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Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO_2 emissions in the delivery service industry

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A B S T R A C T

This research paper estimates carbon dioxide (CO_2) emissions and vehicle-miles traveled (VMT) levels of two delivery models, one by trucks and the other by unmanned aerial vehicles (UAVs), or "drones." Using several ArcGIS tools and emission standards within a framework of logistical and operational assumptions, it has been found that emission results vary greatly and are highly dependent on the energy requirements of the drone, as well as the distance it must travel and the number of recipients it serves. Still, general conditions are identified under which drones are likely to provide a CO_2 benefit – when service zones are close to the depot, have small numbers of stops, or both. Additionally, measures of VMT for both modes were found to be relatively consistent with existing literature that compares traditional passenger travel with truck delivery.

1. Introduction

In March 2012, Silicon Valley startup TacoCopter made headlines as it publicly announced plans for the delivery service of tacos within the City of San Francisco via unmanned aerial vehicles (UAVs), otherwise known as "drones" (Gilbert, 2012) Interested customers would be able to place their order on a smartphone application and comfortably wait as a drone delivers their food to them from above. However, the idea never was able to get off the ground as shortly after the announcement, the U.S. Federal Aviation Administration (FAA) quickly enacted and has since enforced a national moratorium on all commercial activities utilizing drone technology. Nevertheless, interest in the nonmilitary use of drones has increased dramatically with successful operations outside the United States in the delivery of medicine, food, and mail orders. In light of these successes, as well as pressure from the private sector seeking to exploit the potential benefits of drone technology, the FAA has recently created legal and physical space for experimentation, although full commercial operation authorization is not expected for some time (United States Federal Aviation Administration, 2015).

As with past penetration of technology in markets and industries, focus has been heavily placed on the economic and social impacts that the introduction of drone technology may bring. For instance, companies anticipate a reduction in transportation costs (D'Andrea, 2014), concerns exist regarding individual privacy rights (Olivito, 2013), and airspace congestion. As these benefits and costs are weighed, however, little assessment currently exists on the environmental consequences that drone technology may possibly have if fully adopted by industries.

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This research paper seeks to answer this question, specifically in terms of CO_2, which is the most documented and well-known greenhouse gas, and vehicle miles traveled (VMT), a measurement of movement often used to calculate pollution and energy impacts. This paper will first discuss existing literature and then describe the methodology used to model delivery routes while incorporating real-world emission parameters. The resulting estimates on the effects that the replacement of delivery trucks by delivery drones will have on operational CO_2 emissions and VMT, as well as identified patterns by these results, are presented at the end of this paper.

2. Literature review

To understand past efforts in research with regards to the impacts of delivery modes and comparisons amongst them, a literature review was conducted. Ample articles were identified in regards to delivery trucks, each with generally similar results showing significant reductions in CO_2 emissions and/or VMT when delivery trucks replace personal travel. However, when focus was shifted onto the environmental impacts of delivery drones, little could be found. While drones are not as well-studied as trucks, comparisons between delivery trucks and personal light-duty travel models are relevant and telling in how methodology and results could assist or be applied towards this research.

2.1. Evaluations of impacts of delivery trucks

Some of the earliest work comparing delivery services to personal travel was conducted by Cairns, with several papers spanning from the late 1990s to the mid-2000s. Focusing on VMT impacts of grocery delivery services in the United Kingdom, she finds significant reductions when a delivery-by-truck system replaced typical passenger travel, often estimating savings of 70–80% (Cairns, 1997). She also finds it possible to have increased VMT savings as the number of customers simultaneously increases (Cairns, 1998). While these results were pertinent only to the United Kingdom, she later expands her research, examining international results of modeling assessments, and again sees a 70% or more potential savings in VMT (Cairns, 2005). Unfortunately, Cairns work has been limited to estimated changes in VMT only and does not examine emission impacts.

This gap, however, was quickly filled by Kim, et al. as they compare the energy consumption and air emissions of three different delivery systems (Kim et al., 2008). Using U.S. Environmental Protection Agency (EPA) standards and route modeling, they suggest that a system that utilizes centralized drop-off locations has the least CO_2 emissions, closely followed by an e-commerce network in which packages are delivered to customers along a designated route. The third, representing traditional passenger travel, performs the worst with almost 40 times more CO_2 emissions than the e-commerce network. Results of Kim, et al. reflect closely to those of Cairns with a 68% reduction in VMT between the passenger travel and e-commerce delivery models.

