Evaluating the Potential for Demand Responsive Shared Transport to Compliment Conventional Public Transit Buses: a simulation study of BMW Group Mobilität München

Master's Thesis submitted to

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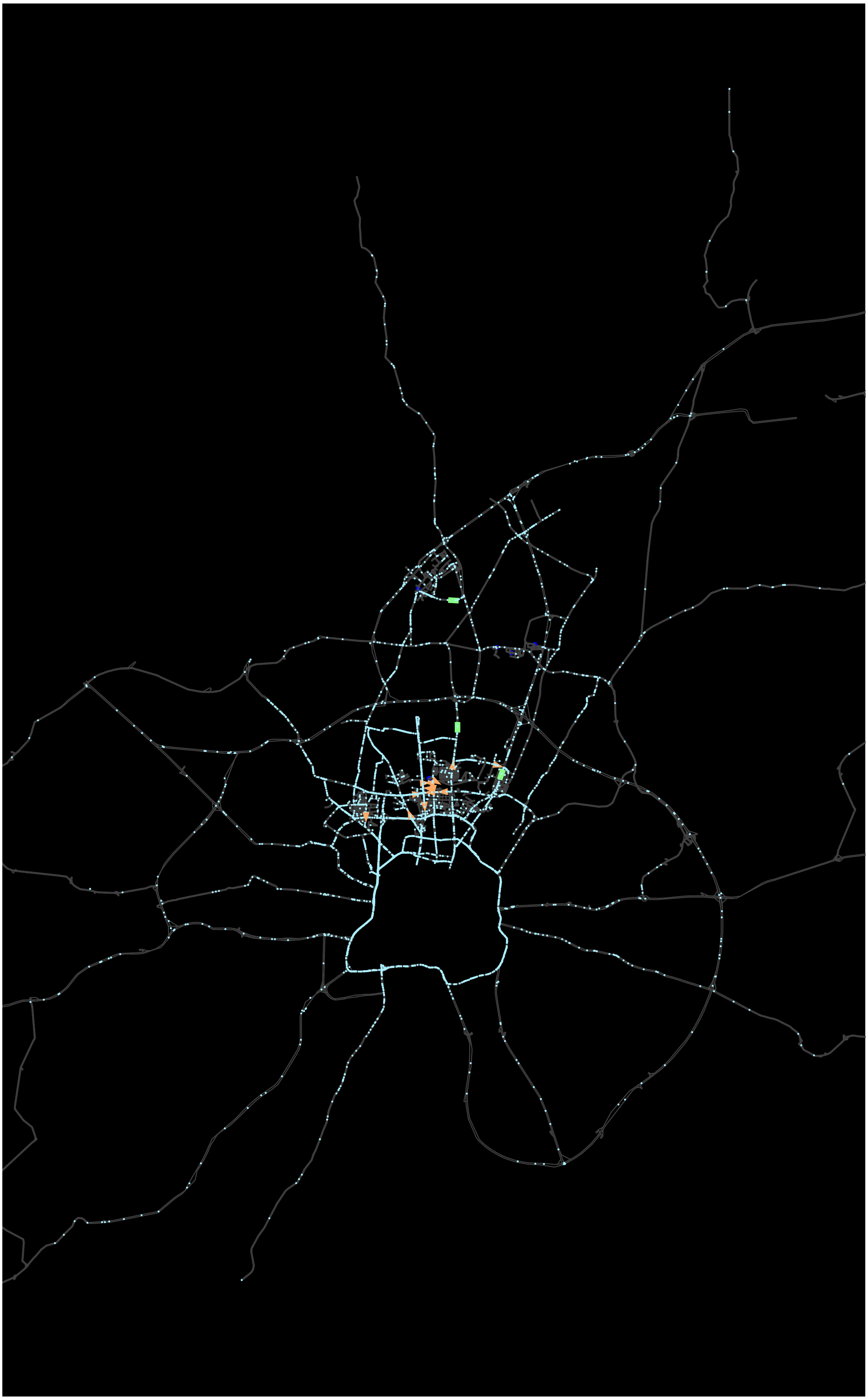

Abstract

Mobility on Demand services have disrupted the transportation landscape through smart-phone enabled peer-to-peer business models, including the notable rise of ride-hailing platforms. Demand responsive shared transport services, which extend the ride-hailing concept by facilitating similar trips to be shared between unfamiliar users, have renewed the notion of exible and dynamic bus transit which was first seen in dial-a-ride public transit programs of the 1990s. These shared services have been positioned between ride-hailing and conventional public transit buses, most notably for the exibilit y of routing and scheduling they offer. The potential for these dynamic and exible services to unlock a range of benefits has been hypothesized in the literature, but quantifying the scale of this potential, as well as unpacking its relationship to conventional public transit has remained largely theoretical due to the small number of case-studies. In partnership with the BMW Group, this thesis presents an agent-based simulation of these two services, drawing on real-world data from the corporate mobility context of BMW Groups 40,000 employees in the Munich region. Following a benchmark simulation of demand responsive and conventional buses as they exist today, the results of three scenarios that modify the temporal and spatial availability of the services are presented. These scenarios frame the research in regards to operator cost and it's relationship to key service quality parameters including wait and travel time, while additional analysis is used to provide a richer understanding of the comparison.

Abstrakt

Mobility on Demand-Dienstleistungen haben die Transportlandschaft in den letzten Jahren weitgehend verändert. Smartphones ermöglichen Peer-to-Peer-Geschäftsmodelle, was zu einem signifikanten Aufschwung von Mitfahrgelegenheitsplattformen geführt hat. Deren Konzepte sind Nachfrage-basiert und schaffen gemeinsam genutzte Transportangebote von sich nicht kennenden Nutzern. Dadurch geben sie dem Verständnis von exiblem und dynamischem Bustransport (das erstmals in den 1990ern im Rahmen von öffentlichen Dial-a-Ride-Programmen verwendet wurde) eine neue Bedeutung. Die gemeinsam genutzten Transportdienstleistungen können zwischen Mitfahrgelegenheitsangeboten und konventionellen öffentlichen Bussen positioniert werden und ermöglichen dabei eine exible Routenplannung. Trotz der Diskussion der Möglichkeiten dieser dynamischen und exiblen Dienstleistungen in der Literatur wurde bisher die Größe dieses Potenzials noch nicht genau quantifiziert, da die Anwendung dieser Systeme auf den öffentlichen Busverkehr auf Grund einer geringen Anzahl von Fallstudien bisher nur theoretisch erörtert wurde. In Zusammenarbeit mit der BMW Group stellt die vorliegende Arbeit eine Agenten-basierte Simulation dieser beiden Dienstleistungskonzepte vor. Dabei basiert sie auf realen Daten von 40,000 BMW Angestellten in München, die im Rahmen der Corporate Mobility erhoben wurden. Basierend auf einer Simulation von Nachfrage-gesteuerten und konventionellen Bussen, wie sie zurzeit existieren, werden die Ergebnisse von drei Szenarien, die in örtlicher und zeitlicher Verfügbarkeit variieren, verglichen. Diese Szenarien werden in Hinblick auf Betreiberkosten und den Ein uss auf Qualitätskriterien wie Warte- und Reisezeit ausgewertet, was einen Vergleich der einzelnen Analysen ermöglicht

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1 Introduction

The majority of this thesis is spent on the design and implementation of a simulation study on the relationship between demand responsive shared transport and existing conventional public transit buses. This work is largely technical in scope, but before diving in and by way of an introduction, I would like to begin with the personal connection.

In 2011 I was bicycle touring through a region of abandoned settlements from the Late Antiquity Byzantine period in the present day Middle East. One day I stumbled across a Roman road stretching north off of the small farming road I had been cycling on, and eager to find out if all roads really *do* in fact lead to Rome, I hopped off my bike and began exploring. There were zero people around, save a singular man watching his goats in the distance and out of the surreal calmness I found myself imagining the farmers and tradesmen, the commuters and freight movers. Walking farther along took me backwards in time as I passed two men negotiating parking rights for their horse carts on the side of the road, and overheard two others discussing congestion around the aqueduct.

My point is that while *planes, trains and automobiles* (to borrow the title of a childhood classic) have brought the dimensions to a new level, I'm fascinated by the degree to which many aspects of the underlying experience of moving from A to B seem to be relatively constant. One example is the Marchetti Constant which emerged from an empirical study of commute times with the finding that regardless of transportation technology or era, humans spend on average about an hour a day moving to and from a primary activity (Marchetti 1994). This finding which has become known as the Marchetti constant, but which Marchetti himself credited to the transportation researcher Yacov Zahavi, was demonstrated across cities and civilizations, with examples as varied as ancient Greek and Roman towns, to African villages, to modern suburban America (Marchetti 1994; Zahavi and Ryan 1978). This principle has been used to help explain the macro trends in the way cities seem to grow in response to the available transportation supply, for example spreading out as transportation becomes faster. But it also hints at the intrinsic relationship we have with our daily travel activities that can be seen elsewhere. Consider the public discourse surrounding bike or electric scooter sharing platforms which have been equally hailed as pragmatic solutions, and demonized as a public nuisance littering the sidewalks. Transportation touches people in their daily lives, and whether it's a Roman road 1500 years ago or a street in the centre of Munich today, we like to both fight and embrace change. Transportation in the 21st century

Figure 1: Original photo of Roman road at Apamea, Syria.

has frequently been guided by goals like going faster and farther while maximizing individual choice and comfort. Stemming from this however, new challenges echoing those from that Roman road have come into focus. For example, the importance of transportation that viably addresses environmental, economic and health externalities have come hand in hand with the centrality of urban regions. And whether it's connecting peripheral locations or providing corporate mobility between office clusters, people are interested in the sharing potential of new business models as well as in the capital Q Quality of their travel experience.

These topics are linked with developments shaping transportation at it's intersection with communications technologies. For example, so called ride hailing platforms have made an attractive bid to the public, allowing users to virtually connect with a peer in their network and track their ride in real time, with payment, navigation and communication handled seamlessly in the background. Relatedly, services that allow ride hailing-like trips to be shared between users with similar origins and destinations have been described in the context of public transport 2.0 (more on this in chapter 2). And while autonomous vehicles including those that y between skyscraper rooftops may be entering the "trough of disillusionment" in the technology hype cycle, highly functioning autonomous driving remains a very real area of research and development at automotive companies the world over, which has the potential to radically in uence the cost and function of what we currently call "driving".

But following from Henry Ford's statement *if I had asked the people what they want, they would have said faster horses*, I often find myself back at the question of the potential of new mobility technologies to fundamentally address the challenges in the transportation sector today, and at the same time, the degree to which they might create new and unseen challenges. These questions are certainly very large and I do not want to give the impression that they will be answered in the course of this thesis, but at a high level they are part of it's motivation.

A little more concretely, this research responds to the idea that exible ride sharing services have the potential to disrupt traditional schedule-based bus platforms with services that are more individual, more real-time and more dynamic by looking at trade offs between the two. The idea that the experience of taking the bus can be improved by making it responsive to user origins and destinations makes intuitive sense. It is also the hypothesis being tested by several public transit providers who have launched pilots to test exible transit, as well as a body of recent scholarly literature which will be unpacked in the following chapter.

1.1 Partnership with BMW Mobilität München

Moreover, these questions are of practical relevance to BMW Group's corporate mobility department in Munich, Germany which is currently investigating ideas to innovate and improve on their corporate mobility offering. BMW Group's Mobilität München[1] manages the corporate mobility services available to employees in the Munich region. Corporate mobility refers to company-related travel during the workday, such as moving from one office to another for meetings, manufacturing inspections and testing amongst other activities. With nearly 40,000 employees in the Munich region, BMW Group has the size of a small city, and therefore MM functions a little like the transportation provider. This includes:

- coordinating a ee t of *Fahrdienst* vehicles (short to mid-term loan of a company vehicle for business travel)
- the *Pendelbus* shuttle bus service which primary serves white-collar workers for travel between the various office building clusters
- shared personal mobility offers including the *Probike* bikeshare, `X2City' – an e-scooter pilot project, and the internal `Urby' MaaS app which integrates the mobility offerings with trip and route planning in one app
- piloting new mobility services such as the *MyShuttle* demand responsive shared trans-

[1] Mobilität München (MM) is an unofficial name that describes several BMW Group departments in operations, research and technology that collaborate in corporate mobility

port program which began in 2019

The goal of these services is ultimately to facilitate the internal function and networking effect of the company. Therefore, using these transport options does not explicitly incur a financial cost to the user – rather the corporate mobility offering is provided privately to employees. In addition to providing an effective and reliable travel option, the direction of these corporate mobility services is also motivated by broader goals such as reducing the ecological intensity of the company, increasing the quality of travel and connectivity between BMW Group office clusters to encourage networking synergies amongst knowledge workers, and to stay in step with the technologically driven direction of the automobile industry at large.

2 Literature Review

There is significant excitement surrounding Mobility on Demand services that has already been touched on in chapter 1. This excitement centres on the emergence of what is essentially a new mode choice that

> *"stand(s) between unsustainable, flexible and individual transport services offered by private vehicles (e.g. cars) and sustainable, shared, but low-flexible traditional public transport services (metro, tram and bus), with different degrees of sustainability/shareability/flexibility according to the service"* (Inturri et al. 2019, 2).

In other words, Mobility on Demand is being connected to the potential for redefining traditional trade-offs between service quality and convenience, or between cost and individual exibilit y - particularly in the space between conventional public transit (CPT) and private automobile ownership. For some, this may be an opportunity to tackle negative externalities of the transport sector including congestion, lost productivity and emissions (Merlin 2019; The World Bank 2018), while others see Mobility on Demand services as a tool to bolster public transport and keep in step with the ever evolving mobility space (Kim, Baek, and Lee 2018). At the same time the possibility to improve service for hard to connect or immobile demographics has been highlighted, and in new business models such as premium chauffeuring, school district transportation and corporate mobility are also being explored (Muñoz and Cohen 2018). But where do these potential benefits stem from, and do we have an understanding of their capacity to generate operator, user or generalized benefits for transportation systems?

This literature review sheds light on the topic by unpacking the state of the art, and organizing it around these and other questions of debate in the wider discussion of Mobility on Demand services. More than a summary of individual articles, the theme areas re ect the methodology and simulation scenarios deployed later in this thesis. For example, after laying out the key concepts and terms in 2.1, 2.2 frames many of the modelling decisions implemented later in the scenario design, and 2.3 informs the DRST-scenarios that are designed to test the service performance of tightly-knit demand areas versus connection to satellite locations. In so doing, the literature review provides an overview of relevant topics surrounding Mobility on Demand, focusing largely on simulation studies that use a relevant methodology.

2.1 Mobility on Demand Key Terms

The disruption of communications technologies in the transportation sector has brought not only an array of new mobility concepts, but a range of overlapping terms used to describe them (Shaheen et al. 2017). These services can be considered **new** in that they: 1) emerged roughly in parallel with the widespread proliferation of smart-phones; 2) that they are related to the sharing economy (either of vehicles or trips); and 3) that they describe a transport mode who's characteristics do not necessarily fit into the classical hierarchy of "car trip" or "public transit trip". Mobility on demand[2] has evolved as an umbrella term for these mobility services, although it does not refer specifically to any one concept or technology and rather is deployed as a catch-all (Alonso-Mora et al. 2017).

Of specific relevance to this thesis, "demand responsive transport" (DRT) has been used as far back as two decades to describe user oriented public transportation that uses exi-ble routing and scheduling enabled by communications technologies (Atasoy et al. 2015). While the origins of DRT are with early dial-a-ride programs (possibly the first fusion of telecoms technology and CPT from the user interface side) , DRT has grown to encompass all services which are designed to be shared, and which do not operate on fixed routes or schedules (Atasoy, Ikeda, and Ben-Akiva 2016). This includes Uber Pool and Lyft Line for example, products of the respective ride hailing platforms which enable dynamic sharing of trips amongst unfamiliar users. But DRT actually excludes Uber and Lyft's ride-hailing (or ride-sourcing) services, which operate similar to smartphone enabled taxi hailing (Inturri et al., 2019).

Indeed, the terminology surrounding these MoD services can be tricky. Perhaps because of this, a distinction between **ride hailing** (individual taxi-like trips), **vehicle sharing** (non-ownership model for sharing vehicles as a resource, but not necessarily trips) and **ride-sharing** (sharing vehicles and trips amongst unfamiliar users) has emerged in the literature (Inturri et al. 2019). With this, DRT which has historically described services like dial-a-ride public transport buses, has morphed into **demand responsive shared transport** (DRST). This seems to emphasize its inclusion in the latter of these 3 groups - defining services where trips themselves are being shared amongst unfamiliar passengers (Bischoff, Maciejewski, and Nagel 2017). From this framework, DRST could theoretically be accessed by the user through a Mobility as a Service (MaaS) platform and served by shared autonomous vehicles (SAVs)

[2] used interchangeably with on-demand mobility in the literature

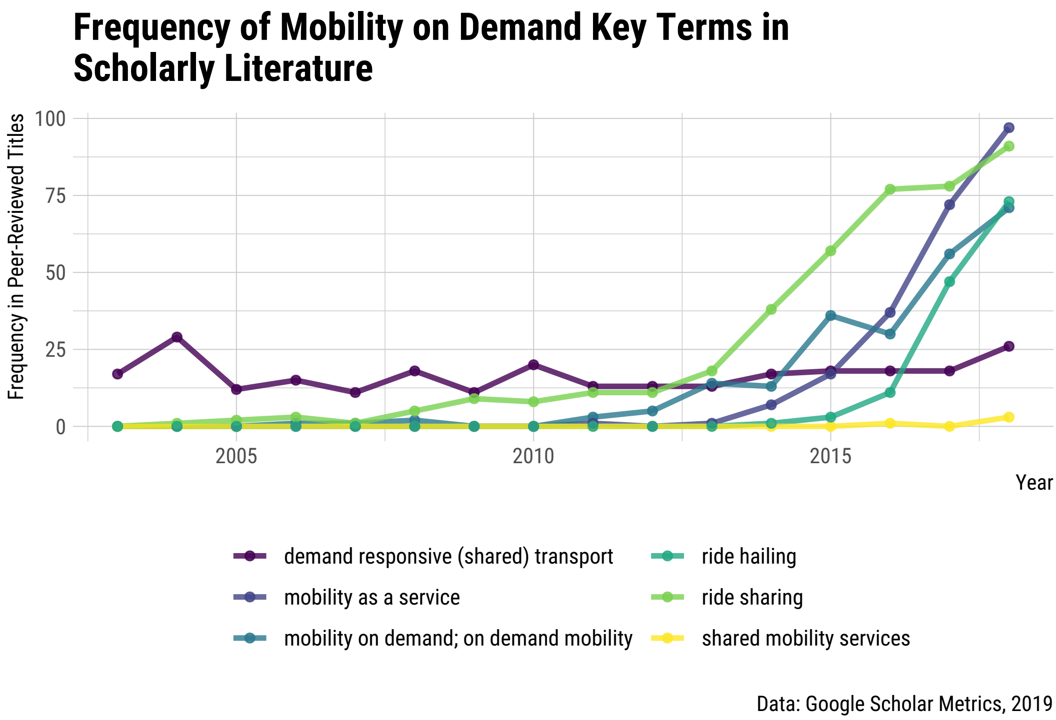


Figure 2: Figure compares the relative use of select MoD keywords in the titles of peer-reviewed literature. The consistient use of DRT/DRST over the past 15 years is highlighted, as well as the more recent growth of concepts that emerged in parallel with the smartphone.

further blending the line between vehicle and ride sharing (Alonso-Mora et al. 2017; Liyanage et al. 2019). Wider definitions of DRST have also been used to suggest that they *" can be regarded as a tool to shift away from a culture where consumers own assets (cars), toward the Mobility-as-a-Service (MaaS) culture, where consumers "share access to assets"* (Inturri et al. 2019, 2), hypothesizing that the knock-on benefits of DRST are about more than just how we get from a to b, and in fact extend to the broader topic of sustainability and the sharing economy. In juxtaposition to this however, one might rightly observe that DRST is only really shared when the users actually share trips, not just because they can (Clewlow, Mishra, and Kulieke 2017; Inturri et al. 2019). Therefore is a capacity 8 DRST van just ride-hailing if it's average occupancy is 1? We will return to this point in the discussion on MyShuttle, the DRST service that is the focus of this thesis, however it is beyond the focus for the moment.

In coming back to a working definition to be used in this thesis, demand responsive shared transport or DRST is the most appropriate description of the type of service being simulated, so the reader can rest easy that it is the only term they need to remember for the remainder. Again, vehicles in a DRST service are *demand responsive* in that they adapt their route and scheduling in response to the demand, and *shared* in that trips can be shared between otherwise unfamiliar agents, with the sharing algorithms being processed on the back-end.

