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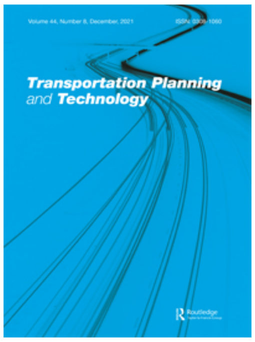
DOI
10.1080/03081060.2021.2017214

Publication date
2021

Document Version
Final published version

Published in
Transportation Planning and Technology



Transportation Planning and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gtpt20

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To cite this article: Jishnu Narayan, Oded Cats, Niels van Oort & Serge Paul Hoogendoorn (2021): On the scalability of private and pooled on-demand services for urban mobility in Amsterdam, Transportation Planning and Technology, DOI: 10.1080/03081060.2021.2017214

To link to this article: https://doi.org/10.1080/03081060.2021.2017214

Published online: 19 Dec 2021.

TRANSPORTATION PLANNING AND TECHNOLOGY
https://doi.org/10.1080/03081060.2021.2017214

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Jishnu Narayan, Oded Cats, Niels van Oort and Serge Paul Hoogendoorn

Department of Transport and Planning, Delft University of Technology, Delft, The Netherlands

ABSTRACT

The emergence of on-demand transport services is set to change the mobility landscape in urban areas. This study investigates the potential scalability of an on-demand mobility system to substitute motorised trips performed by private cars and public transport in Amsterdam, The Netherlands. We adopt an agent-based simulation framework and investigate scenarios where either private and pooled on-demand services replace private car trips, public transport trips, or both private car and public transport trips. Service performance in terms of level of service offered and operational efficiency are analysed. Results indicate that pooled on-demand services fare better than private on-demand in terms of veh-km travelled and the empty drive ratio. Private on-demand services generate 43%, 38%, and 44% more veh-km than pooled on-demand services when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. However, private on-demand services offer shorter total travel times than pooled on-demand for all scenarios.

ARTICLE HISTORY
Received 1 March 2021
Accepted 5 October 2021

KEYWORDS
On-demand mobility; agent-based simulation; urban mobility; trip substitution; operational efficiency; case study

Introduction

Economic growth and rapid urbanisation around the world have caused an increasing need for the efficient mobility of people in urban areas. The various advancements in ICT platforms have facilitated the emergence of innovative mobility solutions where users and service providers interact through an online platform such as a smart phone application. Such mobility systems provide flexible services to users (door-to-door or stop-to-stop, private or shared) and provide them with the flexibility to plan their trips. Preliminary empirical evidence suggests that traditional motorised modes of travel such as privately owned cars, line and schedule-based public transport are increasingly losing their market shares to mobility solutions such as Cabify, Lyft, Uber, Car2Go, DriveNow, and ZipCar (Enoch 2015; Conway, Salon, and King 2018) and that public transport should evolve in the light of such emerging innovative solutions to stay relevant (Enoch et al. 2020). There is therefore a growing need to assess the impact of such

CONTACT Jishnu Narayan j.n.sreekantannair@tudelft.nl Department of Transport and Planning, Delft University of Technology, Gebouw 23, Stevinweg 1, 2628 CN, Delft, The Netherlands
This article has been corrected with minor changes. These changes do not impact the academic content of the article.

services on urban mobility and their potential to substitute for traditional motorised modes such as privately owned cars and conventional public transport.

The literature relevant to this study pertains to the deployment of a large scale on-demand fleet in a city-wide context and their impact on urban mobility. One of the earliest works that examined the problem include Ma, Zheng, and Wolfson (2013). They developed a heuristic-based large-scale taxi ride-sharing service and demonstrated the efficiency and scalability of the model for large-scale instances. More recent studies that examined the deployment of on-demand fleet for US cities include those for Manhattan (Santi et al. 2014; Alonso-Mora et al. 2017), New York (Shen and Lopes 2015), New Jersey (Zachariah et al. 2014), Austin, Texas (Fagnant and Kockelman 2018), and a series of diverse urban cases (Burns, Jordan, and Scarborough 2013). The Manhattan study (Santi et al. 2014) concluded that all taxi trips in Manhattan could be served by pairing up two requests per taxi while minimising travel time. This concept of a shareability graph was later adopted by Alonso-Mora et al. (2017). They developed an algorithm that enables real-time high-capacity ride-pooling for Manhattan. Simulation results indicated that 98% of taxi demand can be served by 3000 vehicles (with a capacity of four) instead of the current fleet which is more than four times larger. The New York study (Shen and Lopes 2015) developed scheduling strategies for dispatching autonomous vehicles and evaluated the model using New York City taxi data. Results showed that the model could achieve a reduction in passenger waiting time by around 30% and an 8% increase in the trip success rate. Implementation of stop-to-stop based autonomous taxis (ATaxis) was carried out for New Jersey by Zachariah et al. (2014). In the Austin, Texas study, the potential of shared autonomous vehicles (SAVs) to replace trips performed by privately owned cars was performed and results indicated that a single SAV could serve the demand offered by 10 privately owned cars. Fleet implementation of shared, self-driving, and autonomous vehicles for three US regional cities was studied in Burns, Jordan, and Scarborough (2013). The cities studied include Ann Arbor, Michigan (mid-sized US city), Babcock Ranch, Florida (low-density suburban development), and Manhattan, New York (large and densely populated urban area). Results for Ann Arbor indicated that a shared fleet could achieve a fleet reduction of 85%. The Babcock Ranch case study indicated a fleet of 3000–4000 vehicles for a population of 50,000 people. In the case of Manhattan, the study found out that a fleet size of 9000 vehicles could replace the trips performed by 13,000 vehicles.