McKinnon and Edwards also examine the last mile stage for small non-food items, contrasting home delivery operations with conventional personal travel shopping in the United Kingdom (McKinnon and Edwards, 2009). Even when considering additional factors, such as trip chaining, product returns and redelivery, and customer bus travel, they still find that goods delivery via coordinated delivery trucks almost always results in less CO_2 emissions than via individual trips of personal vehicles. This was further substantiated by Edwards, et al. with the caveat that environmental impacts may favor private vehicles if enormous amounts of goods are purchased by the customer per trip (Edwards et al., 2010).

Nevertheless, for the purposes of this research, it is Wygonik and Goodchild that provides the most meaningful methodology framework for a comparison between two delivery modes (Wygonik and Goodchild, 2012). On a detailed level, the team constructs proximity and random assignment models using ArcGIS and EPA parameters, and with guiding assumptions, they assess the differences in VMT and CO_2 emissions between passenger travel and delivery vehicles. Their findings of a 95% reduction in VMT with trucks and 86% less CO_2 are similar to previously mentioned studies, but it is their illustrative and easily replicable methodology that has most useful – it was adopted and slightly altered for this research's comparison between delivery trucks and drones, as described in the methodology portion of this paper.

2.2. Evaluations of impacts of delivery drones

D'Andrea provides helpful approximations of drone energy usage in his work calculating hypothetical operational costs of a drone delivery system (D'Andrea, 2014). Using reasonable assumptions in payload, lift-to-drag ratio, headwind, and other variables, D'Andrea determines a worst-case energy requirement for a drone. While his situational parameters and resulting value are too specific for the purposes of this research, the magnitude of the energy requirement creates an insightful scale that has been helpful in this research for comparative analysis once data was collected.

Beyond D'Andrea, however, literature regarding impact assessments of drones is scarce. This is mainly due to the relatively recent introduction and little operational usage of drone technology in the delivery industry, as well as drone diversity and proprietary information barriers. Online publications and editorials exist and have speculated various impacts, but most focus on financial and operational elements (Wang, 2016). Those that discuss possible environmental impacts either do not incorporate CO_2 or VMT calculations (Eng, 2016) or are focused on drones in fields of conservation and wildlife protection

(Hodgson et al., 2013). This gap in the existing literature highlights the potential advancement that the results of this paper can provide.

3. Methodology

This research paper aims to compare the CO_2 emissions, as well as VMT levels, between truck and drone delivery systems. As a result, two models have been constructed, one to represent each mode. Conditions within the models are kept as similar as possible, but due to data constraints and feasibility purposes, assumptions may differ. Discrepancies are noted in the sections below.

3.1. Truck delivery model

To create a fairly robust model of the delivery-by-truck side of the comparison, delivery routes were constructed as simulations of real-world operations. This required: (1) a road network; (2) a delivery depot; and (3) delivery recipients. With these three elements, a route can be produced following the streets and freeways from the depot to the recipients and back again to the depot. From this delivery route, VMT can be measured, of which CO_2 emissions can then be calculated, as explained later in this paper. This research has chosen the Los Angeles region as the study area. The geographic and metropolitan expansiveness, as well as the availability of regional data, made this study area a suitable and appropriate choice.

For the road network, the 2012 Los Angeles County Network Database from the Institute for Digital Research and Education (IDRE) of the University of California, Los Angeles (UCLA), was adopted. The network database uses a combination of the Environmental Systems Research Institute's (ESRI) own collection of maps and data. However, besides trimming the extensive road network of the local region to the confines of the County's borders, IDRE has additionally calculated and appended several cost values, including distance and travel time measurements, for each road segment to allow users to perform meaningful network analyses on the dataset.

For the delivery depot and recipients, The LA County Address Points dataset provided by the Los Angeles County GIS Data Portal was selected and also utilized in ArcGIS. It contains approximately 3 million primary and secondary address points and associated geocoded information, all of which are themselves from other sources, including the Countywide Address Management System (CAMS), various city databases, and the County's House Numbering maps. These address points only represent less than half of all registered addresses within the County and many points do not have their fields entirely complete since it is still an ongoing project. However, all points have real and accurate addresses, and no knowledge exists of systematic bias in the addresses that are or are not included. To serve as a basis for sampling, these data points and attributes are sufficient.

The data point of 5560 Ferguson Drive, Commerce, CA, is the designated depot for deliveries. This address was chosen for two reasons: (1) it is the location of an existing FedEx SmartPost distribution center; and (2) it is centrally located in the region and away from County borders, permitting a large range of different delivery trip distances that can be analyzed. This depot is the geographic center of the model, and it is this depot that will act as the origin and final destination of every delivery route made.