2.2 Relationship Between Fleet Size, Vehicle Capacity & Service Characteristics

The trade-offs between eet size, capacity and the level of service are amongst the most investigated aspects of DRST to date - and the level of service that can be provided is a major part of studies which try to project the replacement of entire eets of cars with DRST. Many of these studies are theoretical in that they look at individual aspects such as comparing route-choice assignment algorithms (Maciejewski et al. 2017) or cost structure (Bösch et al. 2018), while neglecting to look at how the whole DRST package comes together with seemingly practical questions like willingness to share. Indeed at this stage in both the development of DRST services and it's associated literature, the focus has been limited by the lack of large-scale DRST platforms currently in existence. Nonetheless, research focusing on the theoretical replacement of large ee ts, and often particularly taxi- eets, has shown very promising results on the performance of DRST in regards to wait and travel times while utilizing much smaller eet compositions with varying capacities between existing conventional autos up to mini-buses.

More specifically, a strong relationship between increasing eet sizes and decreasing average wait times has been established. In (Ben-Dor, Ben-Elia, and Benenson 2019a), which simulates an SAV replacement of all vehicular traffic in the Tel-Aviv metro area, a eet of 50,000 SAVs was able serve all demand whilst keeping average wait times within a bound of 1.5 times the equivalent trip with an individual car assuming a modest time for parking search, and to walk to and from the parked vehicle. This eet size however resulted in a high rejection rate of 6% due to spatial outliers which could not be served in the max wait time of 12 minutes. Doubling the eet size to 100,000 vehicles reduced wait and travel times marginally,[3] and brought the rejection rate down to 2% which was considered feasible to make the system sufficiently attractive (Ben-Dor, Ben-Elia, and Benenson 2019a).

[3] The author is generally referring to the population average in discussing the plural wait and travel times

Similarly positive results are demonstrated in (Inturri et al. 2019) who develop a multi-agent simulation for planning and designing new shared mobility services with a focus on estimating demand and supply side variables that make DRST feasible. The model, which is based on a Netlogo simulation in the Italian city of Ragusa, demonstrates that a eet size 20% of the replacement is able to meet 78% of all demand whilst reducing fares by 74% (Inturri et al. 2019). This scenario also seeks to increase efficiency in terms of VKT (exceeding to emissions and use of road infrastructure), and therefore the results come with an increase in travel times of 166% and indirect detours for some agents (Inturri et al. 2019).

This brings us to travel time which, while in uenced marginally by eet size depending on the context geography and demand, has been most heavily correlated with vehicle capacity. This is related to the fewer and less extreme route deviations[4] from less people in a single vehicle (Inturri et al. 2019), although the relationship to route directness is closely linked to routing algorithms (Bischoff, Maciejewski, and Nagel 2017). For example, a pioneering study on DRST shows that a modified greedy algorithm[5] to show that capacities of 6-8 could serve demand more efficiently than single-use taxis (Gerrard 1974). More recently others have struggled to utilize vehicle capacities of 4, with vehicles occupied by 2 request only 50% of the time, and 3 request only 10% of operating time, leading to the conclusion that larger vehicle occupies are not always utilized in cases where max time or deviation constraints are applied (Bischoff 2017).

This brings the focus back to travel time and waiting constraints, as routing algorithms are ultimately in uenced by the objective function and the max wait time and target travel time. Indeed, the MATSim DVRP routing algorithm that is implemented in this thesis aims to maximize vehicle workload, creating limitations on the degree of performance improvement that can be achieved by increasing eet size(Bischoff, Maciejewski, and Nagel 2017). The details of this algorithm are discussed further in 6.1.1.

Travel time is sensitive to both capacity and routing algorithm, however it's important to highlight that *decreased* travel times as compared to the equivalent trip[6] are not expected. In other words, when individual DRST travel times are compared to their relevant individual car

[4] Deviations are a measure of indirectness of the trip taken from passengers in reference to the most direct possible route

[5] A greedy algorithm makes the locally optimal decision at each stage instead of waiting for a computationally intense fleet-wide solution

[6] This comparison is usually taken versus a direct (non-shared) auto trip

trip travel times (both as taxi trips, and as auto driver trips where small parking search and access/egress times can be added), we do not expect absolute travel time savings. Rather, research is trying to ascertain if relative travel time increases can be keep within reason while leveraging the other benefits of shared transport, and therefore make sense within an overall cost-benefit analysis. For example, the widely cited study by (Alonso-Mora et al. 2017) proposes that a travel delay of 5min, comparable to retrieving a parked car, can be used to make higher capacity vehicles more feasible. In their mathematical model for dynamic route optimization comparing eets of capacity 4 and capacity 10 in the New York City taxicab data set, a eet of 2,000 capacity 10 vehicles (15% of the taxi eet) is able to serve 98% of demand within a mean wait time of 2.8 minutes and a mean trip delay of 3.5 minutes (Alonso-Mora et al. 2017).

By contrast, absolute travel time decreases can be anticipated when DRST is compared to conventional public transit (CPT). In research on the potential of replacing 90 capacity buses with 30 capacity mini-buses in Singapore, (Koh et al. 2018) find a reduction in travel times of 79% (7.7 to 5.3 minutes) without increasing wait times based on a eet of 24. Holding these parameters but reducing the eet size to 21 brought the travel time down further to 68%, although wait times then increased from 4 to 5.9 minutes, again highlighting the relationship between eet size and wait times (Koh et al. 2018).

2.2.1 Sharability

This complex relationship between eet size, vehicle capacities and travel and wait times has been framed by the metric of shareability. This is helpful because it tends to capture the key element of a DRST service that describe whether it functions more like CPT or ride-hailing (Liyanage et al. 2019), but also because it links DRST to broader performance measures like sustainability and cost effectiveness (Bösch et al. 2018).

In general it is apparent that user costs decrease when sharing increases, and that this has an inverse relationship to travel times due to the necessary additional route deviations. However, the real question is if it is possible to achieve reasonably high levels of sharing without unrealistically disadvantaging service quality, and if so, how should a high level of sharing be bench marked?

(Bischoff, Maciejewski, and Nagel 2017) analyze the sharing potential of shared taxi's and show that a routing algorithm that optimizes vehicle workload[7] has strong sharing potential, such as minimum vehicle occupancy of at least 2 for 50% of time that vehicles are travelling. On the ip side, this algorithm (which will be discussed further in 6.1.1) necessarily limits the in uence of increasing ee t size on improving service quality. This is because the extra capacity is not assigned beyond some threshold, instead choosing to insert agents into vehicles that are already underway (Bischoff, Maciejewski, and Nagel 2017). A similar study by (Leich and Bischoff 2018) tested an over-supply of 1000 capacity 4 vehicles, finding that only 250 were ever in operation at the same time due to the tight constraints of this algorithm. While this was an intentional oversupply of vehicles, it serves to highly the point that in some contexts, the service quality of DRST can be limited by the degree of shareability.

In short, shareability can be taken as a metric that captures some of the trade-offs between eet size, vehicle capacity and average travel and wait times. While it is not a measure of direct service quality, it can provide a useful catch-all metric for a broader interpretation of service performance at the eet scale. Additionally, the evidence highlights that it is not only objective function of the routing algorithm that in uences sharability, but also on the demand geography itself.

2.3 Geography of Service Area Trade-offs

Despite the challenge of comparing the spatial component of DRST service across different service areas, there has been investigation of this relationship within individual service areas. This research suggests that DRST is most strongly viable where there is enough density of users and tightly knit origins and destinations - and that it may be significantly less viable when these conditions are not true (Ben-Dor, Ben-Elia, and Benenson 2019b). This theme has significant consequences for the broader discussion of how and where DRST should be implemented given that in the centre of cities it will often be in the most direct competition with CPT and active travel, as well as the extent to which DRST can compliment CPT.

One fascinating study which has emerged from the cluster of research in the Tel-Aviv Metropolitan Area investigates the temporal and spatial patterns of future SAV services (Ben-Dor, Ben-Elia, and Benenson 2019b). This simulation, which can be considered quite futuristic for it's full replacement of all vehicular traffic, demonstrates that a SAV eet of 50,000 could

[7] Meaning that it aims to maximize capacity and minimize the amount of empty or low passenger kilometres driven within operational constraints

serve the entire region (containing ˜45% of the country's 8M population), amounting to a decrease in congestion by 20%, although overall rejection rates remain high (Ben-Dor, Ben-Elia, and Benenson 2019b). More interestingly, however, the rejection rate for core-periphery trips approaches 20%, which is 4 times higher than the same indicator for core-core trips (Ben-Dor, Ben-Elia, and Benenson 2019b).

This finding hints at an invisible border affecting trips between the core/inner areas to outer areas. Internal travel, analyzed by comparing Rejections/(Rejections + Trips) of OD pairs, can have very low rejection rate approaching 0% for the core,[8] and an external area where DRST also functions locally. But it is the trips *between* core and periphery that essentially seem to break down (Ben-Dor, Ben-Elia, and Benenson 2019b). This finding remains true even after doubling the eet size to 100,000, which outlines the strong in uence of the demand geography on performance (Ben-Dor, Ben-Elia, and Benenson 2019b). Further, simply cutting out the 95th percentile of spatial outliers had the same effect on service performance as doubling the eet size (Ben-Dor, Ben-Elia, and Benenson 2019b). In the case of the Tel-Aviv Metropolitan Area, these findings would seem to suggest that the deployment of DRST (whether autonomously driven as in the study or not) must consider integration with other modes such as CPT to account for core-periphery travel.

Service area optimization simulation is another way to approach this topic. Finding an appropriate service area incorporates the cost/revenue potential component more directly, as any DRST service is understood to have a preferred service area, particularly when considering operator-side profits. (Bischoff et al. 2018), while focusing on the Saturday evening peak which is perceived to have the highest potential for shared rides, identify an optimal service area including operator costs of €50/day per vehicle and €100/day per driver. To both the objectives of reducing overall VKT and improving revenue, the service-area optimization confirms an area around the city-core plus a slight extension performed most optimally (Bischoff et al. 2018).

Finally, (Koh et al. 2018) note in their comparison study of 90 capacity CPT buses that implementing DRST in high demand corridors such as those found in their bus-feeder routes that lead to a light rail station will most likely result in travel patterns that are very similar to fixed routes anyway, suggesting that the added exibilit y of DRST does not add much value. While these studies alone are not enough to fully understand the issue, the trend suggests

[8] Reasonable travel and wait time bounds are implied, although not explicitly provided in the paper

that DRST has the most potential in the densest areas from the both the operations, revenue and VKT reduction perspectives.

2.4 Mode Shift & Public Transit

The questions of how DRST stands to draw mode split from existing modes or inducing demand, as well as the relationship to CPT is a complex one that has not been significantly addressed in the literature. Evidence from the closely related world of ride-hailing which has been around slightly longer and has reached larger scales of penetration might help answer the first part of this question. For example, in a survey-based study of ride-hailing adoption in major U.S. cities, the top two motivations for ride hailing were to avoid parking (37%) and to avoid drinking and driving (33%) (Clewlow, Mishra, and Kulieke 2017). This would seem to suggest that ride-hailing users are tightly linked with existing personal auto users, however the same study found a 6% reduction in the use of bus-transit services and a 3% reduction away from light-rail (Clewlow, Mishra, and Kulieke 2017). Indeed, there is likely to be some mode-change from both directions, although the extent will likely vary by geography and service just as mode splits themselves do. At the same time, it's entirely possible that DRST may induce new demand such elderly or physically-disadvantaged groups, or for young people living in mobility starved locations (Shaheen et al. 2017).

For example, a year into a DRST public private partnership with ride-hailing giant Uber, the town of Innisfill, Ontario raised fares on their public DRST service significantly - citing the platforms overwhelming success and high levels of use that resulted in above-projected costs for the city (Bliss 2019). Despite Innisfill's focus on creating a public transit-like platform, including discounted fares to community hubs and the local library, city officials specifically mentioned the prevalence of a "youth bracket who were using Uber at $3 to go to Starbucks (as an example), purchase a drink, then go back to school or meet their friends" (Bliss 2019) as a key concern behind the fare hike. Leaving judgement about the value of this type of trip aside, it provides a poignant example of the potential for DRST to induce demand.

The Innisfill program, which made international headlines in 2017 as an early examples of replacing CPT services with DRST, has yet to provide any clear consensus. The program consists of a partnership with Uber Canada to run DRST mini-buses with at-fares to and from a handful of key hubs in the town, with the remainder of the fare paid by the customer (Uber 2019). On the one hand, the program, has been lauded by city officials for it's exibilit y, equability, and cost effectiveness in serving a spatially dispersed population (CBC 2018). Users have also reported high levels of satisfaction, and the city has framed the program as part of introducing data-driven and lean governance to their public works (Bliss 2019). The decision to pursue the partnership followed a cost-benefit analysis prior to implementing the town's first bus line, which was projected to serve 17,000 riders annually and cost $270,000 CAD (Bliss 2019). While the initial comparison of the projected CPT service to the DRST partnership that was ultimately chosen was attractive from both a service quality and cost perspectives, the public subsidies for trips made in the Uber partnership have risen from $150,000 CAD in 2017 to $640,000 in 2018 and are projected to reach $900,000 in 2019 (Bliss 2019). Some have also questioned the long-term viability of directly outsourcing public services of this scale, as well as the politics surrounding the imposed fare caps, exceptions and the balance between public subsidy and user-side payments per trip (Bliss 2019).

The Innisfill example at large leads to a broader debate about the future of public transit in the face of technology enabled MoD services. In terms of simulation studies, it remains unclear how this will play out, rather these studies add evidence to the key variables that are likely to in uence the relationship between CPT and MoD, particularly cost and service competitiveness. In their study on replacing CPT with SAVs in a suburban Berlin neighbourhood (Leich and Bischoff 2018) found higher operating costs and only slight travel time savings from the user. This study focused on the concept of replacing feeder buses to a light-rail station, and the main limitation on the service are the added detours required by door to door service (Leich and Bischoff 2018). The possible replacement of CPT with DRST has also been looked at from the perspective of exible routing (Koh et al. 2018), a case-study of a small town in Germany (Viergutz and Schmidt 2019) and from the traveller preference perspective in (Yan, Levine, and Zhao 2019) all of which find a mix of benefits for users and operators, while highlighted the need for additional research.

2.5 Summary & Research Gap

This literature review has combed the state-of-the-art, organized evidence around three key theme areas of relevance to the MM case-study and modelling decisions to be taken in the remainder of this work. Some key metrics were only touched on here, and can be found in a supplementary literature review table in the appendix. One clear message is that the academic attention to DRST is still very much evolving, and has relied heavily on simulation studies that lack real world data. Few studies bring all the aspects together, and rather tend to focus on assignment algorithms or vehicle capacities alone, while making assumptions elsewhere such as keeping demand fixed or replacing 100% of all vehicles. The question of the relationship between DRST and CPT replacement evidence remains somewhat unclear, with the exact results around travel time or fare savings varying from one simulation to the next. Some authors include (Leich and Bischoff 2018) specifically point out that investigation of combination scenarios such as replacing low performing CPT lines and during the off-peak are still missing. And finally there is essentially no evidence surrounding corporate mobility studies, either in how mobility behaviour and demand may differ or in relation to the operator objectives. All these factors culminate in a strong case for the research to proceed around the relationship between DRST and CPT services.

3 Research Objectives & Analysis Criteria

This research investigates the potential for DRST services to compliment CPT bus services. Specifically, it focuses on the trade offs between the quality of service that can be provided under varying scenarios, given the fixed operating costs embedded in the case-study. This topic is framed by the following generalized research questions:

1. Can DRST provide the same quality of service as CPT buses within the same operator costs?

2. (If yes), can the design of DRST services be used to reduce the operations cost of CPT buses while maintaining the same quality of service?

3. (If no), how much does it cost for DRST to match the quality of service provided by CPT buses?

3.1 Quality of Service

These research questions all refer to *quality of service* which needs to be defined. In line with other simulation studies (see table @ref(tab:simulationLitReviewTable in the appendix) for a tabular summary of performance metrics), quality of service is measured with several key analysis criteria that help describe it's quality from a user perspective. These metrics are not exhaustive and do not describe elements such as comfort or safety. Rather they focus on providing an intuitive reference that can be objectively compared across scenarios, and which form the basis for more detailed analysis. In the context of this thesis, *quality of service* refers to:

1. access, wait, in vehicle, and egress times which sum to total travel time
2. number of between pt line or multi-modal transfers
3. rejection rate

The inclusion of rejection rate in the case of DRST performance is of particular relevance, as the routing assignment algorithms are themselves governed by functions that will keep the provided service within bounding targets (primarily, a target and maximum wait time, as well as a threshold for the acceptable detour that is allowed as compared to a direct trip). Put simply, the routing algorithm is designed to handle excess requests by rejecting those that cannot be served within these bounds, resulting in stabilized system performance but with potentially high rejection rates if the requested demand cannot be served. The function of the assignment algorithm is described further in chapter 6.1.1.

Beyond the core research questions which connect costs and service quality, the research will seek to understanding the spatial and temporal aspects of DRST and CPT service performance. For example, how does the relationship between cost and quality change across peak demand and off-peak times of the day, or between bus routes in areas with proportionately high number of stops and demand versus those connecting more distant origins and destinations. These secondary aspects of the research focus are incorporated both in the research design in terms of the DRST scenarios that are tested, and are touched on in the discussion.

4 Simulation Design

The simulation design is rooted in comparing the key service quality indicators defined in chapter 3.1 across multiple DRST scenarios. Firstly, a **base-case** scenario is used to model the network, transport supply and mobility behaviour of the MM population - which is calibrated and validated to the case-study data. While the base-case includes both a CPT and DRST service, it is the service quality indicators from the base-case bus service that provides a benchmark to compare against. Making use of the calibrated base-case simulation, three **DRST scenarios** are then introduced, each of which changes the spatial and temporal supply of CPT and DRST services in order to produce results that can be compared against the base-case values.

Each of the DRST scenarios approaches the research question from a different angle that blends ongoing debates in the literature while remaining grounded firmly in the cost structures of the two services as will be outlined in chapter 5.4. These scenarios will become clearer in the results and discussion section, but for now an overview is as follows:

- **Base-Case:** the CPT and DRST services are simulated as they exist currently, with mode calibrated between the input and output mode splits, and with the model validated to traffic data leveraging the external Here Maps API and to internal bus passenger count data for the CPT service.

- **Scenario One (S1): off-peak replacement of CPT with DRST vehicles.** In this scenario CPT buses are run on their regular schedules until 15:00 and DRST service is introduced from 14:30 to 18:00 which provides a small bumper between the two services. While the demand for bus services varies by line, the assumption of 15:00 as the on/off peak divide was considered reasonable - particularly in response to the observed demand peaks on lines 1 and 2 which carry the majority of passengers.

- **Scenario Two (S2): CPT within clusters - DRST connecting satellites.** In this scenario both CPT and DRST services are run all day. However CPT buses are restricted to lines 1-3 in the central campus that receives the most demand, while lines 4-5 which connect to the Garching and Unterschleißheim clusters are removed. Correspondingly, DRST services are introduced with a service area equivalent to lines 4-5 that have been removed.

- **Scenario Three (S3): DRST within clusters - CPT connecting satellites.** In this scenario both CPT and DRST services are run all day, however the opposite service areas to S2 are implemented. CPT buses are restricted to lines 4-5 which connect to the Garching and Unterschleißheim satellite clusters but which have relatively low existing demand compared to the bus lines in S2, and a corresponding DRST service is introduced with a service area equivalent to lines 1-3 service that has been removed.

Perhaps a simple way to remember this is that S1 is always about time, S2 uses DRST in place of the **2** bus lines that would normally serve the **2** satellite locations, and S3 uses DRST in place of the **3** CPT lines that would normally connect the **3** clusters within the central campus area (that is Campus Freimann, the Central Campus around the FIZ and the Werk/Hochhaus).

4.1 Study Area & Network

The study area is defined to encompass all relevant BMW Group office locations in the Munich region, while attempting to minimize unnecessary network detail which can have a major in uence on computation time. This area is characterized by several clusters:

- The central campus located near Am Hart U-bahn station and includes several of the major design and engineering buildings plus the Werk manufacturing plant and the Hochhaus global headquarters
- Campus Freimann, a recently expending office cluster directly to the east of the central campus
- Garching located in the Hochbrucke business park
- Unterschleißheim where the autonomous driving campus as well as daughter company Alpha City is located

All network elements are from Open Street Map data for Oberbayern (Maps 2019), clipped and manipulated with the command line tool Osmosis and finally converted to MATSim-readable XML inputs using the MATSim plugin developed for the JOSM editor (Nico Kühnel and Michael Zilske 2019).

A notable modification to the network was made to a bridge that is currently under-repair on the road St 2853 north of the A99 south of B471 as this link is forms an important part of the connection between Unterschleißheim and the central campus. The current OSM network had (correctly) marked this link as temporarily closed in the OSM data, but the modelling decision was made to include through-access. The final network uses several scales of resolution as a described below, which help obtain a desirable level of detail around BMW Group office locations, but leaving this level of network resolution out where it is not necessary:

- At the largest extent,[9] all motorway, trunk and primary links were included. This was intended to facilitate background agents from the entire region in making their way onto the major arterial roads where we want to see traffic congestion interactions and not unnecessarily force these agents onto smaller study area road links
- A medium resolution layer was included within a two kilometre dissolved buffer surrounding all of the included BMW demand data origin-destinations, which includes all secondary and tertiary links
- A high resolution layer was brought to the areas immediately surrounding the buildings of the simulation origin and destination points as well as around all 26 Pendelbus stop locations, which includes all residential, livingstreet, service and unclassified links

The high resolution aspect of the network is important for the case study as many of the small OSM links surrounding BMW Group's office clusters are classified as service or livingstreet in the OSM data. This level of detail would likely not be the focus of a larger city-wide model, but given the relatively refined study area and the potential for small changes in access/egress times in the DRST scenarios depending on the availability of small links, the high resolution links were included. That being said, the quality of data at this level was not entirely consistent, for example overlooking access-rights issues to some laneways between buildings. The final high-resolution component of the network re ects some hand-made edits and testing on the network using the author's local knowledge, with the assumption that MM demand and vehicles have access to all service links within the campus area.

