Drone-Truck Fleet Allocation Policies for Courier Deliveries

An Evaluation of Distance and Energy Tradeoffs

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Abstract. This research analyzes distance traveled and energy consumption tradeoffs when electric drones and trucks are utilized for courier delivery services. The research analysis different the impact of different drone-truck fleet allocation policies. The policies analyzed include a) drone fleet determined by profit maximization, b) only truck or only drone service fleets, c) different fleet mix for drones and trucks, and d) a distance-based allocation policy. Results indicate that a relatively simple and intuitive distance-based allocation policy is best in terms of distance driven, energy consumption levels.

Keywords: Drone, Trucks, Courier Service, Allocation Policies, Distance traveled, Energy

1 Introduction

In the last decade e-commerce has grown rapidly from a 6% of USA retail sales in 2014 to 17% of USA retail sales in 2023 (USCB, 2024). The booming e-commerce market is a major driving force behind the increasing use of both traditional courier services and emerging drone delivery solutions. E-commerce growth translates to a significant rise in the number of packages needing delivery. In addition, customers today expect faster deliveries, putting pressure on e-commerce businesses to fulfill orders quickly. Courier services, with their established infrastructure and networks, can ensure timely deliveries, meeting customer expectations and staying competitive.

Regarding drone energy consumption and emissions, there are several studies that have indicated that drones are more sustainable in rural settings than conventional trucks (Figliozzi, 2017; Goodchild and Toy, 2018), but this finding is a function of ground vehicle type and distance to the destination (Figliozzi, 2020). The energy, emissions and distance tradeoffs between driving to a store and store delivery heavily depend on the type of vehicle utilized (Figliozzi, 2020). Other studies have analyzed drone energy consumption models (Zhang et al., 2021). Consumer preferences and the impacts of drones and cargo bikes have been analyzed utilizing surveys and models in

existing urban areas (Serrano-Hernandez et al., 2021). Finally, the size of the drone and its capacity has a direct impact on drone energy consumption (Figliozzi, 2023).

Unlike previous research efforts this research studies the impact of drone and truck fleet size and utilization on sustainability goals, more specifically on distance traveled and energy consumption. Energy consumption is utilized as a sustainability metric because electric drones and ground vehicles are assumed, therefore the amount of carbon emissions is simply proportional the amount of electric energy consumed.

This paper is organized as follows: the problem and case study parameters are presented in the next section. Sections 3 to 6 present the results of four different fleet allocation policies: a) drone fleet determined by profit maximization, b) only truck or only drone service fleets, c) different fleet mix for drones and trucks, and d) a distance-based allocation policy. The paper ends with conclusions in Section 7.

2 Problem and Case Study Description

This research leverages the formulation and optimal solution approach to the drone fleet sizing problem with stochastic demand in terms of deliveries per period and delivery weight (Hadas and Figliozzi, 2024).

2.1 Drone delivery assumptions

The baseline scenario assumes a one-hour period, with two trips per hour per drone and assuming a drone life of 1000 trips and 8 trips per staff with a labor cost of $40 per hour. The following additional parameters were selected for the case study: revenue per delivery is $50, the cost of an unmet delivery is $20, the cost of a drone trip is $5 and the fix cost per kilogram of payload is $2 and the variable cost is $0.1 per kilogram-trip.

The revenue per delivery is based on rush courier delivery rates (Breakaway, 2021) after considering the service area of the drone. For the drone costs, two key assumptions are labor costs per trip and the useful life of the aircraft (Figliozzi, 2018). It is important to note that the profit for a drone delivery assumes a premium due to fast and reliable delivery and the cost of unmet demand is related to using a ground service to cover the demand. Ground services are more expensive because a driver or delivery person is required whereas the drone is unmanned. It is assumed that a high-performance multicopter that can carry up to 11 kg of payload with an effective range of 10 km could be used and for service times, it is assumed that an average drone delivery requires 30 minutes. The demand and weight distributions are assumed to follow Beta distributions and all the details of the optimal solution, using 75 drones, are provided in (Hadas and Figliozzi, 2024). It is important to note that results depend both on drone fleet size and drone capacity. The latter is important because unlike ground vehicles, payload is an important constraint the reduces drone range and impacts its costs. This research assumes a constant (optimal) drone size.

