to travel to town to eat a late-night meal. Then, there may be induced demand as a result of people changing their mode of transport permanently; e.g., people might decide to sell their car and use a combination of public transit and mobility-on-demand instead. Finally, on an even larger time scale, this new form of mobility might change people's choice of where they live and companies' choice of where they set up their sites. Human settlements might thus change fundamentally, as, for instance, discussed in Heinrichs (2016).

The question of induced demand must therefore be considered in detail with studies that are focused on this issue and which take into account a variety of factors from the economics to regulation and policy.

However, using only the models that were used in this study, we are able to identify what would actually limit the applicability of the proposed rural MoD schemes under the assumption of continuous demand growth. We identify two principal limitations: cost and road network capacity. The results presented in Table 3 suggest that above a certain number of passengers per day, the annual fleet costs of the MoD service exceed the cost of the train line operated today. Thus, the intuition is confirmed that at some request density, a system designed for the transportation of large quantities of people is more cost efficient. Differently stated: if the induced demand is so large that the transportation scenario loses the characteristics which are typical for a rural area, a replacement of the train with a MoD system would likely not make sense from an operational viewpoint.

Apart from this cost-induced limitation, it could also be possible that the induced demand brings the road capacity to its limits. In order to assess this possibility, we have conducted an additional experiment for the Homburgertal scenario. Based on the existing set of trips, we have sampled additional identical trips, with a uniformly distributed change in departure time of ± 30 [min] and a uniformly modified position within a 300 [m] radius. Then, with this upsampled population, we evaluated the scenario again and analyzed how the mean drive time evolves for larger populations. If the road network capacity limits were hit, the induced congestion would lead to greatly increased mean drive times. The results are shown in Fig. 7. They suggest that even at a massive increase of the demand by a factor of 40, the mean drive times would not increase by more than 7.8%.

Considering that the number of inhabitants in the communities which are inside the train area⁴ is only 4,278 (Bundesamt für Statistik, 2010-2018), we conclude that a limitation of the applicability of MoD in this type of rural transportation scenario is more likely a result of financial constraints, and not of road network capacity constraints.

6. Conclusion and outlook

In this paper, we assessed whether the replacement of existing rural train lines with a mobility-on-demand service would be beneficial in terms of service level and operational cost compared to the status quo. We have based our study on a demand profile which is currently served by the existing train lines. We assessed four regional, rural train lines in Switzerland. In three out of four cases, an autonomous mobility-on-demand service can operate at lower cost and with a higher service level than the services currently in operation. Especially for areas with a low demand density, a possible substitution could provide economic benefits and increase the service level.

Based on our findings, we recommend policy makers investigate the possibility of serving mobility demands in rural areas with centrally coordinated mobility-on-demand systems. Although there are important open questions, e.g., the amount of newly induced demand, the comparison of service levels and cost with existing fixed-schedule and fixed-line public transit suggests that major

⁴ Diepfingen, Wittinsburg, Rümelingen, Buckten, Känerkinden, Läufelfingen and Häfelfingen.

improvements would be possible in the near future when self-driving cars are available on the markets.

Several potential directions of future research were identified: ride sharing, i.e., having shared trip segments for two or more requests, could additionally reduce the number or required vehicles. Therefore, the study should be extended to also cover ride-sharing mobility-on-demand systems as well. Next, the question of induced demand must be rigorously assessed in all affected time scales, taking into account even the possibility that the structure of settlements would change in response to the introduction of mobility-on-demand systems. Finally, as long as self-driving cars are not available on the market, pilot projects with conventional cars could provide valuable learnings and highlight critical aspects which were so far not discovered.

Appendix A. MoD system design

A.1. Evaluation of fleet properties

The fleet size N and the control strategy influence both the service level and the costs of a MoD system. In this section, we explain in the detail how the two variables were determined for the study presented in the main part of the paper. First, the five control strategies are briefly introduced. Then, the procedure of finding the best settings is explained and some additional information on the fleet operations is provided.

A.1.1. Control strategies

A control strategy has two major parts: the matching and the rebalancing strategy. The first assigns travelers to a vehicle. The latter relocates vehicles in the network to move empty vehicles to locations of future anticipated demand. Other elements such as ride-sharing opportunity identification, congestion mitigation, and routing are also part of fleet control but not covered in this work.

Within this work, five different control strategies were used. The first four are control strategies from the literature and are already implemented in AMoDeus. The fifth is a heuristic approach which was developed to take the special PT line characteristics into account. While the first two control strategies only assign requests to available vehicles, the other three strategies also perform rebalancing.