[9] This is made up of the Fürstenfeldbruck, Freising, Erding, Ebersberg, Dachau, Munich County, Starnberg and Munich City administrative areas bordering which surround Munich

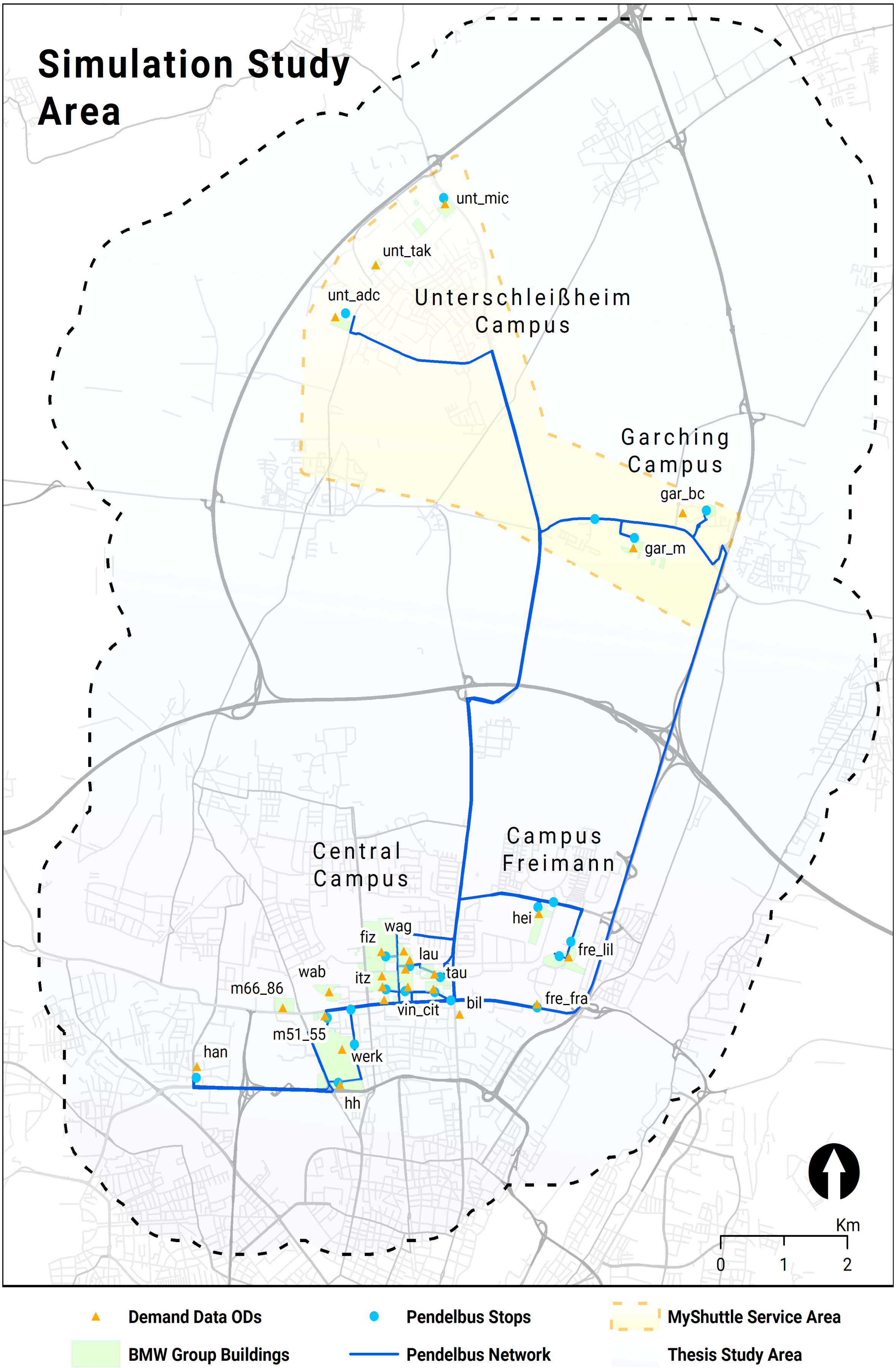


Figure 3: Study area depecting select BMW Group office buildings, Pendelbus network, demand data origin and destination points and MyShuttle pilot service area.

5 Data & Context Overview

The following section provides an overview of the MM data implemented in the thesis, while specific details regarding data scrubbing and transformation are left to the methodology in chapter 6.

5.1 Travel Demand

One of the primary data inputs is a series of origin-destination matrices that describe within the workday corporate mobility trips of the case-study BMW Group population. These demand data were captured in an internal corporate mobility travel survey conducted by Mareike Sigloch of the BMW Group in July 2018 (Mareike Sigloch 2018). The survey, which was sent electronically to 35,510 BMW Group employees, includes a section where respondents recall their previous week's daily travel patterns for the week of July 9th – 13th, 2018 including:

- each trip origin and destination (selected from a list of 29 BMW Group locations + external partner/customer)
- time of departure (within one-hour time brackets during the day)
- travel mode (selected from one of 18 possible options or 'other')

The survey achieved a roughly 28% sample with 9,896 responses. Of the 18 mode choice options recorded in the survey, the data was expanded and aggregated into 4 main travel mode groups. While this data does not contain personal or demographic information that could in any way be linked to an individual, this aggregation strategy was necessary to satisfy data privacy restrictions set by the BMW Group that regulate the internal sharing of potentially sensitive data.

In the detailed travel diary portion of the survey, respondents were asked to record every direction of a trip.[10] However in an earlier section they were also asked about the overall number of trips they did, creating an opportunity to compare the total number of trips that were reported individually in the diary and the personal sum of trips reported by each respondent (overall). Of all responses:

- roughly [redacted]

[10] That is the segment of travel from origin to destination is reported as 1 individual trip, and the following segment going from destination back to origin (or to another destination) is an additional trip record

[redacted]

- [redacted]
- [redacted]
- [redacted]
  - Of these, [redacted] and roughly [redacted]
- [redacted]

This comparison may indicate that the survey under reported trips, particularly in reference to the [redacted] with fewer trips in the diary and particularly those who didn't report any trip. As the first survey of it's kind for this population it is difficult to further assess this. However at the same time, the overall response rate which is considerably higher than many household travel surveys lends confidence. In any way, the data exploration process further confirmed the logical ows of different modes, and the data was generally considered a valid representation of MM demand.

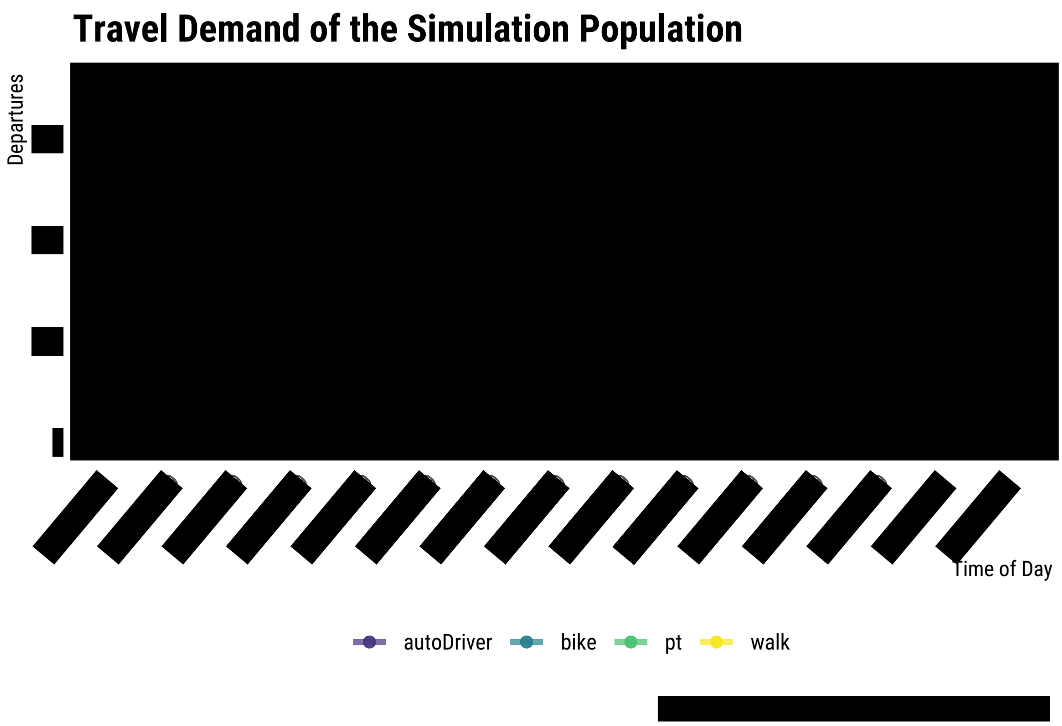
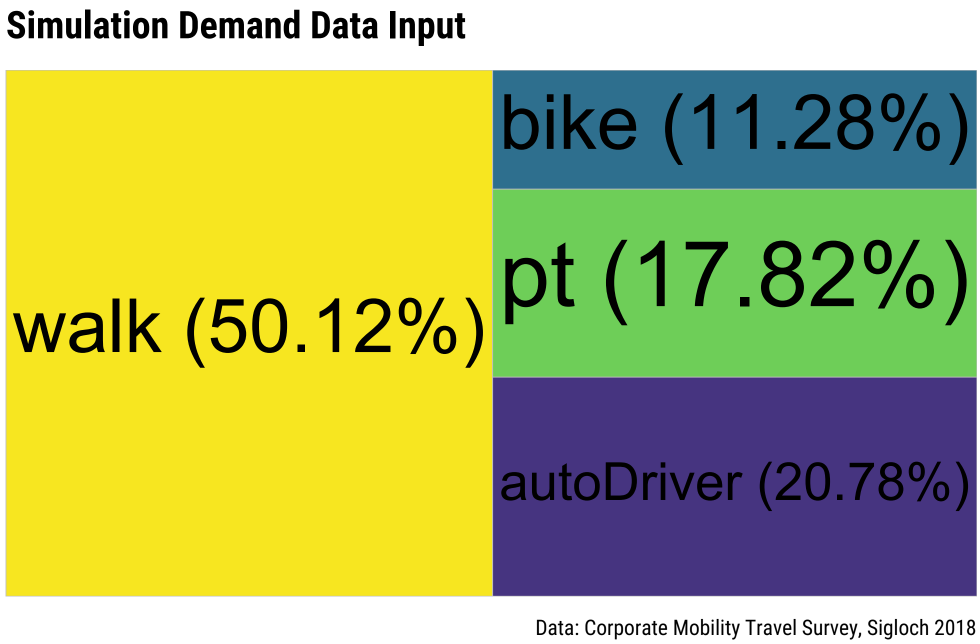


Figure 4: MM travel demand by hour.



5.2 Pendelbus Service Automatic Passenger Count Data

MM has been running an internal, intra-campus bus service since the late 1980s named Pendelbus. The service began with a single line connecting the central campus locations around the Hochhaus and Werk, growing to it's current extent of 5 lines with 12 buses of capacities between 8 and 30 that serve the needs of inter-campus travel including connections to the Garching and Unterschleißim satellite locations. While the service has responded to changes in land-use (by adding additional stops) and to demand (by changing frequencies and vehicle capacities), this evolution has been described as an adhoc approach, and largely void of data-driven planning support.[11]

In 2018 automatic passenger count (APC) technology was installed on 2 buses, and later extended to 6 buses across the 5 lines. The collection of this data is subcontracted to the firm Irma On-Air which provides the raw, uncleaned passenger count information in real-time. In the context of this thesis, this APC data was used to validate the results obtained in the base-case simulation, and not directly as a demand input.

In order to simulate public transit in MATSim, an appropriate set of MATSim-specific inputs

[11] This information is based on discussions with the Pendelbus coordination and operations team, chiefly [redacted]

which capture the characteristics of the transit supply are required. In the context of this thesis, these were generated with a combination of manually editing the (incomplete) GTFS files supplied by MM, and creating MATSim compatible xml outputs with the *pt2matsim* package (Poletti [2016] 2017).

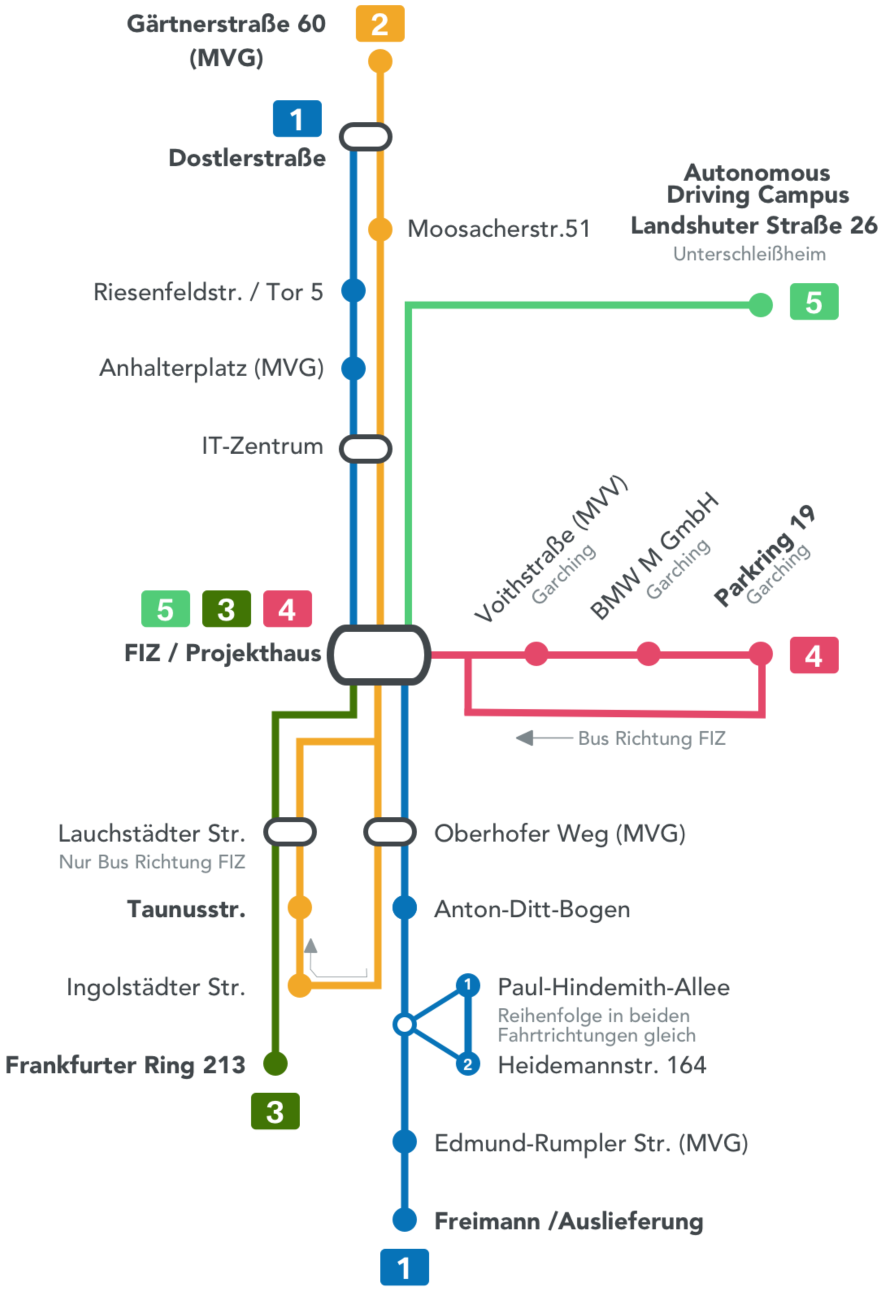


Figure 5: Simplified Pendelbus network map as implimented in the Urby app.

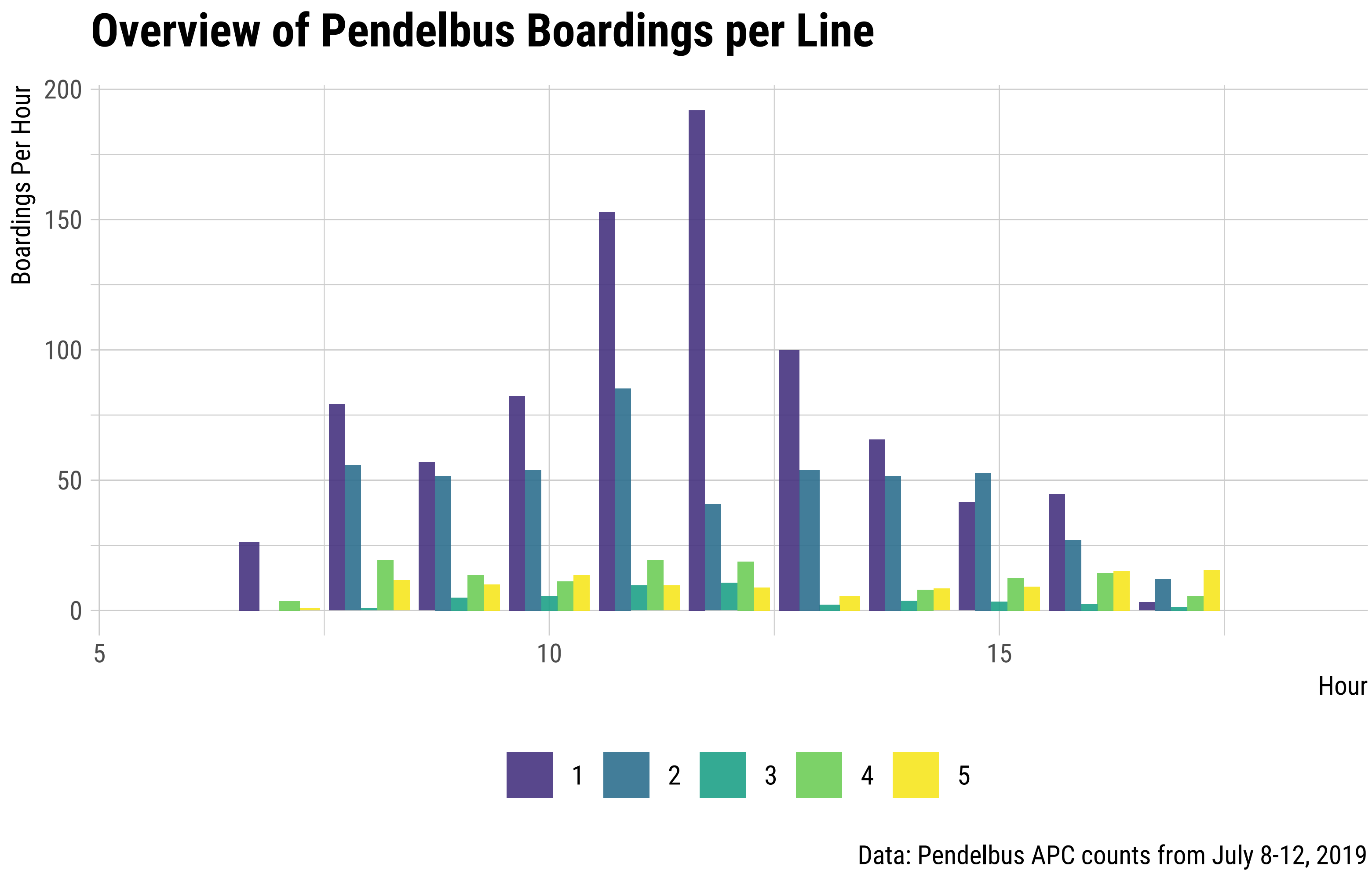


Figure 6: Graphic displays the number of boardings per hour per Pendelbus line. The demand peaks in the middle of the day are most pronounced on lines 1 and 2 although it should be noted the data only samples a single week.

