

# Solutions to the Generalized UAV Delivery Routing Problem for Last-Mile Delivery with Societal Constraints

by

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## Abstract

Unmanned aerial vehicles (UAVs) are becoming an increasingly popular transportation modality to improve efficiency, cut costs and increase customer service levels amongst last-mile industry players and academics alike. UAV operations planning is uniquely challenging because of UAV capacity and range constraints, the host of aeronautic regulation UAVs are subject to, and the significant externalities it imparts on the communities that they operate amongst that could materialize into additional operational restrictions. Previous research contributions have focused on the vehicle routing, environmental life-cycle analysis, economics and policy implications of unmanned aerial vehicles for last-mile delivery (UAV-LMD), typically in isolation.

This thesis complements previous efforts by adopting an inter-disciplinary perspective of anticipated UAV-LMD operations. It first performs a survey of the most significant societal and regulatory barriers facing UAV-LMD today and in the coming decades and offers insight into potential regulatory pathways to constrain operations. Second, it extends existing UAV routing methodologies to capture these constraints and UAV-specific routing features in three competing routing models, offering a comparative analysis of their performance and identifying performance advantages of a heuristics-based routing approach. Finally, this thesis performs a sensitivity analysis of societal and regulatory constraint intensity, technology progression and demand density on realistic demand instances. It finds that, independent of demand density, societal and regulatory constraint intensity as well as UAV technology progression levels drive UAV-LMD operational costs with the potential to render it uncompetitive compared to traditional fulfillment modalities.

Thesis Supervisor: Matthias Winckenbach  
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# Acronyms

<b>AGL</b>	above ground level
<b>AR</b>	augmented reality
<b>ATC</b>	air traffic control
<b>BVLOS</b>	beyond visual line of sight
<b>CAAC</b>	Civil Aviation Administration of China
<b>CAGR</b>	compound annual growth rate
<b>CAPEX</b>	capital expenditures
<b>CPG</b>	consumer packaged good
<b>CS</b>	control station
<b>DC</b>	distribution center
<b>DDP</b>	drone delivery problem
<b>DEP</b>	distributed electric propulsion
<b>EA</b>	Exact Approach
<b>ECDF</b>	empirical cumulative distribution function
<b>ETSA</b>	Exact Two-Staged Approach
<b>ETSA-1</b>	Exact Two-Staged Approach Stage-1
<b>ETSA-2</b>	Exact Two-Staged Approach Stage-2
<b>EU</b>	European Union
<b>EVLOS</b>	extended visual line of sight
<b>FAA</b>	Federal Aviation Administration
<b>FAR</b>	Federal Aviation Regulations
<b>GDPR</b>	General Data Protection Regulation
<b>GPS</b>	Global Positioning System
<b>GURP</b>	generalized unmanned aerial vehicle routing problem
<b>HA</b>	Heuristic Approach
<b>IFR</b>	Instrument Flight Rules
<b>IMSAFE</b>	illness, medication, stress, alcohol, fatigue, emotion
<b>KPI</b>	key performance indicator
<b>LAANC</b>	Low Altitude Authorization and Notification Capability
<b>MILP</b>	mixed-integer linear program
<b>MSL</b>	mean sea level
<b>MTOW</b>	max take-off weight
<b>NAS</b>	The National Airspace System
<b>OEM</b>	original equipment manufacturer
<b>PAVE</b>	personal/pilot, aircraft, environment, and external pressures
<b>R&amp;D</b>	research & development
<b>SMS</b>	short message service

<b>STEM</b>	science, technology, engineering, and mathematics
<b>TFR</b>	Temporary Flight Restriction
<b>TW</b>	time window
<b>U.S.</b>	United States
<b>UAS</b>	unmanned aerial system
<b>UAV</b>	unmanned aerial vehicle
<b>UAV-LMD</b>	unmanned aerial vehicles for last-mile delivery
<b>UK</b>	United Kingdom
<b>UPS</b>	United Parcel Service
<b>URP</b>	unmanned aerial vehicle routing problem
<b>USPS</b>	United States Postal Service
<b>UTM</b>	unmanned aircraft system traffic management
<b>VC</b>	venture capital
<b>VFR</b>	Visual Flight Rules
<b>VLOS</b>	visual line of sight
<b>VRP</b>	vehicle routing problem
<b>VRPD</b>	vehicle routing problem with drones
<b>VTOL</b>	vertical take-off and landing

# Chapter 1

## Introduction

### 1.1 Motivation

Over the past decade, the logistics industry has experienced substantial growth and its fair share of technological disruption. Particularly in suburban and urban settings, consumer demand for same-day or two-hour delivery has ballooned and companies have struggled to meet demand without incurring substantial last-mile delivery costs. The last-mile is defined as the last few stages of a parcel's delivery chain process which typically happens in the congested neighborhoods of today's mega-cities. Whilst shifting consumer expectations have played a pivotal role, a symbiosis of trends has driven immense growth in last-mile delivery operations: intensifying urbanization, increased purchasing power of the global middle class, the rise of new digital retail business models, the shift from commercial to private parcel consumer demand, and advancements in delivery vehicle and routing technologies (Joerss et al., 2016a). In the United States (U.S.), e-commerce players continue to grab market share with online sales' outpacing offline sales' growth with compound annual growth rates (CAGRs) of 16% and 4% from 2012 - 2021 respectively (see Figure 1-1) (Young, 2021).

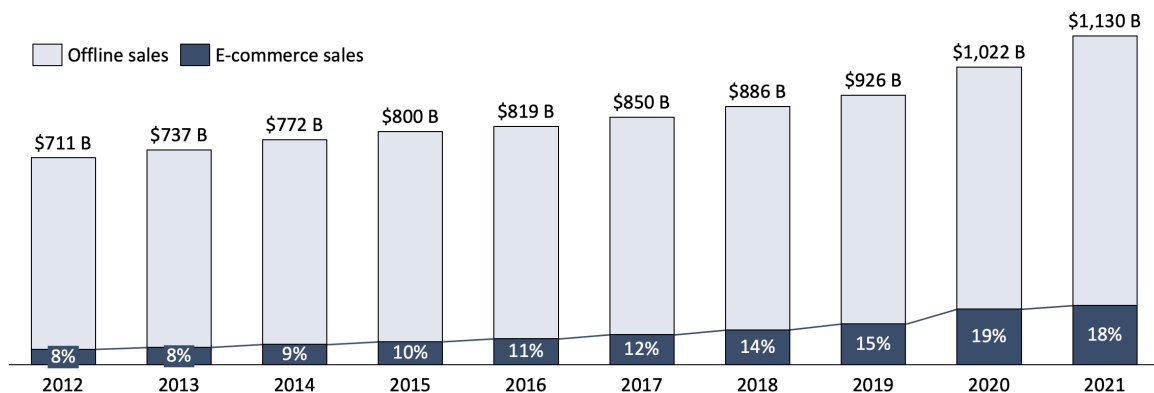


Figure 1-1: U.S. online versus offline sales as a percentage total of retail spend in \$B, 2012-2021.

The global cost of parcel delivery, excluding pickup, line-haul and sorting costs, currently amounts to approximately \$80B annually with China, Germany and the U.S. representing 40% of this demand. Not only is the last-mile market large, it is also growing with recent annual growth rates are between 7-10% for developed countries but almost 300% in developing countries like India (Joeress et al., 2016b).

The last-mile in a delivery chain is vitally important to firms because it constitutes a disproportionately large share of the parcel delivery cost to a customer, particularly in urban areas (Joeress et al., 2016a) (see Figure 1-2 (Jacobs, 2019)). From the perspective of a logistics firm, this problem currently represents an opportunity to differentiate one’s services and products from other logistics specialists but also capture more commercial customers that previously managed their own logistics operations in-house. Amazon, United Parcel Service (UPS), Google and FedEx, among others, are investing heavily in new operational models, technologies, and scientific brain-power to address society’s urban logistics woes.

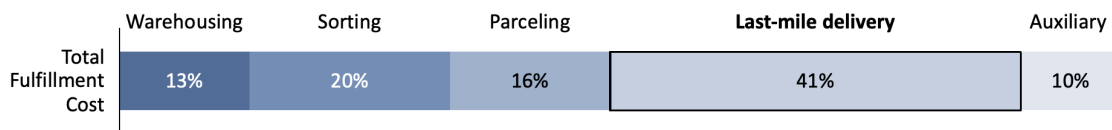


Figure 1-2: Survey of typical U.S. last-mile cost as a percentage of overall fulfillment cost.

The last-mile is also a significant contributor to the broader negative sustainability externalities associated with urban logistics, be it economic, social or environmental (Deloison et al., 2020). In today’s mega-cities, the face of urban last-mile logistics has changed. In half a century, an industry that used to be an peripheral part of daily life has morphed into one patent to every urban consumer. But whilst the last-mile problem is a global one, much of the early investment is being allocated to projects in the U.S. With this in mind, this thesis will focus solely on the state of the last-mile in the U.S., with a handful of allusions to international enterprise.

Due to these key factors, significant market demand exists for new approaches to last-mile delivery that ameliorate the imparted negative externalities and meet increasingly demanding customer service level expectations. Last-mile players are looking to integrate a host of small solutions to achieve the larger objective of efficient urban logistics. Aggregated demand solutions such as parcel lockers and public drop-off points are already being deployed – an ironic reflection of the “traditional” logistics operational models prior to the e-commerce boom. Multi-echelon delivery solutions are also becoming more common in today’s mega-cities as large parcel trucks becoming increasingly ill-suited to navigate today’s dense suburban and urban spaces be it because of congestion, urban built density or unfavorable regulation. But one technology that has received substantial public attention in the past decade for



last-mile delivery is the unmanned aerial vehicle (UAV), colloquially referred to as a drone. UAVs not only have the potential to revolutionize the last-mile industry, but the estimated market size is immense, calculated to exceed \$127B globally (Deloison et al., 2020). UAVs are unique in three ways: low per-vehicle capital expenditures (CAPEX) costs, autonomous delivery capabilities and the ability to rapidly travel point-to-point. These three qualities contribute to the growing popularity of UAVs in the last-mile space.

The key challenges that face the mainstream deployment of unmanned aerial vehicles for last-mile delivery (UAV-LMD) are regulation, technological advances to increase their flight range and enable a smoother integration of UAVs into the existing airspace safety frameworks, and social adoption and acceptance. Since its inception, however, UAV-LMD players, from incumbent last-mile companies to various hardware-, software- and/or operations-focused startups have approached the problem in notably different ways (see Table 2.1). But regardless of their differences – their engineering (UAV designs, level of automation, UAV power-plant decisions) to their operations strategy to their target market segment – players will need to contend with the same reality and its host of real-world constraints. This thesis sits at this nexus: it formulates hypotheses on the real-world constraints facing UAV-LMD and takes a systems-level approach to studying their implications for the viability of commercial operations.

## 1.2 Methodological Gap

In today’s technological world, the rate at which technologies emerge, diffuse into society and die out is accelerating, bringing new opportunities to suppliers and new products to consumers. But whilst this immense level of technological innovation globally promises to improve personal and commercial utility, it is not without its challenges particularly for the entrepreneurs, engineers, business strategists, regulators and operators responsible for that technology’s integration into society.

Even with the growing emphasis on science, technology, engineering, and mathematics (STEM) educations worldwide and the pools of venture capital (VC) funding available to tech-savvy entrepreneurs, many promising technologies fail. But today, these technologies are less black-box devices that can be inserted to solve a static problem in a siloed context but rather a complex tool or extension of our human body or society. Why is this the case? One part of the answer is that humanity has already solved many of the uni-directional, uni-disciplinary problems with the technology currently available to us; the problems of today are highly inter-disciplinary, often embedded into multi-dimensional systems. Take the Google Glass for example. Whilst technologically feasible, the emergent value of the problem it solved (initially to capture photos and videos more spontaneously but positioned to evolve and serve as a tool for users to interact with the world via augmented reality (AR) experiences) did not outweigh the social disconcertment it imparted on its user and others.

This touches upon the idea that the boundaries between technology and society are blurring and that the conceptual design and operationalization of modern-day technologies must reflect that. It also offers us insight into the increasingly important technology policy questions surrounding UAV-LMD that this thesis serves to touch upon the questions:

- Do we understand the technology, its integration into its supporting systems and the role that it plays?
- Is it solving a problem with society’s systemic interests and values in mind?
- Do we understand the direct and indirect effects of integrating this technology in society?
- Is any analysis to understand the effects grounded in frameworks that are consistent with personal liberty, economic development, commercial opportunity and national interest?

These high-level technology policy questions are what motivate this thesis to explore UAV-LMD with an inter-disciplinary lens. This thesis will delve further into the specific literature gaps that it fills in Chapter 2.

### 1.3 Scope

New aeronautic technologies, such as UAV-LMD or On-Demand-Aviation networks, often face significant implementation challenges due to operational constraints, system integration requirements and emergent negative externalities that were not considered during conceptual design. This thesis seeks to develop a systems approach to evaluate potential integration issues around UAV-LMD and identify crucial, non-technical interface challenges that may not have previously been considered by the industry. This thesis is an assessment of the operational and financial viability of UAV-LMD by various regulatory environments, social externalities, technological limitations and real-world operational constraints across select case-study scenarios in the U.S. With that said, this thesis eschews a number of other dimensions of the UAV-LMD proposition:

- This thesis does not address any of the engineering design considerations or optimization that underpin UAV hardware and/or onboard software decisions.

With their various use-cases and design dimensionalities, UAVs evolved to be inherently modular and flexible. Whether it be the on-board power-plant, the lift-generation mechanism, the on-board system suite or the payload capacity, UAVs are typically designed with a specific use-case in mind. Within UAV-LMD, for example, a geographically dense area would likely suit a quadcopter UAV configuration over a lift+push UAV configuration. Thus, UAV-LMD operators would likely need to perform their operations sizing and UAV aircraft design in parallel. But whilst UAV engineering represents a large part of the

UAV-LMD value chain, this thesis does not delve into a sensitivity analysis of the trade-offs between UAV engineering design decisions and their implications for operations.

- This thesis does not explore the potential environmental benefits of UAV-LMD over more traditional ground-based delivery modes. The majority of UAVs do not have tailpipe emissions and, thus, appear less emissions-intensive than delivery trucks. In reality, actual UAV-LMD emissions are heavily dependent on key operational factors such as the number of packages dropped per mile traversed distance, demand density, UAV configuration and macro power-grid efficiency factors such as input energy commodity type and grid loss factors (Goodchild and Toy, 2018). This thesis avoids this discussion, in part, because this analysis is solely focused on the economic viability of UAV-LMD and, as of writing, few environmental incentives exist that would espouse or detract from UAV-LMD viability. Whilst this may change in the face of new emissions regulation in the coming years, any incentive schemes or taxes are unlikely to impact the methodology or analytical results of this thesis but rather change the cost of the status-quo benchmark that UAV-LMD is compared against.
- This thesis eschews making any specific policy or operational recommendations. This thesis strictly serves as an exploratory exercise into solutions to solve the generalized unmanned aerial vehicle routing problem (GURP) with societal constraints and does not seek to provide specific recommendations for federal or local regulators, operators, or active members of the public.
- This thesis does not delve into how UAV-LMD should be integrated into the broader air traffic control (ATC) systems or how UAV-LMD should navigate constraints set by significant airfields nearby an region of operation.

## 1.4 Research Questions

This thesis is motivated by the literature gap in assessing the feasibility of UAV-LMD. It does this by situating itself at the intersection of vehicle routing-based operations planning and the constraints set by societal and regulatory externalities. This thesis presents methodologies to more explicitly evaluate the externalities UAV-LMD may impart on society and its implications for the financial opportunity available to commercial providers. Thus, the formal research questions this thesis poses are:

1. **Operational Constraints**: What are the key social, regulatory, technological and logistical constraints that would constrain real-world UAV-LMD operations?
2. **Operations Modeling**: How can these novel operational constraints be captured in a generalized vehicle routing optimization model?
3. **Feasibility Analysis**: Given realistic demand data and operational parameters, is UAV-LMD financially profitable for service providers? Which constraints

are key cost drivers? What are the social, operational and financial upshots of UAV-LMD?

Although only tangentially, this thesis’s methodological contribution also extends beyond UAV-LMD. Driven by many of the same technological advances and urban livability shortcomings, many nascent markets within the broader urban unmanned aerial system (UAS) transport industry also represent cases where novel emerging technologies are being integrated into urban societies; not without their own set of opportunities, constraints and challenges. There is significant overlap between this thesis’s study of UAV-LMD feasibility and those being performed for these adjacent domains, mainly in the joint modeling of the policy and operations research dimensions to more closely capture the social, operational and economic realities of such operations. Thus, the frameworks and methods developed in this thesis are likely useful for similar feasibility studies of other urban UAS transport technologies in future research.

## 1.5 Methodology, Thesis Overview and Organization

Discussed later in Chapter 2, the relevant literature on the topic of UAV-LMD typically focuses on one dimension of the UAV-LMD problem – be it the policy, operations, technology, economics or environmental value – but only seldom a number of these dimensions at once. This thesis sets out to explore how the societal and regulatory constraints UAV-LMD will likely be subject to in the coming decades can be married with UAV vehicle routing. The hope is to extract insights into the dependencies and trade-offs between aspects of the UAV-LMD problem that have not yet been definitively explored and offer a foundation for future work on the operationalization of UAV-LMD. The over-arching methodology employed in this thesis is illustrated in Figure 1-3. This methodology is further elucidated in the thesis structure overview and organization below.

**Chapter 1: Introduction.** This chapter broaches the concepts around last-mile delivery as well as defines the high-level summary of the methodological gap this thesis attempts to fill, the thesis scope, the research questions and thesis structure.

**Chapter 2: Background and Literature Review.** The concept of UAV-LMD is a recent development. Chapter 2 offers a deeper dive into the UAV-LMD industry, its historical underpinnings, current market definition, market scope and the key enabling technologies behind UAV-LMD. The objective is to offer the reader context as to the key operational features and technology that underpin UAV-LMD. Chapter 2 then reviews previous attempts to evaluate the various dimensions of the UAV-LMD problem commonly focused on in existing literature in isolation and in unified analyses. It concludes by identifying a suitable literature gap for this thesis to fill.

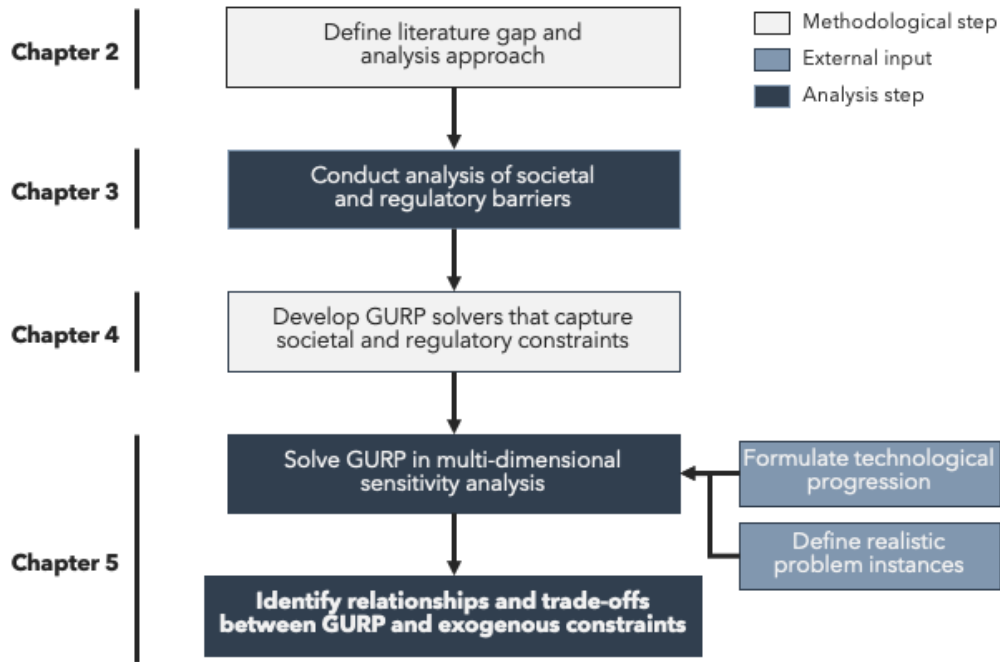


Figure 1-3: Flow block diagram illustrating high-level approach developed in this thesis to holistically explore UAV-LMD operations.

**Chapter 3: Legal and Regulatory Landscape for UAV Last-Mile Operations.** Chapter 3 serves as the bedrock for the analysis of the potential societal and regulatory constraints that may restrict UAV-LMD operations over the coming years. This chapter does so by first analyzing the gamut of current and potential future regulatory constraints. It also ventures into areas of regulatory uncertainty to offer readers insight into regulatory domains that have the potential to impinge on UAV-LMD operations. This analysis is then followed by a similar analysis of the current and future societal considerations of UAV-LMD and how these may constrain operations.

**Chapter 4: The UAV Routing Problem.** Chapter 4 serves to build upon the analyses in Chapters 2 and 3 to formulate models that solve the GURP. The efforts of this chapter seek to uncover the challenges with solving the GURP but also offer a variety of approaches to incorporate such complex features for future work and research. The chapter concludes with a comparative analysis of the various algorithms derived and their suitability to full-scale deployment for UAV-LMD operations.

**Chapter 5: Operations Case Study Analysis.** Chapter 5 brings together Chapters 3 and 4 to offer an example of how holistic operational modeling of the GURP could be performed. The chapter defines a set of realistic scenarios that represent a sensitivity analysis of the UAV-LMD operational cost function to explore its key cost drivers.

**Chapter 6: Conclusion.** Chapter 6 reviews the thesis questions posed in Section 1.4 and provides answers to these questions based on the findings in the subsequent chapters. This chapter concludes with a review of the limitations of the thesis work presented and avenues for future research.

# Chapter 2

## Background and Literature Review

This chapter introduces the notion of unmanned aerial vehicles for last-mile delivery (UAV-LMD) in more detail by describing its relevant, albeit short, history and the role it plays in the existing logistics and, specifically, last-mile industries. Note that this chapter does not provide a comprehensive overview of any the key technological, social, cultural, regulatory or economic drivers behind the emergence of UAV-LMD, for which there are many, but rather primes the reader with relevant academic activity in the space. This chapter performs a review of the literature pertinent to the research questions this thesis poses around UAV-LMD, namely the analyses of its regulatory and non-regulatory implications (see Section 2.2.1) and approaches to model operations (see Section 2.2.2).

### 2.1 Unmanned Aerial Vehicles for Last-Mile Delivery

#### 2.1.1 Historical Underpinnings

The earliest UAV-LMD operation at scale was arguably Zipline’s medical supply network in Rwanda which launched in October of 2016 (Landhuis, 2018). Before 2016, UAV-LMD was first tested by the Swiss Postal Service as early as 2015 in partnership with Matternet, a US-based unmanned aerial vehicle (UAV) logistics start-up (Swiss Post, 2018). But UAV-LMD was an idea first broached by Jeff Bezos, then CEO of Amazon, back in 2013 (Hamilton, 2019). Ever since 2013, UAVs as a delivery fulfillment modality has become increasingly more popular and received wider attention both in academia and industry. Both logistics industry incumbents and new players explored the opportunity of defining the parameters of a new transportation modality, from the aircraft design and configuration to the supporting infrastructure and communication protocols required, to any ancillary services that support the software or hardware fleets of UAVs operating semi-autonomously or autonomously daily. Amazon was faced with legislative barriers domestically in the United States (U.S.) and was impelled to set up a research & development (R&D) center in Cambridge, United Kingdom (UK), where it performed its first successful home delivery

in 2016. Alphabet’s Wing was a close follower, predominantly operating out of test sites at Virginia Tech and in the suburbs of Canberra, Australia. The United States Postal Service (USPS) scrambled to join the race and polled the American public in mid-2016 to evaluate their perception of this novel delivery modality (Singh, 2017).

But the UAV, as a technology, has existed in the civilian domain since as early as the 1990’s, with lightweight quadcopters developed as toys for children in Japan (Darack, 2017). It was not until the mid 2000’s did the necessary technology, discussed further in Section 2.1.2, UAVs become more commonplace in civil society. This was mostly for recreational photo and video capture for both indoor and outdoor flight. This period of recreational use was pivotal in familiarizing populations around the world with the technology to be more likely publicly accepted in the commercial domain. But in line with its research- and military-centric origin, the UAV recently became a technology of national interest, specifically in the U.S.,

“To promote continued technological innovation and to ensure the global leadership of the United States in this emerging industry, the regulatory framework for UAS operations must be sufficiently flexible to keep pace with the advancement of UAS technology” (Trump Administration, 2017).

This initiative helped to dissolve tension between federal regulators and the domestic UAV-LMD industry, encouraging players such as Amazon and Wing to re-shore their experimental operations and prioritize domestic launches for their initial service launches.

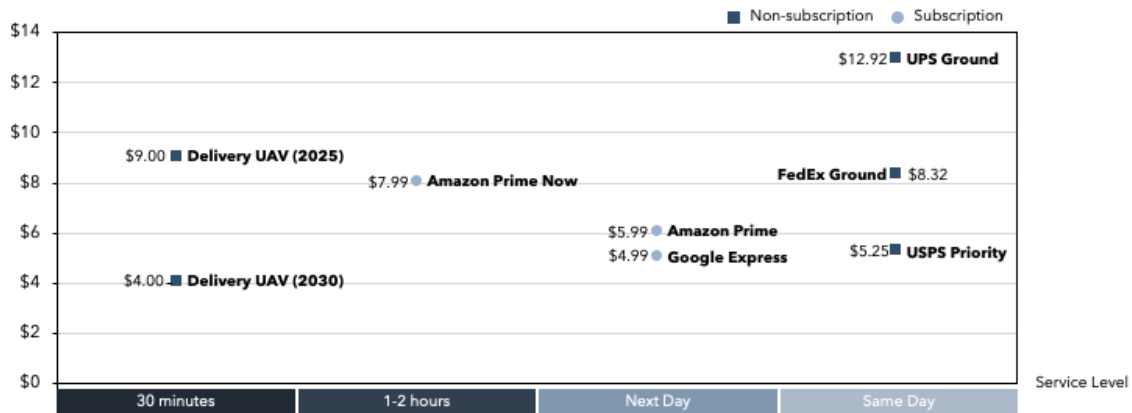


Figure 2-1: UAV-LMD economics – hypothetical UAV fulfillment modality versus alternative current fulfillment competitors for 5 lb. package delivered within 10 mi.

Whilst the original proponents of UAV-LMD such as Amazon or Wing emphasized the immense value of UAV-based fulfillment to consumers, namely shorter delivery times, a more reliable service and lower shipping costs either built onto or into the purchase price of the good, a key driver for UAV-LMD adoption is simply



the economics. Figure 2-1 highlights the advantages that UAVs possess in offering a cheap delivery modality that can meet exceedingly tight order-to-delivery turn-around times (Keeney, 2015; Levitate Capital). This is driven by their lower capital expenditures (CAPEX) requirements, energy requirements and absence of a major labor cost component, especially in the scenario where UAV fleets are autonomously operated.

### 2.1.2 Key Enabling Technologies

Understanding the role UAVs in the last-mile industry can be aided by exploring the key enabling technologies that underpin UAVs emergence and popularity. Such an analysis offers insight into the opportunities that original equipment manufacturers (OEMs) envisaged upon entering the last-mile industry and the pressures the industry exerts on UAV R&D and aircraft design. Whilst technologies can be classified in a variety of ways, this thesis adopts a from-first-principles approach to technology classification that may be relatively uncommon in UAV-relevant literature, see Figure 2-2. With that said, such a classification system is common in the aeronautics and aerospace realms today and will be adopted here to reflect similarly macro-level technology roadmapping best-practices (De Weck, 2022).

