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The Share-A-Ride Problem with Integrated Routing and Design Decisions: The Case of Mixed-Purpose Shared Autonomous Vehicles

Max van der Tholen, Breno A. Beirigo, Jovana Jovanova,
and Frederik Schulte(✉)

Delft University of Technology, Delft, The Netherlands
{m.p.vandertholen,b.alvesbeirigo,j.jovanova,f.schulte}@tudelft.nl

Abstract. The shared autonomous vehicle (SAV) is a new concept that meets the upcoming trends of autonomous driving and changing demands in urban transportation. SAVs can carry passengers and parcels simultaneously, making use of dedicated passenger and parcel modules on board. A fleet of SAVs could partly take over private transport, taxi, and last-mile delivery services. A reduced fleet size compared to conventional transportation modes would lead to less traffic congestion in urban centres. This paper presents a method to estimate the optimal capacity for the passenger and parcel compartments of SAVs. The problem is presented as a vehicle routing problem and is named variable capacity share-a-ride-problem (VCSARP). The model has a MILP formulation and is solved using a commercial solver. It seeks to create the optimal routing schedule between a randomly generated set of pick-up and drop-off requests of passengers and parcels. The objective function aims to minimize the total energy costs of each schedule, which is a trade-off between travelled distance and vehicle capacity. Different scenarios are composed by altering parameters, representing travel demand at different times of the day. The model results show the optimized cost of each simulation along with associated routes and vehicle capacities.

Keywords: Shared autonomous vehicles · Capacity optimization · Vehicle routing problem

1 Introduction

Urbanization is a phenomenon that is becoming ever more apparent across the world. Already in 2018, over 55% of the world's population was located in urban areas with prospects of an increase to almost 70% mid-21st century [22]. The ongoing demographic changes within cities give cause for new developments in the transportation of people and goods. Other trends too will have an impact on transport within urban centres. E-commerce is growing fast, with a massive demand for business-to-customer movements. On top of that comes a desire for

quick deliveries, sometimes even as fast as a couple of hours. Another trend is that of the sharing economy, in which customers and businesses share resources, potentially reducing freight movements and fleet sizes. Finally, climate change awareness and sustainability play an ever-increasing role in reducing emissions and improve quality of life in heavily congested areas [20]. With these aspects in mind, new approaches to vehicle design are taken.

The development of autonomous vehicles is expected to bring significant changes to the mobility patterns of vehicle users. Connecting vehicles through an internet of autonomous vehicles enables services such as intelligent transportation and ridesharing [10]. The concept of ridesharing promises to improve the efficiency of individual, on-demand transportation in densely populated areas. Combining the benefits of autonomous driving and ridesharing allows for the introduction of autonomous mobility-on-demand (AMoD). This approach consists of fully autonomous driving vehicles that can combine multiple traveling requests into one journey. AMoD has the potential to reduce traffic congestion and parking problems while offering fast, on-demand mobility, relieving passengers from the task of driving, and improving safety [24].

Naturally, not only the transport of passengers in urban areas is growing. Transportation of goods through parcel delivery is increasing and is required to become faster and cheaper. Short trips through cities, such as last-mile delivery services, could potentially be done by purpose-built autonomous vehicles (AV) [4].

While AMoD can already be more efficient and sustainable than a conventional approach, the results heavily depend on traveller demand. Passenger request numbers are typically much higher at day time than at night and peak during morning and afternoon rush hours [3]. As a result, large portions of the fleet of vehicles will be idle or inefficiently occupied during low-demand periods. Unifying the separate vehicle fleets for passenger and parcel transport into one fleet with mixed-purpose vehicles can be a solution to improve occupancy levels and further reduce the number of vehicles on the roads. This share-a-ride approach was introduced by Li et al. [12], where taxis can combine single parcel and rider requests, and later expanded by Beirigo et al. [1] in the context of the share-a-ride with parcel lockers problem (SARPLP).