1. The **demand supply balancing strategy** (Maciejewski and Bischoff, 2015) compares the number of available vehicles with the number of unmatched requests at every time step. If there are more available vehicles than requests, for each request the closest vehicle is assigned. If the number of unassigned requests is larger than the number of available vehicles, each vehicle is sent to its closest request. This assignment is not optimized globally as it only iterates over the requests (or vehicles) which are in an arbitrarily sorted list. The strategy bindingly assigns vehicles to open requests, i.e., once a matching is made, it is not changed, even if it would improve the results.
2. The **global bipartite matching strategy** solves a bipartite matching problem between the open requests and the available vehicles at every time step using the Hungarian method to solve the assignment problem. Matchings are continuously updated to obtain the best performance until the vehicle arrives at the location of the passenger. As a distance metric, the shortest path in the network is used.
3. The **feed forward fluidic control strategy** was introduced in Pavone et al. (2012), and a publicly available implementation is presented in Hörl et al. (2018). A network flow problem is formulated and solved to find the most efficient way of rebalancing vehicles in the network. The solution of the problem can be determined with a linear program. Historical data of customer arrival rates as well as the distributions of origins and destinations are necessary inputs. Matching of vehicles is done with global bipartite matching.
4. The **adaptive real time control strategy** was presented as well in Pavone et al. (2012) and the implementation used is presented in Hörl et al. (2018). It solves a similar rebalancing problem as the feed forward fluidic control strategy, but reacts to system imbalances in the loop and does not require historical data. Matching of vehicles is done with global bipartite matching.
5. The **scenario adapted strategy** is introduced here as a heuristic approach to take advantage of the special situation in the line-shaped scenarios. It uses the knowledge that during the morning rush hours people are traveling mostly from the rural regions to the larger cities at the end of the PT line (and vice versa in the evening peak hour). The global bipartite matching strategy was extended with a rebalancing strategy which is only active during these peak times. If in the morning the fraction of idling vehicles outside of the train area (Fig. 4) accounts for more than a certain fraction α of all idling vehicles, the control strategy sends more vehicles into the train area until the fraction drops below α . The destination of the rebalancing vehicles are the PT stations with a probability proportional to the passenger numbers at each station per day. In the evening, the same procedure takes place in the opposite direction. The tuning parameter α was chosen to be 0.3 in this work; it was identified with a parametric study.

A.1.2. Optimal fleet size

As stated in the main body of the paper, the service level for MoD consists of the wait and travel time. To have a reliable system, a certain threshold for the wait time is defined which should not be exceeded. In our case, we want to have a large enough fleet to guarantee a mean peak wait time of less than 5 min. To find the necessary number of vehicles, different simulations with varying fleet sizes N are evaluated. An example of the wait times for different fleet sizes can be seen in Fig. A.8a. As expected, the wait time decreases with a higher N . In this example the mean peak wait time decreases below 5 min if the fleet is operating with slightly more than 50 vehicles. Therefore, in this case N would be chosen to be 50 vehicles. A 20% decrease of the fleet size to 40 vehicles still leads to a mean peak waiting time under 8 min. This shows that the results in this region are stable and small changes in the number

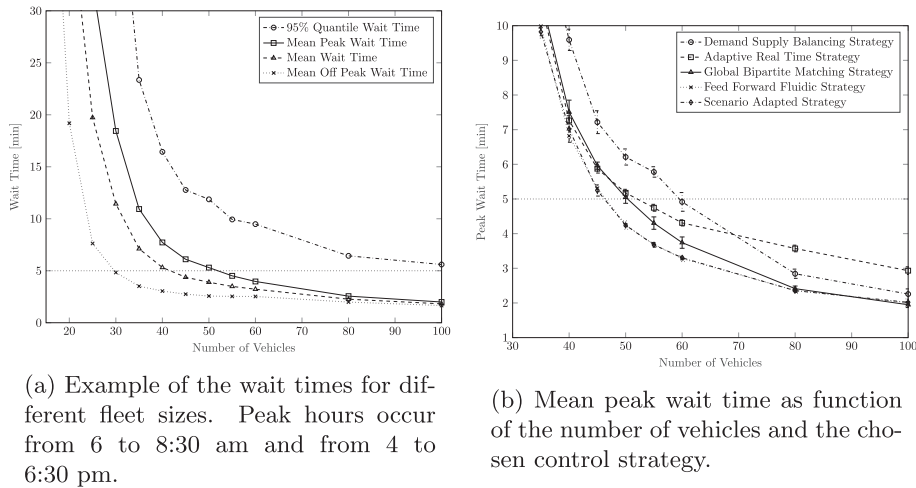


Fig. A.8. Influence of control strategy and fleet size on the mean peak wait time (wait time in the period from 6 to 8:30 am and from 4 to 6:30 pm) in the Homburgertal scenario.

of vehicles do not influence the results substantially. With $N = 50$, the simulated 95% quantile of the wait time is at 12 min. Most of these requests which are waiting relatively long occur around 7:30 am or 6:00 pm. During these peak times, approximately 50% of all requests are submitted. It can be seen that with a fleet size of 50 vehicles the (overall) mean wait time and the off-peak wait time are at 4 min and 2.5 min respectively in this example.