Technology Matrix	Matter	Energy	Information	Value	Organisms
Transform/Process		Distributed electric propulsion	Computer-aided aircraft design		
Transport/Distribute	UAV aircraft design and configuration				
Store/House	Lightweight structural materials	Lightweight, energy-dense battery			
Exchange/Trade			Connectivity and GPS		
Control/Regulate	Guidance, navigation and control				

Figure 2-2: Enabling technologies for civilian UAV-LMD classified in 5x5 technology matrix.

**Distributed electric propulsion (DEP)** can be defined as a propulsion system that leverages electric motors distributed around the aircraft and are commonly associated with increases in propulsive efficiency, fuel or energy economy, vehicle handling and enhanced power plant redundancy, and reductions in emissions and noise pollution. Such systems often suit aircraft with steep climb and descent profiles, extreme flight envelopes and those with innovative control mechanisms. Additionally, they can be cheaper to manufacture, assemble and maintain since power plant mis-function is typically easier to diagnosis and per-unit replacement costs are lower.

**Computer-Aided Aircraft Design** This pertains to advancements in computational power and software that has enabled aircraft designers to more closely capture aerodynamic and structural behaviors of aircraft in computer-based simulations prior

to otherwise expensive iterative build-and-test development phases.

**UAV Aircraft Design and Configuration** refers to novel UAV aircraft design configurations that have emerged via pressures from use-cases in the last-mile industry guiding UAV technology development. The earliest UAVs for last-mile delivery were more commonly quadcopters (see Figure 2-3a). The hexacopter and octacopter configurations had also existed to serve specific heavy-lift and short flight-time use-cases such as advanced aerial filming or rescue operations (see Figure 2-3b). The fixed-wing drone spawned out of the need for a more stable, reliable, long distance UAV; a configuration that Zipline championed in all their operations (see Figure 2-3c). But the fixed-wing configuration requires a large infrastructure footprint for take-off and landing and, hence, the lift+push configuration emerged (see Figure 2-3d). Whilst this is not a novel aircraft configuration – early aircraft such as the Lockheed AH-56 Cheyenne were lift+push aircraft since they were modeled as helicopters with a pusher prop at its rear end – they were notoriously hard to design with complex aerodynamic phenomena disrupting stable flight particularly in the transition between vertical flight and forward flight. The lift+push configuration is becoming the more prominent aircraft design in UAV-LMD operations today with Wing being the most advanced urban last-mile UAV-LMD operator which has adopted this technology. Their UAV design offers a competitive balance between range, maneuverability, vertical take-off and landing (VTOL) capabilities and certifiability.

**Lightweight Structural Materials** are essential in aircraft design beyond UAV design because aircraft need both reliable structural integrity under a variety of loading conditions and reliable materials over the course of many take-off and landing cycles. UAVs are predominantly made of thermoplastics and carbon fiber-reinforced composites. Carbon fiber has become progressively cheaper over the past few decades, pushed down by consumer pressure across a variety of high performance industrial products, from sports equipment to the automotive and racing vehicles industry to the medical industry to passenger aircraft. UAVs have benefited from such material innovation in their structural components as well as in their high-performance components such as propellers and sensors.

**Lightweight, Energy-Dense Batteries** form the basis for UAV’s emergence as a viable transportation modality in the last-mile industry. Lightweight, energy-dense lithium-ion batteries have drastically improved energy density per unit mass, robustness across a wide range of environmental conditions and price-point. They also offer flexible form factors and can continue to provide substantial power and energy outputs after repeated charge-discharge cycles. Figure 2-4 captures these improvements along energy-density and price-point dimensions (Roper, 2020).

**Connectivity and Global Positioning System (GPS) location tracking** that is wide-ranging and reliable are essential for enabling extended visual line of sight (EVLOS) or beyond visual line of sight (BVLOS) UAV-LMD operations and ensuring the UAV network to protect against external malign actors both now and in the



(a) Quadcopter configuration.



(b) Hexacopter configuration.



(c) Fixed-wing configuration.



(d) Lift+push configuration.

Figure 2-3: Commonly occurring UAV configurations.

future. Strong connection links will also enable autonomously operated UAVs to be safely integrated into unmanned aircraft system traffic management (UTM) networks. Such communication links need to be robust against external intruders or blockers but also in the face of inclement weather, congestion in cellular networks or power outages.

**Guidance, Navigation and Control** pertains to a UAV’s ability to detect, process, and avoid obstacles in real-time leveraging only onboard computing resources. This is a difficult technological challenge since such algorithms require both significant computational power and time, potentially too long to avoid an incoming aerial object or obstacle at relative travel speeds. Control pertains to the UAV’s ability to precisely track its own motion and attitude in 3D space using accelerometers and gyrometers and to maintain stability in uncontrolled environments. These sensors should, thus, be precise themselves, have low power requirements, and continually share data with remote operators.

### 2.1.3 Market Definition and Scope

Although UAVs are slowly being assimilated into civil society filling various commercial, industry, and recreational use-cases, a large proportion of the public still perceive UAVs as a sophisticated military technology. This is, in part, because of a lack of specificity in the term “drone” which refers to dual-use quadcopters and fixed-

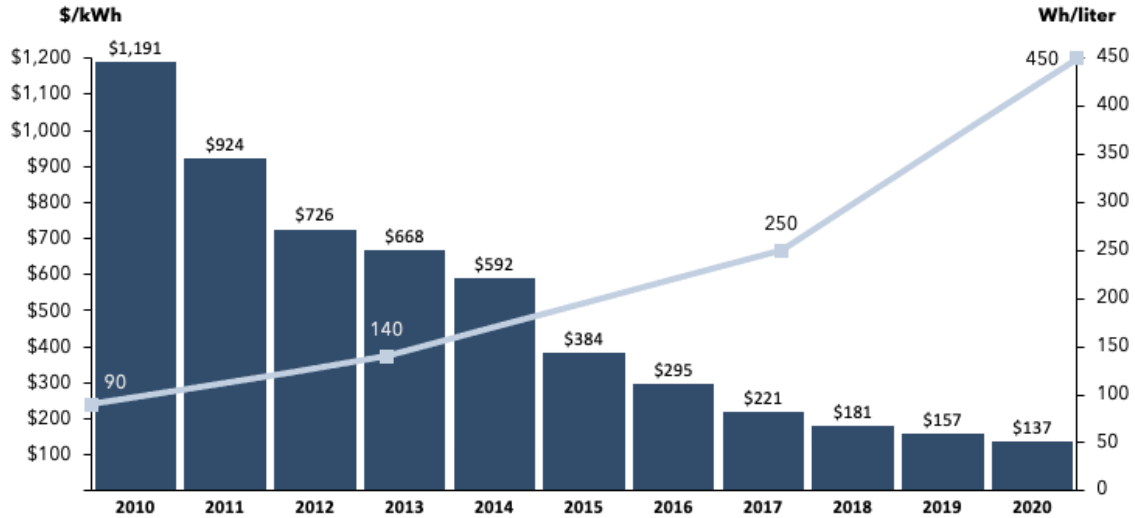


Figure 2-4: Li-ion battery price point and energy density trends over previous decade.

wing UAVs as well as the larger fixed-wing, often weaponized, military unmanned aircraft. This thesis strictly discusses the former non-weaponized small-form aerial vehicles. With the emergence of real-time connectivity and increased societal familiarity with advanced autonomous technologies, businesses and entrepreneurs across many industries realized the dual-use value of UAVs such as for surveillance, photography, video capture, inspection, advanced sensory data collection, goods transport and even passenger transport in larger-form air-taxi configurations. The U.S. represents a significant proportion of the overall market for non-military UAV applications, growing from \$40M to over \$1B from 2012 to 2017 and represents a strong signal how UAVs could be commercially deployed in other markets in later years (Cohn et al., 2017).

UAV-LMD is the specific intersection of commercial UAV deployment for last-mile delivery services. Within this sliver of the broader commercial UAV industry, understanding this market requires an understanding of its value chain (see Figure 2-5). Even within this sub-sector of the market, further segmentation can be made based on the specific goods being transported and operators behind any UAV-LMD fleet. The most common examples of such segments are: 1) retail and e-commerce; 2) postal services and package delivery; 3) food and beverage delivery; or 4) healthcare and emergency services, each involve a fleet of UAVs fulfilling consumer demand over a demand region. But whilst there are players and unanswered questions about industry trajectory in each section of this value chain and across each of the market sub-sectors, this thesis solely focuses on the *Operators* section in Figure 2-5. This is because the majority of the remaining barriers to UAV-LMD are operational in scope. In particular, this thesis asserts that the key remaining barriers to broad-based UAV-LMD deployment are:

- Infrastructure: One major appeal of UAVs for commercial applications is its



Figure 2-5: Commercial UAV-LMD value chain with this thesis predominantly adopting the analytical perspective of an UAV-LMD operator.

relatively modest infrastructure requirements. Zipline’s inaugural operations in Rwanda, for instance, were highly attractive to the Rwandan government because of its low upfront CAPEX requirements and relatively outsized impact on public health. With that said, as UAV applications become more integrated in society and urban landscapes, their infrastructure requirements will become more complex: maintenance shops, charging stations, take-off and landing facilities and other communication assets will all need to comply with the societal and regulatory environment in which they reside. Not only will these systems need to be robust to ensure safe and efficient low-altitude aerial operations in dense urban areas, but they are also mostly untested infrastructure concepts that will require additional testing and certification.

- Technology: This thesis eschews a broader discussion of UAV’s technological underpinnings, in part, because UAVs rely on a number of sophisticated enabling technologies: autonomous flight, collision detection and avoidance, lightweight but energy-dense battery technology, integrated UTM systems and GPS and additional location technologies. This thesis’s perspective is that whilst many of these technologies already exist and operate to a performance level acceptable for commercial deployment, their robustness, failure modes and response pathways or security against external actors have not necessarily been corroborated. This thesis avoids a more detailed discussion here predominantly because many of these technologies span multiple industries and are not being solely developed for commercial UAV deployment or UAV-LMD specifically. Thus, verifying these technologies’ areas of uncertainty will likely come from a variety of industries and, thus, lies beyond the scope of this thesis.
- Regulation: Many national and local regulators are grappling with drafting adequate UAV regulatory frameworks for commercial applications. This is, in part, because both the technology and its applications are novel and, relative to historical aerial operations, they are much more closely integrated with societies, particularly in urban operations. Because vehicles operating in the The National Airspace System (NAS) can present a national security risk, the Federal Aviation Administration (FAA) is notably strict on commercial UAV operations prior to any pre-drafted regulatory framework. Thus, it is likely that

the regulatory process and timeline will ultimately determine when many UAV applications become viable. Because new regulation is often an amalgamation of regulation in adjacent industries, historical case law and newly drafted law, this thesis recognizes an opportunity to survey the landscape of pertinent UAV-LMD regulation to better understand both current regulation and how it could evolve over time. Since regulation has a direct impact on operations, this thesis concludes that a survey of regulation and its implications for operations is a necessary exercise to more closely evaluate operational feasibility of UAV-LMD.

- Public Acceptance: Public acceptance is a pivotal barrier to UAV-LMD since expected operations are likely to be closely integrated into urban landscapes and, thus, have a more direct impact on the quality of lives of civil society members. Discussed in more detail in Section 3.1, even though the FAA is the sole regulator of the NAS, the public do have leverage to impel local regulators to enact regulation that can severely constrain UAV-LMD operations in that local region. This would render any CAPEX or other operational investments in that region by the operator futile. Thus, operators do have to be cognizant and sensitive to local public opinion and acceptance. There is ample literature and historical learnings from the aviation industry and beyond on how to promote public acceptance, but offering contributions to the academic literature on this topic lies beyond the purview of this thesis. With that said, this thesis recognizes the value of surveying current academic and industry opinions on the barriers to public acceptance for UAV-LMD and understanding its implications for operations.
- Economic Drivers: Finally, this barrier captures the question if demand will indeed materialize for commercial UAVs applications, or UAV-LMD specifically over a sufficiently long time frame to sustain an industry and the associated lead-times on regulation, technological development and service deployment. This thesis recognizes the importance of understanding the target customer, their changing needs over time and their suitability to a commercial UAV service. With that said, for the purposes of this thesis's case study analysis, demand is assumed to be derived not by spawning a whole set of new customers and unique demand needs but rather appropriating demand from the existing last-mile industry. In this way, this thesis works closely with logistics partners to understand their demand base characteristics and their customers' suitability to UAV-LMD services specifically.

Note that each of these key barriers directly impacts UAV-LMD operations. Operational feasibility will ultimately determine whether industry players will launch UAV-LMD fulfillment services that support the rest of the value chain since this is where the exogenous demand actually injects revenue into the value chain. In this light, this thesis opts to solely focus on UAV-LMD operations and assimilate its most critical barriers into a operations-centric feasibility analysis. Table 2.1 summarizes the key industry players that reside in the "Operators" section of the UAV-LMD value chain depicted in Figure 2-5 with reference to specific players that span multiple sections in the value chain and represent multi-domain players. Finally, it is

worth noting that this thesis, along with the modeling approaches it adopts, strives to be good type-agnostic. One exception here is if that good has specific operational requirements such as time-dependent cold-storage expiry times. Whilst such needs could be adequately modeled through the available parameters in this thesis’s modeling framework, it is beyond the purview of this thesis to capture these operational edge-cases from the perspective of the goods being transported.

## 2.2 Literature Review

This section attempts to cover the academic literature pertinent to the dimensions of UAV-LMD that this thesis brings into focus. The last few years have seen a large number of publications on UAV-LMD, especially in academic literature. Whilst economics and operations have proved popular topics to analyze via quantitative survey-based, analytical, or simulation-based models, research into regulatory frameworks or the societal externalities of UAV-LMD have been explored less frequently.

The scientific research on UAV-LMD can take many various directions related to the many research questions that have been posed to the industry before commercial deployment at scale. Such questions span the outstanding areas of uncertainty discussed in Section 2.1.3 that present barriers to deployment: technological readiness, regulatory readiness, novel infrastructure needs, communication technologies, public acceptance and evaluating the magnitude of any societal externalities imparted, demand economics, available routing optimization methods, and the implications of each of these issues for operations. This complexity manifests in more difficult operational decisions, for example: 1) larger vehicle fleets to optimize the utility of; 2) operations close to dense urban areas with a multitude of additional constraints and safety risks; 3) complex and random dynamics from temporary flight restrictions to inclement weather to interacting with other aerial vehicles and UAV-LMD operator fleets; and 4) autonomous operations. This problem is seemingly too broad with too many influencing forces to rigorously study in any isolated academic analysis, hence why the majority of literature pieces focus on either one or a few dimensions of the larger UAV-LMD research problem at a time. This thesis makes assumptions around technological readiness, infrastructure needs, and consumer demand and, in doing so, only focuses on the societal and regulatory constraints, routing optimization methods and their implications for operational decisions. Thus, this literature review eschews any review of academic work outside of these three domains.

At a high level, this literature review provides a sound introduction to relevant literature domains for its reader to become familiar with the key qualitative and quantitative topics of discussions, approaches and insights later derived. This is performed in three parts by exploring: 1) the society- and policy-centric literature studies, and 2) the routing-centric literature studies. The thesis then touches upon those contributions that could be considered cross-disciplinary in nature, that attempt

to marry qualitative and quantitative evaluations of UAV-LMD at a systems level to derive insights.

### 2.2.1 Society-Centric Studies

This section summarizes various literature contributions that evaluate UAV-LMD from a society-centric standpoint. This thesis classifies the relevant literature based on their analysis approach and thematic focus, shown in a comparative summary in Table 2.2. The following paragraphs describe literature grouped by their thematic focus for consistency and continuity. Kellermann et al. (2020a) provide a relatively comprehensive overview of the literature in this society-centric domain. They also cover the topical issues that are commonly discussed in such literature in short detail as an informative introduction to any reader new to this domain.

With regards to papers that focus on the societal implications of UAV-LMD, they predominantly consider the positive and/or negative externalities of commercial UAV deployment at scale and generally offer abstract conjectures of the potential externalities. For instance, Bujak and Śliwa (2017) and de Miguel Molina and Santamarina Campos (2018) claim substantial benefits for societies and economies. Such benefits include a reduction in traffic congestion, reduced commuting times and, thus, macro-economic benefits, as per Heutger and Kückelhaus (2014). Kornatowski et al. (2018) also hints at the possibility that UAV-LMD enable an efficient sharing economy. With regards to some of the quoted negative externalities, Applin discusses the liability issues with autonomously operated UAVs. Schlag (2013) and Rao et al. (2016) highlight the potential for UAV-LMD to erode personal privacy barriers. Jensen (2016) suggests this would be made worse if UAV-LMD operators leverage collected data beyond navigation and other operation-based use-cases. Gulden (2017) and Nentwich and Hórvath (2018) caution that UAV-LMD could instigate extreme consumption patterns that adversely affect urban livability. Finally, Kraus et al. (2020) discuss the various ways in which UAV technology is spreading in society based on its popularity and various use-cases.

The following papers discuss the safety and security implications of UAV-LMD. Again, these papers discuss the positive and negative externalities of commercial UAV operations. Examples of positive externalities are typically centered on using a fleet of UAVs as nodes in a law enforcement sensory network. Stöcker et al. (2017) highlight the safety issues of crashes, malfunctions and air collisions, particularly relevant in dense urban areas, as per Clothier et al. (2015). Kitonsa and Kruglikov (2018), Rao et al. (2016) and Smith (2015) discuss UAVs being used for criminal or terrorist purposes either as a vehicle masked to appear as part of a commercial fleet or by remotely hacking one of the UAVs in the fleet.

With regards to ethical dilemmas presented by UAV-LMD at scale, Nelson et al. (2019) suggest the potential for UAV-LMD to violate personal privacy and private spaces, eroding the public sense of anonymity. Schlag (2013) and Chiang et al. (2019)



suggest this is only exaggerated by the fact that UAVs, at typical cruise heights, are almost invisible to the naked eye but still able to perceive objects and people on the ground with accuracy. Nentwich and Hórvath (2018) highlight that UAVs will need to operate high-definition sensors for navigation purposes and are likely to infringe on personal privacy claims by the nature of their operations. Wang et al. (2021) propose that strict no-fly zones could help mitigate some of the negative ethical externalities imparted by UAV-LMD. Chiang et al. (2019) suggest that operators should be highly transparent about the data they collect, why it was collected and how it is being used.

The environmental positive and negative externalities of UAV-LMD at scale are also topics touched upon in literature, with both sides being equally popular perspectives taken by academics and other contributors. Haidari et al. (2016) perform a sensitivity analysis in an applied scenario with real-world vaccine demand data and demonstrates the potential distribution cost savings via UAV-LMD. Figliozzi (2017) performs a life-cycle analysis of UAV-LMD relative to other delivery modes such as bicycles and electric vehicles via continuous approximation, and offer insight that UAV-LMD are more environmentally attractive when other delivery modes are highly under-utilized capacity-wise. Goodchild and Toy (2018) evaluate UAV-LMD along two environmentally motivated metrics: CO<sub>2</sub> and total travel distance. They derive that to minimize the emissions of delivery operations in its entirety, UAV-LMD should be deployed in regions nearby the distribution center (DC), allowing larger ground-based modes to be better utilized in long-range deliveries. Kitonsa and Kruglikov (2018) suggest UAVs, either for goods or passenger transport, represent an opportunity to transition to sustainable mobility. Park et al. (2018) takes a more critical stance, suggesting that few analyses have conducted full life-cycle emissions analysis of commercial UAVs at scale in urban environments. They propose leveraging green energy to charge batteries or locating UAV warehouses strategically to minimize energy consumption.

Other papers discuss the public acceptance barriers. For example, Lidynia et al. and Clothier et al. (2015) suggest that the negative externalities of commercial UAVs operations will likely be apparent to bystanders since they are such novel technologies so closely integrated into urban landscapes. Otto et al. (2018) suggest increased dialogue, transparency of operations and its benefit to the public as key tools to improve public acceptance metrics. de Miguel Molina and Santamarina Campos (2018) suggest that incorporating a set of technical measures that alleviate the worst of the negative externalities and that are effectively transmitted into the public sphere is critical to inspiring public acceptance.




From the perspective of law and regulation, most discuss the need for dynamic and purpose-built regulation to protect societies against the unique negative externalities that UAV-LMD imparts. Luppicini and So (2016) suggest exactly this. Rule (2016) specifically analyzes the benefits of “drone zoning” as a regulatory tool to protect against the variety of negative externalities covered in the literature. Sehrawat (2018) offers a deep dive into the various liability issues with UAV-LMD operations

and potential liability pathways, particularly if operated remotely or autonomously.

In summary, the society-centric literature generally ruminates upon the potential positive and negative externalities of UAV-LMD from a predominantly qualitative standpoint with only a select few papers leveraging quantitative models to derive insights.

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Table 2.1: Overview of the key UAV-LMD industry players.

Company	Description	Competencies
	Amazon first broached their pursuit of UAVs for last-mile delivery in 2013. Within Amazon Prime Air, the company developed UAV hardware, software and operational know-how and pushed the FAA to permit commercial UAV testing operations BVLOS. Nevertheless, Amazon began testing in more favorable regulatory environments in Cambridge, UK and Vancouver, CA.	UAV hardware On-board software Logistics systems Regulation Advocacy
	UPS launched UPS Flight Forward in 2019 but began early testing of their truck-and-drone delivery system, Workhorse Workfly, as early as 2017. In October 2019, UPS were to first to gain FAA full Part 135 Standard Certification, allowing the company to operate a fully remote UAV delivery network across the United States with an unlimited number of UAVs launch hubs, both day and night.	UAV hardware On-board software Logistics systems Regulation Advocacy
	Early in 2014, DHL unveiled their UAV delivery service, announcing their in-house Parcelcopter design in parallel. It was the first to commercially integrate UAV deliveries into their broader logistics network, providing service to remote towns in Germany with a focus on medical supplies and small goods. Now in its fourth iteration, the Parcelcopter has evolved in configuration, payload capacity, range and use-case.	UAV hardware On-board software Logistics systems Regulation Advocacy
	Originally headquartered in Australia, Flirtey partnered with the University of Nevada as it relocated to United States focusing on UAV technology and the UAV-LMD logistics system development. They performed the first FAA-approved commercial UAV delivery in July 2015. Flirtey held partnerships with 7-Eleven (U.S.) and Domino's Pizza (New Zealand), in cases fully integrating the service chain from customer orders through to delivery.	UAV hardware On-board software Logistics systems
	Founded in 2011, Matternet provides end-to-end UAV-LMD offerings to customers. First championing the truck-and-drone delivery model in partnership with Mercedes-Benz Vans, Matternet has since pivoted into pure-play UAV-LMD with standing partnerships with UPS and Japan Airlines. Most recently, Matternet announced a stand-alone medical goods delivery service in Labor, Berlin, DE, as the first urban BVLOS operation globally.	UAV hardware On-board software Logistics systems
	Wing's parent company, Alphabet, has been investing in UAV delivery via its R&D subsidiary, Google X, since 2012. Wing soon showcased their lift+push UAV design and winch delivery technology. Testing in Logan City, AU and Virginia, U.S., Wing has been working with regulators and the public to inform UAV design, operational decisions and their in-house UTM platform.	UAV hardware On-board software Logistics systems Regulation Advocacy UTM/ATC
	The Chinese e-commerce giant launched their UAV delivery venture in 2015 with initial investments into UAV hardware. With a focus on remote regions across China, by the end of 2017, JD.com had already performed thousands of deliveries across outer-Beijing and other provinces. The CAAC permitted JD.com to build out UAV landing platforms across the country.	UAV hardware On-board software Logistics systems Regulation Advocacy Infrastructure
	Founded in 2013, this software-focused Israeli company developed the first cloud-based UAV delivery service and operations management system. The latter system enables suppliers to leverage Flytrex's fleet of UAVs as a shared resource with access to positioning, capacity, range and other live data. Since 2016, Flytrex have announced pilot programs in Ukraine and Reykjavik, IS to provide BVLOS autonomous UAV-LMD service.	UAV hardware On-board software Logistics systems Cloud integration
	In partnership with the Rwandan government, Zipline launched a national UAV delivery service in 2016 to supply remote health facilities. They offer an in-house fixed-wing UAV design, novel launch and retrieval mechanisms, remote BVLOS connectivity and delivery via parachute. Designed around the needs of local doctors, the service is integrated into existing SMS networks. In 2020, Zipline announced a new partnership with Walmart, U.S.	UAV hardware On-board software Logistics systems

Paper	Analysis Approach				Thematic Focus				
	Qual.	Mod.	Soc. Imp.	Saf.	Ethics	Env.	Att. & Acc.	Law and Reg.	
Schlag (2013)	X		X						
Heutger and Kückelhaus (2014)	X		X		X				
Smith (2015)	X		X	X					
Applin	X		X	X			X		
Clothier et al. (2015)	X		X				X		
Haidari et al. (2016)	X		X						
Jensen (2016)	X	X	X						
Luppicini and So (2016)	X		X		X				
Rao et al. (2016)	X		X						
Rule (2016)	X		X					X	
Wang et al. (2021)	X		X	X					
Bujak and Šliwa (2017)	X		X						
Chiang et al. (2019)	X		X	X					
Figliozi (2017)	X	X				X			
Gulden (2017)	X		X	X				X	
Lidynia et al.	X			X					
Stöcker et al. (2017)	X			X					
de Miguel Molina and Santamarina Campos (2018)	X		X						
Goodchild and Toy (2018)	X	X				X			
Kitonsa and Kruglikov (2018)	X					X			
Kornatowski et al. (2018)	X		X						
Nentwich and Hörvath (2018)	X					X			
Otto et al. (2018)	X						X		
Park et al. (2018)	X					X			
Sehrawat (2018)	X							X	
Nelson et al. (2019)	X		X	X					
Kraus et al. (2020)	X		X	X			X		
<b>This Thesis</b>		X	X	X	X	X	X	X	

Table 2.2: Comparative analysis of pertinent UAV-LMD cross-disciplinary literature.

Abbreviations: Qual.: Qualitative; Mod.: Model; Soc. Imp.: Societal Implications; Saf.: Safety; Env.: Environment; Att. & Acc.: Attitude & Acceptance; Reg.: Regulation.

## 2.2.2 Routing-Centric Studies

Discussed in light detail in Section 1.1 and in more detail in Chapter 4, this thesis’s analysis features a generalized unmanned aerial vehicle routing problem (GURP) implementation that aids in its exploration of UAV-LMD operational feasibility given real-world constraints. This model implementation serves the purpose of providing a quantitative pathway to deriving realistic operational performance and cost metrics given varying scenario input parameters; but the structure of this model is not beholden to any other constraints. This section explores the various ways academics have conjectured to capture UAV-LMD operations in a quantitative model and how this thesis builds upon existing literature. Much of the current UAV-LMD operations literature is grounded in more traditional operations research domains that manifest in applied last-mile logistics and routing discourse.

Otto et al. (2018) present a comprehensive overview of current optimization methods to solve problems that emerge as UAVs are applied in commercial settings. They cover problems such as area coverage, search and rescue, data acquisition, communication linking and sequential location visits. Khoufi et al. (2019) provide a classification methodology for UAV-LMD applications centered around the number of vehicles, solution approaches and applications. The analysis by Chung et al. (2020) is centered on UAV-aided vehicle routing, commonly referred to as the truck-and-drone delivery system and, thus, classifies UAV-LMD routing operational models based on whether UAVs operate independently or as part of a mobile multi-vehicle system. Moshref-Javadi and Winkenbach (2021) provide a comprehensive overview of either UAVs leveraged in last-mile delivery from the vehicle routing perspective. They offer insight into the operational models typically modeled in literature, their applications and common solution approaches to solve such UAV-based vehicle routing problems (VRPs). They also provide a comprehensive classification system that succinctly captures the different ways UAVs could be integrated into a last-mile fulfillment network. This classification framework is as follows:

- Pure-Play: UAVs deliver packages directly to customers from a central DC.
- Un-synchronized Multi-Modal: multiple modes of transportation are used in parallel but asynchronously to fulfill customer demand. The customer pool can be split between transportation modes or shared between them such that the same customer can be visited multiple times by different transportation modes.
- Synchronized Multi-Modal: multiple modalities are used in parallel and synchronously to fulfill customer demand. Transportation modes work in symbiosis to enhance each other’s baseline performance capabilities. An example of such a fulfillment mode is a set of UAVs being placed atop of a ground-based truck and launched at strategic locations in the demand region to serve customers whilst the truck also continues to serve customers directly.
- Resupply Multi-Modal: This is similar to the Synchronized Multi-Modal except that the vehicles are not moving around the demand region together but rather

one transportation mode is used to supply an advanced base or transshipment point from where the second transportation mode is operating out of to serve customer demand. This is akin to a two-echelon fulfillment network with each echelon consisting of different transportation modes.

