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Miguel A. Figliozzi
Portland State University, figliozzi@pdx.edu

Dylan Jennings
Portland State University

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A Study of the Competitiveness of Autonomous Delivery Vehicles in Urban Areas

Miguel Figliozzi [1], Dylan Jennings [2]

[1] Professor of Civil & Environmental Engineering, Portland State University, Portland, OR, USA
[2] Research Assistant, Portland State University, OR, USA
{figliozzi@pdx.edu, dwj@pdx.edu}

Abstract. The rapid growth of e-commerce and package deliveries across the globe is demanding new solutions to meet customers' desire for more and faster deliveries. This research focuses on the cost competitiveness of autonomous air and ground delivery vehicles. Three types of autonomous vehicle are analyzed: drones, sidewalk autonomous delivery robots (SADRs), and road autonomous delivery robots (RADRs). Autonomous vehicles are compared against a typical delivery van. The impact of capacity, range and time constraints are analyzed. Results show that each type of autonomous delivery vehicle is suitable in different scenarios and can therefore complement each other to reduce costs or on-road distance traveled.

Keywords: Last mile, delivery, drone, robot, cost, time

1. Motivation and Literature Review

Autonomous delivery robots (ADRs) that travel on sidewalks and roads are being tested in several US cities by startups. Even large delivery companies like FedEx are also testing this technology [1]. Online retailers like Amazon are also testing a drone prototype that can deliver packages under five pounds to customers in less than 30 minutes; this is noteworthy because 75% to 90% of Amazon deliveries weigh less than five pounds [2].

The potential of autonomous vehicles for passenger transportation has been studied extensively. In comparison, significantly less work focuses on the potential of autonomous vehicles in the logistics and parcel delivery sector. Some researchers have studied the implications of autonomous vehicles for long-haul freight. For example, Short and Murray [3] discuss the impact of long-haul autonomous trucks on hours-of-service, safety, driver shortage and driver retention, truck parking, driver health and wellness, and the economy. The work of Slowik and Sharpe [4] focuses on the potential of autonomous technology to reduce fuel use and emissions for heavy-duty freight vehicles.

There are even less studies focusing on urban deliveries or short-haul freight trips. Jennings and Figliozzi [5] recently studied the potential of sidewalk autonomous delivery robots (SADRs). Given the relatively short range of SADRs, these small robots are usually complemented by a "mothership" van that can transport SADRs near the delivery zone or service area. The work of Jennings and Figliozzi (2019) analyzed current SADR regulation in the US, their characteristics, and their potential to reduce delivery times or costs. Jennings and Figliozzi (2020) analyzed the competitiveness of road autonomous delivery robots (RADR) when compared to conventional vans [6]. Results show that RADRs can provide substantial cost savings in many scenarios but in all cases, at the expense of substantially higher vehicle miles per customer served. The novel contribution of this research is to evaluate both air and ground (SADR and RADR) autonomous vehicles potential to reduce delivery times and costs in urban areas. To the best of our knowledge there is no publication comparing the costs of both air and both types of ground autonomous vehicles.

2. Vehicle Characteristics

A conventional van is defined as a delivery van in the traditional sense, with rear storage for parcels and a human driver and delivery person. A mothership for the purposes of our analysis is defined as a van which has been outfitted to transport SADRs, with a human driver who drops off or picks up SADRs. Finally, RADRs are defined as vehicles which operate autonomously to deliver parcels. See Figure 1 to find an illustration of the mothership-SADR and RADR vehicles analyzed in this research.

Figure 1: Mothership Van with Starship SADRs (left) and NURO (right)

A Starship Technologies' SADR in conjunction with a Daimler SADR Van, or "mothership", is utilized in the numerical analysis. Each Starship SADR weighs 40 lbs (18.1 kgs), has a speed of 4 mph (6.4 kph), and a range of 4 miles (6.4 kms). As discussed in [5] it is assumed that a Starship can deliver to up to six customers. A uDelv RADR is utilized in the numerical analysis. The uDelv is a modified Ford Transit Connect that has 32 individual compartments to store delivery items [6]. The Ford Transit Connect can travel at up to 60 mph, with a range of 60 miles before recharging, and a carrying capacity of 1,300 pounds [6]. The uDelv has individual compartments that can be opened one at a time, which would prevent theft of other delivery parcels. The drone analyzed is a cargo multicopter MD4-3000 that was already utilized to analyzed the comparative advantages of drones regarding CO_2 emissions against a Dodge RAM conventional van [7]. Key vehicle characteristics are provided in Table 1.

