Integrating people and freight transportation using shared autonomous vehicles with compartments

Beirigo, Breno A.; Schulte, Frederik; Negenborn, Rudy R.

DOI
10.1016/j.ifacol.2018.07.064

Publication date
2018

Document Version
Final published version

Published in
IFAC-PapersOnLine

Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 51-9 (2018) 392–397

Integrating People and Freight Transportation Using Shared Autonomous Vehicles with Compartments

Breno A. Beirigo, Frederik Schulte, Rudy R. Negenborn

Department of Maritime & Transport Technology, Delft University of Technology, The Netherlands (b.alvesbeirigo@tudelft.nl, f.schulte@tudelft.nl, r.r.negenborn@tudelft.nl).

Abstract: In the realm of human urban transportation, many recent studies have shown that comparatively smaller fleets of shared autonomous vehicles (SAVs) are able to provide efficient door-to-door transportation services for city dwellers. However, because of the steady growth of e-commerce and same-day delivery services, new city logistics approaches will also be required to deal with last-mile parcel delivery challenges. We focus on modeling a variation of the people and freight integrated transportation problem (PFIT problem) in which both passenger and parcel requests are pooled in mixed-purpose compartmentalized SAVs. Such vehicles are supposed to combine freight and passenger overlapping journeys on the shared mobility infrastructure network. We formally address the problem as the share-a-ride with parcel lockers problem (SARPLP), implement a mixed-integer linear programming (MILP) formulation, and compare the performance of single-purpose and mixed-purpose fleets on 216 transportation scenarios. For 149 scenarios where the solver gaps of the experimental results are negligible (less than 1%), we have shown that mixed-purpose fleets perform in average 11% better than single-purpose fleets. Additionally, the results indicate that the busier is the logistical scenario the better is the performance of the mixed-purpose fleet setting.

Keywords: Ride-sharing; People and freight integration; Autonomous vehicles; Pick-up and delivery problem; Sustainable transportation.

1. INTRODUCTION

The world's level of urbanization is likely to steadily increase in the next decades: 2.5 billion people are projected to be added to urban centers by 2050 (UN, 2014). This growth tends to be accompanied by a series of underlying repercussions: while urban land will increasingly become scarce, the demand for cities services and infrastructure will probably rise as well. Besides, the steady growth of online retail and the recent development of speedy delivery services, such as same-day deliveries, are also expected to increase the number of freight movements inside urban centers, challenging even further cities' mobility infrastructure (Savelsbergh and Woensel, 2016). As a result, current deficiencies in urban mobility, such as lack of parking spaces, congestion, and low vehicle occupation rates, might be strongly intensified if the current mobility paradigm remains unaltered (Pavone et al., 2012).

Ride-sharing has been described in the relevant literature as a sustainable solution to mitigate such deficiencies. In fact, as demonstrated by (Tachet et al., 2017), most urban centers world-wide have a high, unexplored "shareability" rate, i.e., the majority of their current single-passenger rides could seamlessly be combined. Consequently, increasing the occupancy rates of vehicles by globally managing empty car seats could drastically improve the efficiency of urban transportation systems (Agatz et al., 2012). For a ride-sharing system to succeed, however, it must be as convenient as private car usage so that it is adopted by a sufficient number of users.

The long anticipated advent of autonomous vehicles (AVs) can possibly represent the necessary change to transportation systems that will finally jump-start widespread vehicle sharing (Spieser et al., 2014). As vehicle automation advances, commuting via shared, self-driving vehicles may eventually become as affordable as public transit modes (McKerracher et al., 2016). Then, stimulated by the additional convenience of a door-to-door on demand service, many passengers might be compelled to subscribe to an autonomous mobility-on-demand (AMoD) provider, reducing their vehicle ownership, and, as a result, cities' congestion and parking requirements (Litman, 2017). Besides reshaping public transit, AVs are also expected to impact last-mile delivery services. Joerss et al. (2016), for example, advocate that autonomous vehicles equipped with parcel lockers will enable affordable and convenient same-day and time-window delivery options in urban areas.

⋆ This research is supported by the project "Dynamic Fleet Management (P14-18 project 3)" (project 14894) of the Netherlands Organisation for Scientific Research (NWO), domain Applied and Engineering Sciences (TTW).

