12-2018

Modeling the Sustainability of Small Unmanned Aerial Vehicles Technologies: Final Report

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Citation Details

Figliozzi, Miguel. Modeling the Sustainability of Small Unmanned Aerial Vehicles Technologies: Final Report. December 2018.

FREIGHT MOBILITY RESEARCH INSTITUTE
College of Engineering & Computer Science
Florida Atlantic University

Project ID: FMRI Y1R1-17

MODELING THE SUSTAINABILITY OF SMALL UNMANNED AERIAL VEHICLES TECHNOLOGIES

Final Report

by

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for

Freight Mobility Research Institute (FMRI)

December 2018

ACKNOWLEDGEMENTS

This project was funded by the Freight Mobility Research Institute (FMRI), one of the twenty TIER University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT).

The author would like to thank TTP lab members Chad Tucker, Polina Polikakhina and Dylan Jennings for their contributions, and Emma Hovley for editing and revising the final report. The Maseeh College of Engineering and Computer Science at Portland State University for hosting this research. Any errors or omissions are the sole responsibility of the author.

DISCLAIMER

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EXCUTIVE SUMMARY

In the past decade, unmanned aerial vehicles (UAV) have become increasingly more popular in the commercial sector. Drones are being used for all kinds of purposes, such as surveillance, inspecting architecture, filming, wildlife research, and more. Freight delivery is a potential application that is getting lots of attention from large companies.

This research presented novel data, relationship, and models for deliveries utilizing small UAVs. Small UAVs were defined as aircrafts with a tare of up to 15 kilograms (kg) and a potential payload of up to 15 kg. Since the weight of the UAVs is capped, only drones with engines that are electric were included; noise and pollution problems are likely to hinder urban deployments of internal combustion engines. Internal combustion engines are mostly used in larger UAVs. The scope of the search was limited to multicopter drones that can potentially deliver in both urban and rural areas. Fixed-wing drones were excluded from the search because currently only copters have the capability of hovering and delivering products in tight spaces (required in urban areas); fixed-wing UAVs typically cannot land or take off vertically. Single copters can hover similarly to helicopters, but were not included in the search because these aircrafts tend to be larger, and the size of the propeller and blade made them unsafe for areas without a large. Multicopters or multi-rotor drones can hover but also have higher stability and maneuverability, which makes them more suitable for navigating tight spaces or flying near humans and/or valuable property.

The survey of currently available UAVs shows that payload, size, energy consumption, and cost are positively correlated and tend to increase together. Unfortunately, potential safety, noise, and last-yard constraints also increase as drone capabilities and size increase.

Cost metrics such as cost per flying hour (CPFH) are the most relevant for small UAVs since they readily take into account the impact of operator labor cost and utilization, clearly the largest cost components. The economic analysis indicates that labor/staff costs can range between 30% and 85% of UAV costs per flying hour. The impact of labor costs will be highly dependent on future regulations and the level of automation of the last-mile delivery process.

A novel analysis of lifecycle UAV and ground commercial vehicles' CO_2e emissions is presented. Different route and customer configurations are modeled analytically. Utilizing real-word data, tradeoffs and comparative advantages of UAVs are discussed. Breakeven points for operational emissions are obtained and the results clearly indicate that UAVs are more CO_2e efficient for small payloads than conventional diesel vans on a per-distance basis. Drastically different results are obtained when customers can be grouped in a delivery route. UAV deliveries are not more CO_2e efficient than tricycle or electric van delivery services if a few customers can be grouped in a route. Vehicle phase CO_2e emissions for UAVs are significant and must be taken into account. Ground vehicles are more efficient when comparing vehicles' production and disposal emissions per delivery.

Currently available UAV technology can fill a delivery service niche in sparsely populated areas with low numbers of customers and density. In rural areas, the regulatory landscape and last-yard delivery constraints are also more relaxed. In rural areas, the economic benefit brought about by

reducing the cost of a driver to visit remote customers are obvious, but in this environment, UAV range is a key consideration. In dense urban areas, several first- and last-mile service, privacy, regulatory, and security issues must be addressed before UAV services are feasible. UAVs are likely to have an edge regarding speed delivery if they are operated in uncongested skies where they can outperform slower ground vehicles delayed by conditions of the congested ground road network. On the other hand, drones may not be able to compete solely in terms of costs with a delivery truck that can deliver hundreds of packages to one location in an urban setting. The urban landscape is a place where larger payload capacity may be more beneficial than flight distance for some delivery types.

The future of UAV deliveries will also depend on other factors such as UAV noise levels, regulations and safety concerns, and last-yard delivery configurations.

1.0 INTRODUCTION

The integration of new vehicles and technologies in goods distribution and service delivery depends on a number of factors related to vehicle costs, technology, infrastructure, energy sources, and financial incentives.

From filming movies or researching a pod of whales to delivering medication or an explosive payload, UAVs are being increasingly utilized for a wide range of tasks. Since 2002 when the Predator drone was first used by the U.S. military in Afghanistan (Sifton, 2012), drones have become smaller and cheaper, making it feasible for people to imagine alternate uses for UAVs, like delivering freight.

Since 2011, big names like UPS, Amazon, and Google have thrown their hat into the UAV delivery ring, while other lesser-known companies like Matternet and Zipline have actually started delivery services in Rwanda, Australia, Switzerland, and Bhutan (Mack, 2018). UAVs have become a popular topic of conversation and an exciting source of speculation regarding how they might change the status quo for many businesses.

1.1 RESEARCH GOALS

Drones are not restricted by the availability of existing infrastructure and can therefore lead to improved last-mile efficiency, safety, and reliability. Unmanned aerial vehicles (UAV) for package delivery have a lot of potential to improve logistics productivity and reduce costs and environmental externalities such as trucking diesel engine pollution.

The main goal of this research is to analyze, based on a survey of state-of-the-art UAVs, main capabilities and limitations of UAVs in the freight industry. The real-world data collection, analysis, and focus is on UAVs with electric engines. The focus is on UAVs that are small enough to be deployed for deliveries in dense urban areas. Hence, small UAVs are defined as aircrafts with a tare of up to 15 kilograms (kg) and a potential payload of up to 15 kg.

This research studies the key factors that affect UAV delivery costs, as well as UAV energy efficiency and the carbon footprint for last-mile deliveries. A survey of current UAVs is utilized to draw real-world data parameters and to model different scenarios such as one-to-one deliveries and one-to-many deliveries.

A novel modeling framework based on a UAV performance model is utilized to analyze key drivers of UAV costs, energy consumption, and CO_2e emissions. The modeling framework includes constraints for battery energy storage, service range, and delivery times.

1.2 ORGANIZATION

This report is organized into nine sections or chapters. An extensive, yet not comprehensive, literature review is presented in Section 2. Key equations governing UAV flight, logistical capabilities, and energy consumption are introduced in Section 3. A survey of existing small UAV aircrafts and graphs showing key relationships among tare, payload, purchase cost, and energy consumption are analyzed in Section 4. The economic analysis of UAV operations utilizing the cost per flying hour metric is presented in Section 5. Models to quantify and compare UAV energy consumption and emissions are discussed in Sections 6 and 7, respectively. The report concludes with a brief discussion of issues that may hinder UAV deployment, and conclusions in Sections 8 and 9, respectively.

2.0 LITERATURE REVIEW

There is a growing literature related to small UAVs. This section highlights some key concepts and references but is not a comprehensive examination of the rapidly evolving and growing body of UAV literature. Many papers in the applied electronics and engine control areas have focused on UAV technology, software, and design issues; these papers, for example, Bristeau et al. (2011), are not reviewed herein because they are not directly relevant to the topic discussed in this report.

2.1 LOGISTICS APPLICATIONS

Potential advantages and disadvantages of UAVs have already been considered by logistics companies. For example, the logistics services company DHL has identified higher last-mile efficiency, reduction of accidents, and faster deliveries as key potential UAV benefits; key potential challenges associated with UAVs are security, privacy, congestion, and regulatory concerns (Heutger and Kuckelhaus, 2014). UAVs have been featured frequently in the media following announcements made by large corporations such as Amazon (Anderson, 2004) but less frequently in the logistics academic literature. The academic literature discussing UAVs' pros and cons or attempting to model UAV performance is rather scant. D'Andrea (2014) provides a succinct and preliminary discussion and modeling of UAV energy usage and delivery costs. Payload, lift-to-drag ratio, headwind, and travel speed do have a significant impact on UAV performance (D'Andrea, 2014).

The academic literature has already documented the advantages UAVs can provide in delivering medicines to remote locations (Thiels et al., 2015). Other researchers have analyzed UAVs' potential applications and challenges (Mohammed et al., 2014) and some authors have focused on the regulatory barriers that can preclude large UAV deployments (Boyle, 2015).

Other researchers have analyzed the fit between product characteristics and UAV performance. For example, Wright et al. (2018) looked at various transport options for a variety of delivery categories using UAVs and modes such as land cruisers and motorcycles to examine the cost-effectiveness of UAVs for the delivery of blood for transfusion, medicines, vaccines, and long-tail products.

2.2 HEALTH APPLICATIONS

UAVs that deliver cargo are already in operation in several different countries. Mostly, these UAVs were specifically tailored to meet the particular demands of the job or service. For example, in Rwanda, there is a great need for life-saving blood medicines in rural parts of the country, but the road infrastructure is very poor. A company called Zipline (2017) has started using fixed-wing autonomous drones to deliver these medicines via parachute faster than any other kind of transportation available.

Some researchers have studied the utilization delivery of UAVs to deliver defibrillators (Boutilier et al., 2017; Claesson et al., 2017) or blood (Amukele et al., 2017). Drones are particularly suitable for emergency applications like search and rescue (Karaca et al., 2018), deliveries of critical medical supplies post-disaster, or for emergency response (Ozdamar, 2011; Anaya-Arenas et al., 2014; Thiels et al., 2015; Scott and Scott, 2018).

2.3 EMISSIONS

Transportation accounts for a large share of total GHG emissions in most developed countries (Hertwich et al., 2009). Regarding UAV operational emissions, Goodchild and Toy (2017) compared VMT and CO_2 emissions using scenarios when deliveries are only made by UAVs or conventional trucks. Results suggest that UAVs emit less emissions when customers are located close to the depot, and trucks emit less for faraway customers. The authors suggest that UAVs and trucks can complement each other. The idea of utilizing both UAV and trucks to improve overall delivery efficiency has also been analyzed by several authors (see subsection 2.5), but this research focuses on the actual design of routes and logistics systems (Mathew et al., 2015; Murray and Chu, 2015; Wang et al. 2017).

Regarding UAV energy consumption, Choi and Schonfeld (2017) model the impact of battery capacity on payloads and flight ranges. Numerical analysis is utilized to optimize the drone fleet size and minimize delivery costs. This study concludes that UAV deliveries are more economical in areas with high customer density and that improved battery technology can significantly reduce UAV fleet size. There are tradeoffs associated with delivery speeds but clear benefits from longer hours of operation.

Figliozzi (2017) uses continuous approximation techniques and derives analytical formulas to compare operational and lifecycle emissions and energy consumptions of UAVs with conventional diesel, electric vans, and tricycle delivery services. Figliozzi (2017) shows that the delivery strategy (grouping of customers in a route) affects the relative CO_2 emission efficiencies. Stolaroff et al. (2018) confirmed previous findings regarding UAV emissions. Moore (2019) compared the operational emissions of six scenarios: conventional class six trucks, electric class six trucks, electric delivery vans, parcel delivery lockers, drones, and the use of electric passenger vehicles for en-route deliveries; results indicate that electric trucks paired with parcel delivery lockers tend to be the most energy efficient combination.

2.4 LOCATION MODELS

Another line of research has focused on the location of UAV facilities. For example, Chowdhury et al. (2017) used a continuous approximation approach to develop a humanitarian logistics supply chain post-disaster, considering both drones and truck deliveries. Golabi et al. (2017) studied the relief distribution center location model, where inaccessible demand points are served using drones. Pulver and Wei (2018) developed a facility location model to maximize primary and secondary coverage in the context of transporting and delivering medical supplies. Kim et al. (2017) developed a two-stage model for drone-based pickup and deliveries of medical supplies, and Hong et al. (2018) studied a drone recharging facility location problem, which can help increase the coverage range of drones for commercial deliveries. Chauhan et al. (2019) model the optimal location of UAV facilities, taking into account drone energy consumption as a function of payload and distance within a drone maximum coverage location problem framework.