Table 1: Key Vehicle Characteristics

Vehicle	Tare (kg)	Max. Speed (kph)	Max. Payload (kg)	Range (km)
Starship	18.1	6.4	18.1	3.2
Nuro	680	56	110	16.1
uDelv	1890	97	590	97
MD4-3000	10.2	72	5.0	36
Dodge RAM	2170	180	1890	695

2.1. Vehicle Costs

While autonomous vehicles are beginning to be tested across the United States, the costs associated with manufacturing autonomous vehicle are still significantly higher than the manufacturing cost of conventional vehicles. A 2015 estimate indicates that the additional cost of just the Light Detection and Ranging (LIDAR) sensors to allow a vehicle to be fully autonomous (level 4+) is $30,000 to $85,000 per vehicle, and over $100,000 per vehicle for LIDAR and other sensors and software [6]. Autonomous vehicles could eventually cost $25,000 to $50,000 more than typical vehicles with mass production, over time, not less than 10 years, reaching prices of around $10,000 per vehicle. Price of automation implementation 20 to 22

years after introduction is expected to be $3,000 per vehicle, eventually reaching a low of $1,000 to $1,500 per vehicle [8].
The mothership and conventional van require a human driver. We assume a cost of $40 USD per hour for motherships and $35 USD per hour for conventional vans. The mothership is a more expensive vehicle since it is larger and requires a specialized configuration. We assume a value of $30 USD per hour for RADR vans after removing driver costs and adding higher autonomous vehicle costs and accounting for an operator monitoring several vehicles. We assume a relatively conservative cost of $1.5 USD per delivery for SADRs [5].
The cost of drone deliveries is estimated utilizing figures provided by Wright et al. [9] and Jenkins et al. [10]. The former reference indicates a cost of $0.41 per kg-km or $0.18 per lb-km for a multicopter; assuming 2.5 lbs per delivery results in $0.47 per km. The latter reference indicates that drone costs range between $0.10 and $0.60 per mile or $0.06 to $0.37 per km. Another report [11] provides a cost of delivery assuming different levels of regulation and labor participation. A low and high cost of $15.98 and $67.64 per hour are estimated. Assuming a 20 m/s operating speed the costs are estimated from $0.22 to $0.94 per km. The differences in drone costs are mainly due to different assumptions regarding the number of staff necessary to operate a drone delivery system. In this research a compromise value of $0.5 per kilometer is assumed which translates into $36 per hour. The drones also incur a fix setup time between flights of 10 minutes; this setup time is necessary to load the drone and swap the battery if necessary.

3. Methodology

The methodology used for comparing travel, time and cost of the studied vehicles is based on continuous approximations. As indicated by Daganzo et al. [12] this type of analytical approximation is appropriate to address big picture questions because they are parsimonious, tractable, and yet realistic when the main tradeoffs and constraints are included. This type of modeling approach has been successfully used in the past by many authors to model urban deliveries and logistic problems [13,14]. A circular area of service is assumed and capacity, range and tour duration constraints are considered. The range of a drone is determined by its weight, flying efficiency, and battery capacity. Drone range calculations are estimated as in [7] assuming a 5 pound delivery weight. According to Amazon 75 to 90% of its parcel deliveries are less than 5 pounds. The following notation is used throughout the paper.

$n =$ Total number of customers served
$k_l =$ Routing constraint (constant value), representing non-Euclidean travel on sidewalks and roads
$a =$ Area (units length squared) of the service area, where n customers reside
$\delta = n/a$, customer density
d = Distance between the depot and the geometric center of the service area
$T =$ Maximum duration of shift or tour (same for all vehicle types)
$l_i(n) =$ Average distance a vehicle travels to serve n customers for vehicle type i
$m_i =$ Minimum number of vans for vehicle type i
$R_i =$ Range of a vehicle for vehicle type i
$Q_i =$ Capacity (number of parcels for vans or number of SADRs for motherships) for vehicle type i
$\tau_i =$ Total van time necessary to make n deliveries for vehicle type i
$\phi_i =$ Stop percentage (percent of the time a vehicle is stopped due to traffic control)
s_i' Average speed of the vehicle on urban streets, not including ϕ
$s_{i,h}' =$ Average speed of the vehicle while on a highway, not including ϕ
$s_i = s_i'\phi_i =$ Average speed of the vehicle on urban streets
$s_{i,h} = s_{i,h}'\phi_i =$ Average speed of the vehicle while on a highway
$t_0 =$ Time it takes to wait for the customer to pick up their order from the vehicle or delivery person
$t_u =$ Time it takes the vehicle and/or driver to unload the delivery
$t = t_0 + t_u =$ Total time vehicle is idle (i.e., not traveling) during a delivery
$c_{h,i} =$ Cost per hour of operating vehicle type i, including cost of a driver if applicable
$c_{d,i} =$ Cost per delivery for vehicle type i