On-demand fleet deployment for European cities was performed for Berlin (Bischoff and Maciejewski 2016), Lisbon (Martinez and Crist 2015), Munich (Moreno et al. 2018), Amsterdam (Narayan et al. 2019), Stockholm (Rigole 2014), and Zurich (Horl et al. 2019; Becker et al. 2020). These studies investigated the potential of SAVs to replace trips performed by privately owned cars and/or public transport. Results from Berlin and Lisbon indicate that a single SAV could replace the demand served by 10 privately owned cars. The Munich study suggests that four shared autonomous vehicles could serve the demand offered by 10 privately owned cars. The potential of ride-sourcing systems offering a taxi-like service to serve all demand currently served by either private car or public transport was performed in the Amsterdam study. It was concluded that one ride-sourcing vehicle could replace the trips performed by nine privately owned cars. In addition, the ride-sourcing fleet required to serve the public transport (PT) demand amounted to 1.3% of PT trips. The Stockholm study showed that a fleet of autonomous vehicles can potentially provide on-demand door-to-door transport with a high level of service, using less than 10% of private cars. For Zurich, Horl et al. (2019) carried out a performance assessment of four different operational control policies for an automated mobility on-demand system. Their results indicated that the automated shared on-demand system can provide six times higher occupancy rates than privately owned cars. A joint simulation of car-sharing, bike-sharing, and ride-hailing (on-demand transport) was performed in a Mobility as a Service (MaaS) framework by Becker et al. (2020). Results indicated that a 25% reduction in energy consumption could be achieved by such a setting and summarised that such a MaaS scheme could lead to increases in system efficiency in terms of travel time and cost and also reduce energy consumption.

Similar studies were conducted for the cities of Melbourne (Dia and Javanshour 2017) and Singapore (Spieser et al. 2014). The results of the former study show that deploying a fleet of shared autonomous vehicles can significantly reduce the total number of vehicles required. The Singapore study suggests that a fleet of self-driving vehicles could replace two thirds of the vehicles currently operating in Singapore while still delivering all trips made by private vehicles.

The abovementioned studies highlight the relevance of research on on-demand mobility and the potential of such services in improving urban mobility overall. Most of these studies (with the notable exception of Martinez and Crist 2015) examined the implementation of on-demand mobility systems either as shared (simultaneously shared) or private (sequentially shared). This study adds to the existing body of knowledge by testing the consequences of scaling the on-demand mobility system – private and pooled – and investigating its potential to replace privately owned car trips, public transport trips, or both car and public transport trips. In addition, the study provides a comprehensive comparative analysis of private and pooled on-demand service in terms of level of service and operational efficiency.

The rest of the paper is organised as follows. The next section describes the modelling framework adopted for assessing the mobility system and presents the case study along with the experimental scenario design. This is followed by presenting the results for level of service offered and operational efficiency and their analysis. We conclude the work by discussing the key findings and offer directions for future research.

Experimental setup

Model

On-demand mobility services are characterised by the real-time dynamics of their operations. Simulation models have been used widely in the literature to model these services. Among those, agent-based simulation modelling has been proven to be particularly effective in modelling the system dynamics and its operation. We therefore adopt in this study an open-source multi-agent traffic simulation framework MATSim (Horni, Nagel, and Axhausen 2016) as the modelling framework. Each user of the transport system is represented as an agent with a corresponding set of travel plans.

The Network, Demand, and Supply comprise the input modules of the model. The Supply module comprises of the modes available to each user for travelling from their origin to their destination. The modes available are: car (privately owned), walk, bike, public transport, and on-demand (private and pooled). The public transport (PT) network pertains to line-based and schedule-based services that follow a pre-defined route and schedule operated by a designated fleet of vehicles. The Network module refers to the super-network which comprises the sub-networks of road and line- and schedule-based public transport. The sub-network of line- and schedule-based public transport consists of the networks of all public transport modes (e.g. train, tram, metro, bus) along with their stop locations. The Demand module denotes passengers with a set of origin and destination points in the network. In this study it is assumed that passengers have full knowledge of the route network and schedules of the line- and schedule-based public transport (PT) system. On-demand service in this study is modelled as a fleet of vehicles operated by a central dispatching unit that assigns travel requests to vehicles in real-time and offers door-to-door service to passengers. Two types of on-demand service are considered in this study, namely: *private on-demand* – offering an individual taxi-like service to passengers; and *pooled on-demand* – offering shared rides where passengers may share their ride with other passengers. Vehicle capacity for pooled on-demand is set to four.

The dispatching strategy of the on-demand system offering a private service is as follows. All on-demand vehicles are initially randomly distributed in the network. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, drives to the travel request destination, drops off the passenger and remains at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand system offering pooled service is as follows. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, possibly makes detour(s) to pick up other pooled requests, drives to their destination, drops off the passenger and stays at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand vehicles has been adopted from Bischoff, Maciejewski, and Nagel (2017). The on-demand vehicles are dynamically routed using an insertion heuristic. The dispatching algorithm searches for feasible insertions when a new request is submitted. The feasible insertions should satisfy wait and travel duration constraints for the new and existing requests and vehicle time window constraint. The maximum amount of time that a user is willing to wait is set to 15 minutes. The request is rejected if no feasible insertion exists and they remain unserved.

Application

Network and demand data

In our experiments, we apply a series of scenarios for a network centred around Amsterdam, The Netherlands (Figure 1). The demand data is adopted from the national activity-based demand model, Albatross (Arentze and Timmermans 2000) which is a learning-based model of activity-based travel behaviour. The number of traveller agents amounts to 168,103 which represents 20% of the population. The underlying network is based on data extracted from OpenStreetMap (Haklay and Weber 2008). The network consists of 17,375 nodes and 31,502 connecting links. The public transport network data were based on the General Transit Feed Specification (GTFS) data for Amsterdam and includes train, tram, bus, and metro with a total of 2517 stops and stations. The travel modes considered next to public transport are: car, walk, bike, and private and pooled on-demand services.