Note that whilst in the strictest sense, UAV-LMD encapsulates any customer fulfillment network that leverages UAVs in any part of its last-mile system, this thesis uses the term UAV-LMD to strictly refer to the Pure-Play fulfillment model. In this sense, this thesis eschews any discussion of multi-echelon or multi-modal last-mile fulfillment networks that may include UAVs as part of the network and, instead, solely focuses on isolated UAV fleets deployed to serve customers directly from a centralized fulfillment DC. This section goes on to highlight the relevant academic efforts to capture the operational considerations of the Pure-Play UAV-LMD model through a structured framework that categorizes literature by the key features, assumptions, and modeling approaches employed.

Table 2.3 offers a comparative overview of key UAV-LMD routing literature along these specific differentiating factors relative to this thesis’s modeling approach in Chapter 4. At a high level, the routing literature solves the UAV-LMD fulfillment problem, what this thesis refers to as the unmanned aerial vehicle routing problem (URP), with differing tools, characteristics and objective functions. Since the earlier literature papers in 2014, more complex versions of the URP problem has been getting progressively more complex and capturing more features and objectives. Some also take a different perspective around determining the optimal location and capacity of a recharging station network whilst others are more focused on the vehicle routing elements.

First, a number of papers take a facility location optimization approach to solving the URP. Hong et al. (2018) solve a location covering problem for UAV recharging stations for a URP problem. The UAVs are modeled to avoid barriers and obstacles in their environment such as buildings or no-fly zones but each UAV can serve only one customer per trip. UAVs can recharge at locations along their flight path to their destination. A mixed-integer linear program (MILP) and heuristic method are proposed to solve this problem. Chauhan et al. (2019) derive a facility location problem solution that maximizes total number of customers served with UAV power consumption derived as a weight-dependent function. But UAV batteries are assumed as not rechargeable or replaceable. Shavarani et al. (2019) also model the URP as a dynamic capacitated facility location problem for UAV-LMD. UAVs are flight and capacity limited but can stop at refueling stations on their way to serve customers. Kim and Matson (2017) solve the URP with pickups and deliveries for medical supplies with the added extension of providing the optimal number of UAV drone launch locations via a location covering problem. Aurambout et al. (2019) model the URP with the motivation of understanding how many people would benefit from the technology and its costs versus added value to society. They identify specific communities that would benefit and solve a location allocation problem to determine the most

beneficial set of beehive locations for UAVs to fulfill demand from. Shao et al. (2020) solve the URP for long-distance UAVs trips using mid-way fulfillment and maintenance stations with the goal to minimize total number of stops at the midway stations.

The following papers take approaches that incorporate midway recharge, maintenance, or goods pickup facilities to extend otherwise limited UAV ranges or minimize customer fulfillment times. Additionally, these papers look at a similar extension of the URP that involves multiple DC locations from which UAVs can depart and return to interchangeably. Rabta et al. (2018) present a model for disaster relief operations whereby UAVs can serve multiple demand locations and recharge either at DCs or at locations on the way to their destination. Yadav and Narasimhamurthy (2017) formulate an extension of the URP in that UAVs can pickup packages from multiple warehouses and deliver packages to multiple customers per trip. Two heuristic solution approaches are offered that maximize UAV utility.

The following papers take a more traditional routing approach to modeling the URP with operational constraints sequentially added to complexify the problem. Some of these papers also include complex power consumption models to better capture the UAV's weight-dependent energy consumption dynamics. Note, whilst some papers model demand stochastically, others assume a static demand set. Finally, some attempt to capture multi-modal fulfillment models that incorporate UAVs into a broader fleet of heterogeneous vehicles. San et al. (2016) describe a swarm of UAVs performing last-mile fulfillment with payload capacity constraints along multiple commodities and a limited flight range, solved with a genetic algorithm. Dorling et al. (2016) present two URP models, one that minimizes total delivery time subject to cost constraints whilst the other minimizes cost subject to time constraints. Both capture energy consumption via a linearized weight-dependent power consumption model. They also present a simulated annealing algorithm that solves these models, performing a sensitivity analysis around specific input parameters. Coelho et al. (2017) solve the URP with some additional complexity: UAVs operate at two cruise altitudes stratified by travel distance and UAV size. They also offer a medley of objective functions and a heuristic approach to solve the problem. Torabbeigi et al. (2020) focus more on the effect of battery consumption on the efficiency of UAV-LMD. They model a facility location problem with energy consumption modeled as linearly dependent on payload weight. Cheng et al. (2020) closely model the GURP solved in this thesis, formulating a number of exact approaches to solving the URP with several operational constraints such as customer time window (TW) and UAV weight-dependent power consumption logic (linearized in the same fashion as Dorling et al. (2016)). Liu et al. (2019) solve a dynamic VRP for on-demand pickup and delivery. UAVs have a fixed payload capacity and flight time. The stochastic demand is accumulated in specific time intervals and then fulfilled. Ulmer and Streng (2019) develop a dynamic multi-modal fulfillment model whereby trucks serve customers nearby the DC, and UAVs venture to serve customers far away from the DC. The results demonstrate that the total ground-based truck fleet size can be significantly reduced if UAVs are incorporated.

In summary, there have been a variety of approaches that academics have taken at a quantitative routing level for a number of different applications that motivates the modeling approach taken. The URP represents a complex extension of the traditional VRP problem since it incorporates a broad set of more complex operational constraints. This thesis leverages the tried-and-tested modeling approaches as inspiration for adopting a specific modeling approach in Chapter 4.

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Paper	Methodology			Demand			Vehicle Characteristics				
	Sol. Appr.	Obj.		Del.	Pick.	TW	Range	M-Comm.	M-Cust.	Cap.	Energy
San et al. (2016)	Ex.	Min-Cost		X			X	X			
Haidari et al. (2016)	Sim.	Min-Cost		X			X		X		
Dorling et al. (2016)	Heur.	Min-Cost, Min-Trip, Min-En.		X				X			X
Coelho et al. (2017)	Heur.	Min-Fleet, Min-Trip, Min-En.		X	X		X		X		
Yadav and Narasimhamurthy (2017)	Heur.	Min-Trip		X			X		X		
Kim and Matson (2017)	Heur.	Min-Cost		X			X		X		
Figliozzi (2017)	Cont. Ap.	Min-Emission		X			X		X		X
Rabta et al. (2018)	Heur.	Min-Cost		X			X		X		
Goodchild and Toy (2018)	Sim.	Min-En.		X			X		X		X
Hong et al. (2018)	Heur.	Min-Max-Visit		X			X		X		
Ulmer and Streng (2019)	Dyn. Prog.	Min-Max-Visit		X			X		X		
Chauhan et al. (2019)	Heur.	Min-Max-Visit		X			X		X		X
Liu et al. (2019)	Sim.	Min-En., Min. Dist.		X			X		X		
Shavarani et al. (2019)	Heur.	Min-Cost		X			X		X		
Aurambout et al. (2019)	Heur.	Min-Cost		X			X		X		
Torabbeigi et al. (2020)	Heur.	Min-Fleet		X			X		X		X
Cheng et al. (2018)	Ex.	Min-Cost		X		X	X		X		
Shao et al. (2020)	Heur.	Min. Dist.		X			X		X		
She and Ouyang (2021)	Num.	Min-Cost, Min-En.		X			X		X		
Chen et al. (2021)	Heur., Ex.	Min-Cost		X			X		X		
Ghelichi et al. (2021)	Ex.	Min-Trav.		X			X		X		
Jung and Kim (2022)	Ex.	Min-Max-Visit		X			X		X		
<b>This Thesis</b>	<b>Heur., Ex.</b>	<b>Min-Cost</b>		<b>X</b>	<b>X</b>	<b>X</b>	<b>X</b>	<b>X</b>	<b>X</b>	<b>X</b>	<b>X</b>

Table 2.3: Comparative analysis of pertinent UAV-LMD routing literature.

Abbreviations: Sol. Approx.: Solution Approximation; Sim.: Simulation; Num.: Numerical; Heur.: Heuristic; Ex.: Exact; Cont. Ap.: Continuous Approximation; Dyn. Prog.: Dynamic Programming; Obj.: Objective; Min-Dist.: Min-Distance; Min-En.: Min-Energy; Min-Trav.: Min-Travel; Del.: Delivery; Pick.: Pickups; M-: Multi; Comm.: Commodity; Cust.: Customer; Cap.: Capacity.

### 2.2.3 Discussion and Research Gap

Much of the society-centric literature touches upon themes that are discussed in more depth in Chapter 3. Whilst the literature, and the concomitant chapter in this thesis, do not cover the whole spectrum of possible society-related externalities that could emerge from UAV-LMD operations at scale, both discuss the issues that are most commonly cited and the set of potential solutions. Much of the motivation for the society-centric work is to inform operators of the potential negative externalities they could unwittingly impart on society and provide material for newly drafted commercial UAV-specific regulation to be enacted either at the local or federal level.

With regards to the routing-centric literature, the majority of the contributions attempt to innovatively model the additional complexity of the URP, thereby adding to the rich body of vehicle routing literature. Some papers incorporate more real-world constraints such as altitude stratification logics or UAV energy consumption patterns to more closely capture real-world UAV-LMD operations. In both the society-centric and routing-centric cases, this thesis identifies a gap in the literature bodies in that whilst the society-centric literature generally avoids quantitative models to further explain their insights, the routing-centric literature leverages little to no society-centric considerations in their modeling of UAV-LMD operations.

There are exceptions to this assertion, however. For example, Haidari et al. (2016) models UAV-LMD for vaccine distribution for Gaza and Mozambique example case studies. They leverage a discrete-event simulation model (termed HERMES) to capture real-world operational constraints such as 1) a more complex cost function that includes storage, transport, infrastructure, and labor, and 2) a realistic benchmark for ground-based transport of vaccines that incorporates non-symmetric distance matrices, variable speed functions dependent on road condition, congestion and seasonality. Marrying such detailed constraints with their simulation model yields detailed results on tipping points in the total cost of UAV-LMD operations to be cost-competitive with the existing ground-based fulfillment modes.

The analysis of Figliozzi (2017) is centered on better evaluating the CO<sub>2</sub> emissions of UAV-LMD via a comprehensive life-cycle analysis of the UAVs. They also offer a comparative analysis to other promising fulfillment modalities such as electric tricycles and electric trucks to offer a benchmark of comparison. They uniquely model UAV-LMD operations in detail for both one-to-one and one-to-many last-mile fulfillment networks and develop a from-first-principles energy consumption model for quadcopter UAVs to more closely quantify real energy consumption patterns.

Goodchild and Toy (2018) take a similarly sustainability-motivated approach to Figliozzi (2017) by attempting to evaluate to what extent UAV-LMD integration into existing ground-based fulfillment networks could reduce overall CO<sub>2</sub> emissions. Whilst they do not perform as comprehensive life-cycle analysis as does Figliozzi (2017) for UAVs fulfilling last-mile demand, their analysis is grounded in a truck-

based CO<sub>2</sub> emissions baseline that is reduced by demand being outsourced to UAVs. The UAVs sport their own CO<sub>2</sub> emissions pattern that is driven by upstream energy production emissions and total energy consumed in flight.

Glick et al. (2022) take a uniquely integrated approach to UAV-LMD for time-sensitive medical supplies fulfillment. They quantitatively model meteorological conditions such as wind, rain and temperature as well as stochastic demand of medical supplies as inputs into a fulfillment reliability model based on a UAV available battery capacity. Such a line of research would likely help operators with time-critical fulfillment constraints to define worst-case boundaries for UAV-LMD to more robustly design their fulfillment networks with additional insights into which meteorological phenomenon is the most impactful to operations.

However, with the exception of such application-specific academic papers above and others, there exists a dearth of cross-disciplinary academic contributions that attempt to model the more nuanced real-world constraints that UAV-LMD will likely face, particularly for commercial consumer packaged good (CPG) demand in urban areas. It is at this nexus that this thesis sits: to capture the operational implications of otherwise nuanced society-specific constraints that typically remains outside the purview of more traditional vehicle routing literature. This thesis does not attempt to derive extensive insights into which of these society-centric constraints will most significantly impact UAV-LMD operations but rather offer a modeling pathway for such constraints in familiar quantitative routing models.

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## Chapter 3

# Social and Regulatory Barriers to Unmanned Aerial Vehicles for Last-Mile Delivery

Full-scale commercial deployment of unmanned aerial vehicles for last-mile delivery (UAV-LMD) promises to fill urban skies with fleets of package-carrying unmanned aerial vehicles (UAVs) flying at low altitudes and at high speeds in close proximity to the many hazards present in today's mega-cities. However, despite the vision and effort of numerous last-mile players over the past decade, UAV-LMD has not yet materialized in this way. The non-existence of these services evinces the fact that there exist significant barriers and operational constraints that continue to bar successful commercial ventures. This chapter explores the host of hurdles and challenges facing UAV-LMD today. It does so in two ways:

1. Legal and Regulatory Barriers: This chapter analyzes the status-quo of applicable regulation in the United States (U.S.) and their related legal interpretations. In light of emerging consumer and industry interest in UAV-LMD, many regulatory and legal questions have surfaced in the past decade and, only recently, has apposite regulation been put in place to offer guidance. That goes without saying that there have been numerous cases already where regulation, societal norms and nascent UAV-LMD operations have prompted legal action. The relevant regulation will continue to evolve as the industry scales, so a survey of remaining areas of regulatory uncertainty is also necessary.
2. Societal Barrier: This chapter explores UAV-LMD's potential societal externalities through a historical lens of low-altitude aerial operations. It also surveys current opinions of academics and industry stakeholders (regulators, commercial players and thought-leaders) to gauge their viewpoints and philosophies that capture society's potential concerns.

This chapter summarizes these challenges and assesses how they will shape future UAV-LMD operations. Thus, this chapter attempts to synthesize these constraints down to which are directly relevant to UAV-LMD routing decisions and which are not.

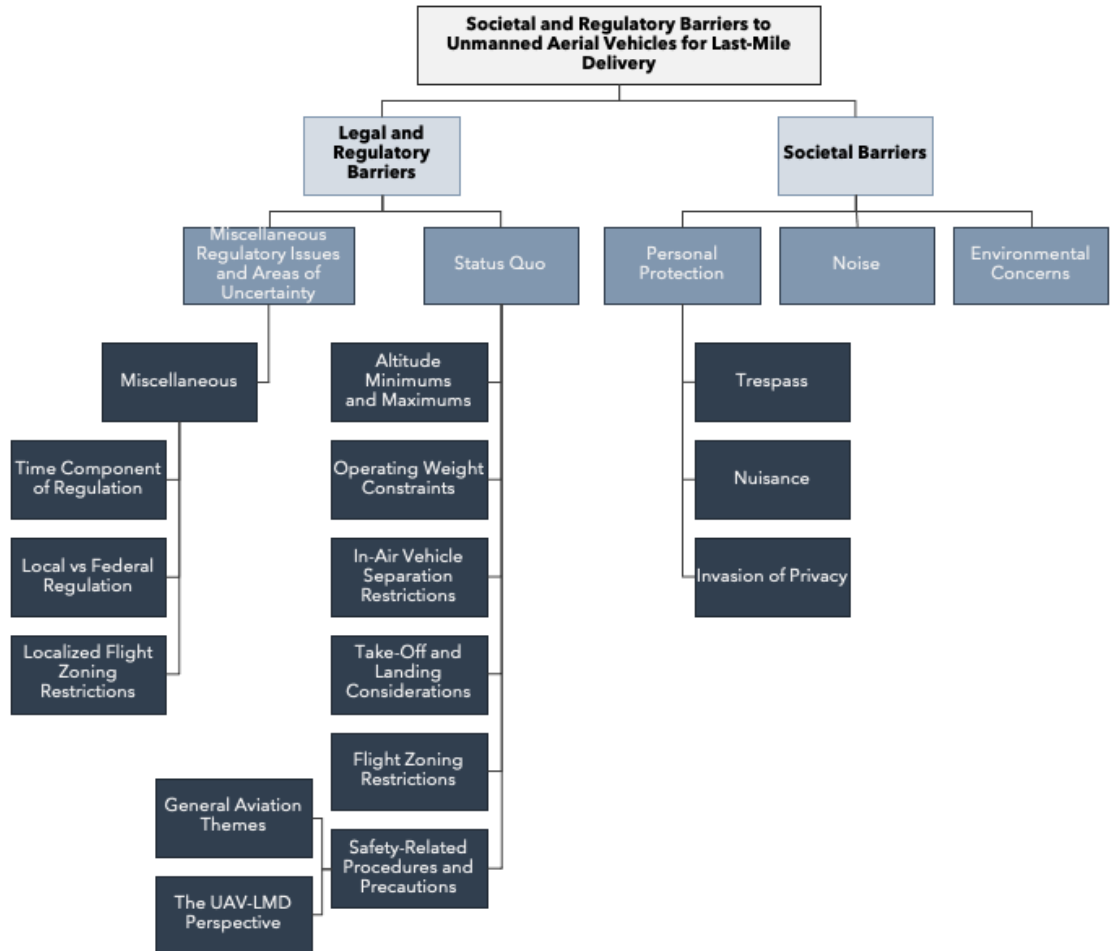


Figure 3-1: Overview of Chapter 3 structure and analysis: social and regulatory barriers to unmanned aerial vehicles for last-mile delivery.

These relevant constraints then guide the generalized unmanned aerial vehicle routing problem (GURP) formulation in Chapter 4 and the spectra of sensitivity scenarios and analyses performed in Chapter 5. Figure 3-1 conveys the structure of this chapter and the topics it discusses diagrammatically. Note, whilst this chapter attempts to provide a comprehensive structural overview of the relevant societal and regulatory constraints to UAV-LMD, this thesis does not claim to pose recommendations for regulators, operators and active members of the public. It summarizes the current status quo and, in places, suggests ways to model specific constraints. These suggestions are simplifications of the constraints for comprehension and ease of modeling, not surmises of how any particular constraint will materialize in future UAV-LMD operations.

## 3.1 Legal and Regulatory Barriers to Unmanned Aerial Vehicle for Last-Mile Delivery Operations

Over the past century the aviation industry has worked closely with local and national regulators to define what has become a complex set of airspace infrastructure and air traffic management protocols through national statutes, regulations, standardized best practices, legal rulings and analysis of aviation accidents. What has resulted is an airspace management ecosystem that offers efficiency and unmatched levels of safety and redundancy compared to other transportation ecosystems.

Widespread deployment of UAV-LMD promises to install multiple fleets of UAVs across various geographies operating numerous daily flights per day at low altitudes. Low-altitude aerial operations at this scale and breadth will represent an unprecedented and untested regulatory conundrum for local and national regulators alike. Please note that regulations in this sector are likely to be in continuous flux over the coming decades. Thus, this thesis highlights the possibility that any regulation quoted here may be re-drafted in the coming years.

### 3.1.1 The Status Quo for Legal and Regulatory Barriers

The current state of air traffic control (ATC), airspace class definition and design, and aircraft operational rights is the product of decades of trial, error and litigation. Fast forward to 1958, the Federal Aviation Act established the Federal Aviation Administration (FAA) and made it responsible for the control and use of navigable airspace within the United States. The FAA created the The National Airspace System (NAS) to protect persons and property on the ground, and to establish a safe and efficient airspace environment for civil, commercial, and military aviation. Thus, all aerial vehicles operating in the airspace above the U.S. are expected to adhere to the appropriate operational, airspace and ATC constraints publicly enforced by the FAA. Figure 3-2 depicts the various airspace classes of the U.S. NAS (FAA Safety Team, 2020). Note that an aerial vehicle seeking entry to an airspace class must at a minimum liaise with the relevant ATC entity and adhere to a unique set of hardware and operational constraints.

Whilst medium- and high-altitude aircraft operations generally follow a homogeneous set of operational constraints across the U.S., operational constraints for low-altitude flight (generally assumed to be sub-5000 ft.) can vary dramatically from one location to the next. Whilst this is not supposed to be the case given the FAA's mandate to be the sole regulator of all navigable airspace in the U.S., this is predominantly due to the non-aviation-related constraints discussed in Section 3.2 and local best practices.

The most relevant existing FAA regulations that applies to UAV-LMD are housed in the FAA Part 107 Drone Regulations and FAA Part 135 Charter-Type Services

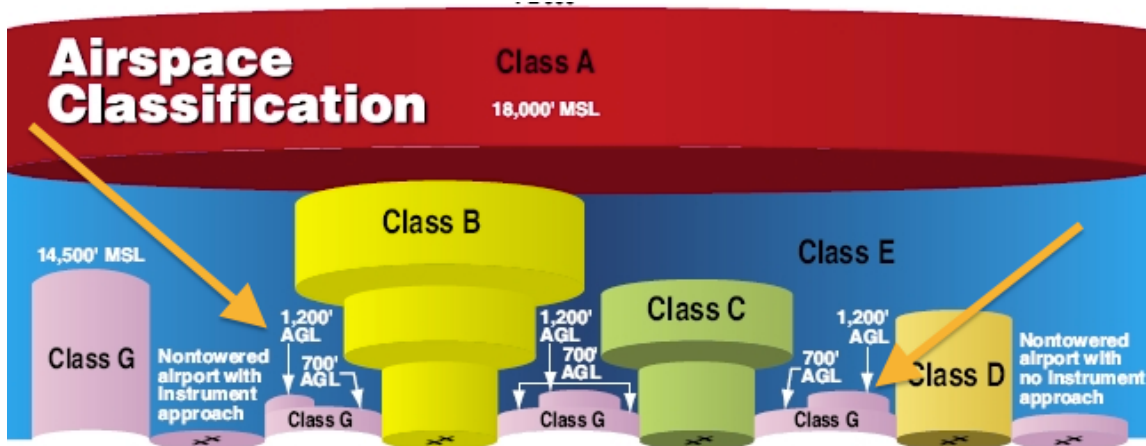


Figure 3-2: Airspace classification structure for U.S. NAS.

(Rupprecht). Unlike Part 107 which was exclusively drafted for UAV flight, Part 135 is an already existing set of rules to govern inter-state and intra-state air delivery of mail and other goods. A UAV-LMD provider can certify its operations under either Part 107 or Part 135, however, each come with their unique set of constraints. The key constraints that emerge out of a Part 107 certification are:

1. The UAV must be flown within visual line of sight (VLOS) of the pilot in command. This is very constraining for operators and the industry is pushing for regulations to permit extended visual line of sight (EVLOS) and eventually, beyond visual line of sight (BVLOS) (FAA § 107.31 Part 107, 2020). Figure 3-3 depicts the differences between these terms, courtesy of (Woo et al., 2018).
2. A UAV operator is mandatory for UAV flight, i.e. the UAV cannot be autonomously flying. Furthermore, there is a strict one-to-one relationship between operator and UAV. Note that waivers have been granted that null this requirement for test purposes (FAA § 107.35 Part 107, 2020).
3. UAVs cannot be operated over a non-participating person, property populated with people or a moving vehicle, again another non-starter for urban UAV-LMD operations (FAA § 107.39 Part 107, 2020).
4. The UAVs cannot be operated in Class B, C, or D airspace and some definitions of class E airspace without an authorization or waiver. These classes are depicted in Figure 3-2.
5. Unless under a 107 waiver, if the UAV is to be considered under Part 107, it must weigh under 55 lbs. and remain under a 400 ft. altitude ceiling (Woo et al., 2018).

On the other hand, a Part 135 certificate can permit BVLOS operations. And the current FAA rhetoric is that Part 135 will continue to be extended and adapted to accommodate for UAV-LMD by including additional constraints and adding exceptions to rules that do not apply to UAVs. With that said, those that seek to comply



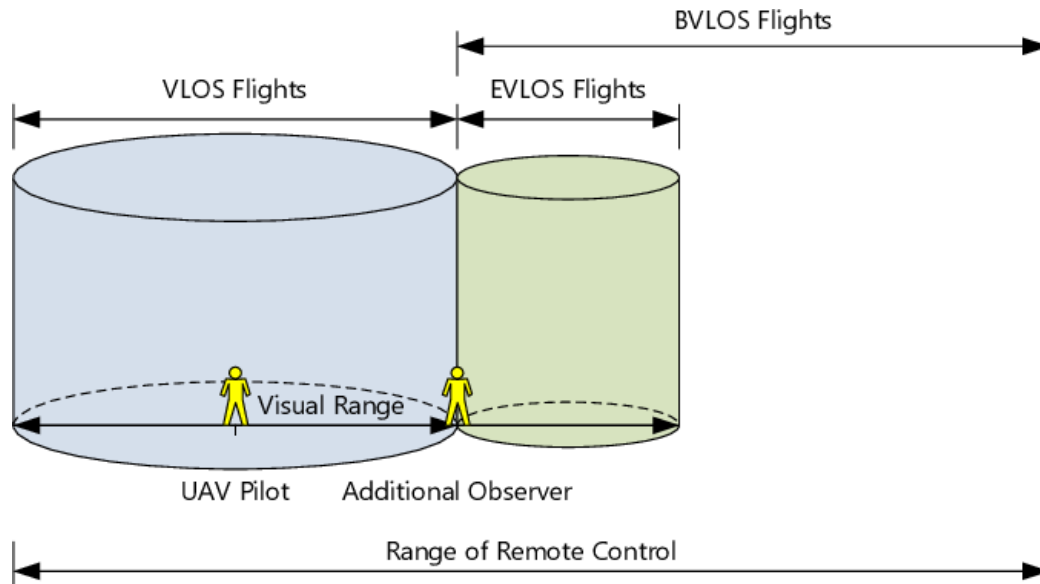


Figure 3-3: Visual illustration of visual line of sight terminology.

with Part 135 will need to meet a long list of requisites including aircraft certification, maintenance standards, operations manuals, training programs enactments, an Economic Authority certificate from the Department of Transportation, and insurance coverage for operations. Part 135 offers four types of certificates each with their own set of pros and cons, in order in general ease of certification:

- Single Pilot Certificate: a single-pilot operator is a certificate holder that is limited to using only one pilot for all Part 135 operations.
- A Single Pilot in Command Certificate: one pilot in command and three second pilots in command. There are also limitations on the size of the aircraft and the scope of the operations.
- A Basic Operator Certificate: a maximum of five pilots, including second in command pilots. A maximum of five aircraft can be used in their operation.
- A Standard Operator Certificate: fundamentally no limits on the size or scope of operations. However, the operator must be granted authorization for each type of operation they want to conduct (Federal Aviation Administration, 2022a).

However, in discussing the regulatory constraints applicable to low-altitude flight in more detail, one can distill current regulatory frameworks, be it Part 107, Part 135 or other relevant Federal Aviation Regulations (FAR)s under some broader operationally relevant constraints: operating weight constraints, operating altitude minimums and maximums, in-air vehicle separation restrictions, take-off and landing locations and procedures, non-airspace related flight zoning restrictions and safety-related procedures and precautions.