The SARPLP considers autonomous vehicles with passenger compartments and parcel lockers, such that both commodity types can be transported simultaneously on single journeys. The effectiveness of this concept has been proven, and 92% of simulated scenarios result in higher profit with one mixed-purpose fleet rather than two single-purpose fleets [1]. However, the model relies on a fixed vehicle capacity. While proving effective, this approach hardly links the logistic challenges of shared autonomous driving to the design of shared autonomous vehicles (SAV). Varying the capacity of SAVs is still an unexplored area.

This study seeks to create a model for a people and freight integrated transportation system (PFIT) in an AMoD setting with variable vehicle capacity. We aim to find the optimal capacity for mixed purpose SAVs whose internal space can be outfitted to simultaneously transport passengers and parcels. This optimal capacity can then be used to constrain the design and give an early

approximation of the dimensions and features of SAVs according to the demand patterns of the service area. The outcome shows whether the SAV will look like an ordinary passenger car, a large bus, or anything in between. From this point on, the problem will be referred to as the variable capacity share-a-ride problem (VCSARP).

This paper will continue by mentioning some of the relevant literature that is related to the subject. After that, the problem definition and model formulation are explained. Next, the experimentation section will picture the scenarios and give the results of the simulations. The final section will summarize the findings, conclude the current research and give recommendations for further research.

2   Related Work

The vehicle routing problem (VRP) is a classical optimization problem that aims to determine the optimal set of routes to be taken by a fleet of vehicles to serve a set of customers [21]. The first mathematical programming formulation and algorithmic approach for the VRP was the truck dispatching problem by Dantzig and Ramser [7] from 1959. Ever since, efforts have been made to extend VRPs and make them more realistic. The VCSARP is based on a combination of previous VRPs. The Dial-a-Ride Problem (DARP) is a well-known VRP variation that consists of designing vehicle routes for on-demand pick-up and delivery requests. The DARP is built up from a combination of existing VRPs, including the Pick-up and Delivery Vehicle Routing Problem and the Vehicle Routing Problem with Time Windows [6]. With the popularization of app-based transportation services, the DARP has been the basis for passenger ridesharing services (see, e.g., [13,19]). More recently, the advantages of autonomous vehicles for ridesharing have been explored, for instance, considering service quality improvements when platforms activate idle/ parked vehicles [2].

However, short-haul integration of passenger and good flows is hardly observed both in practice [20] and in the literature [15], especially in a ridesharing context. Among the few models for PFIT systems is the SARP, an extension of the DARP introduced by Li et al. [12] that allows taxis to transport one passenger and one parcel simultaneously. This problem has been further covered by Nguyen et al. [16] and Do et al. [8], where a taxi is able to carry one passenger and multiple parcels. A more flexible version of the SARP is the SARPLP [1], in which the vehicles consist of passenger compartments and parcel lockers, thus being able to serve several customers at once. This study shows that a shared, mixed-purpose fleet proves more profitable to the transport company. More work on passenger and parcel ridesharing was done by Ronald et al. [18]. Their model considers passengers requesting transport between homes and activity locations and parcels that are transported from shops to homes. Ultimately, they find that ridesharing resources in vans and taxis results in shorter waiting and travel times. Finally, to the best of our knowledge, the only noteworthy contribution considering variable capacity and VRPs is by Louveaux and Salazar-González [14]. Their model, however, does not consider any ridesharing.

3   Problem Description

The VCSARP aims to create the most cost-effective routing schedule for SAVs across a city with a known set of transport requests. The requests consist of pick-up and delivery points and need to be satisfied within a certain time window. The SAVs start and end their routes at a centrally located depot. The output of the model gives the total cost of the routing and the optimal vehicle capacity that is needed to achieve this. The MILP model is explained in the remainder of this section.

