Simulation of Fixed Versus On-Demand Station-Based Feeder Operations

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Abstract
Motivated by lower predicted operational costs, and opportunities for efficient real-time control, automated, centrally coordinated vehicles have in many studies shown great potential as a shared resource within public transit. One particular use case that has grown in popularity over recent years is the application of smaller, automated shuttles as an on-demand feeder to mass transit solution. To investigate differences in fixed versus on-demand operational policies, this paper discusses the operational design and analysis of an automated feeder solution. To this end, a simulation model of demand-responsive transit is developed and incorporated into the transit simulation model BusMezzo. An estimation of operational cost reductions with vehicle automation motivates the case study of two fleets that are deemed comparable with respect to service capacity and operational cost per hour. Results indicate that there are benefits in utilizing an on-demand operational policy when compared to fixed operations for the lowest and highest demand levels tested, and for both fleet compositions. Average total system costs under on-demand operations improve for the lowest demand levels tested due in part to a reduction in vehicle-kilometers traveled compared to a fixed service. The on-demand service also provides shorter in-vehicle times, but without achieving a competitive reduction in waiting times often underperforms with respect to level-of-service and reliability when compared to fixed service operations. When fixed service capacity is exceeded it is found that the on-demand service outperforms fixed operations with respect to average level-of-service, vehicle-kilometers traveled, and total system costs. Furthermore, when planned service capacity is exceeded, it is found that total passenger waiting time is more equally distributed under on-demand operations compared to fixed.

Keywords: demand-responsive transit, feeder, simulation, automated vehicles

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1. Introduction

Demand-responsive transit (DRT) is a form of user-oriented public transport characterized by flexible routing and scheduling that supplies shared rides between pick-up and drop-off locations depending on passenger needs. The definition is broad and, depending on the source, can encompass services ranging from door-to-door shared taxi-like services (Fagnant & Kockelman, 2018), paratransit (Häll et al., 2015), or bus lines that allow for dynamic fleet management in response to evolving demand variations (Errico et al., 2013). One of the most typical applications of DRT is to provide connectivity from suburban areas with lower or dispersed population density to urban mass transit (see Potts et al. (2010) for a review of many practical examples in North America). Due to the operational costs of extending fixed-service transport at higher frequencies in such areas, DRT can help alleviate widely acknowledged trends of increasing congestion by providing competitive shared-trip alternatives to private vehicles with a more personalized service (Chandra & Quadrifoglio, 2013). Many DRT systems fail, however, due to poor implementation, planning and marketing (Enoch et al., 2006). There is also a widely held view that DRT systems are expensive solutions that come at a much higher cost to operators, and must be heavily subsidized if provided as a public service (Ferreira et al., 2007; Davison et al., 2014). This additional cost is often a result of an inability to spread the cost of a given trip over a greater number of passengers. Furthermore, from the perspective of the passenger, route detours and flexible schedules can amplify uncertainty in expected waiting and in-vehicle times relative to traditional fixed route and schedule operations. Variations in the perceived reliability of the service can heavily influence mode and route choice of passengers when presented with multiple alternatives (Carrel et al., 2013), which in turn contributes to the uncertainty of real-time demand predictions in the assignment of a DRT fleet to passenger trip requests.

At the core of any DRT operation is thus the problem of effectively assigning the on-demand fleet to passenger requests pre-booked, forecasted and/or received in real-time, while balancing level-of-service (LoS) and operational cost objectives. In essence, this problem can be formulated as a dynamic variant of the well known vehicle routing problem (VRP). To maintain tractability in dynamic VRPs (which have shown to be NP-hard), solution approaches tend to be based on metaheuristic and heuristic approaches (see for example the reviews of Pillac et al. (2013); Psaraftis et al. (2015)) and apply improvement heuristics that may converge to an optimal solution (e.g., Alonso-Mora et al. (2017)). Solution approaches may furthermore be characterized as reactive to currently known unassigned requests, or proactive by combining these with forecasted requests. What formulation or solution methodology is chosen, and its performance for a given DRT solution, depends on the inherent uncertainty in estimating current and future states of the DRT system as well as the objectives and real-time data available to the modeler.
Emerging technologies are often assumed to be key to efficient implementation of DRT solutions. Innovations in DRT provision over recent decades have gone hand-in-hand with the advancements of Intelligent Transport Systems that make use of networks of sensors and connected vehicles to improve public transit situation awareness and real-time fleet coordination (Mageean & Nelson, 2003). More recently, the developments of automated vehicles (AVs) combined with increasingly convenient on-line alternatives to match shared vehicles and their customers, have inspired research in automated shared mobility solutions (see for example Stocker & Shaheen (2018) for a review of emerging shared automated vehicle business models). There are claims that AVs will enable more cost-efficient and user-friendly provision of DRT. With the elimination of on-board crew costs (which is often estimated to constitute 50-70% of the operational cost of bus transit in developed countries (Australian Transport Council, 2006; Davison et al., 2012)), an automated DRT service could potentially be offered at a lower per-vehicle operational cost (Bösch et al., 2018). As data-collecting vehicles that can share information regarding both current and predicted traffic and demand conditions, AV fleets also offer promising opportunities for efficient real-time coordination. These prospects have motivated numerous pilot studies of automated feeder services worldwide, often utilizing lower passenger-capacity automated shuttles (Ainsalu et al., 2018). DRT systems are difficult to trial, however, due to their cost of implementation, as well as the time-frame required for demand to build up and for stable use patterns to emerge. Furthermore, while AVs with high levels of automation are rapidly developing, they have currently not reached levels of reliability and safety that allow for the broader application needed for offering on-demand services. Simulation is thus an important tool to evaluate the feasibility of an automated DRT system before implementation.

1.1. Simulation based evaluation of fixed- versus demand-responsive transit

Agent-based simulations, with real-time adaptive behavioral representation of passengers and transit operations, lend themselves well to studies of DRT (Ronald et al., 2015). Several agent-based frameworks combining solution methods of dynamic VRPs with simulation of traffic and passenger behavior for the evaluation of public transit have been proposed over the last decade (see for example Maciejewski et al. (2017); Jäger et al. (2018)). The focus and level of detail in suggested frameworks depend on application, ranging from case studies of simplified networks to large-scale simulations of several millions of vehicles.