Varying the fleet size and assessing the effect on the mean wait time is a well-suited method to determine an efficient fleet size. Nevertheless, it is important to check that the distribution over the day stays within an acceptable boundary. Fig. A.9 shows the waiting times over the day for a fleet size of 50 vehicles. In this plot, the lines identify the wait time of all the requests not yet picked up and how long the customer are waiting at this specific time. In this example, there are only rarely more than 20 people waiting for a vehicle. Thus, a single customer who has not been picked up can strongly influence the 95% percent quantile. Again, the largest waiting times occur around the morning and evening rush hours. Only for a few minutes before 6 pm, the mean wait time peaks at 25 min and the maximal value observed for the 95% quantile is 60 min. During off-peak hours the wait times remain at a low level, i.e., below 4 min (mean) and 10 min (95% quantile). The maximum wait time observed is 60 min. This value is a consequence of the fact that none of the strategies has in-built measures to cap the maximum wait time and could likely be avoided in practice.

Summarizing, it can be stated that a fleet size for which the mean peak wait time of 5 min is not exceeded seems practical.

A.1.3. Optimal control strategy

Fig. A.8b shows a comparison of resulting peak wait times for the five control strategies (A.1.1) for different fleet sizes. The control strategies differ in the mean peak wait time up to 3 min for the same number of vehicles. Within the region of interest of 35 to 60 vehicles, the demand supply balancing strategy results in the largest wait times. The adaptive real time policy and the global bipartite matching strategy have slightly smaller wait times. They would require around 51 vehicles to serve the requests with an

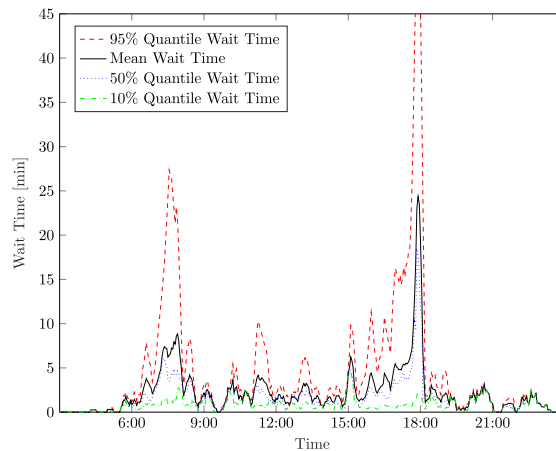


Fig. A.9. Example for the wait time distribution during the day for 50 vehicles in the Homburgertal scenario with the global bipartite matching strategy. The peak value for the 95% quantile around 18:00 which is cut off is 60 min.

average peak wait time of 5 min. The feed forward fluidic policy solves the task with only 48 vehicles. It is the best control strategy from the literature with the lowest wait times. Nevertheless, the new algorithm specially developed for the PT line substitution can serve the demand even faster and only requires 47 vehicles for 5 min mean peak wait time. The scenario adapted strategy can serve the customers with the shortest wait time over the whole range of vehicles presented in Fig. A.8b.