3.1   Model Formulation

The virtual city in which the SAVs operate is expressed as a 20 by 20 grid structure with intervals of 100 m between each node. Within this grid structure, a total of n transport requests is generated, split up into n_h passenger and n_p parcel requests. V represents the complete set of nodes, including requests and start/end depot, while A represents the arcs connecting all those nodes. The distances and travel times between all nodes are captured by $d_{i,j}$ and $t_{i,j}$ respectively.

The requests are characterised by their quantity q_i^r, where resource r is 0 for a passenger request or 1 for a parcel request. Pick-up quantities q_i^r are generated as positive amounts and drop-off quantities q_{i+n}^r are of the same magnitude but negative, representing a loss of load. Each request has a pickup time window $[e_i, l_i]$, which is T^r wide, and a maximum travel time delay δ^r. Both must be satisfied for a feasible solution. All requests are generated within a time horizon H. Each pick-up and delivery stop has a service time delay s.

The set of vehicles is K. Each vehicle has a capacity Q^r, which is variable but constrained by an upper and lower bound $[Q_{min}^r, Q_{max}^r]$ for realism and computational speed. The velocity of the vehicles is assumed to be constant and the same across each arc in A.

The model seeks to minimize the total costs of a routing schedule. The total costs are calculated as the product of travelled distance and cost per unit of distance that varies with vehicle type). The vehicle capacity impacts the travel cost per kilometer because larger-capacity vehicles are heavier and bulkier, thus consuming more energy. This relationship between vehicle capacity and operating costs is visualized in Fig. 1. A complete overview of variables, parameters, sets, and indices needed for the formulation of the VCSARP can be seen in Table 1.

Figure 2 shows some examples of how the VCSARP model works. Each scenario has two passenger and two parcel requests. When requests are positioned close together and very few detours have to be made, the model will most likely choose a larger capacity vehicle to serve multiple requests simultaneously. Figure 2a shows this case. Assuming that each request quantity is equal to 1, the minimum vehicle capacity for the vehicle in this scenario must be 2 for passengers and 2 for parcels. Figure 2b shows a case where the requests are not all located favourably. Here one large vehicle is not able to fulfill all the requests

within their time windows. Using smaller vehicles covering slightly larger distances might even be more efficient. The vehicle capacity in this scenario is 1 for passengers and 2 for parcels.
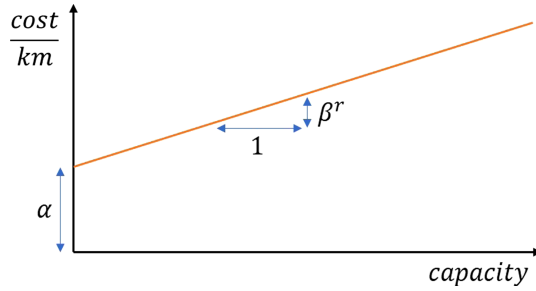
Fig. 1. Linear relation between vehicle capacity and operating cost per unit of distance. Constants α and β^r are explained in Sect. 4.
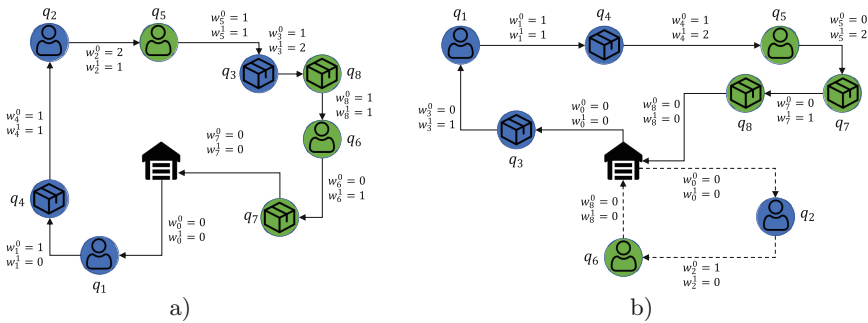
Fig. 2. Two examples of the VCSARP. Blue nodes are pick-ups and green nodes are drop-offs. Example a) shows a scenario in which only one vehicle (solid path) is deployed from the depot. Example b) shows a situation where one vehicle is not sufficient to meet all the constraints, such that two vehicles are deployed (solid and dashed paths). Vehicle loads along each path are displayed for each resource, where q_i^r is the amount of resources that must be loaded at node i and w_i^k is the load of resources on vehicle k after node i. (Color figure online)

Table 1. Sets, indices, parameters and variables of the VCSARP.