After the depot has been designated, addresses have been chosen to act as recipients, or stops along a delivery route. It is assumed that the delivery-by-truck operations are provider-dictated, rather than customer-directed, as it is considered to be the more logistically efficient operations system for a service provider (Wygonik and Goodchild, 2012). This means that rather than arranging routes to respect customer-selected delivery times, a provider can organize recipient households geographically to maximize the spatial concentration of customers.

Thus, to simulate a provider-dictated system, defined areas have been created to act as zones that would be served by the delivery trucks. These service zones are circles of a 1-mile radius, forming an area that is representative of real-world neighborhoods like Downtown Los Angeles. Zones are placed so that, beginning at the depot, their centers are located at some mile increment away, the furthest having a center ten miles away. Additionally, to lessen potential biases in travel metrics, such as those produced by a direct freeway path, and to increase both the diversity of street grid designs and the sample size, service zones have been established every twelve arc degrees around the depot. This results in a layout of 330 circles around the depot – 30 for each mile increment away from the depot and 30 centered and perfectly overlapping in the middle at the depot (Fig. 1). Complete or partial overlaps of service zones, especially near the depot, are frequent but acceptable, as each zone conceptually represents a hypothetical clustering of addresses independent of another zone's existence. It is within these circular service zones that random points have been designated as recipients.

To test if the density of recipients has an impact on the results of the comparative analysis, ten scenarios were created in which each scenario has a different number of recipients, beginning with 50 recipients per service zone and steadily increasing by increments of 50 addresses to 500 recipients per service zone. To clarify, the first scenario has 50 randomly selected addresses in each of the 330 service zones with 16,500 recipients in the entire scenario, while the second scenario has 100 addresses in each service zone, totaling to 33,000 recipients. This continues until the last scenario, which has 165,000 total recipients, or 500 addresses per service zone.

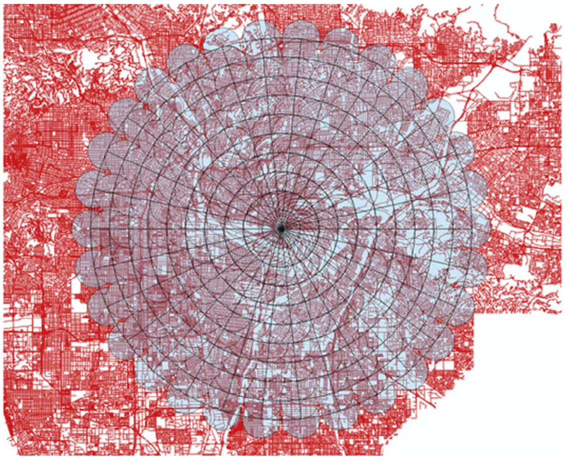

Fig. 1. All 330 service zones (blue) layered on top of the 2012 Los Angeles County Network Database (red). The circular service zones were centered on the intersections of rings and rays (black lines) with the depot as the origin.

3.2. Truck emissions

With just the ten scenarios, VMT of the delivery-by-truck model can be obtained simply by recording the distance of the routes from the depot to the recipient addresses and back to the depot. However, to calculate the CO_2 emissions of the route, more data, namely emission factors for delivery trucks, are needed. Since the model is based in Los Angeles County, it was appropriate to use the web-based EMFAC 2011 Emissions Database (updated January 2013), developed by the California Air Resources Board (CARB), for the delivery-by-truck model for the analysis year of 2014. Since many inputs are required for the database and output results are limited, several assumptions have been made. First, delivery trucks are assumed to be similar to FedEx Express Step Vans and are therefore classified under the EMFAC2011-HD vehicle category list as Medium-Heavy Duty In-state Trucks (GVWR $\leq$ 26,000 lbs.), otherwise listed as "T6 instate small." Second, it is assumed that these trucks run on diesel fuel, as opposed to gasoline. Third, the simulation delivery fleet only includes truck models that are less than 3 years old (2011–2014) to mimic real-world fleets and with an age distribution reflecting a similar, but shifted, distribution as that of Class 3–8 Single-Unit Trucks in the *Transportation Energy Data Book* (specifically, the age distribution was shifted forward by two years to match the temporal setting of the simulation, as the *Transportation Energy Data Book* currently only records truck models up to 2012) (Davis et al., 2014). Fourth, all delivery trips are made under uncongested, free-flow conditions with trip time dictated by the speed limits and distances of each road segment. This assumption greatly benefits the delivery-by-truck model as, unlike with drones, congestion is a large hindrance to operations and greatly increases total emissions. The removal of this factor will most likely produce lower emission levels than real-world results. Fifth, CO_2 emissions rates are based solely on running exhaust and do not account for any potential hot-start, cold-start, or idling emissions produced at every delivery stop along a route. Lastly, it is assumed that the model truck fleet successfully meets all emission standards imposed by California's Pavley I and Low Carbon Fuel Standard state regulations. The resulting weighted average CO_2 emission rates based on these assumptions are listed below by speed in Table 1. These values, coupled with road segment distances, produce total truck emissions by route and have been added to IDRE's 2012 Los Angeles County Network dataset for travel analysis.