2.5 VEHICLE ROUTING

A large body of research has focused on UAV or drone routing and scheduling, leading to several interesting variants of the traveling salesman and vehicle routing problems. Murray and Chu (2015) studied the flying sidekick traveling salesman problem (FSTSP), where a drone and a truck deliver in collaboration to a set of customers. Ponza (2016) modified the drone delivery time constraints in Murray and Chu (2015)'s FSTSP formulation and developed a simulated annealing metaheuristic. Agatz et al. (2018) denoted the FSTSP as Traveling Salesman Problem with Drones (TSPD), provided approximation results comparing TSPD and TSP optimal solution, and developed several route-first cluster second heuristics that vary in the initial tour generation and assignment of drone delivery nodes. Yurek and Ozmutlu (2018) solved the TSPD using a two-stage iterative decomposition approach in which truck routes are determined in the first stage and drone nodes are assigned in the second stage. Ha et al. (2018) focused on the min-cost TSPD variant of Murray and Chu (2015)'s FSTSP and developed a greedy randomized adaptive search procedure that builds TSPD routes from TSP routes. Otto et al. (2018) provide a detailed review of all optimization-based papers on civil applications of drones and UAVs.

Dorling et al. (2017) modeled the drone delivery problem as a single depot multi-trip vehicle routing problem, whereas Kim et al. (2018) use a robust optimization approach to model the impact of air temperature uncertainty on drone battery capacity and studied the ability of a fleet of drones to visit multiple locations.

2.6 REGULATORY CONSTRAINTS

In 2016, the Federal Aviation Administration (FAA) issued restrictions on the non-recreational use of unmanned aerial vehicles, which effectively prohibited freight delivery from using drones in the U.S. (FAA, 2016). Some restrictions do not affect the drones surveyed in Section 4 (400' maximum altitude, 45 m/s (100 mph) maximum land speed). However, other restrictions prevent any business from currently utilizing drones in a freight delivery service. For example, drones must be flown using VLOS (visual line of sight) at all times, which would greatly reduce the size of the service area, especially in forested hilly terrains or dense areas with skyscrapers, and reduce the economic benefit of not having a human pilot in the UAV.

The FAA is partnering with NASA to study when drones can be used in U.S. National Airspace and in what capacities (NASA, 2015). NASA is working on an air traffic management system for drones similar to what exists for today's air traffic, except that the UAV air space resides mainly within altitudes from 200' to 500'. This is critical to ensure that the digital aviation infrastructure, which would be designed to organize the many different paths of the UAVs, would prevent drones from crashing into one another or flying into a restricted zone. A predictable regulatory framework (FAA, 2018) is expected to accelerate large-scale UAV adoption.

3.0 MODELING UAV FLIGHT

Before surveying UAV characteristics or estimating UAV costs/emissions, it is first necessary to understand the physics of UAV flight. This section reviews key formulas and factors that govern airborne vehicles' productivity and energy consumption.

3.1 STEADY FLIGHT

There are many factors that affect airborne vehicles' energy consumption. Drag, lift, weight, and thrust forces act over all self-propelled airborne vehicles, including airplanes, helicopters, and UAVs (Anderson and Eberhardt, 2001).

Maintaining a steady level flight requires a balance of forces, i.e. an equilibrium of all the forces acting upon an airborne vehicle. According to Newton's second law, when any object moving in a steady level trajectory at a constant velocity has zero acceleration, all forces applied to the aircraft are balanced. For an airborne vehicle in a steady level trajectory, there are four relevant forces: (i) weight, the force of gravity that acts in a downward direction, (ii) thrust, the force that propels the airborne vehicle in the direction of motion, (iii) lift, the force that acts at a right angle to the direction of motion through the air, and (iv) drag, the force that acts opposite to the direction of motion. When there is zero acceleration, level flight is at a constant velocity, the lift balances the weight, and the thrust balances the drag (Anderson and Eberhardt, 2001; D'Andrea, 2014).

$$L = W, D = T$$

and

$$\frac{L}{D} T = mg$$

where:

$D =$ drag force [N]

$T =$ thrust force [N]

$L =$ lift force [N]

$W =$ weight force [N]

$m =$ mass [kg]

$g =$ gravity acceleration [m/s2].

An electric cargo UAV has three key mass components: vehicle, battery, and load. For aircrafts, the lift-to-drag ratio or L/D ratio is a key characteristic affecting flight efficiency and the power necessary to fly as a function of travel speed. By disaggregating the vehicle weight into its components and then multiplying by travel speed, it is possible to obtain the theoretical power necessary to move the aircraft:

$$p_t = Ts = (m_t + m_b + m_l)g \frac{v}{\vartheta(s)}$$

where:

p_t = theoretical power required for level flight [watts]

v = constant velocity travel speed [m/s]

$\vartheta(v)$ = lift-to-drag ratio or L/D [unit-less]

m_t = UAV mass tare, i.e. without battery and load [kg]

m_b = UAV battery mass [kg]

m_l = UAV load mass [kg]

m = UAV total mass when loaded [kg], $m = m_t + m_b + m_l$.

The energy necessary to travel a given distance is equal to power by travel time and also affected by the power transfer efficiency from the battery to the propellers (energy loss). The power required for level flight is:

$$p_l t = \frac{(m_t + m_b + m_l)g}{\vartheta(s)\eta_p} d$$

where:

p_l = power required for level flight [watts]

t = travel time [seconds] = d/s

d = travel distance [m]

η_p = total power transfer efficiency [unit-less] < 1.

From (1), it is possible to observe that energy consumption is directly proportional to aircraft mass and travel distance. Expression (1) does not include the power needed to feed the sensors and other electronics, which is relatively small for a long-range delivery drone. Travel speed drops out of expression (1); however, the ratio between Lift and Drag is typically a function of travel speed. For each aircraft, there is a speed where L/D is highest or optimal, which is defined as ϑ^*. Cargo airplanes are more energy efficient than helicopters and UAVs; airplanes' ϑ^*values, in the range of 10 to 20, are several times higher than helicopters' ϑ^*values, in the range of 3.5 to 5.0 (Leishman, 2006).

3.2 HOVER

The power required to hover is proportional to the power of the helicopter weight (Johnson, 2012) and can be approximated by:

$$p_h = k_h \frac{W^{\frac{3}{2}}}{\sqrt{2\rho A}}$$

where:

$p_h =$ power required to hover [watts]

$W = mg =$ weight of the aircraft [N]

$A =$ effective area of the blades

$\rho =$ air density

$k_h =$ parameter that takes into account the aircraft figure of merit and the induced power factor.

Hence, weight and payload are key factors affecting the performance of a UAV and their range. In practice, helicopters tend to be designed assuming a value of gross operational weight (Johnson, 2012).

3.3 STEADY LEVEL FLIGHT OPTIMAL SPEED AND MAX. RANGE

On steady flight drag is the force that opposes the motion of an aircraft. Total drag is produced by the sum of the profile drag, induced drag, and parasite drag.

Profile drag is the drag incurred from frictional resistance of the blades passing through the air. It is almost constant or increases moderately as airspeed increases. Induced drag is the drag incurred as a result of production of lift. In rotary-wing aircraft like small UAVs, induced drag decreases with increased aircraft airspeed.

Parasite drag is the drag incurred from the non-lifting portions of the aircraft. Parasite drag increases rapidly with airspeed and is conceptually equivalent to the aerodynamic resistance found in ground vehicles.

The power required to maintain steady level flight as a function of speed is the sum of the three drag components (Johnson, 2012):

$$p_l(v) = k_0\, v + k_i\, v^{-1} + k_p\, v^3$$

where:

$p_l(v) =$ power required for level flight as a function of speed [watts]

$k_0, k_i, k_p =$ parameters associated to profile, induced, and parasite drag respectively

The maximum range is obtained when drag is minimized and lift-to-drag ratio $\vartheta(v)$ is maximized (Johnson, 2012). Minimizing the drag forces utilizing the first order condition, the speed v^r that maximizes the range is equal to:

$$v^r = \sqrt[4]{\frac{k_i}{k_p}}$$

Hence, the optimal flying speed is dependent on aircraft size, aerodynamic and shape factors as well as environmental conditions that determine the relative value of the parameters k_i and k_p (Johnson, 2012).

4.0 SURVEY DATA AND ANALYSIS

Small drones are still a relatively new type of vehicle. Given the lack of available data regarding their characteristics and performance, a survey was carried out to fill this knowledge gap. The search was focused on UAVs small enough to be deployed for deliveries in dense urban areas (tare up to 15 kg and a potential payload of up to 15 kg).

4.1 METHODOLOGY

To obtain the data for the different UAV models, the researchers conducted an extensive internet search of UAV manufacturers and their products. They utilized information published on their websites, along with downloadable material such as user manuals, technical specifications, and press releases. Though most information was obtained this way, some specifications were procured through consumer tech reports or online retailers. In some cases, customer service was contacted to request additional information.

Unfortunately, not all manufacturers posted all the relevant logistical data needed for a proper analysis. For instance, few manufacturers provided hovering times and most manufacturers did not provide detailed technical specifications regarding battery chargers or recharge times for the battery. In some cases, there was also a lack of detailed performance data that is useful for the freight industry, e.g. flight range with different levels of payload, or the number of cycles a battery can be recharged before replacement. The researchers analyzed data from the of UAVs included in Appendix A and that were available in the market at the time of the research. Due to incomplete data for some UAVs, graphs may have a different number of observations.

The scope of the search was limited to multicopter drones that can potentially deliver in both urban and rural areas. Fixed-wing drones were excluded from the search because currently only copters have the capability of hovering and delivering products in tight spaces (required in urban areas); fixed-wing UAVs typically cannot land or take off vertically. Single copters can hover similarly to helicopters, but were not included in the search because these aircrafts tend to be larger, and the size of the propeller and blade made them unsafe for areas without a large clearance (more discussion about this issue in a later section). The search is also restricted to multicopters or multi-rotor drones because this type of aircraft can hover but also has higher stability and maneuverability, which makes them more suitable for navigating tight spaces or flying near humans and/or valuable property.

The UAVs studied in this report have a tare of 15 kg or less and a payload of 15 kg or less. Since the weight of the UAVs is capped, only drones with engines that are electric were included; noise and pollution problems are likely to hinder urban deployments of internal combustion engines. Internal combustion engines are mostly used in larger UAVs, and a later section discusses issues associated with size and noise limitations.

Finally, this is a rapidly evolving and “young” industry without clear standards yet. Focusing only on electric multicopter drones allows for a more in-depth discussion of state-of-the-art drone delivery capabilities. The lack of standardized data from manufactures provided a major challenge in terms of data presentation. Hence, instead of presenting data in tables that include each model, each topic is discussed in terms of observed trends, the typical value (median) and ranges found (25th and 75th intervals).

4.2 SPEED, FLYING TIMES, RANGES AND PAYLOADS

In shipping, speed is a key logistical consideration. The higher the speed, the faster the cargo can be delivered. Most speeds are in the range of 16 to 20 meters per second (35 to 45 miles per hour). The range of speeds is more than adequate for urban areas, considering that UAVs may travel more direct aerial routes and are not affected by ground road congestion.

Most available flying times are in the range of 20 to 30 minutes. Flying times are mainly restricted by battery constraints. Flight range is heavily dependent on a multitude of factors, such as battery efficiency, battery size, payload size, weather, topography, and whether it is flown within line-of-sight (LOS), autonomously, or remotely. Battery constraints and limited flying times determine that the typical range of current multicopters is between 15 and 35 km (roughly 10 and 22 miles). The practical range should be less than the maximum range stated by the manufacturer. In practice, the UAV operator has to provide a margin of safety, and some factors like headwinds can dramatically increase energy consumption. Hence, a drone with a stated maximum range of 35 km may only serve customers within less than a 14 km (8.7 mile) radius (assuming that it uses 80% of the theoretical range).