References

- Allen, D., Roupail, N., Hummer, J., Milazzo, J., 1998. Operational analysis of uninterrupted bicycle facilities. *Transp. Res. Rec.: J. Transp. Res. Board* 1636, 29–36.
- Bauer, C., Frischknecht, R., Eckle, P., Flury, K., Neal, T., Papp, K., Schori, S., Simons, A., Stucki, M., Treyer, K., 2012. Umweltauswirkungen der Stromerzeugung in der Schweiz, ESU-services Ltd & Paul Scherrer Institute im Auftrag des Bundesamts für Energie BFE, Uster & Villigen.
- Becker, H., Balac, M., Ciari, F., Axhausen, K.W., 2020. Assessing the welfare impacts of shared mobility and mobility as a service (MaaS). *Transp. Res. Part A: Policy Pract.* 131, 228–243.
- Bischoff, J., Maciejewski, M., 2016. Simulation of city-wide replacement of private cars with autonomous taxis in Berlin. *Procedia Comput. Sci.* 83, 237–244.
- Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. *Transp. Policy* 64, 76–91.
- Bundesamt für Statistik, Ständige Wohnbevölkerung in Privathaushalten nach Gemeinde und Haushaltsgrösse, 2010–2018, <https://www.bfs.admin.ch/bfs/de/home/statistiken/kataloge-datenbanken/tabellen.assetdetail.9787085.html> (last accessed: 2019-10-21).
- Der Regierungsrat des Kantons Bern, 2017. Beschluss über das Angebot im öffentlichen Verkehr für die Fahrplanperioden 2018 bis 2021.
- Eidgenössisches Departement für Umwelt, 2013. Verkehr, Energie und Kommunikation UVEK, Hintergrund: Regionale Bahnlinien mit tiefer Kostendeckung und eigener Infrastruktur, <https://www.news.admin.ch/news/message/attachments/30774.pdf> (last accessed: 2019-08-22).
- Ellis, E.H., McCollom, B.E., 2009. Guidebook for rural demand-response transportation: measuring, assessing, and improving performance. *Transp. Res. Board* 136.
- Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transp. Res. Part A: Policy Pract.* 77, 167–181.
- Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of shared autonomous vehicle fleet for austin, texas, market. *Transp. Res. Rec.: J. Transp. Res. Board* (2536) 98–106.
- Google, 2018. Google Maps Distance API, <https://developers.google.com/maps/documentation/distance-matrix> (last accessed: 2018-05-22).
- Google Maps, 2018. Google Maps, <https://www.google.com/maps> (last accessed: 2018-06-22).
- Gray, I., Crichton, M., 2014. Replacing trains with coaches: Implications for social inclusion in rural new south wales. *J. Soc. Inclusion* 5 (2), 89–113.
- Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of us light-duty vehicles. *Nat. Clim. Change* 5 (9), 860.
- Gurumurthy, K.M., Kockelman, K.M., Simoni, M.D., 2019. Benefits and costs of ride-sharing in shared automated vehicles across austin, texas: opportunities for congestion pricing. *Transp. Res. Rec.* 0361198119850785.
- Heinrichs, D., 2016. Autonomous driving and urban land use. In: *Autonomous Driving*. Springer, pp. 213–231.
- Hörl, S., Becker, F., Dubernet, T., Axhausen, K.W., 2016. Induced demand by autonomous vehicles: An assessment. Project report SVI 2016/001, FB 1650, SVI.
- Hörl, S., Ruch, C., Frazzoli, E., 2018. AMoDeus, a simulation-based testbed for autonomous mobility-on-demand systems. In: *Proc. 21th IEEE Conf. Intelligent Transportation Systems*. IEEE.
- Hörl, S., Balac, M., Axhausen, K.W., 2019. Dynamic demand estimation for an AMoD system in Paris. In: *2019 IEEE 30th Intelligent Vehicles Symposium, IEEE*.
- Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: a simulation assessment for Zurich. *Transp. Res. Part C: Emerg. Technol.* 102, 20–31.
- Horni, A., Nagel, K., Axhausen, K.W., 2016. The multi-agent transport simulation MATSim. Ubiquity Press, London.
- König, A., Gripenkoven, J., 2017. From public mobility on demand to autonomous public mobility on demand—learning from dial-a-ride services in germany, *Logistik und Supply Chain Management*. University of Bamberg Press, Bamberg, Germany, pp. 295–305.
- Lebküchner, M., Kugelmeier, N., 2016. Studie zur Zukunft des Regionalverkehrs Spiez – Interlaken Ost, Tech. rep., Amt für öffentlichen Verkehr und Verkehrskoordination Kanton Bern.
- Lin, S.-H., Ho, T.-Y., 2019. Autonomous vehicle routing in multiple intersections. In: *Proceedings of the 24th Asia and South Pacific design automation conference*. ACM, pp. 585–590.
- Lioris, J., Pedarsani, R., Tascikaraoglu, F.Y., Varaiya, P., 2016. Doubling throughput in urban roads by platooning. *IFAC-PapersOnLine* 49 (3), 49–54.
- Litman, T., 2017. Autonomous vehicle implementation predictions. Victoria Transport Policy Institute.