### 3.1.1.1 Operating Altitude Minimums and Maximums

The status quo for operating altitude constraints for general aircraft are prescribed via minimum altitude requirements in FAR Part 91 General Operating and Flight Rules §91.119 states:

“Except when necessary for takeoff or landing, no person may operate an aircraft below the following altitudes:

- (a) Anywhere: An altitude allowing, if a power unit fails, an emergency landing without undue hazard to persons or property on the surface.
- (b) Over congested areas: Over any congested area of a city, town, or settlement, or over any open air assembly of persons, an altitude of 1,000 feet above the highest obstacle within a horizontal radius of 2,000 feet of an aircraft.
- (c) Over other than congested areas: An altitude of 500 feet above the surface, except over open water or sparsely populated areas. In those cases, the aircraft may not be operated closer than 500 feet to any person, vessel, vehicle, or structure.
- (d) Helicopters: Helicopters may be operated at less than the minimums prescribed in paragraph (b) or (c) of this section if the operation is conducted without hazard to persons or property on the surface. In addition, each person operating a helicopter shall comply with any routes or altitudes specifically prescribed for helicopters by the Administrator.” (FAA § 91.119 Part 91, 2020).

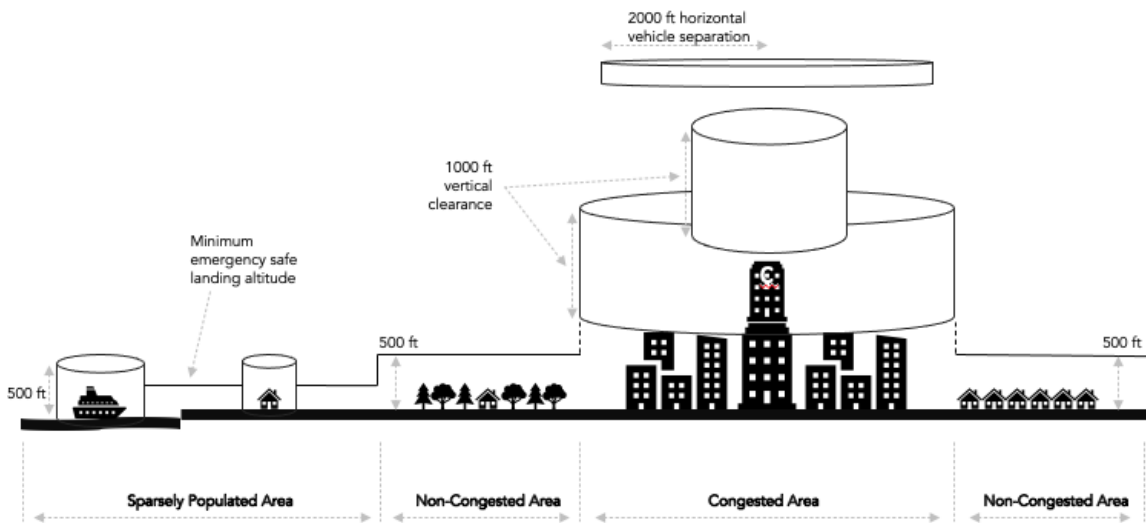


Figure 3-4: Pictorial depiction of current regulatory framework FAR Part 91 §91.119 for aircraft flight minimums.

This is shown pictorially in Figure 3-4. Thus, this FAR suggests that minimum altitude requirements depend on both the vehicle type, population and property density below the flight path and the ability of the pilot to safely execute an emergency

landing without putting bystanders and property at undue risk. Interestingly, section (d) exempts helicopters from all altitude minimums except for the emergency landing contingency. This is also interesting since it does not capture any notion of noise, privacy, trespass or other non-aviation-specific legality concerns that are discussed in Section 3.2. Another interesting insight is the qualitative and subjective nature of the terms “congested” and “sparsely populated” which are often determined on a case-by-case basis. Varying legal interpretations of these terms published by the FAA’s Office of the Chief Counsel in past case-law underscores how such language is commonly misinterpreted by operators, pilots, and legal practitioners alike (Reigel, 2008).

With all this said, these regulations are currently not applicable to UAV-LMD because UAV-LMD must be certified via FAA Part 107 at a minimum and Part 135 to permit broader BVLOS operations at scale. The aforementioned regulations are included to offer insight into the key drivers behind altitude minimums for general aircraft and, thus, what the key drivers for UAV-LMD are likely to be. Under the current regulations for UAV-LMD, FAA Part 107 stipulates that commercial UAVs cannot be flown above an altitude of 400 ft. without special permission from the FAA.

Another reference point is the “Drone Integration and Zoning Act of 2019,” a bill introduced in the U.S. Senate on October 16, 2019 and reintroduced in 2021 which proposes the following key altitude restrictions (Lee Utah, 2019). These restrictions are pictorially interpreted in Figure 3-5 and below:

- S.2607.3.e.1: “Nothing in this section may be construed to ... prohibit the Administrator from promulgating regulations related to the operation of unmanned aircraft systems at more than 400 feet above ground level;
  - (A) The Administrator [FAA] shall not authorize the operation of a civil unmanned aircraft in the immediate reaches of airspace above property without permission of the property owner.
    - ... in the case of a structure that exceeds 200 feet above ground level, the Administrator shall not authorize the operation of a civil unmanned aircraft –
      - (i) within 50 feet of the top of such structure; or
      - (ii) within 200 feet laterally of such structure or inside the property line of such structure’s owner, whichever is closer to such structure.
  - (B) The Administrator shall not authorize the physical contact of a civil unmanned aircraft, including such aircraft’s take-off or landing, with a structure that exceeds 200 feet above ground level without permission of the structure’s owner.
  - (C) The Administrator [FAA] shall ensure that the authority of a State, local, or Tribal government to issue reasonable restrictions on the time, manner, and place of operation of a civil unmanned aircraft system that is operated below 200 feet above ground level is not preempted.”

with the term “immediate reaches” defined as

S2607.2.4: “The term ‘immediate reaches of airspace’ means, with respect to the operation of a civil unmanned aircraft system, any area within 200 feet above ground level.”

and the term “reasonable restrictions” defined as

S2607.2.4.b.3: “reasonable restrictions on the time, manner, and place of operation of a civil unmanned aircraft system include the following:

- (A) Specifying limitations on speed of flight over specified areas.
- (B) Prohibitions or limitations on operations in the vicinity of schools, parks, roadways, bridges, moving locations, or other public or private property.
- (C) Restrictions on operations at certain times of the day or week or on specific occasions such as parades or sporting events, including sporting events that do not remain in one location.
- (D) Prohibitions on careless or reckless operations, including operations while the operator is under the influence of alcohol or drugs.
- (E) Other prohibitions that protect public safety, personal privacy, or property rights, or that manage land use or restrict noise pollution.”

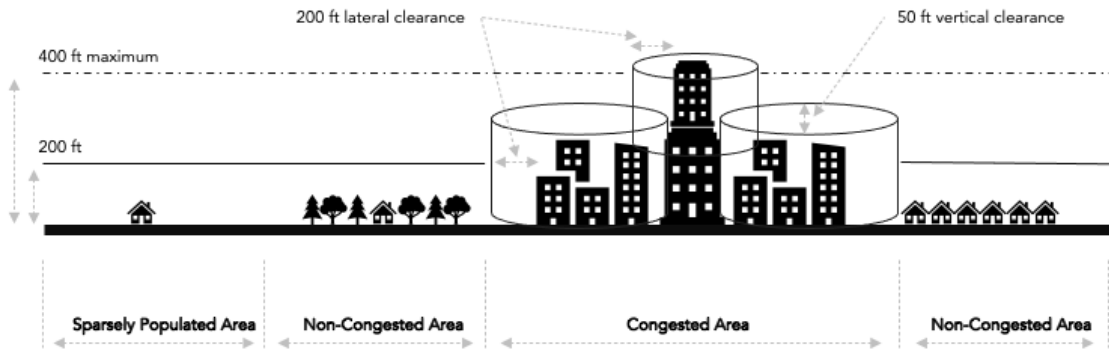


Figure 3-5: Pictorial depiction of suggested regulatory framework in “Drone Integration and Zoning Act of 2019” for aircraft flight minimums.

Whilst the “Drone Integration and Zoning Act” has not progressed past the bill introduction phase as of May 2022, its approach to and frameworks for UAV-LMD altitude minimums can offer a benchmark this thesis can build off of. In translation, the Act suggests that UAV-LMD should:

- not be permitted to fly above 400 ft.;
- not be permitted to fly in the immediate reaches of private property, defined as 200 ft. above ground level (AGL);
- not be permitted to fly within 50 ft. vertically and 200 ft. laterally of a structure that exceeds 200 ft. in altitude;

- be subject to state and local regulation below 200 ft. with the FAA reserving sole authority of regulation above 200 ft.

This structurally means that UAV-LMD is strictly limited to the altitude range of 200-400 ft. nationwide and is subject to local and state regulation in altitude ranges below 200 ft. It also means that UAVs are inherently limited in their ability to vertically scale structures that protrude into this altitude range if they do not offer 50 ft. of clearance between their roof and the 400 ft. altitude ceiling.

A key takeaway is that sub-200 ft. altitudes are emerging as an area of regulatory uncertainty. This is because minimum altitude constraints in these altitudes are likely going to be left to local regulators to manage and that their methodologies for defining such regulations will likely be driven by definitions of noise nuisance, privacy and trespass (discussed in Section 3.2) but also definitions of land-use zoning, perceived congestion levels, protected regions (such as schools or parks), and the eventuality of irregular public events. Many of these definitions are likely to differ between states and municipalities, making minimum altitude constraints all the more complex for UAV-LMD operators.

Finally, in the constraint sensitivity analysis performed in Chapter 5, this thesis assumes the operating altitude minimums and maximums to be kept constant. This is because the operating band of 200 - 400 ft. derived from case law, pertinent but incomplete bills and FAA regulation is already highly constraining and tighter altitudes bound likely conflict with in-air UAV separation requirements that are further discussed in Section 3.1.1.3. Thus, the outer bounds of 200-400 ft. as altitude minimums and maximums are not varied in the sensitivity analysis.

### 3.1.1.2 Operating Weight Constraints

Just as in the case of minimum and maximum altitude constraints, when it comes to operating weight constraints, how local and municipal regulators are likely to constrain operations is the most obvious area of uncertainty. The current status quo for operating weight constraints comes from FAA Part 107 which limits the UAV's max take-off weight (MTOW) to under 55 lbs. actually in the definition of what size vehicle can be legally certified under Part 107, quoted as

“Part 107 defines a small unmanned aerial system (UAS) as any uncrewed aircraft weighing less than 55 pounds” (FAA § 107.3 Part 107, 2020).

The FAA does offer a pathway to operate UAVs with MTOWs with more than 55 lbs. via what is termed a 49 U.S.C. 44807 grant of exemption whereby the operator must prove,

1. “Is in the public interest; and
2. Would not adversely affect safety or would provide a level of safety equal to that provided by the regulation.” (Malecha, 2019).

It is noted that being granted this exemption is particularly difficult for UAVs because, as of now, the vehicles themselves do not go through a standardized and rigorous aircraft design and performance envelope certification process making proving (b) more difficult for operators. Figure 3-6 highlights the key weight dimensions – empty weight, max payload capacity and MTOW – for the major UAV-LMD hardware players. It is worth noting that the majority of players have designed vehicles subservient to the Part 107 MTOW limit of 55 lbs. by way of minimizing their vehicle’s empty weight via aircraft design and by constraining their max payload capacity either artificially or via other dimensional constraints such as volume or safety. Amazon’s delivery UAV is the only outlier here, likely because they possess a fleet of already weight-compliant UAVs and have designed their latest UAV expecting change in the MTOW constraint in future regulation.

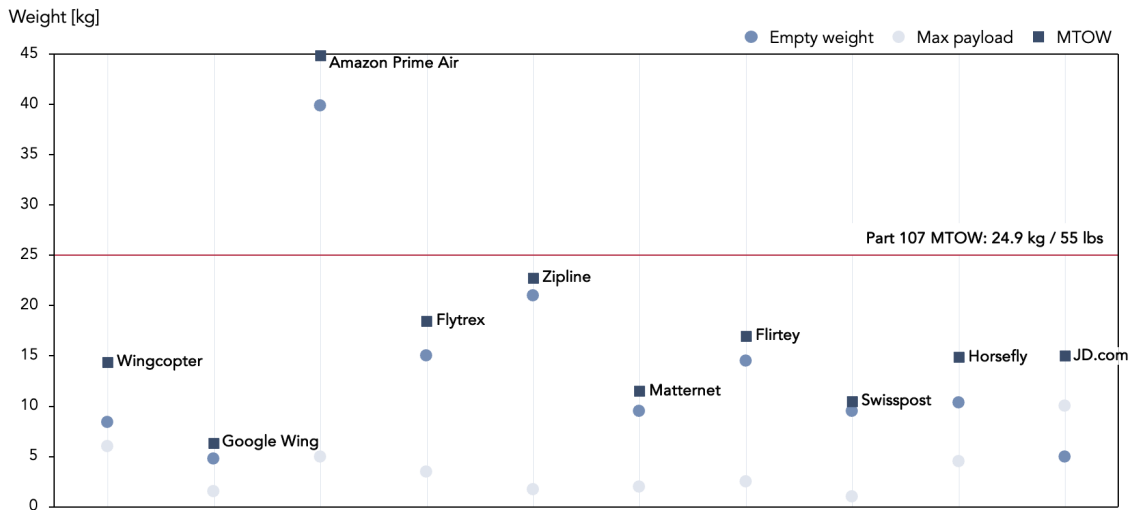


Figure 3-6: Survey of leading UAV-LMD industry leaders in UAV hardware empty weight, max payload weight and MTOW.

Given this anticipated upper bound on weight of 55 lbs., at least in the near future, the next question to evaluate is if there is potential for tighter upper bounds that could further constrain operations. Looking to the “Drone Integration and Zoning Act of 2019”, one can interpret the stipulation to answer this question.

S.2607.3.e.1.C: “The Administrator [FAA] shall ensure that the authority of a State, local, or Tribal government to issue reasonable restrictions on the time, manner, and place of operation of a civil unmanned aircraft system that is operated below 200 feet above ground level is not preempted.” (Lee Utah, 2019).

Firstly, the term “manner” could well provide grounds for local or state regulators to apply operating weight constraints that are more constraining than the FAA’s 55 lb MTOW limit. With that said, the bill is peppered with references to the 200

ft. boundary between national airspace under the purview of the FAA and local regulators. If relevant regulation evolves along the lines of the bill’s rationale, the FAA will likely continue to dominate UAV-LMD regulation with limited authority outsourced to local regulators. Could local regulators restrict total operating weight for periods of a UAV’s flight trajectory that occur below 200 ft. such as take-off, delivery and landing? Whilst it remains unclear how courts will interpret this gray area, this thesis judges the likelihood that local regulators can further constrain total operating weight across a sufficiently large geographic region is too low for variable weight constraints to be integrated into any explicit model.

### 3.1.1.3 In-Air Vehicle Separation Restrictions

The notions of airspace structure and in-air separation exist to provide a priori separation and organization of aerial traffic in what is otherwise an unconstrained operating environment. This is particularly true for altitudes well above geological and urban structures. Thus, in-air separation is not a safety-related or operational challenge unique to UAV-LMD but to both manned and unmanned aviation more broadly. Beyond controlled airspace, aircraft separation services are not typically provided by ATC towers. Instead, aircraft operators are left to their own devices to remain “well clear” of other aerial vehicles and maintain an “acceptable” level of safety. the idea of “acceptable” level of safety is a complex conundrum, particularly in the aviation industry, but it typically comes down to rigorous simulations that certify that the probability of catastrophic disaster and human fatalities are similar to an equivalent probability in another domain in aviation or transport. The notion of “well clear,” on the other hand, stems from FAR Part 91 General Operating and Flight Rules, which states only two requirements to meet compliance:

- 91.111: “... not operate so close to another aircraft as to create a collision hazard”; (FAA § 91.111 Part 91, 2020)
- 91.113: “Vigilance shall be maintained ... so as to see and avoid other aircraft ... pilots shall alter course to pass well clear of other air traffic.” (FAA § 91.113 Part 91, 2020).

FAR Part 91 goes on to state that formation flight is possible if all pilots in command agree to the formation, with the only exception being if there are paid passengers on board any of the participating aircraft. But to translate these FAR Part 91 requirements into guidelines for manned aircraft pilots today, a mixture of rules are applied depending on cruise altitude. The first approach to self-separation is cruise altitude stratification based on flight direction. This often takes the shape of the quadrantal rule, which is enforced within the altitude range of 3000 ft. to FL240 (Ford, 1983). In the quadrantal rule, aircraft with headings between 000–089° are required to fly at odd altitudes in multiples of 1000 ft., whilst aircraft with headings 090–179° are constrained to odd altitudes in multiples of 1500 ft. Similarly, flights with headings between 180–269° must utilize even altitudes in multiples of 1000 ft., whilst flights with headings in the range of 270–359° are constrained to even altitudes

in multiples of 1500 ft. This approach typically applies to aircraft flying under Instrument Flight Rules (IFR) above 2000 ft. mean sea level (MSL) or aircraft flying under Visual Flight Rules (VFR) above 3000 ft. MSL. With that said, all IFR flights must provide specific flight trajectories before take-off which may not precisely follow these altitude separation standards. For aircraft cruising above FL240 (which is a unit of aircraft altitude, or flight level, measured at standard air pressure and expressed in hundreds of ft.) a similar hemispheric rules is commonly used. This rule ensures that cruising aircraft above FL240 with travel directions in ranges of  $000\text{--}089^\circ$  and  $090\text{--}179^\circ$  are assigned to odd altitudes in multiples of 10, while cruising aircraft with headings between  $180\text{--}269^\circ$  and  $270\text{--}360^\circ$  are constrained to even flight levels in multiples of 10 (Ford, 1983). Both airspace structure frameworks exist to lower conflict probability and thus decrease incidence probabilities and increase airspace capacity.

For low-altitude aircraft operations, however, self-separation via altitude stratification based on heading either: 1) has not been comprehensively defined and trialed; 2) is not currently well adopted, or 3) is not currently mandated as part of operational regulations. Instead, self-separation is predominantly maintained via longitudinal and latitudinal separation. One additional dimension to in-air vehicle separation that is relevant to low-altitude flight is that of repeating time intervals between sequential take-off and landing procedures. Both fixed-wing and rotary-wing (i.e., helicopters) aircraft generate strong wake vortices during take-off and landing maneuvers that emanate from the wing-or blade-tips. The kinetic energy contained in these vortices dissipates over the following minutes but, until then, can prove disruptive forces in the aerodynamics of following aircraft. But since the strength of such vortices decreases with the mass of the aircraft responsible, take-off and landing time intervals have not been commonly discussed in the context of UAV-LMD operations. However, if such UAVs are operated in an airfield with other much larger aircraft, such time delays will, indeed, have to be taken into account to ensure the UAVs do not enter potentially unstable flight dynamics.

A commonly cited method for installing low-altitude airspace structure is to simply duplicate the ground-level street network in the air to serve as UAV “highways” (Thompson, 2019). This is a popular idea because urban street networks contain a great deal of positional information about the physical layout and geographical constraints of a city and its buildings. Furthermore, this could minimize the negative externalities that UAV-LMD are likely to impart on society – be it noise, privacy or trespass – just by being strictly situated over streets and highways. With regards to noise, not only would UAV-LMD noise pollution likely be masked by that from the road traffic below, but the public are likely more tolerant of noise emitted on streets because of its historic association with road-traffic and noise. With regards to privacy and trespass, since streets are, on the whole, public goods and assets, UAV-LMD can eschew the risks associated with private property on either side of street. This is to say that much of the information and benefits contained in urban street networks can be quickly assimilated into the low-altitude airspace structure with little overhead. With all its benefits, the notion of UAV “highways” has not yet been adopted in prac-



tice because of some key issues. First, such “highways” could well substantially reduce the efficient point-to-point travel advantages that UAV-LMD has over ground-based delivery modes. Thus, UAV-LMD industry players are actively push back against such regulation. Second, the aviation industry is unfamiliar with the notion of aerial “highways”, particularly true in low-altitude flight, since airspace structures until now have been built upon distinctions between VFR and IFR and the quadrantal and hemispheric rules. Third, such “highways” could constrict UAV-LMD operations to a narrow lateral and vertical band of airspace and inadvertently increase conflict and collision probabilities. Such a narrow band of airspace may simply not be adequate to support expected UAV-LMD delivery volumes.

So although requirements for in-air separation are not well defined for low-altitude aircraft operations or uniquely defined for urban areas, they are currently commonly accepted in more traditional aviation domains to provide a safer and more fluid airspace. In high flight-density regions such as New York City, the FAA has worked with local regulators to define special flight rules and communication frequencies that go beyond FAR Part 91 and accepted airspace management frameworks to further minimize conflict probabilities (Federal Aviation Administration, 2022c). This thesis posits that in-air separation frameworks will either exist as accepted standards in low-density UAV-LMD regions or as special operating procedures, codified in regulation, in high-density UAV-LMD regions. But the shape that such frameworks take in both scenarios remains unclear. Because time-dependent separation during take-off and landing procedures is predominantly driven by safety concerns operating in wake vortices, such operating constraints are not modeled in the UAV-LMD routing model.

With regards to altitude stratification protocols, dynamic detection and avoidance algorithms that UAVs will likely leverage as fail-safe collision avoidance mechanisms are beyond the scope of this thesis. Their dynamism alone defines them as closer to a stochastic routing problem than the static models this thesis is centered around. Instead, this thesis attempts to incorporate a static altitude stratification protocol akin to the hemispheric or quadrantal rules for urban UAV-LMD operations. Based on the analyses of drone collision probabilities based on kinetic theory and interesting insights on how to strictly minimize collision probability in a dense urban area, this thesis adopts the following altitude stratification logic for modeling purposes (also depicted in Figure 3-7):

- UAVs travel due north ( $315-045^\circ$ ) in the altitude range of 200-250 ft.;
- UAVs travel due east ( $045-135^\circ$ ) in the altitude range of 250-300 ft.;
- UAVs travel due south ( $135-225^\circ$ ) in the altitude range of 300-350 ft.; and
- UAVs travel due west ( $225-315^\circ$ ) in the altitude range of 350-400 ft.

The specifics of such a stratification logic is not critical. This thesis, instead, seeks to understand the impact a stratification logic can have on the unmanned aerial vehicle routing problem (URP) solution. Note that such an airspace structure does



Figure 3-7: Graphic of proposed altitude stratification protocol for UAV-LMD.

not address the collision risk when UAVs ascend into and descend from their allocated altitude strata to take-off or land. One approach is to analytically show that the probabilities of collision based on expected UAV numbers meet an acceptable risk threshold, and not intervene with specific protocols (do). Another approach would be to perform take-off and landing procedures in conjunction with unmanned aircraft system traffic management (UTM) systems (as they are today for the majority of larger manned aviation operations) to further minimize collision probabilities.

Such a stratification protocol could also break down if geographical barriers do not permit UAVs to fly due north because of their allocated altitude range but do permit travel due east, south or west. One solution would be to strictly disallow UAVs beyond their allocated altitude strata with UAVs that want to fly due north having circumnavigate any geographical obstacle. Another solution could be to allow UAVs to travel beyond their allocated altitude strata but with safety contingencies such as a maximum time in a different altitude strata or a certain level of on-board collision avoidance capability.

This thesis ignores both scenarios in its modeling of the URP because they represent edge case scenario that are not likely to alter the directional insights that Chapter 5 seeks to uncover about UAV-LMD sensitivity to societal constraints. In the constraint sensitivity analysis in Chapter 5, this thesis assumes that, in the baseline case, no in-air separation is enforced, but in all other cases, the proposed altitude stratification protocol is employed. Note, this constraint is not made more restrictive in any way as part of the constraint sensitivity analysis but rather held constant.

#### 3.1.1.4 Take-Off and Landing Considerations

Traditionally, manned aircraft that could be considered and regulated as low-altitude aircraft operations often spent the majority of their flight time at altitudes well above the prescribed minimum flight altitude and even well above low-altitude heights all together. During take-off and landing procedures, however, these aircraft operated in much closer proximity to urban structures and human populations below. Currently, take-off and landing procedures are regulated as exemptions to the rules that pertain to low-altitude flight. As discussed in Section 3.1.1.1, FAR §91.119 exempts aircraft that are performing take-off or landing maneuvers from the prescribed flight minimums (FAA § 91.119 Part 91, 2020). Pilots of these manned aircraft must ad-

here to procedures and standards that are publicly available and often part of the pre-flight airspace familiarization procedure for that particular airfield. Additionally, pilots are typically informed about local hazards and safety considerations for that particular airfield and nearby airfields. Take-off and landing operations at locations not designated as official airfields are often possible but likely subject to a different set of operational and regulatory constraints often set by local municipal and state regulators. These are typically designed to protect against the societal externalities (see Section 3.2) that landowners and local communities are impacted by.

UAVs involved in UAV-LMD are not only likely to be in close proximity to ground-based hazards during take-off and landing but also during their package delivery procedures and even in cruise flight considering their current altitude range restrictions. Thus, whilst much of this regulatory structure will likely also apply to UAVs involved in UAV-LMD, it is unclear if any additional constraints will emerge for UAV-LMD specifically. Even for manned aircraft, regulations around take-off and landing procedures for low-altitude aircraft are ill-defined at the federal level. Thus, this thesis posits that take-off and landing constraints for UAV-LMD will likely be more heavily dependent on local and state regulations rather than the FAA, and that the shape such constraints take will be highly dependent on the local stakeholders involved and their preferences. §S.2607.3.e.1 in the “Drone Integration and Zoning Act of 2019” empowers local and state regulators to regulate the “time, manner and place of operation” UAV operations. This power could well be exercised to reflect the needs and expectations of the community stakeholders involved. In this eventuality, this thesis expects take-off and landing procedures to also be regulated as to protect those same needs and expectations in a similar fashion, be it via maximum noise emissions standards, flight frequency caps or flight time-of-day restrictions.

Thus, from the perspective of federal regulation, this thesis assumes there to be no additional take-off- and landing-specific regulations relevant for UAV-LMD. And for modeling purposes, this thesis does not attempt to model the different potential eventualities that local and state regulators could enact via local take-off and landing constraints. Instead, this thesis assumes a simple heuristic for take-off and landing procedures: UAVs do not perform a shortened vertical take-off maneuver followed by an angled climb segment to cruise altitude. Instead, it is assumed that UAVs perform a single vertical take-off climb maneuver to their cruise altitude at which they transition to horizontal flight. This avoidance of an angled climb and descent is assumed for the UAVs’ landing maneuvers as well.

