ANALYSIS OF ENERGY EFFICIENCY IN TRUCK-DRONE "LAST MILE" DELIVERY SYSTEMS

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science in Industrial Engineering

School of Industrial Engineering

West Lafayette, Indiana

May 2019

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ACKNOWLEDGMENTS

Foremost, I would like to thank my advisor Dr. Cai whose mentorship and guidance have been invaluable. Without her unwavering support, my research would not have been possible. I wish to thank Dr. Lee and Dr. Nof for their time and efforts as members of my committee that helped shape my thesis.

I am also profoundly grateful to the Purdue Military Research Initiative, and the United States Air Force Civilian Institution program for allowing me the opportunity to conduct my study.

Finally, I owe sincere thanks to the Urban Sustainability Modeling & Analysis Team, for their insights and help.

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ABSTRACT

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Degree Received: May 2018
Title: Analysis of Energy Efficiency in Truck-Drone "Last Mile" Delivery Systems
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Truck-drone delivery systems have the potential to improve how the logistics industry approaches the "last mile problem". For the purposes of this study, the "last mile" refers to the portion of the journey between the last transportation hub and the individual customer that will consume the product. Drones can deliver packages directly, without the need for an underlying transportation network but are limited by their range and payload capacity. Studies have developed multiple truck-drone configurations, each with different approaches to leverage the benefits and mitigate the limitations of drones. Existing research has also established the drone's reduction to package delivery time over the traditional truck only model. Two key model factors that have not been considered in previous research are the distribution of package demand, and the distribution of package weight. This study analyzes the drone's impact to the energy efficiency of a package delivery system, which has taken a backseat to minimizing delivery time. Demand distribution dictates the travel distances required for package delivery, as well as the proportion of delivery locations that are in range for drone delivery. Package weight determines the energy consumption of a delivery and further restricts the proportion of drone eligible packages. The major contributions of this study are the development of a truck-drone tandem mathematical model which minimizes energy consumption, the construction of a population-based package demand distribution, a realistic package weight distribution, and a genetic algorithm used to solve the mathematical model developed for problems that are too computationally expensive to be solved optimally using an exact method. Results show that drones can only have a significant impact to energy efficiency in package delivery systems if implemented under the right conditions. Using truck-drone tandem systems in areas with lower package demand density affords the drone the potential for larger energy savings as larger portions of the truck distance can be replaced. Further, the lower density translates to greater differences between the road-restricted driving distance and the flying distance between delivery points. Finally, energy savings are highly dependent on the

underlying package weight distribution of the system. A heavier average package weight increases the energy consumption of the system, but more importantly the portion of packages above the drone's payload capacity severely limit the savings afforded by the incorporation of drones.

CHAPTER 1. INTRODUCTION

The application of drones in the logistics sector, specifically for package delivery, seeks to fundamentally improve the way packages reach their destination. The utilization of drones for package delivery is a concept that has garnered widespread attention in the last 5 years. In response, Dr. D'Andrea published his initial findings on the feasibility of this concept in his aptly named editorial "Can Drones Deliver?" (D'Andrea, 2014). The increase in attention is due to a few major factors, including the growth of e-commerce and the development of drone technology. The recovery of the U.S. economy after the 2008 stock market crash led to an opportunity of massive growth and expansion among many markets. One particularly successful market was e-commerce. Big data has changed the way that companies can market to consumers and has thus bolstered the explosive growth of companies such as Uber, Postmates, and Amazon (Cordon et al., 2016). According to the U.S. Department of Commerce, e-commerce sales in the 3rd quarter of 2018 totaled roughly $130.9 billion (U.S. Department of Commerce, 2018). This was not only an increase from previous years in terms of sheer volume, but also in terms of total market share (Figure 1) (U.S. Department of Commerce, 2018). The significant increase in online sales demands a much greater need for chipping. Businesses now have an opportunity to find a better way to accommodate the increased demand in package deliveries. Market share in particular is an important metric, as it indicates that the need for package delivery is affecting either more businesses, a larger proportion of existing businesses, or both.

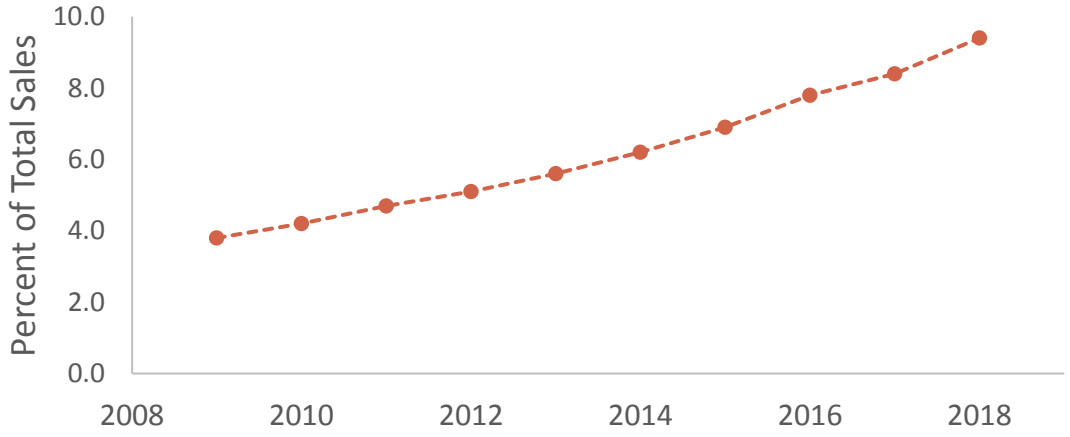

Figure 1. Estimated quarterly e-commerce market share 2009-2019, adjusted for seasonal variation (U.S. Department of Commerce, 2018)

A major challenge in the delivery process is how goods are transported from a business to an individual consumer. This a problem of logistics. When dealing with bulk purchases, such as business to business sales, the approach is relatively straight forward. Producers group together items with the same destination to benefit from economies of scale. However, this concept breaks down at the individual consumer level. While many goods can be consolidated when moving to a hub such as a port or distribution center, once the merchandise reaches the last hub it must traverse the last leg of the journey to the consumer often individually. This is known as the "last mile problem". It is a problem of great importance as the "last mile" is noted to be "the most expensive, the most complicated and, often, the longest" (Cordon et al., 2016). Until recently, the best solution was a large delivery truck that engaged in the classic Traveling Salesman Problem (TSP), to find the shortest distance required to visit all delivery nodes or customers (Roberts & Testman, 2005). Recent development in technology has now opened the doors to new and innovative solutions to this old problem.

Advances in drone technology have led to their use in an expanding number of fields. Drones were once primarily used for their military applications, as evidenced by the drone market share which was 72% military (Balaban, Mastaglio, & Lynch, 2016). The first generation of drones were much more expensive than commercial drones available today. In fact the most common drone system in the military costs roughly $260,000 (United States Air Force, 2017). However, as less expensive models have been developed they have become more readily available and have caused a paradigm shift in various fields to which they have been introduced including photography, agriculture, civil engineering, and now logistics (Balaban et al., 2016). As the introduction of drones to the logistics sector is a relatively new concept, only preliminary research has been done on the application of drones as a solution to the "last mile problem". Moreover, only a fraction of this research focuses on the potential energy savings that can be attained. This problem and its implications to the logistics of a growing global economy have the potential to affect the estimated 65 billion packages delivered per year (Loesche 2017). This potential impact is evidenced in part by the growing interest in drone applications to logistics around the world including the U.S., Germany, Australia, Singapore, Malaysia (Murray & Chu, 2015) as well as Italy, Taiwan, Haiti, New Zealand, Japan, Philippines, and China (Chowdhury, Emelogu, Marufuzzaman, Nurre, & Bian, 2017).

Energy consumption in the logistics sector represents significant costs, but the long-term implications speak to the larger threat of climate change which affects not only businesses in the logistics sector but the world at large. In 2018, the United Parcel Service (UPS) spent over $3.4 billion on fuel costs (United Postal Service, 2019a). This was up from $2.69 billion the year before and $2.12 billion in 2016 (Figure 2) (United Postal Service, 2019a), which reflects the rising demand in package delivery as a result of the steady growth of e-commerce. Considering the approximate 54% market share that UPS owns in package delivery (Lohn, 2017), and assuming the rest of the market operates under similar conditions, this amounts to a nationwide fuel cost of almost $6.3 billion as a result of package delivery. Improving the logistics of package delivery by even a small percentage provides an opportunity for millions of dollars in savings. In fact, it has been estimated that a reduction of just one mile in the route of each UPS driver per day would result in $30 million in savings over the course of one year (Wohlsen, 2013). These savings would benefit both businesses and consumers of package delivery. Still, that number of people pales in comparison to the world's population which would benefit from the reduction in energy consumption through its effect on climate change. According to the Intergovernmental Panel on Climate Change (IPCC), one of the driving factors of greenhouse gas (GHG) emissions is energy use (IPCC, 2014). Further, the panel asserts that carbon dioxide (CO_2) emissions will be the primary determinant of the increase in global surface temperatures by the end of the century (IPCC, 2014). These facts alone provide significant motivation for the search of a more energy efficient system to tackle the growing need of package delivery.

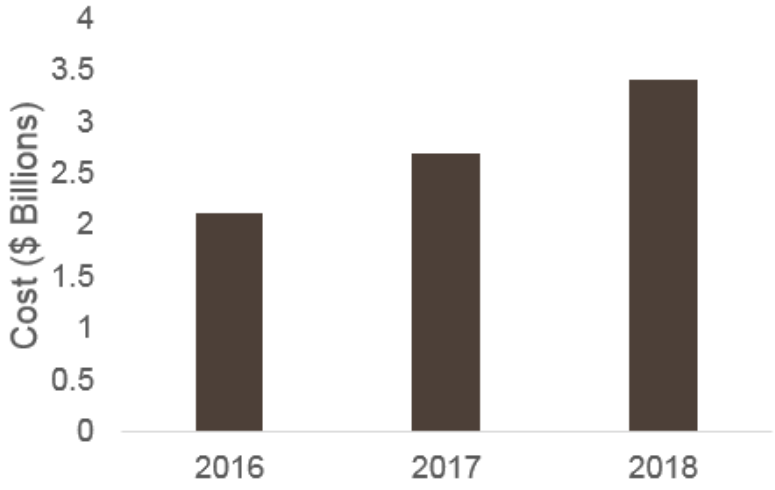

Figure 2. United Postal Service yearly fuel costs (United Postal Service, 2019a)

One of the first steps to the incorporation of drones is to consider their feasibility and the size of the scope to which they can be applied. Perhaps most obviously, how often can drones be used? One major limitation of drones is their payload capacity; thus, package weight is a primary concern when it comes to the application of drones in the logistics sector. According to Amazon CEO Jeff Bezos, about 86 percent of Amazon packages weigh 5 pounds (lbs.) or less (Guglielmo, 2013). Conservative calculations show that lithium ion batteries available as of 2014 can provide the power necessary for drones to handle payloads of 2 kg (4.41 lbs.) (D'Andrea, 2014). Unfortunately, little improvement has been made in battery technology since then. Lithium ion batteries remain the most capable batteries in terms of specific energy, energy provided per unit weight, and the specific energy has only improved from roughly 0.25 kWh/kg to 0.26 kWh/kg (Ulvestad, 2018). This lack of advancement in battery technology contributes to the second major limitation of drones which is delivery range. Still, as drones themselves are much lighter than their truck delivering counterparts, the energy they require to deliver an individual package is orders of magnitude less. A drone would require 0.39 kWh to deliver one 2 kg (4.41 lbs.) package 10 km (6.21 mi) away (D'Andrea, 2014), while a truck would require 1.6 kWh-eq/km (Lohn, 2017) or 16 kWh-eq for the same package. In addition to the lower energy requirement per unit distance traveled, drones can reap energy savings by traveling shorter distances as they are not restricted to the road network. Indeed, drones are capable of handling most package deliveries, and can do so at a fraction of the energy cost of a gasoline or diesel fueled truck. However, with their considerable limitations in terms of payload weight and range, the question becomes how much of an impact can drones have on the energy consumption of a package delivery system and in what situations can they have it?

The focus of many studies including those conducted by Balaban et al. (2016), Ferrandez et al. (2016), Murray and Chu (2015), Dorling et al. (2016), and Chowdhury et al. (2017), among others has been solely on the minimization of delivery time. In cases like emergency response, as is the setting in the research drone by Chowdhury et. al. (2017), the delivery time is of upmost importance. However, when it comes to consumer parcel delivery, other considerations such as energy consumption need to be studied as well. Energy efficiency in a worldwide industry can scale to enormous amounts of energy savings, which can then translate to savings in cost in the millions of dollars. There are two other considerations that can have a significant effect on package delivery systems that have not been addressed in previous studies. First is the location of

delivery nodes within a model, or demand distribution. All research thus far has assumed a uniform distribution of package demand. The second consideration is the distribution of package weight. Most commonly package weight is not considered at all, but when it is considered it is often assumed to be the maximum payload weight of the drone. The focus of this thesis is the energy efficiency of truck-drone delivery systems, with the development of a demand distribution using population density, and a representative package weight distribution using existing package weight data.

The rest of this thesis is organized as follows. Chapter 2 provides a background of related literature, including the basic components of truck-drone delivery systems, how they have been modeled and solved, and the extent to which the gaps addressed in this study have been overlooked. Chapter 3 presents the mathematical formulation and subsequent solution algorithm developed in this study. Chapter 4 contains the results of the case study performed in Tippecanoe county, including the impact of demand density, number of drones, and package weight distributions as well as a sensitivity analysis of the key assumptions made. Finally, a conclusion will summarize the findings and provide a course for future work.