Sets and indices	
P_h	$= \{1, ..., n_h\}$. Human pickup nodes
P_p	$= \{n_h + 1, ..., n\}$. Parcel pickup nodes
P	$= P_h \cup P_p$. All pickup nodes
D_h	$= \{n + 1, ..., n + n_h\}$. Human drop-off nodes
D_p	$= \{n + n_h + 1, ..., 2n\}$. Parcel drop-off nodes
D	$= D_h \cup D_p$. All drop-off nodes
V	$= \{0\} \cup P \cup D \cup \{2n + 1\}$. All nodes including start/end depots
A	$= \{i, j : i \in V, j \in V, i \neq j\}$. Arcs connecting all nodes
K	$= \{1, ..., n_k\}$. Vehicles
R	$= \{0, 1\}$. Resources (0 = human, 1 = parcel)
Parameters	
n_h	Number of passenger requests
n_p	Number of parcel requests
n	$= n_h + n_p$. Total number of requests
n_k	Number of vehicles
v_{avg}	Average vehicle velocity
$d_{i,j}$	Shortest distance between nodes i and j
$t_{i,j}$	Shortest travel time between nodes i and j
q_i^r	Amount of resource r that must be loaded at node i
$\{e_i, l_i\}$	Time window for request i
T^r	Pickup time window width for each resource r
H	Time horizon
δ^r	Maximum ride time delay for each resource r
s	Service time
Q_{min}^r	Lower bound of vehicle capacity for each resource r
Q_{max}^r	Upper bound of vehicle capacity for each resource r
α	Constant of the objective function
β^r	Slope of the objective function for each resource r
pp_h	Passenger pickup probability [residential, industrial, campus]
dp_h	Passenger delivery probability [residential, industrial, campus]
pp_p	Parcel pickup probability [residential, industrial, campus]
dp_p	Parcel delivery probability [residential, industrial, campus]
Variables	
$x_{i,j}^k$	Traveled arcs (i, j) of each vehicle k
τ_i^k	Arrival time of vehicle k at node i
$w_i^{r,k}$	Load of each resource r on vehicle k after node i
tr_i^k	Ride time of pickup i on vehicle k
Q^r	Vehicle capacity for each resource r

3.2 Model Formulation

The MILP formulation of the model is as follows:

Minimize:

$$C = \sum_{i,j \in A} \sum_{r \in R} \sum_{k \in K} (\alpha + \beta^r Q^r) d_{i,j} x_{i,j}^k \tag{1}$$

Subject to:

$$\sum_{\substack{j \in V \\ j \neq i}} \sum_{k \in K} x_{i,j}^k = 1 \qquad\qquad \forall i \in P \tag{2}$$

$$\sum_{\substack{j \in V \\ j \neq 0}} x_{0,j}^k = \sum_{\substack{i \in V \\ i \neq 2n+1}} x_{i,2n+1}^k = 1 \qquad\qquad \forall k \in K \tag{3}$$

$$\sum_{\substack{j \in V \\ j \neq i}} x_{i,j}^k = \sum_{\substack{j \in V \\ j \neq i+n}} x_{i+n,j}^k \qquad\qquad \forall i \in P, \forall k \in K \tag{4}$$

$$\sum_{\substack{j \in V \\ j \neq i}} x_{j,i}^k = \sum_{\substack{j \in V \\ j \neq i}} x_{i,j}^k \qquad\qquad \forall i \in N, \forall k \in K \tag{5}$$