Heavier payloads also reduce the range. For example, a drone may be able to fly 25 km with a 2 kg payload, but only 20 km with a 3 kg payload. The maximum payloads surveyed ranged from 1.8 kg to 6.4 kg (4 to 14 lbs). As a reference, Amazon’s future delivery service limits itself to 2.3 kg or 5 pounds (Amazon, 2016). There is a clear trend linking the size and weight of the drone with its maximum payload capacity. As the drones increase in size and weight, there is also an increase in the amount they can lift. As later discussed, there is also a clear link between battery capacity, battery weight, and payload capacity.

The practical range of drones will determine not only the service area of delivery but also the amount of infrastructure needed to serve an area or to achieve a particular level of service, e.g. Amazon’s 30 minute or less policy. A shorter range would require more closely spaced nodes at which drones could recharge, whether those were mobile vans, warehouses, or simply a charging station that is part of a charging network.

4.3 SIZE AND WEIGHT

In general, larger drones have a higher payload and heavier drones have a longer range (more and heavier batteries). The typical payload/takeoff-weight ratio ranges from 0.33 to 0.20, and the battery/takeoff-weight ratio typically ranges from 0.30 to 0.25. Heavier drones tend to be larger (longer diagonal measurement). The average size across the diagonal is 1,045 mm not including the propellers, with a typical range from 1485 to 350 mm. The typical takeoff weight is approximately 4 kg, but longer-range drones have a takeoff weight of 10 kg or more.

Figure 1 shows a clear positive relationship between the UAV tare and the diagonal length (excluding propellers) of the UAV frame. Figure 2 also shows a remarkably linear relationship between payload and takeoff weight.

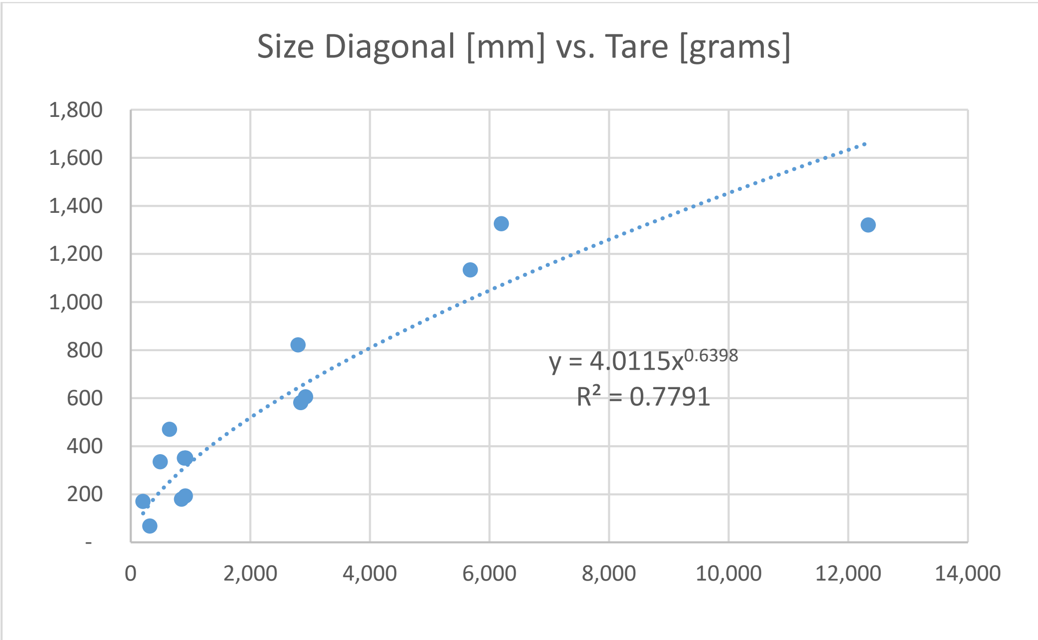

Figure 1: UAV Diagonal vs. Tare

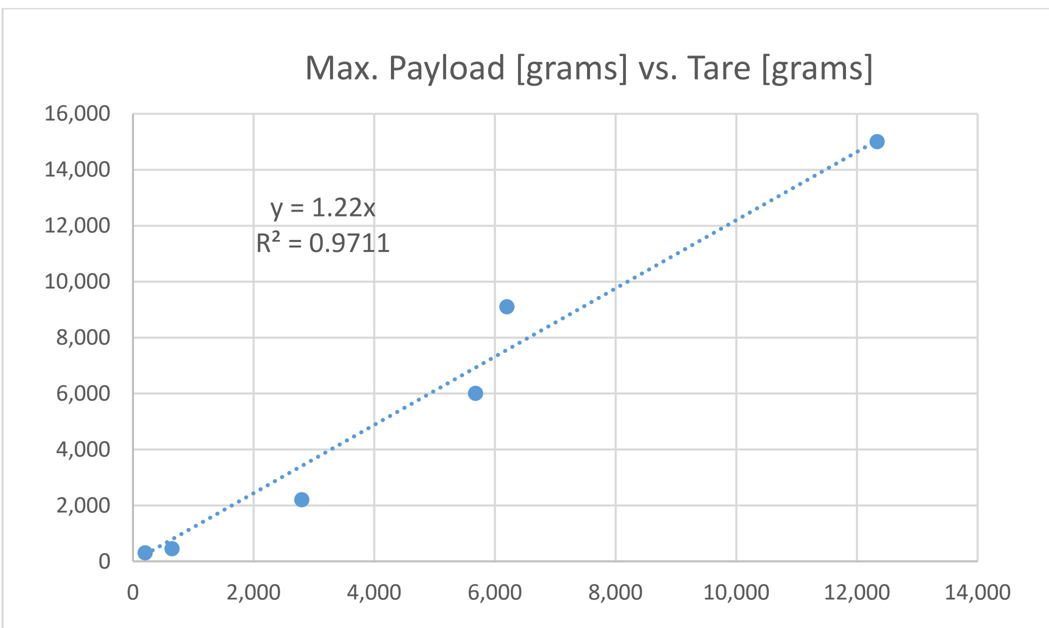

Figure 2: Max. Payload vs. Tare

4.4 BATTERY/ENERGY

Batteries are primarily lithium based (also lithium polymer), though a few UAVs use lithium-ion batteries. Batteries are typically composed of several cells. Voltages are typically between 22.8 and 11.4V. Battery energy typically ranges between 200 and 70 Wh, though some longer range drones like the Microdrone MD4-3000 can have a battery with over 750 Wh.

Batteries are a major component of the weight of a drone. In small drones, the battery can be heavier than the maximum payload. In larger drones, the battery can weigh as much as 80% of the maximum payload. Battery technology is a key constraint for UAV performance; typical lithium-based batteries used in available drones have an energy density ranging from 190 to 175 wh/kg. The consistency of ratios between tare, battery weight, and battery technology is confirmed by Figure 3, which shows a remarkably linear relationship between battery energy and tare.

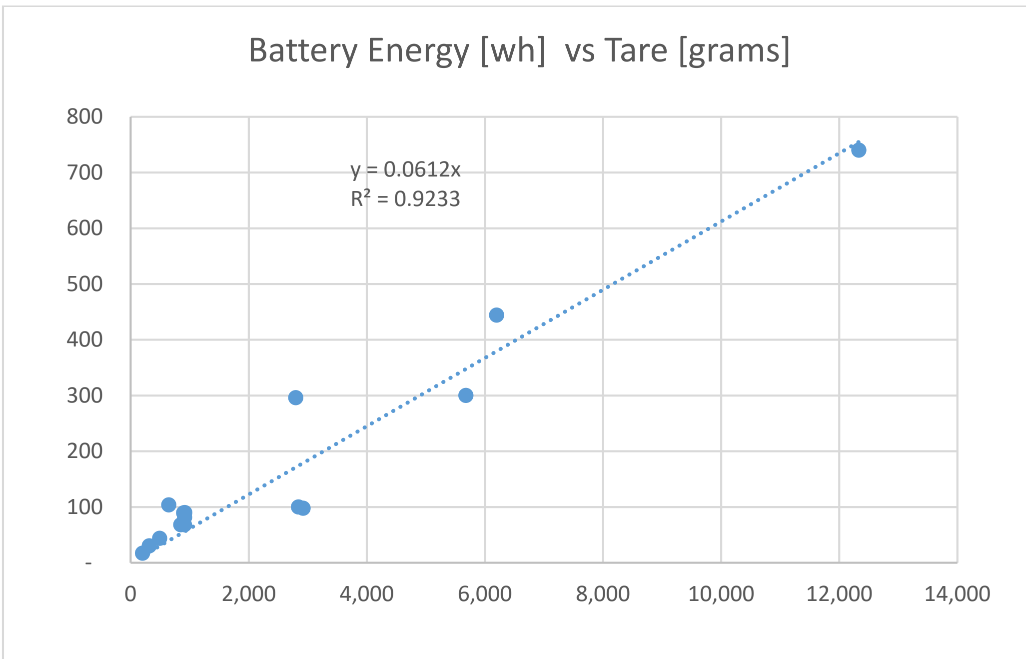

Figure 3: Battery Energy vs. Tare

Recharge time will be an important factor in freight delivery logistics. The longer it takes to recharge a battery, the longer a drone sits on the sidelines being unproductive. Long recharge times might prompt a business to purchase more drones or batteries to be able to maintain an ever-ready drone fleet. The majority of the drones had longer recharge times than flight times: sometimes as much as 500% longer. Recharge times are also affected by the type of battery charger used. Faster recharge times require more expensive chargers. Recharge times tend to increase with battery size, but they also are a function of the recharger type.

Finally, mostly drones of up to 15-20 kg of tare have electric engines. Heavier UAVs use internal combustion engines due to the higher specific energy of fossil fuels. However, as battery technology improves, it is likely that electric drones will also grow in size and weight.

4.5 PURCHASE COSTS

There is a wide range of purchase costs; small multicopters cost a few hundred dollars and the most expensive multicopters cost over $20,000 each. The wide range is explained by the different capabilities and the cost of the batteries. In some cases, the batteries and the charger can be nearly as expensive as the cost of the drone itself (everything but the battery).

UAV purchase cost values are somewhat hard to analyze because they change frequently, and also because many drones can be customized and different features may be added or removed (e.g. charger, additional batteries). In addition, some costs like shipping or taxes vary significantly by state or country. When many costs were available, purchase costs for standard UAVs (i.e. without additional features) were chosen for the analysis.

Figure 4 shows another remarkably linear relationship, in this case between purchase cost and tare. Another linear trend is observed in Figure 5 between battery energy and purchase cost. These trends suggest that the unit cost per mass or energy density is relatively constant for the range of surveyed UAVs. Empty weight cost is a commonly used metric in the aviation industry because it tends to remain constant, even across different aircraft types (Valerdi, 2005). Hence, it is not surprising that it is also a useful metric for estimating UAVs purchase costs.