The energy consumption rate for drones take into account payload and distance travelled as discussed in a review of previous studies (Zhang et al., 2021), where it is possible to observe a range of drones energy consumption with a payload between zero and 2.5 kg (see Figure 3 in Zhang et al. (2021)). We adopt a drone average energy consumption of 100 kJ/km.

2.2 Ground vehicle delivery assumptions

It is assumed that the service that is not provided by drones it is going to be provided by an alternative ground delivery service. This is reasonable for courier deliveries where customers are willing to pay extra for a fast and speedy delivery (Gulc, 2017). Therefore, drones provide new courier services that were previously covered only by ground vehicles and now both options are available. For example, during the COVID-19 pandemic the need to delivery medicines and food has greatly expanded and the food courier delivery problem is gaining attention (Steever et al., 2019). In addition, there is a move towards 1-hour or faster delivery business (Repko, 2021). In both cases, the problem is characterized by short delivery times of 1 hour or less. In this case study we assume a delivery time window of 1/2 hour and a ground vehicle average speed of 9.8 mph (15.8 kph) that is ½ of the US EPA urban driving cycle schedule (US EPA, 2015) to take into account delays due to congestion or delays in the ground transportation network and also the performance of small electric delivery vehicles. In the US, under current regulations, drones have to perform circuitous routing to avoid flying over people unless a waiver is granted (FAA, 2021). Favorable conditions and a waiver are assumed for drone flights with a 1.05 circuitousness factor. For ground deliveries a factor equal to 1.21 is assumed because it is reasonable figure for large urban areas like Chicago or Los Angeles (Boeing, 2019).

The ground vehicle is assumed to be an electric delivery vehicle (Alke, 2022) with an energy consumption of 350 kJ/km and with a top operating speed of 44 kph (27.3 mph). All the energy consumption results presented in the figures herein are in MJ (megajoules).

The vehicle routing problem (VRP) that arises when trucks are utilized to supplement drones, i.e. the number of drones is less than 100 that is the maximum number of requests per time period, is solved utilizing the iterative route construction and improvement algorithm for the vehicle routing problem detailed in (Figliozzi, 2011, 2010). The ground delivery problem per period can be considered as a simplified version of the classical vehicle routing problem with time windows where the time window is the period of delivery and ground vehicle capacity is unlimited. The problem can be briefly formulated as follows:

- Sets include:

  $\boldsymbol{V}$: Set of vehicles (indexed by v)
  $\boldsymbol{C}$: Set of customers (indexed by i where the index zero correspond to the depot and the last one too)

- Parameters include:

d_{ij}: Distance between customer i and customer j
q_i: Demand of customer i
T_v: Capacity of vehicle v (unlimited in our scenario)
a_i: Lower bound of the time window for customer i (start of the period)
b_i: Upper bound of the time window for customer i (end of the period)
t_{ij}: Travel time between customer i and customer j
s: Service time at a customer that is negligible when compared to travel times.

Decision Variables:
x_{ijv} : Binary variable equal to 1 if customer i is visited directly after customer j by vehicle v, and 0 otherwise.
u_{iv} : Binary variable equal to 1 if customer i is visited by vehicle v, and 0 otherwise.
t_{iv} : Arrival time of vehicle v at customer i

- The objective function is the minimization of travel distance:

$$\text{Minimize} \sum_{v \in V} \sum_{i \in C} \sum_{j \in C} d_{ij} x_{ijv}$$

- Constraints include:

1. Flow conservation, each customer is visited exactly once by exactly one vehicle and it is also required that subtours are not allowed.