CHAPTER 2. LITERATURE REVIEW

Though research on the application of drones in the logistics and other sectors is in its infancy, the results so far have been promising. The research gaps lie in the optimization of energy savings with regards to system configuration, distribution of package demand, and the distribution of package weights. The problem analyzed in this study is how best to leverage the advantages of drones in order to maximize the energy savings in package delivery. In order to understand the complexity of this problem, it is necessary to look at its roots. At the most fundamental level, it is in fact a variant of the TSP, but the problem has evolved and shifted over time to reach the problem of today. The first step towards the present is the multiple Traveling Salesman Problem (mTSP), which allows for more than one salesman to service the nodes in question (Bektas, 2006). This may seem like a trivial change to the classic TSP, yet the complexity this small change brings is immense since additional salesmen multiply the number of possible solutions by the number of salesmen. Even in the smallest case of two salesmen, this means doubling the solution space to an already NP-hard problem. While closer to today's problem, this was just one small step in the direction of drone applications as drones and trucks are not equal salesmen. An extension of the mTSP is the Vehicle Routing Problem (VRP), which incorporates limiting capacities to the salesmen or vehicles (Bektas, 2006). The VRP was viewed as "one of the most challenging" in combinatorial optimization (Solomon, Cordeau, Etudes, & Desrosiers, 1999). However, the VRP has since been extensively studied with over 1,000 articles published by 2008 and hundreds more by 2015 (Braekers, Ramaekers, & Nieuwenhuyse, 2016). The extent to which the VRP has been researched is in part due to its ability to be adapted to vastly different real-world problems. The VRP can account for the different capabilities that a delivery truck and drone have. This includes limiting factors such as their payload capacities and delivery range. The VRP is the starting point for the inclusion of drones in package delivery.

2.1 System Configuration

A delivery system that involves a truck and/or drones can have four different fundamental configurations (Figure 3). The current system which is shown in Figure 3 (a) uses a delivery truck that engages in the classic TSP between the depot and the customers. The depot represents

the last hub in the path from the seller to the customer, and thus contains all the packages that now need to travel to customers in the “last mile problem”.

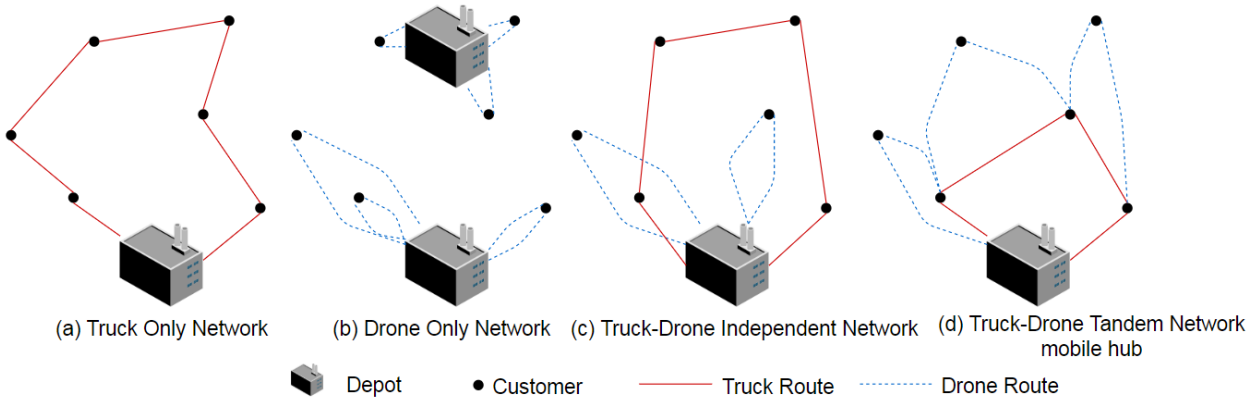

Figure 3. Different package delivery network configurations

The simplest configuration which uses drones for package delivery is to consider them as standalone replacements of delivery trucks as illustrated in Figure 3 (b). One study that modeled drones this way, delivering from a business location to a consumer location and back to the original building, proposed the use of drones for delivery of real-time orders (Balaban et al., 2016). A benefit of this configuration is that since it does not have an underlying TSP it is not NP-hard, and thus can be solved to optimality using exact methods for large scale problems (100 customers or more). Balaban et al. (2016) used simulation in their drone delivery analysis. However, as this study considers a drone-only system it assumes all packages are deliverable by drone and does not address package weight or its impact. Still, it provided insight into the effect of certain factors that are applicable to any delivery system that incorporates drones. Some of the results include that the maximum velocity of the drone is positively correlated with the number of packages a drone is able to deliver and with the number of customers that are eligible for delivery (Balaban et al., 2016). Though insight from this configuration is useful, the application of a standalone drone system is heavily limited by the range and payload capacity of drones. The range limitation could be solved by adding more depots as illustrated in Figure 3 (b), which would allow drones to service more customers. However research has discovered that with this approach energy consumption is dominated by the additional depots required to service all the customers (Stolaroff et al., 2018). Payload capacity on the other hand is a hard limitation that can only be addressed by advancement in drone or battery technology. Thus, this configuration could

not be implemented in general parcel delivery which can deliver packages up to 150 lbs. (United Postal Service, 2019b). In order to implement drones on a large scale, they must be implemented in addition to the trucks that are already in use. This addition can either be an independent system or work in tandem with the truck.

Another fundamental configuration for drone incorporation uses both a truck and a drone that both depart from and return to a depot, which is demonstrated in Figure 3 (c). Though both trucks and drones are used in this system, they operate independently. This configuration was considered by Lohn, whose study concluded that drones result in an increase of energy consumption on a per package basis (Lohn, 2017). This is due to two factors: the much larger capacity of a truck, and the assumption that drones can deliver to any customer regardless of range. While a truck uses significantly more energy than a drone, it can also deliver hundreds of packages along its route, while a drone can only deliver one package per route. Moreover, Lohn's assumption that the range of drones is proportional to the area of the city assumes that drones can deliver to any location in a city with an area of up to 2,500 km (1553.43 mi) (Lohn, 2017). Consequently, a drone can deliver a package to a customer near a different customer that was serviced by the truck. Since the truck could have delivered both packages by only adding the small distance between them rather than the drone making a roundtrip from the depot to the customer, the drone's delivery and this assignment is largely inefficient. Still, Lohn found that energy savings could be seen by increasing the number of depots (Lohn, 2017). This would allow drones more options from which to fly and thus cut the flying distance, and corresponding energy consumption, of some trips. Again, the additional depots would add to the overall energy consumption of the system. However, an alternate solution exists. By changing the configuration to allow drones to work in tandem with the truck, drones would see an increase in flight path options, a decrease in flight time needed to reach delivery nodes, and a reduction in inefficient delivery assignments.

A fourth type of configuration uses a truck which departs from and returns to a depot, but a drone which can depart from and return to the truck as well as the depot. This configuration considers the truck a mobile depot and is demonstrated in Figure 3 (d). However, the classical VRP does not account for the special relationship between the truck and drone when the truck is used as a mobile depot. The latest extension that accounts for this relationship was only introduced in 2015 as the Flying Sidekick Traveling Salesman Problem (FSTSP) (Murray &

Chu, 2015). Murray and Chu (2015) sought to optimize the delivery time of a truck and single drone delivery system using this configuration. The key contribution of this configuration is the increase in effective range for the drones. Since the drone uses the truck as a launch point, it can theoretically reach any node if the truck route is close enough. This allows the drone to service more customers, with package weight becoming the primary restriction. Using the mobile hub configuration developed by Murray and Chu (2015) and thereby increasing the effective range of the drone, it is possible to leverage the energy efficiency of the drones at a much higher rate. The system configuration is just the first factor to consider when modeling truck-drone delivery networks.

2.2 Additional Key Model Factors

Other factors that must be considered in an analysis of truck-drone delivery systems include:

- Number of drones
- Distribution of package demand
- Package weight distribution
- Objective function

A summary of the existing literature including how each study addressed each key factor is presented in Table 1.

The number of drones used in the system is an important factor. Early results show that even the addition of one drone can reduce the delivery time of package delivery systems (Murray & Chu, 2015). A later study found that the benefits were greater with the incorporation of multiple drones (Ferrandez et al., 2016). Ferrandez (2016) also acknowledged the increased energy efficiency of a drone over a truck but did not explore the extent to which this could be leveraged as its goal was the reduction of delivery time. Moreover, we know that “last mile” packages often travel to their final destination in isolation (Cordon et al., 2016). Having multiple drones allows the system the flexibility to maximize the of use advantageous locations, by way of depots or trucks acting as mobile depots, by launching multiple drones at once. Thus, it is important to study the potential energy consumption benefits of having multiple drones within a delivery network.

The distribution of package demand within a particular area is another factor that must be incorporated into a delivery model. This distribution will determine the distance between delivery points and their distance from the depot, which informs a limiting factor of drone delivery: range. The effect of this limiting factor is amplified in “last mile” package delivery as this portion of the journey is often the longest (Cordon et al., 2016). Yet demand distribution has yet to be considered in any depth. Murray and Chu, for example, used a demand of 10 delivery points in an area of 8 square miles (Murray & Chu, 2015). On a larger scale, Ferrandez et al. considered a demand of 100 delivery locations in 100 square kilometers (38.61 square miles) (Ferrandez et al., 2016). Regardless of the scale, all studies have only considered a uniform distribution of package demand.

Similarly, the distribution of package weight is a driving factor in a truck-drone delivery model. Aside from range, the other major limitation of drones with regards to package delivery is payload capacity. The underlying weight distribution informs the impact of this limitation in a model in terms of both how many packages are deliverable by drone and how much energy is required to deliver each package. Similarly, package weight will play a role in determining the cost of delivering a package and even the resulting emissions. Even so, package weight distribution has received even less attention than demand distribution. In studies done by Ferrandez et al. (2016), Kim and Matson (2017), and Balaban et al. (2016) package weight is not considered at all, as all packages are assumed to be deliverable by drone. Murray and Chu also do not consider package weight, but do assume that 80-90% of packages are deliverable by drone (Murray & Chu, 2015). On the other hand, in studies done by Chowdhury et al. (2017) and Lohn (2017), package weight is assumed to be the maximum payload capacity of the drone with 70% and 86% respectively being drone eligible. Stolaroff et al. (2018) also assumes package weight to be the maximum payload, but assumes all packages are drone eligible.

Lastly, the objective function influences the solutions in any model. All other key factor being equal, changing the objective function can yield significantly different optimal solutions. Consider the package delivery problem in Figure 4. The underlying problem represented by the delivery points is the same, yet the solutions differ. Under the objective of reducing delivery time, two drones are assigned to make deliveries using the truck as a mobile depot. However, one of these delivery points lies near the truck route. When the objective is changed to reduce energy consumption, this point is assigned to the truck instead of a drone. This assignment adds

only a small marginal energy cost to the truck route while eliminating the entire cost of one drone route and significantly reducing the cost of the other. Other objective functions can include the total cost of delivery as explored in Chowdhury (2017) and greenhouse gas emissions (Stolaroff et al., 2018). Interestingly, even objective functions which are correlated can yield contradictory results. For example, energy consumption and greenhouse gas emissions are heavily correlated as emissions are in part estimated by the energy consumption of the vehicle (Stolaroff et al., 2018). Yet even in this case Stolaroff et al. (2018) found that when drones were the more energy efficient option, they did not always reduce emissions compared to a diesel truck.

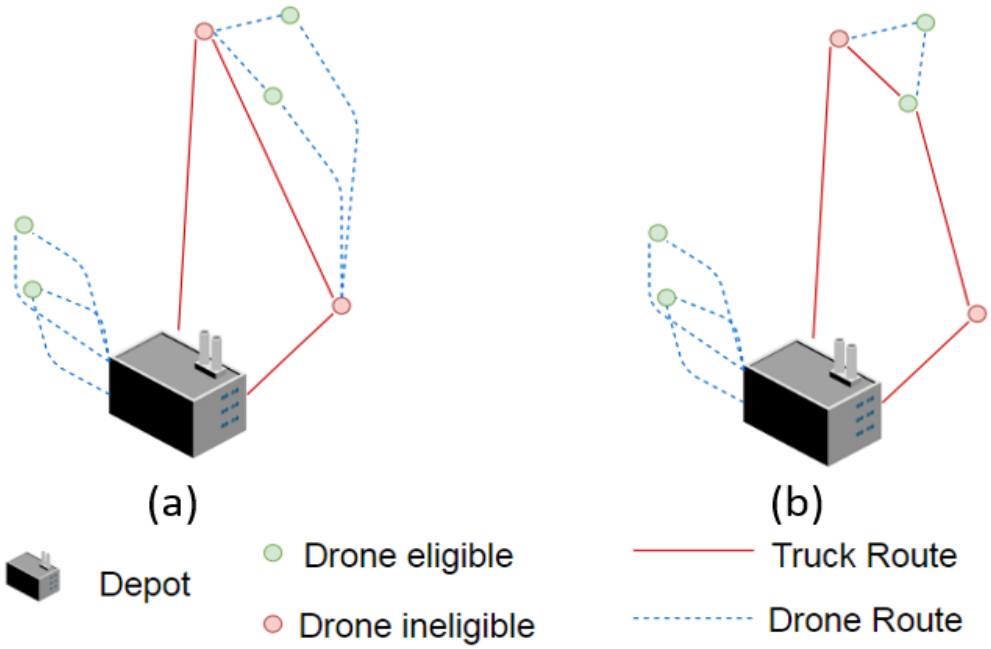

Figure 4. Comparison of optimal solutions under different objective functions (a) delivery time and (b) energy consumption

2.3 Research Gaps

Based on the above discussions, the existing truck-drone delivery system modeling has the following three limitations. First, few studies have analyzed the energy efficiency of truck-drone delivery systems. Instead, the focus has been on minimizing delivery time, yet minimizing energy consumption can have potential monetary and climate benefits. The second limitation is the lack of a proper demand density distribution for delivery points in the model. This is of significant importance in “last mile” package delivery, as the destination is an individual

consumer. All previous studies have used a uniform distribution, yet this is far from reality as people do not live uniformly within a country, state, or even city. Downtown areas and cities are much more densely populated than rural areas and small towns. Furthermore, even within a town or city, residential areas will be more densely populated than business districts and other parts of that town or city. To address this gap, this study will use population as a proxy for package demand. Using census data, demand can be generated at the census block level. Another aspect of truck-drone delivery systems that has typically been overlooked is the impact of package weight. In many cases, the assumption is made that packages are the maximum allowable weight. While this assumption is acceptable in studies considering only the delivery time of systems, it is insufficient for one focusing on energy efficiency. This study will consider both parcel data from the 2012 Commodity Flow Survey (U.S. Census Bureau, 2015a), as well as information provided by one of the largest companies considering drone delivery: Amazon. This data and information will then be used to estimate underlying package weight distributions.