The average distance $l(n)$ to serve n customers can be estimated as a function of customer density, number of vehicles, network characteristics and route constraint coefficients, and the distance between the depot and the delivery area [15]. In this paper, the equation used to calculate the distance traveled to visit n customers by a ground vehicle is:

$$l_i(n) = 2dm_i + k_l\sqrt{an/m_i} \tag{1}$$

In equation (1), d represents the average distance from the depot or distribution center (DC) to the customer(s). The parameter d is multiplied by two, the number of times the vehicle goes to and from the service or delivery area (SA). The parameter k_l is a constant value representing network characteristics and routing constraints in the SA [15]. The average area of the SA where customers are located is represented by a. The number of parcels or stops is represented by n. The following formula is used to calculate the route duration constraint of a ground vehicle accounting not only for driving time but also waiting for the customer and unloading the parcels:

$$\frac{2d}{s_{h,i}} + \frac{k_l\sqrt{an}}{s_i\sqrt{m_i}} + (t_0 + t_u)\frac{n}{m_i} < T \tag{2}$$

3.1. Baseline

In equation (2), the first term represents the driving time and the second term represents the time it takes to park, wait for or go to the customer and unload the parcels. To determine the maximum number of deliveries that can be made by the conventional van within a shift of duration T, equation (2) is solved for n when the available time is T (to ease notation the sub index for conventional van i is dropped). The resulting equation for the maximum number of customers that one conventional van can deliver is:

$$n = \left\lfloor \frac{k_l^2 a + 2s^2Tt - \frac{4ds^2t}{s_h} - k_l^2\sqrt{\left(\frac{4ds^2t}{k_l^2 s_h} - \frac{2s^2Tt}{k_l^2} - a\right)^2 - \frac{4t^2s^2}{k_l^2}\left(\frac{s^2T^2}{k_l^2} + \frac{4d^2s^2}{k_l^2 s_h^2} - \frac{4s^2Td}{k_l^2 s_h}\right)}}{2s^2t^2} \right\rfloor \tag{3}$$

The floor function is used in equation (3) to avoid a fractional number of customers. In this research, a conventional van is utilized as a baseline and equation (3) provides the maximum number of customers that can be served with one vehicle. Vans route duration constraints is given by (2) and capacity and range constraints are as follows (4):

$$m_i \geq \left\lceil \frac{n}{Q_i} \right\rceil \tag{4}$$

$$\frac{k_l\sqrt{an}}{\sqrt{m_i}} + 2d < R_i$$

For the conventional van constraints (2) and (4) are always satisfied in the scenarios analyzed, given the high value of R (range) and the large capacity of conventional vans when compared to SADRs and RADRs. Formulas and constraints for drones are simpler since there is one costumer per delivery [7]. For SADRs the range, time, and capacity constraints presented in [5] are utilized.

3.2. Scenarios

Table 2 shows a summary of the key scenario parameters by delivery vehicle type. These parameters are set to meet vehicle characteristics or reasonable operational values in urban areas. As area size a changes, following equation (3), the maximum number of customers that can be served by one conventional delivery van also changes. Hence, one conventional delivery van is the baseline utilized to create different scenarios that are labeled from A to I as the area size a increases from 10 to 130 square miles or 26 to 337 square kilometers (see Table 3). In all cases it is assumed that the delivery time per customer is $t = 3$ minutes and that the depot-SA distance is $d = 10$ miles or approximately 16.1 kilometers.
Fleet size and utilization for the other vehicles (uDelvs, motherships, SADRs and drones) also changes to meet the respective time, range, and capacity constraints as shown in Table 3. More customers can be served when the delivery area is smallest (scenario A) than largest (scenario I). Hence the customer delivery

density is reduced as the area increases. There are tradeoffs among number of customers served, area size, and fleet size; fleet size varies to satisfy range, capacity, and time constraints per vehicle type.