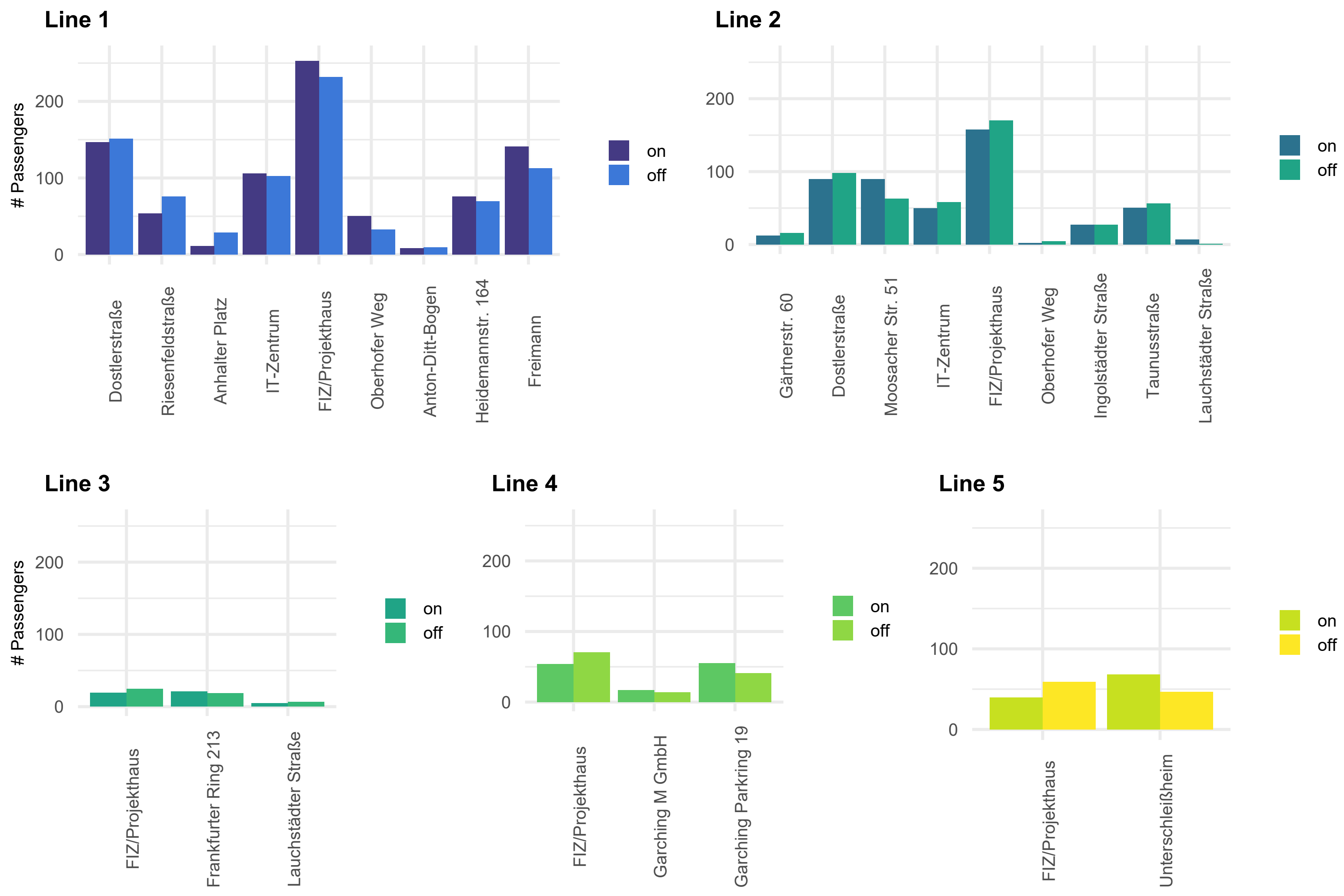


Figure 7: Graphic displays the number of boarding and exiting counts per Pendelbus line and stop. Lines 1 and 2 function more like normal bus lines even use of most stops, whereas lines 3-5 function more like shuttle connections with maximum 3 stops per line.

5.3 MyShuttle Pilot Program

Data surrounding the operations of the MyShuttle pilot were available in high resolution from the programs start in May 2019 until the time of writing, and provided a critical glimpse to DRST response and usage that is incorporated in the model calibration. This data is in the form of aggregated trip information available through a real-time mobility dashboard provided back the back end service provider, door2door. The primary purpose for this data is to provide a service benchmark on the performance and quality indicators that is driven by a real world DRST operations. This included detailed information on the numbers, distances and duration of trips, as well as eet specific metrics like average wait times, average travel times and pooling rate amongst others.

As a pilot program, MyShuttle faced many unknowns in regards to how it would be used, as there were essentially no comparable travel options available to provide a reference. This is visible in spikes in ridership and total occupied vehicle km's driven which have risen in the months of September and October following the slow month of August where many employees were on vacation. A continued publicity campaign inside the company that aimed to promote and inform employees about MyShuttle was also a likely helpful aspect.

As a general comment, a lack of awareness was seen as an early challenge in higher adoption rates of MyShuttle. Secondly, it should also be noted that one of the conceptual goals of the pilot was to provide connectivity between locations least well served by Pendelbus. This meant that the MyShuttle service area was implemented to specifically limit MyShuttle being in any direct competition with routes served by Pendelbus as depicted in the study area map.

5.4 Pendelbus & MyShuttle Costs

While existing simulation studies (Alonso-Mora et al. 2017) model the exible element of DRST in regards to user costs, presenting exible and scalable services depending on what the customer is willing to pay, this approach does not fit the context of corporate mobility where the customer, as an employee of the service provider, does not pay a monetary cost for travelling. This creates a duality where the cost constraint comes at the level of the entire service over the number of trips it is able to fulfill. The quality of the service in this context then stands to in uence how much it is used, and therefore is an appropriate indicator in balance to the system-wide operational costs.

Incorporating a realistic cost structure is an important aspect of the research design, both in emphasizing the connection to a non-theoretical case-study which is an existing gap in the DRST literature, and in ensuring the relevance of the analysis to MM which is ultimately an operational department. To this end, detailed costs for the operations of Pendelbus 1 and MyShuttle 2 were made available.

	vehicles (day)	capacity	startTime (min)	endTime (min)	opTime (hr)	km (day)	km (day/veh)	cost(€) (km)	cost(€) (hr)	cost(€) (veh/hr)
Line1	4	30	465	1080	10.25	560.5	140.12	[redacted]	[redacted]	[redacted]
Line2	3	30	465	1050	9.75	459.0	153.00	[redacted]	[redacted]	[redacted]
Line3	1	8	480	1020	9.00	185.6	185.60	[redacted]	[redacted]	[redacted]
Line4	2	19	450	1080	10.50	504.0	252.00	[redacted]	[redacted]	[redacted]
Line5	2	19	480	1050	9.50	494.0	247.00	[redacted]	[redacted]	[redacted]

Table 1: Summary of relevant Pendelbus costs

The Pendelbus data is available at the level of each of the 5 lines, from which a further breakdown by vehicles per time unit can be calculated. The item-specific costs like driver-compensation, insurance, maintenance or other overhead are therefore bundled inside this value.[12] Of particular relevance are driver specific costs which are generally put at 55-70% of vehicle operating costs in Germany (Bösch et al. 2018). Therefore, a figure of €15/hr was decided on as realistic in consultation with MM, which would put the driver-compensation component of Pendelbus at the low end of this range.

The cost structure of Pendelbus is otherwise nondescript. Lines with more VKT cost more, to the tune of roughly €[redacted]/hr, while line 3 with a smaller and lower capacity vehicle has the lowest costs. When considering line cost over number of passenger trips however, it's interesting to note that lines 4 and 5 (the two long-range lines connecting the satellite locations) provide a much lower cost-trips ratio which will come up again in the results.

In the MyShuttle cost data, item-specific costs were made available. Here we see explicitly that the driver-compensation component is well above that of Pendelbus, and it can potentially increase further when VKT increases due to an addition €[redacted]/km driver compensation.[13] The current cost of MyShuttle drivers is considered well above average, with

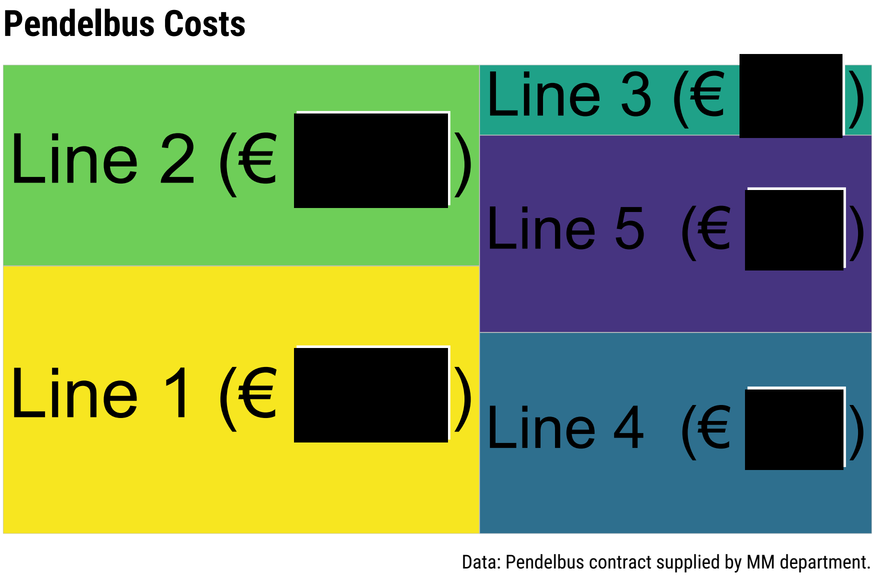
[12] The Pendelbus has been run on contract to bus operator Stanglymier since it's inception with public bids for each contract iteration

[13] As an in-house pilot program, MyShuttle vehicles are driven by internal BMW Group employees who's com-

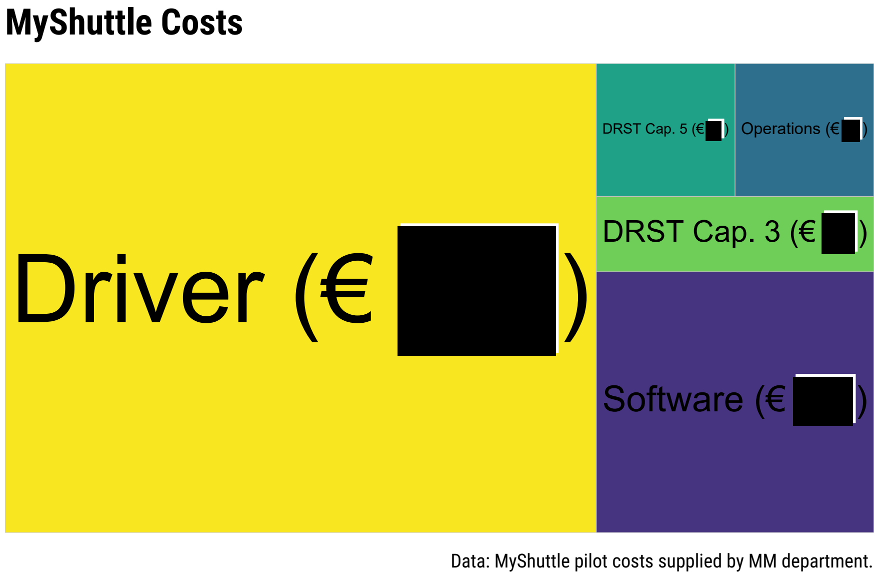
implications on the scenario design. This point is further addressed in the 6.

	vehicles (day)	capacity	startTime (min)	endTime (min)	opTime (hr)	km (day)	km (day/veh)	cost(€) (km)	cost(€) (hr)	cost(€) (veh/hr)
Vehicle	1	3	480	1080	10	4	4	[redacted]	[redacted]	[redacted]
Vehicle	1	5	480	1080	10	4	4	[redacted]	[redacted]	[redacted]
Software									[redacted]	[redacted]
Operations									[redacted]	[redacted]
Driver									[redacted]	[redacted]

Table 2: Summary of relevant MyShuttle costs



pensation must have both a time and performance-based component



5.4.1 Discounting

In order to compensate for the uncharacteristically high unit costs of MyShuttle that stem from it's inception as a pilot project and to make the results more generalizable to existing and future contexts, the simulation implements cost discounting for the DRST portion of costs. This process was the result of a collaborative consultation with the existing project leaders within the MM department. Firstly, a significant portion of the MyShuttle costs are made up of the software licencing for the back end dispatching tool provided by door2door. The current cost of this service is for up to 5 vehicles. In the first cost assumption, the software cost is kept constant regardless of eet size which was kept the same for larger eets. Additionally, a future discounting of software costs of 15% was considered appropriate as this technology can are likely to be lowered as the technology matures. The more significant area of DRST discounting are driver costs which were discounted in line with average driver cost in Germany. This amounted to a at rate driver cost of €15.00/hr which is considered a high average value for the cost of drivers in Germany (Bösch et al. 2018).

6 Simulation Implementation

6.1 Transport Modelling with MATSim

MATSim is an "activity-based, extendable, multi-agent simulation framework" (Axhausen 2019, 4), designed around the principles of transparency and collaboration. Through it's modular design allowing contributions to be developed openly by anyone in the world, it's strengths include both the exibility to adapt to a variety of available inputs, as well as sim-ulating a range of transportation scenarios including cutting-edge technologies. In short, it is a fundamentally agile open-source tool that has been implemented by researches and practitioners alike to help shed light on the pressing questions in transportation. These qualities together with the author's desire to dive further into the world of computer programming made it a suitable choice for this thesis.

A MATSim *run* which commonly models a single day, consists of agents running around in the network and available transport supply as they attempt to fulfill their daily activity plans by travelling between locations. As agents interact with one another and the system over many iterations, they adapt their behaviour in an attempt to maximize personal welfare, and in so doing, a calibrated simulation can move toward convergence. This approach to "co-evolutionary" simulation is based on different groups of agents testing varying strategies, with each executed plan being scored, and with the best performing plans surveying in the evolutionary process as the simulation runs through it's iterations (Axhausen 2019). In the scope of MATSim's development, this has most often been implemented in the form of modelling the chained activity tours of agents, but the developers note the opportunity to use MATSim with "dummy" trips (Axhausen 2019) as is implemented in this thesis given the available data.

6.1.1 DVRP Extension Algorithm

A key aspect of MATSim which made it a suitable choice for this thesis are the DVRP (Dynamic Vehicle Routing Problem) (Maciejewski et al. 2017) and the Demand Responsive Transport (Maciejewski 2016) contributions which allow MATSim to simulate DRST services. During the simulation these contributions handle the optimization of active requests by inter-jecting in the MOBSim, organizing vehicle routing, dispatching and eet re-balancing, before passing this optimization back to the controller. Additional functionality is included for the control of special vehicle attribute files, service areas and operation times, and control over a host of other configurable parameters.

The stock routing objective implements an insertion heuristic that attempts to optimize the work-time of the shared DRST vehicles (Bischoff, Maciejewski, and Nagel 2017). Simply put, the objective function seeks to use vehicles as efficiently as possibly, therefore maximizing the sharing potential of the service within the constraints "(i) the wait and travel duration constraints are satisfied for both the new and already inserted requests, (ii) the vehicle time window is satisfied". (Bischoff, Maciejewski, and Nagel 2017, 2).

To make a small detour, the DVRP problem is described in the optimization research as an *NP-Hard* (non-deterministic polynomial-time) extension of the classical travelling salesman problem (Koh et al. 2018). In working terms, this means that the complexity of finding an optimal solution within polynomial time increases exponentially as the size of the problem rises. Bringing this back to the DVRP, as more agents, vehicles, possible routes, departure times etc. are introduced, the solution to which vehicle should be assigned to pick up agent Bob cannot be solved optimally within any realistic computational time. This is why the branch of DVRP optimization research instead focuses on sub-optimal solutions to these NP-hard optimizations that are light-weight enough to be implemented in real-time DRST interfaces (Koh et al. 2018).

Understanding the optimization constraints of the DVRP is important in the context of the implemented MATSim algorithm. Specifically, this insertion algorithm can be considered sub-optimal in that it does not allow the reordering of stops or moving of requests between vehicles, while the authors instead choose control performance by using tight maximum waiting time and travel time constraints (Bischoff, Maciejewski, and Nagel 2017). These are an alpha factor which essentially defines the detour factor allowed against a comparable direct trip,[14] and the beta parameter which defines the target for the maximum wait time.[15]

Importantly, these contributions do not currently support pre-booking which is a limitation on their ability to accurately capture true DRST service. Without prebooking, the agent requests the trip exactly when the previous activity is completed (or more usefully, exactly when the agent wants to depart and *would* depart if they were taking any other mode in the

[14] This is defined as "the slope of the maxTravelTime estimation function (optimization constraint), i.e. maxTravelTimeAlpha * estimated_drt_travel_time + maxTravelTimeBeta" in the code

[15] This is defined as the "shift of the maxTravelTime estimation function (optimization constraint), i.e. maxTravelTimeAlpha * estimated_drt_travel_time + maxTravelTimeBeta" in the code

simulation).

6.2 Data Expansion

Calculating appropriate factors to expand the survey data required manipulating and merging several different employee databases in order to build a singular reference for the employee population at each location. The location database supplied the location of departments by name during the survey period in July 2018, and the population database contained a more detailed description of those department's population by age group and access to a company car (a Führungskräftedienstfahrzeug or FKD).

This process was completed collaboratively by the author (responsible for data manipulation and the production of a final department "key" list of locations), and Mareike Sigloch (responsible for the conditional logic behind the process, as well as determining determining and applying the expansion factors.

The first part of this process was complicated by the availability of different resolutions of population data depending on the department size, hierarchy and FKD availability as well as changing department codes between the 2018 location and 2019 population databases. Distinguishing between demographics with and without an FKD was desirable due to the fact that a majority of upper management (many of whom are with FKD) may make significantly more corporate mobility trips than others due to the nature of their jobs. Therefore capturing this level of detail and assigning it to the correction location was considered a worthwhile improvement on accuracy. At the same time, the population record came from self-reported employee locations, and therefore may be inconsistent in cases where employees changed location which supported the decision to assign departments to locations where the majority of their population was recorded but not at a higher resolution. The accuracy of all these variables was not verifiable, but was nonetheless considered a reliable reference point for the expansion factors.

The process of coding the department hierarchies and automatically assigning them a location based on their composition was accomplished in R. While a method was developed to automatically assign departments with at least 50% of workers in the same location, and then further subdivide and manage the spatially diverse departments at increments of 10% -[16] the locations were ultimately assigned with the simplest method of choosing the location with

[16] This occurs when one department is represented at multiple different office locations

the highest proportion of workers. This simplification was justified given the potential (and un-verifiable) inaccuracy of the population records. This may have led to small office locations being under represented, however this factor was investigated and the overall in uence was negligible. The final handing of this data and it's application to the origin-destination data was handled by Mareike Sigloch, with expansion factors between 2.1 and 16.9.

6.3 Improving Travel Time & Congestion Interactions

In order to create more realistic traffic conditions for the MM agents in the simulation, a seemingly novel solution was developed. This included:

1. the simulation of additional background agents in order to load the network and emulate traffic o w dynamics across peak and off-peak times
2. modifying select network link free o w speeds to achieve calibrated travel times for the study population

These steps were an important aspect of improving the realism of the simulation, as the MM demand itself was too small to adequately load the network. This was relevant for trips on small residential roads between central BMW Group offices, and for the major highway connections passing through the study area which are used for trips between the central offices and Garching and Unterschleißheim.

A common MATSim approach to working with a sample of the total population is to implement network o w and capacity adjustment factors which allow to scale the network supply proportionately to the population size (Llorca and Moeckel 2019). This approach is implemented in (Ben-Dor, Ben-Elia, and Benenson 2019a; Bischoff et al. 2018) who both use a 10% population and scale accordingly. However implementing o w and capacity factors in the MM case-study was unfeasible due to the comparatively small size of the MM population to the overall study area. Therefore the required o w and capacity factors would be too small, creating issues for the number of vehicles that can fit into a link and resulting in unrealistic bottlenecks.

6.3.1 Sampling of Background Agents

The first part of the implemented solution consisted of sampled the population of a much wider area in the Munich region, and calibrating this sample against real-time values. The background population data was provided by the TUM Chair of Modelling Spatial Mobility as a list of trips for the entire Munich region.

The simulation keeps all agents who start and end trips within a 1km buffer of the study area (see figure 3).[17] In order to capture through-traffic, a random 30% sample of trips which either originate or destinate within the Landkries 8 area was added.[18]

With the background population and MM trips merged into a common MATSim plans file, the two populations were ultimately handled as sub populations with explicitly defined strategies. Unlike the MM strategy outlined in 6, the background traffic agents only optimize their route choice (20%/iteration) with the remaining choosing from the best existing plans in the evolutionary MATSim process.

6.3.2 Modifying Freeflow Speeds

With a sampled population for background traffic, the next step involved increasing the proportion of background agents until realistic travel times for MM agents were reached. However this approach was not sufficient to increase the travel times of MM agents.[19] Specifically, travel times between central location clusters remained stubbornly fast compared to real-world expectations which was likely due to the modelling choice of including a higher resolution network in areas around BMW Group office clusters (see 3), and the nature of the queue-based mobsim which does not capture microscopic elements of car trips such as traffic lights. Therefore, a direct trip in the simulation between the IT Zentrum and the Hochhaus to take an example, was consistently under 5min in the simulation, while the real-world expectation would be more like 9-14min.