Many frameworks have been utilized in the evaluation of large-scale shared automated taxi services to serve urban demand (Martinez et al., 2014; Fagnant & Kockelman, 2018). Stiglic et al. (2018) evaluate the possibility of integrating ride-sharing with mass transit as a feeder/last-mile solution using park-and-ride facilities. Winter et al. (2018) evaluate the prospects of fully replacing fixed public transit with an automated DRT service providing direct connections. A model to compare the operational costs of automated versus non-automated
fleets and determine minimal fleet size with respect to total system costs is developed. This model is applied in evaluating automated DRT as a stop-based service for a case study of Arnhem, the Netherlands. Among presented results, passenger generalized travel costs are found to dominate total system costs. Higher demand levels are found to yield lower total system costs per passenger due to higher achievable degrees of vehicle utilization. With a similar use case, Jäger et al. (2018) present the development and application of a multi-agent based simulation model. Vehicles and their customers are connected through what is referred to as 'intelligent stops' that provide decentralized matching between customers and vehicles. A many-to-many, station-based DRT system is evaluated as a replacement for fixed-service public transit for the city of Singapore. Energy consumption and fleet utilization is found to improve, while travel times and travel distances are found to underperform compared to fixed operations.

The narrower use case of evaluating automated station-based feeder services relative to fixed transit is sometimes mentioned as a potential application of proposed simulation frameworks, however few studies on this topic were found. Often using an analytical approach, earlier studies of feeder solutions have focused on the determination of cutoff points with respect to LoS and operational cost for switching between fixed versus flexible operational policies (for an early example see Daganzo (1984)). Based on a continuous approximation model and analysis of operator and passenger costs Quadrifoglio & Li (2009) found that on-demand operations could provide a higher LoS when demand density is below a given threshold. More recently, Winter et al. (2016) performed a simulation study examining the potential of replacing a fixed feeder/last-mile service between two stations with an automated on-demand service. Using the demand data and network configuration of an ongoing pilot study, fleet size requirements and system performance with respect to LoS and operational costs are evaluated for 2-40 passenger capacity vehicles. Increased demand levels, and utilizing vehicles with capacities larger than 10 passengers/vehicle are among the most effective ways found to reduce system cost per passenger. Scheltes & de Almeida Correia (2017) evaluated the utilization of automated, single-person capacity vehicles within a station-based, on-demand feeder/last-mile system. Based on survey data of user acceptance and OD, system performance is simulated under varying scenarios of network structure, booking scheme and on-demand operational strategies. The automated service is shown to reduce both average travel times and waiting times when compared with active modes.

Previous studies of demand-responsive feeder/last-mile solutions have extracted valuable relationships between service design variables and resulting LoS and operational costs. To the best of our knowledge, however, studies based on analytical models or those motivated by pilot studies of automated shuttles, have either focused on single-vehicle, single-person capacity vehicles, or single-route service architecture. Simulation studies evaluating automated DRT tend to focus on the replacement of fixed-transit at a city-wide scale. Studies of
emerging ride-sharing solutions are often dedicated to evaluating the potential of sharing private door-to-door or ride-hailing trips, and comparisons with fixed public transit alternatives are thus not included. Furthermore, although a rapidly developing body of research, there is to date no established model or method for the evaluation of automated public transport, or for comparing fixed and on-demand operational policies.

1.2. Contribution

The research contributions of this paper are: (1) the development of a modeling framework for station-based DRT and integrating this with an existing framework for fixed public transit, and (2) the design and analysis of an automated, station-based feeder service. The study presented in this paper focuses in greater detail on the application of AVs within the context of a station-based, shared-ride, multiple-route transit feeder solution. Furthermore, we perform a comparison of fixed versus on-demand operational policies and resulting performance.

1.3. Scope

In this study the potential benefits of utilizing demand-responsive AVs within a stop-based feeder service is examined as an alternative to fixed-service operations. The core purpose of the service is thus to provide transport from a fixed set of stops at various network demand centers to a local center that enables transfer to an urban mass transit network. This fixed set of stops and the set of service segments connecting them can be referred to as the service area of the feeder solution. Demand in this scenario can be characterized by a many-to-few origin-destination pattern. To gain access to the on-demand feeder service, travelers will submit a request to a centralized coordinator of the on-demand fleet, referred to in this paper as the fleet manager. Attributes associated with the travel request are at minimum a timestamp of when the request was submitted, a desired time of departure and a stop for pickup-up and drop-off. A request may often include additional specifications such as a desired time of arrival, or a request for a particular vehicle type. Travelers will submit a request upon arrival to a stop within the service area of the fleet manager. Requests are thus made known to the fleet manager in real-time without requirement of prior notification and travelers are assumed to desire departure at the earliest possible time when arriving to a stop. A 'pay-up-front' policy is also assumed and the cancellation of requests is not considered.

1.4. Outline

The structure of the paper is as follows. Section 2 presents the simulation framework along with the modeling principles of on-demand operations, and the analysis of potential operational cost reductions with vehicle automation. Section 3 describes the experimental set-up in terms of inputs and outputs to the simulation framework and definitions of simulated scenario variations. Computational results and analysis of fixed versus on-demand operational policies
is presented in Section 4. The paper concludes with an analysis of scenario outcomes followed by a discussion regarding study limitations and potential improvements in Section 5.

2. Methodology

To enable experimentation, a simulation framework for DRT services is developed. To allow for consistent comparison between fixed and on-demand services, this framework is embedded within the agent-based, dynamic public transit simulation framework BusMezzo. BusMezzo includes many important components for evaluation of public transit operations such as adaptive passenger behavior representation (Cats et al., 2016), as well as individual stop characteristics, several flow-dependent dwell time functions and trip chaining representation (Toledo et al., 2010). The framework is event-based and embedded within the mesoscopic traffic simulation model Mezzo (Burghout, 2004).

For the representation of on-demand services, a "fleet manager" functionality is developed and incorporated into BusMezzo, as displayed in Figure 1. The purpose of the fleet manager is to act as an interface between travelers and the demand-responsive fleet and collect real-time information (travel requests, vehicles states and estimated travel times) necessary to dynamically assign connected vehicles to trips. In defining the on-demand service, the fleet manager is provided as input a service area (i.e., a subset of stops within the transit network), fleet characteristics (i.e., vehicle types, starting positions and starting times) as well as a strategy used to coordinate the assignment of transit vehicles to traveler requests. This component is described in greater detail in Section 2.1.