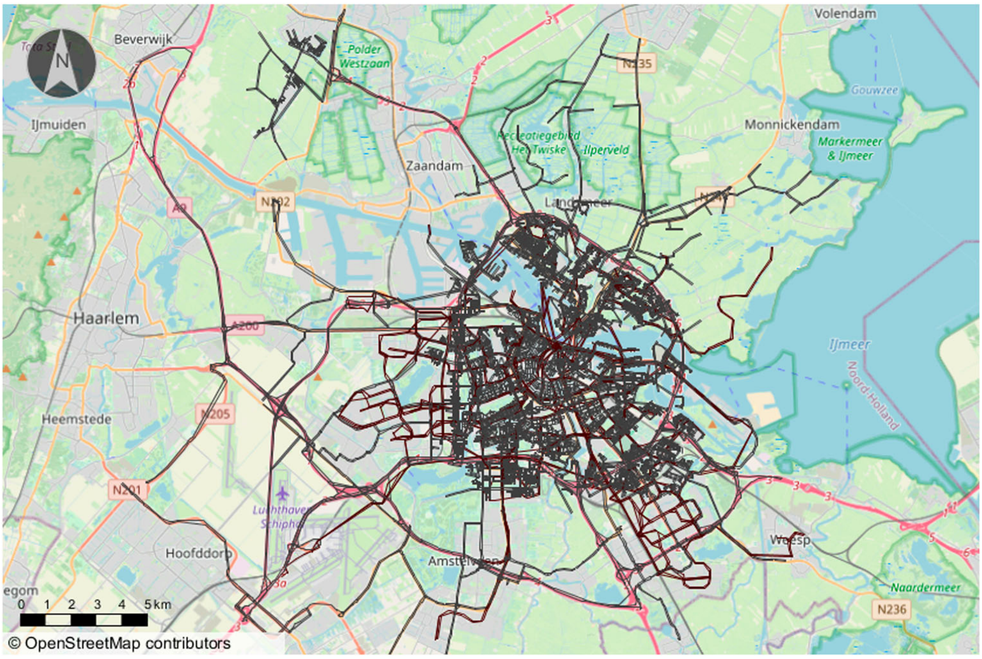


Figure 1. The model application network of Amsterdam.

Simulating 20% of the population was chosen for two reasons. The first is regarding computation time; considering the model complexity and the scale of implementation, simulating the day-to-day evolution with on-demand within-day dynamics for the entire population was not feasible in terms of computation time. Second, past research has shown that simulating a fraction of the actual population yields reasonable results and is a realistic representation of the actual scenario (cf. Bischoff and Maciejewski 2016). This provides confidence in the simulation results when assessing system performance for scenarios where on-demand services is an order of magnitude larger than their typical small market share.

The calibration of the demand and network data was performed following the calibration guidelines of MATSim. As the demand data represents a scaled down population, the network parameters indicating flow-capacity and storage-capacity were scaled down accordingly. We set the marginal utility of travelling to a fixed value as suggested in the calibration guideline of MATSim and investigate the alternative specific constants (ASCs) of the available modes. We then calibrate the ASCs so that the equilibrium assignment results yield the modal shares of existing modes (car, walk, bike, and PT) for our case study area of Amsterdam. This has proven to be especially important for bike travel which otherwise would have been significantly underestimated. Simulation runs were performed for each tested configuration of ASC until an equilibrium modal share was attained; and 500 iterations were found to be sufficient to attain equilibrium. The output demand data that yielded the desired modal share was used as the final demand data for all the simulation runs. The mode share (%) at equilibrium is as follows: Car (29%), Walk (28%), Bike (22%), public transport (21%) and the total

Table 1. Experimental scenario design.

Index	Scenario	Description
1	Base case	Available modes are: car, walk bike, and PT
2(a)	Car → private on-demand	All private car trips from Base case are served with private on-demand
2(b)	Car → pooled on-demand	All private car trips from Base case are served with pooled on-demand
3(a)	PT → private on-demand	All PT trips from Base case are served with private on-demand
3(b)	PT → pooled on-demand	All PT trips from Base case are served with pooled on-demand
4(a)	Car and PT → private on-demand	All private car and PT trips from Base case are served with private on-demand
4(b)	Car and PT → pooled on-demand	All private car and PT trips from Base case are served with pooled on-demand

number of trips performed are 556,437. [The open-source data of the developed dataset is publicly available (Winter and Narayan 2019)].

Simulation scenarios

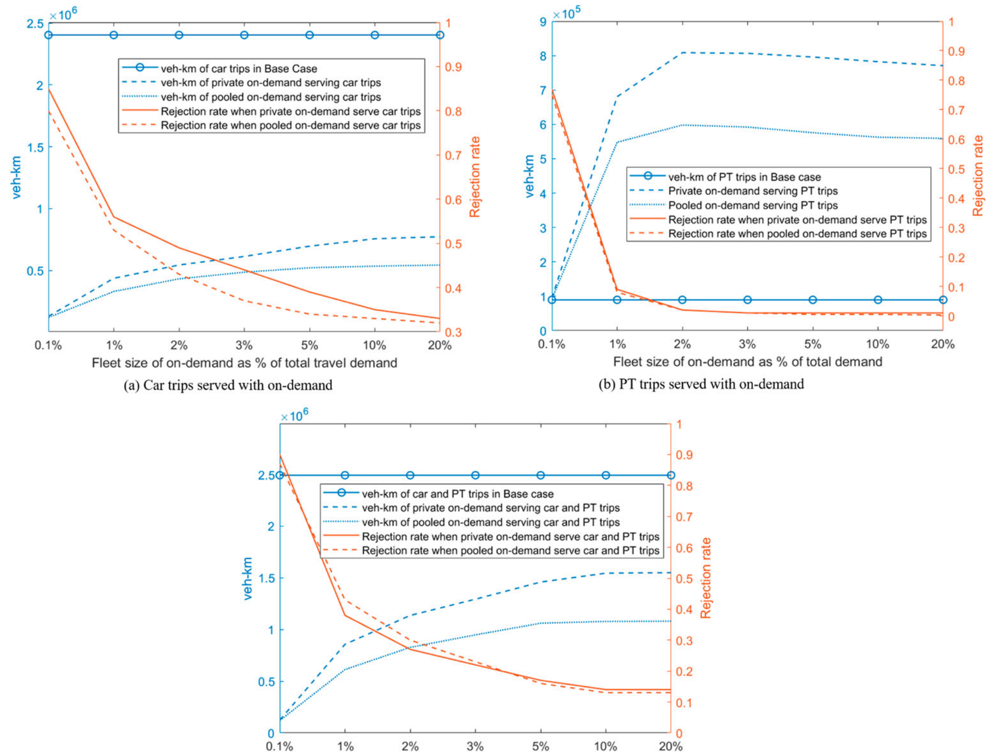
We devise seven simulation scenarios to investigate the potential of on-demand services to serve motorised trips in Amsterdam, The Netherlands (summarised in Table 1). The first scenario is the Base case. The modes available to users are: car, walk, bike, and PT. In the second scenario (scenario 2(a)), all car trips performed in the Base case are served instead by a fleet of private on-demand vehicles. In the third scenario (scenario 2(b)), all car trips from the Base case are served by a fleet of pooled on-demand vehicles. Next, all public transport trips from the Base case are served with a fleet of private on-demand vehicles in scenario 3(a), or alternatively by a fleet of pooled on-demand vehicles in scenario 3(b). This is followed by scenarios where both car and public transport trips are substituted by on-demand services. In scenario 4(a), all car and PT trips from the Base case are served with a fleet of private on-demand vehicles. Finally, in scenario 4(b), all car and PT trips from the Base case are served with a fleet of pooled on-demand vehicles.