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2018.07.064

Recent studies have consistently shown that AMoD systems employing fleets of shared autonomous vehicles (SAVs), can be more efficient (Boesch et al., 2016; Alonso-Mora et al., 2017) and sustainable solutions (Fagnant and Kockelman, 2016) for urban logistics. However, they also show that vehicle occupation is highly dependent on demand fluctuation. In fact, passenger transportation demand greatly varies throughout the day (see, e.g., Stiles et al. 2014), so that any fleet, shared or not, would be inevitably idle during off-peak hours. As an alternative to harness the full potential of its vehicles, a fleet operator might take advantage of the inherited flexibility of parcel transportation to also meet freight demands whenever adequate. Besides improving profitability by dealing with passenger and parcel requests interchangeably, such integrated approach would also enable the creation of low cost routes by combining heterogeneous overlapping journeys.

Although people and freight integration is already present in some long-haul modes (e.g., aircrafts, ferries), short-haul integration is hardly observed in practice (Savelsbergh and Woensel, 2016). To the best of our knowledge, integration on a ride-hailing setting was only explored in (Li et al., 2014), (Li et al., 2016a) and (Li et al., 2016b). The authors describe the share-a-ride Problem (SARP), a variation of the well known dial-a-ride problem (DARP), in which people and parcels can share the same taxi. However, ride-sharing is limited in such approach, since each vehicle can only combine a single passenger request with a single parcel request.

In this study, we model and evaluate a people and freight integrated system (PFIT) in which both commodities, i.e., passengers and parcels, are transported simultaneously by compartmentalized mixed-purpose SAVs. We assume passenger compartments are private cabins tailored for human transportation whereas freight compartments can be parcel lockers of different sizes. Differently from previously mentioned SARP implementations, we consider all possible ride-sharing people and freight integration scenarios. Hence, each vehicle is allowed to (1) carry one or more passengers, (2) carry various sized parcels, and (3) carry a number of passengers and parcels. Finally, to assess the performance of such mixed-purpose fleets, we compare them with equivalent single-purpose fleets in which there is no people and freight integration.

The subsequent sections define the examined share-a-ride with parcel lockers problem (SARPLP) and present a mathematical model for the problem as well as a numerical study leading to managerial insights and conclusions for the future of shared autonomous transportation of passengers and parcels.

2. PROBLEM DEFINITION

We consider a PFIT system comprised of mixed-purpose SAVs with parcel lockers, i.e., shared vehicles featuring people and parcel compartments. Next, we identify some potential types of compartments as well as the commodities they are supposed to accommodate:

`XS`: documents, e.g., mail, envelopes;
`S`: small objects e.g., jewelry, electronics;
`M`: average sized objects e.g., bags, purses;
`L`: large objects e.g., suitcases, groceries;
`XL`: extra large objects e.g., household appliances;
`A`: adult seat;
`C`: children seat (above 3 years of age);
`B`: baby seat (under 3 years of age);
`W`: wheel chair space.

The set of human compartments is $H = \{A, C, B, W\}$ and the set of freight compartments is $F = \{XS, S, M, L, XL\}$. While passenger requests must be attended as soon as they are revealed, parcel requests have more flexible pick-up and delivery times, i.e., they do not have to be immediately addressed. This characteristic of the parcel transportation requests aims to emulate current courier services, in which senders and receivers previously agree on the delivery conditions. For instance, an online store might determine a 24h delivery policy whereas a restaurant might require a much shorter time span. In our static approach, however, we consider that the details of both types of request, such as, number of compartments, pick-up/delivery coordinates and time windows, are know in advance. Still, pick-up windows and travel delays are assumed to be much shorter for passenger requests.

Regarding the fares of the transportation service, we consider that human and freight commodities are charged not only according to the distance entailed by their rides, but also by the type of compartment specified in the demand. For freight transportation, for example, the cost can be proportional to the dimensions of the compartments. Ultimately, to properly determine a service fare a request must include (1) the pick-up and delivery coordinates and (2) the number of units required for a determined type of compartment. This information is essential during the scheduling phase: only vehicles whose available number of compartments match the order specifications are suited to attend a potential commodity transportation demand.

Theoretically, the problem can be modeled as a variant of the classic pick-up and delivery problem (PDP), in which transportation requests consist of point-to-point transports, i.e., movements of people or cargo between origins and destinations (Toth and Vigo, 2014; Berbeglia et al., 2010). According to Berbeglia et al. (2010), depending on the way vehicles move between points, such problems can be categorized as 1) many-to-many, 2) one-to-many-to-one and 3) one-to-one. In 1), any point can serve as a source or as a destination for any commodity and in 2), commodities might be transported from the depot to the customers and from the customers to the depot. Finally, in 3) each commodity has a given origin and a given destination, such as the door-to-door system presented in this study.