To more accurately represent travel times for the MM agents in the simulation, the free o w travel times of select network links were modified. This process was tested iteratively and calibrated using an API query to HERE Technologies historic travel time database that

[17] These 171,116 trips are assumed to be purely internal trips given a reasonably direct connection, although technically this is not verified as the method does not estimate the trip routing

[18] These 101,141 trips, a 30% sample of potential through-trips, is mostly loaded onto the Outer and Mittlerer Rings thanks to the network sample which extends well beyond the study area into the respective Landkries zones. It excludes trips that originate or destinate in any of the 4 quarters surrounding the study area to avoid artificially forcing trips onto the network that did not pass through the study area, however it should be noted that this was an approximation

[19] samples up to 70% or 235,996 additional trips of the overall through-travel were tested, but samples above 50% resulted in resolvable congestion on motorways that did not clear within the simulation time, and did not reliably influence the travel times on local roads

has been developed in the MATSim Analysis vsp contribution (Axhausen 2019). The final modification of network links within the study area reduced the free o w speed of residential and service links by 25%, and primary and motorway links by between 10-15%.[20]

The final changes to the network free o w speeds were validated with the following results:

- The original OSM network (figure left) presented a Pearson's r coefficient of 0.9464 and a RMSE of 173.35
- The network with modified free o w speeds (figure right) improved on this with a Pearson's r coefficient of 0.9762 and a RMSE of 81.34

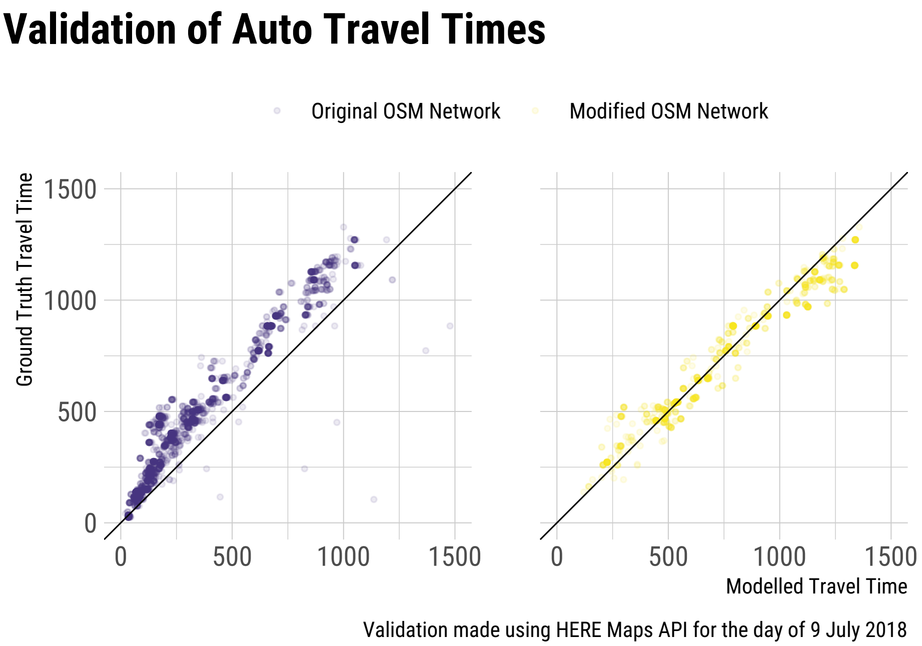


Figure 8: Comparsion of travel times on original OSM and modified networks.

6.4 Model Parameters

As recommended in the MATSim survival guide (Axhausen 2019), the model design changes as few parameters as possible. Simulation runs of up to 500 were tested, but equilibrium was reached by 100 which is inline with the experience of other MATSim simulations (Llorca and

[20] For example primary_100 was reduced from 27.777 to 24.222 m/s, while primary_60 was reduced from 16.666 to 14.9994 m/s

Moeckel 2019). Innovation was also turned off after 0.75 of each run, limiting agents to pick from their 5 best performing plans from the first 75 iterations. Public transit, DRST and auto are fully simulated in the network, while walk and bike are simulated via teleportation with a beeline distance factor.

6.4.1 Strategy Settings

Two features defined the initial DRST scenario simulation setups which had to be addressed to improve the model and obtain meaningful results on the service quality metrics. Firstly, mode change was possible for all MM agents between all modes including private auto without regards to vehicle ownership. This is not necessarily state-of-practice for other MATSim simulations, where additional demographic variables such as "has license" can be used to provide more refined mode change behaviour when these variables are available in the data. While the base-case model was calibrated to the input mode choice and the costs of driving are incorporated in each agent's score, this still allowed for somewhat unrealistic mode switch behaviour which became evident when the CPT supply was removed at 15:00 in S1.

Specifically, many agents who had previously held a pt plan for which no service was provided (either because the trip occurred after 15:00 in S1, or because it was outside the service area in S2 and S3) experimented with DRST services but simply switched to personal auto which had a better score. Modifying the parameter "fromAllModesToSpecifiedModes" as outlined in section 6.4 was used to overcome this issue, and had the effect of much more realistic levels of DRST service use. This modelling decision was reinforced when the base-case was re-calibrated, as the magnitude of the mode-specific constants to calibrate to mode split where reduced.

Besides mode change, the additional strategy innovations MM agents make in the first 75 iterations are TimeAllocationMMutator (0.1) which allows the agent to mutate their departure time within 15 minutes, ReRoute (0.1) which allows the agent to experiment with new routes, and ChangeExpBeta (0.8) which simply chooses the top performing plan held by the agent in that iteration and is required to maintain some level of stability between iterations so that not all agents are changing their behaviour all the time.

6.4.2 DVRP Settings

Secondly, the initial DRST scenario setup featured high request rates but as well as high rejection rates due to the DRST insertion algorithm which rejected all requests if they could not be filled within the alpha and beta parameters. This resulted in lots of experimentation during the first 75 iterations, and then seemingly few completed trips after the agents stopped innovating in iterations 75-100. As a result of allowing rejections, the few trips scheduled to DRST in the final iteration tended to be relatively few, long distance high occupancy trips which satisfied the assignment algorithm constrains and resulted in high workload efficiency of the eet. In other words, instead of observing decreasing service quality, with rejections on the algorithm will assign only within the service quality targets and the result will be high rejection rates. Therefore turning rejections off was the suitable decision in order to study the in uence of the cost/ eet size on our key quality indicators. This decision was also supported by the fact that the CPT service we are comparing against essentially cannot reject a user.

In an effort to further clarify the exact implications of the assignment algorithm on these two circumstances, a discussion with several of the MATSim dvrp extension creators was facilitated on GitHub where the following details were clarified:

- agents who would have been rejected in my first simulation setup with rejections will now endure longer wait times (the desired output in order to compare wait time changes across scenarios), however those already in a vehicle cannot be delayed beyond their initial detour tolerance (Maciejewski and Bischoff 2019)

- rejections can still occur in the case of DRST vehicles becoming fully booked within their scheduled operation time. This explains the rejection rate for the 2 DRST vehicles in the base-case scenario, but in all DRST scenarios the rejection rate never rose above 0.01 (Maciejewski and Bischoff 2019)

In regards to the other relevant DVRP settings, the alpha and beta parameters were tested between alpha 1.5 - 1.7 and beta 240s - 1600s range. However, since the focus of this research is not the performance of the assignment algorithm, alpha 1.7 and beta 360s were ultimately implemented across all simulations. This combination was informed by (Bischoff, Maciejewski, and Nagel 2017) who extensively test alpha and beta performance of the MATSim DVRP contribution. Additionally, a maxWalkDistance of 130m was required for the agents to reach the nearest link from their starting position in the model. This may seem unnecessary for door to door operations, but it can be seen as a representation of the distance agents would be walking inside large buildings to get to the nearest pickup location. The average access and egress DRST times of a minute and a half were considered well within reason for door to door service.

6.4.3 Public Transit Extension

The final area of model input was the public transit contribution, where a search radius of 400m was selected as appropriate in reference to the CPT frequency and stop spacing (Nielsen and Lange 2007). This was important, as the transit_walk is routed with a non-network beeline distance factor that ignores the high proportion of bridge/underpasses in the central campus area that create long walking detours in the real world but which are otherwise be overlooked by the model. The global score parameter for waitingPt was made slightly more negative from -6.0 (default) to -8.0. This had a small in uence on the attractiveness of CPT, and was justified due to the uncompleted nature of the simulated transport service (average # transfers 0.02) as compared to the city-wide services often simulated in MATSim.

6.5 Calibration to Mode Split

The final mode specific constants, and the calibrated are below.

	walk	**bike**	**pt**	**drst**	**auto**
mode specific constant	*2.235*	*0.395*	*-2.615*	*-2.150*	*0.000*
input mode split (percent)	50.120	11.280	17.820	NA	20.780
calibrated modesplit (percent)	51.399	12.079	17.729	0.157	18.637
change (percent)	1.279	0.799	-0.091	0.157	-2.143

Table 3: Model calibration displaying final mode specific constants of calibrated model as well as input and output change.

6.6 Validation of Automatic Passenger Count Data

The automatic passenger count (APC) data described in 5.2 was made available for model validation. While this was the only internal data available to validate the Pendelbus network

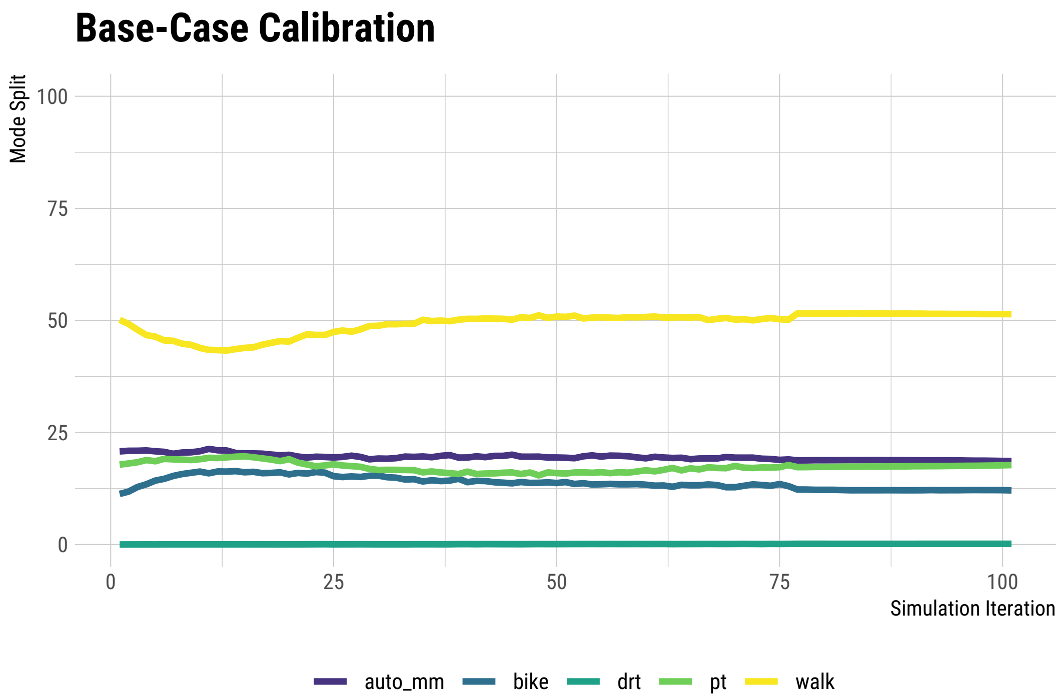


Figure 9: Figure highlights the calibration of the base-case simulation to the input mode split across 100 iterations.

and was a considering a seemingly attractive option for validation, the data exploration process revealed the following possible limitations:

Sampling:

- buses (and their counters) run on different lines between days of the week and sometimes within a day such as bus #2765, making organizing data difficult
- this made obtaining a large sample size difficult, as the lack of obvious patterns required significant human input and checking. Ultimately a single week sample (like the demand input data) was selected

Counter accuracy:

- the records contain many counts that do not match real stops, and in some cases occur in suspicious locations such as the middle of a major intersection or Autobahn The author's best guess is that some of these may be due to passengers moving too near to the counting censor at the door mid-trip creating false positives, although this was not verified

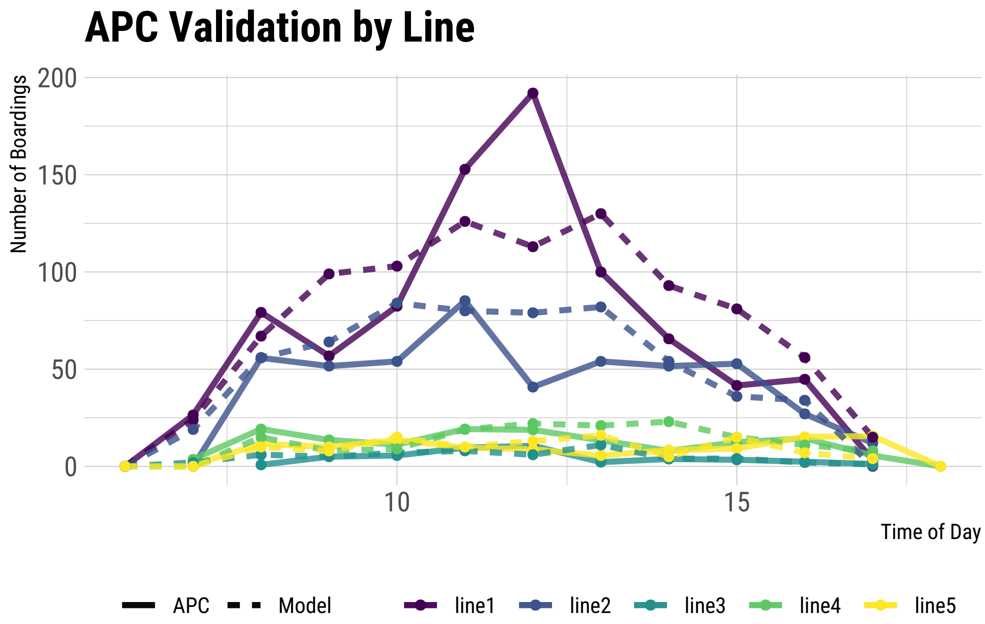


Figure 10: Line comparison of APC and model data outputs.

- negative occupancy following terminus stops. This appeared to happen every time the bus waits for departure at a stop more than a 5 minutes which always happens at the end of some lines (e.g. Line 1 at Hochhaus (Dostlerstraße)). The author's best guess is that the APC counter has not re-established a GPS signal in time following the vehicle being turned off, or more simply, that passengers get on the bus when it is turned off and waiting for departure at these terminus stations resulting in missed alighting counts, although these were not verified

Scaling of APC record to whole eet:

- as outlined in (Hammerle, Haynes, and McNeil 2005), advanced statistical methods are generally preferred when scaling APC data records from the sample of a eet of public transit vehicles to the whole. These methods were outside the scope of this thesis, so the process used here was to multiply records by the number of buses running on each line Time period inconsistency:
- APC data were only implemented on one functional bus line in the week of July 2018 corresponding to the demand input data, and of this the Monday data was missing as the vehicle with the counter appeared to be out of use that day

- therefore, the validation data implemented here was taken from the corresponding week of July 8-12th, 2019 which also had 5 normal working days

Despite these limitations on the quality and relevance of the APC validation data, the validation of bus passenger count data with the corresponding model output shows a general correlation as described below. This was tested at two spatial resolutions (bus lines, and bus stops) per hour. Validation results confirmed:

- Stop Level: a Pearson's r correlation of 0.8640 and a RMSE of 7.65
- Line Level: a Pearson's r correlation of 0.8865 and a RMSE of 18.15

The correlation between ground-truth APC and modelled data visualized in figure 10 highly the way the APC data was expanded. Specifically, by multiplying the observed records by the number of buses on that line, we are magnifying the error - or said another way, we have the same number of samples for each line which carry a different number of passengers. This helps explain the greater correlation between lines 3-5, and the deviation observed in the peak demand times on lines 1-2 which have the highest volumes.

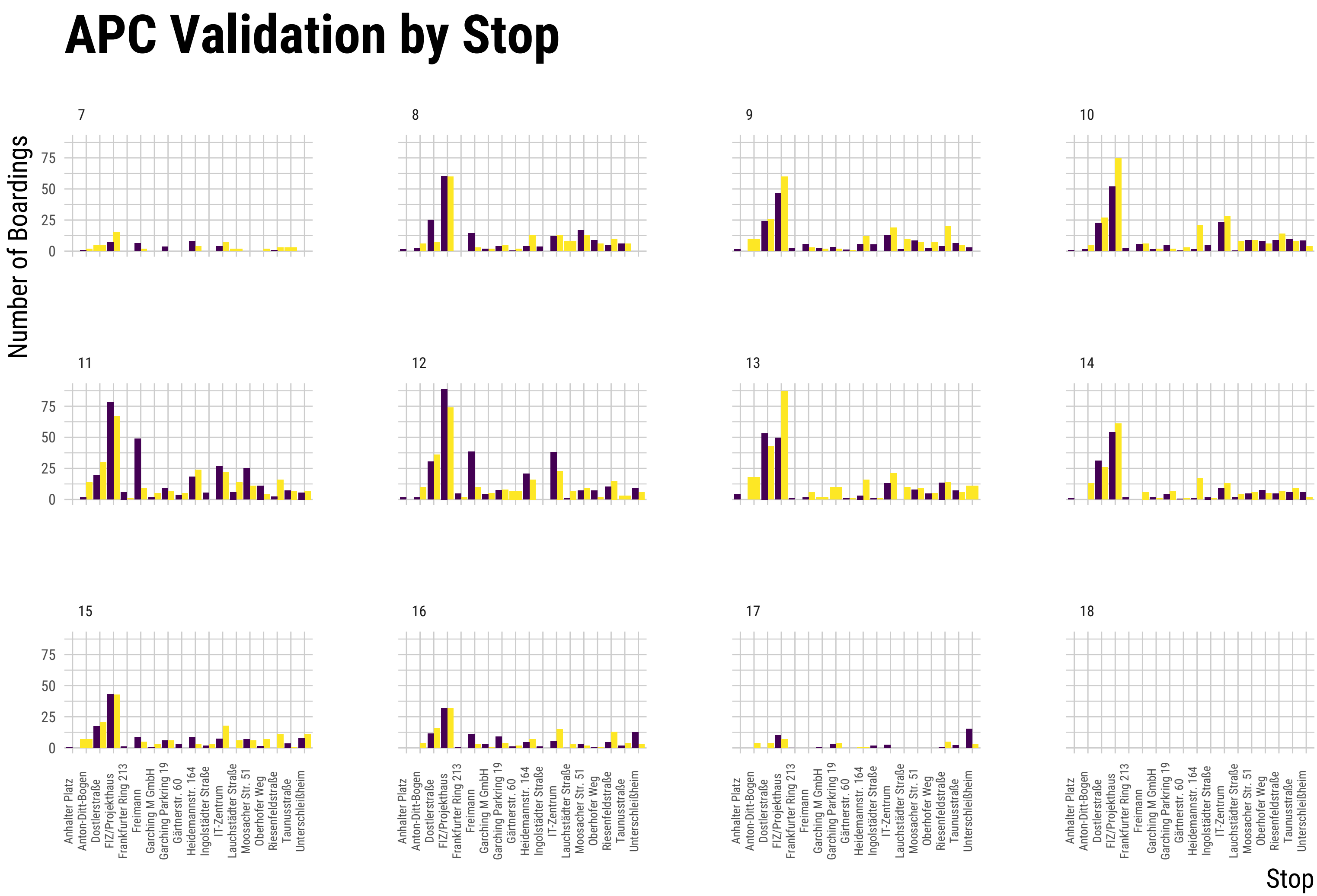


Figure 11: Comparison of APC (purple colour) and model (yellow colour) data outputs by line per stop per hour.

7 Results & Discussion

As outlined in chapter 4, the three DRST scenarios (S1, S2 & S2) investigate the spatial and temporal relationship between demand responsive shared transport and conventional public transit services. Specifically we recall that scenario S1 is about off-peak times, S2 uses DRST in place of the **2** bus lines that would normally serve the **2** satellite locations, and S3 uses DRST in place of the **3** CPT lines that would normally connect the **3** clusters within the central campus area. A graphical overview of these service areas is provided in 12, and a summary of the three scenarios from an operator perspective is provided in 4.

With a refreshed overview of the scenarios, the remainder of this section is organized around the research questions defined in chapter 3.1. This begins with the relationship between cost and service quality between scenarios with an equal cost. Keep in mind that in the context of corporate mobility, cost exclusively refers to operator cost, and is for all intensive purposes synonymous with eet size. This analysis is then expanded on in the second section which explores the same scenarios at varying cost levels as a response to the second and third research questions.

	Base-Case	Scenario One: off-peak DRST service			Scenario Two: CPT in clusters - DRST to satellites			Scenario Three: DRST in clusters - CPT to satellites		
Vehicles	2	13	26	39	5	10	15	8	16	24
Capacity	3 & 5	6 seats	6 seats	6 seats	6 seats	6 seats	6 seats	6 seats	6 seats	6 seats
VKT	104	451	498	489	1250	1125	1137	2058	2846	2838
Empty VKT	72	89	42	69	241	139	126	243	368	356
Empty Ratio	0.69	0.2	0.08	0.14	0.19	0.12	0.11	0.12	0.13	0.13
Rides	13	47	65	61	126	123	127	997	1565	1625

Table 4: DRST service overview of select scenarios from a eet operations perspective.