Table 1. Summary of truck-drone "last mile" delivery system research

Configuration	**Study**	**Objective Function**	**Number of Drones**	**Package Demand Distribution**	**Package Weight Distribution**
Drone Only	(Balaban et al., 2016)	Delivery Time	Multiple	Uniform	Not Considered
Truck-Drone Independent	(Chowdhury et al., 2017)	Cost	Multiple	Uniform	Maximum Payload
Truck-Drone Independent	(Lohn, 2017)	Energy Consumption	Multiple	Uniform	Maximum Payload
Truck-Drone Independent	(Stolaroff et al., 2018)	GHG Emissions, Energy Consumption	Multiple	Uniform	Maximum Payload
Bus-Drone Tandem	(Kim & Matson, 2017)	Cost	Multiple	Uniform	Not Considered
Truck-Drone Tandem	(Murray & Chu, 2015)	Delivery Time	Single	Uniform	Not Considered
Truck-Drone Tandem	(Ferrandez et al., 2016)	Delivery Time	Multiple	Uniform	Not Considered
Truck-Drone Tandem	(Jeong, 2018)	Delivery Time	Single	Uniform	Normal
Truck-Drone Tandem	This Study	Energy Consumption	Multiple	Population-Based	Beta

CHAPTER 3. METHOD

3.1 Problem Formulation

In an effort to increase energy efficiency, this model seeks to expand on the findings of previous research by using a configuration of multiple drones per truck (Ferrandez et al., 2016), which use the truck as a mobile hub (Murray & Chu, 2015). With this configuration, the drones and truck make their deliveries simultaneously, and the effective range of the drones is increased. As each truck can carry multiple drones, this problem is an extension of the FSTSP and can be called the multiple flying sidekick traveling salesman problem (mFSTSP). This problem, like its predecessors is NP-hard. The mFSTSP seeks to deliver packages from a depot to a number of delivery points n. Each point must be delivered to only once by either the truck or a drone. Packages whose weight exceeds the drone payload capacity or are beyond drone range must be delivered by the truck. Finally, the truck must depart from and return to the depot while drones may also depart from and return to the truck.

3.1.1 Key Model Assumptions

In order to develop a mathematical formulation, the following assumptions are made:

- Each delivery point represents the demand for one package.
- All drones in the system are identical.
- Each drone can only make one delivery at one location and cannot retrieve anything from delivery locations.
- Drones are loaded with the package they will deliver prior to the start of the route.
- Drones must depart from and return to either the truck or the depot.
- Drones that depart from or return to the truck must do so at different delivery nodes.
- The truck must arrive at a “return” node before the drone runs out of power.

The first assumption considers that if multiple packages are going to the same location they are consolidated into one package at the depot. The second establishes that the capabilities of all drones are the same. Next is a simplifying assumption which facilitates the incorporation of

multiple drones without having to account for battery charges made during the delivery route. The fourth assumption reduces the workload on the driver during the route and lowers the delivery time by eliminating the need for a processing time to attach a package to a drone. This assumption is reasonable as the optimal routes and assignments can be solved for prior to the start of the route. This is further supported in the case of "last mile" delivery, where packages start at a hub (in this case a depot). The fifth and sixth assumptions go hand in hand, as the truck would need to be stationary to process the return of a drone and adding stops outside of the delivery nodes would decrease delivery efficiency and increase the computational complexity of the problem. The sixth assumption also prevents the truck from waiting for the drone at one node while the drone makes its delivery. Allowing the truck to wait at one node is another factor that would vastly increase the complexity of the problem, and will be restricted in this model as it has been in previous research (Murray & Chu, 2015). The last assumption ensures that drones do not run out of power waiting for the truck at their return node, as drones that arrive before the truck will need to hover while they wait for the truck.

3.1.2 Notation and Mathematical Model

The notation shown in Table 2 is used to develop the mathematical model associated with the mFSTSP.

Table 2. Notation used in the mathematical model

Set	
N	set of all delivery nodes as well as the depot (denoted as nodes 1 and $n+2$)
$Indices$	
i, j, k, l	used to represent delivery nodes
$Constants$	
e_{ij}	energy required for the truck to travel from node *i* to node *j*
e'_{ij}	energy required for a drone to travel from node *i* to node *j*
n	the number of delivery nodes
t_{ij}	time required for the truck to travel from node *i* to node *j*
t'_{ij}	time required for a drone to travel from node *i* to node *j*
t'_{ijk}	maximum flight time for a drone delivery from node *i* to node *j* and a return to *k*
U	the total number of drones
w_j	1 if the package to be delivered to node *j* is above the drone payload capacity; 0 otherwise
M	a sufficiently large number

$Variables$	
a_i	arrival time of the truck at node i
u_i	indicates the position of node i within the truck route
x_{ij}	1, if the truck delivers to node j after departing node i; 0, otherwise
y_{ijk}	1, if a drone departs from node i, delivers to node j, and returns to node k; 0, otherwise

The objective of this study is to minimize energy use while delivering all packages to the required nodes and is represented in the following formulation.

$$Min \quad \sum_{i=1}^{n+1}\sum_{j=2}^{n+2} e_{ij}x_{ij} + \sum_{i=1}^{n+1}\sum_{j=2}^{n+1}\sum_{k=2}^{n+2}\left(e'_{ij} + e'_{jk}\right)y_{ijk} \tag{1}$$

$s.t.$

$$\sum_{i=1}^{n+1} x_{ij} + \sum_{i=1}^{n+1}\sum_{k=2}^{n+2} y_{ijk} = 1, \forall j \tag{2}$$

$$\sum_{i=1}^{n+1}\sum_{j=2}^{n+1}\sum_{k=2}^{n+2} y_{ijk} \leq U \tag{3}$$

$$\sum_{i=1}^{n+1} x_{ij} \geq w_j, j = 2, \dots, n+1 \tag{4}$$

$$\sum_{j=2}^{n+1} x_{1j} = 1 \tag{5}$$

$$\sum_{i=1}^{n+1} x_{i(n+2)} = 1 \tag{6}$$

$$x_{1,n+2} = 0 \tag{7}$$

$$\sum_{i=1}^{n+1} x_{ij} = \sum_{k=2}^{n+2} x_{jk}, j = 2, \dots, n+1 \tag{8}$$

$$\sum_{l=2}^{n+2} x_{il} \geq \left(\frac{1}{U}\right)\sum_{j=2}^{n+1}\sum_{k=2}^{n+2} y_{ijk} \quad , i = 2, \dots, n+1 \tag{9}$$

$$\sum_{l=1}^{n+1} x_{lk} \geq \left(\frac{1}{U}\right)\sum_{i=1}^{n+1}\sum_{j=2}^{n+1} y_{ijk} \quad , k = 2, \dots, n+1 \tag{10}$$

$$a_1 = 0 \tag{11}$$

$$a_j \geq a_i + t_{ij} - M(1 - x_{ij}) \quad \forall i, j = 2,3 \dots n+1 \tag{12}$$

$$a_k \leq a_i + \left(t'_{ijk}\right)\left(y_{ijk}\right) + M\left(1 - y_{ijk}\right) \forall ijk \tag{13}$$

$$1 \leq u_i \leq n+2 \; \forall i \tag{14}$$

$$u_i - u_j + 1 \leq (n+2)\left(1 - x_{ij}\right) \; \forall i, j \tag{15}$$

The objective function (1) minimizes the total energy consumption of the truck-drone tandem system, where the first and second terms represent the energy consumption of the truck

and drones respectively. Constraint (2) ensures that each node is delivered to by either the truck or a drone. This guarantees that all customers are serviced and only serviced once. Constraint (3) states that each drone only delivers one package. Constraint (4) ensures that packages whose weight make them ineligible for drone delivery are delivered by truck.

Constraints (5) and (6) ensure that the truck departs from the depot at the beginning of its route and returns to the depot at the end of its route. Further, constraint (7) states that the truck's return happens after making its deliveries. This is to ensure that the truck makes at least one delivery, so that the configuration fits that of a truck-drone tandem system where the truck acts as a secondary, mobile depot. Constraint (8) enforces the continuity of the truck movement, leaving from the delivery node it visits.

Since the truck acts as a mobile hub, the drones will need to depart from and return to the truck at different nodes. Constraints (9) and (10) ensure the drone departure and return process happens at nodes that the truck visits. Note that only the delivery nodes need to be checked, as the depot (represented at both ends of the route by node 1 and $n + 2$) can always process drone returns and departures.

Constraints (11) to (13) ensure that all drone departures and returns are time coordinated with the truck. Constraint (11) initializes the truck route. Constraint (12) finds the truck's arrival time at its next stop a_j based on the travel time required from its previous stop t_{ij}. Constraint (13) ensures that the arrival time of the truck at a rendezvous node a_k is earlier than the time the drone returning to the truck at node k runs out of energy. Finally, constraints (14) and (15) serve as subtour elimination. These are standard for a TSP or TSP extension and are adapted from Bektas (2006).

3.2 Genetic Algorithm

Because even finding the truck route alone is an NP-hard problem (Bektas, 2006), a genetic algorithm (GA) is developed to solve the mFSTSP to determine the delivery points that will be serviced by the truck or drones and the sequence of visits. Unlike the two-step approach taken by Ferrandez et al. (2016), this algorithm will solve for both the vehicle assignments and visit sequence simultaneously. Though Ferrandez et al. (2016) simplified their problem to only require a heuristic algorithm for the truck route, this study requires a heuristic algorithm for the drone routes as well due to the added complexity of the truck being mobile while the drones are

delivering. In general, the GA will randomly generate a population of possible solutions. It will then evaluate each of these solutions, assigning a fitness score in the process. Next, a percentage of the solutions are chosen to become parents for the next iteration. Each of these parent solutions is modified using a randomly selected crossover point, which will shift the solution. Finally, randomly selected members of the new population, which includes parents and children, undergo mutation which shifts some node within the solution either one spot to the left or right. A second type of mutation allows for the truck-drone assignments to swap with adjacent delivery points. The resulting population becomes the new generation. This generation is evaluated and given a fitness score, which begins the next iteration of the algorithm. The algorithm is stopped when no improvement is seen across a number of generations, based on the number of nodes, which dictates the size of the solution space. An overview of this process is illustrated in Figure 5.

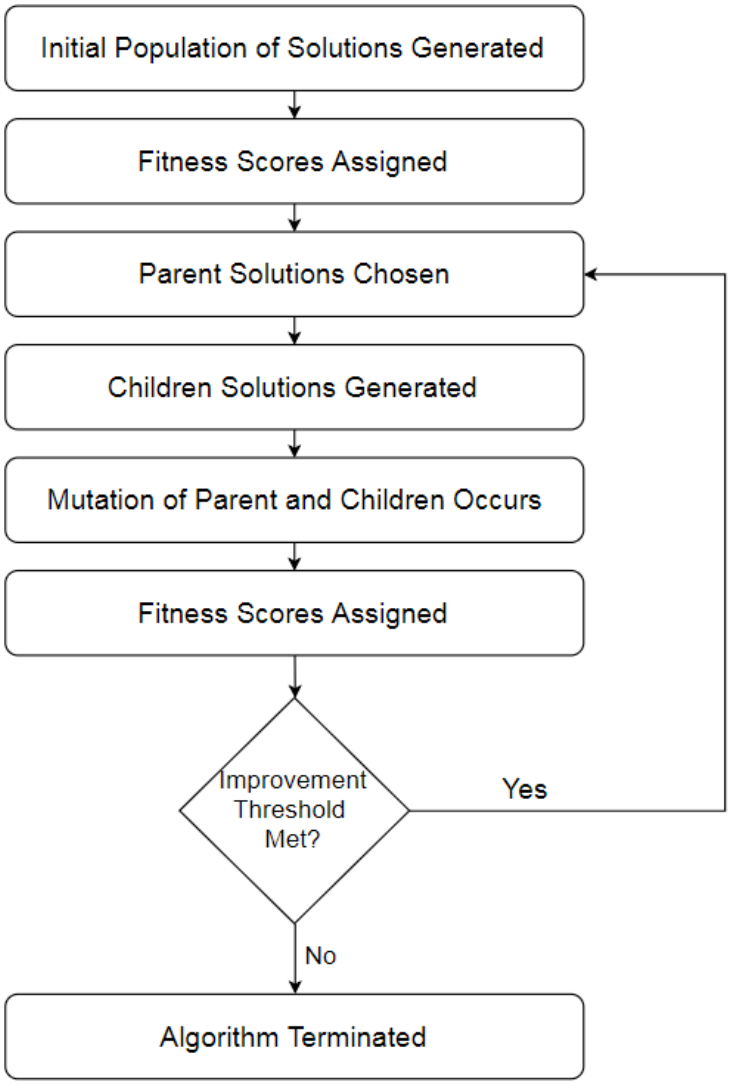

Figure 5. Overview of developed GA

3.2.1 Initial Population

The size of the initial population is based on the number of customer nodes and is set to n^2. Possible solutions are encoded using a three-layer gene. The first layer represents visitation order, the second indicates truck or drone assignment, and the last layer sets the departure and return nodes for the drone deliveries. Each gene (member) of the initial population is generated by constructing a random permutation of the customer nodes. This makes up the first layer of a member. For a problem with n nodes, our model assigns the depot to be stop 1 and stop $n + 2$. Thus, our algorithm only generates the delivery nodes $2,3, \ldots, n + 1$. The second layer is generated by constructing a random semi-feasible set of drone assignments, where a 1 denotes a

customer assigned to a drone. A semi-feasible assignment would be one in which only packages below the drone payload capacity are assigned to drones and where the number of packages assigned to drones do not exceed the number of drones in the system. These are only semi-feasible, as the range of the drone is not considered until the selection portion of this algorithm. The third layer is generated by randomly selecting a node that is visited by the truck prior to the drone delivery and a node visited by the truck after the drone delivery. For a problem with 7 customers and 3 drones, Figure 6 (a) illustrates one sample member.