$$\sum_{v \in V} \sum_{j \in C} x_{ijv} = 1 \quad \forall i \in C$$

$$\sum_{i \in C} x_{0iv} = 1 \quad \forall v \in V$$

$$\sum_{i \in C} x_{ihv} - \sum_{j \in C} x_{hjv} = 0 \quad \forall v \in V, \forall h \in C$$

2. Capacity constraint, the total demand of customers visited by a vehicle cannot exceed the vehicle's capacity:

$$\sum_{i \in C} q_i u_{iv} \leq T_v \quad \forall v \in V$$

3. Time window constraints, the arrival time at a customer must be within the period time window and there should be enough time to travel between customers:

$$a_i \leq t_{iv} \leq b_i \quad \forall i \in C$$

$$t_{iv} + t_{ij} x_{ijv} \leq t_{jv} \quad \forall i, j \in C, \forall v \in V$$

4. Non-negativity constraints, all decision variables must be non-negative:

$$x_{ijv} \geq 0 \qquad \forall i, j \in C, v \in V$$

$$u_{iv} \geq 0 \qquad \forall i \in C, v \in V$$

$$t_{iv} \geq 0 \qquad \forall i \in C, v \in V$$

Simulation is utilized in this research to evaluate sustainability tradeoffs between drones and ground vehicle fleets of different sizes. Because electric engines are assumed in for both drones and ground vehicles, changes in energy consumption are directly related to emissions changes without having to add the many variables that may affect supply chain emissions and different type of energy sources (Piecyk and McKinnon, 2010; Shrestha et al., 2009). For the sake of simplicity and to better understand the tradeoffs between vehicle types, the settings include an idealized circular service of radius equal to 10 kilometers with uniform spatial demand. The number of customer requests and payload per period follow Beta distributions.

3 Results with optimal drone fleet size

In this section it is assume that the courier company utilizes the number of drones N that maximizes profits, i.e. N= 75. To understand the energy tradeoffs, it is useful to start observing a scatterplot of energy per delivery and number of requests (see Fig. 1 left). Because N = 75 different colors have been assigned to the ranges 0-25, 25-50, 50-75, and 75-100. Two trends stand out: (a) there is a steady increase in energy consumption per delivery when the demand is higher than 75 and (b) there is an increase in variability at both extreme ranges. These trends are readily confirmed by the boxplots by range shown in Fig. 1 right.