Results and analysis

This section presents the results and analysis of the scenarios detailed in the previous section. For all scenarios we consider two aspects of system performance namely, Operational efficiency and Level of service. Operational efficiency is analysed using key performance indicators that pertain to veh-km travelled, occupancy rate, and empty drive ratio. Level of service is investigated from a user's perspective with key performance indices such as travel time (in-vehicle time and waiting time) and share of demand satisfied. For all scenarios, we consider various instances of on-demand fleet size, represented as a percentage of total demand. We test the impact of fleet sizes corresponding to 0.1%, 1%, 2%, 3%, 5%, 10%, and 20% of total demand.

Operational efficiency

Figure 2 shows veh-km travelled and the on-demand rejection rate for all scenarios. Figure 2(a) shows veh-km travelled by car trips in the Base case and when those are substituted by an on-demand service and the corresponding on-demand rejection rate. Similarly, Figure 2(b) and (c) depict the veh-km for PT trips and car and PT trips in the Base



(a) Car trips served with on-demand

(b) PT trips served with on-demand

(c) Car and PT trips served with on-demand

Figure 2. Vehicle-kilometers travelled and on-demand rejection rate in all the scenarios.

case scenario and the respective private and pooled on-demand services scenarios along with their rejection rates. As can be seen from Figure 2(a), the veh-km travelled by private car trips in the Base case is significantly higher than that when either private or pooled on-demand services serve car trips. The difference between veh-km travelled for private and pooled on-demand service notwithstanding, the difference of veh-km for the two on-demand services from the Base case can be explained from the on-demand rejection rate in the figure. It shows the rejection rate for the on-demand travel requests for scenarios when car trips, PT trips, and car and PT trips are replaced with private and pooled on-demand services. As can be seen from the figure, for the scenario when on-demand services serve car trips, the rejection rate is still significant (0.3). Hence a considerable portion of car trips in the Base case is not satisfied for the scenario when on-demand serves car trips, which then results in lower veh-km travelled.

In the case of substituting public transport with on-demand transport, we observe from Figure 2(b) that the total veh-km travelled by on-demand services is significantly higher than that travelled by PT vehicles in the Base case. The total veh-km travelled when private and pooled services serve PT trips are approximately eight times and six times, respectively, more than the Base case. As can be seen from the rejection rate in Figure 2(b), the rejection rate for scenario 3 drops rapidly from 0.7 to < 0.1 when fleet size increases from 0.1% to 1%. This indicates that most of the PT demand is satisfied when fleet size amounts to 1% of total demand. The rejection rate drops further when fleet size increases to 2% and thereafter stabilises at a negligible rejection rate. This also explains the trend of veh-km travelled by on-demand visible in Figure 2(b). The veh-km also marginally decreases beyond a fleet size of 2%. This is explained by a reduced pick-up distance travelled by on-demand vehicles due to an increase in the number of vehicles in the network. This along with a stable share of satisfied demand beyond a fleet size of 2% results in a reduction in veh-km travelled.

Similarly, in the case of travel demand for both car and PT is to be served by the on-demand service, we observe from Figure 2(c) that the total veh-km of car and PT trips in the Base case is higher than when car and PT trips are replaced by on-demand services. This reduction is also attributed to the unsatisfied demand as can be observed from the rejection rate in Figure 2(c). In all cases, it can be observed that the veh-km travelled by private on-demand services is higher than that by pooled on-demand. At the fleet size instances where the rejection rates start to stabilise, private on-demand services generate 43%, 38%, and 44% more veh-km than pooled on-demand when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. This is attributed to the extra veh-kms travelled by private on-demand services in order to pick-up passengers compared to pooled on-demand services.