Figure 1 highlights the differences from Li et al. (2014) implementation, making explicit the concept of compartmentalized requests. A mixed-purpose SAV comprised of 5 compartments of type "A" and 5 compartments of type "XL" is supposed to find the best route to attend a set of transportation requests structured as follows: `id_request:id_compartment[number]`. From the departure moment until the delivery of the last customer, the load configuration of the vehicle in each point can be represented by the following sequence { 1:A[1]-XL[0], 3:A[3]-XL[0], 1':A[2]-XL[0], 3':A[0]-XL[0], 2:A[0]-XL[2], 4:A[2]-XL[2], 4':A[0]-XL[2], 6:A[3]-XL[2], 6':A[0]-XL[2], 5:A[0]-

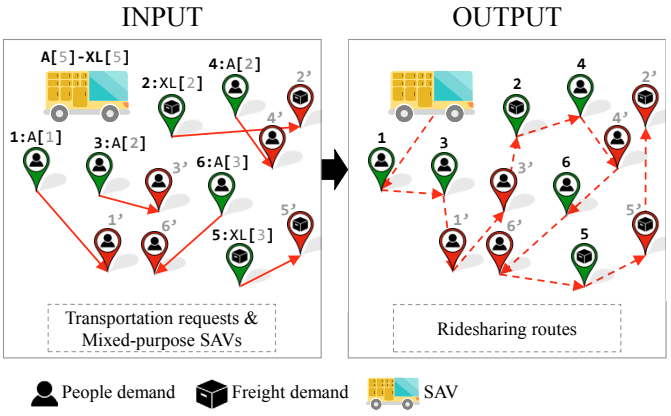

Fig. 1. Example of the operational behaviour of a PFIT system comprised of mixed-purpose capacitated SAVs. Passengers and parcels requests are consolidated in the same vehicle.

XL[5], 5':A[0]-XL[2], 2':A[0]-XL[0]}. Assuming the request's IDs are related with the order they are revealed, notice that the ride-sharing route generated privileges people demands, occasionally postponing the service at freight demands.

We extend the MILP model presented by Li et al. (2014) to define a pick-up and delivery problem able to handle the constraints involving our performance demands, vehicles' specifications and requests' heterogeneity. Firstly, we define a set K of vehicles such that each vehicle $k \in K$ is equipped with a set of available compartments C_k and geographically located at a starting point s_k. Additionally, for each vehicle k, the number of compartments $c \in C_k$ is $Q_c^k > 0$. From the vehicles' compartments definition, we can derive the overall set of compartments $C = \{C_1 \cup C_2 \cup ...C_k... \cup C_{|K|}\}$. The set of compartments C can be further partitioned into two sets, F and H, according to the nature of the commodity being transported, namely, freight or human.

Secondly, we define a request as a transportation demand to move commodities between two geographical points in a map. Hence, given a set of requests R, every request $i \in R$ determines a set of compartment demands $D_i \subseteq C$ as well as the number of units q_i^c of compartment $c \in D_i$. We assume that all compartment demands D_i can be totally satisfied by a vehicle $k \in K$, therefore $\forall i \in R$ $\exists k \in K : D_i \subseteq C_k \wedge \forall c \in D_i, q_i^c \leq Q_c^k$. Furthermore, besides defining a transportation demand, every request i has an origin destination pair (pk_i, dl_i), so that the set of requests' pick-up nodes can be defined as $P = \{pk_i : i \in R\}$ and the set of requests' delivery nodes as $D = \{dl_i : i \in R\}$. Following Cordeau et al. (2007)'s DARP formulation, the SARPLP is defined on a directed graph $G = (V, E)$ in which the vertex set V is partitioned into $\{P, D, O, f\}$ where $O = \{s_1, s_2, s_3, ..., s_k, ..., s_{|K|}\}$, i.e., the set of vehicles' starting points and f is an dummy final point where all vehicles are supposed to finish. Defining O and f is necessary to model the particular characteristics of a free-floating fleet, in which vehicles can depart from different locations and finish at the delivery location of their last attended request.

Thirdly, to guarantee an adequate flow of commodities, compartment demands are associated to all nodes in V. For each request $i \in R$ and compartment $c \in D_i$, we assume that $q_{pk_i}^c \geq 0$ and $q_{dl_i}^c = -q_{p_i}^c$. In turn, $q_f^c = 0$ $\forall c \in C$ and $q_{s_k}^c = 0$ $\forall k \in K, \forall c \in C_k$.