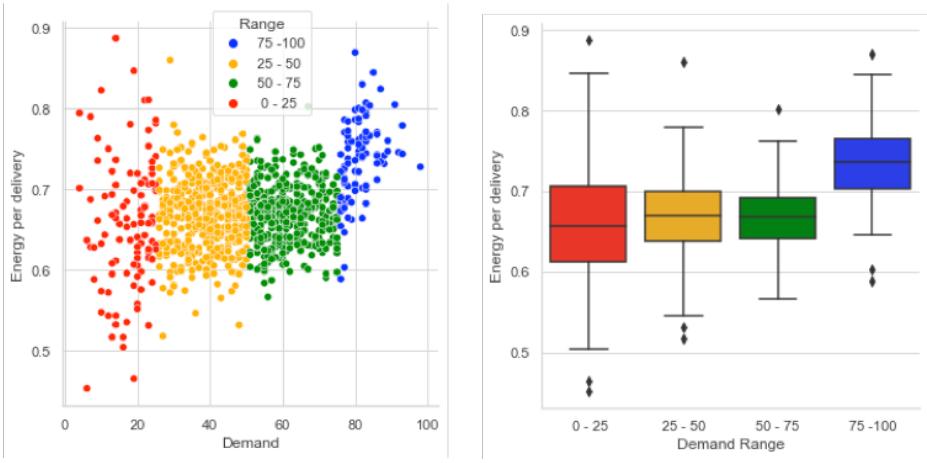


Fig. 1. Energy consumptions per delivery [MJ] as function of demand with N = 75

When demand is lower than 25 only drones are utilized and the increase in variability is likely related to the smaller sample size. For example, assuming a demand distribution that follows $fd(x) \sim Beta(\alpha = 3, \beta = 3, l = 0, u = 100)$, a histogram for 1000 random samples is shown in Fig. 2. For samples that fall in the 0-25 range there are less customers per sample and therefore the weight of a customer too far or near to the depot increases, therefore the overall variability increases as the demand size decreases. When demand is greater than 75 only ground vehicles are utilized to server the extra demand and the increase in variability is also likely related to the spatial dispersion of customers and the low number of customers per route. However, the trends observed in Fig. 1 do not necessarily prove that drones consume less energy per delivery than ground vehicles. When analyzing the results obtained with different drone fleet sizes a more complex picture emerges.

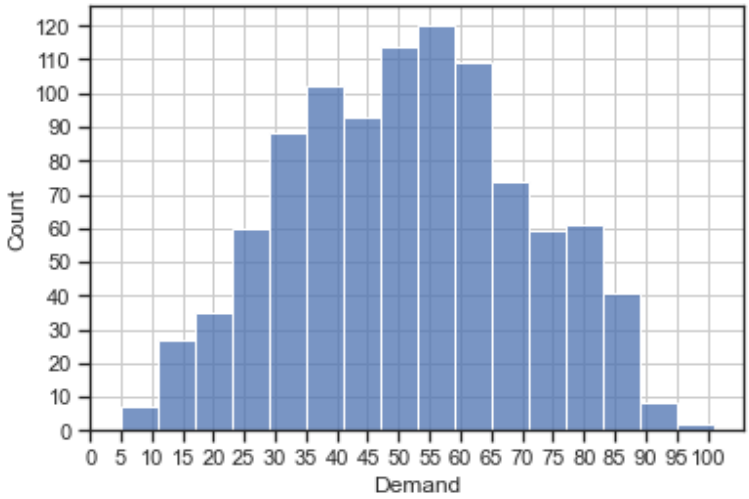


Fig. 2. Demand Histogram

4 Results with varying drone fleet size

Energy consumptions per delivery is a function of drone fleet size as shown in the box plots of Fig. 3.

Two different trends stand out: (a) there is less variability as the drone fleet size increases and (b) there is a decrease in median and mean energy consumption when the drone fleet size is less than 25. Trend (a) can be explained by the reduction in ground vehicle utilization as discussed previously. To understand trend (b) it is necessary to see the results obtained when only drones or ground vehicles are utilized.

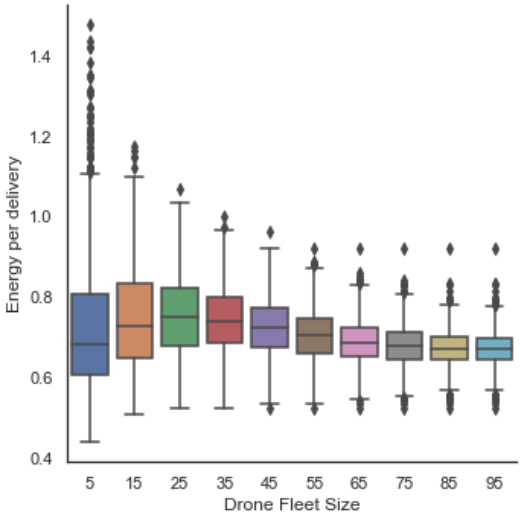


Fig. 3. Distribution of energy per delivery [MJ] as a function of drone fleet size (N)

5 Results utilizing only drones or trucks.

Energy consumption observations when only drones or trucks are utilized can be shown in Fig. 4 as a function of demand size. It is possible to see that drone average energy consumption is rather constant given that the drone can only deliver to one customer per trip, however, there is a somewhat subtle increase in variability when the demand per period approaches zero (as observed previously). In the case of ground vehicles, there is also a decreasing trend since it is possible to take advantage of economies of scale by adding more customers per route when the number of deliveries per period increases. When the demand per period is approximately 40, the mean energy consumption per delivery is similar for both trucks and drones.