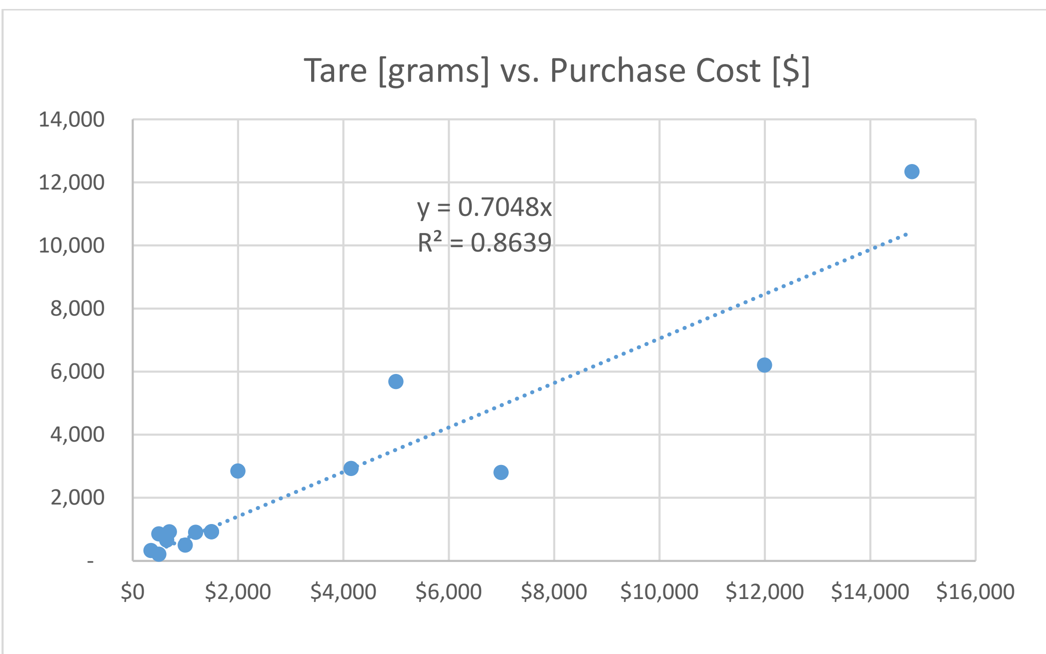

Figure 4: Tare vs. Purchase Cost

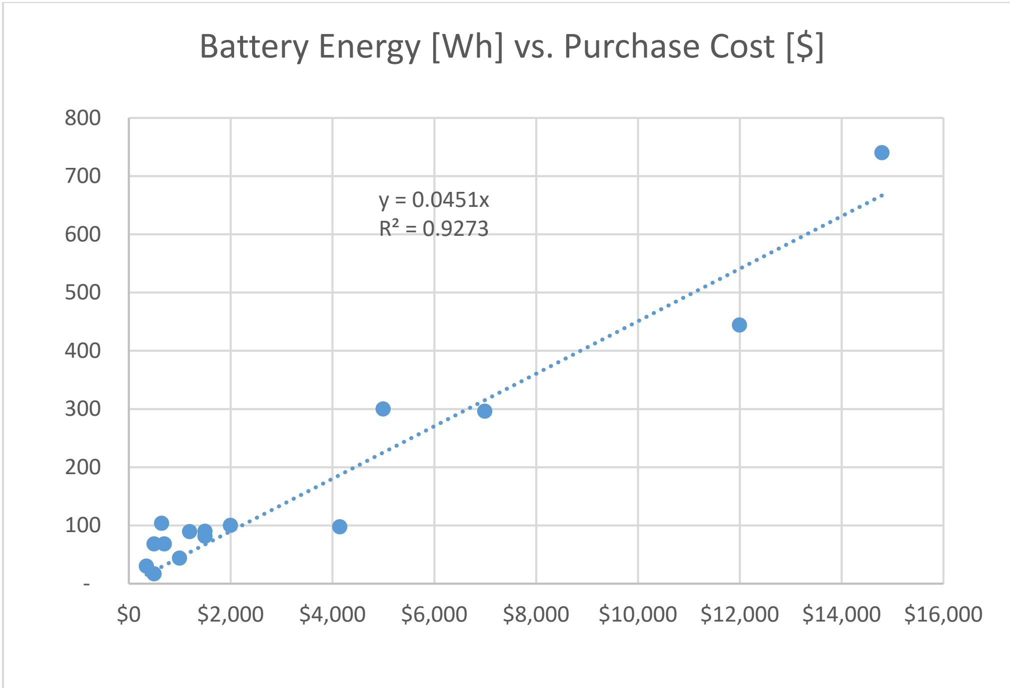

Figure 5: Battery Energy vs. Purchase Cost

4.6 PERFORMANCE

In the past, the performance of UAVs has been measured in terms of the product of UAV tare and flying time (USOSOD, 2005). The product of UAV tare and flying time incorporates a metric such as flying time that is closely linked to range. Hence, this is a key metric for understanding and comparing UAV capabilities. As shown in Figure 6, the relationship is also remarkably linear.

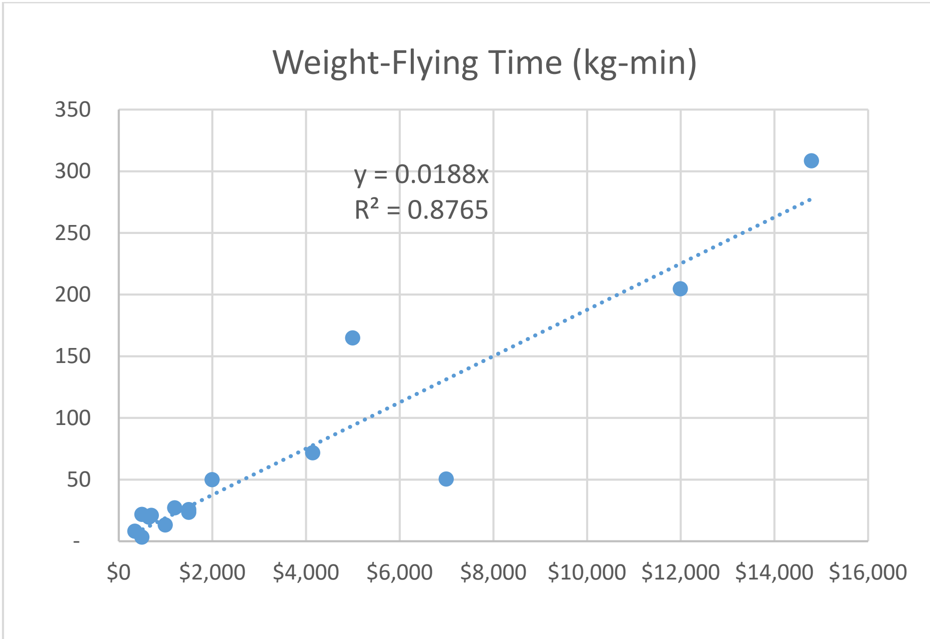

Figure 6: Flight time-tare vs. Cost

The same relationship holds if the natural logarithm of costs and tare-flying time is plotted (see Figure 7).

Valerdi (2005) also observed a linear relationship when plotting natural logarithms of costs and tare-flying time. For Valerdi's data, natural logarithms (nl) were a logical choice, since the ratio between most expensive and least expensive military UAV included in the graph was approximately 600, whereas in our survey, the ratio between most expensive and least expensive civilian UAV is approximately 40.

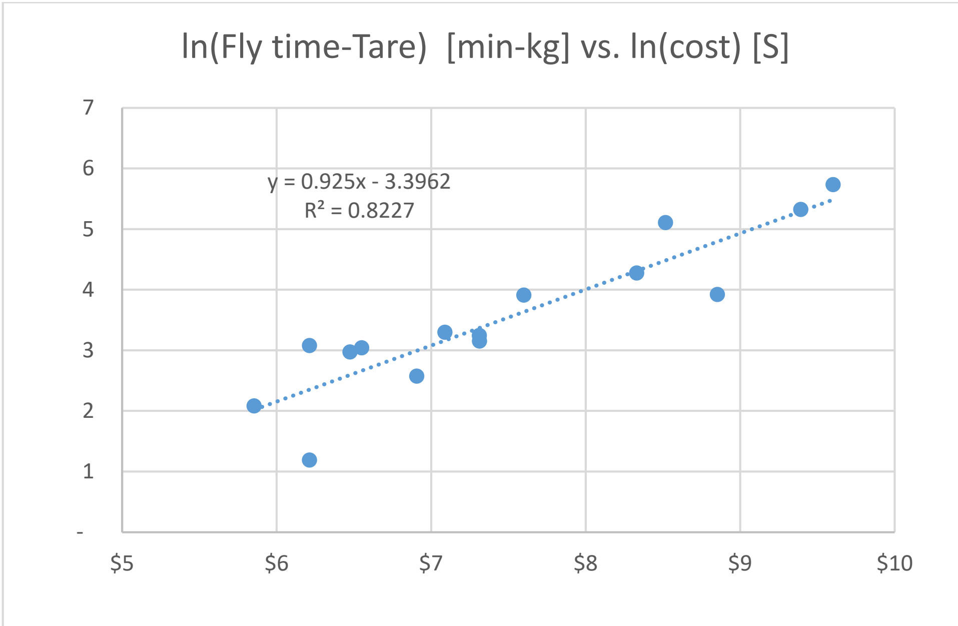

Figure 7: ln(flight time-tare) vs. ln(cost)

The scarcity of UAV performance data was also noted by Valerdi (2005): only seven observations were included in Valerdi's graphs.

4.7 ENERGY CONSUMPTION

UAV energy consumption increases as a function of UAV flying time and weight, as discussed in Chapter 3. Figure 8 shows the relationship between energy consumed, measured as battery energy content, per unit of flying time and tare. As expected, there a clear link between battery energy content, fly time, and tare.

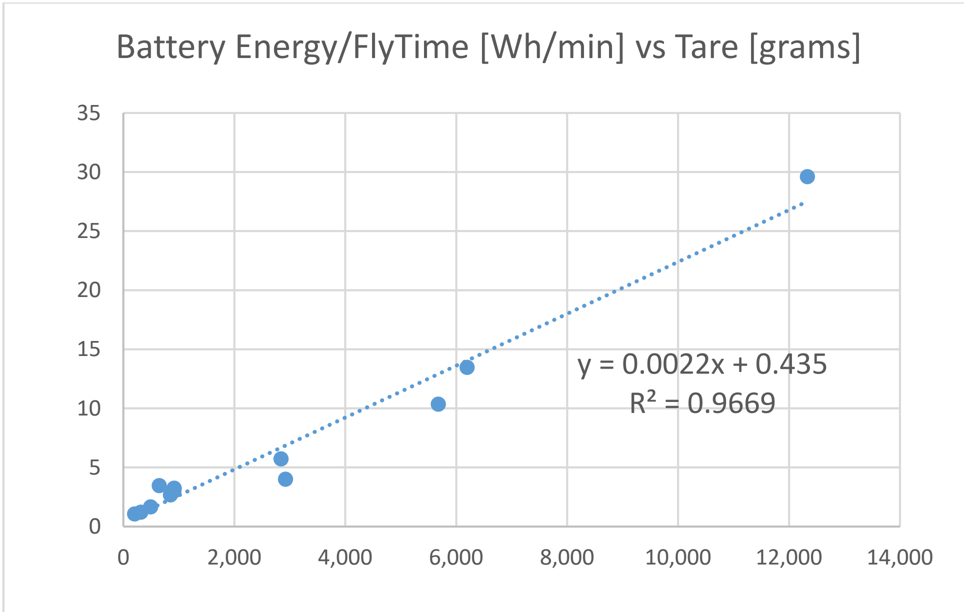

Figure 8: Battery Energy / Flight Time vs. Tare (linear relationship)

The relationship can be linear but there are also theoretical reasons to think that it can be a power function of weight (see Figure 9).

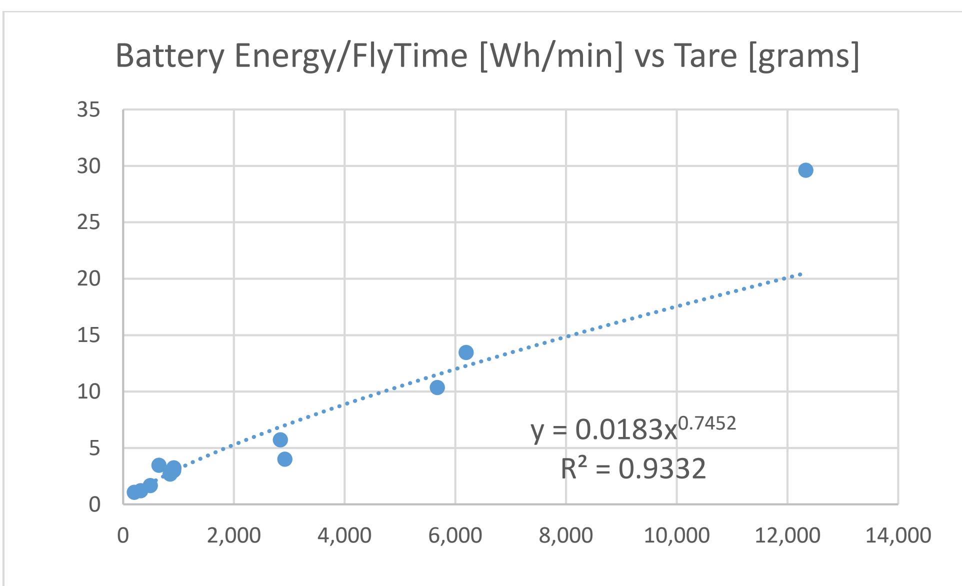

Figure 9: Battery Energy / Flight Time vs. Tare (power relationship)

The upper efficiency, in terms of energy consumed per distance traveled, can be estimated utilizing the battery energy and the maximum flying time and speed. The relationship between energy consumed per distance traveled and tare are shown in Figures 10 and 11 (linear and power relationship respectively).