### **3.1.1.5 Flight Zoning Restrictions**

Today, UAV-LMD airspace restrictions and flight zoning is predominantly instituted by the FAA and are termed “No Drone Zones.” The FAA operates an online platform, B4UFLY, in partnership with ALoft, formally Kittyhawk, that informs UAV operators where they are permitted and not permitted to fly. It also guides users through the process of submitting for automatic authorization to fly in non-controlled airspace

regions but does not facilitate this process for controlled airspace regions, known as the FAA’s Low Altitude Authorization and Notification Capability (LAANC), since such authorization must be granted by the ATC unit of the relevant airport or airfield. The types of “No Drone Zones” that currently exist are (Federal Aviation Administration, 2022b):

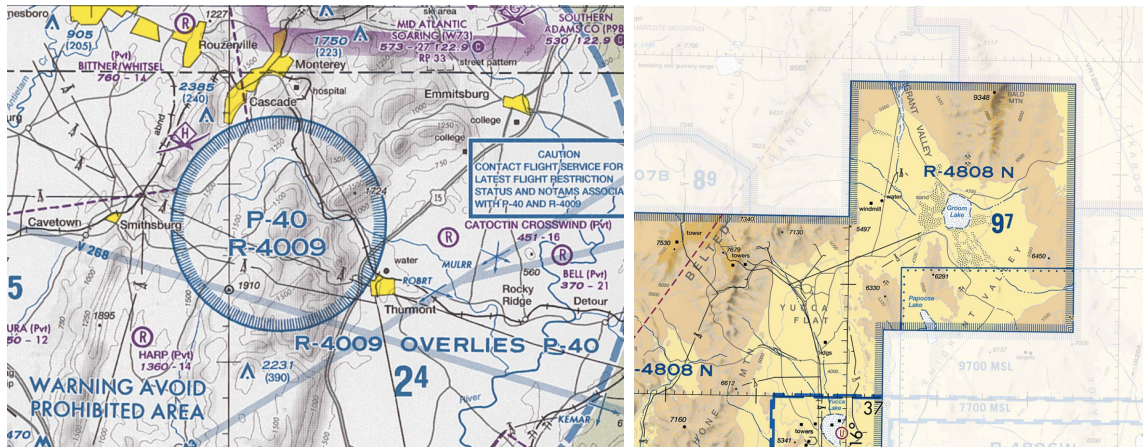
- Prohibited airspace: these regions of airspace fully prohibit aerial operations, both manned and unmanned, and are typically time-independent. Such areas are established under national welfare interests. Examples of such areas are Thurmont, MD, the site of Presidential retreat Camp David or Naval Submarine Base Kings Bay, GA. These are typically clearly depicted and publicized on aeronautical charts, see Figure 3-8a, and also feature on the B4UFLY application.
- Restricted airspace: regions of airspace through which any civilian aviation traffic, both manned and unmanned, are not permitted but may only be exercised during certain “active” times. These regions often contain unusual and hazardous operations such as missile launch sites, air combat training, military bases.
- Local restrictions: in some locations, UAV take-off and landing operations are restricted by state, local, territorial or tribal regulatory agencies. Note that these operators have the power to specifically restrict take-off and landing operations but currently do not possess the power to restrict flight in the airspace above the identified area. This will be discussed in further detail in Section 3.1.2. Additionally, national, state and potentially municipal parks or prisons and detainment locations, sport stadiums, schools and hospitals also represent locations that are often capable of imposing zoning restrictions through various regulatory or advisory pathways. Whilst many of these locations are explicitly stated on public forums and informational pages, it can often be unclear whether a specific location is, indeed, restricted airspace mandated through regulation or rather through a flight zoning advisory memorandum.
- Temporary flight restrictions: these are specific areas for which UAV operations are not permitted for a limited period of time with pre-approved certification by the FAA. Examples of such restrictions may include sporting events, presidential movements, natural disasters or security-sensitive areas designated by other federal agencies. Such restrictions can include geo-fencing, altitude minimums and maximums, time and the types of operations that are permitted.

In addition to “No Drone Zones” and the various levels of zoning restrictions mentioned above, there are likely to be additional context-specific restrictions based on the agreements the UAV-LMD operator has reached with any ATC operators of airfields that have jurisdiction of the region of operation. For example, an UAV-LMD operator in Boston, MA, will likely have had to gain an operations waiver from both the FAA and work directly with Boston Logan International Airport to establish additional zoning and time-dependent zoning restrictions based on any emergency

take-off or landing events centered at Logan. So whilst, today, UAV-LMD operators may be totally barred from the Class B airspace imposed by Boston Logan unless granted a waiver, closer collaboration between operator and Boston Logan could mean that UAV-LMD has to simply avoid a tighter geo-fence around Boston Logan and the projected take-off and approach flight paths into its six runways. UAV original equipment manufacturer (OEM) DJI actually provides an informational flight zoning service worldwide for its customers through which they advise to avoid high-altitude flight in Boston Logan’s published approach flight paths (DJI, 2022). This thesis leverages these vaguities around potential additional zoning restrictions as part of the constraint sensitivity analysis in Chapter 5. This thesis posits that many of the locations that are now only considered “restricted airspace” and “local restriction” locations above in certain regions across the U.S. will become more commonly enforced across the country, these locations being: stadiums and sporting locations, prisons and detainment locations, schools, national, state and certain municipal parks and hospitals.

In the case study analysis in Chapter 5, this thesis first leverages existing flight restrictions instituted by the FAA as a baseline for solving the GURP. But because the case study analysis intends to vary the intensity of the exogenous constraints on UAV-LMD operations, this thesis must assume additional flight zoning restrictions that surpass the current baseline zoning restrictions. Thus, based on historical temporary flight restriction ordinances and cases of apposite local regulation, this thesis posits that the additional locations are iteratively added to the GURP problem definition as the intensity of the exogenous constraints is increased. For the Greater Boston region, the location of the case study in Chapter 5, this thesis manually geofences these regions forming lateral polygons that act as no-fly zones for UAV-LMD operations. These polygons feed into the visibility graph logic discussed in Section 3.3 that defines the permissible flight trajectory a UAV can take between two points to serve demand, which in turn dictates the distance matrix that the GURP models employ.

Currently “No Drone Zones” are exclusively instituted by the FAA with state and local regulators only permitted to enact pseudo-zoning restrictions via take-off and landing operations constraints. The trade-offs of federal versus local regulation particularly with regards to UAV-LMD zoning restrictions will be discussed in more detail in Section 3.1.2. But as mentioned in Section 3.1.1.4, potential local take-off and landing restrictions will not be modeled in this thesis. Furthermore, because of the temporal dimension of temporary flight restrictions, they too will not be captured in the models this thesis leverages since it is the static URP that this thesis seeks to capture. The notion and importance of time-dependent regulation, however, will be discussed in more detail in Section 3.1.2.



(a) Prohibited airspace, Camp David, MD. (b) Restricted airspace Yucca Flat nuclear test site, AZ.

Figure 3-8: Prohibited and restricted airspace aeronautical chart examples.

### 3.1.1.6 Safety-Related Procedures and Precautions

When it comes to precautionary safety measures, the aviation industry is steeped in history and regulation and typically receives a substantial amount of public scrutiny around safety practices and track records. In 1926 to 1927, there were a total of 24 fatal commercial aircraft accidents amounting to an accident rate of 1 for every 1 million miles flown. Scaled to today's flight hours, this would equate to 7000 fatal incidents per year. Today's actual rate (during the period of 2002 to 2011 assumed to be comparable to today's safety record) is 0.6 fatal incidents per 1 million miles or a 99.9% decrease (CAA, 2013). Whilst aviation safety is an incredibly detailed and complex topic, there is value in exploring some of the overarching themes that aviation safety is centered around. This section does not seek to explore the broad topic that is how UAV-LMD safety precautions will likely evolve over the coming years. Instead, this section aims to simply filter the safety precautions taken for general manned aircraft operations for those constraints potentially relevant for UAV-LMD and supplement these constraints with any UAV-specific safety constraints that could emerge. ost offers an accessible summary of key aviation safety themes.

#### General aviation safety themes.

##### *Safety hazards*

- Weather: from lightning strikes to ice and snow, aircraft are designed to minimize the risk of catastrophic system failure in these eventualities. For instance, aircraft are covered in a metal "skin" that offer the first line of protection from lightning strike but they also contain a second metal mesh "skin" that conducts electricity around the outside of the vessel, minimizing risk of voltage shocks to those onboard and onboard flight controls and wiring. Of course, flight trajectory planning to minimize lightning strike risk is also a critical precautionary

strategy. Pre-flight de-icing procedures and built-in de-icing technologies on aircraft wings and engines intakes also exist.

- Component or structural failures: whilst there are a number of precautionary measures (discussed below) taken to minimize the risk of foreign object damage, excessive load cycling and material fatigue or manufacturing defects, aircraft are designed with numerous redundancies and flight envelope buffers to mitigate catastrophic engineering failures.
- Human factors: pilot error is often cited as the most common factor in aviation accidents. Typical causes of human error are pilot fatigue, communication failures or incompetence, all of which are combated via training procedures and certification processes such as rigorous pilot licensing, Crew Resource Management procedures, rules and regulations around protecting crew health and alertness and a technological push to flight autonomy and augmenting onboard decision making processes.
- Runway safety: Runway incidents typically fall within the following incident types: runway excursion (the aircraft exits the runway incorrectly), overrun (runway overshoot), incursion (a foreign object incorrectly enters the runway), and confusion (miscommunications or misunderstandings during take-off or landing procedures).

#### *Accident survivability*

- Airport design: ground-based infrastructure design can have a large impact on aviation safety, also often dictated around the types of aircraft the airport was designed around (propellers versus jets). Runway buffers and technologies (one example being engineered materials arrestor systems), security protocols and onsite emergency services all serve to minimize the likelihood of accidents becoming fatal.
- Emergency response procedures: from onboard evacuation procedures and associated technologies to aircraft design centered around frictionless evacuation to onboard and airport-based emergency response equipment and materials, the aviation industry and aircraft design is designed around worst-case emergency response scenarios.

#### *Precautionary measures*

- Certification: is the means through which regulators, namely the FAA, manage risk through safety assurance providing a level of confidence that a proposed product or operation will meet the safety expectations set by the regulator and the society that regulator is representing. Certification is pervasive in the aviation industry and can be categorized in the following buckets:
  - Airmen: pilot, mechanic and crew typically fall in this category;

- Aircraft: airworthiness (whether a particular aircraft meets safety standards as is fit to fly) and type certificates (whether a particular kind of aircraft is approved to fly) based on aircraft design and testing. Special airworthiness also falls in this category and is often used to cover experimental aircraft to promote research & development (R&D), but with severely limited scope for operations.
  - Production: pertains to a manufacturer’s approval to manufacture the vehicle or vehicle components that fall under an approved vehicle type certificate, based on the manufacturers personnel, equipment, quality control and product testing.
  - Air carrier: typically covers airline and airline operator, pilot and training school, repair station and maintenance training certification.
  - Airport: certifies airports for their ability to serve scheduled and unscheduled aircraft with all necessary safety equipment, procedures, personnel, training and infrastructure available.
- Information and communication: information overload, pronunciation issues and communicative misunderstandings are key reasons behind aviation incidents. ATC providers, pilots and crew are often required to speak several languages as a redundancy to the de-facto worldwide aviation language, English, for which trainees must pass examinations for to receive their licenses. Furthermore, a host of standardized phrases and communication protocols used across airports and countries are adopted to minimize the risk of misunderstandings.
  - Pre-flight checks: these are typically a list of tasks that should be performed by pilots and crew prior to take-off or after the aircraft docks at its final landing gate to improve flight safety by ensuring no important tasks are forgotten or overlooked. Pre-flight checks also serve to identify any damage or material fatigue that might have accrued during recent flights but between larger maintenance overhaul schedules that could compromise performance in an upcoming flight.
  - Aircraft maintenance: because of the often extreme performance routines that aircraft undergo and the natural cycling of aircraft operations (repeated take-off, climb, cruise and landing operations), the components and materials on the aircraft typically undergo wear-and-tear and material fatigue. Extensive documentation, protocols and regulations exist to ensure aircraft maintenance is performed comprehensively and to an acceptable standard regardless of where it is performed and by whom. Maintenance licensing also serves this purpose. Aircraft design can also be significantly guided around maintainability.

### **The UAV-LMD perspective.**

Much of these high-level safety priorities has been and will need to continue to be translated into FAR Part 107, FAR Part 135 and any additional regulatory



frameworks in the coming years to ensure the safety expectations of the stakeholders involved are met, one key stakeholder being the urban communities in which UAV-LMD will likely operate. However, whilst many of these safety precautions will necessarily be translated over to UAV-LMD before substantial commercial operations could commence, it is beyond the purview of this thesis to extrapolate how these best practices in commercial manned aviation could look in UAV-specific regulation. This section addresses only those safety precautions considered relevant to and implementable in the URP this thesis solves, i.e. impact UAV operational times and procedures between the start and end of the delivery day.

Safety hazards for instance typically refer to factors extrinsic to the operation of the UAV itself such as weather, human factors, take-off and landing safety and vehicle component failures. Whilst component and structural failures could well be related to how a UAV is operated, it is more likely to a manufacturing default or material failure. Thus, this thesis eschews conversations around safety hazards. Accident survivability also falls into this category of safety precautions that lie outside of the day-to-day operations of UAV-LMD and is, thus, not considered in this thesis's URP.

Certification, particularly from the perspective of manufacturing, materials testing, operational fatigue and degradation and maintenance and standardization of personnel training, is pivotal to ensure a certain level of safety is met across UAV-LMD operations and it remains a clear gap in current regulatory frameworks for UAV-LMD. But however pivotal such certification is to UAV-LMD safety, this thesis is only concerned with regulation that directly pertains to operations. This also applies to the information and communication protocols currently standard in manned aviation. Much of this is already captured in FAR Part 107 and will not be discussed in more detail here. One dimension of precautionary measures that could emerge as an operational constraint, however, is that pertaining to pre-flight checks and post-flight inspections. This is because pre-flight checks are, indeed, operational constraints that current commercial air-freight and airlines contend with as they strive to minimize time that the aircraft is grounded, i.e. airport turn-around times. This section begins to analyze current FAR Part 107 pre-flight check requirements for UAVs and supplements this with additional pre-flight check requirements from current manned aircraft operations that this thesis suspects may be appended to current requirements as UAV-LMD continues to scale. Future UAV-LMD operators will likely leverage other standard pre-flight procedures such as the personal/pilot, aircraft, environment, and external pressures (PAVE) and illness, medication, stress, alcohol, fatigue, emotion (IMSAFE) checklists.

FAR Part 107 §107.49 “Preflight familiarization, inspection, and actions for aircraft operation” currently stipulates the following with additional additional guidance provided through an Advisory Circular 107-2A on §107.49:

- (a) “Assess the operating environment, considering risks to persons and prop-

erty in the immediate vicinity both on the surface and in the air. This assessment must include:

- 1) Local weather conditions;
  - 2) Local airspace and any flight restrictions;
  - 3) The location of persons and property on the surface; and
  - 4) Other ground hazards.
- (b) Ensure that all persons directly participating in the small unmanned aircraft operation are informed about the operating conditions, emergency procedures, contingency procedures, roles and responsibilities, and potential hazards;
- (c) Ensure that all control links between ground control station and the small unmanned aircraft are working properly;
- (d) If the small unmanned aircraft is powered, ensure that there is enough available power for the small unmanned aircraft system to operate for the intended operational time;
- (e) Ensure that any object attached or carried by the small unmanned aircraft is secure and does not adversely affect the flight characteristics or controllability of the aircraft; and
- (f) If the operation will be conducted over human beings under subpart D of this part, ensure that the aircraft meets the requirements of §107.110, §107.120(a), §107.130(a), or §107.140, as applicable.” (FAA § 107.49 Part 107, 2020a).

Advisory Circular 107-2A on §107.49 goes on to assert:

7.3: “Pursuant to the requirements of §107.49 ... the remote PIC must inspect the small UAS to ensure that it is in a condition for safe operation prior to each flight. This inspection includes examining the small UAS for equipment damage or malfunction(s). This preflight inspection should be conducted in accordance with the small UAS manufacturer’s inspection procedures when available ... and/or an inspection procedure developed by the small UAS owner or operator.” (FAA § 107.49 Part 107, 2020b).

and details specific pre-flight inspection items for UAVs in §7.3.4:

1. “Visual condition inspection of the small UAS components;
2. Airframe structure (including undercarriage), all flight control surfaces, and linkages;
3. Registration markings, for proper display and legibility;
4. Moveable control surface(s), including airframe attachment point(s);
5. Servo motor(s), including attachment point(s);
6. Propulsion system, including powerplant(s), propeller(s), rotor(s), ducted fan(s), etc.;
7. Check fuel for correct type and quantity;
8. Check that any equipment, such as a camera, is securely attached;

9. Check that control link connectivity is established between the aircraft and the control station (CS);
10. Verify communication with small unmanned aircraft and that the small UAS has acquired GPS location from the minimum number of satellites specified by the manufacturer;
11. Verify all systems (e.g., aircraft and control unit) have an adequate power supply for the intended operation and are functioning properly;
12. Verify correct indications from avionics, including control link transceiver, communication/navigation equipment, and antenna(s);
13. Display panel, if used, is functioning properly;
14. Check ground support equipment, including takeoff and landing systems, for proper operation;
15. Verify adequate communication between CS and small unmanned aircraft exists; check to ensure the small UAS has acquired GPS location from the minimum number of satellites specified by the manufacturer;
16. Check for correct movement of control surfaces using the CS;
17. Check flight termination system, if applicable;
18. Check that the anti-collision light is functioning (if operating during civil twilight and night);
19. Calibrate small UAS compass prior to any flight;
20. Verify controller operation for heading and altitude;
21. Start the small UAS propellers to inspect for any imbalance or irregular operation;
22. At a controlled low altitude, fly within range of any interference and recheck all controls and stability; and
23. Check battery levels for the aircraft and CS.”

Between FAR Part 107 and the Advisory Circular, the FAA has provided ample material for operators to build upon and for this thesis to postulate how pre-flight checks will be integrated into daily operations. However, the FAR Part 107 pre-flight check regime detailed above would be required before every UAV flight and, thus, may strike the reader as stringent and costly both in time-delay and labor. UAV operators can also expect to be required to perform periodic maintenance checks as is required for commercial aircraft. On top of the standard pre-flight check, commercial aircraft undergo a series of more involved maintenance checks termed line-, A-, B-, C-, and D- checks which are done on a periodic basis measured by total flight hours or total number of flight cycling since the last check of the same type (National Aviation Academy, 2020). Whilst flight cycling may seem an arbitrary unit of maintenance measure, it is deemed important, particularly in commercial aircraft, to prevent excessive material cycling and fatigue. However, in both Part 107 and the Advisory Circular 107-2A the FAA has not detailed specific maintenance schedules for UAVs but only stipulates:

7.2: “[S]cheduled and unscheduled overhaul, repair, inspection, modification, replacement, and system software upgrades ... necessary for flight. ... operator

should maintain ... in accordance with manufacturer’s instructions ... or, if one is not provided, ... may choose to develop one.”

7.2.1: “The manufacturer may identify components of the small UAS that should undergo scheduled periodic maintenance or replacement based on time-in-service limits (such as flight hours, cycles, and/or the calendar-days). Operators should adhere to the manufacturer’s recommended schedule for such maintenance.”

7.2.1.1: “If the small UAS manufacturer or component manufacturer does not provide scheduled maintenance instructions, the operator should establish a scheduled maintenance protocol.”

The FAA’s maintenance guidelines, thus, do not provide specific time-limits for maintenance and defer to 1) UAV OEMs to provide suggested maintenance schedules; and 2) UAV operators to supplement or define their own maintenance schedules to maintain safe operations. This thesis, thus, posits that the key drivers that operators will respond to that will guide maintenance check time limits will likely be 1) operators seeking to minimize the time-delay, labor cost and equipment cost associated with more frequent maintenance checks; 2) ad-hoc FAA inspections to ensure maintenance compliance; and 3) consumer, societal or internal pressure to maintain high safety standard or reputation. To determine a ballpark figure for maintenance check time-limits that are the current industry standard, this thesis’s author collaborated closely with industry partners and stakeholders to glean the expected maintenance schedules and pre-flight check execution time requirements and quoted these in Table 4.7. In the constraint analysis of Chapter 5, this thesis simply intensifies the magnitude of these maintenance and pre-flight check time delays relative to this posited benchmark with the baseline run assuming no pre-flight and maintenance check requirements.

### **3.1.2 Miscellaneous Regulatory Issues and Areas of Uncertainty**

This section is a qualitative survey of areas of regulatory uncertainty that remain unresolved in current regulatory frameworks, literature and discussions. A recent techno-ethical review of commercial UAV literature quoted the most cited concerns for commercial UAV deployment were the safety of ground-based bystanders and legal pathways that espouse personal protection legal claims. Whilst these concerns are well documented both in the literature and this thesis, public concern will continue to guide how the relevant regulation evolves. Whilst much of the discussion in this section is not directly relevant for this thesis’s modeling approach, unresolved issues can provide insight into the evolution and trajectory of UAV-LMD regulation in the coming years.

#### **3.1.2.1 The Time Component of Regulation**

To increase the efficiency and applicability of regulation, regulators could leverage time-dependent regulation to a greater degree than currently so in FAR Part 107

and 135 (Rule, 2016). UAV-LMD operations are likely to be short-lived interferences that repeat multiple times a day. Thus, they are also more likely able to adapt to time-dependent regulation. Furthermore, the specific time of day or year can significantly alter on how UAV operations are perceived by bystanders. For example, residential communities may prioritize privacy, particularly in the afternoon hours on the weekends during the summer months when their outdoor back yards and swimming pools are more frequently used. UAV-LMD operations could well be considered more disruptive, annoying and intrusive at these times compared to afternoon hours on the weekends during the winter months. Thus, whilst currently only seen in FAA issued Temporary Flight Restrictions (TFRs), time-specific operational constraints via localized regulatory pathways could become common-place.

### **3.1.2.2 Local and State Versus Federal Regulatory Divergence**

The balance of regulatory authority between local versus federal regulators is an issue that exists in legislation beyond just UAV-LMD; however, UAV-LMD is distinct in the aviation sector in that it is very closely integrated with local geographies and communities. Historically, the regulatory authority in this sector has generally been more heavily skewed towards the federal regulators (Rupprecht). Indeed, the FAA is well suited to address many of the emerging regulatory challenges associated with UAV-LMD: flight restrictions around otherwise federally regulated entities such as airports, military facilities, national borders and other manned aerial traffic (Mark Connot, 2016). National UAV registration and tracking programs also enable a level of traceability, standardization and identification for law enforcement officials. Finally, uniform federal certification addressing manufacturing, maintenance and operational safety provides a nation-wide industry standard for UAV aircraft design and sales across the country.

However, until now, the FAA's roll-out of pertinent regulation in response to the rapid appearance of commercial and private UAV deployment has been widely criticized as slow and insufficient to protect against the localized externalities imparted by UAV operations. On the other hand, local and state regulators are commonly thought quicker-to-legislate and better suited to draft regulation more closely aligned with local community sentiments and requirements. The FAA currently claims preemptive regulatory authority over the majority of these local issues as well. Whilst the FAA allows some flexibility when it comes to creating and implementing UAV regulation at local levels, it advises states and municipalities not to stray too far away from their operational guidelines. However, in many contexts, their ability to enact standardized regulation at the national level has little to no bearing on addressing these localized concerns. With more and more states and municipalities drafting their own set of UAV usage laws through alternative regulatory pathways such as personal protection law or laws that protect property rights, it is becoming increasingly apparent that gaps exist in the FAA's ability to protect the public. For example, in 2013, the Oregon state legislature passed a law providing landowners the right to legal action against individuals operating UAVs below 400 ft. above their property

(Koebler, 2013). The law assumed that these were repeated UAV flights and the operator had been notified. So whilst not in direct contradiction to the altitude-minimum guidelines in the ‘Drone Integration and Zoning Act of 2019’, this highlights 1) the ability of local regulators to constraint UAV-LMD operations even without substantial aviation-specific regulatory authority, and 2) their willingness to take regulatory stances in direct conflict with federal regulators.

Whilst local regulators may be better suited to translate the needs of local communities into regulatory frameworks, there is a trade-off between localized representation and the emergence of a “patch-work” of differing low-altitude regulatory frameworks (Rule, 2016). In this case, operators will incur a compliance cost of adjusting operations to each regional regulatory framework which could result in differing altitude, trajectory, speed, MTOW or operating time requirements. This thesis supports the need for increased local and state regulatory authority but with the keeping of this trade-off in mind for the economic feasibility of UAV-LMD operators.

The method of analysis that this thesis undertakes could well be informative for quantitatively measuring this trade-off: by varying levels of specific regulatory-specific operational constraints, a better understanding of UAV-LMD’s sensitivity to specific constraints could be gleaned. This could inform along which dimensions local and federal regulators should be willing to concede authority with minimal impact on operations and which other dimensions more significantly harm an operator’s ability to provide UAV-based service. Furthermore, by instituting varying intensities of constraints in different sub-regions of the same demand set, this model could provide insights into how harmful a patchwork of regulatory constraints would be to operations.

### **3.1.2.3 Localized Flight Zoning Restriction**

One of the greatest potential advantages for increase local regulatory authority is for a systematic tailoring of UAV no-fly zones and other localized flight restrictions specific to the needs and requirements of specific communities. Naturally, these needs will likely stem from the personal protection expectations discussed in further detail in Section 3.2.1. Since these are needs that emerge out of local phenomena such as population demographics, expected background noise levels or familiarity with UAV technology, it is expected that these needs vary from neighborhood to neighborhood. Localized UAV flight zoning authority can enable the national low-altitude airspace account for such differences in the same way that land use zoning has served that function for nearly a century (Rule, 2016). Adjusting the flight restrictions based on the changing needs of the local community is also easier if regulated locally, especially if resistance to UAV-LMD begins to thaw and operators seek to serve that regional market.

This thesis posits, however, that continually changing flight zoning restrictions could represent a heavy drag on establishing stable UAV-LMD operations in a specific

area because of the high up-front infrastructure, regulatory compliance, public acceptance and supply chain costs associated with establishing operations in that region. It remains unclear how local regulators will approach zoning restrictions, but local regulators adopting different methodologies is a possibility.

## 3.2 Societal Barriers

On February 15, 2015, President Obama issued a public memorandum titled “Promoting Economic Competitiveness While Safeguarding Privacy, Civil Rights, and Civil Liberties in Domestic Use of Unmanned Aircraft Systems” (The White House, 2015). In the memorandum, the administration asserted their expectation that the FAA account for privacy, security, and transparency while integrating UAVs into the NAS. This section dissects the potential for negative societal externalities that would likely emerge from commercial UAV-LMD in urban environments at scale. This analysis is informed predominately by available literature pertaining to UAVs in urban areas and low-altitude aviation operations in the past. But the reader should note that much of this analysis is predictive and estimative since there are few societies that have, up to today, experienced UAV-LMD and document its set of longer-term negative externalities.

### 3.2.1 Personal Protection

Under the umbrella of personal protection, private individuals have the right to protect themselves and their property from the potentially harmful encroachment of others. These rights often, but not exclusively, manifest in legal claims such as trespassing, nuisance and invasion of privacy. This section will explore each of these claim types in turn and determine how relevant, if at all, are they to UAV-LMD operations.

#### 3.2.1.1 Trespass

Trespass is typically defined as knowingly encroaching upon another person’s land or property without permission. The Second Restatement of Torts at §159 states that an aerial vehicle can be deemed trespassing if it “enters into the immediate reaches of the air space next to the land, and it interferes substantially with the [owners] use and enjoyment of his land” (Sugarman, 1991). The Second Restatement of Torts offers additional guidance for such cases by suggesting flights a) over 500 ft. are unlikely to be intrude into private airspace, b) flights under 50 ft. most likely are and c) flights at 150 ft. is circumstance dependent. And a strong trespassing case typically requires the vehicle’s intrusion to detract from the use and enjoyment of that private property.

Interestingly, in 2015 the FAA issued guidance which anticipated that states and cities will likely regulate UAV-LMD operations, but encouraged close consultation with the FAA prior to enacting laws. This is in line with broader separation of powers between state and federal regulation, particularly in local policing domains

– including land use, zoning, privacy, trespass, and law enforcement operations. In 2018, however, the FAA modified this guidance by adding the comment that state and local governments “are not permitted to regulate” UAV flight paths and altitudes.

“[F]lying at legal altitudes [that is, less than 400 feet] over another person’s property without permission or a warrant would reasonably be expected to constitute a trespass.” (Skorup, 2021).

Whilst the frameworks that will guide accusations of trespassing of low-altitude aerial vehicles remain vague, legal risk in this domain will likely force UAV-LMD operators to adapt their operations accordingly. UAV-LMD players may well establish direct trespass easements with their direct customers via terms and conditions contracts. But, of course, this does not capture those external to the transaction.