Figure 1: High-level overview of the public transit simulation framework.
2.1. Fleet manager

Figure 2 displays relationships between classes of the simulation framework relevant for matching demand-responsive transit vehicles with travel requests. In short, the FleetManager functions as a facade for TransitVehicle and Passenger clients, where the problem of matching travel requests with connected transit vehicles is partitioned and solved sequentially by supporting modules. A FleetManager is initialized with a set of one or several connected TransitVehicle and Stop objects, defining the corresponding fleet and service area of an on-demand service. Five supporting classes are defined as members of the FleetManager. The core responsibilities of these classes are:

- **RequestHandler** - receiving, bundling and sorting requests,
- **TripPlanner** - generating feasible trip plans for vehicles to serve currently known and/or forecasted requests,
- **Matcher** - performing a cost evaluation of candidate trip plans in order to create a matching with available vehicles,
- **Scheduler** - adjusting dispatch, pick-up, and drop-off schedules of matched vehicles,
- **Navigator** - provide shortest path estimations used by the other supporting classes.

![Class diagram of FleetManager](image_url)

Figure 2: Class diagram of FleetManager (blue) and member supporting classes (purple), with one or several strategies (orange). Arrows display relationships relevant for connecting Passenger and TransitVehicle agents (red).

In Figure 2, four of the supporting classes (all but the Navigator) may have one or several strategies (e.g., a RequestHandler may have access to one or several
BundlingStrategy implementations) inheriting from an abstract class (colored orange) containing shared methods and an interface for each vehicle-to-passenger assignment subproblem. To clarify, in this context the bundling of requests refers to grouping and filtering the set of all currently known and/or forecasted requests such that a subset of these is to be considered by the TripPlanner. A RequestHandler may thus also have no BundlingStrategy, meaning the entire group of known requests is considered. This structure is considered flexible in the sense that it allows the FleetManager to switch between individual strategy components dynamically depending on for example resulting fleet utilization and LoS quality.

The FleetManager monitors connected TransitVehicle state changes (e.g., 'unassigned', 'assigned', or 'driving') throughout the simulation. A Passenger intending to use an on-demand service in real-time is connected to a FleetManager when a decision has been made to wait at a Stop within the on-demand service area. Once connected, the FleetManager will await a Request submission from this Passenger containing desired specifications for the trip.

2.2. On-demand vehicle-to-passenger assignment

To model on-demand operations for the service settings considered in this paper, a greedy heuristic for assigning direct trips between origin and destination stops is implemented. The algorithm functions as a baseline for further development and comparison, as well as a demonstration of how the structure of the simulation framework can be sequenced. The greedy heuristic iteratively assigns the closest (in terms of expected travel time) empty vehicle to the origin stop within the service area of the FleetManager with the highest count of known requests with shared OD. Two events are set up to initiate the process of matching groups of travel requests to transit vehicles: (1) when a passenger makes a decision to stay at a stop and (2) when a transit vehicle finishes a trip with no future assignments. To demonstrate how the greedy heuristic is implemented within the described framework, an activity diagram is presented in Figure 3.
Figure 3: Activity diagram for greedy vehicle-to-passenger assignment. Lane headers and coloring correspond to classes displayed in Figure 2. Activities are displayed as rounded rectangles, diamonds as conditional branches, and straight rectangles as data structures passed between classes. Orange activities are associated with strategies of the containing class.

The passenger activated initial state is displayed to the top left of Figure 3, when a decision has been made to stay at a stop within the service area of the FleetManager. The Passenger submits a Request to the RequestHandler which verifies that the destination attribute of this request is contained within the on-demand service area and adds it to a RequestSet containing all currently known unassigned requests.

The RequestHandler groups requests by calling a BundlingStrategy that sorts the RequestSet by the highest number of members with shared ODs. Following this, the TripPlanner receives and delegates the RequestSet to a PassengerTripStrategy. The PassengerTripStrategy sends a request to the Navigator to check for vehicles at the origin stop of the OD with the highest request count, and to estimate the shortest route in terms of expected travel time for this OD if such a vehicle exists. If a route is found, the PassengerTripStrategy generates a trip plan consisting of an ordered sequence of stops (in this case simply the OD) and a preliminary schedule for when these stops are visited based on the shortest expected travel time. If a route is not found the RebalancingTripStrategy of the TripPlanner is called, following a similar procedure as for a passenger trip. In this case, however, a request is sent to the Navigator to estimate the shortest route between the locations of all vehicles that are currently unassigned to any trip to the origin stop of the OD pair with the highest request count. If a route is found, the RebalancingTripStrategy generates a rebalancing trip plan for the unassigned vehicle that is closest in terms of expected travel time to the origin stop of the prioritized OD pair. If a vehicle is already en-route to the origin stop of the OD with the highest passenger count, a rebalancing trip plan is not generated.
If either a passenger carrying or rebalancing trip plan has been found it is added to a set of TripPlans which is delegated to the Matcher. The MatchingStrategy matches all current trip plans to the vehicle at the origin stop of each trip plan that has been unassigned for the longest time period. The paired trip plans and vehicles are added to a set of MatchedTrips and the state of each unassigned vehicle is updated. Following an update of fleet state, the MatchedTrips set is delegated to the Scheduler. In this case the SchedulingStrategy will simply book pick-up and drop-off times as soon as possible based on the shortest estimated travel times found with no delays. The process is concluded when the scheduled trips have been added to the list of events of the simulation time loop with a scheduled time of departure, and the schedule of the trip is communicated to the Passenger.

The transit vehicle activated initial state is displayed on the top right of Figure 3. The same process as described above, but beginning instead with a call to the BundlingStrategy of the RequestHandler, follows a TransitVehicle state change signaling that it is no longer assigned to any trip.

### 2.3. Estimation of operational cost reductions with vehicle automation

In this paper, a potential reduction in operational cost per hour for a fixed transit service with vehicle automation is estimated to motivate an increase in fleet size. The operational cost estimates in this paper are based off the model developed by Zhang et al. (2019). The authors detail a comparison of conventional buses and automated buses for fixed public transit operations. Based on estimates of public transit per hour and per kilometer operational costs from Australian Transport Council (2006) for 5 different vehicle sizes (ranging from a maximum passenger capacity of 20-100) and the estimated linear relationship between running cost and vehicle size suggested by Jansson (1980), the authors propose a linear model for estimating vehicle unit cost per hour dependent on the maximum passenger capacity of the vehicle.