It is possible to see in Fig. 5 that energy consumption per delivery decreases as the required truck fleet size increases. Since the objective function of the VRP problem is to minimize travel distance, there is consolidation of customers per routes or vehicles but up to a point, because there is a time window that hinders further consolidation of costumers per vehicle when the customer demand rate is high. There are some results with high energy consumption, for example the point with a 2.36 MJ value and fleet size 3 in Fig. 5 where customers are widely dispersed and cannot be efficiently grouped into routes.

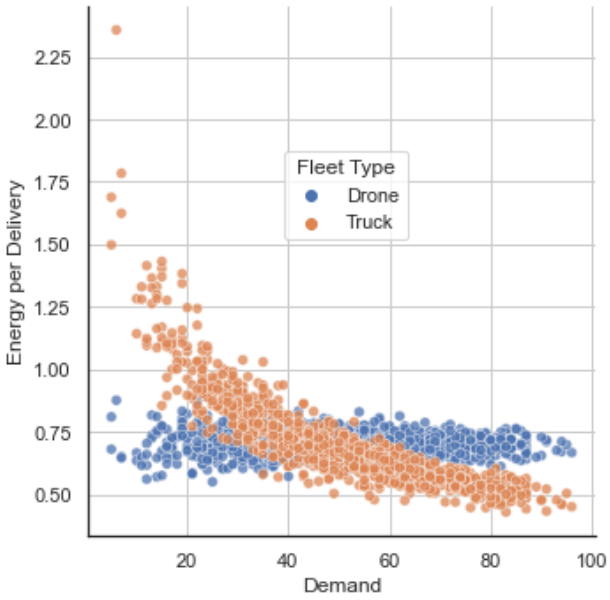


Fig. 4. Comparing Drones and Trucks energy [MJ] per delivery as a function of demand size

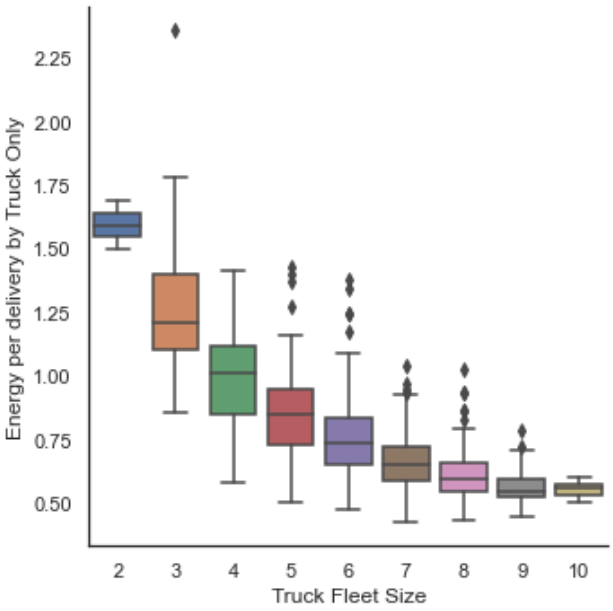


Fig. 5. Truck energy per delivery [MJ] a function of truck fleet size

6 Results with a distance-based allocation policy

The difference performance of drone and ground vehicles as a function of number of deliveries and fleet size shown in Fig. 4 can be leveraged to reduce energy consumption even when the optimal drone size (from a profit perspective) is utilized.

One example of a drone/truck allocation policy that tries to take advantage of each mode energy efficiency is a distance-based allocation policy. Only drones are utilized when the number of requests per period is less than 75 (which is compatible with profit optimization). However, when the number of customers per period is greater than 75, ground vehicles are utilized to serve customers that are closer to the depot because in this case it is easier to consolidate more customers per route.