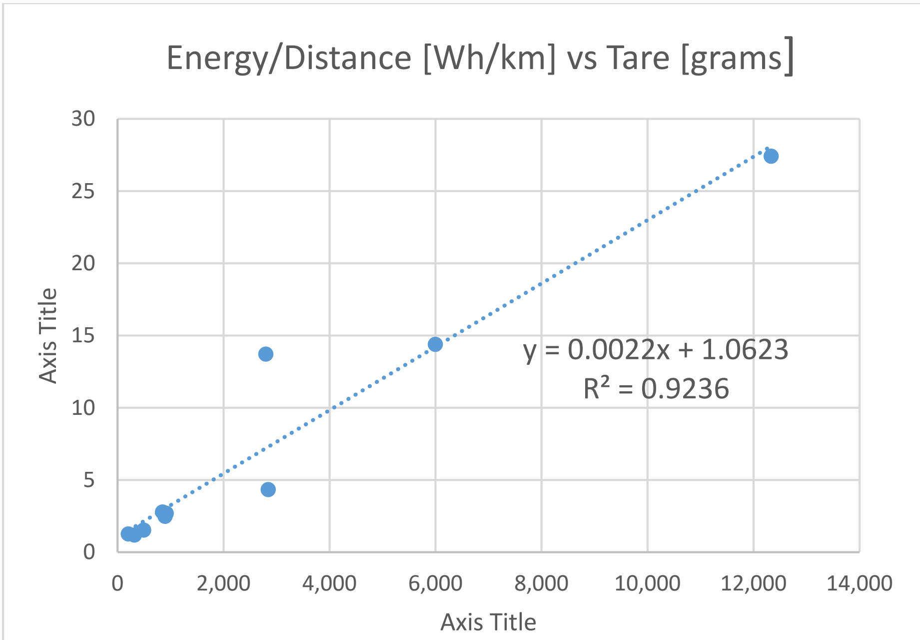

Figure 10: Energy / Distance vs. Tare (linear relationship)

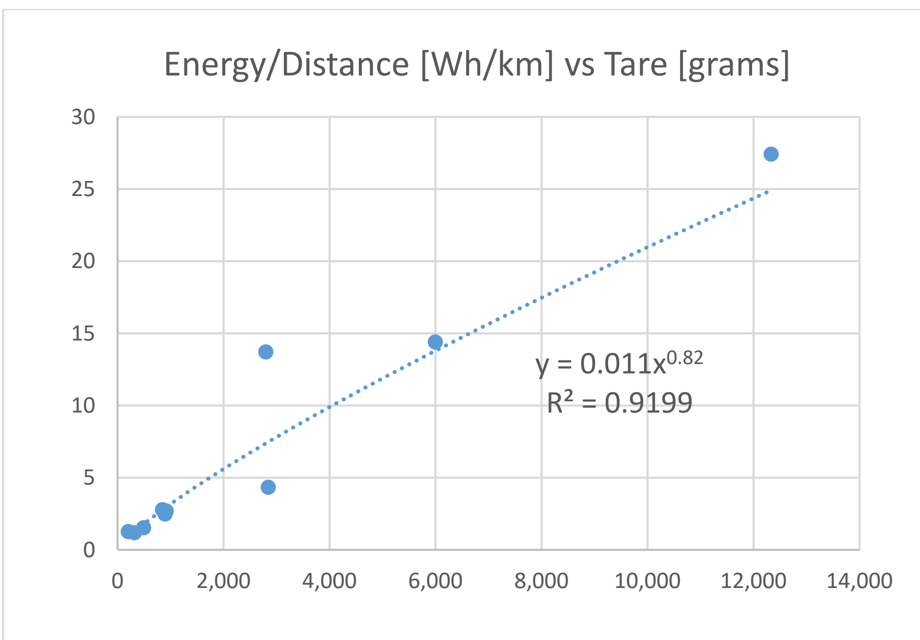

Figure 11: Battery Energy / Flight Time vs. Tare (power relationship)

The previous graphs, Figures 8, 9, 10 and 11, imply economies of scale regarding energy consumed per unit of mass flown or distance traveled.

4.8 OPERATIONAL LIMITATIONS

Most drones can operate with headwinds of less than 10 meters per second, though larger drones are less susceptible to adverse weather conditions. Hence, many drones cannot be reliably deployed in windy areas due to either potentially limited service times or a reduction in flying range caused by strong headwinds.

The operating temperature ranges typically between -10° C and 45° C; hence, drones cannot be deployed in extremely hot or cold areas. Finally, remote controlled maximum transmission distance is typically far less than the maximum flying range, though this limitation can be overcome by designing UAVs with more expensive sensors and communication devices.

4.9 SUMMARY

This section highlights some important trends, mostly linear, among UAV tare, payloads, battery energy, purchase costs, and energy consumption per unit of time flown. Though the trends are intuitive, the reader is reminded that they are drawn from a relatively small set of observations, that manufactures information is difficult to compare, and that UAVs are evolving rapidly.

According to FAA (2016) rules, drones must not be flown over populated areas, less than 400' from any structure, when visibility is a less than three miles and when there is reduced daytime visibility. These restrictions allow freight to be delivered in rural environments over short distances and on very clear days. Most of the surveyed multicopter drones' basic capabilities, e.g. speed, altitude, and payload, do not violate FAA's restrictions. However, restrictions governing where and what the drone can fly over, how it can be piloted (beyond line of sight or autonomously), and how far it can fly from its origin may severely limit UAVs' business and geographical scope.

5.0 ECONOMIC ANALYSIS

This section focuses on the economic analysis of UAVs. Most airplane costs are proportional to the hours flown, and costs are linear in time (Swan and Adler, 2006). Assuming a constant operating speed, time costs are also proportional to distance. In addition, non-time costs are also commonly proportional to departure cycles and kilometers (Swan and Adler, 2006). The cost per hour flown or cost per flying hour is also a basic metric to understand and measure aircraft costs for military aircrafts (Laubacher, 2004).

For civilian aircrafts, typically, the analysis is also done at the seat-hour level. In this research, the costs of UAVs will be analyzed as a function of costs per flying hour (CPFH).

5.1 COST ASSUMPTIONS

The cost of operating commercial aircrafts can be broken down into two main categories: airborne cost and ground costs. UAVs' airbone costs include energy and UAV/battery depreciation plus operator cost per hour. Ground costs include maintenance plus ancillary staff, services, and facilities.

5.1.1 UAV Operation Staff Costs

Many uncertainties exist in quantifying the number of staff per UAV and labor cost variables. Labor costs should include not only wages but also fringe benefits, training costs, and employee turnover. Regulation may play a crucial role; relaxing line of sight operation rules may increase UAV operator productivity, i.e. being able to control and monitor two or more UAVs simultaneously. Based on salaries paid in the trucking industry, a $40 per hour total cost per UAV operator seems reasonable. However, it is important to highlight that staff costs will include not only operators but also support staff such as maintenance technicians, customer service, administration, security, etc.

5.1.2 Maintenance costs

Specialized staff for routine maintenance or for diagnosing problems and repairing or replacing parts will be required. In the aviation industry, many routine monitoring and maintenance costs are related to hours of operation or flying hours. Compensation for aircraft mechanics can be $80 per hour and electronics technicians $90 per hour or more (Perritt and Sprague, 2016).

5.1.3 Other Ground Costs

Other ground costs include UAV storage, facilities, and ancillary services. This tend to be fixed costs and harder to incorporate into CPFH estimations without major assumptions regarding business economies of scale and productivity.

5.1.4 Energy Costs

UAVs analyzed in this research have electric propulsion systems, and based on their size, it is possible to have good estimations of energy consumption and electricity costs per hour flown. Combining the average price of a kilowatt-hour and the energy consumption (see Survey chapter) of a UAV, it is possible to estimate an electricity cost of approximately \$0.15 per hour.

5.1.5 Purchase Cost and Economic Life

The purchase cost of a UAV is related to its size and tare (see Survey chapter). The economic life of UAVs is uncertain. Scarce data is available from which to estimate the economic life of a small UAV, but it is likely that one year and no residual value are reasonable assumptions (Perritt and Sprague, 2016).

Another significant cost element is related to battery cost and life. There is a linear relationship between battery energy and its cost. In addition, batteries have a life that is related to charging/discharging cycles, with approximately 500 cycles before replacement.

5.1.6 Software and Communications Cost

If UAVs do not operate within line of sight of the operator, more sophisticated software, sensors, data processing chips, and communication devices are required to detect and avoid potential collisions and problems.

5.1.7 Productivity

The UAV productivity measured as the number of deliveries per hour will depend on many factors. Simplifying assumptions are necessary to develop values for UAVs CPFH:

- Highest UAV productivity is achieved by continuous flying, though in the real world there are also setup times related to takeoff, drop-off, swapping batteries, and reloading the UAV with a new shipment. A six minute setup time per delivery is assumed in the CPFH values presented in this chapter.

- From the UAV survey data chapter, typical UAV range and operating speeds are drawn. Drone purchase costs and battery size are estimated based on a UAV range of 30 km. A circular service region and homogenous demand distribution is also assumed. An average of 1000 deliveries per square-kilometer per year is assumed.

- It is important to consider that UAVs may not be able to operate with adverse weather conditions or at night (due to noise regulations, for example). In addition, demand is likely to have highs and lows, which reduces potential utilization. Accounting for all the mentioned limitations and for periods of high and low demand, an average of 55.6 deliveries per drone-week are assumed.

5.2 CPFH ESTIMATIONS

Based on the previous assumptions, it is possible to estimate UAV CPFH. The preliminary estimations show that energy costs are almost negligible. UAV and battery costs are significant, but the largest item is staff costs. Two scenarios are chosen to illustrate the relative weight of staff costs.

In the first scenario, an ideal scenario where regulation allows for beyond line of sight control, one staff member can control 10 UAVs simultaneously. This figure includes UAV operators and also support staff such as technicians, customer service, support staff, etc. The figures contained in Table 1 show that even in this optimistic scenario, staff costs account for more than 1/3 of the CPFH.

In the pessimistic scenario where regulation does not allow for beyond line of sight control, one staff member can control 0.9 UAVs simultaneously. This figure must be less than one because it includes one UAV operator per flying UAV and also support staff such as technicians, customer service, etc. The cost figures included in Table 2. This figure indicate that staff costs can account for a CPFH share of 85% or more.

Table 1: CPFH – Assuming 10 UAVs per staff

Cost Item	Cost		Percentage
Drone	$/hr	5.57	37.2%
Battery	$/hr	4.06	27.1%
Energy	$/hr	0.15	1.0%
Staff	$/hr	5.21	34.8%
TOTAL	$/hr	14.98	100.0%

Table 2: CPFH – Assuming 0.9 UAVs per staff

Cost Item	Cost		Percentage
Drone	$/hr	5.57	8.2%
Battery	$/hr	4.06	6.0%
Energy	$/hr	0.15	0.2%
Staff	$/hr	57.87	85.6%
TOTAL	$/hr	67.64	100.0%

5.3 SUMMARY

This section focused on the economic analysis of UAVs, and key insights include the high impact of labor/staff costs. Regulation regarding staff needed per UAV-hour is likely to play a sizable role, and therefore there is large amount of variability in the figures provided.