Using similar notation, the operating cost per vehicle hour \( g_{s}^{oper} \) and capital cost per vehicle hour \( g_{s}^{cptl} \) for an AV of size \( s \) (seating and standing capacity) is given by

\[
g_{s}^{oper} = (1 - \eta)c^{oper} + b^{oper} s
\]

and

\[
g_{s}^{cptl} = (1 + \zeta)c^{cptl} + b^{cptl} s
\]

respectively. The parameters \( c^{oper} \) and \( c^{cptl} \) correspond to unit fixed operating, and capital costs per vehicle-hour respectively. Parameters \( b^{oper} \) and \( b^{cptl} \) correspond to unit size-dependent operating, and capital costs per vehicle hour respectively. The parameter \( \eta \) is defined as a percentage decrease in unit operational costs due to the reduction in labor costs when replacing a non-AV
with an AV with a high level of automation. The parameter $\zeta$ corresponds to a percentage increase in unit capital cost due to changes in acquisition costs of AVs.

2.4. Performance evaluation

As is displayed in Figure 1, LoS measurements are included among outputs of the model. A passenger’s experienced LoS is calculated by observing the amount of time spent in different segments of their trip and with this calculate a generalized travel cost term via value-of-time estimates. LoS attributes included in simulation output are for each passenger agent a waiting time ($t_{\text{wait}}$), in-vehicle time ($t_{\text{ivt}}$), walking time ($t_{\text{walk}}$), and number of transfers ($n_{\text{trans}}$). A distinction is made between waiting time for the first vehicle that a passenger wishes to board and additional waiting time $t_{\text{denied}}$ if a passenger is denied boarding until their next opportunity to board. The travel cost of a passenger is calculated by selecting corresponding weighting parameters ($\beta_{\text{walk}}$, $\beta_{\text{wait}}$, $\beta_{\text{denied}}$, $\beta_{\text{ivt}}$, $\beta_{\text{trans}}$) and summing over each weighted trip component.

The performance of a public transit system may also be assessed in terms of equity in the distribution across passengers of costs and benefits provided. In order to quantify equity in public transit, the Gini coefficient (Gini, 1912) is sometimes used (e.g., Delbosc & Currie (2011); Jang et al. (2016)). In this paper, the Gini coefficient is used to compare the distribution of total waiting times (i.e., $t_{\text{twait}} = t_{\text{wait}} + t_{\text{denied}}$) under fixed and on-demand operational policies. There are several ways of expressing and calculating the Gini coefficient. In this paper the Gini coefficient of total waiting times ($G_{t\text{wait}}$) is calculated as half the relative mean absolute difference (as in Sen & Foster (1973)) of total waiting times for all passengers within the evaluated time period:

$$G_{t\text{wait}} = \frac{1}{2n^2t_{\text{twait}}} \sum_{i=1}^{n} \sum_{j=1}^{n} |t_{i\text{wait}} - t_{j\text{wait}}|,$$

where $n$ is the total number of passengers in the evaluated time period, $t_{i\text{wait}}$ is the total waiting time experienced by passenger $i$, and $t_{\text{twait}}$ is the average total waiting time over all passengers 1,...,n. $G_{t\text{wait}}$ can interpreted as an inequality metric, ranging from 0% (perfect equality of total waiting times for all passengers) to 100% (perfect inequality of total waiting times). Litman (2019) discusses two categories of equity in transportation: horizontal equity and vertical equity. Horizontal equity is defined as the distribution of costs or benefits between individuals or groups considered equal in abilities and needs, and vertical equity between individuals or groups that are considered to differ in terms of abilities and needs. The total waiting times of each passenger in the calculation of $G_{t\text{wait}}$ are weighted equally. $G_{t\text{wait}}$ can in this sense be interpreted as a measure of horizontal equity.
3. Experimental set-up

To isolate the effects of fixed versus on-demand operational policies a case study aimed at capturing key features of a real-world feeder to mass transit network is devised. The simulation framework is applied to the network, operations and demand pattern displayed in Figure 4.

Two operational policies (displayed on the left-hand side of Figure 4) for feeder services are simulated. Passenger arrivals are modeled as Poisson processes with total arrival rates of 25-300 passengers/hour over one simulated hour. The passenger origin-destination pattern is asymmetric, with arrivals uniformly distributed among origin stops A, B, C and D, with a destination at transfer stop E (e.g., a total arrival rate of 25 passengers/hour corresponds to an arrival rate of 6.25 passengers/hour per stop as displayed on the right-hand of Figure 4). Fixed and on-demand fleets have the same operational speeds of 30 km/h on all links in the network and all links are bidirectional. Perimeter links (e.g., A→B or A→E) have a length of 1.5 km. Diagonal distances (e.g., A→D or C→E) are 2.4 km. Dwell times are modeled as a linear function of the number of boarding and alighting passengers for all vehicle types and for all stops.

Two fleet compositions are evaluated utilizing fixed versus on-demand operational policies. In the on-demand scenarios there are no pre-booked requests, i.e., requests are received in real-time to be served as soon as possible. Furthermore, once a request has been made, it cannot be canceled by the passenger nor the operator. Passengers are generated over one simulated hour. Output statistics are calculated for both on-demand and fixed scenarios for the time period starting with the first passenger arrival and until all passengers have
reached their destination. Prior to the first passenger arrival a warm-up time is included to distribute fixed service vehicles with an even headway along the circular route. Given the network and demand configuration above, two buses with capacities of 50 passengers/vehicle are required to provide a 12-minute headway policy for the fixed circular feeder route with a maximum service capacity of 250 passengers/hour. Using this as a base case, we estimate the planned operational cost per hour for this service and evaluate the potential of expanding the existing fleet size with a larger fleet of AVs.

The estimated reduction in operational and capital costs used in the study by Zhang et al. (2019) depend on expected operational speeds of 15km/h for urban transit. Given the same data (Australian Transport Council, 2006) but with an expected operational speed of 30km/h, the estimated intercepts and slopes of the relationships in (1) and (2) are $c_{oper} = 39.24$ €/vehicle/hour, $b_{oper} = 0.145$ €/vehicle/hour, $c_{ptl} = 1.4$ €/vehicle/hour, and $b_{ptl} = 0.099$ €/vehicle/hour, using a conversion rate of 1AUD = 0.63€.