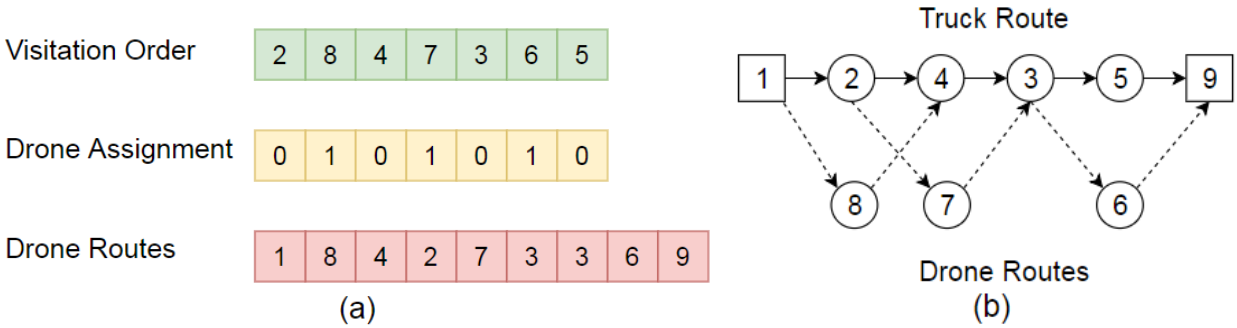

Figure 6. Possible solution to a 7 delivery point problem with 3 drones. (a) Sample member in the developed GA. (b) Corresponding solution visualization.

This member represents the solution with the truck route 1-2-4-3-5-9, where nodes 1 and 9 represent the depot, and customers 8,7, and 6 are delivered to by drones (Figure 6 (b)). More specifically, a drone departs from the depot to deliver to node 8 then returns to the truck at node 4. Similarly, another drone departs the truck at node 2 to deliver to node 7 before returning to the truck at node 3. Likewise, a third drone delivers to node 6 by departing the truck at node 3 and returning to depot. Note that the first two layers are of length 7, corresponding to the number of delivery points as the depot is always the first and last stop. The third layer is of length 9 corresponding to 3 drone deliveries each with a departure and return node.

3.2.2 Selection

The selection process begins by evaluating each member of the current population. Members are given a fitness score reflecting their total energy consumption as calculated in the objective function (1) of the mathematical model. In this case, a lower score represents a better or fitter solution. In addition to this, penalties are added for infeasible solutions. Feasibility is based on drone payload, range, and flight endurance. For example, a solution which denotes a

drone waiting for a truck for longer than its battery would allow or delivering to a node outside of its flight range will receive a penalty of M to its fitness score. If a solution is currently infeasible but contains drone and truck assignments which would make it feasible, it will receive a smaller penalty of $M/10$ to its fitness score. Thus, infeasible solutions are kept because they can become feasible and even optimal through future crossover and mutation induced changes. After fitness scores are assigned, a percentage of population (based on the progression of the algorithm) is picked to become parents of the next generation based on their fitness score. In the first iteration of this algorithm, the top half of the population is always selected. In future generations a smaller percentage of parents are selected as the generations of solutions move closer to the optimal solution. This selection method, known as truncation selection, is used for two reasons. First, it is used when dealing with large populations (Jebari & Madiafi, 2013). Since our solution space is based on $n!$, it needs a large population for the algorithm to succeed. Second, truncation typically runs the danger of eliminating genetic diversity needed to form the optimal solution but, because all solutions contain all of the genetic information needed to form the optimal solution, this is not a problem with this study.

3.2.3 Crossover

Once the parents are selected, each parent is modified using a randomly generated 'crossover point', then both the child and the parent form the next generation. The 'crossover point' will indicate which stop in the visitation sequence will become the last node visited in the new sequence. The sequence of customers following this point will be moved to the front of the new sequence. For example, consider the member generated in Figure 6, if our crossover point was 4 (indicating the 4th visited delivery node), the resulting modification is illustrated in Figure 7.

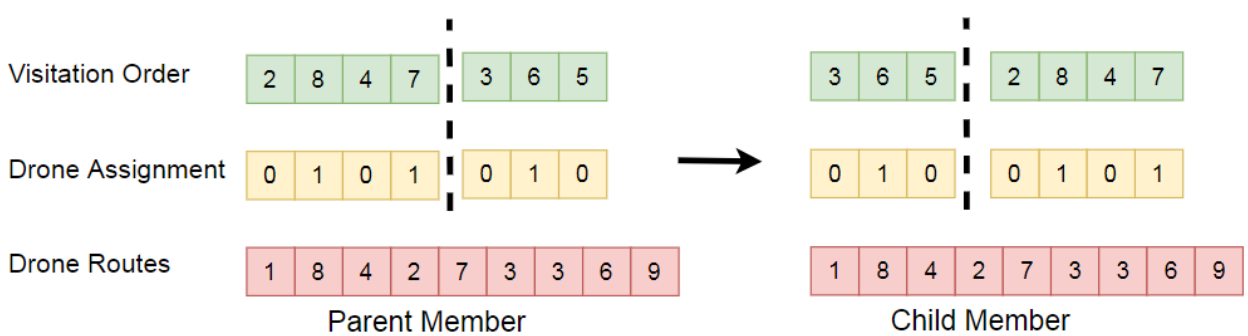

Figure 7. Crossover example for a sample member with a crossover point of 4.

Since the ‘crossover point’ was 4, the 4th stop of the visitation sequence (delivery point 7) is now the last node visited. Delivery nodes 3-6-5, which were the final three nodes visited, now become the first three in the visitation sequence. In this particular case, the first and third drone deliveries are still valid based on the truck route, but the second is not. Since node 3 is visited by the truck before node 2, the drone cannot deliver to node 7 and return to the truck at node 3. This infeasible route will be fixed later in the algorithm by assigning a departure node that precedes the drone assignment in the visitation sequence and a return node that follows the drone assignment in the visitation sequence. Though the canonical genetic algorithm chooses two parent members to generate the child during crossover (Whitley, 1994), this single-parent crossover method was chosen due to the fact that every possible solution contains all of the information needed to form the optimal solution.

3.2.4 Mutation

Following the crossover of parent members to generate child members, the new generation consisting of both parents and children are subject to mutation. Each solution has a certain chance of undergoing mutation dictated by the mutation rates. In this algorithm, there are two types of mutation (Figure 8), each mutation occurs independently of the other and has its own mutation rate which decays over the lifetime of the algorithm. A type 1 mutation takes one randomly selected node in the visitation sequence and swaps its location with that of an adjacent node, having an equal probability of swapping left or right. This type of mutation is applied to the first two layers of the member simultaneously. While crossover makes large changes to the visitation sequence in the solution, this type of mutation results in small changes to the sequence. This type of mutation has an initial mutation rate of 35%. A type 2 mutation selects one random drone assignment and swaps it with one of its adjacent nodes with equal probability. Note that this mutation can select any node in the second layer of the gene, including those currently not assigned to a drone. This mutation only applies to the second layer of the member and has an initial mutation rate of 10%. In the type 1 mutation shown (Figure 8), consider that the mutation point generated was 4 and a shift to the right was randomly determined. In the second type, consider the mutation point generated was 6 and a shift to the left was randomly determined.

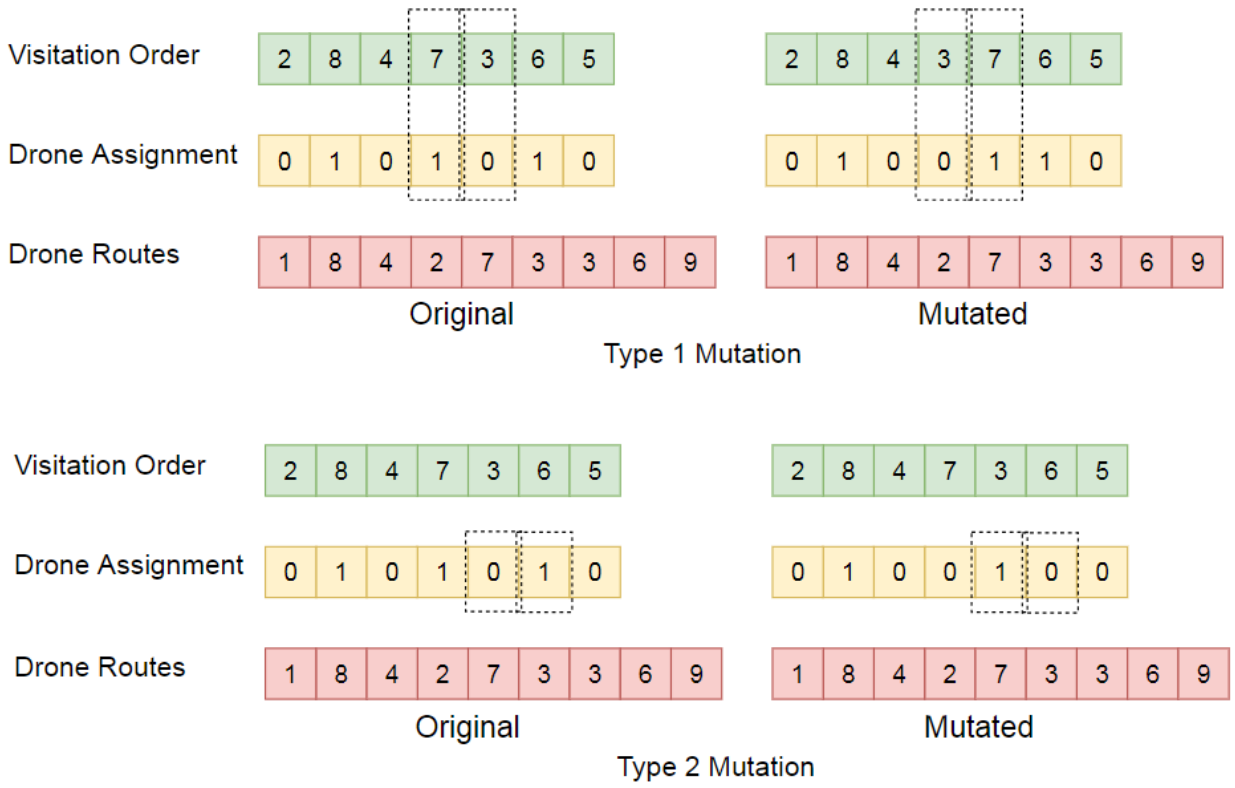

Figure 8. Mutation examples on the member generated in Figure 4

3.2.5 Termination

The selection, crossover, and mutation steps are repeated for the new population. Since the fittest individual always remains in the new population, the best solution in future generations can never be worse. However, after enough generations, the best solution will no longer show any improvement. The algorithm is terminated based on several continuous generations showing no improvement. The number of generations for this threshold is based on the number of delivery points, which is proportional to the complexity of the problem. This study uses termination criteria of 15 generations with no improvement for a 10-delivery point problem and an additional 10 generations per additional delivery point. Thus, for a 20-delivery point problem, the algorithm will terminate after 115 continuous generations without improvement.

3.2.6 Performance

To validate the proposed algorithm, 21 test sets were generated over 7 system sizes using 3 different seeds. These test sets were solved using both the mixed integer linear programming (MILP) model and the genetic algorithm developed in this study. The MILP was only capable of

solving the 15 delivery node scenario to optimality in one of the 3 test sets, and was incapable of solving any larger problem in any scenario. The genetic algorithm vastly outperformed the MILP in all test sets. For example, the 15 node problem that the MILP was able to solve to optimality required nearly 20 minutes, while the GA solved it in less than 20 seconds. The results of the test sets with the seed which resulted in the best performance by the MILP are summarized in Table 3.

Table 3. Performance comparison of MILP and GA on different system sizes

	MILP		**GA**		
n	**Runtime (seconds)**	**Solution**	**Average Runtime (seconds)**	**Runtime Range (seconds)**	**Solution**
5	10	Optimal	<1	<1	Optimal
8	43	Optimal	2	2-3	Optimal
10	128	Optimal	3	2-5	Optimal
12	304	Optimal	3	2-6	Optimal
15	1183	Optimal	9	8-12	Optimal
18	7237	Integer Feasible	15	14-18	
20	N/A	None	26	20-40	

CHAPTER 4. CASE STUDIES AND RESULTS

4.1 Case Studies

To evaluate the energy saving potential of a truck-drone tandem delivery system, we applied the developed model to case studies of package delivery in Tippecanoe county with different system settings and package densities.

4.1.1 Demand Distribution

Just as the density of people varies among different areas, be it urban, suburban, or rural, so does the package demand among those areas. Although some demographics of people may have higher demand than others, it is reasonable to assume that the population density in an area is positively correlated to its demand for package deliveries. In this study, we adopted the approach from Lohn (2017) in calculating the number of parcels delivered on any given day. "The total number of packages to be delivered is about 0.04 per person per day" (Lohn 2017), calculated by dividing the total number of domestic packages delivered to individual consumers per day by the national population. Although Lohn (2017) uses this number to estimate the number of packages to be delivered in cities of different sizes, he does not use it to generate population-based demand within each of those cities. In this study, we use the census population data (U.S. Census Bureau, 2015b) at the census block level to generate package demands. Note that the per person demand is used to find the number packages that need to be delivered in each census block, thus each demand location generated will represent exactly one package. Specifically, we used Tippecanoe county, where Purdue University is located, as the case study region. Tippecanoe County is approximately 500 square miles and contains over 100 census blocks. The size and shape of census blocks are determined in part by "the extent, age, type and density of urban and rural development" (Luo & MacEachren, 2014). This means that the population density and distribution is more likely to be similar within a census block than across any other arbitrary boundaries. Thus, using census data to generate package demand yields a sensible picture of what real demand might look like. Applying this method to Tippecanoe county yields the demand depicted in Figure 9, where demand in different census blocks is shown in separate colors.