### **3.2.1.2 Nuisance**

Nuisance is typically defined as the substantial and unreasonable interference of an individual’s enjoyment of their property through a thing or activity. Thus, it is likely to be more applicable to UAVs operating at low altitudes. Unlike trespassing, nuisance describes the type of harm that is inflicted and is not tied to property boundary or private airspace definitions. It is simply whether a thing or activity interferes with an individual’s enjoyment of their private property. Historically, in general aviation and commercial aircraft operation, nuisance claims have been submitted against owners of aircraft, airports. They are also typically based in state law or municipal regulation. There has been no guidance to date on if this will remain in the hands of local regulators or be absorbed into federal aviation regulation.

Whilst UAV’s dust disturbance and noise footprints are typically smaller compared to helicopters and, thus, less likely to qualify as a nuisance claim, UAV-LMD will mean aerial pass-overs will be more frequent, operations will be more geographically dense and the average flight altitude will be lower because of repeated take-off and landing maneuvers. This thesis posits that whilst nuisance claims may be put forward against future UAV-LMD operations, operators themselves will not actively consider nuisance externalities with the precautions taken for the other societal externalities likely sufficient to also cover nuisance concerns.

### **3.2.1.3 Invasion of Privacy**

Finally, invasion of privacy is defined as the unjustifiable intrusion into the personal life of another without consent. The Second Restatement of Torts at §652b asserts

“[o]ne who intentionally intrudes, physically or otherwise upon the solitude or seclusion of another or his private affairs or concerns, is subject to liability to the other for invasion of his privacy, if the intrusion would be highly offensive to a reasonable person.” (Sugarman, 1991).



In this light, the tort of invasion of privacy would not require the disclosing of information or images, just acquiring. Thus, the risk to UAVs is clear. UAVs will likely require an array of cameras and sensors that will continuously monitor their surroundings to avoid collisions surrounding objects: buildings, trees, telephone and power lines, birds, and other aerial vehicles. This is particularly true if operations become near-autonomous, but this will be discussed further in Chapter 5.

As a back-stop to minimize legal exposure, UAV-LMD operators may be motivated to record, store and even review a UAV's flight mission footage. Should a UAV-LMD operator's employee have the right to review imagery or video captured by the UAV in flight? Should UAV operators be able to utilize the data a UAV collects for other commercial uses either internally as a commodity sold onto a third party? Just as Apple contends with pressure from security agencies and courts to disclose stored data on iPhones that could be used as evidence in legal proceedings, will UAV-LMD operators need to contend with such requests to share aerial data in similar contexts? Based on The Second Restatement of Torts, if an operator obtains data of a property that is deemed "highly offensive" by the courts, they would be liable to a claim for damages and/or an injunction for invasion of privacy.

In the U.S., March 15, 2017 signified the most resolute effort yet by Sen. E. Markey (D-Mass.) and Rep. P. Welch (D-Vt.) to introduce federal legislation to regulate UAVs. It actually took the form of a UAV privacy framework. Entitled the "Drone Privacy and Transparency Act of 2017", the proposed regulations suggested three methods to safeguard personal privacy threatened by UAVs: 1) require every person or firm seeking to use a UAV for commercial purposes to obtain pre-authorization to operate the UAV. This entails providing certain information about where, when, and for what purposes the UAV will be flown, and whether it will collect, sell, or otherwise use personal information about any individuals; 2) require the FAA to publicly disclose this information on the Internet; and 3) ban any use of UAVs by law enforcement personnel without a warrant (Hall, 2017). Whilst it was never enacted, this piece of legislation signals to industry stakeholders the general intentions of Congress active members – the issues that face UAV-LMD extend far beyond the mere operational regulations.

#### **3.2.1.4 Regulatory Pathways to Limit Personal Protection Externalities**

Over the years, federal and state courts have handled many cases that challenged the legality of aerial footage of bystanders and private property being taken and stored by persons or companies. Such legal action typically questioned the admissibility of data collected in this way through filings for trespassing or personal nuisance. These cases often concluded supporting the aerial vehicle operator as long as they operated in accordance to FAA regulations rather than siding with or expanding on the rights of landowners or bystanders.

To what extent a landowner owns the airspace above their property has been a question with an unclear answer since the 1946 *United States v Causby* case, in which a chicken farmer sued the U.S. government for flying military planes at such low altitudes over his home that his chickens committed suicide out of agitation (Legal Information Institute). The U.S. Fourth Amendment protects citizens from unreasonable search and seizure, particularly in areas where they can expect a certain level of privacy, namely their home or the curtilage of their home. But whilst one can expect privacy under the Fourth Amendment, objects, activities or statements that are exposed in plain view are not subject to the same privacy entitlements. This is why the Fourth Amendment has never required passers-by to shield their eyes when passing by a home (Brenner, 2005). This begs the question, which interpretation of the Fourth Amendment should UAVs be subject to?

Recent rulings in the U.S. can provide insights into how privacy concerns will be viewed in UAV-LMD operations. In *Florida v Riley* U.S. Supreme Court case, it was argued

“there is reason to believe that there is considerable public use of airspace at altitudes of 400 feet and above[.]” ((Supreme Court of United States, 1988))

Below 400 ft., this argument defending privacy encroachment weakens. Additionally, such issues are often heavily influenced by state and federal circuit law. With that said, as of today, FAA Part 135 air carriers are protected by the Airline Deregulation Act that prevents states from enforcing laws

“related to a price, route, or service of an air carrier.” (49 U.S.C. 41713, (United States Code, 2006 Edition, Supplement 5, Title 49 - Transportation, 2005))

The European Union (EU) more advanced when it comes to enacting data privacy regulations than the U.S. In 2016, the European Commission and the Council of the European Union approved the General Data Protection Regulation (GDPR), instituted on 25 May, 2018 (Voigt and Von dem Bussche, 2017). One key facet of the GDPR is its purpose to “return control” to EU citizens over their personal data. One key dimension of the GDPR is that personal data is considered significant and “sensitive” to the private citizen if that data reveals information about that individual’s racial or ethnic origin, political opinions, religious or philosophical beliefs, trade-union membership, genetic makeup or bio-metric, health or sexual characteristics (Hoffmann and Prause, 2018). For UAV operators, the following excerpt applies:

“the controller shall be able to demonstrate that the data subject has consented to the processing of his or her personal data and the data subject shall have the right to withdraw his or her consent at any time.” Article 7, GDPR, (Voigt and Von dem Bussche, 2017)

The GDPR makes a distinction between the “data subject,” the “controller,” and the “processor” in data collection processes. In future UAV-LMD operations, the

lines between these stakeholders will become blurred. UAVs will become more autonomous, the software engineers responsible will reside in remote locations and a number of UAV-LMD operators will operate across various locations with different integration and deployment strategies.

The perspective of UAV-LMD operators can be dissected into two viewpoints: 1) the three most common personal protection externalities discussed above are already captured in the various flight trajectory, operating time or minimum altitude constraints set forth by the FAA; or 2) it is the operator's responsibility to minimize this risk and the snowball effect of worsening public relations with the public and, potentially, serviceable available market. To this end, this thesis seeks to explore along which dimensions a UAV-LMD operator would self-constrain operations to minimize such externalities:

- Flight trajectory constraints: actively avoid areas with community members that are likely sensitive to personal protection violations.
- Minimum altitude constraints: artificially set higher minimum altitude constraints either across all parts of a flight mission or over specific areas with community members that are likely sensitive to personal protection violations;
- Operating time constraints: self-regulate UAV-LMD operating times to more closely align with periods of the day during which any impacted community members are less likely to be impacted by UAV-LMD operations and avoid more personally sensitive periods of the day.

Note that these societal constraints reflect community needs that are extremely local in scope, hinting at the broader discussion of how local versus federal regulatory authority will be balanced for UAV-LMD in the future. Also note that the operator's tools to minimize personal protection externalities are predominantly the same as those present in FAA regulations, namely trajectory, altitude, and operating time constraints. Whilst this thesis could hypothesize as to whom these sensitive communities are, an analysis of which communities are more sensitive to these externalities has not been performed in literature and only briefly touched upon in industry-led efforts. A Virginia Tech report centered around public perspectives on Wing's operation concludes that, amongst those surveyed, 87% "like the idea of drone [UAV] delivery" and 89% "would use the service" (Xu, 2017). This survey-based report does not detail the characteristics of those communities not in favor of Wing's UAV-LMD operations and their specific qualms with the service. A survey-based approach to defining these sensitive communities is likely the most effective way to inform any society-driven operational constraints that operators who opt for self-regulation should adhere to. Because of this disconnect between literature and necessary public opinion field-work to translate such societal constraints to operational constraints, this thesis eschews these constraints in its modeling of the URP.

### 3.2.2 Noise

While urban communities tend to tolerate public safety helicopter flights (such as for medical or emergency operations) they have historically opposed frequent non-essential helicopter use in urban environments. This is, in part, because of the low frequency and clear community value of public sector helicopter use. Until now, only isolated municipal regulation has allowed small helicopter transportation services to take hold in cities like New York and Sao Paulo. Across other geographies, noise concern has often limited the scalability of any commercial helicopter urban aerial mobility operation, from flight frequency to route flexibility. But UAV-LMD will be just this: it will likely operate closer to bystanders on the ground, in a variety of geographic areas, at different times of the day and more frequently than current low-altitude aircraft operations.

Estimating the impact of noise on a society is non-trivial from both a technical and social level. With that said, it is likely that the public will naturally benchmark the noise impact of UAV-LMD with the only other commonly-occurring low-altitude aerial vehicle: helicopters. Compared to helicopters, UAVs emit a higher-pitched noise that may be perceived as incessant, since a UAV remains at low altitudes for longer periods than helicopters, which typically just perform brief pass-overs. It is this characteristic – their acoustic profile and operational pattern – that will dictate how UAVs are received in urban areas.

The UAV-LMD industry is dominated by either quadcopter or lift+push vehicle UAV configurations. Both sport propellers with the latter differing in that forward flight is not powered by a thrust imbalance between front and back rotors but via a separate forward thrust system altogether. The dominant noise sources can be understood via Figures 3-9a, 3-9b:

- Propeller blades: UAV propeller blades are the most notable broadband noise source. Their high blade tip generates significant downwash and associated lift disturbances that contribute to the unique tonal noise of the craft compared to traditional aircraft or helicopters.
- Payload: UAVs with heavier payloads generate more noise since more lift is required to counteract the added payload weight translating to high propeller speeds, additional air displacement, more turbulence and, thus, more noise.
- Forward flight: In a quadcopter configuration, forward flight is achieved by an imbalance in thrust vectors between the rear and front propeller disks, tipping the UAV in the direction of travel. This difference in rotational speeds can generate lift disturbances that increase noise production.
- Wind: Whilst wind can have a masking effect on UAV noise, it can also require the UAV to perform compensatory thrust maneuvers to maintain controlled flight. This results in additional irregular, high-pitched noises on top of the base noise profile.

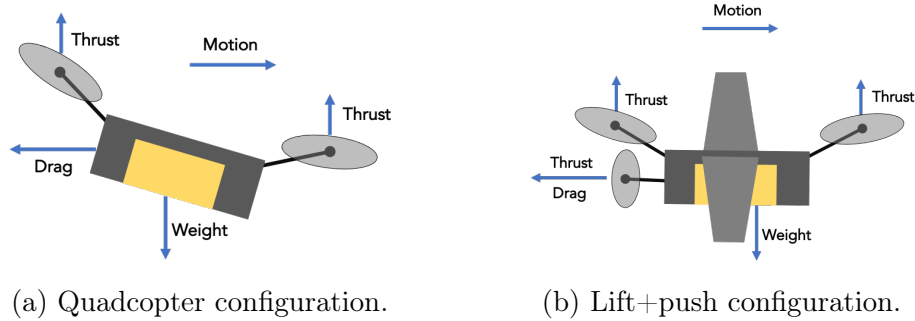


Figure 3-9: UAV force diagrams in quadcopter and lift+push configurations.

Beyond this, however, estimating noise levels emitted from low-altitude commercial UAV-LMD operations is non-trivial from both a technical and social level. This is because little data and research exists that characterize the acoustic profile of UAVs or how the public would respond to such frequent noise disturbances. Furthermore, UAVs are likely to undergo substantial design adjustments as firms learn more about their demand base, operational limitations and regulatory constraints. But whilst analyzing UAV noise pollution on a quantitative level may be a difficult and, potentially, futile exercise, there are a variety of qualitative insights one can make to guide future regulatory and commercial decisions.

For one, it is not precisely the amount of noise pollution that matters but rather its annoyance factor. This comprises of the pitch, frequency, length of time and variability of the noise that matters. Furthermore, whilst considering the acoustic profile of a single UAV is important, the fleet noise profile over an extended time period is what bystanders take note of. Thus, frequency of UAV-LMD operations in a specific area also drives the annoyance factor. UAV-LMD network design will likely play a pivotal part in municipal and commercial strategy to minimizing the negative externalities of UAV noise pollution. For example, some research suggests that a highly decentralized launch and retrieval network would reduce the overall noise footprint since the UAVs would spend less time in the air and travel shorter distances to their destinations (Lohn, 2017).

### Regulatory pathways to limit noise externalities

The FAA has historically defined noise regulations in the NAS although local and state regulators do have a non-binding say in how their community noise standards are define. With that said, there are numerous examples of where aircraft or helicopter operations were curtailed or prohibited altogether because stakeholders objected to the aircraft noise pollution. One example is that of low-flying helicopters in Los Angeles prompting California representatives to push Congress to, in turn, push the FAA to draft new helicopter noise regulations and ultimately resulting in the Los Angeles Residential Helicopter Noise Relief Act of 2013 (Rep. Schiff, 2013). Whilst the Act did not strictly prohibit low-altitude helicopter operations outright, it

provided voluntary measures for operators in the Los Angeles region to reduce noise. Historically, larger manned aircraft and helicopter noise emissions are curtailed via airfield-specific operational constraints. For example, specific airports would limit operations that 1) fly in a certain direction over especially sensitive communities; 2) occur in noise-sensitive times (most commonly late at night and early morning hours); and 3) the total number of take-off and landing maneuvers performed per unit time of operation. This is effective since such aircraft and helicopters are most noise-polluting when performing these low-altitude take-off and landing maneuvers but not necessarily during climb, descent or cruise flight regimes. But since UAVs in UAV-LMD are expected to operate at low-altitudes for the majority of a flight mission, this thesis expects noise constraints to extend beyond just take-off and landing procedures. With that said, take-off and landing locations will naturally increase flight density as UAVs will necessarily originate and finish their missions at that location. Looking specifically at FAR Part 107, it currently only quotes noise as a potential operational issue but concludes the following:

“the FAA lacks sufficient evidence at this time to justify imposing operating noise limits on ... UASs” (Federal Aviation Administration, 2021).

Part 107 does currently limit noise emissions, however, through two pathways: 1) it constrains the MTOW of UAVs certified under Part 107 to 55 lbs.; and 2) commercial UAVs are not permitted to fly over people not directly involved in the UAV’s operation. However, such constraining flight trajectories are changing with FAR Part 135 exceptions being granted to UAV-LMD operators. So whilst there does not yet exist a comprehensive set of UAV noise emissions standards either for individual UAVs or a fleet of commercial UAVs, there are some high-level approaches to minimizing UAV-LMD noise emissions that have been discussed in literature that would emerge in future FAA regulation:

- Technological: FAA regulation or public pressure can incentivize UAV OEMs to explore engineering solutions to noise emissions mitigation such as improved propeller designs, increased distributed propulsion or vibration and acoustics redesign. Such regulation can be both binding or voluntary with the latter more commonly seen in advisory circulars in historical noise mitigation efforts.
- Operating constraints: The FAA frequently institutes TFRs around special public- or other noise sensitive-events that prohibit flight over these areas either during specific times, at certain altitudes or with maximum MTOWs. Specific helicopter routes, airport transition routes and VFR highways for reduce broad-based noise pollution by aggregating flights over sparsely populated areas or areas less sensitive to noise such as industrial parks or highways. Finally, the FAA enables airports to alter low-altitude approach and departure paths for noise-mitigation purposes through the FAA Airport Noise Program, through which pilots can be asked to adhere to specific noise emission guidelines. Aside from specific mitigation strategies, acoustic noise mapping pertaining to UAV-LMD is a field being heavily researched as a tool to combat noise pollution.

Such a model combines a representative noise model for the UAV type and configuration in question, a translational scaling of a single UAV to a fleet of UAVs operating over the course of a time period, an understanding how such noise emissions propagates in the surrounding environment capturing factors such as the weather, exogenous noise polluters, and any noise muting characteristics. Such a model would be valuable to UAV-LMD stakeholders, be it regulators, operators or the public, since it provides a set of measurable metrics for noise emissions given differing operating circumstances against which regulations, operations and public expectations can be tuned. Thus, acoustic mapping would be an enabler of other noise mitigation solutions.

Whilst it remains unclear which of the two noise mitigation approaches are being more heavily pursued by the FAA and UAV-LMD industry players, this thesis leverages existing operations-based noise mitigation strategies for urban helicopter operations as a foundation for the UAV-LMD industry:

- cruise at higher altitudes;
- steeper take-off and landing procedures to minimize total time spent at low-altitudes;
- minimize specific noise emission profiles that are considered highly noticeable, penetrating or annoying. One example for helicopters is impulsive noise generation which is the loud repeated beating noise helicopters generate often when cruising at high speeds, also commonly referred to as “blade slap”; and
- avoid noise sensitive areas via detailed flight trajectory planning.

This thesis adopts all of these noise mitigation approaches in its modeling effort to capture operating noise pollution constraints except for that pertaining to noise emissions profile management. This thesis assumes that UAV-LMD operators introduce self-imposed constraints to minimize noise externalities with additional minimum altitude restrictions in addition to minimum altitude constraints that emerge from UAV regulation. This thesis also assumes additional drone zoning restrictions around locations that are likely to be noise-sensitive. that there are many factors that dictate what defines a noise-sensitive area. In literature, some methodologies collect key geographic features and characteristics and leverage predictive models trained on submitted noise complaint data to measure noise sensitivity. Other methods rely on surveys to gauge noise sensitivity in place of noise complaint metrics. Some examples of geographic features are: population density, age, race and ethnic demographic spreads or land zoning types or proximity to other noise-pollution sources. With this said, delving into the details of noise sensitivity science is beyond the scope of this thesis. In the case-study analysis in Chapter 5, this thesis leverages the 2016 Greater Boston Noise Report and, specifically, the Neighborhood Sound Annoyance Levels Map (see Figure 3-10) to discern regions in the Greater Boston Area that will likely be more noise-sensitive to UAV-LMD (Walker et al., 2016).

Neighborhood Sound Annoyance Levels

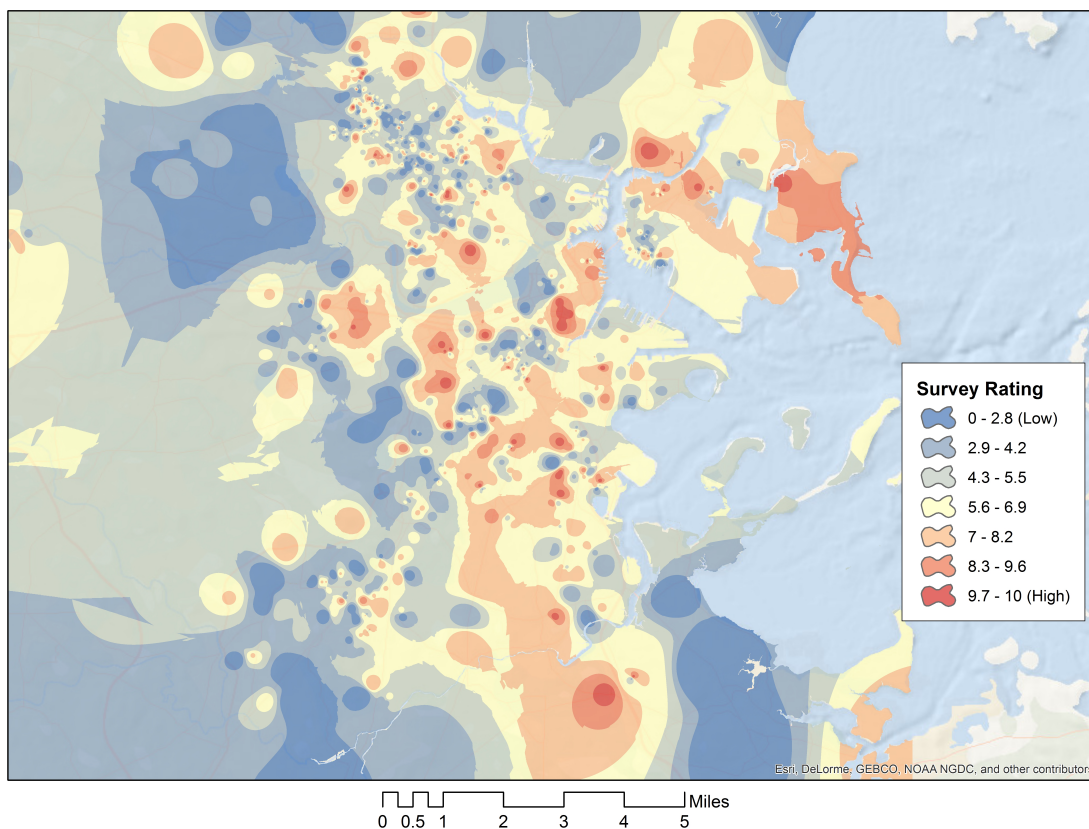


Figure 3-10: Neighborhood sound annoyance levels map.

The intensity of these restrictions are increased incrementally in the sensitivity analysis in Chapter 5. But rather than incrementally adding noise-sensitive regions to the GURP problem definition, this thesis incrementally increases the additional altitude a UAV must cruise at above its minimum flight altitude, as discussed in Section 3.3 and specifically in Table 3.1.

### 3.2.3 Environmental Concerns

Unrelenting growth of the last-mile industry has taken its toll on local urban and global environments alike due to an ever increasing number of trucks required to fulfill demand and the fuel consumption and emissions associated with operations. The World Economic Forum study forecasts a 36% rise in the number of delivery vehicles in the world's top 100 cities by 2030, leading to an emissions increase of over 30% (Deloison et al., 2020). UAV-LMD excites many industry firms because of its potential to transport goods in a fraction of cost, time, and energy of today's methods. The majority of UAVs consume electricity and, thus, have no emissions when compared to a ground-based fuel-consuming truck at the tailpipe. But, the environmental friendliness of UAVs depends on factors that extend past the tailpipe and might be



offset by: a) the UAV configuration, b) the size and weight of the cargo, c) the potentially longer linehaul distances they incur to fulfill a set of demand given their limited payload and battery capacities, d) the additional warehouses or charging stations required to extend their limited flight ranges, e) the carbon intensity of different upstream power generation systems, and f) the economic- or energy- competitiveness of alternative-fuel vehicles (e.g., electric and natural gas trucks). Furthermore, several studies point towards a lack of scientific evidence of the environmental benefits of UAV-LMD as compared to existing modes of transport (Kellermann et al., 2020b; Park et al., 2018; Stolaroff et al., 2018).

In UAV-LMD, emissions savings generally stem from the reduction of deploying under-utilized ground-based vehicles rather than fully replacing traditional ground-based vehicles (Chiang et al., 2019). This is particularly relevant in rural areas where distances traversed by ground-based vehicles are longer than by an aerial UAV and demand is not easily consolidated into single vehicles. Thus, it is not fair to compare UAV-LMD and traditional delivery vehicles on a one-to-one basis but rather measure by how much do the total fulfillment network emissions drop due to an introduction of UAV-LMD as part of the fulfillment mix. For example, UAV-LMD could have a net-positive effect on fulfillment network emissions if specific routes that, if performed by traditional ground-based modes, are mired in significant ground-based congestion, long and indirect road network routes (such as around large geological features or bodies of water) or across challenging terrain like steep gradients. Re-allocating many of these specific delivery routes to UAV-LMD could increase the overall sustainability of the entire fulfillment system.

Looking at the literature, however, it is relatively deep, albeit awash with operational, regulatory, and performance assumptions to constrain this problem. Across the board, there is consensus in literature that if deployed deliberately, small UAV-LMD services delivering small payloads over short distances could almost halve CO<sub>2</sub> emissions as compared to the same set of demand being served by a traditional ground-based diesel delivery vehicle (Goodchild and Toy, 2018). These results depend on a variety of assumptions – upstream energy generation fuel sources, warehouse networks design, or UAV battery technology improving in the coming years. Findings also suggest that as UAV size, distance, and payload weight increase, these savings do not scale linearly, but rather UAV emissions tend towards that of a typical diesel ground vehicle (Stolaroff, 2018).

Aside from CO<sub>2</sub> emissions, there exists a series of other sustainability concerns pertinent to the UAV-LMD discussion. A broader life-cycle analysis of the UAVs, infrastructure, components and equipment necessary is also vital to fairly assess UAV-LMD’s long-term sustainability feasibility (Figliozzi, 2017). A life-cycle analysis usually involves all the necessary steps to consume a product, the product being UAV-LMD for consumer packaged goods (CPGs), foods or other consumer goods, including raw material production, manufacturing, distribution (the UAV-LMD step that this thesis predominantly focuses on), disposal and auxiliary transportation re-

quirements. A large part of the vehicle disposal carbon footprint is the degradation and disposal of the lithium-ion polymer battery. Because of their long charge times and general ease of exchange, some UAV-LMD operators may allocate multiple battery packs per UAV platform. This enables higher utilization of the UAV asset that, over the course of the asset lifetime, is re-captured in saved capital expenditures (CAPEX) and extra labor costs in asset down times.

There is little to no regulatory pressure to minimize UAV-LMD emissions, however, minimizing 1) the CAPEX costs of UAVs or lithium-ion batteries that are no longer functional; and 2) electricity costs in charging depleted batteries; and 3) under-utilized labor costs when assets are grounded (for battery charging or otherwise), is fundamentally aligned minimizing life-cycle and routing emissions for UAV-LMD. In assessing what all of these sustainability implications mean for operational constraints, this thesis discerns the following operational incentives:

- to efficiently combine customers in single trips in a one-to-many versus a one-to-one delivery manner to avoid unnecessary line-haul energy consumption patterns, increased battery switching time delays and labor costs and battery degradation both from a cost and sustainability perspective;
- to find the trade-off between excessive payload weight with the associated non-linear increase in energy consumed and repeated flights;
- to fly at lower altitudes to minimize unnecessary energy consumed in vertical take-off and landing maneuvers; and
- minimize flight distances and fly point-to-point as much as possible adhering to strict no-fly zones.

These are directly translated into modeling decisions in Section 3.3.

### 3.3 Translating Societal and Regulatory Constraints into Modeling Extensions

This section summarizes this chapter, highlighting the specific exogenous societal and regulatory constraints that are explicitly modeled in the coming chapters and GURP model formulations. Each potential societal or regulatory constraint discussed in this chapter is included in Table 3.1 with their set of associated operational constraints also included alongside. This section concludes with a summary of which operational constraints are prioritized and how they are integrated into the model.

Note that whilst these societal constraint modeling implementations are included here, they are not leveraged in the modeling results of Chapter 4. This is because Chapter 4 is fundamentally a benchmarking exercise with its results culminating in Section 4.4. Chapter 4 exists to benchmark the various GURP models against one another and corroborate the value of the *Heuristic Approach (HA)* in faster

computational run-times and near-optimal solutions. Instead, the finalized exogenous constraints discussed in this section are only implemented in the GURP model that is employed in Chapter 5 as the analysis attempts to marry the routing algorithms with exogenous constraints to solve the GURP. Finally, note that the intensity of the exogenous constraints quoted in Table 3.1 is varied as part of the sensitivity analysis in Chapter 5. See Section 5.3 and Figure 5-3 for more details on how these operational constraints are varied between case study scenarios.