Then, to create a set of edges E in which any vehicle $k \in K$ can only traverse arcs $(i, j) \in (V, V)$ where both compartment demands of i and j match k's loading capabilities, we define the following auxiliary sets, V_w and V_v. V_w is the set of tuples (i, k, c) where each tuple indicates that a demand for an individual compartment c of a node i can be attended by vehicle k, i.e., $V_w = \{(i, k, c) : i \in V, k \in K, c \in C_k \cap D_i, Q_k^c \geq | q_i^c |\}$. In turn, V_v is the set of tuples (k,i) where each tuple indicates vehicle k can completely accommodate all compartment demands of node i, i.e., $V_v = \{(k, i) : k \in K, i \in V, \forall c \in C_k, (i, k, c) \in V_w\}$. Thus, the set of valid edges

Table 1. Variables and parameters for the SARPLP formulation.

Compartments	
C	$\{c : c \in C_k \forall k \in K\}$. Additionally, $C = \{H, F\}$, i.e., C is a composite of human and freight commodities.
α_c	Initial fare for delivering commodity $c \in C$.
β_c	Fare charged for delivering the commodity c based on the direct estimated travel time (in seconds).
d_c^{pk}	Pickup delay associated with the embark/load of commodity $c \in C$.
d_c^{DL}	Delivery delay associated with the disembark/unload of commodity $c \in C$.
Requests	
R	Set of requests.
(pk_i, dl_i)	Pick-up and delivery pair of request $i \in R$.
P	Set of requests' pick-up points, $P = \{pk_i : i \in R\}$.
D	Set of requests' delivery points $D = \{dl_i : i \in R\}$.
D_i	Set of demanded compartments of request $i \in R$.
q_i^c	Amount of compartments of type $c \in C$ requested by vertex $i \in D_i$.
ϖ_i^{pk}, ϖ_i^{tt}	Maximum pick-up and travel time delays of request $i \in R$.
$[e_i, l_i]$	Pick-up time window for request $i \in R$, where $l_i = e_i + \varpi_i^{pk}$.
d_i	Delay at node $i \in P \cup D$. If $i \in P, d_i = \sum_{c \in D_i} q_i^c * d_c^{pk}$ and if $i \in D, d_i = \sum_{c \in D_i} q_i^c * d_c^{DL}$.
Vehicles	
K	Set of all vehicles.
s_k	Start point of vehicle k.
O	Start points of all vehicles $k \in K$.
C_k	Set of compartments c present in vehicle $k \in K$.
Q_c^k	Number of compartments of type $c \in C_k$ of vehicle $k \in K$.
γ_k	Average operational cost/s (fuel, tolls, etc.) of vehicle k.
Model ancillary entities	
f	Dummy final destination point to which all vehicles must finish in.
V	$= P \cup D \cup O \cup \{f\}$.
$t_{i,j}$	Travel time between nodes i and j in seconds. $t_{if} = 0, \forall i \in P \cup D \cup O$.
V_w	Valid loads. Set of tuples representing valid load configurations, $V_w = \{(i, k, c) \mid i \in V, k \in K, c \in C_k \cap D_i, Q_k^c \geq \mid q_i^c \mid \}$.
V_v	Valid visits. A vehicle $k \in K$ can attend a request i only if i's demand can be completely accommodated. The set of valid visits $V_v = \{(k, i) \mid k \in K, i \in V, \forall c \in C_k, (i, k, c) \in V_w\}$.
E	Valid rides. Set of tuples representing the viable rides of vehicle k from point i to point j. $E = \{(k, i, j) : k \in K, i, j \in V, i \neq j, j \notin o_k, i \neq f, (k, i), (k, j) \in V_v\}$.
Model variables	
$X_{i,j}^k$	Binary decision variable equal to 1 if vehicle $k \in K$ travels from point $i \in V$ to point $j \in V$, with $i \neq j$.
τ_i^k	Arrival time of vehicle k at point i.
r_i^k	Time spent by request $i \in R$ in vehicle $k \in K$.
$w_i^{k,c}$	Load of compartment $c \in C_k$ of vehicle $k \in K$ after visiting point $i \in V$. For $w_{o_k}^{k,c} = w_i^{k,c}$

E is comprised of tuples (k, i, j) representing a viable ride from vertex i to vertex j traveled by vehicle k, i.e., $E = \{(k, i, j) : k \in K, i, j \in V, i \neq j, j \notin o_k, i \neq f, (k, i) \in V_v, (k, j) \in V_v\}$. Finally, we define as t_{ij} the time spent by any vehicle k to go from vertex i to vertex j. Table 1 compiles the previously defined entities and defines the remainder parameters necessary to build the model.