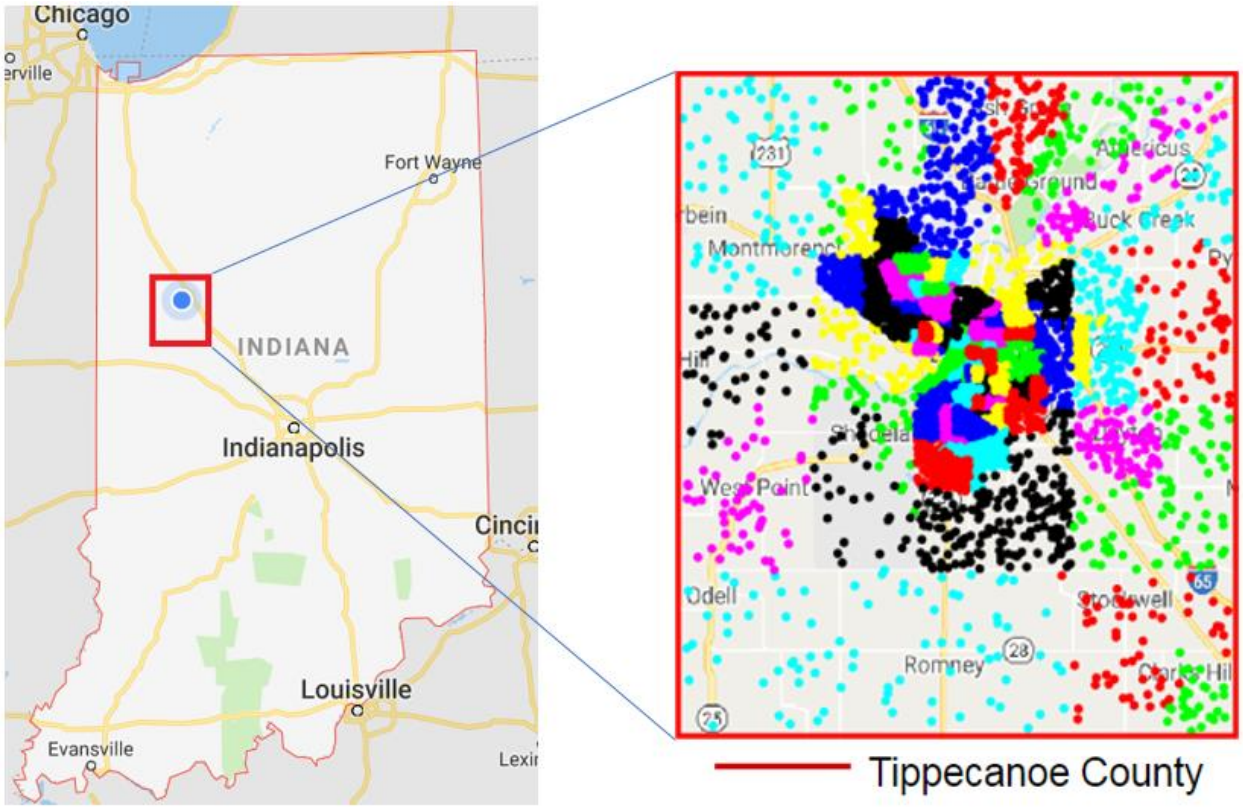

Figure 9. Sample demand in Tippecanoe County, Indiana

4.1.2 Package Weight Distribution

Another aspect of drone delivery that this study seeks to improve is the generation of package weight distributions in order to increase the resolution of energy consumption within the truck-drone delivery system. Many previous works opt to use the maximum payload capacity of the drone as the package weight for drone-delivered packages, which can be useful when trying to make conservative assumptions regarding the energy use of drones. However, as the goal of this study is to analyze the extent of energy savings possible with truck-drone delivery systems, using the upper bound of payload weight will not suffice. Since package data from parcel distributors is not publicly available, data obtained from the 2012 Commodity Flow Survey (CFS) (U.S. Census Bureau, 2015a) was used in its place. Figure 10 (a) shows a histogram of this data, a right skewed distribution

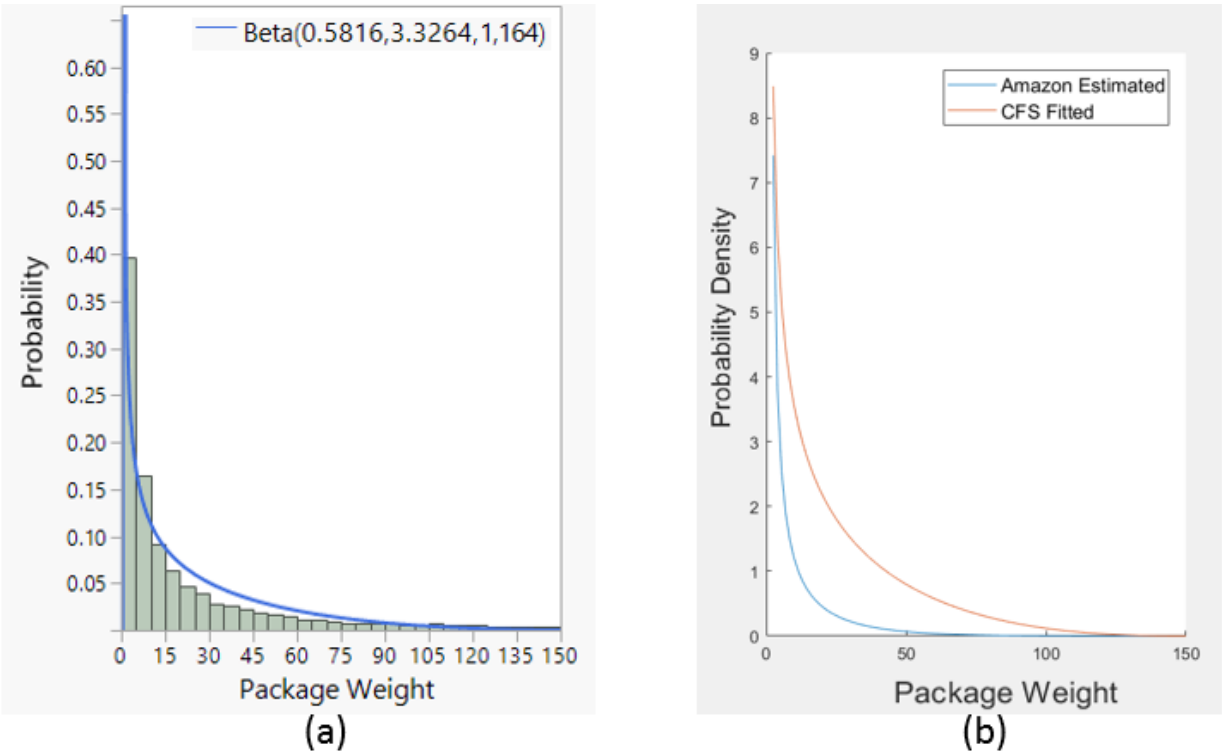

Figure 10. (a) Histogram of CFS parcel weight data. (b) Comparison of probability density functions for the fitted distributions of the CFS packages and the estimated Amazon packages.

The average parcel weight is roughly 19 pounds. The CFS data shows that less than half of the parcels weigh less than 5 pounds. The skewness and kurtosis values of the CFS data suggest that that a beta distribution is the best fit, specifically a Beta distribution with parameters $\alpha = 0.582, \beta = 3.326$. This data set includes shipments "in mining, manufacturing, wholesale, auxiliaries, and selected retail and services trade industries" (U.S. Census Bureau, 2015b). However, as this study focuses on the application of drones to the solution of the "last mile" problem which deals with consumer parcel delivery, the CFS data may not be the best representation. Still it gives us foundation from which to derive a more representative weight distribution. Amazon CEO Jeff Bezos has claimed that 86 percent of parcels delivered by its company are 5 pounds or lighter (Guglielmo, 2013). Using this information and solving for new parameters for a Beta distribution that results in 86 percent of packages being drone eligible, gives a good way of estimating the weight distribution of parcels to be delivered to consumers in accordance with the "last mile problem". The resulting distribution which satisfies both the requirement that 86 percent of parcels are within the 5 pound weight limit and the approximate

shape of the distribution of known shipments across the country is a Beta distribution with parameters $\alpha = 0.1001$, $\beta = 4.989$. A comparison of this distribution and the originally fitted CFS distribution are shown in Figure 10 (b).

4.1.3 Demand Densities

To leverage the benefits of the demand distributions developed in this study, demand was sampled in five different areas of the county (Figure 11) whose demand densities are listed in Table 4. Each area was sampled for 120 delivery points, the average number of deliveries made by a UPS truck in one day (Wohlsen, 2013). These five areas were chosen for two reasons. First, they cover the range of demand densities within the county from the densest area with a demand of 311 packages per square mile to the least dense area with a demand of 0.3 packages per square mile (ppsm). Second, they contain at least three different census blocks. This ensures that the population-based density distribution is reflected in the results of our case studies. Since Tippecanoe County was chosen for this study, the demand densities are inherently limited by the population densities within the county. However, the range of demand densities generated can be expanded by taking smaller samples from the larger 120 point samples. Specifically, the size of the area from which the smaller samples are taken can be changed to generate the desired demand density. This study uses this technique to evaluate demand densities outside of those that naturally exist in Tippecanoe county.

Table 4. Demand distributions of the five different sampled areas

Area Sampled	**1**	**2**	**3**	**4**	**5**
Demand Density (packages/ sq. mi)	311	149	9	3.7	0.3

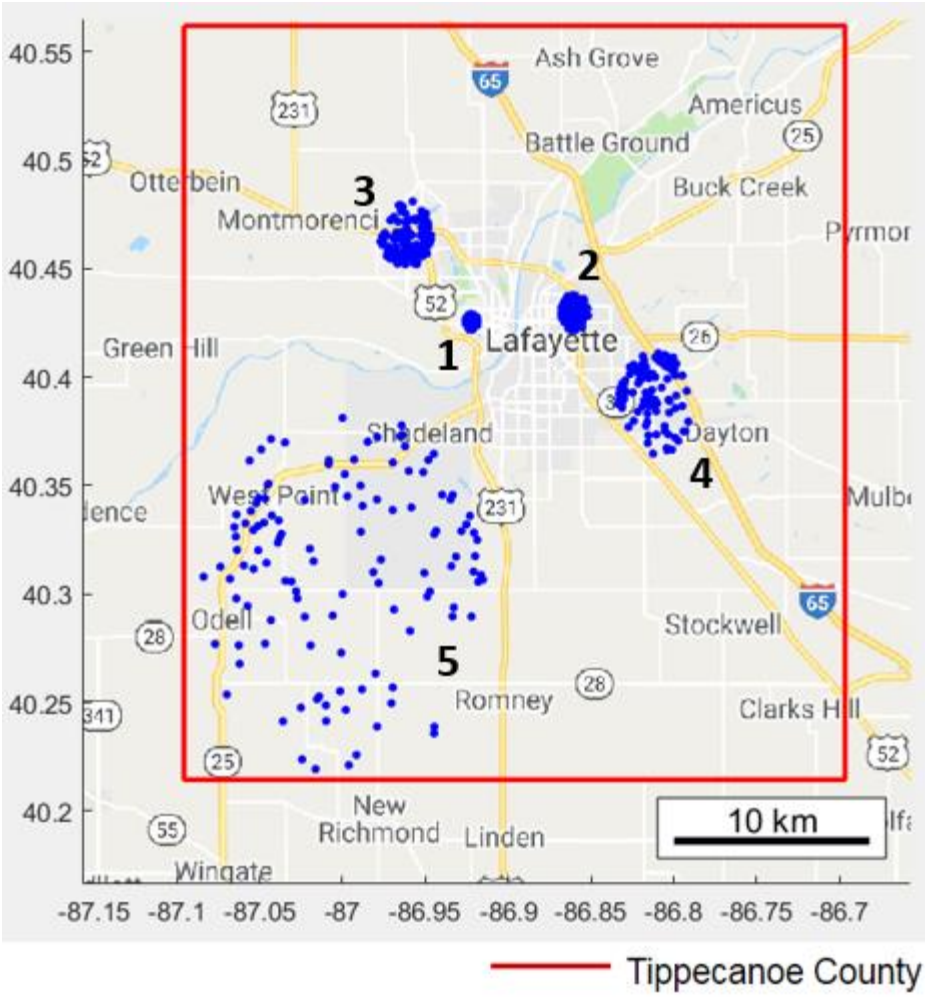

Figure 11. Five sampled areas within Tippecanoe county with different demand densities

4.1.4 Energy Consumption

This study adopts the approach taken in D'Andrea (2014) to calculate the energy consumption of the drone. This method gives an estimate of energy consumption flexible enough to accommodate for technological advances such as the increase in power transfer efficiency of drones or lift coefficients of drone design. The accuracy and flexibility of this method is further evidenced by its use in recent drone research such as the large scope study done by the RAND corporation in 2017 (Lohn, 2017). D'Andrea (2014) gives us a simple but effective equation (16) to estimate the energy requirement of a drone based on its payload weight, mechanical capabilities, and cruising velocity. Using these inputs, the equation is general enough to be implemented with many drone variants instead of being restricted to one design or model as is the case with studies conducted by Dorling el al. (2016) and Stolaroff et al. (2018). Equation (16)

gives a conservative estimate as it assumes a constant headwind reflected in the headwind to velocity ratio w, with flight distance $d(km)$, payload and drone mass m_p and $m_v(kg)$ respectively, cruising velocity $v(\frac{km}{h})$, power transfer efficiency η, lift-to-drag ratio r, and power consumption of onboard electronics $p(kW)$.