Table 2: Default values for variables used in calculations

Variable	Description of variable	Units	uDelv	SADR	Mother.*	Conv. Van	Drone
T	shift time (max)	hours	10	10	10	10	10
R_i	range of vehicle (max)	Miles (km)	60	4 (6.4)	400	400	22.4 (36)
Q_i	capacity (max)	unitless	32	6	8**	200	1
$c_{h,i}$	cost per hour of operation	USD	30	n/a	40	32	36
$c_{d,i}$	cost per delivery	USD	n/a	1.5	n/a	n/a	
s_i'	full unlimited vehicle speed in residential	mph (kph)	30 (48.3)	4 (6.4)	30 (48.3)	30 (48.3)	44.8 (72)
$s_{i,h}'$	full unlimited vehicle speed on highway	mph (kph)	60 (96.6)	n/a	60 (96.6)	60 (96.6)	44.8 (72)
s_i	vehicle speed in residential	mph (kph)	21 (33.8)	2.8 (4.5)	21 (33.8)	21 (33.8)	44.8 (72)
$s_{i,h}$	vehicle speed on highway	mph (kph)	42 (67.6)	n/a	42 (67.6)	42 (67.6)	44.8 (72)
k_l	routing constraints	unitless	0.7	0.7	0.7	0.7	n/a
ϕ	stopping factor	unitless	0.3	0.3	0.3	0.3	n/a

* Motherships can make multiple tours and ** capacity is number of SADRs per mothership instead of parcels

Table 3: Scenario Characteristics

Measure	Scenarios								
	A	B	C	D	E	F	G	H	I
Time per customer [min]	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Number of customers	163	149	140	133	127	122	118	114	110
Delivery area [mi^2]	10	25	40	55	70	85	100	115	130
Delivery area [km^2]	26	65	104	142	181	220	259	298	337
Cust. density [cust./ km^2]	6.3	2.3	1.4	0.9	0.7	0.6	0.5	0.4	0.3
Number of uDelvs	6	5	5	5	4	4	4	4	4
Number of motherships	1	1	1	1	1	1	1	1	1
Rounds per mothership	4	4	3	3	3	3	3	3	3
Number of SADRs	28	25	24	23	22	21	20	19	19
Number of drones	5	5	5	5	5	5	5	5	5

4. Results

In this section results obtained for scenarios A to I are analyzed. Table 4 shows the delivery distance per customer as a function of vehicle type and delivery scenario. In the case of the drones the distance per customer increases considerably as the service area increases. However, for the other vehicles the change is less marked as there is a tradeoff between the efficiency of the vehicle fleet size, the number of customers served, and the size of the delivery area. In the case of the conventional van with constant fleet size, it is possible to observe a clear trend with an increase in the delivery distance per customer as the customer density decreases from scenario A to I. RADRs can bring about more congestion in scenarios A to I as their on the road travel (per customer served) is substantially higher distance.

Table 4: Delivery distance per customer [km.] by vehicle type

Vehicle Type	Scenario								
	A	B	C	D	E	F	G	H	I
uDelv Van	1.5	1.5	1.8	1.9	1.9	2.0	2.1	2.3	2.4
Mothership	1.5	1.7	1.3	1.4	1.5	1.6	1.7	1.8	1.9
SADR	0.3	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2
Conv. Van	0.5	0.7	0.8	1.0	1.1	1.2	1.3	1.4	1.5
Drone	3.8	6.1	7.7	9.0	10.1	11.2	12.1	13.0	13.8

Table 5 shows total time spent per customer by vehicle type in each of the different scenarios. Although drones are fast and can reach a given customer in a short time, their overall efficiency is heavily penalized by two factors: the battery swap time and the numerous trips to the depot since their capacity is just one package per delivery. The average drone time per customer increases substantially as the delivery area increases. However, for the uDelv and vans the changes are less marked as there is a tradeoff between the efficiency of the vehicle fleet size, the number of customers served, and the size of the delivery area. There is a large increase in SADRs time per customer as a consequence of longer travel distances and the slow speed of the SADRs.

Table 5: Total delivery time per customer [min.] by vehicle type

Vehicle Type	Scenario								
	A	B	C	D	E	F	G	H	I
uDelv Van	4.5	4.8	5.1	5.4	5.4	5.6	5.8	6.0	6.2
Mothership	2.4	2.7	2.4	2.5	2.6	2.8	2.9	3.0	3.1
SADRs	6.7	9.1	11.0	12.6	14.1	15.5	16.8	18.1	19.3
Conv. Van	3.7	4.0	4.3	4.5	4.7	4.9	5.1	5.3	5.4
Drone	16.2	18.0	19.4	20.5	21.4	22.3	23.1	23.8	24.5

Regarding costs, Table 6 summarizes the results. Drones are clearly more expensive than the other modes. The drone flight time per customer is reduced substantially as the service area decreases but this reduction is not enough to compensate for the swap times and low efficiency of the drone routes.