The results of this distance-based allocation policy are shown in Fig. 6. When compared to Fig. 1 it is possible to see a reduction in both energy consumption median and variability when demand is greater than 75. If the same company is providing drone and ground service, there is also a collateral benefit by reducing ground transportation costs. The potential benefits of coordinating drone-truck deliveries from a central depot had been mentioned in the literature (Figliozzi, 2017; Goodchild and Toy, 2018), but not in the context of stochastic deliveries.

Although there are some clear benefits, in a dynamic stochastic environment the distance-based policy requires a close monitoring of demand conditions and drone utilization. Furthermore, relaxing strict time windows and allowing a slight delay in customer service with the introductions of softer time windows can results in greater energy savings (Hsu et al., 2007).

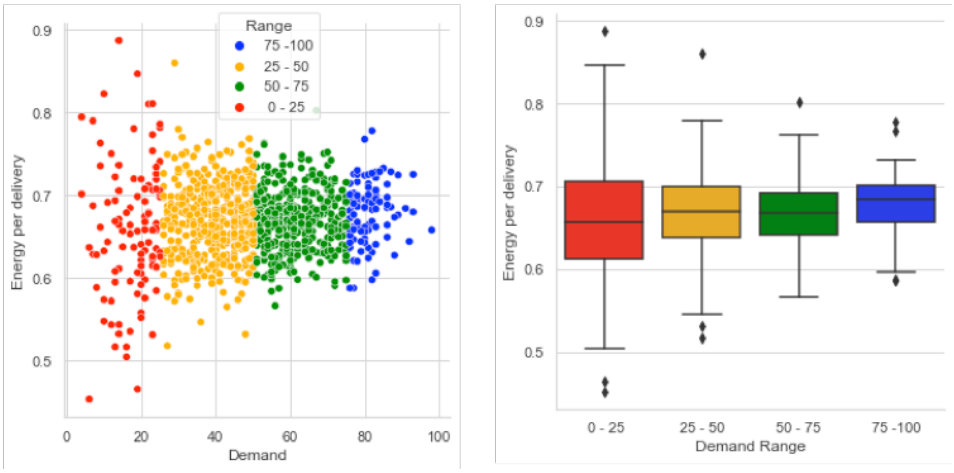


Fig. 6. Energy consumptions per delivery [MJ] with a distance-based policy, $N = 75$ and $V = 2.38$ kg.

7 Conclusions

The last mile delivery is particularly challenging for stochastic deliveries with narrow time windows, drone-truck allocations policies that try to balance profit and sustainability are necessary to reduce costs and emissions.

The results of the simulation study indicate that profit maximization and energy minimization goals are not necessarily compatible. In some cases, it may be possible to achieve both goals simultaneously, but in general it is more sustainable to utilize drones only when demand density is low and/or ground vehicle energy consumption variability is high because costumers cannot be efficiently consolidated. This research also shows that it is possible to utilize profit maximizing drone fleet sizes and reduce also ground vehicle energy consumption by adopting relatively simple allocation policies based on depot-customer distance during high demand periods.

Having a fleet of drones and a fleet of trucks is also a more resilient approach since drones may not be able to operate effectively with adverse weather conditions and similarly ground vehicles may be hindered sometimes by congestion or ground network disruptions (Glick et al., 2022). However, having two different vehicle types is also likely to increase costs not only in terms of labor but also in terms of facilities and capital costs, and modeling these costs and tradeoffs requires a major research effort.

Further research is necessary to study the impact of vehicle type and energy source. There is a wide range of energy consumption rates by ground vehicle type (from e-bikes and motorcycles to small trucks) and a wide range of emissions per kWh of electric energy generated (from clean energy obtained from renewable sources to dirty electricity generated by burning coal). For drones, payload capacity is a key factor because unlike ground vehicles, payload is an important constraint the reduces drone range and impacts its costs. This research assumed a constant (optimal) drone size. Future research efforts could also consider the impact of drone size on costs and sustainability metrics.

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