$$Energy\ Required_{horizontal}\ (kWh) = \frac{d}{1-w}\left(\frac{(m_p+m_v)}{370\eta r} + \frac{p}{v}\right) \tag{16}$$

The resulting energy requirement is used to estimate the horizontal component of the drone energy consumption in the model developed in this study. One shortcoming of this approximation is that it only accounts for the energy used to travel the direct distance between points, but not the energy used for takeoff, landing or hovering. To account for this, this study uses the same approximation from equation (16), the flight distance, and the velocity of the drone to calculate the energy use of the drone per second of travel (equation 17). The energy requirement per second is then multiplied by the hover time in seconds h to calculate the energy required for the drone to wait for the truck. To account for the takeoff or landing energy consumption, the per second requirement is multiplied by 40 seconds as this is the time it takes for a drone to reach the maximum allowable flying altitude of 120 m as dictated by the Federal Aviation Administration (FAA) (Federal Aviation Administration, 2018). These can be used as reasonable estimates for hover, takeoff, and landing because drones use roughly the same energy in all stages of flight (Dorling et al., 2016). It is notable that the estimate for takeoff or landing is doubled to account for landing as well as takeoff and added to the total energy requirement of a drone delivery. Adding all stages of flight together gives the total energy requirement of the drone (equation 18).

$$Energy\ Required_{per\ second}\ (kWh/s) = \frac{3600d^2}{v(1-w)}\left(\frac{(m_p+m_v)}{370\eta r} + \frac{p}{v}\right) \tag{17}$$

$$Energy\ Required\ (kWh)_{total} = \frac{d}{1-w}\left(\frac{(m_p+m_v)}{370\eta r} + \frac{p}{v}\right) + \frac{3600d^2}{v(1-w)}\left(\frac{(m_p+m_v)}{370\eta r} + \frac{p}{v}\right) * h + 80 * \frac{3600d^2}{v(1-w)}\left(\frac{(m_p+m_v)}{370\eta r} + \frac{p}{v}\right) \tag{18}$$

To estimate the energy consumption of the truck, this study used the results from a year-long evaluation done on UPS trucks by the National Renewable Energy Laboratory (Lammert, 2009). The evaluation found that the fleet of diesel trucks averaged a fuel efficiency 10.2 mpg over the course of a year (Lammert, 2009). By comparison, Lohn used a value of 15 mpg (Lohn, 2017) but did not cite how he settled on this fuel efficiency. This study uses the driving distance calculated by interfacing with Google Maps API, to find the distance that the truck must travel along the road network as it makes its deliveries. This contrasts with the assumption made by Ferrandez et al. (2016), that the truck could travel directly between delivery points.

In order to evaluate the total energy consumption of the truck-drone system, this study converted the energy requirements of the drone to their gallon of diesel equivalent (gal. diesel-eq). This was done using the fuel properties reported by the U.S. Department of Energy, which state that a gallon of gasoline contains 33.70 kWh of energy and that one gallon of diesel contains the energy of 1.13 gallons of gasoline (U.S. Department of Energy, 2014).

4.1.5 Truck and Drone Parameters

We used conservative values in all aspects of performance to keep energy savings found in this study valid for present day situation. Future technological advancements can be accounted for by adjusting the values used in this study. A truck velocity of 25 mph was used given the finding that UPS diesel delivery trucks have an average driving speed of 24.1 mph (Lammert, 2009). This truck velocity was also in line with the velocity used by Murray and Chu (2015). The power transfer efficiency η and lift-to-drag ratio r were kept at 0.5 and 3 respectively, as these were used in the original estimates made by D'Andrea (2014) and were noted to be easily attainable. The speed of the drone was set to a conservative 27.96 mph (45 km/h). Other studies have considered a drone speed of up to 55 mph (Balaban et al., 2016), however traveling at this speed would be less energy efficient due to wind resistance. Additionally, not all drone models are capable of reaching such speeds. The range of the drone was determined to be 6.21 miles (10km). This is the range feasible with current battery technology according to Stolaroff et al. (2018) with an increase to almost 18km (11.18 miles) estimated to be available in 2022. The payload capacity of the drone was set to 5 lbs. Though most drones considered for package delivery have a payload capacity of up to 10 lbs. (Stolaroff et al., 2018), 5 lbs. was used as a conservative limit for the base scenario.

4.2 Results

The following results are based on six scenarios used to test for the effect of five factors on the energy savings of the truck-drone tandem system. Test sets of size 18-21 were generated for each scenario to test a range of demand densities. A seventh scenario was used to analyze the sensitivity of four key assumptions. Each assumption was tested for plus and minus 25-percent variation three separate times, yielding 24 test sets in addition to the base case. The details of each scenario are summarized in Table 5.

Table 5. Summary of tested scenarios

Scenario	Section	Factor Analyzed	Number of Drones	Number of Delivery Points	Demand Density	Package Weight Distribution
1	4.2.1	Demand Distribution	1	10	0.03 - 478	Amazon Estimated
2	4.2.2	System Size	1	10	0.40 - 98.80	Amazon Estimated
3	4.2.2	System Size	1	15	0.52 - 108.79	Amazon Estimated
4	4.2.2	System Size	1	20	0.69 - 112.51	Amazon Estimated
5	4.2.3, 4.2.5	Number of Drones, Emissions	1-3	20	1.90 - 332.38	Amazon Estimated
6	4.2.4	Package Weight Distribution	1	20	1.90 - 332.38	CFS Fitted
7	4.2.6	Key Assumptions	3	20	1.69 - 1.89	Amazon Estimated

4.2.1 Package Demand Distribution

Drone delivery may not be suitable in all regions. To evaluate how demand density impacts the efficacy of drones in package delivery, we generated 20 test sets with demand densities which ranged from 0.03 ppsm up to 478 ppsm. Each test set was solved for a truck only system and a truck-drone tandem system with one drone, and the energy savings was recorded. The results are presented in Table 6A of the appendix and summarized in Figure 12. These show the stark difference in savings between the highest and lowest demand density test sets. The sets can be grouped into three major regions of demand density. The densest, 10 to 500 ppsm, reaped

an average savings of 0.02 gall. diesel-eq per trip. Sets between 1 and 10 ppsm saved an average of 0.08 gal. diesel-eq per trip, four times more than the densest regions. Lastly, sets with a demand density of less than 1 ppsm saved an average of 0.32 gall. diesel-eq per trip.

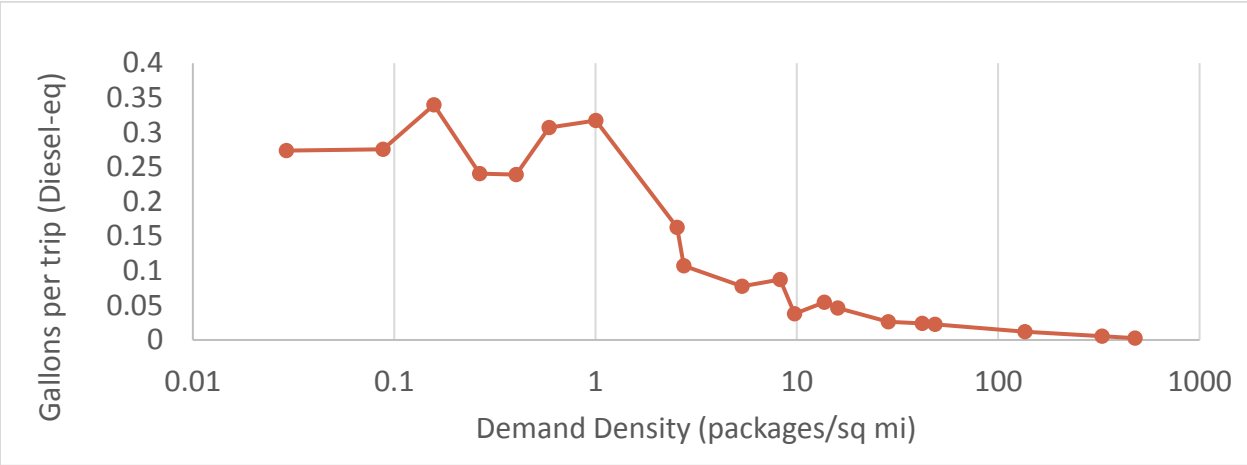

Figure 12. Energy savings across different demand densities using a truck-single-drone tandem system

The densest regions showed the smallest benefit from the addition of drones for three primary reasons which are presented in the test set with package a density of 328 ppsm (Figure 13). First, the distance between any two delivery points and thus the truck travel distance saved by delivering one package by drone is small. In the sample scenario the average driving distance between any two points is 0.05 miles (264 feet). Second, since all delivery points in the system are relatively close to each other, many points lie on the way to others. Such cases lend themselves to truck delivery as the additional distance needed to travel to deliver to these points is small or none at all. Consider the sample scenario (Figure 13) where delivery points 7 to 11 all lie on the same side of one street. Delivering to point 11, results in points 7 to 10 lying on the truck route. Thus assigning them to the truck does not add any travel distance to the truck route. Third, in areas with delivery points so close together, the driving distance is nearly the same as the flying distance. Thus the drone cannot leverage its advantage of being unrestricted from the road network.

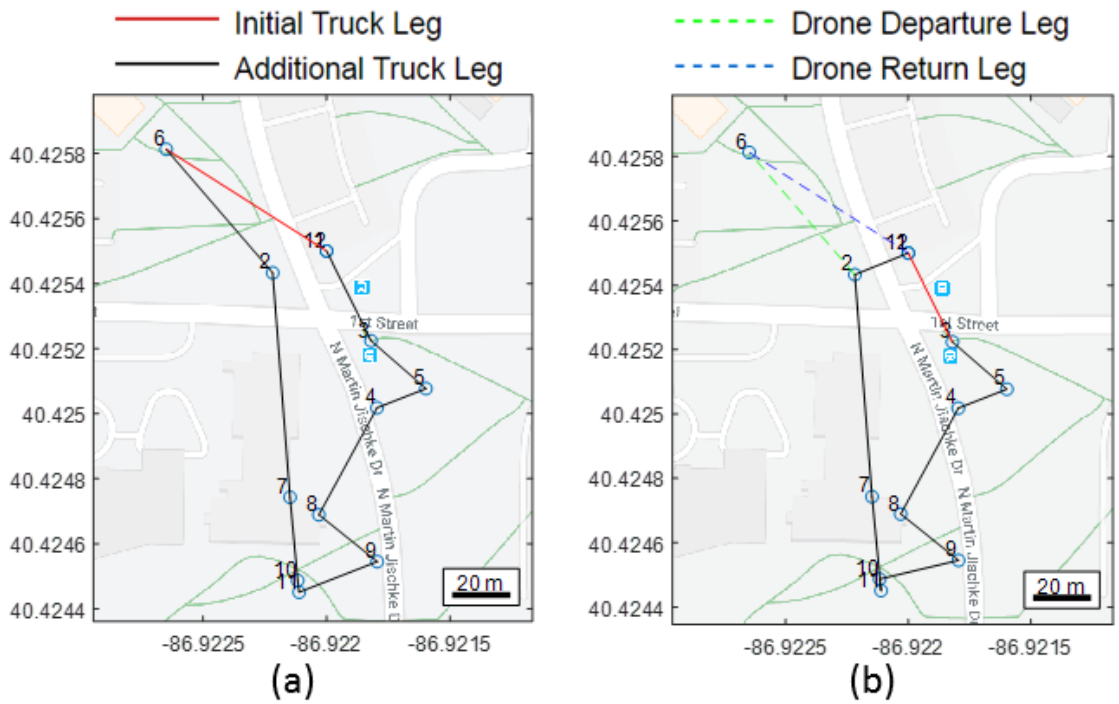

Figure 13. Sample scenario with a package demand of 328 packages per square mile. (a) The truck only solution. (b) The truck-single drone solution.

Using Lohn's (2017) estimated number of 12.8 million packages delivered per day, the finding that 82% of the country lives in urban areas with an average population density of 283 people per square mile can give us an estimate for the potential large-scale impact of drones. A population density of 283 people per square mile translates to an average package demand density of 11 packages per square mile. According to our results, adding one drone to each truck as a truck-drone tandem system would yield a savings of about 0.046 gal. diesel-eq per trip. This results in an estimated savings of 4,900 gal. diesel-eq per day, and 1.79 billion gal. diesel-eq per year country wide. These results held true for varying number of delivery points.

4.2.2 Number of Delivery Points

Energy savings with the incorporation of a truck-drone tandem system over a truck only system was found to be insensitive to the number of customers the system delivers to. These results are reflected in Figure 14. The corresponding data is available in Table 7A of the appendix.

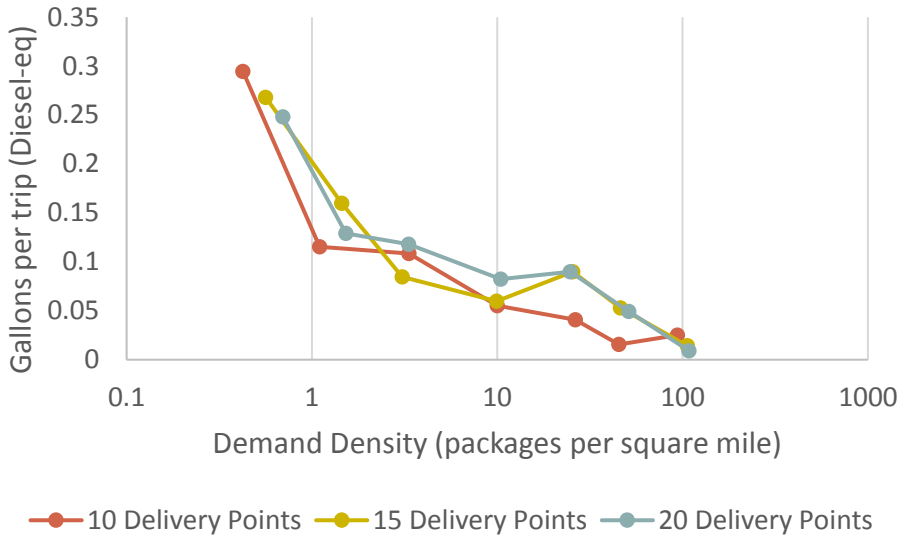

Figure 14. Comparison of energy savings across three different numbers of delivery nodes

Due to this result, further analysis was done on the 20 delivery point system.