With the reasoning that crew costs could be eliminated by utilizing fully AVs, $\eta$ is estimated to be 53%. This is given by the ratio between per-hour labor costs (20.79€/vehicle/hour independent of vehicle capacity) and the estimated fixed operating cost per vehicle hour $c_{oper}$. Note that there may be additional changes in operational costs besides driving crew costs that are not included (e.g., vehicle insurance, fleet operator costs, or vehicle maintenance). The parameter for $\zeta$ is set to 50%, assuming an increase in acquisition cost due to the additional equipment required to enable automated driving, but also speculating that current costs of AVs will decrease if mass production is achieved. Plugging the estimated values into (1) and (2) gives us the vehicle-size dependent operational cost per vehicle-hour for both non-AVs (i.e., $\eta$ and $\zeta$ are 0%) and for AVs when operated as a fixed service.

With this it is estimated that two non-automated buses of capacity 50 passengers/vehicle can be replaced by approximately four automated minibuses of capacity 25 passengers/vehicle, for the same operational cost per hour and while keeping planned service capacity the same when operated as a fixed service. With a fixed operational policy the scheduled headway with a doubled fleet size is thus reduced to 6 minutes.

For consistency, the value of in-vehicle time $\beta_{ivt} = 5.9$€/h for peak hour bus transport recommended in Australian Transport Council (2006) is used. As passengers are all destined to transfer stop E, there is no other incentive than to wait for the most direct route available. The number of transfers is thus considered the same for both fixed and on-demand feeder services and is excluded from the comparison of LoS results. Access and egress time at stops are assumed to be the same for both services hence performance with respect to walking time is also omitted. Besides in-vehicle time the analysis of LoS is therefore focused on the remaining variables of trip segments that may differ:
namely $t_{\text{wait}}$ and $t_{\text{denied}}$. The weight of perceived waiting time is set to double that of in-vehicle time, $\beta_{\text{wait}} = 2 \cdot \beta_{\text{ivt}}$, based on the study of Wardman (2004). The value of waiting time due to denied boarding $\beta_{\text{denied}} = 7 \cdot \beta_{\text{ivt}}$ is used based on the study of Cats et al. (2016).

In summary a total of 20 scenarios are simulated: two vehicle sizes ($s \in \{25, 50\}$ passengers/vehicle with corresponding fleet size $f_s$) and five demand levels (combined rates of $\lambda \in \{25, 50, 100, 200, 300\}$ passengers/h) for fixed and on-demand operational policies. In Section 4 each scenario is denoted by FC($f_s, s, \lambda$) for fixed operations and DRT($f_s, s, \lambda$) for on-demand operations.

4. Computational Results

The simulated scenarios are evaluated based on metrics of passenger cost, individual passenger travel time components and total vehicle-kilometers traveled. Given the stochastic nature of the simulation (the random passenger arrivals are the main source of stochastic variation), each scenario is simulated with 400 replications. This results in a smaller than 1% standard error for all mean estimates. Table 1 displays the computed averages ($\bar{t}$) and standard deviation ($\sigma$) of all $t_{\text{ivt}}$, $t_{\text{wait}}$ and $t_{\text{denied}}$ over all simulation replications. Furthermore, average and standard deviation of passenger total travel time ($\bar{t}_tt$, $\sigma_{tt}$), weighted travel cost per passenger ($\bar{c}_{\text{pcost}}$, $\sigma_{\text{pcost}}$) and total VKT ($\bar{d}_{\text{vkt}}$, $\sigma_{\text{vkt}}$) are displayed.
Scenario Performance metrics
\( (f_s, s, \lambda) \)
\( \bar{t}_{\text{tot}}; \sigma_{\text{tot}} \quad \bar{t}_{\text{wait}}; \sigma_{\text{wait}} \quad \bar{t}_{\text{denied}}; \sigma_{\text{denied}} \quad \bar{t}_{\text{tt}}; \sigma_{\text{tt}} \quad \bar{t}_{\text{pcost}}; \sigma_{\text{pcost}} \quad d_{\text{vkt}}; \sigma_{\text{vkt}} \)
\[ \text{[sec]} \quad \text{[sec]} \quad \text{[sec]} \quad \text{[sec]} \quad \text{[E]} \quad \text{[km]} \]
FC(4,25,25) 454; 203 180; 105 - 634; 229 1.22; 0.44 112.77; 0.04
FC(4,25,50) 458; 205 181; 105 - 639; 231 1.23; 0.44 111.13; 0.03
FC(4,25,100) 459; 205 180; 105 - 639; 230 1.23; 0.44 112.60; 0.02
FC(4,25,200) 466; 207 180; 105 7; 51 653; 228 1.32; 0.65 111.02; 0.02
FC(4,25,300) 469; 208 181; 104 324; 682 974; 587 4.81; 7.16 112.60; 0.02
DRT(4,25,25) 238; 55 302; 304 - 540; 313 1.28; 0.95 59.12; 9.26
DRT(4,25,50) 240; 56 351; 304 - 591; 312 1.43; 0.95 77.42; 8.18
DRT(4,25,100) 243; 56 378; 295 - 620; 303 1.52; 0.92 88.91; 7.20
DRT(4,25,200) 248; 56 398; 291 - 646; 299 1.59; 0.90 96.35; 6.53
DRT(4,25,300) 253; 56 413; 296 3; 52 669; 306 1.67; 1.05 99.09; 5.61
FC(2,50,25) 458; 204 358; 208 - 817; 291 1.77; 0.71 59.38; 0.02
FC(2,50,50) 460; 206 362; 207 - 822; 291 1.79; 0.70 59.33; 0.02
FC(2,50,100) 465; 208 362; 208 - 827; 293 1.79; 0.71 59.31; 0.01
FC(2,50,200) 477; 212 360; 209 3; 48 840; 294 1.85; 0.84 59.30; 0.01
FC(2,50,300) 484; 213 363; 209 276; 632 1123; 567 4.87; 6.63 74.56; 0.01
DRT(2,50,25) 238; 55 421; 371 - 659; 377 1.64; 1.15 53.03; 5.85
DRT(2,50,50) 241; 55 505; 395 - 746; 400 1.91; 1.22 61.88; 3.89
DRT(2,50,100) 244; 56 546; 392 - 789; 398 1.90; 1.21 65.54; 2.78
DRT(2,50,200) 252; 56 587; 404 - 838; 408 2.18; 1.25 66.94; 2.20
DRT(2,50,300) 259; 56 617; 418 - 876; 422 2.28; 1.29 66.62; 2.19

Table 1: Summary of simulation results for all scenarios.