$$\tau_j^k = (\tau_i^k + t_{i,j} + s) x_{i,j}^k \qquad\qquad \forall i,j \in A, \forall k \in K \tag{6}$$

$$\tau_{i+n}^k \geq \tau_i^k \qquad\qquad \forall i \in P, \forall k \in K \tag{7}$$

$$e_i \leq \tau_i^k \leq l_i \qquad\qquad \forall i \in P, \forall k \in K \tag{8}$$

$$w_j^{r,k} \geq (w_i^{r,k} + q_j^r) x_{i,j}^k \qquad\qquad \forall i,j \in A, \forall r \in R, \forall k \in K \tag{9}$$

$$\max(0, q_i^r) \leq w_i^{r,k} \leq Q^r \qquad\qquad \forall i \in V, \forall r \in R, \forall k \in K \tag{10}$$

$$Q_{min}^r \leq Q^r \leq Q_{max}^r \qquad\qquad \forall r \in R \tag{11}$$

$$tr_i^k = \tau_{i+n}^k - \tau_i^k \qquad\qquad \forall i \in P, \forall k \in K \tag{12}$$

$$t_{i,i+n} \leq tr_i^k \leq t_{i,i+n} + \delta^r \qquad\qquad \forall i \in P, \forall r \in R, \forall k \in K \tag{13}$$

$$x_{i,j}^k \in \{0,1\} \qquad\qquad \forall i,j \in A, \forall k \in K \tag{14}$$

$$\tau_i^k \in \mathbb{N} \qquad\qquad \forall i \in V, \forall k \in K \tag{15}$$

$$w_i^{r,k} \in \mathbb{Z} \qquad\qquad \forall i \in V, \forall r \in R, \forall k \in K \tag{16}$$

$$tr_i^k \in \mathbb{N} \qquad\qquad \forall i \in V, \forall k \in K \tag{17}$$

$$Q^r \in \mathbb{Z} \qquad\qquad \forall r \in R \tag{18}$$

The objective function (1) aims to minimize the total cost, which is calculated as (cost/km)*(travelled distance). Based on [11] and [23], we consider the energy consumption and running costs (denoted by cost/km) increase linearly with vehicle capacity. Parameters α and β^r are the intercept and slope of the linear function and are quantified in Sect. 4. Equation (2) guarantees that each request is served once. Each vehicle must start and end its route at the depot, which is controlled by (3), while (4) ensures that pick-up and delivery of one request are done

by the same vehicle. The final routing constraint (5) guarantees conservation of flow, meaning that a vehicle entering a node must also leave that node again. The definition of the arrival time of SAVs at nodes is given by (6). Vehicles must first complete the pick-up of a request before the drop-off, which is guaranteed by (7). Equation (8) ensures that arrival at the pick-up nodes is on time and within the required time window. The vehicle load or weight after each node is defined by Eq. (9). This load must never become negative, be always larger than the previous request quantity, and never exceed the maximum loading capacity, of which (10) makes sure. The vehicle capacity has a lower and upper bound, which are imposed by (11). Each request has a total time spent on the vehicle. The minimum ride time is given by (12). The actual ride time cannot exceed this by more than the maximum ride time delay, which is guaranteed by (13). The model's five decision variables are traveled arcs, arrival times, compartment loads, ride times, and vehicle capacities. These are defined respectively by (14), (15), (16), (17), and (18).

4   Experimental Study

Once traffic flows and transportation demand fluctuate throughout the day, we carry out an experimental study to obtain insights into the ideal capacity of an SAV considering different demand scenarios. Ideally, an SAV system should function efficiently at any time, consistently featuring high occupancy rates and low idleness. First, to simulate the various times of day in which an SAV operates, the following scenarios have been considered:

– **Morning rush hour:** During morning hours, there is a high density of passenger requests from homes to workplaces. This causes traffic to flow from residential areas to industrial and commercial areas. The amount of parcel movements is significantly smaller.
– **Afternoon:** A well-mixed blend of parcel and passenger movements. Parcels tend to move from industrial areas towards residential areas, while passenger travel patterns are more evenly distributed across the city.
– **Late-afternoon rush hour:** Similar to the morning hours, passenger demand is higher than parcel demand. However, passenger traffic flow is reversed from industrial/commercial areas to residential areas.
– **Evening:** The time of day at which most people are at home creates great opportunities for parcel deliveries. This scenario is dominated by parcel transport requests from industrial to residential areas, but some scattered passenger transport occurs too.