Cost metrics such as cost per flying hour (CPFH) are the most relevant for small UAVs since they readily take into account the impact of operator labor cost and utilization, clearly the largest cost components. Other researchers have also concluded that UAV staff costs are likely to be more economically significant than other costs at any reasonable level of utilization (Perritt and Sprague, 2016).

6.0 MODELING ENERGY CONSUMPTION

This sections deals with the estimation of UAV energy consumption. Two basic scenarios are analyzed; first, a one-to-one scenario where a vehicle travels to a destination and drops its load and then returns empty to its depot, and later, a one-to-many scenario where a vehicle delivers to multiple destinations before returning empty to its depot.

6.1 ONE-TO-ONE ENERGY CONSUMPTION

In this scenario, a vehicle (UAV or van) travels to a destination and drops its load and then returns empty. By reversing the order, it is possible to model a pick up. Without loss of generality, drop-off services will be assumed herein. Due to noise and pollution concerns, it will also be assumed that electric UAVs are utilized for urban services (internal combustion engines pollute more and are noisier). Only one vehicle is utilized, i.e. there is no load transfer or intermediate depots. Utilizing the equations derived in Section 3, the energy consumed by a UAV to reach a customer and travel back empty is:

$$\frac{(m_t + m_b + m_l)g}{\vartheta(s)\eta_p} d + \frac{(m_t + m_b)g}{\vartheta(s)\eta_p} d$$

This expression can be simplified utilizing c_m the ratio between the tare and the gross vehicle weight of the UAV, i.e. the ratio between the weight of the unloaded UAV and the weight of the fully loaded UAV. In the case of electrical batteries, the weight of the battery does not change as a function of distance traveled. However, when batteries are charged, there are losses that are captured by the recharging efficiency. The total energy consumed to serve one customer is:

$$E_1^u = \frac{gd}{\vartheta(s)\,\eta_p\eta_r}(m_t + m_b + m_l) + (m_t + m_b) = \frac{gdm}{\vartheta(s)\eta_p\eta_r}(1 + c_m)$$

where:

E_1^u= UAV energy necessary to serve one customer [joules]

c_m = empty weight fraction [unit-less], $c_m = \frac{(m_t + m_b)}{(m_t + m_b + m_l)} < 1$

η_r = battery recharging efficiency [unit-less].

The energy necessary to serve one customer utilizing a conventional vehicle can be expressed as:

$$E_1^c = 2k_c d\, f_e c_f$$

where:

E_1^c= conventional vehicle energy necessary to serve one customer [joules]

f_c = fuel consumption [liters/100 km]

c_f = conversion fuel energy factor [J/liter]

k_c = depot-customer distance circuitous factor relative to the UAV[unit-less].

In this research, it is assumed that k_c = 1.0 unless stated otherwise. The energy needed per unit distance traveled can be obtained by dividing the previous expressions by $2d$. The result is respectively:

$$e_1^u = \frac{gm}{\vartheta(s)\eta_p\eta_r}\frac{1+c_m}{2}$$

$$e_1^c = k_c\, f_e c_f$$

where:

e_1^u= UAV energy necessary to serve one customer per unit of distance traveled [joules/meter]

e_1^c= Commercial vehicle energy necessary to serve one customer per unit of distance traveled [joules/meter].

To quantify the energy efficiency of UAVs, the ratio of latter two expressions can be estimated as follows:

$$\rho_1^{en} = \frac{2k_c\, c_f f_c\, \vartheta(s)\, \eta_p \eta_r}{gm(1+\ c_m\ )}$$

where:

ρ_1^{en} = relative energy efficiency of UAVs when serving one (1) customer (one-to-one service).

It can be observed from this last equation that distance to the customer drops out from the expression. As expected, the relative efficiency of UAVs increases as the mass of the UAV decreases when the cargo has a higher share of the total UAV mass, and when the UAV power delivery and battery recharging efficiencies increase. The relative efficiency of the UAV decreases when the fuel consumption of the conventional vehicle decreases.

6.2 RESULTS FOR ONE-TO-ONE ROUTES

This section applies the formulas developed in the previous section to compare the energy efficiency of a typical U.S. conventional cargo van and a mainstream UAV, assuming one-to-one deliveries (one customer per route). Table 1 shows the relevant aircraft and vehicle characteristics. Data for the cargo van was obtained from Saenz et al. (2016) and data for the MD4-3000 UAV was obtained from the manufacturer's website (MicroDrones, 2016).

Table 3: Vehicle characteristics and emissions parameters

	UAV	**Diesel cargo van**
Specification	**MD4-3000**	**RAM ProMaster 2500**
Take off / Gross weight m	15.1 kg	4060 kg
Tare / Curb Weight m_t	10.1 kg	2170 kg
Payload m_l	5.0 kg	1890 kg
Empty weight factor c_m	0.67	0.53
Battery/Fuel Storage Capacity*	777 wh	8.63 kWh
e_{gtb} or e_{wtt}	1.235 lbs CO_2e / kWh	5.108 lbs CO_2e / gallon
e_{btp} or e_{ttw}	-	22.72 lbs CO_2e / gallon
Range	36 km	695 km
Energy/fuel consumption	21.6 wh/km*	1016 wh/km*

* Calculated utilizing manufacturer information. It was assumed that the energy content of gasoil is 34200 kJ/liter and therefore 22 mpg = 1016 wh/km. To improve readability, numbers have been rounded.

The MD4-3000 is a state-of-the-art UAV that can be used to carry objects or for aerial photography/filming purposes. The manufacturer's website contains all the data necessary to estimate energy consumption for a given load. The MD4-3000 capabilities seem similar to the HorseFly UAV tested by UPS in February 2017. The battery-powered HorseFly drone recharges while docked in the UPS van, has a 30-minute flight time, and can carry a package weighing up to 4.5 kg (HorseFly, 2017).

When comparing the aircraft and the vehicle, there is a large difference in vehicle mass, carrying capacity, engine power, and energy stored. The application of the formulas developed in the previous sections generate the numbers contained in Table 4. Assuming a payload of 5.0 kg, the UAV is almost 47 times more efficient ($\rho_1^{en} = 47$) than the van in terms of energy consumed per unit distance. The same energy is consumed if the van travels one time and delivers 47 packages at once (assuming UAV utilizes 21.6 wh/km) or if the UAV travels back and forth 47 times and delivers one package at the time.

What is generating this $\rho_1^{en} = 47$ value? It is possible to disaggregate ρ_1^{en}, i.e. expression (6), into two components, assuming that k_c = 1:

$$1 < \frac{2}{(1+ c_m)} < 2 \qquad \text{[unit-less]}$$

$$\frac{c_f f_c}{gm/\left(\vartheta(s)\,\eta_p\eta_r\right)} \qquad \text{[unit-less]}$$

The first term is bounded in the interval (1, 2) and is a function of the relative mass size of the load with respect to the total UAV mass and approximately equal to 1.2 in the case study. The second term is approximately 39 and accounts for the large difference in energy consumption between the conventional vehicle and the UAV. This term can be interpreted as the ratio between the energy necessary to move (per unit distance) the van and the energy necessary to move (per unit distance) a mass equivalent to the UAV mass.

There is a significant mass difference between the van and the UAV, but electric engines also produce simpler and more efficient machines. The product $\eta_p\eta_r$ is the overall efficiency to deliver power to the battery and then to the propellers and is assumed to be $(0.90)(0.73) = 0.66$; in comparison, typical diesel vehicles may utilize 25% of the potential energy stored in the fuel to move the vehicle (most of the energy contained in diesel fuel is dissipated as heat).

6.3 MODELING ONE-TO-MANY ROUTES

This section presents the analytical framework to analyze the efficiency of ground vehicles when several costumers can be grouped in a route (one-to-many configuration). In this scenario, there are two or more customers per route served by the same ground vehicle (one ground vehicle and many stops or customers per route).

The ground delivery vehicle can combine customers in one route; however, the UAV cannot do multiple drops without first returning to the depot to reload. The UAV travels to a destination, drops its load, and then returns empty to the launching location, where a new package is loaded, and so on (still one-to-one service for UAVs). For the sake of simplicity, it is assumed that there are n customers that are delivered the type of same package (weight).

Assuming that a UAV can serve only one customer at a time due to volume and/or weight limitations, the energy necessary to serve n customers by a UAV is:

$$E_n^u = \frac{n\, grm}{\eta_p \eta_a \vartheta(s)}(1 + c_m)$$

where:

E_n^u= UAV energy necessary to serve n customers [joules].

Conventional vehicles' typical delivery (or pick-up) routes serve many customers. Continuous approximation models can be utilized to model the average distance traveled to serve n customers (Daganzo, 2005). A continuous approximation formula, empirically validated, that is appropriate for customer delivery areas located away from the depot is the following (Figliozzi, 2008):

$$d_n = 2k_c\bar{d} + k_l\sqrt{nA}$$

where:

d_n = average distance traveled to serve n customers by one vehicle [km]

$\bar{d}$ = average distance between customers and the depot [km]

n = number of stops or deliveries [unit-less]

A = size of service area containing n customers [km2]

k_l = local customer distribution distance circuitous factor [unit-less].

Then, the energy necessary to serve n customers utilizing v conventional vehicles is:

$$E_n^c = c_f f_c[2k_c\bar{d} \ + k_l\sqrt{nA}]$$

The ratio of expressions E_n^c and E_n^u can be estimated as follows:

$$\rho_n^{en} = \frac{c_f f_c[2k_c\bar{d} + k_l\sqrt{nA}]\, \vartheta(s)\, \eta_p\eta_r}{n\bar{d}\ \ gm(1 + c_m)}$$

where ρ_n^{en} is the relative energy efficiency of UAVs when one ground vehicle serves n customers per route (one-to-many service). As previously demonstrated, it is possible to disaggregate the last equation into the following unit-less components:

$$0 < \frac{1}{(1 + c_m)} < 1 \qquad \text{[unit-less]}$$

$$0 < \eta_p\eta_r < 1 \qquad \text{[unit-less]}$$

$$\frac{c_f f_c}{gm/\,\vartheta(s)} \qquad \text{[unit-less]}$$

$$\frac{2k_c\bar{d} + k_l\sqrt{nA}}{n\bar{d}} \qquad \text{[unit-less]}$$

Distance traveled increases linearly with the number of customers for the UAV but at a lower rate for the conventional vehicle. This is reflected in the last expression that is the ratio between conventional vehicle distance and UAV distance; as n increases, the relative efficiency of the UAV decreases continuously. Hence, there is a breakeven point for a large enough n.

6.4 RESULTS FOR ONE-TO-MANY ROUTES

This section utilizes the same vehicle and UAV already described in the one-to-one case study. Average travel distances and distribution areas that are approximately binding the UAV 25 km range constraint are utilized in this section; the reader should know that this is the most favorable scenario for UAVs. A 25 km distance is approximately 70% of the maximum UAV theoretical range. In practice, the UAV operator has to provide a margin of safety and account for unknown factors that can increase energy consumption, such as headwinds.

When assuming a constant and binding UAV range, average distances between depot to customers and service areas are negatively correlated (see Table 4). In Table 4, the value n^* is the breakeven point, or the number of customers that equalizes the efficiency of a UAV and a conventional vehicle. There are three columns under n^*. The central column under 21.6 wh/km contains the breakeven point based on the efficiency estimated from the UAV manufacturer specifications. The left column under 10.8 wh/km contains breakeven points based on the efficiency of a future UAV whose efficiency has doubled. The right column under 32.4 wh/km contains breakeven points for a MD4-3000 UAV whose efficiency has decreased by 50%. This low efficiency is not unrealistic under adverse conditions that include more headwinds, hovering time, or maneuvering up/down/sideways to avoid obstacles, reach the destination, or complete the delivery.