For convenience, using the equivalent fixed scenario as a reference, the relative change with on-demand operations is shown in Table 2.
Table 2: Relative differences under on-demand operations using the equivalent fixed scenario as a reference. $\Delta_{ivt}$ denotes the difference in average in-vehicle time, $\Delta_{twait}$ difference in average total waiting time, $\Delta_{tt}$ difference in average total travel time, $\Delta_{cost}$ difference in average passenger cost and $\Delta_{vkt}$ difference in average VKT.

With more direct routes in-vehicle times are on average 47% shorter in all DRT scenarios resulting in shorter average total travel times for all levels of demand and for both fleet compositions. Average VKT also decreases with on-demand operations for all scenarios with a larger fleet size. However, total waiting times as well as weighted passenger travel costs are in general higher for all DRT scenarios, with the exception of the highest level of demand.

4.1. Weighted travel costs

For comparison of absolute and relative differences in average travel time and travel cost components for passengers, Figure 5 displays average nominal travel times (left) and weighted travel costs (right) for all passengers per scenario. Unsurprisingly, average passenger travel times and weighted travel costs are lower when a larger fleet is deployed (left group of bars in both charts) for both operational policies and for all levels of demand. With constant operational speeds and identical dwell time functions for all stops and vehicle types, the average in-vehicle times for all levels of demand stay relatively stable for all the simulated scenarios. Average waiting time is also stable between demand levels for the fixed service when there is slack in service capacity (i.e., for scenarios with demand intensity $\lambda < 250$ passengers/hour). The core source of differences in average passenger costs between fixed and on-demand operational policies thus stems from differences in waiting times. While with lower in-vehicle times the on-demand service results in total travel times that are on average shorter, average waiting times are generally longer and grow with demand level relative to the fixed service. When evaluated at double the weighted travel cost relative to in-vehicle time the discount in total travel time does not compensate for increases in required waiting times. However, for the highest level of demand, when the planned service capacity of the fixed fleet is exceeded, a substantial
number of passengers are denied boarding, which has a large impact on the total travel times for these scenarios and an even larger impact on the weighted travel costs. Notably this does not occur for the on-demand service.

![Figure 5: Average nominal travel times (left) and weighted travel costs (right) for all scenarios. The left group of both plots corresponds to results from the scenario with 4 vehicles of size 25 passengers/vehicle, and the right group corresponds to scenarios with 2 vehicles of size 50 passengers/vehicle.](image)

Let FC(4,25,\sim), FC(2,50,\sim) denote fixed service operations for demand levels 25 to 200 passengers/hour where maximum service capacity is not exceeded. With relatively consistent estimates of average total waiting and in-vehicle times for these demand levels, the resulting average weighted travel cost of 1.25\,€ and 1.80\,€ per passenger for FC(4,25,\sim) and FC(2,50,\sim) respectively can be viewed as representative of these services under ‘normal’ circumstances. With no passengers being denied boarding and a near constant 47% in-vehicle travel time discount, the average weighted travel cost of the on-demand scenarios depends primarily on resulting waiting time. The average weighted travel cost of the on-demand service can then be approximated by

\[ \bar{c}_{\text{drt}}^{\text{cost}} \approx \beta_{\text{ivt}} \left( \bar{t}_{\text{drt}} + k\bar{t}_{\text{wait}} \right), \]

where \( \bar{t}_{\text{wait}} \) represents the resulting average waiting time of the DRT service for a given demand level and \( k = \frac{\bar{t}_{\text{wait}}}{\bar{t}_{\text{ivt}}} \) representing the perceived cost of waiting time relative to in-vehicle time. If the average 242 second in-vehicle time between all DRT scenarios is assumed constant, cutoff points for when average weighted travel cost per passenger is the same for both fixed and on-demand operations can be calculated as displayed in Figure 6.
Figure 6: Average weighted travel cost breakpoints for $\beta^{\text{tot}} = 5.9\text{€/h}$, $k = 2$ and $\bar{t}^{\text{ivt}}_{\text{drt}} = 242$ seconds.

For a larger fleet of smaller vehicles the on-demand service must achieve an average total waiting time of less than 285 seconds (or at most a 57% increase in average total waiting time) to result in a lower average weighted travel cost per passenger relative to FC(4,25,$\sim$). For a smaller fleet of larger vehicles, the cutoff point of 463 seconds corresponds to at most a 28% increase in total waiting time relative to FC(2,50,$\sim$). As seen in Table 2, the on-demand service achieves this only in one scenario for the lowest level of demand, DRT(2,50,25). Note from the points of intersection in Figure 6 that if the slope of $\bar{t}^{\text{pcost}}_{\text{drt}}$, the parameter $k$, is decreased or increased, the allowable average total waiting time of the on-demand service changes at a faster rate when compared against FC(2,50,$\sim$) relative to FC(4,25,$\sim$). Whether on-demand operations is competitive with respect to average weighted travel cost per passenger is thus more sensitive to the perceived cost of waiting time relative to in-vehicle time for the smaller fleet of higher capacity vehicles.

4.2. Waiting time distribution

A key difference between fixed and on-demand operations is in the perceived reliability of waiting times for the service. To investigate differences in service reliability with respect to waiting times for each operational policy, total waiting time coefficients of variation are displayed in Figure 7 for each level of demand. The relative variance of waiting times for the fixed service is always lower than for the on-demand service with the exception of when passengers are denied boarding. With higher rates of passenger arrivals, greedy and reactive routing and scheduling results in a relative variance of waiting times that decreases with higher levels of demand for both fleet compositions.
To evaluate the distribution of waiting time costs, Table 3 displays the Gini coefficients of total waiting time distribution for all scenarios. Across all demand levels under maximum service capacity the fixed policy results in a more equitable distribution of waiting time among passengers relative to on-demand operations. Inequality of passenger total waiting times increases drastically for the fixed service for the highest demand level, indicating that a decrease in the availability of the service affects passengers very unevenly. For the on-demand case the induced increase in total waiting times with higher demand is instead distributed more evenly among all passengers.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Demand level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25</td>
</tr>
<tr>
<td>FC(4,25)</td>
<td>34%</td>
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<tr>
<td>DRT(4,25)</td>
<td>47%</td>
</tr>
<tr>
<td>FC(2,50)</td>
<td>33%</td>
</tr>
<tr>
<td>DRT(2,50)</td>
<td>43%</td>
</tr>
</tbody>
</table>

Table 3: Gini coefficients of total waiting times.