Taking the various exogenous constraints quoted in Table 3.1, this thesis then aggregates the constraints into the specific operational constraint pathways that are captured in the GURP problem formulation. These constraint pathways are: 1) altitude minimums and maximums; 2) MTOW constraints; 3) flight restrictions; and 4) maintenance and pre-flight checks.

- Altitude minimums and maximums: all UAVs must cruise in the 200-400 ft. altitude range and adhere to region-specific altitude minimum requirements. These region-specific altitude minimums do not stem from any specific regulatory structure but from this thesis's supposition that, in certain areas, there exist urban structures that extend beyond the 200 ft. altitude minimum forcing UAVs to maintain a 200 ft. lateral and 50 ft. vertical clearance. Furthermore, due to the in-air separation constraints, depending on the UAV heading, it must adhere to the altitude stratification protocol depicted in Figure 3-11. Additionally, because of the environmental concerns and incentive to minimize energy consumption, UAVs are assumed to always cruise at their lowest permissible cruise altitude given the aforementioned constraints. It is assumed that the UAV ascends to its minimum-permissible cruise altitude based on its flight trajectory and remains at that altitude for the flight duration instead of performing a staged ascent. See Figure 3-12 for a pictorial example of this logic. Finally, because of noise pollution externalities, UAVs operate at either a 15, 30 or 45 ft. (depending on the assumed exogenous constraint intensity) clearing above the otherwise optimal cruise altitude over noise-sensitive areas as defined in Section 3.2.2. This is further elucidated in Figure 5-3.
- MTOW constraints: the total UAV weight can never exceed 55 lbs throughout the duration of its route. This constraint extends beyond MTOW since UAVs can pick up customer demand, meaning in-flight operating weight can exceed MTOW unlike traditional commercial passenger aircraft.
- Flight restrictions: UAVs must strictly adhere to FAA instituted no-fly zones at all times. The types of locations included in the flight zoning restrictions varies based on the exogenous constraint intensity assumed. See Figure 5-3 for more details. Flight trajectories are laterally plotted around flight zoning restrictions leveraging a visibility graph algorithm. An asymmetric distance matrix is then built upon the resulting visibility graph. A visibility graph is a computational geometry methodology often used in robot motion and trajectory planning given a confined feasible region of operation. Within this region, a set of start and end points exist as well as a set of obstacles that any agents cannot

enter into. With this initial state, a visibility graph initializes nodes at each point in the region and at each corner of each obstacle. It then builds edges from every node to every other visible node, a visible node defined as a node that can be reached in a straight line from the start node without intersecting with any obstacle boundaries. Thus, when the visibility graph is queried to get the shortest path between two points, a shortest-path algorithm, such as the popular A\*-Algorithm, is employed whilst only traversing existing edges. This thesis leverages the `extremitypathfinder` Python package (Michelfeit et al., 2021).

- Maintenance and pre-flight checks: all UAVs must adhere to a maintenance and pre-flight check schedule in line with the expected industry standards as defined with industry partners. The magnitude of the associated time delays varies based on the exogenous constraint intensity assumed. See Figure 5-3 for more details.

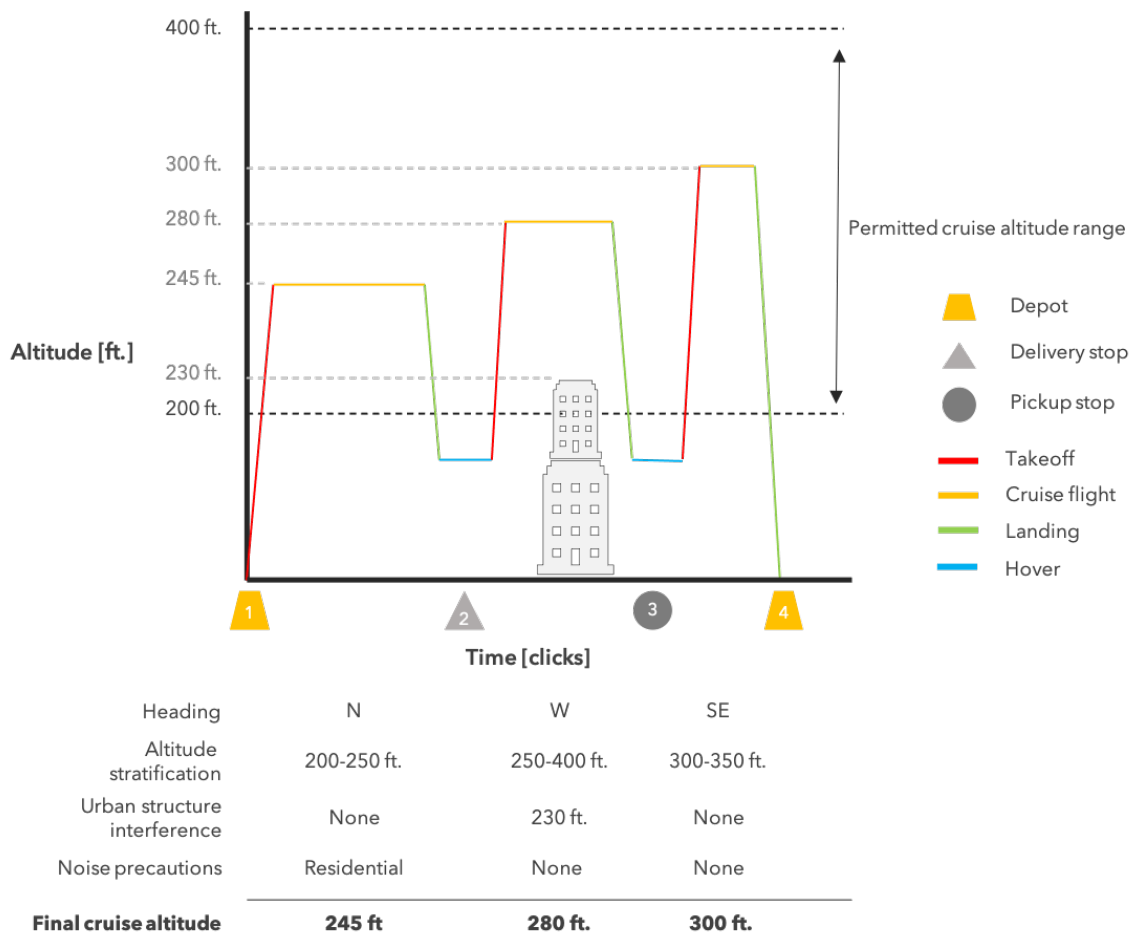


Figure 3-11: Cruise altitude determination logic aggregating exogenous constraints.

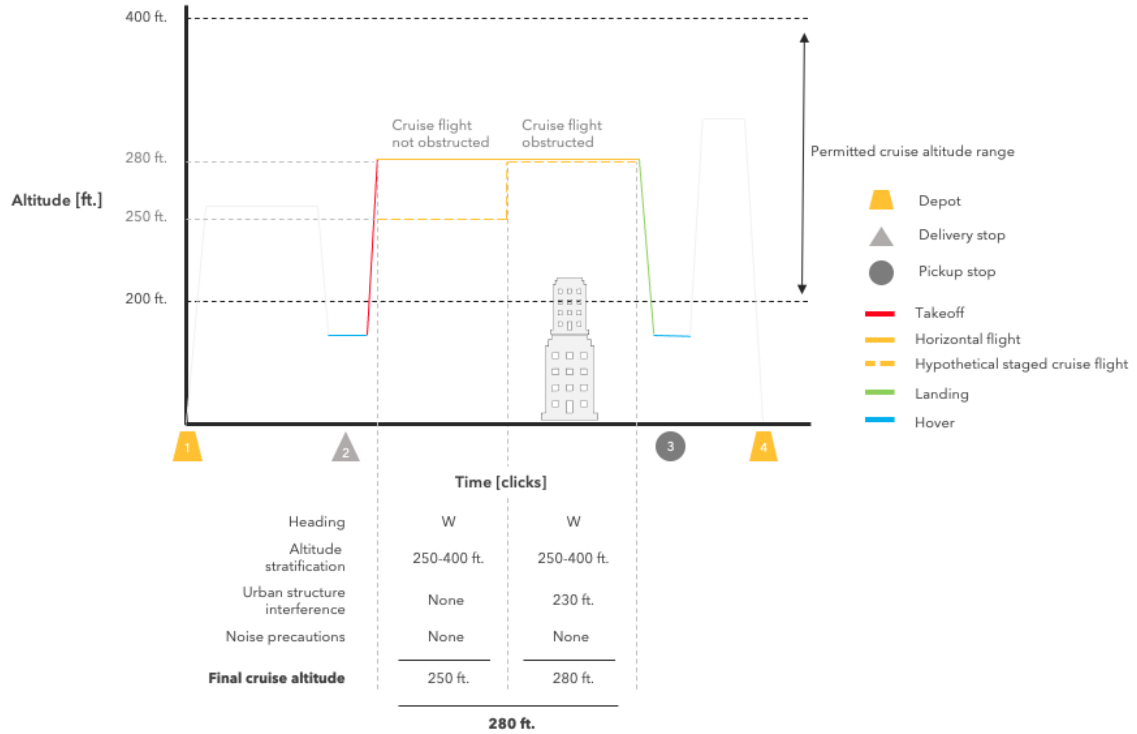


Figure 3-12: Pictorial illustration of non-staged cruise altitude determination logic, expanded illustrative example for UAV traversing arc between nodes 2 and 3.

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<b>Constraint Type</b>	<b>Description</b>	<b>Operational Constraint</b>
<b>Regulatory</b>	Status Quo	Assume operational waivers granted for all restricting airspace classes
	Altitude Minimums and Maximums	Altitude between 200-400 ft. and maintain 50 ft. vertical and 200 ft. lateral separation from structures that exceed 200 ft.
	Operating Weight Constraints	MTOW of 55 lbs.
	In-Air Vehicle Separation Constraints	Altitude stratification protocol: Bearing 315-045° within 200-250 ft.; Bearing 045-135° within 250-300 ft.; Bearing 135-225° within 300-350 ft.; Bearing 225-315° within 350-400 ft.
	Take-Off and Landing Considerations	–
	Flight Zoning Restrictions	Non-temporary FAA issued flight restrictions.
	Safety-Related Procedures and Precautions	Maintenance and pre-flight check requirements driven by cumulative operational metrics as per Table 4.7.
	Miscellaneous Regulatory Considerations	–
<b>Societal</b>	Personal Protection	–
	Noise Pollution Concerns	Assume 45 ft. additional vertical clearance over noise-sensitive areas such that UAVs operate at upper-end of permissible cruise altitude range given altitude stratification protocol.
	Environmental Concerns	Optimal routing approach, energy cost objective function component, weight-dependent energy consumption logic, cruise at minimum permissible altitude and visibility-graph approach to flight trajectory definition.

Table 3.1: Summary of exogenous societal and regulatory constraints translated into GURP modeling decision.

# Chapter 4

## The UAV Routing Problem<sup>1</sup>

### 4.1 Introduction

This thesis, up until now, has introduced unmanned aerial vehicles for last-mile delivery (UAV-LMD) and the key societal and regulatory hurdles between it, major commercial deployment and widespread adoption. As a reminder, the research questions this thesis poses are:

1. **Operational Constraints:** What are the key social, regulatory, technological and logistical constraints that would constrain real-world UAV-LMD operations?
2. **Operations Modeling:** How can these novel operational constraints be captured in a generalized vehicle routing optimization model?
3. **Feasibility Analysis:** Given realistic demand data and operational parameters, is UAV-LMD financially profitable for service providers? Which constraints are key cost drivers? What are the social, operational and financial upshots of UAV-LMD?

To answer these questions, in particular the second question, this thesis derives a methodology to understand the key operational routing decisions in light of the societal and regulatory constraints. This model ought to capture:

1. the fundamental daily routing constraints of a UAV-LMD fleet;
2. the advanced operational routing constraints unique to unmanned aerial vehicles (UAVs);
3. the additional social and regulatory constraints relevant to day-to-day operations; and
4. the notion of realistic total operational cost for a representative customer demand set.

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<sup>1</sup>This chapter contains content that is partially under review for publication in a peer-reviewed journal.

The problem this thesis and, thus, this method, solves is termed the generalized unmanned aerial vehicle routing problem (GURP). In order to solve the GURP, this thesis first develops an exact mathematical programming formulation of the problem (see Section 4.3.1) before presenting an efficient two-stage formulation of the problem (see Section 4.3.2) as well as an efficient heuristic to solve larger problem instances (see Section 4.3.3).

The first two solution approaches are developed to innovatively solve the GURP and to corroborate the computational efficiency, consistency, robustness and optimality of the heuristics approach. As detailed in Chapter 2, there is ample literature material around vehicle routing (and its variants) to build upon. Thus, these two exact solution approaches, termed the *Exact Approach (EA)* and *Exact Two-Stage Approach (ETSA)*, are based upon formulations to solve the vehicle routing problem (VRP) but extended to capture the additional UAV-LMD-specific constraints. The heuristics approach, on the other hand, termed the *Heuristic Approach (HA)*, serves as this thesis’s core GURP model to optimize UAV-LMD operations at scale in reasonable computation time. This chapter describes all three solution approaches in detail.

## 4.2 Problem Definition

As detailed in Chapter 2.2, the VRP literature is steeped in decades of history. The VRP has previously been extended in many of the dimensions that this thesis necessitates to solve the GURP, namely:

- multi-commodity flow and capacity constraints;
- ability to jointly serve delivery and pickup demand;
- deterministic time window (TW) constraints; and
- fixed-fleet, multi-vehicle, multi-trip functionality.

In the extant literature, the unmanned aerial vehicle routing problem (URP), alternatively referred to as the drone delivery problem (DDP) or vehicle routing problem with drones (VRPD), has been formulated as an extension of the VRP additional novel energy consumption constraints. This thesis seeks to combine all of these constraint extensions into a set of three routing solution methods (the *HA*, *EA* and *ETSA*) extending functionalities as required. Furthermore, this thesis incorporates the relevant societal and regulatory constraints in the model as novel extensions, referred to as exogenous constraints going forward. This package of extended constraints and real-world restrictions specific to UAV-LMD is what is captured by the term “generalized” in GURP. This section also introduces the set and parameter definitions used across all three GURP solution approaches. Tables 4.1 and 4.2 provide overviews of the sets, model parameters, and constants used in the model formulation.



The problem is defined as a directed graph  $G = (N, A)$  where  $N$  is defined in Table 4.1. The total number of customer nodes in a given demand set is  $n$  and nodes  $0, n+1$  denote the starting and returning distribution center (DC) nodes respectively. Each customer is associated with a non-negative demand across three commodities – package count, weight and volume. Note that customers are disaggregated at the package level such that each package’s commodity characteristics aggregate to the customer’s total demand across the commodities. This package-level data echelon is important since the model assumes that customers that cannot be served in one trip can be disaggregated and served across multiple trips. Finally, each customer node is either a delivery or pickup, as defined in Table 4.2.

Each customer node is associated with a hard TW with starting and ending times as defined in Table 4.2, including the DC nodes denoting the operation’s earliest possible start and latest possible end times. A fleet of  $K$  UAVs, see Table 4.1, is initialized and strictly operates out of the DC with no limits on the total number of flights performed, flight hours, customers served or otherwise for each UAV. Each UAV sports a series of vehicle parameters defined in more detail in Section 4.4.1 and are capacitated along each commodity dimension as well as available on-board energy. Between nodes, UAVs must incur a pre-defined travel distance and time, dictated by the geography, each UAV’s vehicle parameters and set of geography-specific exogenous constraints. It is worth noting here that the GURP is notionally formulated as a heterogeneous VRP to offer additional modeling flexibility; however, for the scope of this thesis’s analysis, this functionality is not exercised. Finally, the modeling extensions to capture the exogenous constraints is covered in more detail in Section 3.3.

Set	Definition	
$N$	set of nodes	$N \in \{0, 1, 2, \dots, n, n+1\}$
$N'$	set of customer nodes	$N' \in \{1, 2, \dots, n\}$
$N^+$	set of customer nodes and starting DC	$N^+ \in \{0, 1, 2, \dots, n\}$
$N^-$	set of customer nodes and ending DC	$N^- \in \{1, 2, \dots, n, n+1\}$
$A$	$\{ (i, j) : i \in \{0\}, j \in N' \text{ and } i \in N', j \in \{n+1\}, i \neq j \}$	$A \in \{(0, 1), (0, 2), \dots, (n, n+1)\}$
$A'$	$\{ (i, j) : i \in N', j \in N', i \neq j \}$	$A' \in \{(1, 2), (1, 3), \dots, (n-1, n)\}$
$K$	set of UAVs in fleet	$K \in \{1, 2, \dots, L\}$

Table 4.1: Notation of GURP model formulation: set definitions.

For notational convenience, sets  $A$  and  $A'$  are defined to denote the possible set of inter-node traverseable arcs with set  $A$  including the two DC nodes  $(0, n+1)$ .

## 4.2.1 Key Problem Assumptions

This section covers the key problem assumptions inherent to VRPs and additional assumptions made in formulating the GURP. Whilst this may not be a comprehensive list, the hope is that this list informs the reader of any room for additional fidelity and espouses the notion that the GURP being solved is adequately reflective of real-

Parameter	Definition	Domain	Units
$D_{i,j}$	distance between $i, j$	$\forall (i, j) \in A$	km
$T_{to,i,j}$	take-off travel time when traversing arc $i, j$	$\forall (i, j) \in A$	deci-time
$T_{la,i,j}$	landing travel time when traversing arc $i, j$	$\forall (i, j) \in A$	deci-time
$T_{tr,i,j}$	cruise travel time when traversing arc $i, j$	$\forall (i, j) \in A$	deci-time
$T_{i,j}$	total travel time when traversing arc $i, j$	$\forall (i, j) \in A$	deci-time
$Q_{i,j}$	trip count incurred when traversing arc $i, j$	$\forall (i, j) \in A$	[-]
$S_i^k$	UAV $k$ 's service time of node $i$	$\forall i \in N', \forall k \in K$	deci-time
$U_0^k$	UAV $k$ 's standard load time at DC	$\forall k \in K$	deci-time
$U^+$	UAV $k$ 's maintenance check time at DC	$\forall k \in K$	deci-time
$U^+$	UAV $k$ 's pre-flight check time at DC	$\forall k \in K$	deci-time
$P_i^+$	delivery package demand at node $i$	$\forall i \in N'$	[-]
$W_i^+$	delivery weight demand at node $i$	$\forall i \in N'$	kg
$V_i^+$	delivery volume demand at node $i$	$\forall i \in N'$	m <sup>3</sup>
$P_i^-$	pickup package demand at node $i$	$\forall i \in N'$	[-]
$W_i^-$	pickup weight demand at node $i$	$\forall i \in N'$	kg
$V_i^-$	pickup volume demand at node $i$	$\forall i \in N'$	m <sup>3</sup>
$P^k$	vehicle package capacity	$\forall k \in K$	pkgs.
$W^k$	vehicle weight capacity	$\forall k \in K$	kg
$V^k$	vehicle volume capacity	$\forall k \in K$	m <sup>3</sup>
$F^k$	UAV $k$ 's battery capacity	$\forall k \in K$	kQh
$T$	UAV flight time capacity before maintenance check	$\forall k \in K$	deci-time
$Q$	UAV trip-count capacity before maintenance check	$\forall k \in K$	[-]
$A_i$	start commit time of node $i$	$\forall i \in N$	deci-time
$B_i$	end commit time of node $i$	$\forall i \in N$	deci-time
$C_F^k$	UAV $k$ 's daily depreciation cost	$\forall k \in K$	\$/day
$C_D^k$	UAV $k$ 's distance travel cost	$\forall k \in K$	\$/km
$C_W^k$	UAV $k$ 's regular shift wage cost	$\forall k \in K$	\$/km
$C_E^k$	UAV $k$ 's energy cost	$\forall k \in K$	\$/kwh
$L$	No. UAVs in fleet		[-]
$\Gamma^k$	UAV $k$ 's average fraction of DC maintenance checks	$\forall k \in K$	0-1
$R$	total hours in a day's operation		deci-time

Table 4.2: Notation of GURP model formulation: model parameters.

world circumstances as to be informative in case-study analysis of Chapter 5. The assumptions made can be aggregated as follows:

- Operational decisions:
  - each route starts and ends at the DC, i.e. starts at node 0 and ends at node  $n + 1$ ;
  - each customer must be visited exactly once or be considered strictly infeasible to serve based on the infeasibility algorithm defined in Algorithm 3;
  - each UAV has a unique set of vehicle parameters but is part of a fixed fleet size (this functionality is excluded for the purposes of the analysis in this chapter and Chapter 5);
  - all UAV capacity constraints and node TWs must be strictly respected.
- Energy consumption model:

- battery capital expenditures (CAPEX) degradation costs associated with how the battery is charged and discharged are neglected;
- energy consumption can be disaggregated into three unique flight regime consumption models – horizontal, hover and vertical flight – that, in turn, inform the energy consumption patterns for four flight maneuvers, specifically: take-off, landing, customer service and cruise (see Figure 4-1 for a pictorial illustration of the flight regimes modeled);
- power consumption can be linearized from non-linear from-first principles equations derived in Appendix A;
- the UAV does not consume energy when waiting in the field.

Finally, this chapter defines the GURP but notably only solves this problem over the course of a single operational day, in part, because the assumption that only the daily operational perspective simplifies the problem and is sufficient to assess UAV-LMD feasibility. VRPs have typically been solved on the scale of a single day’s operation mainly because a day was and still is the more repeatable unit of operational cost incurred by the fleet operator. Demand materializes daily and many of the exogenous factors relevant to operators evolve on a daily basis – traffic, incoming supply of goods to be delivered, the availability of labor etc. – and, thus, a daily solution to the VRP for their operations became the status quo. Granted vehicle fleet composition can, indeed, change across days and weeks forcing the operator to solve a slightly modified VRP. Furthermore, the demand location, density, volume, and type can evolve in patterns on the weekly or monthly, or seasonal time-scale. However, on the whole, the daily unit of measure captures all the key measures of operational cost for which individually modified VRPs can be solved. This thesis opts to solve the GURP on a daily basis since an evaluation of economic and operational feasibility of UAV-LMD can adequately be determined based on the operational cost patterns that emerge from solving the GURP for daily demand across a range of societal, regulatory, geographical and technological constraints. Any additional insights that could evolve on the week, month, or seasonal time-scales can be adequately gleaned qualitatively.

## 4.3 Methodology

### 4.3.1 Exact Model Formulation

This section introduces the *EA* model formulation. Firstly, Table 4.3 defines the decision variables used across the two mixed-integer linear program (MILP)-based formulations. The *EA* is formally defined by first formulating the basic capacitated VRP with TWs in Section 4.3.1.1, followed by an extension of this basic model with additional UAV-specific constraints in Section 4.3.1.2. Section 4.3.1.3, proposes a number of measures to improve the computational performance of the extended model.

Variable	Definition
$x_{i,j}^k$	UAV $k$ traverses arc $i, j$
$y_j^k$	UAV $k$ serves customer $i$
$z_{i,j}^k$	UAV $k$ visits DC between $i, j$
$u_{i,j}^k$	UAV $k$ maintenance between $i, j$
$t_{i,j}^k$	UAV $k$ elapsed time by arc $i, j$ since maintenance
$q_{i,j}^k$	UAV $k$ no. trips by arc $i, j$ since maintenance
$p_{i,j}^{k+}$	UAV $k$ delivery no. packages on arc $i, j$
$w_{i,j}^{k+}$	UAV $k$ delivery weight on arc $i, j$
$v_{i,j}^{k+}$	UAV $k$ delivery volume on arc $i, j$
$p_{i,j}^{k-}$	UAV $k$ pickup no. packages on arc $i, j$
$w_{i,j}^{k-}$	UAV $k$ pickup weight on arc $i, j$
$v_{i,j}^{k-}$	UAV $k$ pickup volume on arc $i, j$
$p_{i,j}^k$	UAV $k$ total no. packages on arc $i, j$
$w_{i,j}^k$	UAV $k$ total weight on arc $i, j$
$v_{i,j}^k$	UAV $k$ total volume on arc $i, j$
$\tau_j^k$	arrival time of UAV $k$ at node $j$
$u_{i,j}^k$	UAV $k$ time spent at DC between $i, j$
$e_{i,j}^k$	UAV $k$ energy consumed traversing $i, j$
$f_j^k$	UAV $k$ energy consumed by $i$
$f_i^k$	UAV $k$ energy consumed at DC from $i$
$a^k$	UAV $k$ activated
$c_f$	fleet depreciation cost
$c_d$	cost of distance travel
$c_w$	cost of wage
$c_{tr}$	cost of time travel
$c_{cd}$	cost of wage spent at DC
$c_{wt}$	cost of wage spent waiting
$c_s$	cost of wage spent serving customers
$c_e$	cost of energy
$c$	total cost

Table 4.3: Notation of GURP model formulation: decision variables.