The formulation of the SARPLP is as follows:

Maximize:

$$\sum_{\substack{(k,i,j)\in E\\ i\in P}} \sum_{c\in D_i} (\alpha_c + \beta_c t_{i,dl_i}) X^k_{i,j} - \sum_{(k,i,j)\in E} \gamma_k t_{i,j} X^k_{i,j} \tag{1}$$

Subject to:

$$\sum_{(k,i,j)\in E} X^k_{ij} \leq 1 \qquad \forall i \in P \tag{2}$$

$$\sum_{(k,s_k,j)\in E} X^k_{s_k,j} = \sum_{(k,i,f)\in E} X^k_{i,f} = 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{(k,i,pk_j)\in E} X^k_{i,pk_j} = \sum_{(k,i,dl_j)\in E} X^k_{i,dl_j} \qquad \forall k \in K, \forall j \in R \tag{4}$$

$$\sum_{(k,i,j)\in E} X^k_{i,j} - \sum_{(k,j,i)\in E} X^k_{j,i} = 0 \qquad \forall k \in K, \forall j \in P \cup D \tag{5}$$

$$\tau^k_j \geq (\tau^k_i + t_{i,j} + d_i) X^k_{i,j} \qquad \forall (k, i, j) \in E \tag{6}$$

$$e_i \leq \tau^k_i \leq l_i \qquad \forall (k, i) \in V_v \tag{7}$$

$$r^k_i = \tau^k_{dl_i} - (\tau^k_{pk_i} + d_{pk_i}) \qquad \forall (k, i) \in \{(k, i) | (k, pk_i) \in V_v\} \tag{8}$$

$$t^k_{i,dl_i} \leq r^k_i \leq t^k_{i,dl_i} + \varpi^{tt}_i \qquad \forall (k, i) \in \{(k, i) | (k, pk_i) \in V_v\} \tag{9}$$

$$w^{c,k}_j \geq (w^{c,k}_i + q_j) X^k_{i,j} \qquad \forall (k, i, j) \in E, \forall c \in C_k \tag{10}$$

$$w^{c,k}_i \geq max\{0, q^c_i\} \qquad \forall (i, k, c) \in V_w \tag{11}$$

$$w^{c,k}_i \leq min\{Q^c_k, Q^c_k + q^c_i\} \qquad \forall (i, k, c) \in V_w \tag{12}$$

$$X^k_{i,j} \in \{0, 1\} \qquad \forall (k, i, j) \in E \tag{13}$$

$$w^{c,k}_i \in \mathbb{N} \qquad \forall (i, k, c) \in V_w \tag{14}$$

$$\tau^k_j, r^k_i \in \mathbb{N} \qquad \forall (k, i) \in \{(k, i) | (k, pk_i) \in V_v\} \tag{15}$$

The objective function (1) maximizes the total profit obtained from the commodity delivery revenue minus the operational cost of the active vehicles. Regarding the constraints, (2) guarantees there is at most one arc leaving every pick-up point, i.e., service denial is allowed. In turn, constraint (3) guarantees all vehicles leave their origin nodes and ultimately arrive at the destination dummy node while (4) guarantees that if a vehicle visits a request pick-up node it also must visit the associated delivery node. Constraint (5) ensures that every pick-up node has the same number of inbound and outbound arcs, in other words, a vehicle visiting a node must subsequently leave it. (6) defines the minimum arrival time of a vehicle at node j as the sum of the arrival time of the previously visited node i, its associated delay (boarding or/and loading times at i) and the travel time from i to j. Next, constraint (7) imposes that the arrival time of a vehicle at a pick-up point occurs within a predetermined time window, (8) defines the ride time a customer spends inside a vehicle and (9) defines the lower and upper bounds for this time. Constraints (10), (11) and (12) ensures vehicles compartment loads are feasible. Finally, we declare the model's variables in (13), (14) and (15).

3. NUMERICAL STUDY

A numerical study has been conducted considering various experimental settings and instances in order to determine the benefits of different fleet compositions. Particularly, we focus on the performance assessment of fleets comprised by mixed-purpose vehicles, whose internal space is divided among freight and people compartments, and fleets composed by single-purpose vehicles, in which all compartments are dedicated to a specific class of commodity.