In Figure 8, distributions of total waiting time are displayed for the lowest and highest demand scenarios with the largest difference in total waiting time equality. The reactive fleet coordination strategy utilized in on-demand operations is reflected in three peaks in waiting time frequencies for this service, most clearly seen for the lowest level of demand (left). Each peak corresponds to the current closest location of a DRT vehicle when a new request has been received. The peak at zero total waiting time corresponds to when a vehicle is already at the origin of the passenger, 180 seconds when the closest vehicle is at a neighboring stop to the origin of the passenger, and 235 seconds when the closest vehicle is at diagonal stop to that of the passenger’s origin. From the distributions on Figure 8 (right) it is apparent that the reduction in available service capacity most heavily influences only a portion of the passengers for the fixed service. With a fixed circular feeder that serves stops sequentially, passengers furthest
downstream towards the transfer stop are most heavily affected by a decrease in service availability and are continuously denied boarding until demand subsides. With an operational policy where all stops are interchangeable in terms of supply provision, the shape of the waiting time distribution remains the same for all stops for the on-demand service. As seen in Figure 8, both average and standard deviation of total waiting time is lower for the fixed service relative on-demand operations. For the highest demand level this is reversed, with a lower average and standard deviation of total waiting times for the on-demand service.

![Figure 8: Passenger total waiting time distributions for FC(4,25) (blue) and DRT(4,25) for the lowest (left) and highest (right) demand levels. Error bars display the mean and ±1 standard deviation of each distribution.](image)

### 4.3. Fleet utilization

To evaluate differences in fleet utilization for fixed and on-demand operational policies, average VKT for each demand level is displayed in Figure 9. As expected, VKT for the fixed service is near constant for both fleet compositions when service capacity is below maximum. For the highest demand level when passengers are sometimes denied boarding, additional VKT is required to serve passengers left behind. Figure 9 (left) displays the average VKTs and average travel cost for the larger fleet of smaller vehicles. On-demand scheduling will in this case result in lower average VKT per passenger for all levels of demand as vehicles may sometimes remain idle when there is slack in the number of vehicles required to serve current demand. Variance in VKT increases with lower demand levels due to the sensitivity of on-demand routing to stochastic demand arrivals. Figure 9 (right) displays VKT and weighted travel costs for the smaller fleet of larger vehicles. For all levels of demand besides the lowest and highest, VKT per passenger is in this case higher for the on-demand service. Without detours once a passenger has boarded, a smaller fleet size results in more deadhead trips to satisfy the same demand in the on-demand service relative to fixed for all but the lowest demand level under maximum service capacity.
4.4. System cost

In the study of Zhang et al. (2019), the operating cost parameters $c_{oper}$ and $b_{oper}$ used in calculating vehicle-size dependent operating costs per vehicle hour ($g_s^{oper}$ in equation (1)) are estimated based on a sum of time-related operating costs and distance-related operating costs. Of these cost components, the distance based costs per operating hour used in comparing fleet compositions in Section 3 are approximated based on the assumption that a fixed service transit vehicle will drive continuously along known fixed routes at expected operational speeds during service hours, and that running costs are proportional to distance driven. For on-demand services, however, total vehicle-kilometers traveled per operating hour is more difficult to estimate a priori, as this depends on the policy utilized to coordinate the on-demand fleet as well as prevailing demand patterns.

Assuming time-related operating and capital costs ($g_s^{opt}$ in equation (2)) are the same between fixed and on-demand operations, the difference between average VKT with on-demand operations ($\bar{d}_{vkt,dr}$) and the average VKT of the equivalent fixed scenario in terms of demand intensity and fleet composition ($\bar{d}_{vkt,fc}$) can be used to estimate the operational costs for each on-demand scenario. The vehicle-size dependent distance-based operating cost per vehicle-kilometer ($c_{km}$) is estimated using the same data from Australian Transport Council (2006). The difference in average distance based costs for each on-demand scenario (with corresponding vehicle size $s$) relative to fixed ($\delta_{dcost}$) is then given by

$$\delta_{dcost} = c_s^{km} \cdot (\bar{d}_{vkt,dr} - \bar{d}_{vkt,fc})$$

where $c_{25}^{km} = 0.54 \, \text{€/km}$ and $c_{50}^{km} = 0.66 \, \text{€/km}$. The average time required to serve all passengers is also dependent on operational policy and demand level. Average operating hours required to serve all passengers ($t_{oper}$) are thus calculated over all simulation replications for each scenario. The average total operational cost (i.e., both time and distance-related costs) required to serve
all passengers ($z_{oper}$) in each scenario (with corresponding fleet size $f_s$) is then given by

$$z_{oper} = \bar{t}_{oper} \cdot f_s \cdot (g_{oper} + g_{cptl}) + \delta_{dcost}$$

for on-demand scenarios, and

$$z_{oper} = \bar{t}_{oper} \cdot f_s \cdot (g_{oper} + g_{cptl})$$

for fixed scenarios. Average total passenger costs ($z^{tpcost}$) are given by

$$z^{tpcost} = \lambda \cdot \bar{c}_{pcost}$$

where $\lambda$ and $\bar{c}_{pcost}$ corresponds to the demand level and average weighted travel cost per passenger trip respectively for a given scenario. The average system cost ($z^{sys}$) for each scenario is then defined as the sum of the corresponding average operational cost and average total passenger cost:

$$z^{sys} = z_{oper} + z^{tpcost}$$

A summary of the aforementioned system cost components is displayed in Table 4.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$\delta_{dcost}$</th>
<th>$\bar{t}_{oper}$</th>
<th>$\bar{c}_{pcost}$</th>
<th>$z_{oper}$</th>
<th>$z^{tpcost}$</th>
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<td>684</td>
<td>835</td>
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</table>

Table 4: System cost components for all scenarios.
Figure 10 displays the relative change in system cost with on-demand operations using the equivalent fixed scenario as a reference. For demand levels under maximum fixed service capacity and for both fleet compositions, the on-demand policy results in a lower average system cost only for the lowest demand level. On-demand operations for these demand levels outperforms fixed service operations with respect to both average operational cost required to serve all passengers and total passenger costs only for the lowest demand level and the smaller fleet of larger vehicles. When planned fixed service capacity is exceeded, on-demand operations substantially reduces average system cost.