Considering that previously the city map was formulated as a rather abstract grid structure without any information on the function of each node, neighbourhoods are added to the grid. These are described as four rectangular sections on the map. Two sections are representing residential areas, one section is an industrial area, and the final section is a campus with a university and offices. These sections or neighbourhoods can now be used to create scenarios. Request

locations are generated using a probability distribution that can shape the traffic flow patterns of the scenario. For example, in the morning scenario, there will be a high probability that passenger pick-ups will occur on any of the nodes within the residential areas and a much lower probability of them occurring at industrial or campus nodes. Likewise, passenger destinations will more likely occur in the industrial or campus neighbourhood, rather than in one of the residential areas. A visual representation of the map with the different neighbourhoods is shown in Fig. 3.
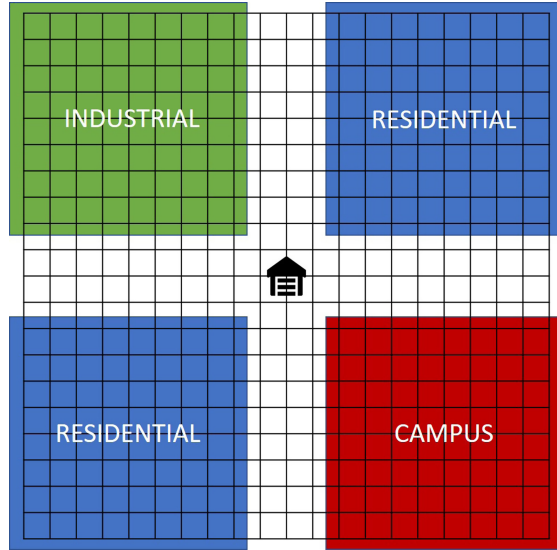
Fig. 3. City grid divided into neighbourhoods with different functions. The depot is located in the middle.

The general parameters of the VCSARP are constant across all scenarios. The total number of requests and available vehicles are set to 8 and 4, respectively. These relatively low numbers are needed to limit computation times, which can become very large due to the complexity of the model. To make up for the low number of requests, request quantities are chosen randomly from a $U(4, 8)$ distribution. The case of a few large requests (quantities between 4 and 8) can be considered analogous to a larger number of smaller requests with similar origin and destination, essentially creating a scenario that serves much more customers. The parcel and passenger capacity lower and upper bounds are both set to 4 and 24, respectively. Assuming that one passenger seat takes up the space of about 4 large parcels, that results is a total "passenger size" capacity between 4 and 30. Passenger time windows and delivery delays are set quite tight once most people would not want to experience much delay during their trip. Conversely, parcel time constraints are much less strict, allowing for a maximum delay of 1 h

at delivery. The average speed is set at 20 km/h, which is realistic in cities with short stopping intervals [17]. A short 10-min total time horizon is chosen because of the small number of requests. To simulate the (un)loading of resources, a 1-min service time at each node is added. The objective function parameters α and β^r are retrieved from real-life electricity costs and consumption data of electric vehicles (see [9] and [5]) (Tables 2 and 3).

Table 2. General parameter values.

Parameter	Value
n	8
n_k	4
q_i^0	$U(4,8)$
q_i^1	$U(4,8)$
$[Q_{min}^0, Q_{max}^0]$	[4,24]
$[Q_{min}^1, Q_{max}^1]$	[4,24]
T^0	3 min
T^1	30 min
δ^0	10 min
δ^0	10 min
v_{avg}	20 km/h
H	10 min
s	1 min
α	0.022 euro/km
β^0	0.00308 euro/(km $\times$ passenger)
β^1	0.00077 euro/(km $\times$ parcel)

Table 3. Scenario specific parameter values.