Table 4: UAV and Diesel Van Breakeven Energy Scenarios - One-to-one Routes

Avg. Dist. depot to Customers (km)	**Service Area** (km^2)	$\boldsymbol{n^*}$		
		ρ_1^{en}~94 10.8 wh/km	ρ_1^{en}~47 21.6 wh/km	ρ_1^{en}~31 32.4 wh/km
8	60	1,340	362	173
9	40	785	224	113
10	20	413	131	72
11	7	219	83	50
12	1	127	58	37

The figures in Table 4 show a positive correlation between service area size and breakeven number of customers, and a negative correlation between depot distance and breakeven number of customers. As a reference, a typical UPS delivery truck in a dense urban area can deliver 200 to 300 pieces and packages. In some cases where there are multiple deliveries of pieces/packages at the same address—e.g. a large office complex—the number can go up to 300 to 500 pieces. Under adverse delivery conditions, that UAV is not competitive if the truck can deliver more than 50 packages in a dense area.

7.0 MODELING CO_2 EMISSIONS

This sections deals with the estimation of UAV emissions. Leveraging the results of the previous section, two scenarios are analyzed. First, a one-to-one scenario where a vehicle travels to a destination and drops its load and then returns empty to its depot, and later, a one-to-many scenario where a vehicle delivers to multiple destinations before returning empty to its depot.

7.1 CO_2E EMISSIONS

For conventional vehicles, the carbon footprint of the vehicle utilization phase includes well-to-tank (WTT)—emissions that take place along the fuel/energy supply chain—and tank-to-wheel (TTW)—emissions associated with the combustion of the fuel. For a UAV, the carbon footprint includes generation-to-battery (GTB) emissions associated with the electricity supply chain and battery-to-propeller (BTP) emissions. For electric UAVs, the BTP component is zero.

WTT emissions for fossil fuels include several stages: petroleum pumping, extracting, transporting, refining in factories, distributing, and dispensing to the vehicles. WTT emissions are estimated using the GREET model (USDoE, 2016); 5.1 lbs CO_2e/gallon of diesel or 0.22 kg CO_2e/liter of diesel. The TTW emissions associated with burning one gallon of diesel is approximately 22.7 lbs CO_2e/gallon of diesel or 2.7 kg CO_2e/liter of diesel (USEPA, 2017). The Emissions & Generation Resource Integrated Database (eGRID), published by the U.S. Environmental Protection Agency, is utilized to estimate GTB emissions (USEPA, 2016). The eGRID values include the generation of electricity at the power plants, as well as electricity transmission and distribution losses. The operational GHG emissions per mile are calculated for each vehicle using the following expressions for UAVs and diesel vehicles, respectively.

$$co_2e^u \ \frac{E_n^u \, f \ e_{gtb}}{2\, rn} = \frac{gm}{\eta_p \eta_m \eta_a \vartheta(s)} \frac{(1+c_m)}{2} \, f_{kwh} \, e_{gtb}$$

$$co_2e^c = 100 \, f_c \, (e_{wtt} + e_{ttw})$$

where:

co_2e^u = UAV equivalent carbon dioxide emissions per unit of distance traveled [kg.CO_2e/km]

co_2e^c = van equivalent carbon dioxide emissions per unit of distance traveled [kg.CO_2e/km]

f_{kwh} = factor to convert Joules to kWh = 1 / 3.6 10^6 [kWh / Joule]

e^i_{gtb} = emissions of the GTB phase [kg.CO_2e / kWh)]

e^i_{wtt} = emissions of the WTT phase [kg.CO_2e / liter)]

$e_{ttw}^{i} =$ emissions of the TTW phase [kg.CO_2e / liter)].

The ratio of the last two equations is ρ_1^{em} or the relative emissions efficiency per unit distance of UAVs with respect to ground vehicles. If the last two equations are divided by payload, it is possible to estimate the efficiency per unit of distance and payload.

7.2 RESULTS FOR ONE-TO-ONE ROUTES

If the analysis is conducted in terms of emissions per unit distance, the advantage of the UAV is even higher because electricity generation is "greener" per unit of energy than diesel fuel. The electricity consumed for the UAV is more than 22 times cleaner than the energy consumed by the van, and the ratio between van and UAV CO_2e emissions per unit distance is $\rho_{1,1}^{em} = 1{,}056$.

Table 5: One-to-one service performance measures

Performance Measure	Unit*	Van (1)	UAV (2)	Ratio (1)/(2)
Energy consumed per unit distance	wh/km	1,016	21.6	47
Emissions per unit energy consumed	gCo_2e/wh	12.6	0.6	22.5
Emissions per unit distance	kgCO_2e/km	12.83	0.012	1,056
Payload	kg	1,890	5.0	378
Energy cons. per unit distance-load	wh/km-kg	0.54	4.32	0.12
Emissions per unit distance-load	kgCO_2e/km-kg	6.79	2.42	2.8

To improve readability, numbers have been rounded.

The performance measures are more favorable for the conventional van when the analysis is done in terms of energy consumption and emissions per unit distance and per kilogram of payload delivered. The van can deliver 378 times more cargo than the UAV; assuming maximum payloads, the van is eight times (1/0.12) more efficient in terms of energy consumption but still almost 2.8 times less efficient regarding GHG emissions.

7.3 RESULTS FOR ONE-TO-MANY ROUTES

This subsection utilizes the same vehicle and UAV already described in the one-to-one case study. Average travel distances and distribution areas approximately binding the UAV 25 km range constraint are utilized in this section; the reader should note that this is the most favorable scenario for UAVs. A 25 km distance is approximately 70% of the maximum UAV theoretical range. In practice, the UAV operator has to provide a margin of safety and account for unknown factors that can increase energy consumption, such as headwinds.

In terms of emissions, given that $\rho_1^{em} = 1056$ is so high, in practice, it is difficult to find delivery routes where the van is more efficient than an electric UAV in terms of operational emissions. The same emissions are generated if the van travels one time and delivers 1056 packages at once or if the UAV travels back and forth 1056 times and delivers one package at the time.

An electric truck will be more competitive in terms of energy and emissions. When comparing an electric truck and UAV, the relative efficiencies in terms of energy and emissions are the same, i.e. $\rho_1^{en} = \rho_1^{em}$, because the same energy source is utilized to power the electric engines. Assuming that the electric truck has an energy consumption of 760 wh/km (Davis and Figliozzi 2013; Feng and Figliozzi, 2013), then $\rho_1^{en} = \rho_1^{em}$ = 35. Table 4 shows the results assuming that one electric truck serves the one-to-many route. There is a noticeable decrease in the values of n^* and electric trucks can now compete with UAVs in terms of both energy and emissions efficiency in realistic routes with more than 50 customers and/or a relatively small delivery area.

Electric vehicles have steadily become more efficient in the last five years. Small electric vans are also now in the market (mainly in Europe). For example, the 2017 Renault ZE Kangoo has a payload of 600 kg and will consume approximately 205 wh/km in temperate temperatures (Renault, 2017). The 205 wh/km value used in Table 6 is more conservative than the ideal value given by the manufacturer (150 wh/km). Against an electric van that can carry 120 times more cargo, the UAV is not competitive in dense delivery areas with more than 10 customers per route, as shown in Table 6, right column.

Table 6: UAV and Electric Van Breakeven Scenarios – One-to-one Routes

Avg. Dist. depot to Customers (km)	**Service Area** (km^2)	$\boldsymbol{n^*}$ $\boldsymbol{\rho_1^{en} \sim 35}$ vs. E-truck	$\boldsymbol{n^*}$ $\boldsymbol{\rho_1^{en} \sim 9.5}$ vs. E-van
8	60	214	26
9	40	137	20
10	20	85	15
11	7	58	12
12	1	42	10

An electric tricycle is even more efficient than an electric truck or van in terms of energy consumption and emissions. According Saenz et al. (2016), the real-world energy consumption of a delivery tricycle is approximately 48.65 wh/mile or 30.24 wh/km. With this value, the relative efficiency between an UAV and an electric tricycle is $\rho_1^{en} = \rho_1^{em}$ = 1.4. When the number of customers per route is relatively small ($n < 10$), the following expression (Figliozzi, 2008) is a better approximation for the VRP distance (used for the tricycle case):

$$d_n = 2k_c\bar{d} + k_l \left(\frac{n-m}{n}\right)\sqrt{nA}$$

Table 7 shows the results assuming one electric tricycle serves the one-to-many route. There is a sharp decrease in the values of customers needed to breakeven; tricycles outcompete UAVs in terms of efficiency when two or more customers can be grouped in a route. In Table 7, the values of n^* are so small that decimals are necessary to show changes. Against an electric tricycle that can carry 40 times more cargo, the UAV is not competitive in routes where it is possible to group two or more customers.

Table 7: UAV and Electric Tricycle Breakeven Scenarios – One-to-one Routes

Avg. Dist. depot to Customers (km)	**Service Area** (km^2)	$\boldsymbol{n^*}$ $\boldsymbol{\rho_1^{en} \sim 1.4}$ vs. E-tricycle
8	60	2.1
9	40	1.9
10	20	1.7
11	7	1.6
12	1	1.5

The competitiveness of ground vehicles is even higher if vehicle phase emissions are also taken into account, as discussed in the next section.

7.4 MODELING VEHICLE PHASE CO_2E EMISSIONS

The focus of this section is on emissions tradeoffs between UAVs and different types of ground delivery vehicles. It has been correctly argued that the analysis of transportation systems energy and emissions levels should include not only direct tailpipe emissions but also emissions associated with vehicle production and disposal, the fuel/energy source, and required transportation infrastructure (Chester and Horvath, 2009). Lifecycle assessment (LCA) of vehicle emissions provides a more comprehensive view of transportation emissions than the traditional approach based on tailpipe emissions.

LCA separates emissions along life cycles or phases: extraction of raw materials from the earth, materials processing, manufacturing, distribution, product use and disposal or recycling at the end. We compare last-mile UAVs' and ground vehicles' lifecycle CO_2e emissions in two distinct phases: (a) vehicle utilization and (b) vehicle production/disposal. In this research, ground vehicle emissions associated with utilization includes well-to-tank (WTT)—the lifecycle of fuel production and distribution—and tank-to-wheel (TTW) or direct tailpipe emissions. These concepts are extended for the aerial vehicle or aircraft with an electric engine; for the UAV, WTT emissions are replaced by generation-to-battery (GTB) and TTW emissions are replaced by battery-to-propeller (BTP) emissions. The vehicle phase (b) includes emissions from materials extraction and processing, manufacturing, distribution, and vehicle disposal or recycling, but without considering vehicle utilization.

In the previous subsections, a detailed analysis of operating emissions was presented, including both WTT and TTW CO_2e emissions for ground vehicles and GTB and BTP CO_2e emissions for UAVs. This subsection focuses solely on the vehicle production and disposal phase. The vehicle phase includes emissions associated with the extraction of raw materials from the earth, raw materials processing, manufacturing, distribution, and disposal or recycling at the end.

GHG emissions for the vehicle phase are estimated using the GREET model, which uses vehicle weight as the functional unit (USDOE, 2016). The GREET model contains hundreds of parameters with default values based on national/regional statics or industrial practice. Detailed documentation of assumptions in relation to industrial processes and technologies are available on GREET publications (USDOE, 2016). For diesel vans and electric tricycles, the same values utilized in previous research efforts are employed. Regarding UAVs, the GREET model does not include a UAV vehicle type. Unlike other flying machines, a major component of the UAV weight is the lithium-ion polymer battery. Hence, the electric UAV was modeled as the sum of two elements: (a) the lithium-ion batteries, and (b) the rest of the UAV (engines, sensors/processors, and the body/frame). Battery lifecycle values were obtained from the paper by Kim et al. (2016) that analyzed electric vehicles' lithium-ion batteries.

7.4.1 CO_2e for Production and Disposal

The results of the analysis are shown in Table 8. The UAV has a much smaller mass and lower vehicle phase emissions per vehicle, but the battery is 40% of its tare. Due to the long recharge time, it is common to have three or more batteries per UAV. Conservatively, only four batteries over the lifetime of the drone are assumed; this is a conservative estimate because a properly maintained lithium-ion polymer battery has less than 1000 recharge cycles on average (Peters et al., 2017). In addition, in proportion to its weight, the UAV has more processors, sensors, electronics, and other aircraft materials that are more energy intensive to produce and recycle; hence, the UAV has a significantly higher rate of CO_2e emissions per vehicle mass and per payload mass—see rows three and four of Table 8.