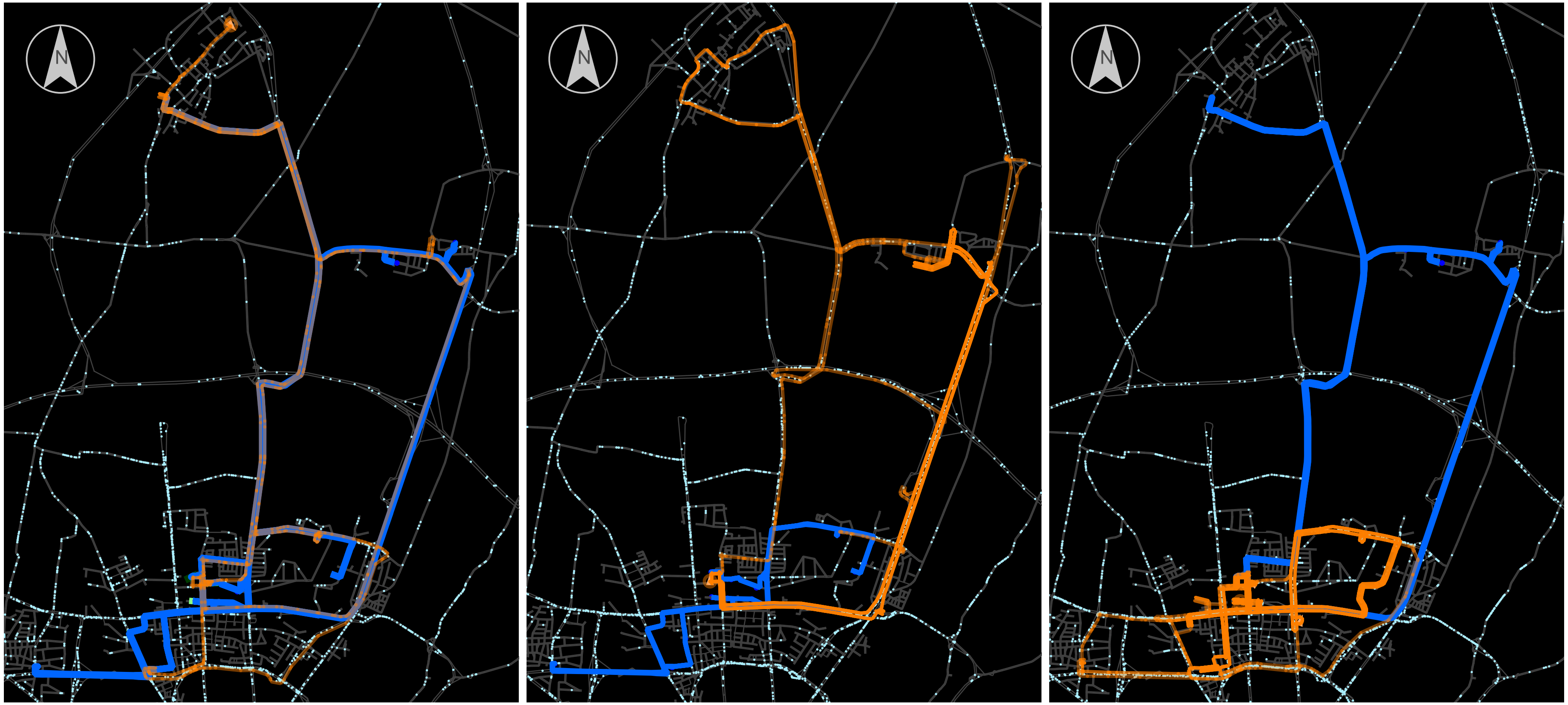


Figure 12: Comparison of DRST and CPT service areas across scenarios S1 (left), S2 (centre) and S3 (right). A single DRST vehicle track is highlighted in organge, while the available CPT netwok is highlighted in blue.

7.1 Analysis of Service Quality & Cost

The the first element of the research concerns the quality/cost relationship between CPT and DRST services which is made explicit in the question *can DRST provide the same quality of service as CPT buses within the same operator costs?* Therefore this aspect of the research is exclusive to the simulated scenarios where the total cost of the combined CPT and DRST services does not exceed the initial case-study cost of €5,096 per day or approximately €500 per operating hour. For example, S1-13 which has 13 DRST vehicles corresponds to the total cost of the CPT system, which is being entirely replaced during the off-peak period. Similarly in S2 and S3, the respective DRST eet sizes of 5 and 8 correspond to the equivalent cost of the CPT service area they are covering.

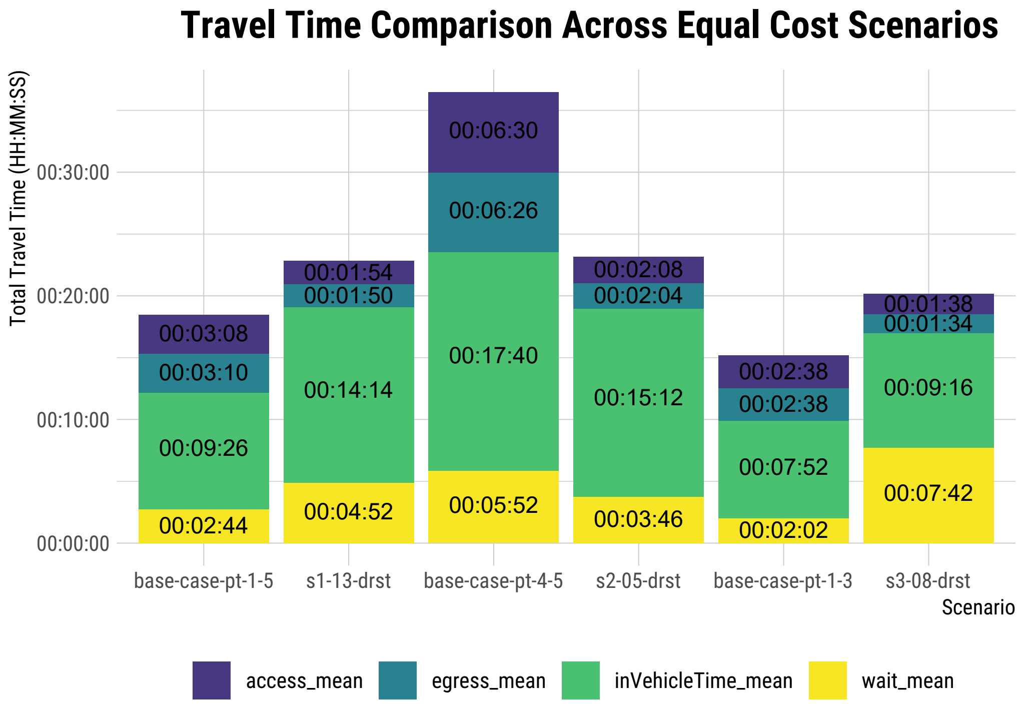


Figure 13: Figure highlights the travel time components of all equal cost scenarios and their corresponding base-case pt values are alsop provided as a reference - for example service of CPT bus lines 4-5 provides the benchmark for DRST service area in S2 which is replacing it.

7.1.1 Comparison Across Equal Cost Scenarios

Figure 13 highlights this core analysis, comparing the service quality metrics of average access, wait, in vehicle, and egress times with the base-case CPT values. However, comparing the

DRST scenarios directly to the base-case is only appropriate in S1 when the entire CPT eet is replaced. By contrast in S2 and S3, the DRST travel times should be compared with the CPT services they are replacing. Failing to make this distinction would distort the results, as the average travel times on lines 4-5 are significantly longer than on lines 1-3, a variation that is masked in the combined lines 1-5 average of the entire base-case.

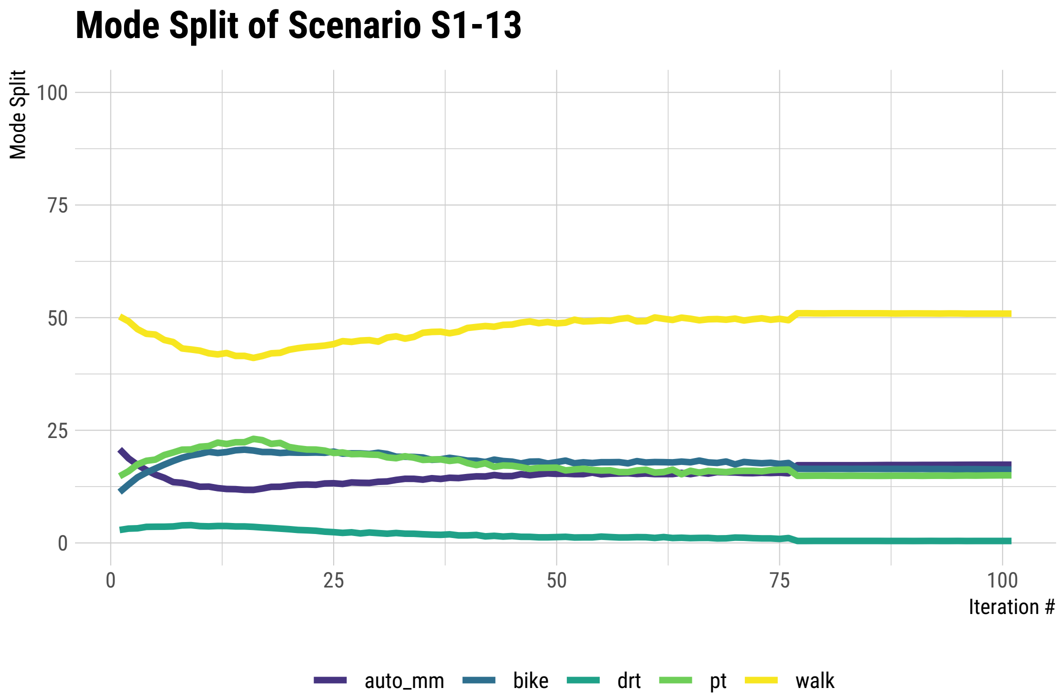
S1 Equal Cost Scenario The S1-13 off-peak scenario experienced a 123.6% increase in overall travel time, rising from 18:28 to 22:50 which was observed across 47 trips. This increase was mostly made up of in-vehicle time as well as slightly longer wait times as depicted in 13. The largest concentration of DRST ows in this scenario was between FIZ and the Garching Campus with 11 and 9 trips respectively, accounting for nearly half of all trips. This resulted in a kind of corridor, with agents being collected or dropped within nearby offices at either end in FIZ or Garching. Finally, the vehicle occupancy (depicted in figure 17 in the appendix) found a maximum of 3 passengers between 17:00-17:30, remaining between 1-2 passengers the rest of the time. The primary expression then of S1 was a tendency towards long-distance trips that could reach the highest demand within a concentrated area at each end, and with vehicle occupancies falling well below the total occupancy of 6.

To unpack this result, it is necessary to recall both MATSim's evolutionary process in regards to mode choice, and the objective function of the dvrp assignment algorithm that governs requests. Under the evolutionary MATSim process, agents test out new modes randomly throughout the first 75 iterations, scoring performance against the previously executed plans. In these iterations, the 13 vehicles in this scenario served 200 trips on average (4 times the volume served in the final iteration) reaching a maximum of 403 trips in one early iteration. However particularly wait and in vehicle times remained high in these 75 *innovation iterations*, resulting in a drop to the 47 trips which occurred in each of the last 25 iterations.

This drop is explained by the poor performance of the off-peak DRST service relative to the available alternatives. Specifically, agents making short trips between the various central campus locations were likely to have a higher performing plan with an alternative mode such as walk, bike or car (with car only available to agents who began with an autoDriver trip). Meanwhile, these alternative modes were not viable alternatives in the long distance trips,[21] which helps explain the drop in the total number of trips between the innovation and non-innovation iterations, as well as the concentration of the remaining 1/4 of trips as long

[21] That is to say their score would not have realistically outperformed DRST due to the distances involved

distance, between cluster journeys.



Additionally, the dvrp assignment algorithm demonstrated a bias towards these long distance, between cluster trips due to 1) their strong potential for low detour rates which averaged 1.26 for the first 75 iterations (peaking as high as 1.6) and then stabilized near 1.0 (representing almost no detour); and 2) their high potential for maximizing high occupancy VKT and low empty VKT rates. These characteristics essentially encapsulate the objective function of the assignment algorithm which focuses on *maximizing vehicle workload* over providing the maximum service quality as discussed in chapter 6.1.1.

In summary, the spatial drag of spatially dispersed and low volume demand in S1 highlighted the DRST service's inability to effectively provide a matching quality of service. This is highlighted in poor performance amongst many requests in the first 75 iterations that result in only about 1/4 of those trips being chosen as the best option after the mode innovation period has been turned off. At the same time, the tendency towards long distance journeys between satellite clusters appears to be both a function of the dvrp assignment algorithm which maximizes the efficient use of vehicles over service quality, as well as the creation of conditions where the relative attractiveness of the DRST service is greater (and therefore chosen) for agents in distant locations due to their lack of viable alternatives, more so than the high quality service itself.

This points to a broader critique of the research design, that by removing the CPT services during the off-peak that did exist when the real demand behaviour was recorded, coupled with few viable alternatives for long trips[22] the DRST service is forced to respond to demand that may not actually have existed without a CPT service. To further investigate these conditions, future research would need to focus on both experimentation with the governing alpha and beta parameter constrains as well as implementing an alternative DRST assignment algorithm that places more emphasis on maximizing service quality over vehicle workload.

At the same time, the proportion of long-distance trips in S1-13 draws into question the the comparison against the base-case-pt average across lines 1-5. Since the entire CPT system is being replaced after 15:00 this remains the appropriate metric to compare service quality against, however in comparison to the travel times of similarly long distance trips on lines 4-5 alone, the results do improve somewhat.

[22] there is no "no travel" option and only agents who began with an autoDriver mode can switch to car

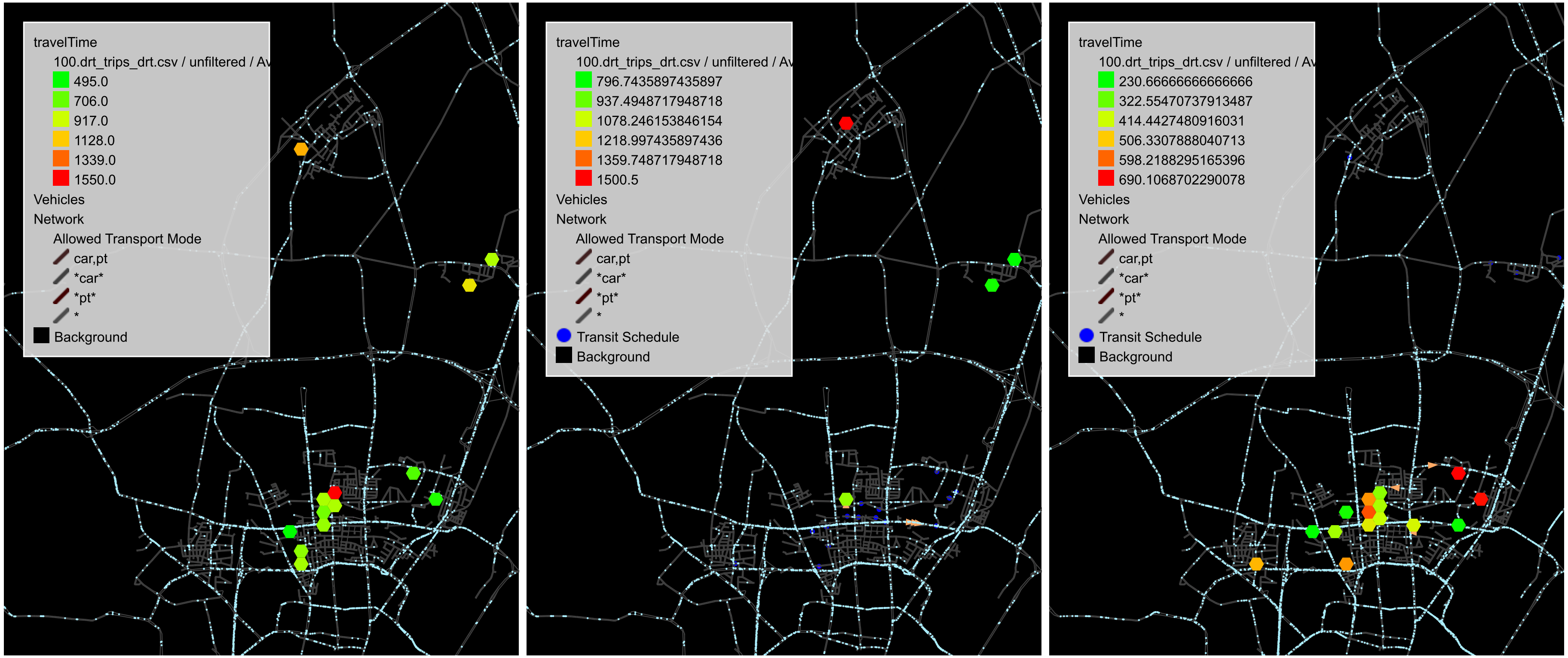


Figure 14: Comparison of DRST and CPT average total travel time (shown in seconds) for S1 (left), S2 (centre) and S3 (right).

S2 Equal Cost Scenario The S2-5 CPT within clusters - DRST connecting satellites scenario saw a significant decrease in overall travel time of 63.5% from 36:28 to 23:10 which was observed across 126 trips, and the scenario that most strongly demonstrates the potential for DRST serves to enhance CPT in the context of this thesis. This decrease was mostly concentrated in reduced access and egress times, which in the relevant CPT comparison for lines 4-5 were notably high due to the fewer stops (only 1 in the case of the FIZ connection to the central campus) which many agents are accessing by foot.

In fact the spatial results of S2 reinforce what was seen in S1 in regards to the concentration of trips between satellite and central campus, although in scenario S2, this is made explicit through the service area. However in contrast to S1-13, the results demonstrate the importance of a certain threshold level of demand. Tracking this demand through the simulation iterations, far fewer requests were made throughout the innovation period, growing linearly from around 20 to 126 of the final iteration which was the maximum observed. Because of the ability to serve these trips more effectively, fewer agents had poor performing scores and as well as very low rejection rates, which resulted in the more minimal drop off. Therefore, what we see in S2-5 is the potential of combining both a defined service area that greatly minimizes the spatial drag on the system, together with higher overall rates of demand that allow the DRST assignment algorithm to function more optimally due to the service running all day and not only in the off-peak period.

At the same time there is one element of this scenario that makes the comparison to lines 4-5 alone unfair and therefore warrants an additional critique of the research design. Importantly, in the base-case scenario, the agents being served on lines 4-5 are not originating exclusively from it's terminus station at the FIZ, but by contrast are making (mostly) walk access and egress trips to and from the high density of demand points within a close proximity of the FIZ. This is the primary explanation for the high average access and egress times for these lines which are the largest contrast to the S2-5 DRST service.

This highlights that the DRST service in S2 does not benefit from the full range of exibilit y afforded in S1 to DRST services in S1, as their service area is limited to the 5 demand locations in the satellite clusters and one in the central campus at the FIZ. In terms of the scenario design, this boils down to the fact that the S2 service area covers the technical service area of the CPT lines it is replacing, but not the demand area for agents that may be taking this line. Therefore, while the result is very positive, the direct comparison to lines 4-5 with their large access and egress times does not perfectly compare apples and apples. On the one hand, expanding this service area is expected to reduce service quality (although how significantly is not clear), particularly given the small eet size of 5 capacity 6 vehicles. On the other hand, the potential to reach more locations in the DRST service is a real world benefit inherent in that service over CPT that is not fully captured in the framing of service quality, and therefore can be considered to contain additional value even in the face of incurring slightly longer in vehicle or wait times.

In summary to S2, it is the absolute levels of demand together with the tightly defined service area that seem to be the key to the improvements in service quality. Diving further into the the dynamics between service area and service quality presents an additional possible direction for future research, for example allowing all agents to make DRST requests in all service areas, while forcing them to access/egress to within the study area. In a way this is represented in S2 via the max walk of 130m, but in the case of S2 this only made the 1 nearest demand location to the FIZ available. This technical limitation is an inherent aspect of the dvrp extension which only allows agents to request a ride if they are within 130m of the service area. Agents in the simulation however are not smart enough to realized they could take the existing CPT service, walk or bike into the service area and then request a ride which is a technical limitation of the MATSim dvrp contribution. Nonetheless, within the established research design S2 remained the only scenario that demonstrated the potential to provide an operator cost savings without sacrificing service quality in response to the second research question.

S3 Equal Cost Scenario In the final of the equal cost scenarios, the overall travel time increased by 132.9% from 15:10 to 20:10 compared to the relevant base-case which was observed across 997 trips within the central campus area. This increase was almost entirely concentrated in longer in-vehicle times, which is consistent with other simulation studies with regard to the relationship between eet size and wait time. Like S2, the innovation phase of the 100 total simulation iterations saw linear growth in the number of trips from about 350 in the first iteration, reaching a peak near 1100 before dropping down to the final 997, and therefore these agents were served well within the service quality bounds and rejection rate remained extremely low throughout.