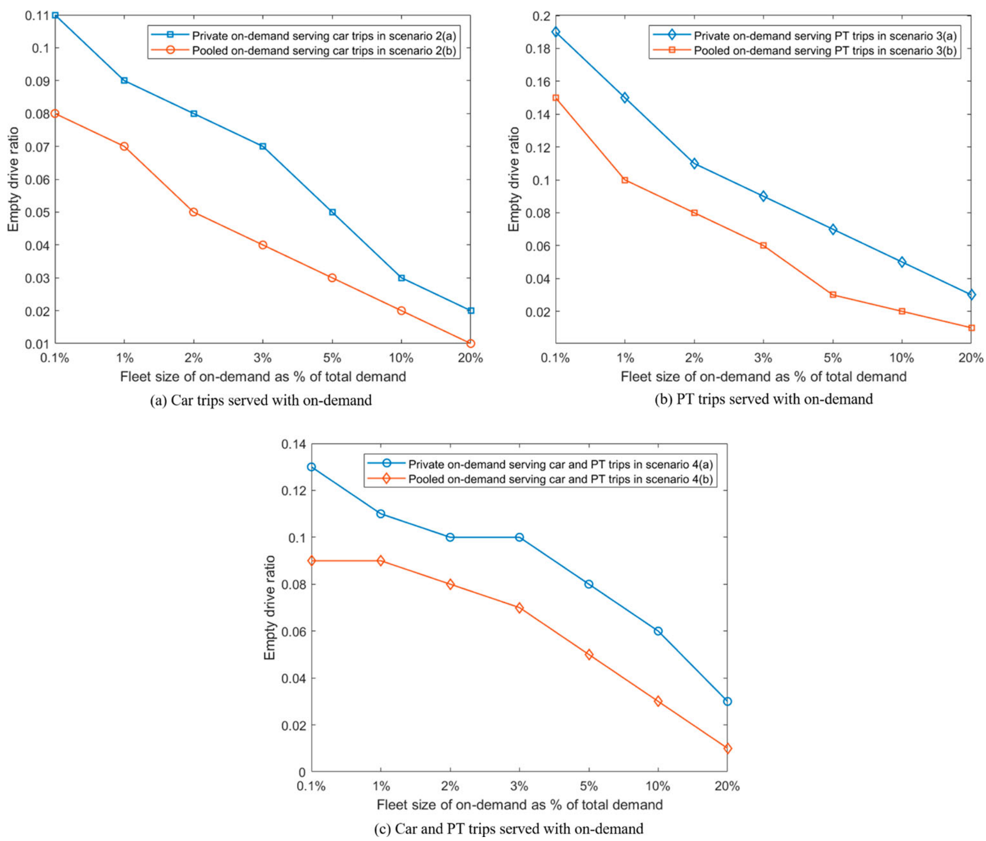


Figure 3. Empty drive ratio of on-demand services in veh-km travelled.

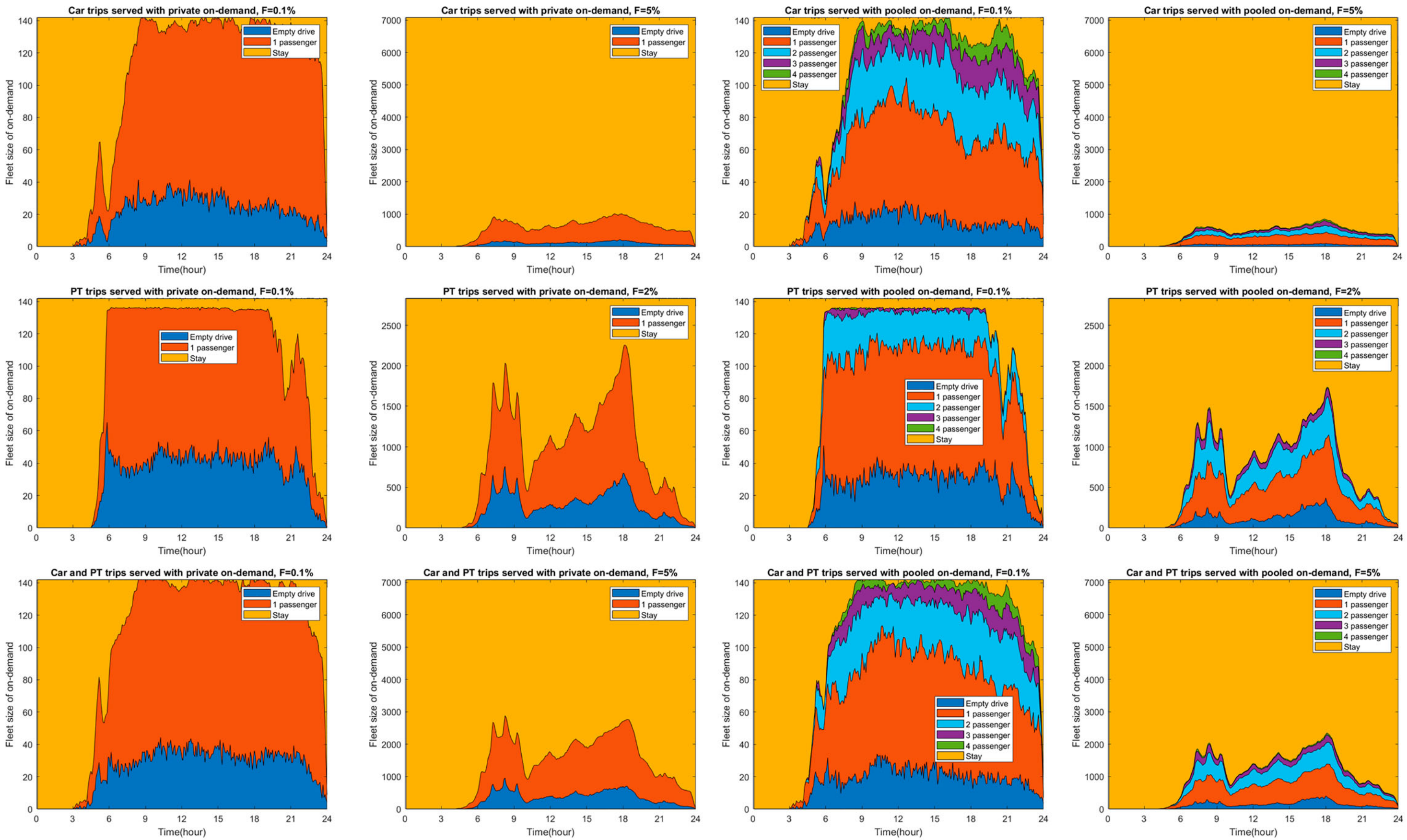


Figure 4. Occupancy level of on-demand services for selected cases. Notes: Top row – scenarios 2(a) and 2(b); middle row – scenarios 3(a) and 3(b); bottom row – scenarios 4(a) and 4(b).

In order to further analyse operational efficiency, we plot the empty drive ratio (Figure 3) which is the ratio of empty distance to total distance travelled by the on-demand vehicles. From the figure it can be seen that for all scenarios, the fleet size of on-demand is inversely proportional to the empty drive ratio, indicating that with an increase in fleet, vehicles spend less time driving in the network to pick-up passengers.