Table 6: Cost per customer by vehicle type [$/cust.]

Vehicle Type	Scenario								
	A	B	C	D	E	F	G	H	I
uDelv Van	2.3	2.4	2.6	2.7	2.7	**2.8**	**2.9**	**3.0**	**3.1**
SADR +Moths.	3.1	3.3	3.1	3.2	3.2	3.4	3.4	3.5	3.6
Conv. Van	**2.2**	**2.3**	**2.5**	**2.6**	**2.7**	2.9	3.0	3.1	3.2
Drone	9.7	10.8	11.6	12.3	12.9	13.4	13.9	14.3	14.7

Regarding ground vehicles, the RADR is more competitive than the conventional van when the vehicle capacity is not binding and the fleet size is four or less vehicles (in bold, scenarios F to I). The conventional van is more competitive with higher densities and longer routes that can be served by just one vehicle (scenarios A to E). SADRs are not the most competitive option in any scenario, but they are very competitive if the mothership vehicles is not utilized, i.e. for deliveries near the depot.

5. Discussion and Conclusions

RADRs can be more competitive than conventional vans but they are limited by their relatively short range and limited storage capacity. The short range can be addressed by more and better batteries. Though this would be at the expense of additional vehicle weight and cost, batteries are one of the major barriers to the electrification of freight [16]. SADRs can be more than conventional vans when delivery time per customer is relatively high. They can also be very competitive if they can operate from a depot and without the support of a mothership [5]. However, this type of operation is only feasible in dense delivery areas near a depot and not in the scenarios discussed in this research where the depot-delivery area distance is 10 miles or 16.1 kilometers. Drones have many potential advantages over ground vehicles, for example they can arrive quickly to a customer by taking more direct paths and avoiding ground-based obstructions. However, drones underperform in terms of payload capacity and delivery costs.

The largest uncertainties related to drone, SADRs, and RADRs are perhaps their cost and future regulatory barriers. The rate and speed of adoption of air and ground autonomous delivery vehicles will greatly depend on their operational costs and ease of regulation and entry into the delivery market, as discussed by previous studies focusing on the adoption of autonomous trucks by freight organizations [17,18].

5.1. Non-monetary considerations

Large-scale introduction of autonomous air and ground vehicles can bring about new business and service models that are made possible by 24-hour operations since autonomous vehicles are not subject to limitations like driver fatigue as well as lunch and rest breaks. On the other hand, RADRs can bring about more congestion unless they become more efficient than conventional vans in terms of vehicle-distance traveled per customer. Although most deployments are still at the pilot level, air drones and ground ADRs may soon be able to complement traditional delivery methods to meet the growing delivery demands caused by e-commerce, which is growing at a double-digit annual rate [19].

According to a recent survey, a large majority of people in the US believe that delivery robots will be in use within the next five years [20]. According to this USPS study, customers highly value the ability to receive deliveries when and where recipients choose. Since RADRs deliver freight, they can prioritize safety of pedestrians and other road users over the safety of the freight being carried by the RADR. Hence, RADRs are not faced with potential ethical issues that passenger autonomous vehicles are likely to face regarding tradeoffs between the safety of passengers and other vulnerable road users such as pedestrians and/or cyclists. Because of this advantage, it is likely that RADRs may be widely used before autonomously driven passenger vehicles. On the other hand, urban freight is complex and the tasks associated to parking, unloading, and delivering may be more difficult to automate than is currently expected. High safety standards for RADRs may result in high delivery times per customer, which in turn decreases RADRs economic appeal as shown in the previous section.

From a public policy perspective, the utilization of RADRs may significantly increase the number of vehicle-miles related to package delivery. The scenarios analyzed indicate that RADRs generate more vehicle-miles per delivery than conventional vans (substantially more in many scenarios). As a secondary effect, new delivery/service models (anytime/anywhere) plus a reduction in delivery costs brought about by a large-scale introduction of RADRs may further increase the already high growth of ecommerce. The combination of higher vehicle-miles per delivery plus the growth of ecommerce can compound congestion and high curb utilization problems in many urban areas.

5.2. Limitations and future research opportunities

This research is a first step towards understanding the key tradeoffs between air and ground automated delivery vehicles and conventional vans. A few scenarios have been analyzed but more research is necessary to analyze specific case studies, future vehicle capabilities and cost figures, and how these new technologies can be integrated into efficient supply chains in urban areas and to optimize their joint deployment [21]. Future research can also study the broader impacts of urban freight autonomous vehicles on urban sustainability as well as future distribution networks and land use patterns.

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