Parameter	Scenario			
	Morning	Afternoon	Late-afternoon	Evening
Number of requests				
n_h	6	4	6	2
n_p	2	4	2	6
Pickup and delivery probabilities [res, ind, cam]				
pp_h	[1, 0, 0]	[$1/3$, $1/3$, $1/3$]	[0, $1/2$, $1/2$]	[$1/3$, $1/3$, $1/3$]
dp_h	[0, $1/2$, $1/2$]	[$1/3$, $1/3$, $1/3$]	[1, 0, 0]	[$1/3$, $1/3$, $1/3$]
pp_p	[0, 1, 0]	[$1/5$, $4/5$, 0]	[0, 1, 0]	[$1/5$, $4/5$, 0]
dp_p	[1, 0, 0]	[$4/5$, $1/5$, 0]	[1, 0, 0]	[$4/5$, $1/5$, 0]

5   Results

The computations were performed by an Intel Core i7 @ 2.20 GHz processor, 16 GB RAM computer. The programming was done in Python, and the MILP model was solved using Gurobi Optimizer 9.0.2.

Table 4 shows for each scenario the average optimal vehicle capacity for both resources and the total vehicle capacity (i.e., the combination of passenger and parcel capacities). One passenger space is considered the same size as 4 parcel spaces. A vehicle with a passenger capacity of 4 and a parcel capacity of 8 would thus have a total capacity of 6. This value determines the overall interior volume of the vehicle, which can be of use for the design of the vehicle, and, ultimately, the number of vehicles used. Simulations that did not converge to a 0% optimality gap, thus not reaching the most optimal solution, within a 30-min time limit were discarded. In total, at least 30 simulations with optimal solutions were generated for each of the four scenarios. Table 5 shows the average total costs, distance travelled, and cost/km across scenarios and Fig. 4 illustrates the outcome routes of a single simulation for each scenario.

Table 4. The results of each scenario that are related to vehicle capacity and design. These are average values from 30 instances on each scenario.

Scenario	Passenger cap.	Parcel cap.	Total cap.	# of vehicles
Morning	12.8	8.23	14.9	3.60
Afternoon	8.50	11.9	11.5	3.31
Late-afternoon	12.9	8.93	15.2	3.50
Evening	6.75	17.6	11.1	2.05

Table 5. Average costs, distance travelled, and cost/km for each scenario across 30 different instances.

Scenario	Costs [e]	Distance travelled [km]	Cost/km [e/km]
Morning	1.84	20.6	0.0898
Afternoon	1.46	18.3	0.0793
Late-afternoon	1.67	18.5	0.0907
Evening	1.14	15.1	0.0783

Table 4 shows that the optimal vehicle composition and fleet size differ markedly for each scenario. As input parameters heavily influence the model's outcome, engineers can take multiple approaches to design suitable SAVs that ultimately match the operational requirements. The most straightforward approach would be designing vehicles using the maximum capacity for each resource