![Figure 10: Relative differences in system cost with on-demand operations using the equivalent fixed scenario as a reference for the (4,25) fleet (left) and the (2,50) fleet (right). \( \Delta^{\text{opr}} \) denotes the difference in average operational cost required to serve all passengers, \( \Delta^{\text{tpcost}} \) the difference in average total passenger cost and \( \Delta^{\text{sys}} \) the difference in average system cost.]

5. Conclusions and discussion

The design and operational control of automated transit is a rapidly developing research area. The widespread growth of shared mobility services, as well as innovations in forecasting and situation awareness technology to enable more efficient flexible transit fleet coordination, have inspired pilot studies of automated transit feeders to existing urban mass transit around the globe. To date, however, only partial access to the dynamics and interactions of automated transit fleets and their customers is available. New models are required to quantify the impacts of emerging transit services prior to their implementation and to assess their feasibility. This paper presents a simulation framework encompassing essential components for modeling demand-responsive transit services and for prototyping a wide variety of demand-responsive operational policies. This framework was embedded within an existing public transit simulation model that has previously been utilized in evaluating fixed transit services and that includes detailed representation of adaptive passenger behavior. The combined framework allows for quantifying LoS and operational cost impacts of demand-responsive services under alternative operational settings and enables consistent comparison of such services with fixed transit alternatives. An on-demand
operational strategy was implemented within this framework and applied in a specific case study of an automated, station-based feeder service. Two fleet compositions were simulated under varying conditions of demand intensity. With estimated reductions in labor costs, the two fleet compositions are considered comparable with respect to both operational cost per hour as well as expected service capacity at fixed service frequencies.

Results indicate that the increase in fleet size with smaller automated vehicles can improve the LoS of passengers regardless of operational policy. This naturally comes with an increase in total vehicle kilometers traveled per passenger, in particular for fixed service operations where vehicles drive continuously regardless of demand level. In comparing operational policies, fixed operations provide an on average higher LoS to passengers for most levels of demand where there is slack in service capacity. On-demand operations are in such circumstances more competitive with respect to passenger costs with decreasing demand level. For the lowest demand level and a smaller fleet, the on-demand service provides an on average higher LoS to passengers for lower VKT per passenger. Average system costs were also found to improve under on-demand operations for the lowest demand levels. This result seems consistent with previous comparisons of fixed versus on-demand feeder operations for single-vehicle fleets. Furthermore, when fixed service capacity is exceeded, on-demand operations was found to be superior to fixed service operations with respect to both average LoS, VKT per passenger and total system costs.

Given the assumptions made in the simplified scenarios the core difference in LoS provided between operational policies lie in the variability of waiting times when applying an on-demand service. With the provision of direct routes, the on-demand service reduces in-vehicle times such that average passenger travel time in all scenarios is lower relative to fixed operations. Furthermore, a lower VKT per passenger served is required when the fleet size is larger. Despite this, average waiting times are not reduced to the same degree relative the fixed service regardless of fleet composition, which results in higher average weighted travel costs for most scenarios. The decreasing trend of VKT per passenger in particular for the larger fleet size suggests that there is slack in the number of vehicles required to provide the resulting LoS with on-demand operations.

A key difference in fixed versus on-demand services is service reliability. The greedy on-demand strategy results in a relative variance of waiting times that decreases with increasing demand levels but that is still higher than for fixed operations for all demand levels below maximum service capacity. Total waiting time Gini coefficients also indicate that a fixed service is more equitable for lower demand levels. Limitations in available capacity for the highest demand level, however, most heavily effect passengers downstream when stops are served sequentially. Average weighted travel costs are in this case dominated by costs associated with waiting time due to denied boarding. In contrast, the distribution of total waiting times under limited service capacity is spread equally among
passenger groups when utilizing the on-demand operational policy. While this result is specific to the assumptions made in this case study and should not be generalized, the analysis highlights that differences in the dispersion of negative effects under scenarios of disrupted service availability may be worth considering in an evaluation of fixed versus on-demand operations for similar networks and demand patterns.

The performance of an on-demand transit system is highly dependent on the strategy used to assign service vehicles to travel requests. The objective of the greedy algorithm used in this paper can intuitively be interpreted as maximizing service frequency for locations with the highest passenger counts with shared OD at any given time. With this objective it is likely that on-demand LoS performance is sensitive to alternative demand patterns, as stops with consistently lower passenger counts are continuously deprioritized. The reactive rebalancing policy is also likely to induce unnecessary deadhead trips for lower demand settings, where holding at the current stop rather than rebalancing may result in shorter average waiting times and VKT. Furthermore, the time windows of traveler requests are not considered and are thus weighted equally in counts regardless of desired departure or arrival time. The capacity of individual vehicles is also not considered in the sense that if a vehicle has been assigned to travel to the origin stop of a group of unassigned requests, a second vehicle will not be considered for this OD until the first has arrived and unserved demand remains. Without consideration of traveler time-windows, anticipated demand it is also speculated that the simplified on-demand strategy utilized in this paper is likely to underperform, with respect to variability of waiting times, a coordination strategy that takes these into account. The LoS and fleet utilization results of this paper for the on-demand service should in this sense be viewed as a conservative lower bound on potential performance.

Finally, it is worth emphasizing that both operational and capital cost changes induced by the automation of public transit is still highly uncertain. Furthermore, the uncertainty of changes in traffic dynamics, operational speeds, and passenger behavior with AVs and their influence on estimated performance are not negligible. While this limits the external validity of inferences one can make from the presented results, the simulation framework and study of this paper contribute in isolating important performance indicators and allowing the analysis of different specifications and design alternatives of fixed and on-demand transit systems.

Acknowledgments

This paper is part of the SMART (Simulation and Modeling of Autonomous Road Transport) project, financed by the Swedish Transport Administration Trafikverket. This support is gratefully acknowledged.
References