3.3. Truck travel analysis

ESRI's ArcGIS is the platform used to calculate emissions for the model. Each of the ten scenarios with the depot and 330 service zones are individually uploaded and analyzed by several tools within ArcGIS. The 2012 Los Angeles County Network,

Table 1
CO_2 tailpipe emission rates (kg/mi) of model truck fleet by age and travel speed.

Simulation truck fleet			Speed (mph)							
Model year[a]	Age (years)	%	15	20	25	35	45	50	55	65
2014	<1	25.13	1.7102	1.3492	1.2588	1.1175	1.0287	1.0041	0.9925	1.0089
2013	1	23.99	1.7102	1.3492	1.2588	1.1175	1.0287	1.0041	0.9925	1.0089
2012	2	25.22	1.7141	1.3523	1.2617	1.1201	1.0311	1.0064	0.9948	1.0112
2011	3	25.65	1.7141	1.3523	1.2617	1.1201	1.0311	1.0064	0.9948	1.0112
Weighted average emission rates (kg/mi)			1.7122	1.3508	1.2603	1.1188	1.0299	1.0052	0.9937	1.0100

modified with emission rates, is also added so that the Network Analyst Routing tool can be utilized. This tool uses entries within data fields to optimize routes on the network based on available metrics, such as distance or time. For the purpose of this research, the Routing tool is adjusted to identify the fastest route for a truck to deliver to all recipients within a service zone. Routes have been programmed so that they always begin and end at the depot, but stops within a service zone are permitted to be reordered to further minimize travel time. As a route is being processed, it records and sums the total distance traveled, which is equivalent to VMT.

To calculate the associated total kg of CO_2 emissions for an entire delivery route or service zone, ArcGIS is programmed to perform the following equation for each road segment along the route

$$\sum_{i=1}^{n}(WAER_i \times d_i)$$

where i is a particular road segment along the route, n is the total number of road segments in the route, $WAER$ is the weighted average emission rate of a particular road segment based on that segment's speed limit in kg per mile (see Table 1), and d is the length of a particular road segment in miles. This summation of all the road segments along a delivery route results in an estimated value for the total CO_2 emissions along the route. This process for VMT and CO_2 calculations is repeated for each of the 330 circular service zones and for all ten scenarios, resulting in a total of 6600 measurements.

3.4. Drone delivery model

Since it is was assumed and determined that drone flight operations are immune to the street grid below, IDRE's 2012 Los Angeles County Network Database was abandoned for the delivery-by-drone model, and no network is used. However, like the delivery-by-truck model, there is still a need for a depot and list of recipients to act as delivery origin and destination. With the previous development of the ten scenarios for truck route simulations, not much had to be done. The ten scenarios were simply adopted by the delivery-by-drone model, even though the drones are assumed not to be operated under a provider-dictated constraint (nor a customer-directed one). It was deemed important to keep the depot, the recipients, and the scenarios all the same for the purpose of comparing and evaluating the impacts of drones against those of trucks.

3.5. Drone emissions

To calculate the emission factors for the delivery-by-drone model, a different method than that for trucks has been employed. Since most real-world delivery drones do not have tailpipe emissions, this research seeks to find the amount of CO_2 that would be emitted at power generation facilities due to drone electricity demand. To do so, significant sinks or inefficiencies in power delivery must first be identified. This can then help determine the amount of electricity that needs to be generated at the source in order for a drone's batteries to receive 1 W-hour (Wh) of charge. It is assumed in the model that drones utilize rechargeable lithium-ion batteries, which have charge/discharge efficiencies between 78% and 92% (Valøen and Shoesmith, 2007). This percentage represents the amount of electricity a battery would deliver to the drone compared to the amount needed to charge the battery. For the purpose of this research, a modest average efficiency of 85% is used.