The empty drive ratio of pooled on-demand is lower than private on-demand under all scenario pairs, indicating that pooled on-demand vehicles spend less time in the network to pick-up passengers compared to private on-demand vehicles. The results and analysis of veh-km travelled and empty drive ratio indicate that the pooled on-demand service fares better than the private on-demand service with respect to those key performance indices.

Following these results, we turn to analysing the service performance of the on-demand fleet. We investigate performance over a 24-hour period. For the fleet of vehicles, we investigate vehicle status and occupancy which may at any moment be one of the following categories:

- Empty drive: Time spent to pick-up passengers
- Stay: Time spent without being assigned any request
- 1 passenger: Time spent with a single passenger in the vehicle
- 2 passengers: Time spent with two passengers in the vehicle
- 3 passengers: Time spent with three passengers in the vehicle
- 4 passengers: Time spent with four passengers in the vehicle.

We plot these key performance indices of on-demand vehicles in Figure 4 for all on-demand scenarios for selected fleet size rates. The fleet size instances are selected as follows. For each of the scenarios we examine the occupancy levels for two instances of fleet size – one with the highest unsatisfied demand and one where the addition of more vehicles does not induce a significant increase in demand satisfaction. To this end, we choose the fleet size instance where the rejection rate is maximum and one where the rejection rate starts to stabilise. For the scenarios when car trips and car and PT trips are replaced with on-demand, the range is from 0.1% to 5% and for the scenario when PT trips are replaced with on-demand services, the range is from 0.1% to 2%. We plot the occupancy levels of the on-demand vehicles for all these cases in Figure 4.

We use the Stay ratio as a fleet utilisation index with a higher Stay ratio indicating lower fleet utilisation levels and hence higher service efficiency. As can be seen from the figure, the highest fleet utilisation (lowest Stay ratio) is achieved for the case when the rejection rate is highest (fleet size = 0.1%). For private on-demand and a fleet size of 0.1%, the majority of the fleet operates with a passenger on-board throughout the day (and hence low shares of vehicles in states Stay and Empty drive). Similarly, for pooled on-demand and a fleet size of 0.1%, the majority of the fleet operates with a single passenger on board followed by increasing passenger loads, from two to four in descending prevalence. For all these cases, the Stay ratio is considerably low.

For the scenario when car trips are served with on-demand services, the occupancy level of private and pooled for fleet size of 5% indicate that a large fraction of the fleet

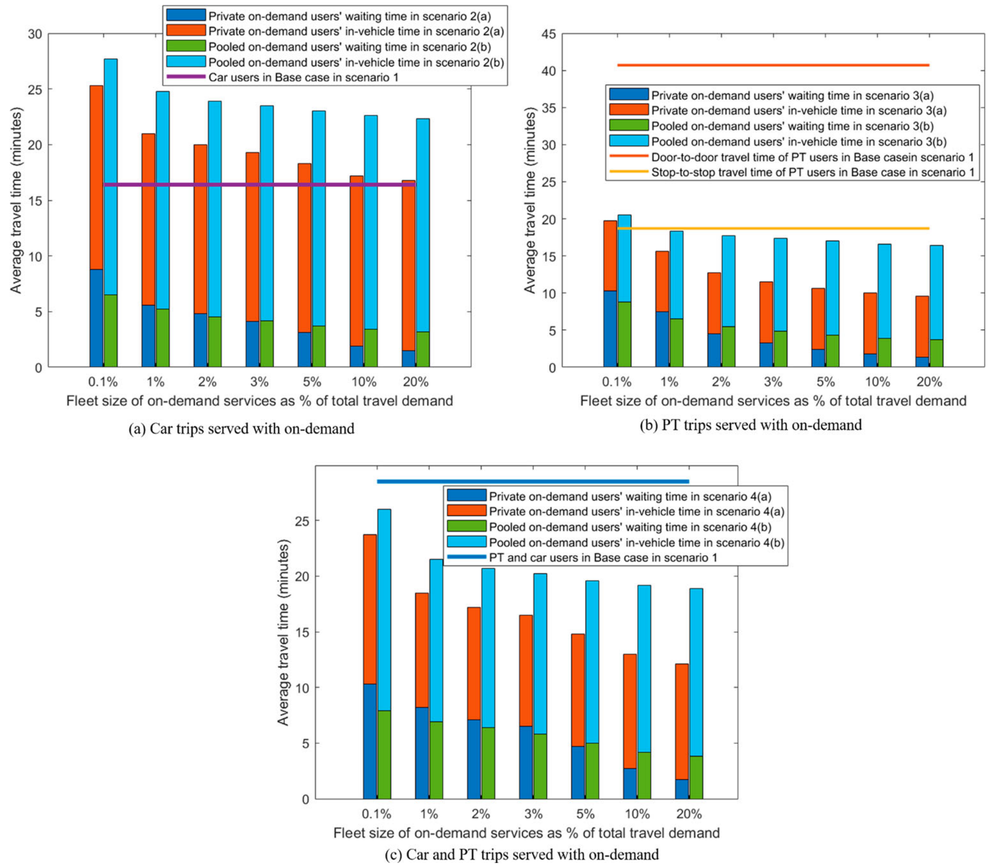


Figure 5. Travel time of users in all scenarios.

remains without being assigned any request throughout the day. This trend is observed again for the scenario when car and PT trips are served with on-demand. However, fleet utilisation is much higher in the scenario when car and PT trips are replaced compared to the one where car trips are replaced with on-demand. The highest fleet utilisation is attained in the case of substituting demand for PT only (at a fleet size of 2%). This can be explained by the public transport demand pattern. Unlike car trips, public transport trips are characterised by greater directionality, which offer more opportunities for pooling travel requests.

The trends in the occupancy plots in Figure 4 indicate a high level of fleet utilisation for the lower bound of fleet size considered; and that the fleet at the upper bound remains largely underutilised. When comparing private and pooled on-demand services, it can be seen that for the same fleet size rate, the private on-demand service has a higher Empty drive ratio than the pooled on-demand service. However, the pooled on-demand service has a higher Stay ratio than the private on-demand service. This indicates that while vehicles offering a private on-demand service spend more time en-route to pick up passengers, vehicles offering pooled on-demand services have a higher share of the fleet being unassigned with requests throughout the day.