3.1 Experimental settings

This section describes how we configured our MILP model and how the instances were constructed. When creating the instance scenarios, our ultimate goal was to provide insights on how distinct factors concerning particular characteristics of vehicles and requests may influence the model's outcome, especially in terms of: 1) the number of vehicles in fact used to address the requests, 2) the overall profit gleaned during the fleet's operation and 3) the overall occupancy level. Regarding 3), we assume the occupancy level of a single vehicle is proportional to the share of time and number of loaded compartments occupied throughout the entire operational route, i.e., from the dispatching moment until the delivery of the last customer. Hence, for a particular test case, the overall occupancy level consists of the average occupancy levels of all vehicles actually involved in the solution.

SARPLP general operational settings Table 2 presents the model's general parameters, shared by all our instances. Every vehicles accommodates 10 compartments of types "A" and/or "XL", and both compartments are assumed to have equal dimensions and service fares. However, human and freight compartments differ when time related parameters are considered. Passenger requests impose more pressing constraints once passengers must be attended within 3m and the total travel delay can't be higher than 10m. In contrast, freight requests are more flexible, allowing a 1h time window to be picked-up and a 5h delay. Additionally, delays for embarking and disembarking passengers are set to 1min, and delays to load and unload parcels are set to 5min.

Table 2. Summary of the general parameters for the SARPLP formulation.

Parameter	Values	Parameter	Values
H, F	{A}, {XL}	ϖ^{pk}_A, ϖ^{tt}_A	3m, 10m
d^{pk}_A, d^{dl}_A	1m	ϖ^{pk}_{XL}, ϖ^{tt}_{XL}	1h, 5h
d^{pk}_{XL}, d^{dl}_{XL}	5m	α_A, α_{XL}	16€
γ_k	0.005€/s	β_A, β_{XL}	0.0016€/s
$\mid Q^k_c \mid$	10		

Instances Due to the intrinsic limitations of an integer programming formulation, we were unable to consider large scale test cases with large numbers of vehicles and requests. Hence we limit our investigation to small fleet sizes, $|K| \in \{4, 8, 16\}$, and small number of requests, $|R| \in \{8, 16, 32\}$. Nonetheless, we defined a series of parameters that enable the generation of a considerable number of scenarios where many fleet and request's aspects are taken in consideration, namely:

(1) *Fleet composition:* Two types of AVs equipped with parcel lockers are considered. Single-purpose vehicles are comprised of either freight or human compartments and mixed-purpose vehicles have their internal space equally shared among people and freight compartments.
(2) *Share of freight requests:* For each request set of size n we check the influence of the proportion of freight requests on the model outcome. As shown in (Stiles et al., 2014), ride-hailing demands strongly vary throughout the day, and it might be the case of freight demands as well. In order to further investigate the differences of handling these commodities, freight requests may correspond to 25%, 50% and 75% of the total number of requests.
(3) *Interval between requests:* In real-world large-scale transportation systems, many new requests may occur every second, whereas in smaller systems or less busy scenarios, intervals between requests might be bigger. Let $[i_l, i_u]$ be the range of possible integer intervals (in minutes) between requests. We investigate two possible intervals' ranges: 1) $[0, 0]$, i.e., no interval between requests and 2) $[5, 10]$.
(4) *Range of route distance:* Since our PFIT system is intended to operate within urban centers, we expect to deal with small distance trips (from 500m to 1km). However, we also investigate longer distance trips varying from 5km to 10km.
(5) *Compartment demand/Req.:* The compartment demand per request, i.e., the number of compartments associated with a single request, can be either low ($\leq$ 50% of available compartments in vehicle) or high ($\geq$ 50% of available compartments).

Table 3. Summary of scenarios' parameters.

Parameter	Values
Number of vehicles $\mid K \mid$	$\{4, 8, 16\}$
Number of requests $\mid R \mid$	$\{8, 16, 32\}$
Share of freight requests	$\{25\%, 50\%, 75\%\}$
Interval between requests	$\{[0, 0], [5, 10]\}$
Range of route distance	{0.5km-1km, 5km-10km}
Compartment demand/request	{low($\leq$ 50%), high($\geq$ 50%)}
Fleet composition	{single-purpose, mixed-purpose}

For each fleet composition (single-purpose or mixed-purpose), a total of 216 scenarios are generated from the combination of the parameters investigated (summarized in Table 3). We run each scenario in 3 different geographical distributions of vehicles and requests, resulting in 1296 instances (2 fleet compositions $\times$ 3 geographical distributions $\times$ 216 scenarios). Each distribution is created based on distinct datetime windows of the New York City taxicab public dataset. Although it contains a number of fields, we only make use of the origin/destination latitude and longitude coordinates as a reference to build our instances. Given a particular scenario, we chose 3 time windows and for each window, we extract $|K|$ vehicle's origins and n pairs of requests' pick-up/delivery locations. Additionally, when extracting requests, we only select those in which the distance traveled by the taxi is within the preferred route distance specified in the scenario. Finally, all travel times between vehicles and requests coordinates are queried from the Mapbox Matrix API (www.mapbox.com) using the driving profile. Given a set of points, the API returns a matrix of average trip durations based on the fastest car routes.