The other significant sink considered in this model is electricity transmission and distribution losses incurred through the power grid between power sources and points of usage. This includes inevitable energy dissipation within the built infrastructure, such as in conductors and transformers, as well as power losses from resistance in cables. According to the U.S. Energy Information Administration's (EIA) *State Electricity Profiles*, California had losses of around 7.24% in 2012, the most recent year in its dataset (United States Energy Information Administration, 2014). This value has been adopted for the model, which like the delivery-by-truck model, is set in year 2014. With these two inefficiencies, it has been found that for a drone to use 1 Wh of electricity, approximately 1.2683 Wh must be produced at power generation facilities (see Fig. 2).

To find the emissions associated with the production of this amount of electricity, the EIA is again referenced for state-level data. For a total of 199,518,567 MWh generated across all sources of power in 2012, California emitted 59,369,012 metric tons of CO_2. These values, used for the model year of 2014, mean that an average of 0.2976 kg of CO_2 was released for every kWh of electricity generated. When adjusting for the inefficiencies mentioned previously, this rate further increases – for every kWh used by a drone, 0.3773 kg of CO_2 is emitted at power generation facilities.

It should be noted, however, that this is an average emission rate, which in California, is considered to be lower than the marginal emission rate (Mahone et al., 2009). While the latter incorporates power grid operations and analyzes which power plants will be utilized to address an increase in electricity demand at a given hour, this research seeks to provide a picture focusing on the emissions that drones would release through today's power generation facilities and so uses the average emission.

3.6. Drone travel analysis

For the delivery-by-drone model, it is assumed that drones travel in straight paths, are not constrained by the built road infrastructure, and can only carry one parcel at a time. Additionally, similar to the delivery-by-truck model, this model will

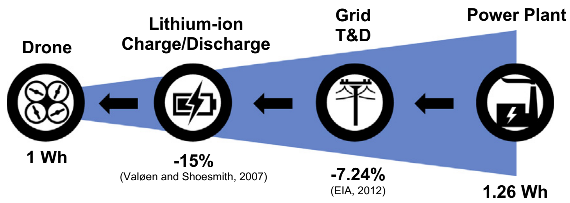

Fig. 2. Due to inefficiencies present in lithium-ion battery technology and in the existing electric grid, for every 1 Wh a drone consumes, approximately 1.26 Wh must be produced at power generation facilities.

only incorporate energy expended while travelling and does not consider other factors such as dwell time at the depot or recipient locations. Therefore, especially with the absence of the road network as mentioned previously, the Routing tool was found to be inappropriate, and rather, the Point Distance tool in ArcGIS is used instead. This tool calculates the direct distance between designated points, which in this case, is the length between the depot and individual recipient addresses. These distances are doubled to include the return trips and are recorded as VMT. This roundtrip distance is then inserted into the following equation to calculate the associated total kg of CO_2 emissions per service zone

$$3.773(10^{-4}) \times AER_{drone} \times \sum_{J=1}^{N}(D_J)$$

where $3.773(10^{-4})$ is the kg of CO_2 emitted at power generation facilities per Wh used by a drone, AER_{drone} is the average energy requirement of the drone in Wh per mile, J is a particular recipient in a service zone, N is the total number of recipients in the service zone, and D is the roundtrip distance in miles. For AER_{drone}, this research assumes a wide range of energy requirements to be inclusive since this can vary greatly across existing and future product models. Thus, for each of the ten scenarios, ten sub-scenarios are created, with AER_{drone} starting at 10 Wh per mile, increasing at increments of 10 Wh per mile until 100 Wh per mile. Essentially, this research paper does not adopt the energy needs of one particular drone product, but instead measures ten different hypothetical drone products over a spectrum against the delivery-by-truck model. In doing so, the effect of a drone's energy requirement in its VMT and CO_2 impact compared to that of a delivery truck can be highlighted.

4. Results

4.1. VMT comparison

VMT for both delivery-by-drone and delivery-by-truck models have been obtained by summing the total distance traveled outputted from ArcGIS travel analysis. To normalize across the different scenarios, VMT for each model has been divided by the total number of recipients in all ten scenarios. The comparison can be viewed in Fig. 3.

As expected, the drone model witnessed significantly more VMT than that of the delivery truck. The 98.4% decrease in VMT from drone to truck is relatively consistent with the Wygonik team's finding of 95.6% from personal-use vehicles to shared-use in a similar provider-dictated scenario (Wygonik and Goodchild, 2012). The higher figure, however, was somewhat unexpected as a drone's straight-line travel advantage was thought to reduce VMT when compared to personal-use vehicles which still must navigate the street grid. This result could partly be attributed to the fact that as recipient addresses are located further away from the depot, the VMT discrepancy between drones and trucks widens at a faster rate, with drones increasingly travelling farther than trucks to deliver the same amount of packages. Since this model uses a larger geographic scope than in Wygonik and Goodchild's model, a higher drone VMT (and thus, a larger VMT discrepancy) emerges.