4.2.3 Number of Drones

In general, adding drones provided further energy savings. The exception to this was in areas with package demand density so low that additional drones did not have eligible customers to service due to flight range restrictions. The first instance of this occurrence was found at a package demand density of 0.18 packages per square mile. The results are illustrated in Figure 15, with the full data set in Table 8A.

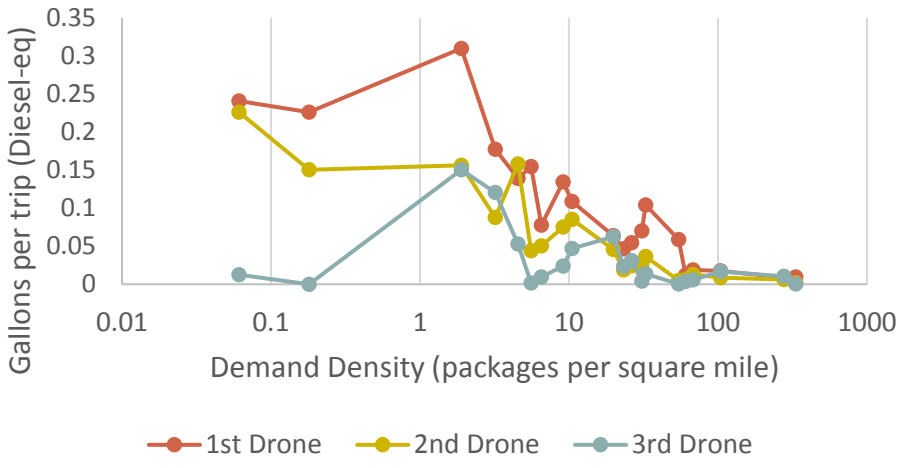

Figure 15. Comparison of energy savings for additional drones on a 20 delivery point system

Varying the number of drones also revealed that additional drones give the system diminishing energy savings in all but one set of circumstances. This makes sense intuitively; since the model minimizes energy consumption, the first drone would deliver to the node which would maximize energy savings. Consequently, the next drone added to the system should provide less energy savings than the first. An increase in additional energy savings was only seen when multiple packages near each other, but far from the rest of the packages, were assigned to drones. This resulted in the truck not having to visit that section of the delivery area, thereby granting a larger energy savings than typically expected by adding one drone to the system. An example of this is shown in Figure 16. In this example, though the second drone (assigned to delivery point 21) provides less marginal energy savings than the first drone, the third drone (assigned to delivery point 14) yields larger marginal savings than the second. Assigning a third drone to delivery point 14 eliminated the top right section of the service area from the truck route, which provides a large reduction in the energy consumption of the truck and therefore the system as a whole.

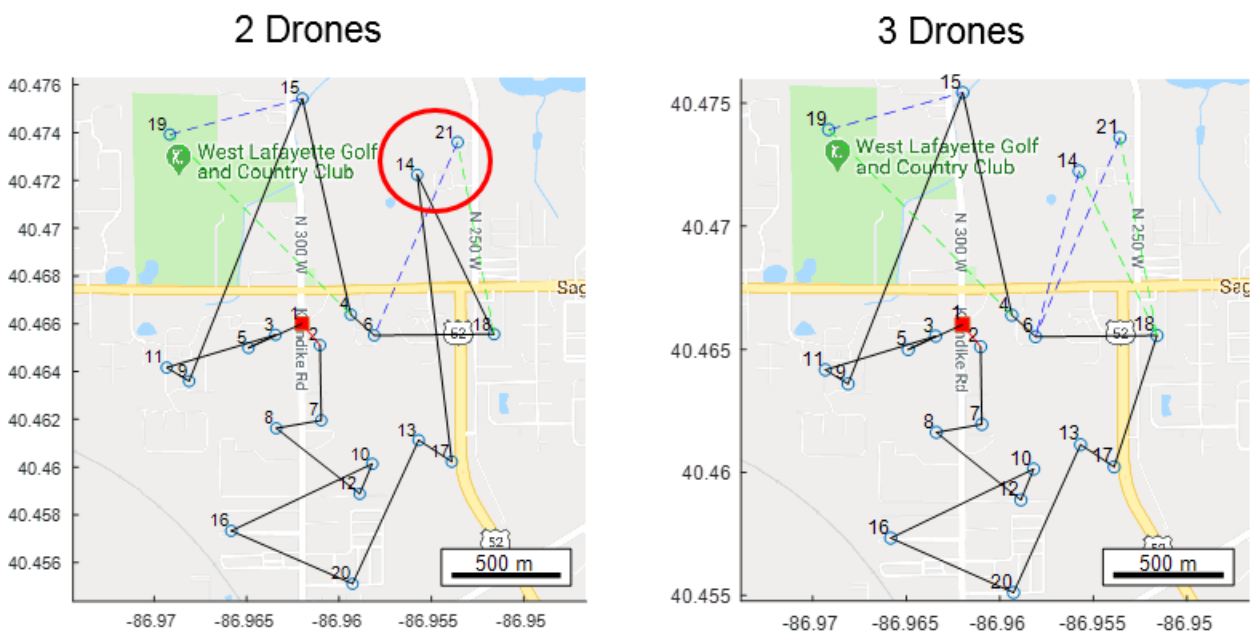

Figure 16. Sample scenario where a third drone provides larger marginal energy savings than the second drone in a 20 point system.

4.2.4 Package Weight Distributions

The distribution of package weight had a significant effect on the energy savings possible. Due to the payload capacity limit of the drone, changing the weight distribution from one that reflects average consumer parcels to one that reflects all packages shipped across the U.S. drastically reduced the energy savings possible in a majority of test sets (Figure 17). In all but one case, the package weight distribution reflective of all CFS packages (U.S. Census Bureau, 2015a) resulted in lower energy savings. This is due to both the increased energy requirement as a result of heavier packages and the reduction in the proportion of drone eligible packages.

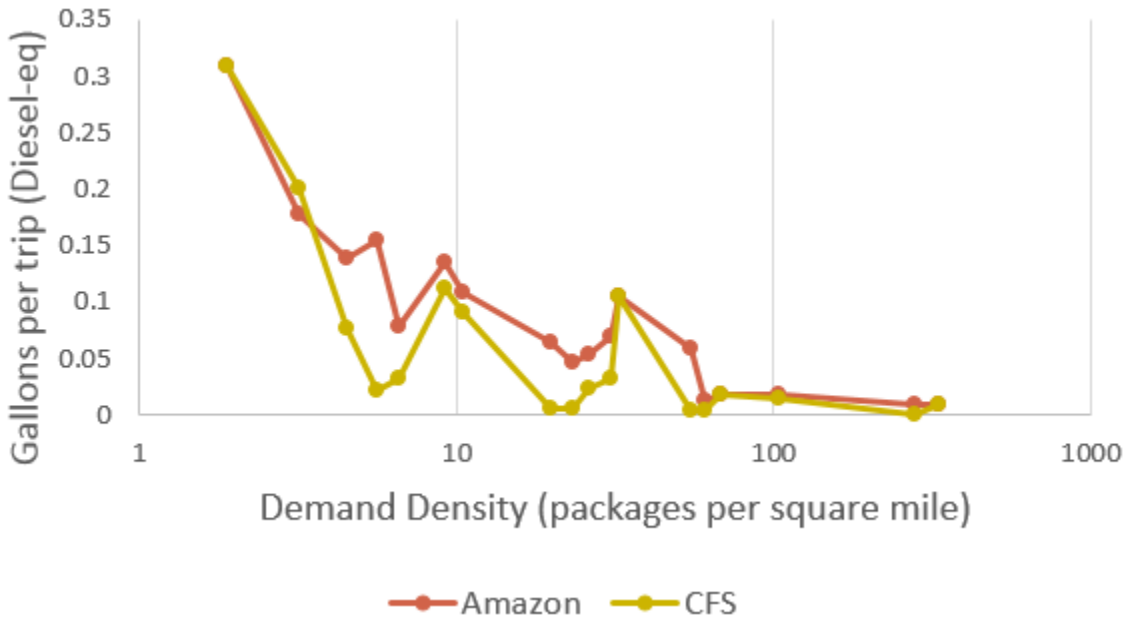

Figure 17. Comparison of energy savings between the CFS package weight distribution and the derived Amazon package weight distribution

4.2.5 Emissions Reduction

Analyzing the resulting emission reductions provides another reason to implement drones in demand dense areas. The truck's emissions are estimated using a factor of 996 g CO_2-eq per gallon of diesel (Stolaroff et al., 2018). While estimates for the electricity needed to power the drone can vary widely based on the source, this study used the national average of 568 g CO_2-eq per kWh (Stolaroff et al., 2018). Applying these estimates to the 20 delivery point, single drone scenario from Table 8A yields the emission reduction shown in Figure 18. In areas of demand density higher than 60 packages per square mile, the tandem system causes an increase in CO_2

emissions. However, as demand density decreases, the tandem system provides increasing benefits in emission reduction. In the scenario with the lowest package demand (1.9 packages per square mile), the emissions savings reached 262 g CO_2-eq per trip.

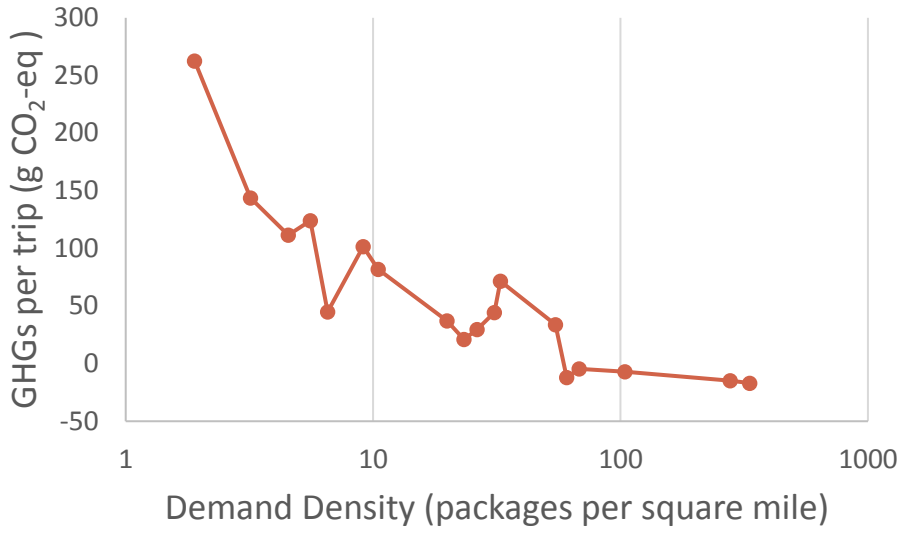

Figure 18. Reduction in emissions resulting from implementing a truck-single-drone system over a truck only system

4.2.6 Sensitivity Analysis of Key Assumptions

Based on the results, the base scenario for the sensitivity analysis was set to conditions favorable to energy savings with the implementation of a truck-drone tandem system. The demand density was set to 1.8 packages per square mile, with 3 drones, and a package weight distribution representative of Amazon packages. The assumptions tested were drone payload capacity, range limit, truck fuel efficiency, and drone energy efficiency. In this study, these parameters were assumed to be 5 lbs., 6.21 miles, 10.2 mpg, and determined by the energy consumption equation (18). To determine which of these assumptions energy consumption is more sensitive to, the base case parameters were varied by plus and minus 25%. The results of this analysis are summarized in Figure 19, with the full data shown in Table 9A.

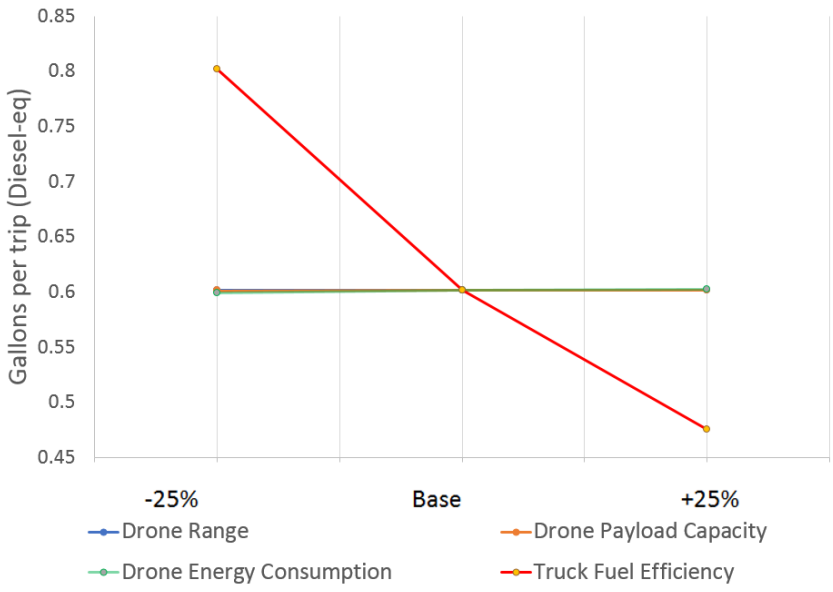

Figure 19. Sensitivity analysis of key assumptions

Drone range was the least sensitive assumption. This was due to the package demand density in the scenario. Neither increasing nor decreasing the drone range by 25% changed the energy savings attained in the base case. With a package demand density of 1.8 ppsm, delivery points were close enough to one another such that the average drone delivery route was about 1 mile. This is significantly lower than the range capability of 6.21 miles, thus changes of only 25% would not impact the optimal route.