3.2 Results

Test instances were solved on an Intel Core i7, 2.30GHz CPU, 16GB RAM computer. Gurobi 7.0.2 Python interface was used to implement the SARPLP model and the maximum runtime of each instance was set to 10 min.

Table 4 compiles the results of the instances in which the MIP gap between the lower and upper objective bound is less than 1%. This constraint guarantees only near optimal results are compared in order to draw more accurate conclusions about the performance of mixed-purpose and single-purpose fleets. As a result, both fleet compositions are ultimately assessed over 149 scenarios, i.e., about 30% of the scenarios with non-optimal solutions are eliminated. For each combination of number of vehicles ($|K|$) and number of requests ($|R|$) we indicate in the first column (#) how many scenarios were left out, and in the subsequent columns we present the following averages for each vehicle type: number of vehicles used to devise a solution (#Veh.), the occupancy rate (Occ.(%)) of these vehicles and the profit gleaned during the operation. In terms of acquired profit, mixed-purpose fleets are able to reach superior results in 92% of the instances tested, having profits in average 12.3% higher than single-purpose fleets. However, the additional profit comes at a cost: in average, 18% more mixed-purpose vehicles must be assigned, resulting in a 22.5% lower occupancy rate. Naturally, if a single-purpose fleet is able to address roughly the same number of requests of a mixed-purpose fleet with less vehicles, the occupancy rate of the vehicles in fact used in the solution will be higher. However, from the perspective of a fleet operator who wants to make the most of his fleet capabilities, idleness would only be welcomed if it did not influenced fleet's profitability.

It is also worth mentioning that since we are dealing with a static setting, all people and freight demands are known in advance, enabling single purpose vehicles to be timely dispatched to attend each type of commodity request. In contrast, when an unpredictable environment is considered, i.e., when mixed-type demands occur dynamically, single-purpose vehicles may potentially miss several opportunities to address overlapping human and freight routes. This phenomenon can also be identified in busy scenarios in which service will inevitably be denied to a great share of the demands. In fact, such scenarios ultimately induce vehicles to seek for the most profitable set of customers while keeping a low operational cost. To make this relation more explicit in our results, we compile the average profit for both fleet compositions in Table 5, grouped once again per number of vehicles and requests. The busier the logistical scenario, i.e., the lower is the number of vehicles available to attend a set of requests, the higher is the superiority of the average profit of mixed-purpose fleets over single-purpose fleets. This relation can be particularly verified for the 4-vehicles instances: when 8, 16 and 32 requests are considered, mixed-purpose fleets perform 13%, 24% and 33% better respectively. For this setup, it can also be verified that this profit is greatly

Table 4. Results of SARPLP instances whose MIP gaps are lower than 1%.

			Mixed-purpose			Single-purpose		
#	$\|K\|$	$\|R\|$	Occ.(%)	#Veh.	Profit	Occ.(%)	#Veh.	Profit
24	4	8	28.5	3.4	253.6	34.7	2.7	224.6
17	4	16	27.8	3.7	465.4	39.7	3.2	375.0
8	4	32	29.6	4.0	731.5	42.7	3.3	551.6
24	8	8	29.3	4.3	273.8	33.5	3.6	260.7
17	8	16	27.6	6.1	542.7	33.3	5.4	504.7
8	8	32	25.7	7.1	972.0	31.8	6.3	861.0
24	16	8	30.0	4.8	294.4	33.2	4.3	275.8
18	16	16	29.4	8.4	590.7	33.7	7.4	566.5
9	16	32	27.9	11.4	1074.9	30.7	10.2	1010.1

Table 5. Profit breakdown of mixed-purpose and single-purpose fleets.

		Mixed-purpose		Single-purpose		
$\|K\|$	$\|R\|$	Revenue	Cost	Revenue	Cost	Diff.
4	8	290.7	37.0	256.92	32.35	13%
4	16	528.9	63.5	423.62	48.63	24%
4	32	825.0	93.5	620.72	69.11	33%
8	8	310.8	36.9	296.08	35.41	5%
8	16	610.0	67.4	565.54	60.86	8%
8	32	1087.7	115.7	971.22	110.20	13%
16	8	330.0	35.6	310.77	35.00	7%
16	16	651.4	60.7	625.97	59.48	4%
16	32	1156.6	81.7	1093.53	83.39	6%

influenced by the increased revenue that far surpasses the respective growth in the operational costs. On the other hand, when a considerable number of vehicles is available, single-purpose fleets show a similar performance to mixed-purpose fleets once virtually every request can be attended by a vehicle.