- Maciejewski, M., Bischoff, J., 2015. Large-scale microscopic simulation of taxi services. *Procedia Comput. Sci.* 52, 358–364.
- Maciejewski, M., Bischoff, J., 2018. Congestion effects of autonomous taxi fleets. *Transport* 33 (4), 971–980.
- Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: an agent-based model applied to the city of Lisbon, Portugal. *Int. J. Transp. Sci. Technol.* 6 (1), 13–27.
- Mendes, L.M., Bennässar, M.R., Chow, J.Y., 2017. Comparison of light rail streetcar against shared autonomous vehicle fleet for Brooklyn-Queens connector in New York City. *Transp. Res. Rec.: J. Transp. Res. Board* (2650) 142–151.
- Nykqvist, B., Sprei, F., Nilsson, M., 2019. Assessing the progress toward lower priced long range battery electric vehicles. *Energy Policy* 124, 144–155.
- Open Data Platform Swiss Public Transport, 2018. Open Data Platform Swiss Public Transport, <https://opentransportdata.swiss/de/dataset/timetable-2018-gtfs>, (last accessed: 2018-05-22).
- OpenStreetMap, 2018. OpenStreetMap, <https://www.openstreetmap.org/> (last accessed: 2018-05-22).
- Osti, G., 2010. Mobility demands and participation in remote rural areas. *Sociologia Ruralis* 50 (3), 296–310.
- Pavone, M., Smith, S.L., Frazzoli, E., Rus, D., 2012. Robotic load balancing for mobility-on-demand systems. *Int. J. Robot. Res.* 31 (7), 839–854.
- Postauto Schweiz, A.G., Publicar, Postauto Schweiz, A.G., <https://www.postauto.ch/en/publicar>, (last accessed: 2018-06-11).
- Pucher, J., Renne, J.L., 2005. Rural mobility and mode choice: Evidence from the 2001 national household travel survey. *Transportation* 32 (2), 165–186.
- Salonen, M., Toivonen, T., 2013. Modelling travel time in urban networks: comparable measures for private car and public transport. *J. Transp. Geogr.* 31, 143–153.
- Santos, A., McGuckin, N., Nakamoto, H.Y., Gray, D., Liss, S., 2011. Summary of travel trends: 2009 national household travel survey, Tech. rep..
- SBB Open Data, 2018. SBB Open Data Linie mit Betriebspunkten, <https://data.sbb.ch/explore/dataset/linie-mit-betriebspunkten/> (last accessed: 2018-05-22).
- SBB Open Data, 2018. Passagierfrequenzen, <https://data.sbb.ch/explore/dataset/passagierfrequenz/> (last accessed: 2019-08-27).
- SBB Open Data, 2018. Anzahl Züge, https://reporting.sbb.ch/_file/155/t02xd-sbb-anzahl-zuege-auf-den-abschnitten-des-streckennetzes.xlsx, (last accessed: 2019-08-27).
- SBB Personenverkehr, 2018. Recommendation SBB Personenverkehr, Angebotsplanung (04 2018).
- Shen, Y., Zhang, H., Zhao, J., 2018. Integrating shared autonomous vehicle in public transportation system: a supply-side simulation of the first-mile service in singapore. *Transp. Res. Part A: Policy Pract.* 113, 125–136.
- Simoni, M.D., Kockelman, K.M., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: an analysis of different strategies in alternative future scenarios. *Transp. Res. Part C: Emerg. Technol.* 98, 167–185.
- Spieser, K., Treleven, K., Zhang, R., Frazzoli, E., Morton, D., Pavone, M., 2014. Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study Singapore. In: *Road vehicle automation*. Springer, pp. 229–245.
- Starkey, P., Ellis, S., Hine, J., Ternell, A., 2002. Improving rural mobility: options for developing motorized and nonmotorized transport in rural areas. *The World Bank*.

- Stillwell, D., Pini, C., Cummings, J., Fazi, A., 2016. National Travel Survey: England 2016, Tech. rep., Department for Transport (07 2017).
- Velaga, N.R., Nelson, J.D., Wright, S.D., Farrington, J.H., 2012. The potential role of flexible transport services in enhancing rural public transport provision. *J. Public Transp.* 15 (1), 7.
- von Mörner, M., 2018. Sammelverkehr mit autonomen Fahrzeugen im ländlichen Raum, Ph.D. thesis, Technische Universität.
- Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transp. Res. Part A: Policy Pract.* 86, 1–18.
- Weidmann, U., 1992. Transporttechnik der Fussgänger, Schriftenreihe/Institut für Verkehrsplanung, Transporttechnik, Strassen-und Eisenbahnbau 90.
- Zachariah, J., Gao, J., Kornhauser, A., Mufti, T., 2014. Uncongested mobility for all: A proposal for an area wide autonomous taxi system in New Jersey, Tech. rep., Transportation Research Board 93rd Annual Meeting.
- Zonetaxi, N.S., Zonetaxi, N.S., 2018. Netherland, <https://www.ns.nl/en/door-to-door/consumers/ns-zonetaxi.html> (last accessed: 2018-06-10).