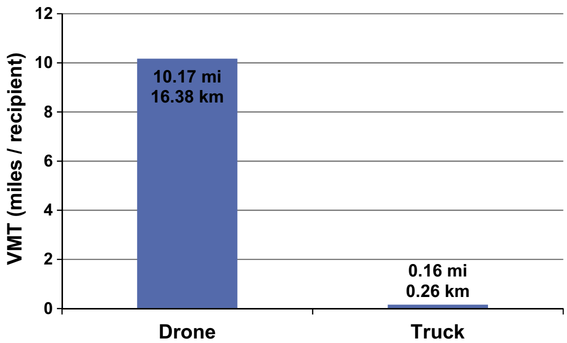

Fig. 3. Comparison of distance traveled per recipient for drone and truck delivery models.

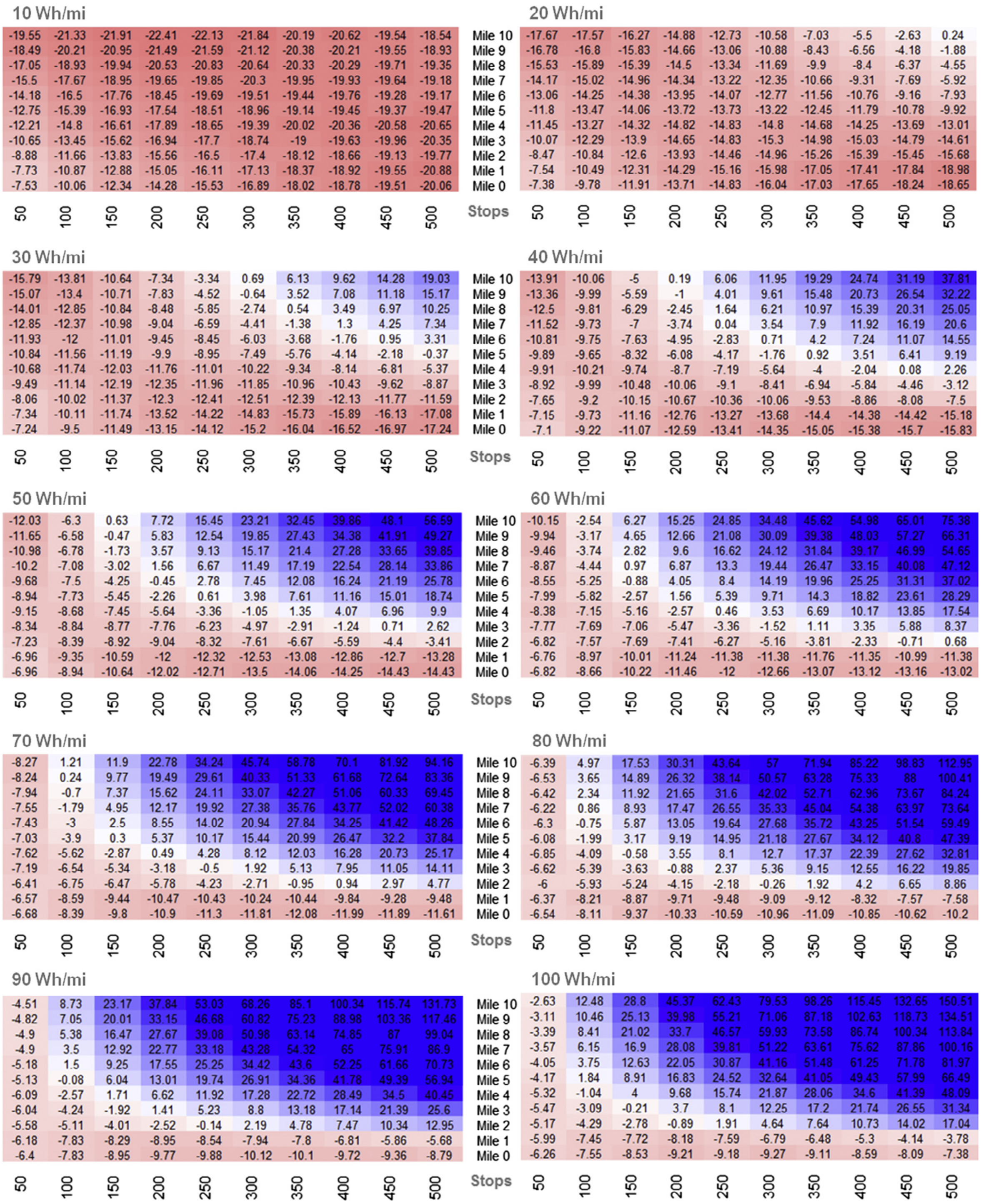

Fig. 4. Heat maps of CO_2 emission differences (kg) between drones and trucks by delivery conditions and varying drone energy requirements. Cells with negative values (red) denote conditions in which drones emit less CO_2 than trucks. Cells with positive values (blue) are situations in which drones produce more.