4. CONCLUSION

This study proposed a MILP formulation to deal with a variation of the people and freight integration transportation problem. The performances of single-purpose and mixed-purpose fleets of AVs are compared to determine whether dividing vehicles internal space among people and parcel requests is financially advantageous for a fleet operator wanting to implement such service in an urban center. Overall, the results have shown that employing a fleet of mixed-purpose vehicles is in fact more profitable once geographically overlapping people and freight demand can be further combined to design more efficient routes. Nevertheless, it is important to stress that although we have tested many different scenarios with varied characteristics, the results are still highly dependent on the general parameters assumed. The adoption of different compartment fares, for example, could create a bias towards a specific commodity and higher operational costs could drive to solutions where farther requests are not worth attending. Hence, future will focus on finding an adequate balance between these factors to provide a sensible range of parameter options for fleets' operators. Additionally, more complex and realistic instances shall be investigated throughout the implementation of a dynamic formulation.

REFERENCES

Agatz, N., Erera, A., Savelsbergh, M., and Wang, X. (2012). Optimization for dynamic ride-sharing: A review. *European Journal of Operational Research*, 223, 295–303.

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., and Rus, D. (2017). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences of the United States of America*, 114(3), 462–467.

Berbeglia, G., Cordeau, J.F., and Laporte, G. (2010). Dynamic pickup and delivery problems. *European Journal of Operational Research*, 202(1), 8–15.

Boesch, P.M., Ciari, F., and Axhausen, K.W. (2016). Autonomous vehicle fleet sizes required to serve different levels of demand. *Transportation Research Record: Journal of the Transportation Research Board*, 2542, 111–119.

Cordeau, J.F., Laporte, G., Savelsbergh, M.W., and Vigo, D. (2007). Vehicle Routing. *Transportation*, 14(06), 367–428.

Fagnant, D.J. and Kockelman, K.M. (2016). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, 44(8), 1–16.

Joerss, M., Schröder, J., Neuhaus, F., Klink, C., and Mann, F. (2016). Parcel delivery: The future of last mile. *McKinsey & Company*.

Li, B., Krushinsky, D., Reijers, H.A., and Van Woensel, T. (2014). The Share-A-Ride Problem: People and parcels sharing taxis. *European Journal of Operational Research*, 238(1), 31–40.

Li, B., Krushinsky, D., Van Woensel, T., and Reijers, H.A. (2016a). An adaptive large neighborhood search heuristic for the share-a-ride problem. *Computers and Operations Research*, 66, 170–180.

Li, B., Krushinsky, D., Van Woensel, T., and Reijers, H.A. (2016b). The Share-a-Ride problem with stochastic travel times and stochastic delivery locations. *Transportation Research Part C: Emerging Technologies*, 67, 95–108.

Litman, T. (2017). *Autonomous vehicle implementation predictions*. Victoria Transport Policy Institute.

McKerracher, C., Itamar, O., Wilshire, M., Tryggestad, C., Mohr, D., Hannon, E., and Moeller, T. (2016). An integrated perspective on the future of mobility. *McKinsey & Company and Bloomberg New Energy Finance*.

Pavone, M., Smith, S.L., Frazzoli, E., and Rus, D. (2012). Robotic load balancing for mobility-on-demand systems. *The International Journal of Robotics Research*, 31(7), 839–854.

Savelsbergh, M. and Woensel, T.V. (2016). City logistics: challenges and opportunities. *Transportation Science*, 50(2), 579–590.

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., and Pavone, M. (2014). Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in singapore. In *Road vehicle automation*, 229–245. Springer.

Stiles, R., Siegel, L., Garber, J., Neger, H., and Ullah, A. (2014). 2014 taxicab factbook. *Taxi & Limosine Commission, New York City*.

Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S.H., and Ratti, C. (2017). Scaling law of urban ride sharing. *Nature Publishing Group*, 1–6.

Toth, P. and Vigo, D. (2014). *Vehicle routing problem, methods, and application*. Society for Industrial and Applied Mathematics, 2nd edition.

UN (2014). *World Urbanization Prospects: The 2014 Revision-Highlights*. UN.