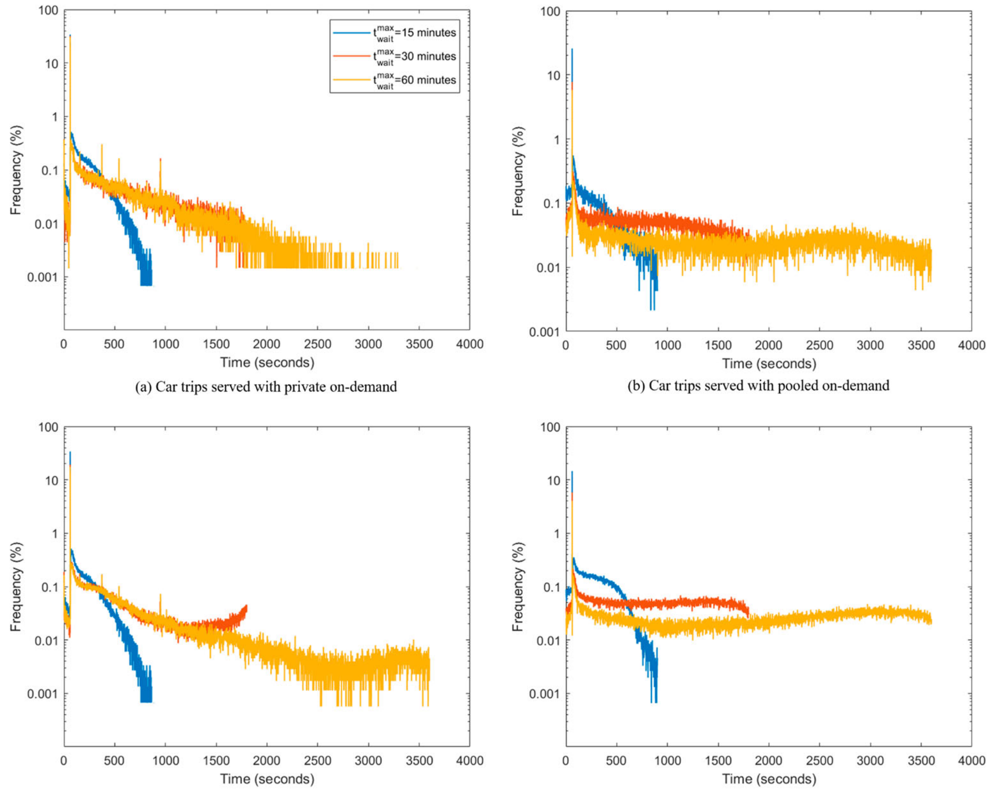
Level of service

In this section, we analyse the Level of Service experienced by users. We analyse in-vehicle time and waiting time for private and pooled services for all scenarios along with the average travel time experienced by car users, PT users, and car and PT users in the Base case and discuss the underlying trends. We start by investigating the travel time split experienced by users for all scenarios. Figure 5(a) shows the travel time of car trips in the Base case and those when the on-demand service replaces car trips. Figure 5(b) plots the travel time of PT users in the Base case (stop-to stop and door-to-door) and those when the on-demand service replaces PT trips. Similarly, Figure 5(c) displays the travel time of car and PT users in the Base case (door-to-door travel time) and those when on-demand the service replaces car and PT trips.

As can be seen from Figure 5, increasing the on-demand fleet size results in an overall reduction of travel time in all scenarios for both private and pooled services. The in-vehicle time of pooled on-demand users is higher than that of private on-demand users for all fleet sizes. This could be explained by the detours performed by pooled on-demand services to pick-up other passengers which results in additional in-vehicle time. The private on-demand service being a direct door-to-door service does not involve such detours. Furthermore, the in-vehicle time remains stable for different fleet sizes for both service types indicating that vehicle congestion does not come into effect for the fleet sizes considered. It can also be observed that the average waiting time of on-demand users decreases with the increase in fleet size for both private and pooled services. However, the effect of increasing fleet size on average waiting time is more pronounced for private on-demand users than pooled on-demand users. This is due to the direct door-to-door service provided by private on-demand service without any detours. Hence an increase in fleet size entails more vehicles to serve the demand and hence a subsequent reduction in waiting time. While this is true for both private and pooled on-demand services, for pooled on-demand services, the reduction in waiting time becomes less pronounced because of the detours performed.

We now compare the waiting times experienced by private and pooled service users and analyse the underlying trend. It can be seen from Figure 5 that at lower fleet size, pooled on-demand users experience shorter waiting times on average compared to private on-demand users. However, as fleet size increases, the average waiting time of private on-demand users decreases at a higher rate than pooled on-demand users. Consequentially, with larger fleet sizes private on-demand users experience a shorter waiting time than pooled on-demand users.

Travel time comparison with the Base case indicates that in the case of substituting car trips (Figure 5(a)), the Base case performs better for all fleet size instances for both private and pooled on-demand services. Among private and pooled on-demand services it can be seen that private on-demand provides lower travel time. In the case of replacing PT trips (Figure 5(b)), it can be seen that both private and pooled on-demand services perform better than the Base case for all fleet size instances in terms of total door-to-door travel time. In terms of stop-to-stop time, both private and pooled on-demand services perform better than the Base case for all fleet size instances, with the exception of a very



(a) Car trips served with private on-demand

(b) Car trips served with pooled on-demand

(c) Car and PT trips served with private on-demand

(d) Car and PT trips served with pooled on-demand

Figure 6. Waiting time distribution of on-demand users for scenarios 2 and 4 with varying t_{wait}^{max}.

small fleet size (fleet size of 0.1%). Even in the case of combined car and PT trips being replaced (Figure 5(c)), both private and pooled on-demand services outperform the level of service offered in the Base case for car and PT users, albeit at a persistently high rejection rate.