4.2. CO_2 comparison

For each of the ten density scenarios, delivery-by-truck emission values outputted by ArcGIS are ordered by their service zone distance from the depot. They are then averaged across by distance from the depot so that only one mean emission

Table 2
Maximum Allowable AER_{drone} (Wh/mi) for Drones to Emit Less CO_2 than Trucks.

	50 Stops	100 Stops	150 Stops	200 Stops	250 Stops	300 Stops	350 Stops	400 Stops	450 Stops	500 Stops
Mile 10	113	66	48	39	33	29	25	23	21	19
Mile 9	118	69	50	41	35	30	27	24	22	21
Mile 8	122	72	53	44	37	33	29	27	24	23
Mile 7	126	76	57	47	39	35	31	28	26	24
Mile 6	135	83	62	50	45	38	34	3	29	27
Mile 5	143	90	68	55	48	43	38	35	32	30
Mile 4	169	106	82	68	58	52	47	43	39	37
Mile 3	195	126	101	83	71	64	57	52	48	45
Mile 2	225	152	122	105	90	81	73	67	61	58
Mile 1	408	296	234	207	180	159	148	134	124	119
Mile 0	544	370	301	263	230	209	191	175	163	152

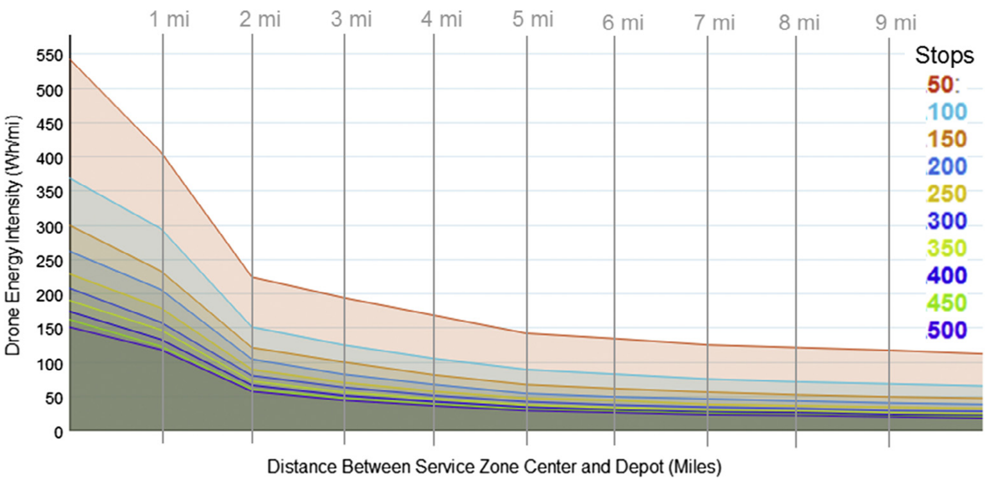

Fig. 5. Graphical representation of a drone's maximum allowable average energy requirements (Wh/mi) in order to emit less CO_2 than trucks by number of stops per service zone (see Table 2). For example, a drone delivering to 50 addresses (stops) to a service zone 1 mile away from the depot must require no more than an average of 408 Wh/mi to operate in order to be environmentally competitive with trucks in terms of CO_2 emissions.

value represents each distance category. These scenarios are subsequently combined to form a 10×11 matrix with each cell entry representing the average CO_2 emissions of a truck delivering to a certain number of recipients in a service zone that is a certain distance away from the depot.

The setup is somewhat different for the delivery-by-drone model. It is the average distances traveled by drone, rather than emissions, that are initially organized into a matrix. This matrix is then multiplied, as explained in the methodology section, by the drone emission rate calculated previously ($3.773(10^{-4})$ kg of CO_2 per Wh). The new matrix is then further multiplied by distinct energy requirements, producing several emission matrices to simulate different drone models. The resulting delivery-by-drone emission matrices are finally subtracted by the delivery-by-truck emission matrix, generating the resulting heat maps as illustrated in Fig. 4.