S3 is notable as the only scenario which comes close to matching the base-case in the number of trips made as will be discussed in the next section, however the equal cost eet size of 8 was not sufficient to keep waiting times within the range of the corresponding base-case

Interpreting the base-case-pt values for access/egress and wait does require some additional discussion. On the one hand, comparatively short CPT access and egress values are a feature of the case study where 16 of 21 Pendelbus stops are located within a 100m radius of a demand origin/destination point. This draws from the nature of the corporate mobility bus network, which is designed around the specific and known demand it is serving. This value however is not entirely representative of the real world situation and needs to be interpreted accordingly. On the other hand, the wait time of base-case public transit agents may be under-represented in the simulation, where the simulation dispatcher handles agents making transit connections by routing them from their location with exactly the right amount of time according to the public transit schedule. Therefore the mean CPT wait time of under 3 minutes for all lines, and about 2 minutes on lines 1-3 only re ects delays to the buses resulting from network congestion, agents experimenting with altering their departure time as a strategy and from buses "waiting for departure" with agents on board which was enabled in the simulation to re ect the real behaviour of Pendelbus drivers.

Switching over to the DRST service, a current limitation of the MATSim dvrp contribution is the lack of so-called pre-booking. In reality a major benefit of DRST service is the ability to communicate with the vehicle and track it's progress in real time - affording the user the ability to avoid or greatly reduce waiting time by aligning their activities to the vehicle arrival. However without prebooking, agents in the model currently make their DRST request at the moment they want to realize the trip and then begin waiting for the vehicle. True behaviour likely falls somewhere between the two extremes, with some agents (particularly considering large multi-story office buildings where the user may have a long walk to the DRST pickup) still arriving too early, and others waiting until they see the DRST vehicle outside their window.

In summary, the analysis of equal cost scenarios shows the most promising results in scenario S2 where access and egress times are significantly reduced. This is in line with expectations set out in the literature, as the 5 vehicles are able to provide a high service quality due to the relatively low absolute levels of demand.

Finally, S3 is notable for coming close to matching the relevant in vehicle travel time (9:16 as compared to 7:52), but across a significantly higher numbers of absolute trips at 997 compared to 126, but only 3 extra vehicles in the eet (see the Appendix for the complete list of key indicator outputs). With the afforded eet size of 8 in S3, and despite the tight knit geography, wait time was the primary drag on service quality. Given the relationship between eet size and wait times laid out in chapter 2.2, S3 will be a scenario to watch when the eet size is increased as is discussed next.

7.1.2 Comparison Across Varying Cost Scenarios

The previous section looked at service quality across scenarios of equal cost in order to address the first aspect of the research. Additionally, detailed descriptions of each scenario helped understand what was happening inside the model and to explain the results in more depth. This section looks at the second and third aspects of the research which asked *can the design of DRST services be used to reduce the operations cost of CPT buses while maintaining the same quality of service* and *how much does it cost for DRST to match the quality of service provided by CPT buses.*

The equal-cost comparison already sheds light on this, outlining that under the scenario designs tested, only S2 demonstrated potential to reduce operations cost while matching service quality. Nonetheless, a range of eet sizes including those under the maximum available cost per scenario were simulated. Figure 15 shows these results, with 5 simulated DRST eet sizes per scenario - one of which is under the maximum available cost. As in the previous section, each scenario needs to be evaluated against it's corresponding base-case-pt value as opposed to the system wide average. In line with expectations, a decrease in average wait time is observed across all scenarios as eet size increases, although this is most clearly seen in S3, where a eet size of 24 capacity 6 vehicles (3 times the equal cost scenario of 8) is also able to match the relevant base-case-pt quality. Otherwise, in vehicle travel times remain fairly constant across all scenarios which is the logical expression of the distances travelled. These are also impacted by the detour factors which are lower in S1 and S2 at 1.07 and 1.28 respectively, and higher in S3 at 1.99. However the relatively shorter distances involved in S3 mean these detours remained less severe in terms of overall distance and therefore did not translate into longer in-vehicle times.

This point can be linked back to the literature review, specifically that the largest potential in uence on in-vehicle travel time is vehicle capacity. Here we would generally expect smaller capacity vehicles to reduce deviations and improve service quality. This point is most relevant

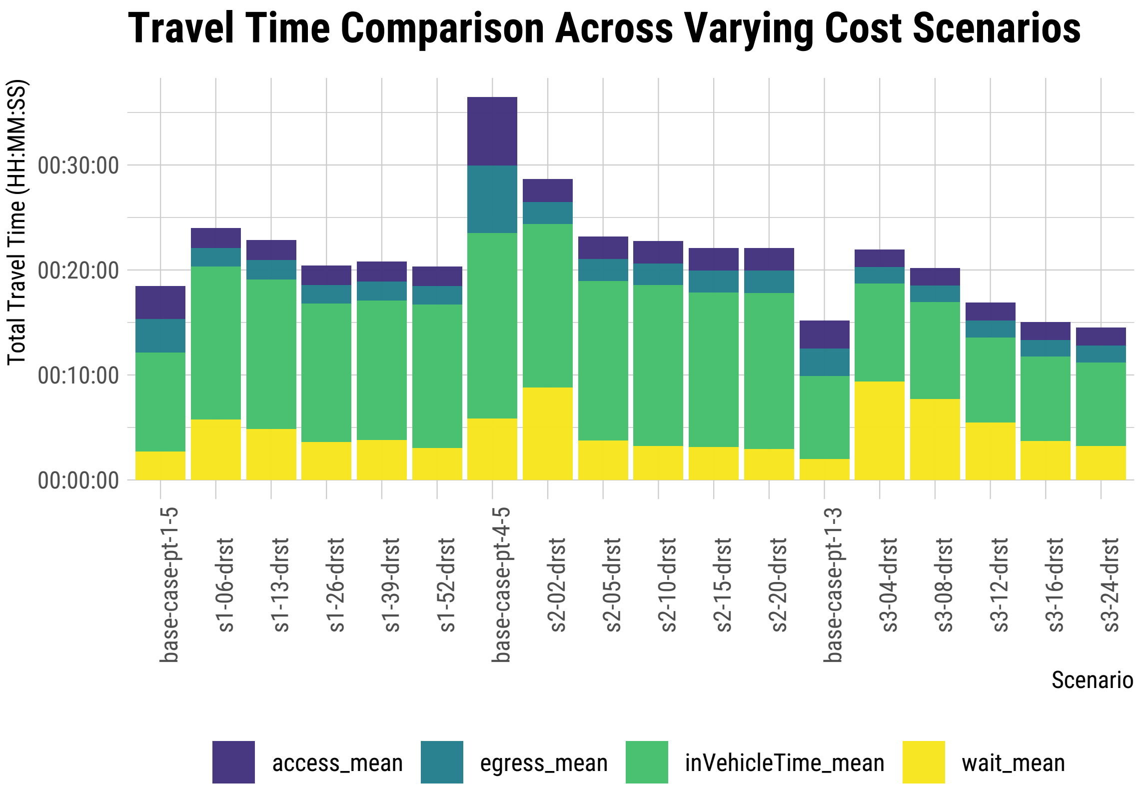


Figure 15: Figure highlights the change in service quality as eet size is changed across scenarios. The corresponding base-case-pt values for each scenario are also provided as a reference.

to scenario S3 which is the only scenario that approaches the max occupancy as seen in figure 19 in the appendix. However this parameter is of marginal relevance to scenarios S1 and S2, where the tight bounding parameters of the assignment algorithm and absolute volume of requests, resulted in vehicle occupancies that rarely approached the maximum of 6.

Comment on Access & Egress The uniformity of access and egress times across all scenarios seems to be a result of the relatively few possible combinations of routing to and from demand locations, and the fact that agents will be routed with a beeline distance as opposed to in the network for the access and egress portion of the trip. In the case of the Pendelbus network, the distances in the simulation are fixed for all demand pairs resulting in low variance, while for the dvrp extension, the agent is always routed to the middle of the nearest link they can reach within their *maxWalkDistance* of 130m, which again results in the same link being chosen for each demand location. If the demand had been dis-aggregated into polygon areas instead of a single point, we would likely have observed greater variation, with different links being chosen based on the agents exact start or end position. However it was determined that implementing this level of detail would have added limited value to the simulation results overall. Nonetheless, the access/egress context is interesting because it highlights the tight alignment of origins and destinations relative to the CPT bus stops in the corporate mobility context. Particularly within the central campus area, the tight spatial alignment produced access and egress results that were very favourable for the CPT agents on these lines, and this made it hard for the door to door DRST service in S3 to match that aspect of the service quality. By contrast in S2, it was the access/egress where the largest benefit was seen for DRST services, specifically in regards to long access/egress trips to the single terminus station of lines 4-5 in the central campus.

Comment on Flow Volumes Although beyond the core research question, table 5 highlights that the absolute number of DRST trips made in scenarios S1 and S2 did not increase meaningfully with eet size, peaking at about 65 and 130 trips respectively. Therefore the in uence of small number of trips were not meaningfully observed on the overall mode split, and for example, the reduction of absolute number of trips in S1 as the eet size increases might be explained by the random variation in mode innovation across scenario runs[23]

By contrast, the number of DRST trips in scenario S3 more than doubled when the eet size was increased from 4 to 8 vehicles, and continued to rise exponentially levelling off after a eet size of 16. At the largest S3 eet size of 32, the total number of trips reaches 1660, which approaches the number of trips made in the overall CPT network in the base-case. On the one hand, this is re ectiv e of the significantly higher demand between locations in the central campus, and on the other it may indicate that trips that the deployment of DRST service in S3 drew users from other modes.

Comparing the final mode split of scenario S3-16 (the eet size at which S3 exceeded the service quality of the base-case CPT) indicates an increase of 9.08% DRST mode share, alongside a -14.17% decrease to CPT. The remaining change in mode share was with bike which gained 3.83%, walk which gained 2% and auto driver which decreased -0.74%. In other words, following the replacement of CPT by DRST, those agents who had taken CPT in the S1 service area mostly switched to DRST, but of those who didn't the majority chose to bike or walk.

[23] The absolute number of trips in S1 drops from 65 to 61 to 58 as fleet size increases

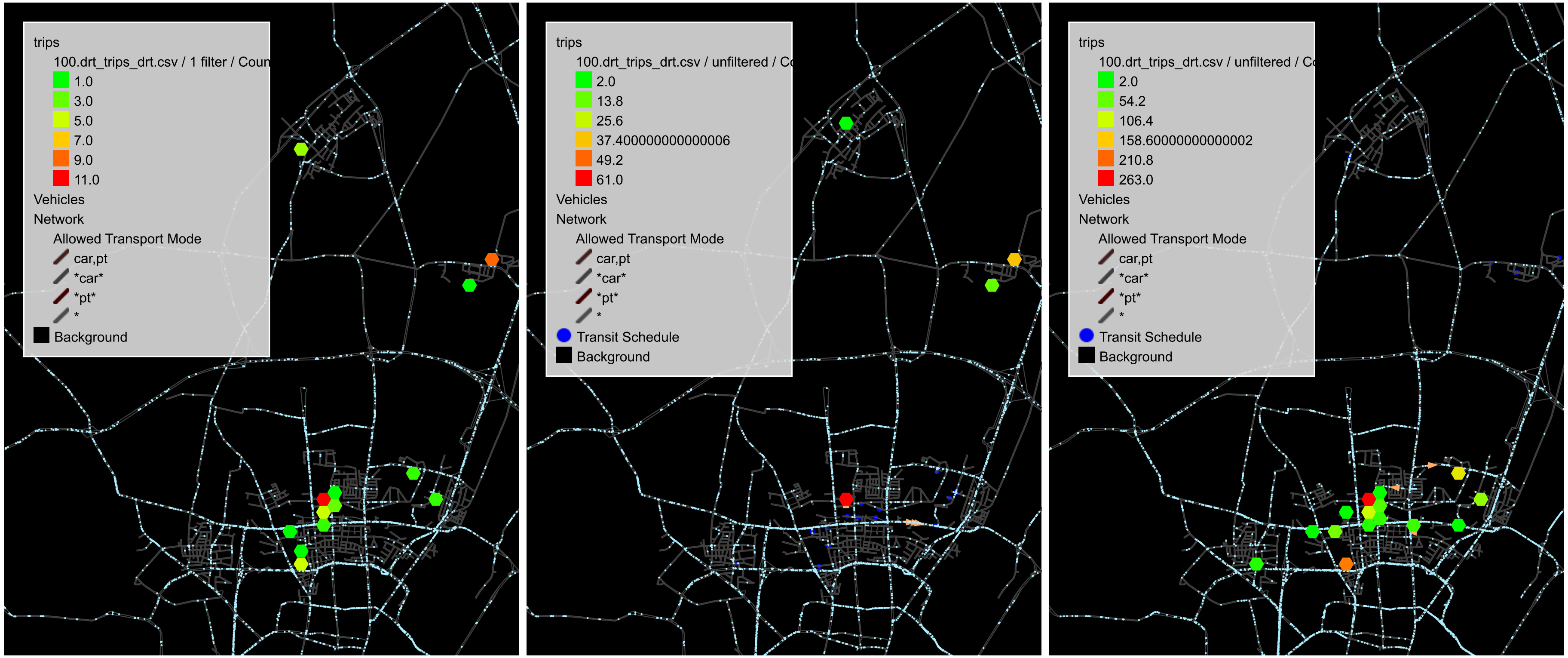


Figure 16: Comparison of DRST and CPT average total travel time (shown in seconds) for S1 (left), S2 (centre) and S3 (right).

In summary to the varying cost section, the findings of scenario S2 are significant as the only scenario that was able to offer an absolute operator cost benefit, although it must be stressed that this is related to the relatively low volume of absolute trips in that scenario. In scenario S1, it was not possible to match the average system-wide performance even with a eet size of 52, however as discussed previously, this is related to the fact that the average base-case-pt-1-5 in vehicle time is brought down by the high volume of short-distance trips. When S1 is compared against the base-case-pt-4-5, it matches service quality at the equal cost eet size of 13 and exceeded quality at a eet of 26. Finally scenario S3 is notable as the only scenario that matches the level of service of CPT at scale, a finding that is also highlighted by the much higher occupancy rates.

Scenario	Service	Daily Cost (€)	Fleet Size	Completed Trips	Access Time (mean)	Wait Time (mean)	Wait Time (p95)	In Vehicle Time(mean)	Egress Time (mean)	Total Travel Time (mean)	Transfer Rate	Rejection Rate
base-case-pt-1-5	**pt**	**5097**	**12**	**1759**	**188.30**	**164.59**	**576.10**	**565.54**	**189.74**	**1108.17**	**0.03**	**0.00**
base-case-pt-1-3	pt	3141	8	1474	158.59	122.61	352.35	472.59	158.65	912.44	0.01	0.00
base-case-pt-4-5	pt	1956	4	237	390.18	352.42	1052.60	1060.22	386.47	2189.30	0.00	0.00
base-case	drst	840	2	13	103.08	261.77	505.00	283.54	92.92	741.31	0.03	0.00
s1	drst	713	6	34	111.31	345.38	1001.50	873.68	107.66	1438.03	0.00	0.00
s1	**drst**	**1545**	**13**	**47**	**113.92**	**291.04**	**601.40**	**854.45**	**110.64**	**1370.04**	**0.00**	**0.00**
s1	drst	3090	26	65	110.89	217.62	593.70	791.78	106.77	1227.06	0.00	0.00
s1	drst	4636	39	61	112.23	227.03	523.60	798.02	109.01	1246.29	0.00	0.00
s1	drst	6181	52	58	110.35	184.72	459.60	819.53	106.54	1221.14	0.00	0.00
s2	drst	792	2	101	130.90	530.14	1364.30	932.70	128.76	1722.50	0.00	0.01
s2	**drst**	**1981**	**5**	**126**	**127.31**	**225.75**	**634.20**	**912.94**	**123.81**	**1389.81**	**0.00**	**0.00**
s2	drst	3962	10	123	127.43	193.18	506.60	920.28	123.61	1364.50	0.00	0.00
s2	drst	5943	15	127	126.05	189.93	505.00	882.10	126.37	1324.45	0.00	0.00
s2	drst	7924	20	120	128.99	177.34	495.75	891.77	125.78	1323.88	0.00	0.00
s3	drst	1585	4	378	98.66	561.93	1195.00	560.59	95.20	1316.38	0.00	0.00
s3	**drst**	**3170**	**8**	**997**	**98.51**	**462.75**	**1072.00**	**555.74**	**94.74**	**1211.74**	**0.00**	**0.00**
s3	drst	4754	12	1456	100.04	327.50	747.60	487.46	95.32	1010.32	0.00	0.00
s3	drst	6339	16	1565	100.81	223.26	487.00	482.52	96.06	902.65	0.00	0.00
s3	drst	9509	24	1625	101.31	196.81	411.70	475.51	97.92	871.55	0.00	0.00

Table 5: Table of simulation outputs for all scenarios and all key performance metrics. All time indicators are given in minutes. Scenarios of Equal costs are bolded.

7.2 Limitations

The limitations of this work can be seen from the perspective of both the simulation itself, and the broader approach to understanding the research topic.

7.2.1 Simulation

In the simulation side itself, there were important technical aspects that could be improved. For example while the network modifications were a pragmatic solution to the problem of incorporating background traffic dynamics, a more elegant solution remains the complete simulation of all agents without the selective editing of network elements which limits the research reproducibility. Additionally, the evolutionary mode choice scoring function of MATSim falls short of the sophistication of full multi-nominal logit models which needs to be taken into consideration when interpreting the results, and is part of why mode choice was less of a focus in the results section (Axhausen 2019). This limitation was most prevalent in scenario S1, where the entirely random function of *experimenting* with a DRST mode even in contexts where it was not practical seemed to negatively affect the final ridership values after innovation was turned off. It's possible that running the simulation for 500 or 1000 iterations may have overcome this, but such an implementation was not practically possible.

Additionally, MATSim is designed around the concept of simulating agents in their full range of activity tours which was not possible due to data restrictions. As discussed in the methodology, the data necessitated the implementation of single direction trips, instead of multiple trips being connected to a single agent. The MATSim manual notes that this "loses some of its expressiveness, but the basic concepts, including route and even departure time adaptation, still work in exactly the same way" (Axhausen 2019, 24). Where this simplification may have been most significant in regards to the real mobility behaviour of the case study is in trip chaining, such as users taking their own vehicle to the last meeting of the work day, allowing them to then continue directly home afterwards. Capturing these interactions is fully supported in MATSim, but their implementation in this thesis was a limitation of the available data.

While the incorporation of the real-world MyShuttle pilot data improved the simulation and particularly helped link it to the corporate mobility context, the size of the pilot DRST service was also a limitation in calibrating the base-case. Specifically, calibration of the mode constant was made against the average ridership experienced by MyShuttle across the months of July-August-September which amounted to 7-9 trips with DRST per day. During calibration, it was difficult to move this number around with the mode specific constant, likely because the demand between the locations of the MyShuttle pilot area was limited to only 51 trips.[24] Of these 51 trips, 28 were autoDriver; 7 were autoPassenger; 1 was pt[25] and the remaining 14 were walk trips which occur between the two Garching locations. The point is both the potential demand and requested demand were proportionally very low which may have had a disproportionate effect on the sensitivity of the DRST calibration constant. The simulation proceeded with the best possible calibration to the observed MyShuttle pilot ridership data, but with additional time it would be desirable to perform sensitivity analysis on the DRST mode specific constant to understand it's sensitivity when the DRST service is scaled.

7.2.2 Research Design

Firstly, it is necessary to note that two of the research design service quality criteria of transfer rate and rejection rate ultimately did not lead to meaningful results. Transfer rates remained extremely low in the base-case at just 0.03 which may be a function of the real mobility behaviour, although there is no available data to compare to better understand this. While agents had the capability to engage in multi-modal trips in the simulation setup, (for example taking DRST for a leg and then switching to CPT), the scenario design did not focus on these interactions. This is particularly relevant to the access/egress times to CPT lines 4-5 in S2, where almost all agents were making long access/egress trips by walk on the central campus side of these lines. As all MATSim defaults were kept with regard to the negative score of transfers, it's possible that the simulation over-penalized transfers, although again the true transfer rate of the population is not well understood. The point on the rejection rate criteria was thoroughly discussed in the methodology and does not so much justify a limitation as a necessary modelling compromise in order to get meaningful results. In all DRST scenarios the rejection rate remained at 0% in the final iteration (with the sole exception of scenario S2-2 which is logical given the small eet sizes as discussed in chapter 6.1.1). This means neither CPT or DRST are rejecting users which is the most relevant comparison, but it also sets this simulation apart from the majority of simulations covered in the literature review who do allow small rejection rates of 2-6%.