For scenarios where car trips are replaced with on-demand service (Scenario 2) and where car and PT trips are replaced with on-demand service (Scenario 4), we perform additional simulation runs with varying maximum allowable waiting time (t_{wait}^{max}) criteria for the on-demand service. In addition to the Base case level of t_{wait}^{max} = 15 minutes, we perform simulation runs with t_{wait}^{max} = 30 minutes and t_{wait}^{max} = 60 minutes. Results indicated that for both scenarios 2 and 4, t_{wait}^{max} of 30 minutes results in a significant reduction in the rejection rate; and no significant reduction in rejection rate is achieved beyond t_{wait}^{max} = 30 minutes. The rejection rate for scenarios 2 and 4 at t_{wait}^{max} = 30 minutes are 0.15 and 0.06, respectively. Additional analysis indicates that the rejected trips in both of these scenarios are car trips with origins well beyond the on-demand operational area of Amsterdam. Figure 6 shows the waiting time distributions for scenarios 2 and 4 for t_{wait}^{max} = 15, 30, and 60 minutes. The X-axis represents the waiting time of on-demand users and the Y-axis represents the corresponding frequencies. As can be seen from the figure, no significant variation in waiting time distribution is observed with an increase in t_{wait}^{max} from 30 to 60 minutes for private and pooled on-demand services for both scenarios. As can be seen from Figure 6(a) and (b), for the scenario where car trips are replaced with on-demand, a significant portion of trips are satisfied with a waiting time of 0–5 minutes. For scenario 4, the waiting time distribution is relatively spread out compared to scenario 2. This can be explained by the larger number of trips that need to be served in scenario 4 (car and PT) compared to scenario 2 (only car trips).

The Level of Service analysis indicates that on-demand services could effectively absorb all PT trips from the Base case by providing improved travel times (both stop-to-stop and door-to-door). In contrast, car trips cannot be substituted without leading to considerable rejections of 30% and 10% for the cases of car trips and car trips and PT trips, respectively. Additional analysis with increased $t_{\text{wait}}^{\max}$indicated that all the car trips with origin and destination points within the operational region of on-demand transport can be served while offering a $t_{\text{wait}}^{\max}$ of 30 minutes. For all scenarios and fleet size instances, private on-demand services offer shorter travel times than pooled on-demand. Similar to the comparative analysis of veh-km, travel time analysis of on-demand users at the fleet size instances where the rejection rates start to stabilise was performed. Pooled on-demand users' travel time was 33%, 39%, and 48% more than that of private on-demand users when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively.

Conclusions

This study has investigated the potential of an on-demand service to serve the motorised trips in Amsterdam. An agent-based simulation model was adopted for model implementation. Scenarios where private and pooled on-demand services replace private car, public transport, and combined private car and public transport (all motorised trips) were analysed. On-demand service performance in terms of Level of Service offered and operational efficiency were analysed. Results indicated that pooled on-demand services were more efficient in terms of veh-km travelled and empty drive ratio and that private on-demand vehicles spend more time picking up passengers than pooled service for the same fleet size instance. Private on-demand services generated 43%, 38%, and 44% more veh-km than pooled on-demand when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. Occupancy levels of on-demand service for the scenarios indicated an under-utilisation of fleet for higher fleet sizes.

While there was a significant share of unsatisfied demand for the scenario when car trips were served by on-demand service, it was found that all PT trips could be served with a relatively low fleet size of on-demand for both private and pooled services. Analysis of travel time indicated that the travel time of car users in the Base case was lower than when on-demand services were used for both private and pooled services. However, the travel time of PT users was found to be lower when on-demand was used to serve the trips than the Base case. The combined average travel time of car and PT users was also lower when on-demand served the trips than the Base case. In all these scenarios, the travel time of private on-demand was lower than that of pooled on-demand users. Pooled on-demand users' travel time was 33%, 39%, and 48% more than that of private on-demand users when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. While in-vehicle time was stable throughout the fleet size instances, the increase in fleet size resulted in the reduction of average waiting time for both private and pooled service users. However, the effect of fleet size increment on waiting time of users was more pronounced for private on-demand than pooled on-demand.

The study also assessed the scalability of an on-demand system when scaled-up to a city-wide level and its potential to serve trips performed by private car and public transport. The on-demand service included a fleet of vehicles that stay at the drop-off location until further requests are assigned. This led to an under-utilisation of the fleet where a significant fraction was parked (staying idle) throughout the day as shown in the occupancy analysis. Hence a more efficient vehicle distribution and relocation strategy based on demand anticipation is expected to result with a considerable performance improvement. Moreover, as the on-demand service was able to serve all PT trips while providing a lesser travel time, this suggests that PT could lose its share to on-demand if the mode choice of users is based solely on travel time, which is consistent with other studies (cf. Enoch 2015; Conway, Salon, and King 2018; Martinez and Crist 2015). However, from an operational perspective, this is not an ideal scenario as an on-demand service generates about five times more veh-km compared to PT. Furthermore, the lesser economies of scale of even shared on-demand services, when compared with PT, are expected to result in affordability and financial sustainability issues for service users and service providers, respectively. In the case of car trip demand, on-demand services are simply not able to serve all demand with the considered allowable maximum waiting time of 15 minutes.

Finally, multiple factors might influence the extent to which the results can be extended to other cities. For example, the distribution of demand throughout the network, the activity patterns of users, the on-demand dispatching algorithm, and the PT share are expected to be the most important among these. Hence, though the overall relations found are general and will hold for other cities (i.e. more veh-km for private compared to pooled, less travel time for private on-demand services), the specific values (the magnitude of these differences) might be specific to each application scenario (city).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research is part of the project SCRIPTS (Smart Cities' Responsive Intelligent Public Transport Systems) funded by NWO (Netherlands Organisation for Scientific Research). This research is also supported by the CriticalMaaS project (grant number 804469), which is financed by the European Research Council and the Amsterdam Institute of Advanced Metropolitan Solutions.

ORCID

Jishnu Narayan http://orcid.org/0000-0002-5301-5754
Oded Cats http://orcid.org/0000-0002-4506-0459
Niels van Oort http://orcid.org/0000-0002-4519-2013
Serge Paul Hoogendoorn http://orcid.org/0000-0002-1579-1939

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