Table 8: Vehicle Phase CO_2e Emissions

Parameter	UAV	Tricycle	Diesel Van
Batteries (kg CO_2e)	435	306	(*)
Vehicle (kg CO_2e)	56	346	10,076
Emissions per unit of vehicle mass or tare (kg CO_2e per kg)	48.6	8.7	4.6
Emissions per unit of payload mass (kg CO_2e per kg)	69.2	2.6	5.3

(*) Included in the vehicle chassis. To improve readability, numbers have been rounded.

To estimate the UAV vehicle phase emissions, the following formula was utilized:

$$n_b \, w_b \, e_b + m_t \, e_t$$

where:

n_b: number of batteries utilized during the UAV lifetime

e_b: emissions per kwh (140 kg CO_2e per kwh battery)

w_b: battery storage capacity (777 wh)

e_t: emissions per vehicle tare weight (9.3 kg CO_2e per kg).

To compare vehicle phase emissions with utilization emissions, it is necessary to estimate vehicle phase emissions per delivery, assuming values for the average number of deliveries per day, number of vehicle working days per year, and vehicle productive life. It was already mentioned that in an urban area, a parcel delivery van can easily deliver 150 or more parcels per day; the van assumed in this research can carry up to 375 packages if each package weighs 5 kg. A tricycle is more limited in terms of operating speed and capacity, and the number of deliveries per day is around 25 stops or customers per day (Saenz et al. 2016), but it can carry up to 54 packages if each package weighs 5 kg. It is assumed that on average, four deliveries per day are made by the UAV. Three years may be considered an optimistic guess given that UAV multicopters is a very young technology. Unfortunately, there is no available data regarding UAV life and average deliveries per day, but these numbers can be easily updated when data become available. The total number of deliveries over the lifetime of a vehicle is simply the product of working life duration (years) by service days per year (days/year) and by average deliveries per day (deliveries/day).

7.4.2 CO_2e per Delivery

Table 9 shows the CO_2e efficiency per delivery with the assumed values. Different assumptions will lead to different values, but on a per delivery basis, the tricycle and diesel van seem to have a clear advantage (fourth row of Table 9). To compare the results, it is useful to obtain the equivalent travel distance that will produce the same level of vehicle phase emissions per delivery (fifth row of Table 9). Vehicle phase emissions per delivery are a negligible addition for the diesel van but a major addition for the UAV. The UAV vehicle phase emissions per delivery are of the same order of magnitude as half the practical range of the UAV. Hence, the UAV emissions per delivery can increase by up to 50% when the vehicle phase is taken into account. Taking into account both operational and vehicle phases, the tricycle is likely to be more CO_2e efficient than the UAV.

Table 9: Per Delivery Vehicle Phase CO_2e Emissions

Parameter	UAV	Tricycle	Diesel Van
Number of daily deliveries	4	25	150
Delivery days per year (days)	260	260	260
Vehicle life (years)	3	5	10
Emissions per delivery			
(kg CO_2e per delivery)	0.16	0.02	0.03
Equivalent travel distance (in km)			
(kg CO_2e per delivery)	13.0	1.2	0.002
Range (km)	25	48	625
Equivalent travel distance as % of range	52	2.5	0.0

(*) Included in the vehicle chassis. To improve readability, numbers have been rounded.

8.0 OTHER KEY CONSIDERATIONS

This research has focused on the analysis of UAV delivery costs, energy consumption, and CO_2e emissions. Other important factors that must be considered are briefly summarized in this section but left as future research topics.

8.1 SAFETY

There is a concern about the risk of a UAV malfunctioning in mid-air, falling from the sky, and damaging property or injuring people. A report commissioned by the FAA (Arterburn et al., 2017) indicates that three vehicle characteristics may contribute to fatal drone collisions: kinetic energy, ignition sources based on vehicle power systems, and vehicle rotating components. The kinetic energy is proportional to the takeoff weight and the square of the aircraft speed. Drone batteries, motors, and potential cargo may increase the severity of the crash because they are dense objects. The propeller blades attached to quadcopter drones can slice skin, and blade guards may better protect people (Arterburn et al., 2017).

8.2 NOISE

UAV noise is a potential problem for urban deliveries. Noise may hinder deployment or hours of operation and can negatively affect communities and land values (Nelson, 1979) around future UAV depots. Research efforts are still not conclusive regarding the seriousness of UAV noise (Bulusu et al., 2017). However, from a health perspective, the negative impacts of noise are well understood (Passchier-Vermeer and Passchier, 2000; Stansfeld; and Matheson, 2003).

8.3 LAST-YARD CONSTRAINTS

An often overlooked problem in UAV delivery discussions is the issue of the last yard of the delivery (Figliozzi et al., 2018). Though UAVs' aerial paths avoid ground congestion and last-mile delivery problems associated to truck parking and unloading, there is a major challenge in terms of the last yard of the delivery process.

Urban last-yard deliveries are likely to require landing pads or delivery stations, as well as safe spaces for takeoff and landing (some companies are discussing dropping or parachuting packages). For single home or unit dwellings, the cost implications of the last-yard delivery infrastructure are not yet clear. As discussed in the previous sections, there are clear tradeoffs between UAV size, efficiency, and safety, and size of the last-yard infrastructure.

For a multiunit building, rooftops are a largely underutilized urban area that, if retrofitted properly, could become prime delivery nodes for the building (whether it is a condominium, business, or factory). Provided a suitable structure could be built that would protect the packages from the elements as well as proper retrofits that would ensure the safety of people retrieving (or dropping off) their packages, rooftop delivery zones would also keep the items secure from theft. Coupling these landing pads with rooftop charging stations throughout a downtown area would mean the UAVs would be capable of longer flight distances or larger payloads. This kind of network would offer a viable complementary freight delivery option to that on the ground level. There are stark differences between last-yard constraints and possibilities when comparing single home versus multiunit dwellings or buildings. Last-yard costs and constraints may limit the size of the UAVs and therefore limit their efficiency and competitiveness.

8.4 URBAN VS. RURAL UAV ECONOMICS

The last-yard configuration will influence turnaround time and UAV productivity. Therefore, the economics of UAV deliveries in terms of CPFH will depend on the type of delivery system. Likewise, if additional gear or specialized devices are required to improve package security or safety, the UAV purchase costs will increase and may be another element that differentiates the economics of UAV urban and rural deliveries.

Rural areas may also utilize fixed-wing UAVs and parachute-based delivery systems that are more efficient than rotatory wing systems, which require hovering and/or vertical landing and takeoff. There are still a lot of unknowns regarding future costs of UAV deliveries in urban areas.

8.5 POTENTIAL MARKETS

UAVs for package delivery have a lot of potential to improve logistics productivity and reduce environmental externalities such as trucking diesel engine pollution. However, safety concerns and last-yard constraints are likely to limit the benefits that can be achieved through economies of scale.

It is expected that multicopter UAV technology, capabilities, and costs will improve substantially in the near future. Hence, there are still many areas to research and model in terms of UAVs' costs, markets, potential benefit, and supply chain impacts.

9.0 CONCLUSIONS

This research presented novel data and models for deliveries utilizing small UAVs. Small UAVs were defined as aircrafts with a tare of up to 15 kg and a potential payload of up to 15 kg.

The survey data shows that UAV payload, size, energy consumption, and cost are positively correlated and tend to increase together. Unfortunately, potential safety, noise, and last-yard constraints also increase as drone capabilities and size increase.

Cost metrics such as cost per flying hour (CPFH) are the most relevant for small UAVs since they readily take into account the impact of operator labor cost and utilization, clearly the largest cost components. The economic analysis indicates that labor/staff costs can range between 30% and 85% of UAV costs per flying hour. The impact of labor costs will be highly dependent on future regulations and the level of automation of the last-mile delivery process.

Currently-available UAV technology can fill a delivery service niche in sparsely populated areas with a low number of customers and density. In rural areas, the regulatory landscape and last-yard delivery constraints are also more relaxed. In rural areas, the economic benefit brought about by reducing the cost of a driver to visit remote customers are obvious, but in this environment, UAV range is a key consideration.

In dense urban areas, several first- and last-mile service, privacy, and regulatory and security issues must be addressed before UAV services are feasible. UAVs are likely to have an edge regarding speed delivery if they are operated in uncongested skies where they can outperform slower ground vehicles that are delayed by conditions of the congested ground road network. On the other hand, drones may not be able to compete in terms of costs with a delivery truck that can deliver hundreds of packages to one location in an urban setting. The urban landscape is a place where larger payload capacity would be more beneficial than flight distance. Furthermore, new technologies like sidewalk delivery robots may also reduce costs and delivery times (Jennings and Figliozzi, 2019) and therefore reduce potential UAV market share.

This research also has introduced a framework to analyze the real-world energy and emissions efficiency of UAVs and different ground commercial vehicles. The results of the analysis show that UAVs can significantly reduce operational first- and last-mile energy consumption and emissions (both well-to-tank and tank-to-wheel) in some scenarios. The analysis utilizing real-world data indicates that UAVs presently available in the market are significantly more CO_2e efficient (around 47 times) than typical UPS diesel delivery vehicles in terms of energy consumption. In terms of emissions, the differences are even greater (more than 1000 times). However, the efficiency measures are more favorable for the conventional van when the analysis is done in terms of energy consumption and emissions per unit distance and per kilogram of payload delivered. The van can deliver almost 380 times more cargo than the UAV; assuming maximum payloads, the typical U.S. van is 8 times more efficient in terms of energy consumption but still almost 2.8 times less efficient regarding GHG emissions. Electric trucks and vans are much more efficient than the typical U.S. van. Hence, the UAV is not more efficient than electric vans in delivery scenarios with more than 10 customers per route.

The lifecycle analysis shows that UAV vehicle phase emissions are significant and must be taken into account. When vehicle phase emissions are considered, the UAV lifecycle efficiency can be reduced by a significant amount. Considering lifecycle emissions, an electric tricycle is likely to be more CO_2e efficient than the UAV. Hence, in dense urban areas where tricycle deliveries are economically feasible (Tipagornwong and Figliozzi, 2014), tricycles are likely to outperform UAVs in terms of both energy consumption and lifecycle CO_2e emissions.

Although it is expected that small UAV technology, capabilities, and costs will improve substantially in the near future (Floreano and Wood, 2015), it is implausible that UAVs will outcompete commercial vehicles in some scenarios. Conventional vehicles outperform UAVs in cases where payloads are not small or if a customer is located far beyond the relatively limited range of a UAV—range is a function of payload and other variables, but for small quadcopter UAVs, practical range is currently less than 25 km.

Breakthroughs in UAV technologies may affect the typical range of UAVs' energy consumption (assumed to be 10 to 32 wh/km in this research). For example, small fixed-wing UAVs with VTOL (vertical takeoff and landing) capabilities may become suitable one day for urban deliveries. Fixed-wing UAVs are considerably more energy efficient than multicopters in terms of energy consumption per unit distance flown. The methodology developed in this research will still be applicable even if there are major improvements in terms of UAV design, battery energy storage, range, and carrying capacity.

The future of UAV deliveries will also depend on other factors such as UAV noise levels, safety concerns, and last-yard delivery configurations. Future research efforts should study the logistical impacts of these factors.

10.0 APPENDIX

APPENDIX A

UAVS SURVEYED

Table 10: List of UAVs and companies surveyed

UAV Model	*UAV Manufacturer*
Aibot X6	Aibotix
Alta 8	Freefly
AR180	AirRobot
AR200	AirRobot
Bebop 2	Parrot
Inspire 1	DJI
Inspire 2	DJI
Matrice 600	DJI
Mavic PRO	DJI
Mavrik X8	SteadiDrone
MD4-1000	Microdrones
MD4-3000	Microdrones
Phantom 3 Pro	DJI
Phantom 3 Standard	DJI
Phantom 4	DJI
Phantom 4 Advanced	DJI
Phantom 4 Pro	DJI
Sky Tech	Flytrex
Skyranger	Aeryon
Spark	DJI
Vader HL	Steadidrone

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