Drone payload capacity was the next least sensitive parameter. Increasing the payload capacity to 6.25 lbs. did not impact the energy consumption of the system. This is not surprising as the underlying package weight distribution indicates that 86% of packages are less than 5 lbs. and 87.7% are below 6.25 lbs., meaning this change would only increase the percentage of drone-eligible packages by 1.7%. Decreasing the payload capacity to 3.75 lbs. only decreased the energy savings of the system by 0.044%. This result can be explained through two factors. First, the change in drone eligible packages falling by only 2.2%. Second, the energy consumption of the truck dominates the total system consumption (over 99% in the base case).

Changes to drone energy consumption has small proportional effects on the total system consumption. Increasing the drone energy consumption by 25%, resulted in a 0.15% increase in the total energy consumption of the system. Similarly, decreasing the drone energy consumption by 25% showed a 0.46% decrease in energy consumption of the system. Though changes in the

energy consumption of the drone always translate to corresponding changes in the total system consumption, the resulting change on the total system is nearly two orders of magnitude smaller than the original change in the drone due to the drone's relative energy efficiency as compared to the truck.

Truck fuel efficiency was by far the most impactful change to the total energy consumption of the system. Increasing the fuel efficiency of the truck to 12.75 mpg from 10.2 mpg, decreased the energy saving provided by drones by 21%. Conversely, decreasing the fuel efficiency of the truck to 7.65 mpg, increased the impact of the drones by 33%. As the energy consumption of the truck-drone system is highly sensitive to fuel efficiency of the truck, this is an important parameter to set to the correct value. This in part, helps to explain Lohn's (2017) conclusion about the limited impact of drones on energy savings, as he assumed a fuel efficiency of 15 mpg which is almost 50% better than the efficiency found by Lammert (2009) and used in this study.

CHAPTER 5. CONCLUSION

The next paradigm shift in package delivery may come at the inclusion of drones. Existing research has primarily focused on the drone's capability to reduce delivery time; however, this study focuses on the effect of energy savings. This study is the first to develop a population-based demand distribution and use package weight data to estimate a package weight distribution. Both distributions are key model inputs that give more realistic results and are essential when analyzing a truck-drone delivery system for energy consumption. These inputs further allowed this study to be the first to evaluate the suitability of truck-drone tandem systems for energy savings based on different demand density.

The potential impact of drones on the energy consumption of "last mile" package delivery systems is highly dependent on how and where drones are implemented. To overcome the limitations of payload capacity and range, this study proposes the use of a truck-drone tandem system, which increases the drone's effective range and allows the truck to deliver packages beyond the drone's payload capacity. To leverage the drone's advantages in terms of relative energy efficiency and capability to travel unrestricted to road networks, it is beneficial to implement drones in areas with lower package demand density (below 1 package per square mile). This yields over tenfold the energy savings as compared to areas with high package demand density (above 25 packages per square mile). Further, the energy savings provided by drones can be maximized by using multiple drones in areas where delivery points are clustered together. Finally, drones are best implemented in delivery systems whose package weights are mostly below the payload capacity of the drone. In systems where this is not the case, it will be difficult to estimate the potential energy savings as it will depend on where the drone eligible delivery points lie.

The development of the mFSTSP model with the objective of minimizing energy consumption, as well as the creation of both a package demand and weight distribution, provides a new foundation for future research. While this study sought to minimize the energy consumption of the delivery system, a possible vector for future research could be the consideration of a multi-objective function model. This would allow package delivery companies to place varying emphasis on not only energy consumption but also delivery time and total cost all at once. Such a model could be used to optimize delivery networks based on the individual

needs of each network. For example, networks delivering time sensitive packages could weigh the delivery time more heavily while networks seeking to reduce their carbon footprint could opt to place greater weight on the energy consumption portion of the objective function. The model in this study assumed that the drone batteries could not be recharged and that drones could only make one delivery. This is different from a single drone model that allows the drone to make multiple trips as the model in this study allows drones to depart for their deliveries simultaneously. This capability is especially important in service areas with clustered nodes that are isolated from the rest of the delivery points, as this situation affords the truck-multi-drone system larger marginal energy savings with additional drones. Future models could expand upon this by allowing the drones to swap or recharge their battery while on the truck or at the depot. Furthermore, the drones could be allowed to deliver more than once package at a time. As drone technology improves, leading to higher payload capacities and longer range, delivering multiple packages may lead to greater impacts. Another possible way to increase the drone's impact on the delivery system is to allow for the retrieval of packages from customer nodes. This small change could greatly increase the value of the drone at a marginally small energy cost. However, possible barriers include time coordination and safety concerns. Package retrieval would necessitate a customer being present at the time of retrieval, which presents a challenge in the already demanding underlying TSP. Furthermore, customers interacting with the drone present a safety hazard for both the customer and drone. This issue may be mitigated through future drone implementation and advances in drone design. Technological improvements may also necessitate models that allow for the use of multiple types of drones in the same system, thereby assigning the most appropriate type of drone to each package based on its weight and delivery location. This study does not consider the adverse weather effects on flying conditions. Additional research may be conducted to incorporate such effects by adding time windows to the drone routes during poor weather conditions. Such research is especially needed for insight on potential benefits in areas where whether is frequently detrimental to flying conditions. Another flight limitation not considered are restricted flying areas, which have been researched in the truck-single-drone configuration (Jeong, 2018).

While numerous avenues for future research exist, the contributions of this study will prove helpful in identifying which are more promising and how they may be optimized. The importance of package demand density and package weight established in this work, will help

future models more accurately depict delivery systems. Operationally, insights gathered on the conditions that facilitate energy savings can help inform decision makers on whether and how drones should be implemented in existing delivery systems.

APPENDIX

Table 6A. Energy savings of a truck-single-drone system on 10 delivery point problems

		Energy (gallons diesel-eq)				
Test Set	**Demand Density**	**Truck only**	**Truck-Drone**	**Truck**	**Drone**	**Savings**
1	478.42	0.0248	0.0222	0.0220	0.0002	0.0026
2	328.38	0.0290	0.0233	0.0232	0.0001	0.0057
3	135.62	0.0588	0.0470	0.0469	0.0002	0.0118
4	48.49	0.1064	0.0840	0.0838	0.0002	0.0224
5	41.92	0.1088	0.0850	0.0849	0.0002	0.0238
6	28.47	0.1273	0.1008	0.1005	0.0003	0.0265
7	15.94	0.2083	0.1621	0.1619	0.0002	0.0462
8	13.70	0.2092	0.1546	0.1543	0.0003	0.0546
9	9.73	0.2154	0.1774	0.1772	0.0002	0.0380
10	8.27	0.3148	0.2274	0.2271	0.0003	0.0874
11	5.33	0.3631	0.2856	0.2853	0.0003	0.0775
12	2.75	0.7161	0.6089	0.6085	0.0005	0.1072
13	2.54	0.6834	0.5209	0.5206	0.0003	0.1625
14	1.00	0.9247	0.6075	0.6069	0.0006	0.3172
15	0.59	1.4827	1.1756	1.1748	0.0008	0.3071
16	0.40	1.3024	1.0633	1.0622	0.0011	0.2391
17	0.27	1.6519	1.4115	1.4109	0.0006	0.2404
18	0.16	1.9091	1.5694	1.5678	0.0016	0.3397
19	0.09	2.6570	2.3817	2.3805	0.0012	0.2753
20	0.03	4.3302	4.0564	4.0537	0.0027	0.2738

Table 7A. Energy savings of a truck-singe-drone system on 10,15, and 20 delivery point problems

Delivery Points	Test Set	Demand Density	Energy (gallons diesel-eq)			
			Truck	Truck-Drone	Drone	Savings
10	1	0.40	1.6525	1.1267	0.0029	0.5258
	2	0.45	1.5448	1.4226	0.0032	0.1222
	3	0.40	1.3003	1.0644	0.0022	0.2359
	4	1.11	0.9886	0.8846	0.0015	0.1040
	5	1.11	0.9154	0.8300	0.0011	0.0854
	6	1.09	1.0499	0.8935	0.0020	0.1564
	7	3.38	0.5672	0.5149	0.0009	0.0523
	8	3.33	0.4977	0.3756	0.0011	0.1221
	9	3.28	0.6184	0.4675	0.0011	0.1509
	10	9.73	0.2181	0.1781	0.0009	0.0400
	11	10.07	0.3068	0.2368	0.0009	0.0700
	12	10.28	0.3211	0.2650	0.0012	0.0561
	13	25.48	0.2080	0.1435	0.0008	0.0645
	14	27.18	0.1783	0.1379	0.0009	0.0404
	15	25.99	0.1824	0.1649	0.0009	0.0175
	16	48.49	0.1064	0.0846	0.0008	0.0218
	17	45.24	0.0967	0.0951	0.0009	0.0016
	18	41.92	0.1091	0.0857	0.0009	0.0234
	19	98.80	0.0739	0.0356	0.0008	0.0383
	20	94.64	0.0562	0.0409	0.0008	0.0153
	21	88.64	0.0714	0.0494	0.0008	0.0220
20	1	0.53	2.1057	1.9189	0.0014	0.1868
	2	0.52	1.9538	1.4886	0.0012	0.4652
	3	0.61	1.4152	1.2624	0.0016	0.1528
	4	1.40	1.2848	1.1122	0.0013	0.1726
	5	1.50	1.3190	1.1746	0.0013	0.1444
	6	1.44	1.2673	1.1043	0.0011	0.1630
	7	3.07	0.7316	0.6234	0.0012	0.1082
	8	2.97	0.9587	0.8786	0.0010	0.0801
	9	3.16	0.8405	0.7745	0.0010	0.0660
	10	10.60	0.4698	0.4141	0.0010	0.0557
	11	9.26	0.3601	0.3136	0.0009	0.0465
	12	9.80	0.3749	0.2980	0.0009	0.0769
	13	24.51	0.2690	0.1792	0.0008	0.0898
	14	26.64	0.2475	0.1577	0.0008	0.0898
	15	25.61	0.2734	0.1835	0.0009	0.0899
	16	45.18	0.1539	0.1378	0.0009	0.0161

	17	44.89	0.2530	0.1695	0.0008	0.0835
	18	47.35	0.1996	0.1408	0.0009	0.0588
	19	104.16	0.1149	0.1104	0.0008	0.0045
	20	108.79	0.1277	0.1027	0.0008	0.0250
	21	102.88	0.1136	0.1001	0.0008	0.0135
30	1	0.70	2.5195	2.3188	0.0028	0.2007
	2	0.70	2.1523	1.8269	0.0025	0.3254
	3	0.69	2.4095	2.1914	0.0019	0.2181
	4	1.55	1.1325	0.9865	0.0013	0.1460
	5	1.50	1.6079	1.4765	0.0015	0.1314
	6	1.54	1.5546	1.4446	0.0012	0.1100
	7	3.20	1.2314	1.0586	0.0013	0.1728
	8	3.21	1.1135	1.0195	0.0015	0.0940
	9	3.44	1.1081	1.0208	0.0011	0.0873
	10	10.47	0.5616	0.4434	0.0009	0.1182
	11	10.61	0.5340	0.4546	0.0010	0.0794
	12	10.30	0.4875	0.4381	0.0009	0.0494
	13	23.27	0.3000	0.2597	0.0009	0.0403
	14	25.63	0.4296	0.3028	0.0009	0.1268
	15	26.26	0.4251	0.3227	0.0009	0.1024
	16	50.85	0.2715	0.1650	0.0012	0.1065
	17	50.93	0.1792	0.1594	0.0012	0.0198
	18	51.60	0.2230	0.2014	0.0001	0.0216
	19	109.77	0.1530	0.1504	0.0013	0.0026
	20	112.51	0.1628	0.1535	0.0008	0.0093
	21	104.14	0.1550	0.1395	0.0009	0.0155

Table 8A. Energy savings of multi-drone systems on 20 delivery point problems

Test Set	Demand Density	Energy (gallons diesel-eq)				
			Marginal Savings			
		Truck Only Consumption	1st	2nd	3rd	Total Savings
1	332.38	0.0635	0.0094	0.0020	0.0002	0.0116
2	277.71	0.0902	0.0089	0.0063	0.0104	0.0256
3	104.14	0.1550	0.0175	0.0088	0.0168	0.0431
4	68.10	0.1465	0.0186	0.0129	0.0058	0.0373
5	60.58	0.1586	0.0122	0.0060	0.0037	0.0219
6	54.52	0.2133	0.0587	0.0048	0.0005	0.0640
7	32.68	0.2925	0.1043	0.0363	0.0136	0.1542
8	30.87	0.2659	0.0702	0.0266	0.0040	0.1008
9	26.28	0.3227	0.0545	0.0244	0.0309	0.1098
10	23.27	0.3000	0.0465	0.0188	0.0235	0.0888
11	19.89	0.4560	0.0639	0.0455	0.0624	0.1718
12	10.47	0.5742	0.1089	0.0852	0.0469	0.2410
13	9.13	0.6887	0.1345	0.0751	0.0239	0.2335
14	6.54	0.6359	0.0777	0.0503	0.0094	0.1374
15	5.58	0.7184	0.1545	0.0440	0.0015	0.2000
16	4.54	1.0369	0.1392	0.1579	0.0530	0.3501
17	3.20	1.2830	0.1771	0.0879	0.1207	0.3857
18	1.90	1.3646	0.3098	0.1561	0.1504	0.6163

Table 9A. Sensitivity analysis of key assumptions

Drone Range (miles)	**Energy Savings (gallons Diesel-eq)**	**Drone Payload Capacity (lbs.)**	**Energy Savings (gallons Diesel-eq)**
4.6575	0.6020	3.75	0.6018
6.21	0.6020	5	0.6020
7.7625	0.6020	6.25	0.6020
Drone Energy Consumption	**Energy Savings (gallons Diesel-eq)**	**Truck Fuel Efficiency (mpg)**	**Energy Savings (gallons Diesel-eq)**
-25%	0.5992	7.65	0.8020
Base	0.6020	10.2	0.6020
+25%	0.6029	12.75	0.4757

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