across all scenarios, resulting in a vehicle with around 15 passenger seats and 18 parcel spaces. Naturally, these vehicles would end up under-occupied most of the time, and costs would be higher than calculated, but most requests could be satisfied easily. Another approach consists of repeating the simulations for the afternoon and evening scenarios with adjusted capacity constraints. Considering that vehicles tend to be idler in these scenarios, using a smaller parcel capacity and deploying more vehicles would also satisfy the conditions. This results in higher overall costs but more efficient vehicle occupation.
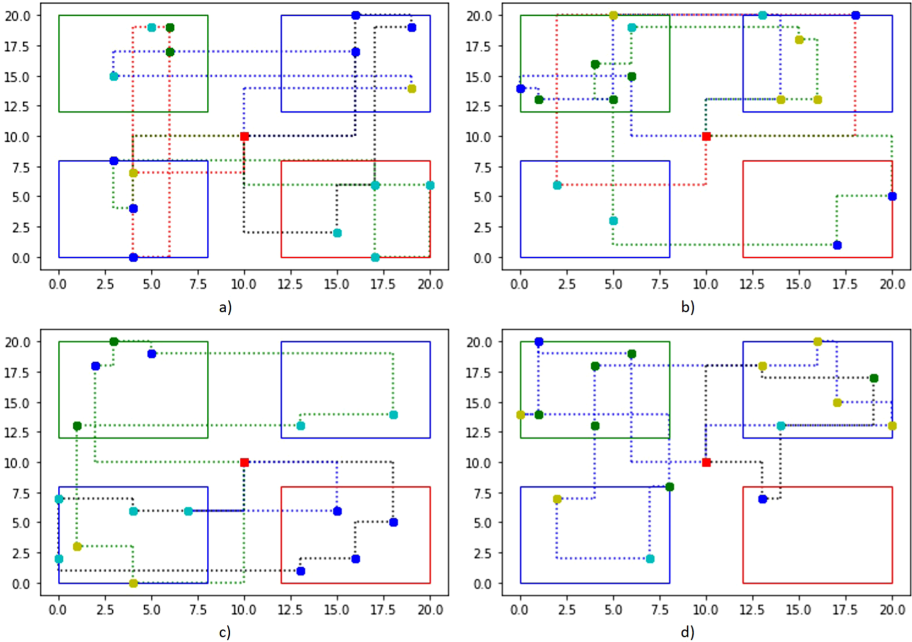
Fig. 4. The results of 4 simulations, where a) is a morning scenario, b) is an afternoon scenario, c) is a late-afternoon scenario, and d) is an evening scenario. The red node is the depot, the blue nodes are human pick-ups, the cyan nodes are human drop-offs, the green nodes are parcel pick-ups and the yellow nodes are parcel drop-offs. Different colour dotted lines represent different vehicles in operation. The neighbourhoods are also displayed, as rectangles (see Fig. 3). (Color figure online)

6   Conclusions

This research paper presented a MILP formulation for the variable capacity share-a-ride problem. The SARP was reformulated to set vehicle capacity as a decision variable and allow for shared autonomous vehicles. The objective was to find the optimal capacity of SAVs to give insights into the design of such vehicles given several operational scenarios, featuring various parcel and people demand patterns.

Overall, the model provides a basis for estimating the optimal capacity of SAVs in a static scenario. The parameter inputs are flexible and allow for a wide variety of scenarios. A point of critique is the limited number of requests that the model is able to solve within a reasonable time. This was countered by using larger quantity requests, each representing multiple single requests that have similar origins and destinations.

The results show that the optimal capacity is highly dependent on the scenario parameters. Scenarios with high passenger transport demand call for vehicles with large passenger capacity and smaller parcel capacity. Scenarios with more parcel movements have an opposite effect on both capacities. While this is to be expected, it makes it hard to find an optimum capacity that will satisfy all scenarios and be cost-efficient at the same time. The concept of SAV in this paper uses separate compartments for passenger and parcel transport. Empty passenger spaces cannot be used for parcels and vice versa. One could rethink this concept and go for a more flexible utilization of interior space. Possible solutions include foldable seats for additional parcel storage, under-seat storage of parcels, or a simple flat floor with standing/leaning space for passengers and freely usable space for parcels. These concepts could easily be implemented into the current model with simple reformulations. Alternatively, a more flexible solution could be considered, where AVs are dynamically outfitted at service points, having their people and parcel compartment capacity adjusted to match the demand changes. Future work will focus on modeling such a flexible setting considering additional operational characteristics such as different revenues for passengers and parcels, penalties for extended ride time, premiums for private travel requests, vehicle and compartment purchasing costs.

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