[24] These were between "UNT_MIC", "UNT_TAK", "UNT_ADC", "GAR_M", "GAR_BC"

[25] This could be a real MVG public transit trip or a 2-legged Pendelbus trip via FIZ

In regards to the cost comparison aspect, the projected discounting of DRST did introduce some uncertainty as well. Elements of the DRST cost were verifiable such as the heavy investment in on-the- y vehicle assignment software which is echoed by (Viergutz and Schmidt 2019). But it is important to note, particularly from the case-study operator cost perspective, that the simulated eet sizes correspond to the discounted DRST costs as opposed to those observed in the case-study pilot. Fortunately as the case-study corporate mobility context is only concerned with operator costs which scaled linearly with eet size, the results can be transposed to different operator budgets quite easily. This means that for for example, the S2-2 scenario with eet size 2 which is calculated with the discounted DRST service costs is roughly equivalent to the equal cost eet size 5 scenario under the non-discounted pilot MyShuttle cost structure. Additionally, the operator costs per kilometre were included as static costs in the DRST cost structure, meaning additional kilometres driven in the DRST scenarios were not re ected in higher operator costs.

Finally, there was a general limitation in the ability to quantify the true quality of DRST. For example, there was no metric used to evaluate the role of exibilit y in booking the transportation option, or the ability to reach locations that were not served by the CPT service. An additional direction for this could be a metric that counts the number of locations reached with the DRST service over the CPT service, although this was not explored here. Additionally, the results highlighted the potential limit of essentially forcing all trips to take place that existed in the input demand data. This is a limitation because in reality the users may have chosen not to travel at all, a point which may be stronger in the corporate mobility context.

8 Conclusion

The simulation study presented in this thesis demonstrates a holistic approach to the topic, focusing on a specific core research area in the question of travel time components, while also striving to remain in the realm of analysis that is operationally relevant and actionable. The key findings which are analyzed at varying operator cost, and across temporally and spatially diverse service schemes, echo the narrative of similar simulation studies - and the hypothesis that DRST services may indeed be able to enhance or compliment CPT has gained evidence. In particular, the importance of spatial clustering and a minimum threshold level of demand are emphasized throughout the analysis, although the broader implications of this finding for transport systems at large remains an open question. Interesting observations that may be unique to corporate mobility also emerged, such as the potential for operator-side benefits in long-distance, low-demand contexts - a finding which would most likely not hold in other cases where user-costs apply. Similarly the seemingly efficient design of the CPT system when it only has to serve a selection of known demand locations emerged as a potential strength of CPT in the corporate mobility context.

The methodology developed in this thesis creates ample opportunity for future work that is actionable from both the BMW side of the thesis partnership and for research more broadly. A large volume of simulation results have already been created, of which the research-defined analysis only scratched the surface. Deepening this could include in-vestigation of travel distances and emissions, the role of parking which was not represented in the simulation, and sharing potential of DRST. Additionally, the simulation platform as it stands now provides the opportunity to implement hybrid scenarios such as off-peak and between satellite service, or indeed to test completely removing CPT services and supplying DRST for the entire demand with multiple eet sizes and capacities.

Indeed one can imagine a scenario where it is not the side-by-side spatial and temporal comparison of two *different* services that is being evaluated, but rather the spatial and temporal integration of a single service that combines the benefits of fixed-schedule operations and the exibility of DRST, with vehicles themselves shifting roles dynamically. Whether or not such services will emerge in a future mobility landscape remains to be seen, however simulation studies like this one provide a starting point for discussion. Perhaps most importantly, future work should strive to connect to the demand responsive shared transport topic at the scale of human behaviour, including our reactions to the changing mobility landscape, as understanding both the system and the human side of the equation remains paramount.

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A Appendix

citation	context	key terms	methodology	veh cap	fleet size	findings	wait (min)	tt (min)	KPIs
(Alonso-Mora et al. 2017)	dynamic route optimization; tradeoffs fleet size, capacity, wait time	NYC taxi dataset	integer linear program w passenger assignment and fleet rebalancing	2 - 10	2,000; 3,000	2,000 veh cap 10 or 3,000 cap 4 serve 98p demand	2:30	-3:30 (over base)	max delay compared to directly taking a taxi
(Ben-Dor, Ben-Elia, and Benenson 2019)	simulate SAV scenarios	SAVs; MATSim; Tel-Aviv	n = 0.1 pop, door to door, random initial position, no dynamic repositioning; tmax 1.5 times longer than prt equlivent, max wait 12min	4	50,000 - 150,000	Fleet size 50K rejection rate 0.6p, 100K reduces to 0.2p, and 150K does not signficantly improve over 100K. Outer ring most disadvantaged	-	-	rejections
(Koh et al. 2018)	dynamic CPT routing	MoD; DBR; R; Singapore	bus lines planning optimization model for first-last mile integration	30;	21-24	68-79p decrease tt depending on fleet size; wait increases	4:00 to 5:50	79p reduction (7:45 to 5:20)	wait; tt
(Leich et al. 2018)	autonomous taxi's replacing buses	SAVs; MATSim; Berlin	door-to-door; rejection ¡ 5p; mode choice fixed; no pre-booking	1;4;8;12;20	120; 150; 200	higher operating costs, slight tt savings compared to CPT; cap ¿ 8 rarely used	14:50 (pt) + 6:00(drt)	9:00	wait; tt; op costs; rejections
(Spieser et al. 2014)	design of automated mobility-on-demand	SMoD; SAVs; Singapore	mathmatical financial model; replace all personal transport with SAVs, find min fleet to keep baseline performance; no PT;	NA	1/3 base-case	demand met fleet size 1/3 of current. AMoD service cost half of current in Singapore and US. In in Singapore due o sharing vehicle ownership and in US due to reduced time parking activites and higher quality of service.	-	-	wait
(Viergutz and Schmidt 2019)	demand responsive vs. CPT in Colditz, Germany	CPT; MATSim	4p CPT users; focus door-to-door vs. stop; tmax 30min to compare to CPT headways;	CPT 20; DRST 4-10	5; 10	operator - poor door 2 door performance - gained 9 riders but 54 more trip legs, much higher VKT; user - CPT wait and TT 2x stop-based DRST	2:44 (stop-based); 3:22 (door2door)	2:52 (stop-based); 3:51 (door2door)	fleet size, cap, VKT, rides, agents, p.empty

Note:

p in this table refers to percent. Similarly abbreviations for vehicle capacity (Veh Cap) wait time (wait) and travel time (tt) are also used

Table 6: Detailed literature review details

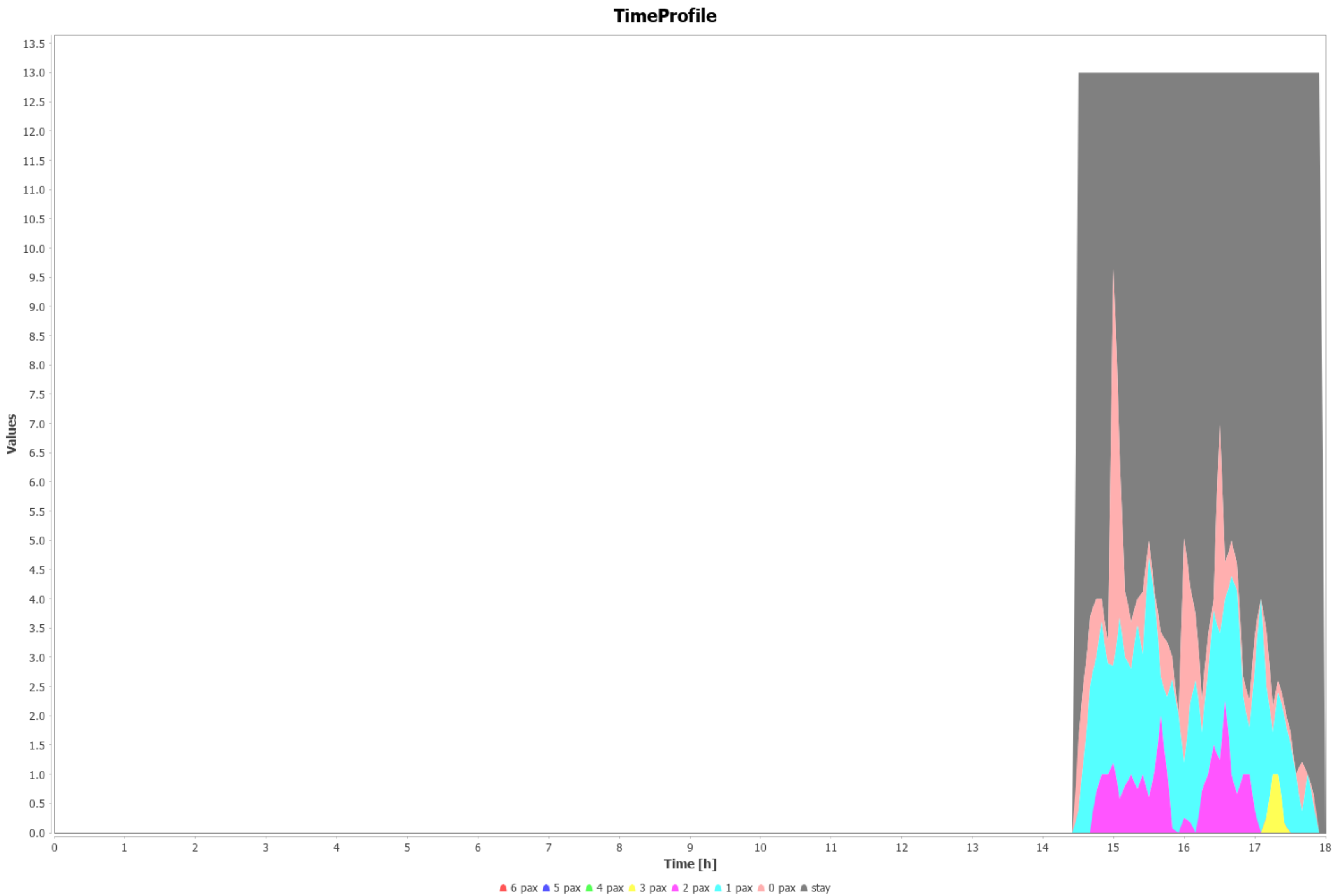

Figure 17: DRST occupancy in scenario S1. Graphic is an original MATSim dvrp output.

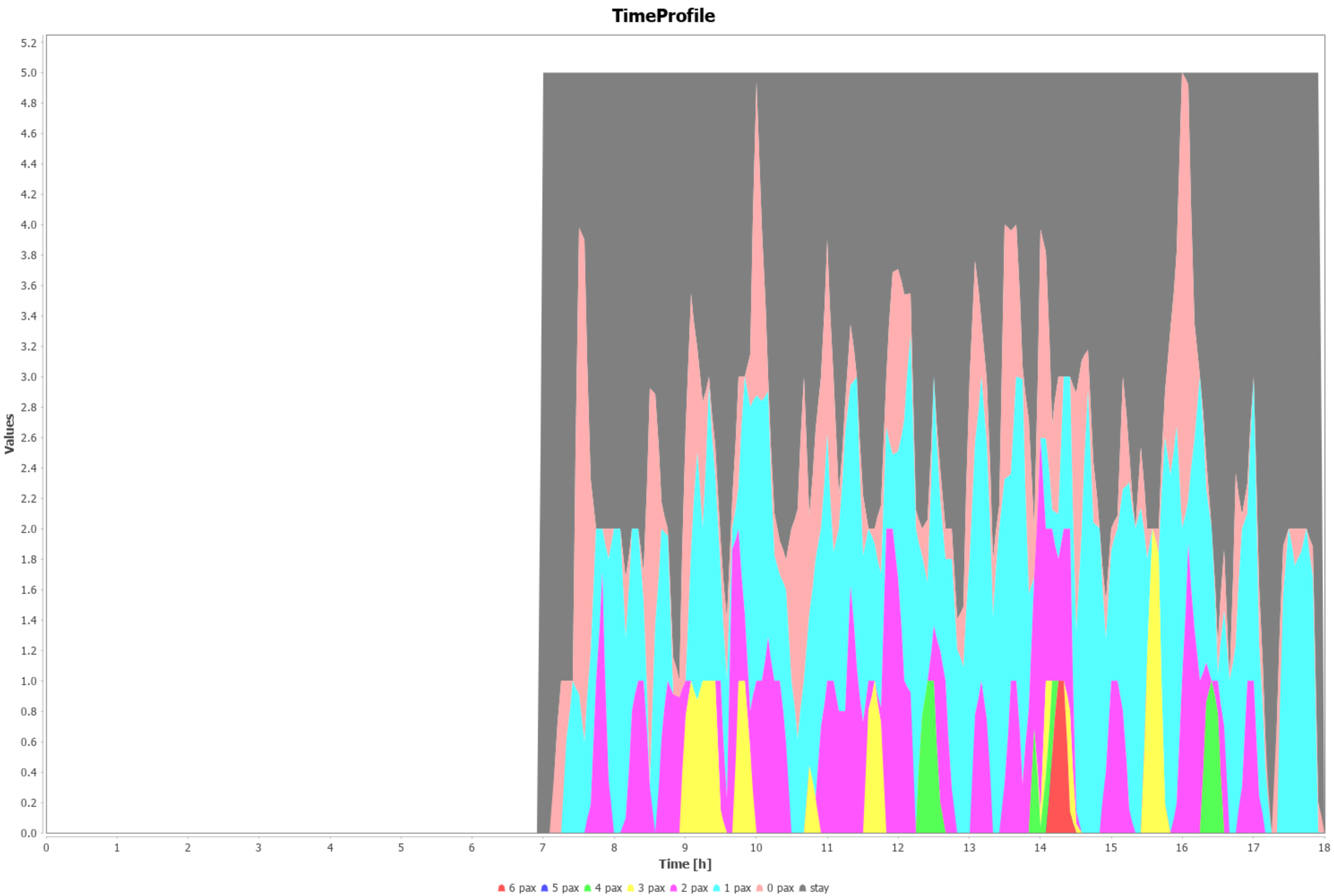

Figure 18: DRST occupancy in scenario S2. Graphic is an original MATSim dvrp output.

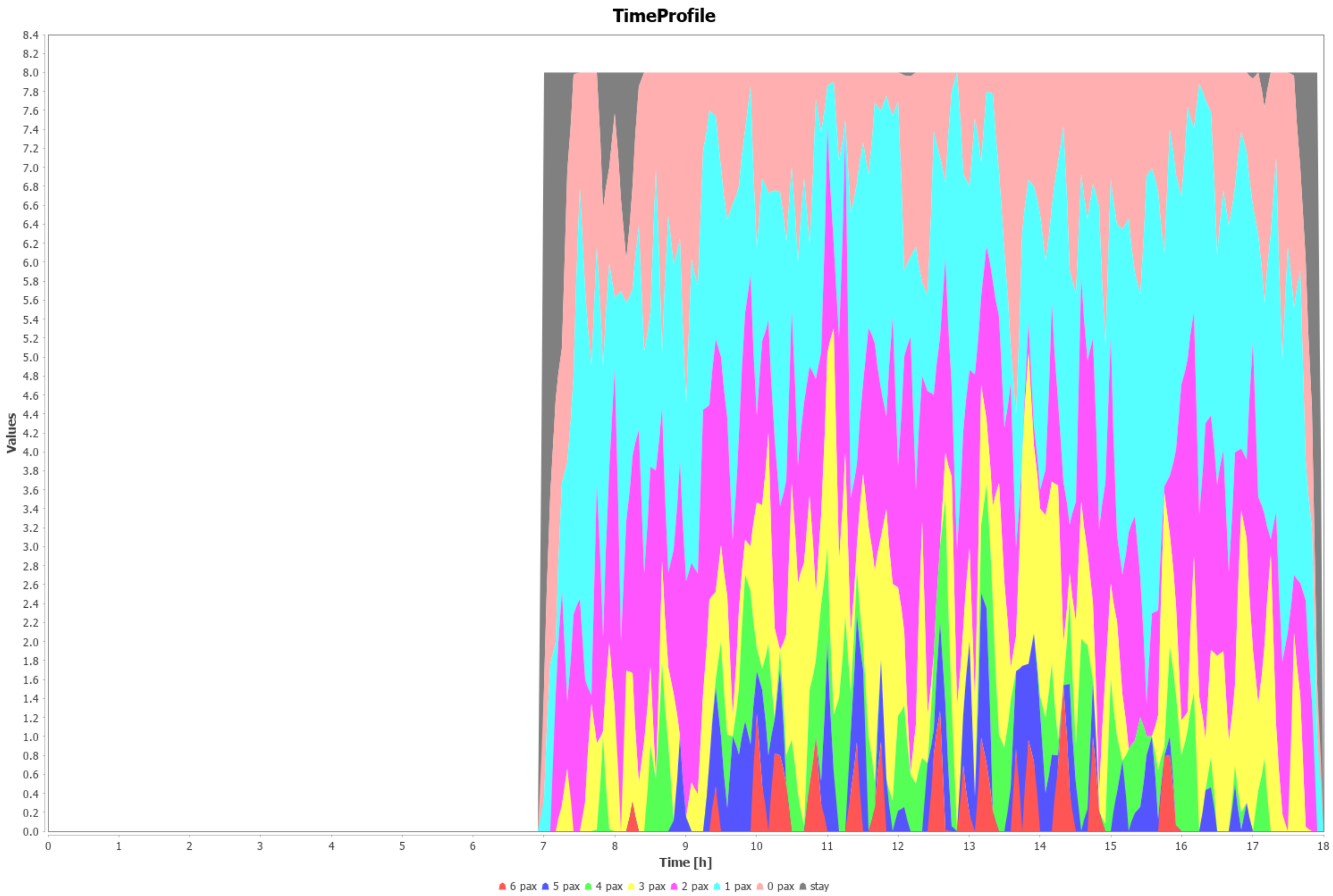

Figure 19: DRST occupancy in scenario S3. Graphic is an original MATSim dvrp output.

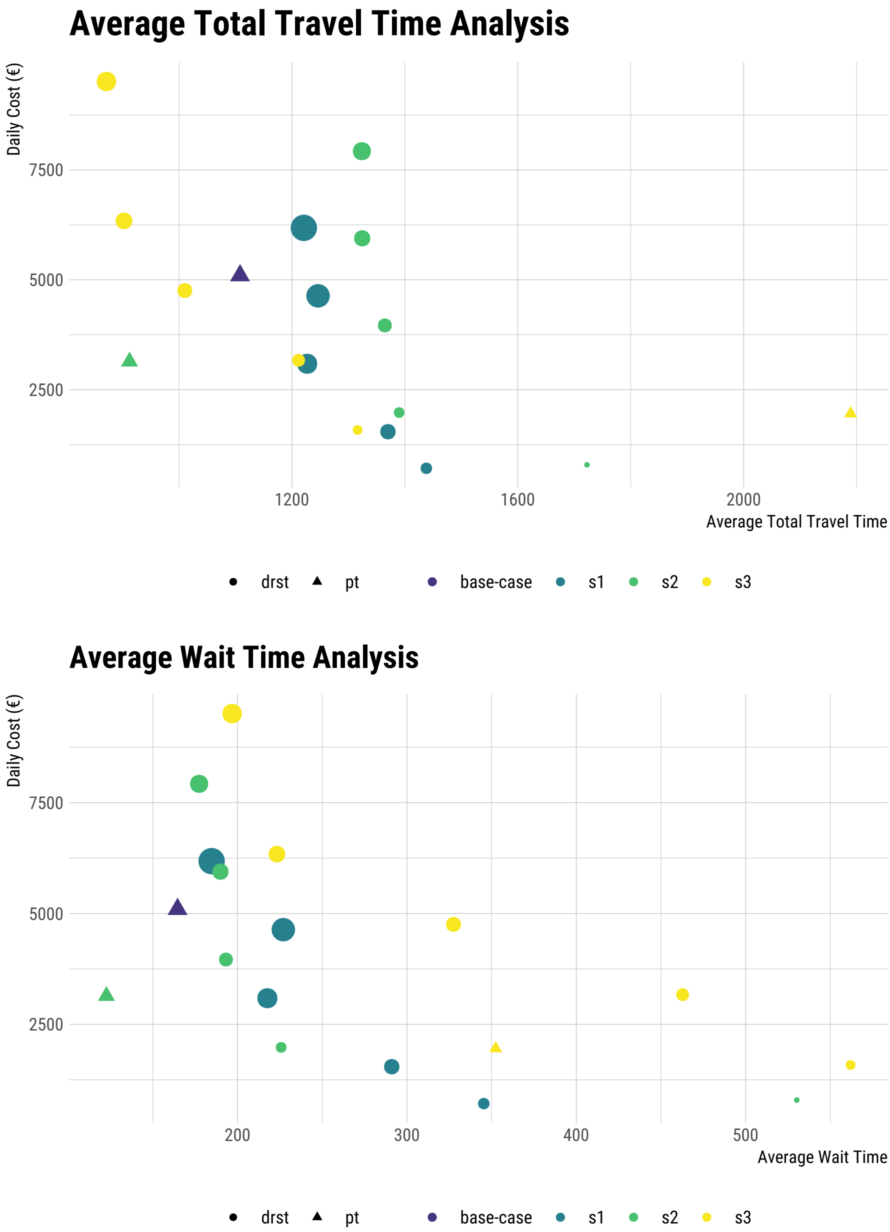

Figure 20: Figures provide a further visualization of the relationship between cost, average wait time and average total travel time.

Declaration of Authorship

I hereby confirm that I have authored this Master's Thesis independently and without use of others than the indicated sources. All passages which are literally or in general matter taken out of publications or other sources are marked as such.

Munich, December 6 2019

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Thomas B. Willington