The results show several trends. First, in general, as a drone's average energy requirement (AER_{drone}) increases, trucks become more advantageous in terms of emitting less CO_2. As explained earlier, this is attributed to the fact that as more electricity is needed to charge a drone, more emissions are produced at power generation facilities. Second, the delivery conditions that begin to favor trucks first are expectedly the cells (or service zones) that are furthest away and with the most recipient addresses. These cells experience a much higher rate of change in emissions for every Wh/mi increase in energy requirement than other cells. This is due to the assumption in this comparative analysis that drones can only deliver one package at a time and so must make a return trip after visiting each individual recipient, dramatically increasing their VMT. This trend is quite clear in Table 2, which lists the maximum allowable AER_{drone} in order for drones to emit less CO_2 than trucks, with cells of lower value representing more distant and crowded service zones. With current and future delivery drone technology and energy usage unknown or not disclosed, it can be generally, but reasonably, said that the upper-right portion of Table 2 is the domain of trucks (or conditions in which trucks would most likely perform better in terms of CO_2 emissions), while the lower-left portion is the domain of drones, which can be observed with the gradual heat maps in Fig. 4.

Fig. 5, which graphically shows the data in Table 2, helps reveal a noticeable, but less apparent, third trend. As a service zone moves closer towards the depot from two miles away to one mile, the maximum allowable energy requirements of a drone increases dramatically, at least doubling in more than half of the ten density scenarios. This corresponds with an approximate halving of drone VMT and CO_2 emissions from the two-mile to one-mile rings of service zones. The causes of such dramatic changes are not entirely certain but can be partially attributed to the street grid and geometry in emission calculations, as well as potentially the greater concentration of service zones near the depot.

5. Conclusions

The goal of this research paper is to determine whether or not drone technology in the delivery industry would have a net positive environmental impact in terms of VMT and CO_2 emissions. In order to do so, models of varying scenarios were created in which trucks and drones originate from a central depot and deliver parcels to recipient addresses in circular service zones. These simulations, coupled with algorithms and emission constants, provided estimations of VMT and CO_2 emissions that would be contrasted between modes of delivery.

Through the results of the comparative analysis, this research has demonstrated some of the complexities in looking for a definitive answer on the potential environmental impacts. For instance, drones that require an average of 40 Wh/mi to operate will generally have a net positive impact in most delivery situations, while drones at an 80 Wh/mi average energy requirement will not. Even at a particular energy requirement level, net emissions differences can vary tremendously across delivery service zones, as they are heavily influenced by the number of recipients and distance away from the depot. Additionally, these VMT and CO_2 estimates produced are highly dependent on and are products of the assumptions and conditions within the models. Slight changes, such as to power sources, the truck age distribution, or the street network, can easily magnify or diminish values.

Still, a number of general, but significant, conclusions can be made as to the role of drone delivery in VMT and CO_2 emissions:

(1) It appears that drones tend to have CO_2 emissions advantage over trucks in service zones that are either closer to the depot or have smaller numbers of recipients, or both.
(2) In these service zones, maximum allowable average energy requirements for drones are high – much higher than what a typical drone would ever need to deliver a light package. This suggests the existence of a plausible market for drones in the delivery industry if CO_2 emissions are the weighing factor.
(3) Trucks almost firmly have CO_2 emissions advantage over drones under conditions in which service zones are both far away and have high amounts of recipients.
(4) Regarding VMT, drones expectedly far outpaced trucks, having to return to the depot after every stop.
(5) Overall, results suggest that within an environmental framework, a blended system would perform best (emit the least) with drones serving nearby addresses and trucks delivering to ones farther.

It should be mentioned that since these models are built upon spatiotemporal-specific data as a foundation, these results are a function of the conditions defined in this paper. For instance, as emphasized earlier, an alteration in depot and recipient locations, even within the same Los Angeles County region, will cause changes in the results as the local street and highway layout is not uniform in all directions throughout the area. However, while the exact VMT and CO_2 emission values may not be wholly transferable to other regions or future years, this well-connected road network is typical of many urban and suburban regions in the United States, and the analytical framework used in this research allows for consideration of various densities and other variables. Therefore, it is still quite likely that these general trends and conclusions identified in this paper hold true for similar scopes of investigation.

To help answer the question on net environmental impacts, future research in this field should explore other emissions, including nitrous oxides and particulate matter, and other logistical structures, including the use of depots not central to the delivery region. Additionally, as drone technology progresses and begins operating within the delivery industry, a complete life cycle assessment (LCA) should be pursued to acquire a more holistic perspective on environmental impacts. Nonetheless, this paper provides important insight into the comparative CO_2 emissions between drones and trucks and highlights the CO_2 advantage drones may provide in some circumstances.

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