#### 4.3.1.1 Basic Capacitated Multi-Commodity Routing Model With Time Windows

This section details the foundational model formulation that supports a capacitated multi-vehicle VRP with TWs which will then be extended further in sections below to capture the full extent of the GURP.

$$\text{Minimize } c = c_f + c_d + c_w + c_e, \quad (4.1)$$

where

$$c_f = \sum_{k \in K} a^k C_F^k, \quad (4.2)$$

$$c_d = \sum_{k \in K} C_D^k \sum_{i \in N'} \sum_{j \in N' i \neq j} D_{i,j} x_{i,j}^k, \quad (4.3)$$

$$c_w = c_{tr} + c_{dc} + c_{wt} + c_s \quad (4.4)$$

$$c_{tr} = \sum_{k \in K} C_W^k \sum_{i \in N'} \sum_{j \in N' i \neq j} T_{i,j} x_{i,j}^k, \quad (4.5)$$

$$c_{dc} = \sum_{k \in K} \left( C_W^k \sum_{i,j \in A'} u_{i,j}^k * U_0^+ + \sum_{i,j \in A'} (z_{i,j}^k - u_{i,j}^k) * U_0^- + \sum_{i,j \in A'} z_{i,j}^k * U_0 \right), \quad (4.6)$$

$$c_{wt} = \sum_{k \in K} C_W^k \sum_{j \in N'} \tau_{w_j}^k \quad (4.7)$$

$$c_s = \sum_{k \in K} C_W^k \sum_{j \in N'} T_{s_j} \quad (4.8)$$

$$c_e = \sum_{k \in K} \sum_{i \in N'} \sum_{j \in N' i \neq j} C_E^k e_{i,j}^k, \quad (4.9)$$

subject to

$$a^k \geq y_i^k, \quad \forall i \in N', \forall k \in K, \quad (4.10)$$

$$\sum_{k \in K} \sum_{i \in N^+} x_{i,j}^k = 1, \quad \forall j \in N', \quad (4.11)$$

$$\sum_{i \in N^+} x_{i,j}^k - \sum_{i \in N^-} x_{j,i}^k = 0, \quad \forall j \in N', \forall k \in K, \quad (4.12)$$

$$\sum_{i \in N^+} x_{i,j}^k + \sum_{i \in N^-} x_{j,i}^k = 2y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.13)$$

$$\sum_{j \in N'} x_{0,j}^k - \sum_{j \in N'} x_{j,n+1}^k = 0, \quad \forall k \in K, \quad (4.14)$$

$$\sum_{i \in N^+ i \neq j} p_{i,j}^{k+} - \sum_{i \in N^- i \neq j} p_{j,i}^{k+} = P_j^+ y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.15)$$

$$\sum_{i \in N^+ i \neq j} w_{i,j}^{k+} - \sum_{i \in N^- i \neq j} w_{j,i}^{k+} = W_j^+ y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.16)$$

$$\sum_{i \in N^+ i \neq j} v_{i,j}^{k+} - \sum_{i \in N^- i \neq j} v_{j,i}^{k+} = V_j^+ y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.17)$$

$$\sum_{i \in N^+ i \neq j} p_{i,j}^{k-} - \sum_{i \in N^- i \neq j} p_{j,i}^{k-} = -P_j^- y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.18)$$

$$\sum_{i \in N^+ i \neq j} w_{i,j}^{k-} - \sum_{i \in N^- i \neq j} w_{j,i}^{k-} = -W_j^- y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.19)$$

$$\sum_{i \in N^+ i \neq j} v_{i,j}^{k-} - \sum_{i \in N^- i \neq j} v_{j,i}^{k-} = -V_j^- y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.20)$$

$$p_{i,j}^{k+} + p_{i,j}^{k-} = p_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.21)$$

$$w_{i,j}^{k+} + w_{i,j}^{k-} = w_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.22)$$

$$v_{i,j}^{k+} + v_{i,j}^{k-} = v_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.23)$$

$$p_{i,j}^k \leq P^k x_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.24)$$

$$w_{i,j}^k \leq W^k x_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.25)$$

$$v_{i,j}^k \leq V^k x_{i,j}^k, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.26)$$

$$p_{i,n+1}^{k+} = 0, \quad w_{i,n+1}^{k+} = 0, \quad v_{i,n+1}^{k+} = 0, \quad \forall i \in N', \forall k \in K, \quad (4.27)$$

$$p_{0,j}^{k-} = 0, \quad w_{0,j}^{k-} = 0, \quad v_{0,j}^{k-} = 0, \quad \forall j \in N', \forall k \in K, \quad (4.28)$$

$$\tau_i^k + T_{tr_{i,j}}^k + S_i^k - M' (1 - x_{i,j}^k) \leq \tau_j^k, \quad \forall (i,j) \in A', \forall k \in K, \quad (4.29)$$

$$\tau_i^k \geq A_i, \quad \tau_i^k \leq B_i, \quad \forall i \in N^-, \forall k \in K, \quad (4.30)$$

$$U_0^k + u_{i,j}^k U_0^{k+} + (1 - u_{i,j}^k) U_0^{k-} \leq v_{i,j}^k + M_{i,j}'' (1 - z_{i,j}^k), \quad \forall (i,j) \in A', \forall k \in K, \quad (4.31)$$

$$\tau_i^k + T_{tr_{i,n+1}}^k + S_i^k + T_{tr_{0,j}}^k + v_{i,j}^k \leq \tau_j^k + M_{i,j}'' (1 - z_{i,j}^k), \quad \forall (i,j) \in A', \forall k \in K, \quad (4.32)$$

$$\sum_{i \in N', i \neq j} z_{i,j}^k \leq x_{0,j}^k, \quad \forall j \in N', \forall k \in K, \quad (4.33)$$

$$\sum_{j \in N', j \neq i} z_{i,j}^k \leq x_{i,n+1}^k, \quad \forall i \in N', \forall k \in K, \quad (4.34)$$

$$\sum_{i \in N'} \sum_{j \in N', i \neq j} z_{i,j}^k + a^k = \sum_{j \in N'} x_{0,j}^k, \quad \forall k \in K, \quad (4.35)$$

with

$$x_{i,j}^k \in \{0, 1\}, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.36)$$

$$u_{i,j}^k z_{i,j}^k \in \{0, 1\}, \quad \forall (i,j) \in A', \forall k \in K, \quad (4.37)$$

$$y_j^k \in \{0, 1\}, \quad \forall j \in N', \forall k \in K, \quad (4.38)$$

$$a^k \in \{0, 1\}, \quad \forall k \in K, \quad (4.39)$$

$$f_j^k, f_j'^k, t_j^k, q_j^k \geq 0, \quad \forall j \in N', \forall k \in K, \quad (4.40)$$

$$\tau_j^k \geq 0, \quad \forall j \in N, \forall k \in K, \quad (4.41)$$

$$p_{i,j}^{k+}, w_{i,j}^{k+}, v_{i,j}^{k+}, p_{i,j}^{k-}, w_{i,j}^{k-}, v_{i,j}^{k-}, p_{i,j}^k, w_{i,j}^k, v_{i,j}^k, e_{i,j}^k \geq 0, \quad \forall (i,j) \in A, \forall k \in K, \quad (4.42)$$

$$v_{i,j}^k \geq 0, \quad \forall (i,j) \in A', \forall k \in K, \quad (4.43)$$

and

$$M' = R, \quad M_{i,j}'' = T_{tr_{i,n+1}}^k + S_i^k + U_0^k + U_0^{k+} + U_0^{k-} + T_{tr_{0,j}}^k + B_i. \quad (4.44)$$

**Domain constraints.** Constraints 4.36 - 4.43 denote the domains of the decision variables and ensure non-negativity where required.

**Routing constraints.** Constraints 4.10 activates the UAV if it is used to serve at least one customer. Constraints 4.11 ensures each customer is visited only once whilst Constraints 4.12 ensures each incoming arc is paired with an outgoing arc.

Constraints 4.13 connects the traversed arc variable with the customer service variable whilst Constraints 4.14 ensures each DC launch is associated with one other DC return.

**Flow conservation and sub-tour elimination constraints.** Constraints 4.15, 4.16 and 4.17 enforce commodity flow through each node whilst ensuring each node’s demand is satisfied for each delivery commodity: package count, weight and volume. Constraints 4.18, 4.19 and 4.20 are the equivalent for each pickup commodity. These six constraints also eliminate sub-tours.

**Capacity constraints.** Constraints 4.21, 4.22 and 4.23 sum the delivery and pickup amounts for each commodity into a total commodity amount for each arc. Constraints 4.24, 4.25 and 4.26 ensure the UAV commodity capacity is respected along each arc. Constraints 4.27 enforce delivery package, weight and volume commodities on the UAV to be zero when the UAV returns to the DC whilst Constraints 4.28 ensure the same for each pickup commodity when launching from the DC.

**Timing constraints.** Constraints 4.29 establishes a time relationship between two consecutive nodes within a trip. Constraints 4.30 maintains TW feasibility. Constraints 4.31 simply captures the expected time spent at the DC in an auxiliary variable between the final and start nodes of two consecutive trips. Finally, Constraints 4.32 establishes a time relationship between the final and start nodes of two consecutive trips.

**Multi-trip constraints.** Constraints 4.33, 4.34 and 4.35 tie variables  $\mathbf{x}$  and  $\mathbf{z}$ . Specifically, Constraints 4.33 and 4.34 ensures a DC return can only be performed if DC-return and DC-launch arcs exist for those nodes. Constraints 4.35 ties the number of DC returns to the number of launches and the UAV activation variable, allowing a UAV in the fleet to remain inactive if necessary. Finally, Equation 4.44  $M'$  can be shown to be equal to the total time of operation and  $M''_{i,j}$  equal to the longest possible travel time between nodes  $i, j$  with an intermediary DC-return adjusted by node  $i$ ’s end-commit-time.

### 4.3.1.2 Model Extension with UAV-Specific Operational Constraints

In this section, we define the UAV-specific operational constraints added to the models, namely energy, flight time and trip count constraints.

**Energy constraints.** The following details the from-first-principles energy equations that capture UAV energy consumption in various flight regimes and the subsequent energy constraints.

$$f_j^k \leq F^k y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.45)$$

$$f_i'^k \leq F^k x_{i,n+1}^k, \quad \forall i \in N', \forall k \in K, \quad (4.46)$$

$$f_j^k \geq f_i^k + e_{i,j}^k - M_{i,j}^{'''k} (1 - x_{i,j}^k), \quad \forall i, j \in A', \forall k \in K, \quad (4.47)$$

$$e_{i,j}^k \geq s_{a_{i,j}}|_{w_{i,j}^k} + s_{s_{i,j}}|_{w_{i,j}^k} - M_{i,j}^{'''k} (1 - x_{i,j}^k), \quad \forall i, j \in A, \forall k \in K, \quad (4.48)$$

$$f_i^k \geq f_i^k + e_{i,n+1}^k - M_{i,n+1}^{'''k} (1 - x_{i,n+1}^k), \quad \forall i \in N', \forall k \in K, \quad (4.49)$$

$$f_j^k \geq e_{0,j}^k - M_{0,j}^{'''k} (1 - x_{0,j}^k) - M_{i,j}^{'''k} u_{i,j}^k - M_{i,j}^{'''k} (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.50)$$

where  $M_{i,j}^{'''k} = s_{a_{i,j}}(W^k) + s_{s_{i,j}}(W^k) + F$ . The non-linear energy equations for travel (tr), takeoff (to), landing (la), and hover (ho) are as follows:

$$s_{arc}|_{w_{i,j}^k} = h_{to}|_{w_{i,j}^k} T_{to_{i,j}} + h_{tr}|_{w_{i,j}^k} T_{tr_{i,j}} + h_{la}|_{w_{i,j}^k} T_{la_{i,j}}, \quad \forall (i, j) \in A, \forall k \in K, \quad (4.51)$$

$$s_{serve}|_{w_{i,j}^k} = h_{ho}|_{w_{i,j}^k} U_i, \quad \forall (i, j) \in A, \forall k \in K. \quad (4.52)$$

Constraints 4.45, 4.46 ensure the battery capacity is not exceeded. Constraints 4.48 defines the energy matrix whilst Constraints 4.47, 4.49 enforce energy conservation through the nodes. Finally, constraint 4.50 sets a lower bound reset for the energy tracker at each trip start. Equation 4.51 captures the total energy consumed traversing an arc whilst Equation 4.52 captures the energy consumed serving a customer if hover-based service is assumed. These equations are dependent on the power-consumption equations for a quadcopter UAV:

$$h_{tr}|_{w_{i,j}^k} = TWR^3 \frac{\left( (M + w_{i,j}^k) g \right)^3}{\rho \sqrt{2}}, \quad \forall (i, j) \in A, \forall k \in K, \quad (4.53)$$

$$h_{to}|_{w_{i,j}^k} = TWR \sqrt{TWR - 1} \left( (M + w_{i,j}^k) g \right)^{\frac{3}{2}} \sqrt{\frac{1}{\rho A}}, \quad \forall (i, j) \in A, \forall k \in K, \quad (4.54)$$

$$h_{la}|_{w_{i,j}^k} = h_{to}|_{w_{i,j}^k}, \quad \forall (i, j) \in A, \forall k \in K, \quad (4.55)$$

$$h_{ho}|_{w_{i,j}^k} = \sqrt{\frac{\left( (M + w_{i,j}^k) g \right)^3}{2\rho A}}, \quad \forall (i, j) \in A, \forall k \in K, \quad (4.56)$$

where  $g = 9.81ms^{-2}$ ,  $M$  is the total UAV mass ( $kg$ ),  $\rho$  is the fluid density of air ( $kgm^{-3}$ ), and  $A$  is the UAV's total rotor disc area ( $m^2$ ). Equations 4.53, 4.54, 4.55 and 4.56 represent the non-linear power consumption equations for a quadcopter A. Note, it is assumed take-off and landing power consumption patterns are identical. In both Dorling et al. (2016) and Cheng et al. (2018), only the horizontal flight regime is considered, with horizontal power consumption modeled as hover flight as per Equation 4.56. Whilst we arrive at the same result for the hover flight regime, we derive each additional flight regime's power consumption equation from first principles. See Appendix A. Again, see Figure 4-1 for a pictorial version of the energy consumption logic broken into the independent flight regimes.

**Flight time constraints.** In a similar fashion to Constraints 4.45–4.50, the following constraints track and constrain a UAV's flight time as it pertains the maintenance



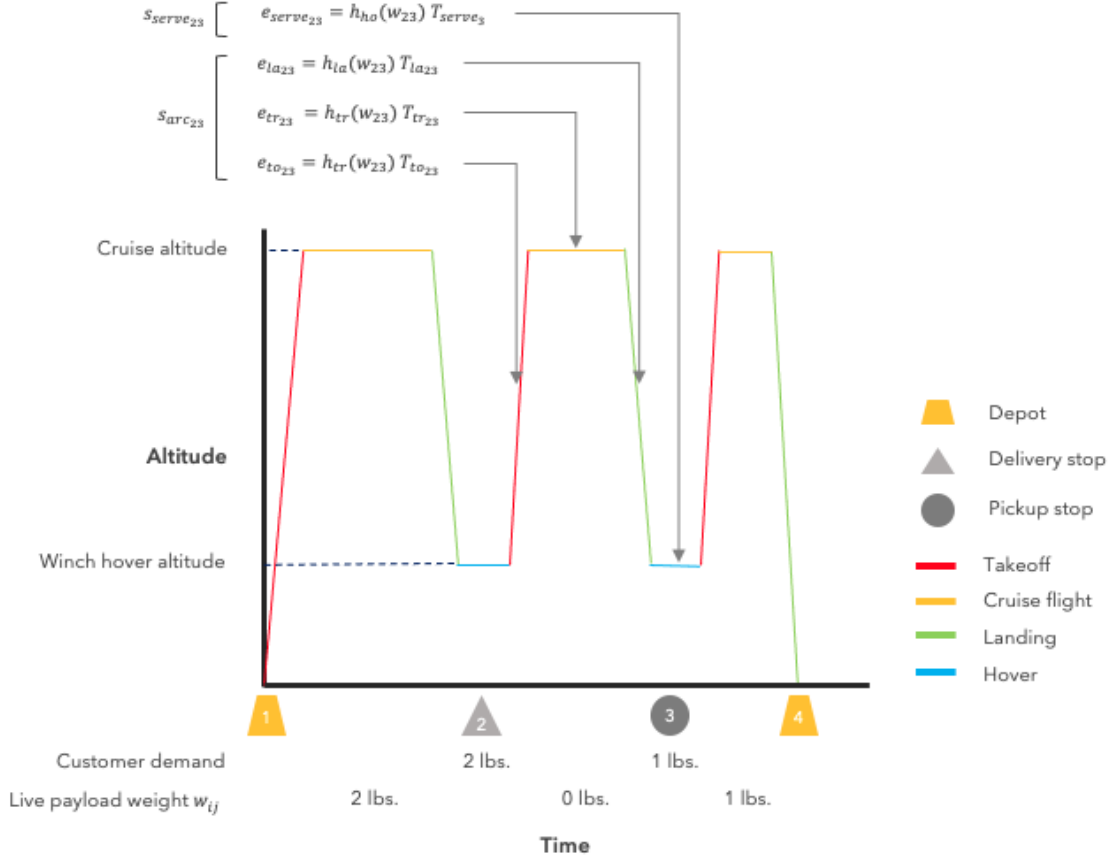


Figure 4-1: UAV energy consumption formulation logic disaggregated into independent flight regimes.

check logic.

$$t_j^k \leq T^k y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.57)$$

$$t_i^k \leq T^k x_{i,n+1}^k, \quad \forall i \in N', \forall k \in K, \quad (4.58)$$

$$t_j^k \geq t_i^k + T_{i,j}^k - M_{i,j}^k (1 - x_{i,j}^k), \quad \forall i, j \in A', \forall k \in K, \quad (4.59)$$

$$t_i^k \geq t_i^k + T_{i,n+1}^k - M_{i,n+1}^k (1 - x_{i,n+1}^k), \quad \forall i \in N', \forall k \in K, \quad (4.60)$$

$$t_j^k \geq T_{0,j}^k - M_{0,j}^k (1 - x_{0,j}^k) - M_{i,j}^k u_{i,j}^k - M_{i,j}^k (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.61)$$

Constraints 4.57, 4.58 ensure the flight time capacity is not exceeded. Constraints 4.59, 4.60 ensure flight time conservation through the nodes. Finally, constraint 4.61 sets a lower bound reset for the flight time tracker at each trip start.

**Trip counts.** Just as with energy and flight time, this section details the constraints that track and constraint a UAV's trip count as it pertains the maintenance check

logic.

$$q_j^k \leq Q^k y_j^k, \quad \forall j \in N', \forall k \in K, \quad (4.62)$$

$$q_i^k \leq Q^k x_{i,n+1}^k, \quad \forall i \in N', \forall k \in K, \quad (4.63)$$

$$q_j^k \geq q_i^k + Q_{i,j}^k - M_{i,j}^{''''k} (1 - x_{i,j}^k), \quad \forall i, j \in A', \forall k \in K, \quad (4.64)$$

$$q_i^k \geq q_i^k + Q_{i,n+1}^k - M_{i,n+1}^{''''k} (1 - x_{i,n+1}^k), \quad \forall i \in N', \forall k \in K, \quad (4.65)$$

$$q_j^k \geq Q_{0,j}^k - M_{0,j}^{''''k} (1 - x_{0,j}^k) - M_{i,j}^{''''k} u_{i,j}^k - M_{i,j}^{''''k} (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.66)$$

Constraints 4.62, 4.63 ensure a UAV's max trip count capacity is not exceeded. Constraints 4.64, 4.65 ensure trip count conservation through the nodes. Finally, Constraint 4.66 sets a lower bound reset for the trip count tracker at each trip start.

**Maintenance check constraints.** This section details additional constraints that enable the *EA* model to track the maintenance check dimensions – energy, flight time and trip count – between trips.

$$f_j^k \geq f_i^k - M_{i,n+1}^{''''k} (1 - x_{i,n+1}^k) + e_{0,j}^k - M_{i,j}^{''''k} u_{i,j}^k - M_{i,j}^{''''k} (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.67)$$

$$t_j^k \geq t_i^k - M_{i,n+1}^{''''k} (1 - x_{i,n+1}^k) + T_{0,j}^k - M_{i,j}^{''''k} u_{i,j}^k - M_{i,j}^{''''k} (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.68)$$

$$q_j^k \geq q_i^k - M_{i,n+1}^{''''k} (1 - x_{i,n+1}^k) + Q_{0,j}^k - M_{i,j}^{''''k} u_{i,j}^k - M_{i,j}^{''''k} (1 - z_{i,j}^k), \quad \forall j \in N', \forall k \in K, \quad (4.69)$$

with

$$M^{''''} = 2T, \quad M^{''''} = 2Q. \quad (4.70)$$

Note that Constraints 4.67 is identical to Constraints 4.61 except with two additional starting terms which, together, capture the final energy of the trip immediately preceding. The same logic applies for Constraints 4.68 and 4.67, and Constraints 4.69 and 4.69 but for flight time and trip count, respectively.

### 4.3.1.3 Improving Model Performance

In this section, we introduce linearization strategies followed by valid inequalities and user cuts implemented to further strengthen model performance.

**Model linearization.** The power consumption are linearized in Equations 4.53-4.56 and are rewritten as follows, where the  $\alpha$ 's and  $\beta$ 's are the linearized coefficients as shown in Appendix A.4:

$$h_{tr}(w_{i,j}^k) = \alpha_{tr}(M + w_{i,j}^k) + \beta_{tr}, \quad \forall(i, j) \in A, \forall k \in K, \quad (4.53')$$

$$h_{to}(w_{i,j}^k) = \alpha_{to}(M + w_{i,j}^k) + \beta_{to}, \quad \forall(i, j) \in A, \forall k \in K, \quad (4.54')$$

$$h_{la}(w_{i,j}^k) = \alpha_{la}(M + w_{i,j}^k) + \beta_{la}, \quad \forall(i, j) \in A, \forall k \in K, \quad (4.55')$$

$$h_{ho}(w_{i,j}^k) = \alpha_{ho}(M + w_{i,j}^k) + \beta_{ho}, \quad \forall(i, j) \in A, \forall k \in K. \quad (4.56')$$

**Valid inequalities: routing.** Finally, we implement valid inequalities to further strengthen the model:

$$x_{j,i} \leq y_i^k, \quad \forall i \in N', \forall j \in N^-, \forall k \in K, \quad (4.71)$$

$$\sum_{k \in K} \sum_{j \in N'} x_{0,j}^k \leq n, \quad (4.72)$$

$$\sum_{k \in K} \sum_{i \in N'} \sum_{j \in N', j \neq i} z_{i,j}^k \leq n - 1, \quad (4.73)$$

$$\sum_{i \in N', i \neq j} z_{i,j}^k + \sum_{i \in N', i \neq j} z_{j,i}^k \leq 2a^k, \quad \forall j \in N', k \in K, \quad (4.74)$$

$$z_{i,j}^k + x_{i,j}^k \leq 1, \quad \forall i, j \in A', k \in K. \quad (4.75)$$

$$\sum_{k \in K} \sum_{j \in N'} x_{0,j}^k \geq \max \left( \left\lceil \frac{\sum_{i \in N'} P_i^+}{P} \right\rceil, \left\lceil \frac{\sum_{i \in N'} W_i^+}{W} \right\rceil, \left\lceil \frac{\sum_{i \in N'} V_i^+}{V} \right\rceil, \right. \\ \left. \left\lceil \frac{\sum_{i \in N'} P_i^-}{P} \right\rceil, \left\lceil \frac{\sum_{i \in N'} W_i^-}{W} \right\rceil, \left\lceil \frac{\sum_{i \in N'} V_i^-}{V} \right\rceil \right), \quad (4.76)$$

Constraints 4.71 is a logical inequality between customer service and arcs traversed whilst Constraint 4.72 sets an upper bound for total number of DC launches. Constraint 4.73 and 4.74 set upper bounds for the total number of DC-visits. Constraint 4.76 all set lower bounds for the total number of DC-launches based on the total demand for each commodity type across relative to the UAV commodity capacity in both delivery and pickup dimensions. Finally, Constraints 4.75 enforces that there can only exist either a DC-return, a traversed arc or neither of these actions between two nodes but not both simultaneously.

**Valid inequalities: energy.** Additionally, Constraints 4.77 sets the lower bound for the energy matrix assuming that the minimum energy consumed between any two

nodes is equal to the UAV consumption with zero payload,

$$e_{i,j}^k \geq x_{i,j}^k (s_{a_{i,j}}|_0 + s_{s_{i,j}}|_0) \quad \forall (i, j) \in A, \forall k \in K. \quad (4.77)$$

**Valid inequalities: commodity capacities.** Additionally, there exist logical cuts that exclude sequences of arcs that can be pre-determined as infeasible via simple commodity or energy capacity calculations. For any given arc sequence,  $A$ , of length  $l$  (e.g.,  $[0, 1, 4, 6, 8, n + 1]$  where the indices of this arc are  $[i_0, i_1, \dots, i_5]$ ) and where  $n + 1$  is the return DC node, this constraint is implemented as

$$x_{i_1, i_2} + \dots + x_{i_3, i_4} \leq l - 1. \quad (4.78)$$

And if the implementation of Constraints 4.78 results in the following holding for node  $j$ ,

$$x_{i,j} = 0, \quad x_{j,i} = 0, \quad \forall i \in N', \quad (4.79)$$

then the following valid inequality can be additionally implemented:

$$\sum_{i \in N', i \neq j} z_{i,j}^k + \sum_{i \in N', i \neq j} z_{j,i}^k \geq y_j^k, \quad \forall j \in N', k \in K. \quad (4.80)$$

Constraint 4.78 arises when a UAV traversing sequence of arcs  $A$  exceeds any of its commodity or energy capacities on any of the arcs. As Constraints 4.78 is continually implemented in the pre-solve phase, Constraints 4.79 could simultaneously arise, suggesting there are no feasible customer arcs in or out of node  $j$ , only from- or to- DC arcs. Thus, node  $j$  must be singly served from the DC and Constraints 4.80 can be implemented which ensures that if node  $j$  is being served by UAV  $k$ , there must exist a node pairing  $i, j$  or  $j, i$  between which a DC-return is performed so that node  $j$  can be singly served.

### 4.3.2 Exact Two-Stage Approach

In this section, we introduce the iterative model formulation which leverages much of the  $EA$  formulation, except it solves one sub-problem of the  $EA$  in an second MILP-based model. This approach seeks to simplify the core problem the routing model is required to solve by making assumptions around the fraction of maintenance checks each UAV is required to make at the DC over the course of its operational day. By fixing this maintenance check fraction, the possible solution space is tightened and

the computational speed is improved. Determining the optimal fraction of maintenance checks is performed in a second-stage model, and this is done in an iterative manner such that the overall solution approach takes a staged approach to reaching the optimal or near-optimal solution in shorter time.

From hereon the two models that form the *ETSA* will be referred to as *Exact Two-Stage Approach Stage-1 (ETSA-1)* and *Exact Two-Stage Approach Stage-2 (ETSA-2)*. Figure 4-2 is a schematic of how the iterative model functions. Note, each time the *ETSA-2* receives a valid solution from *ETSA-1*, it works to reduce the solution cost further by re-ordering the trip sequence and reducing the maintenance check fraction in an effort to minimize asset downtime. The *ETSA-1*, on the other hand, receives an improved solution from *ETSA-2* and attempts to switch both trip and stop sequences to further improve the overall solution cost whilst assuming a fixed maintenance check fraction. Importantly, whilst *ETSA-1* operates across the UAV fleet, *ETSA-2* operates on each UAV in the fleet individually.

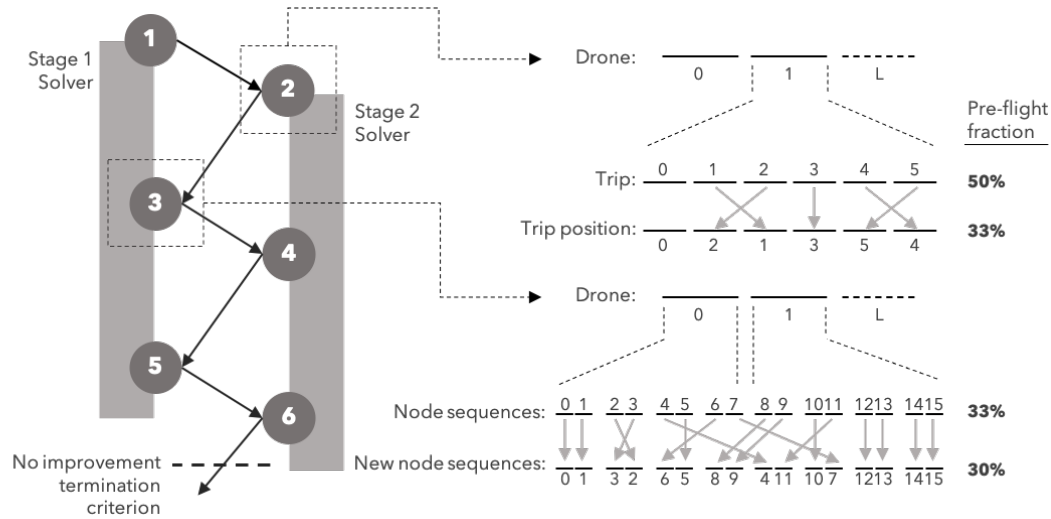


Figure 4-2: *ETSA* solution approach schematic, highlighting iterative solution logic and customer-based versus trip-based sequencing improvement formulations for *ETSA-1* and *ETSA-2* respectively.

#### 4.3.2.1 Exact Two-Stage Approach – Stage 1

The *ETSA-1* is structurally identical to the *EA* model formulated in Section 4.3.1, specifically Equations 4.1–4.80 with Equations 4.57–4.66 omitted. During the *ETSA-1*, the only operational constraints that need to be adhered to are the per-trip energy capacity and per-trip flight time constraint. The multi-trip energy, flight time and trip count constraints can be outsourced to the *ETSA-2*. This is to simplify the problem of determining during which DC visit to activate the maintenance check. Instead, the *ETSA-1* is provided a minimum maintenance check count fraction determined

by the *ETSA-2* model. To replace the omitted Constraints 4.57–4.66, the following constraints are included:

$$\sum_{i \in N'} \sum_{j \in N'} u_{i,j}^k \geq \Gamma^k \sum_{i \in N'} \sum_{j \in N'} z_{i,j}^k, \quad \forall k \in K, \quad (4.81)$$

$$u_{i,j}^k \leq z_{i,j}^k, \quad \forall i, j \in A', \forall k \in K. \quad (4.82)$$

Constraints 4.81 ensures the number of activated maintenance checks does at least exceeds the minimum number of maintenance checks determined by the *ETSA-2* model, calculated as the total number of DC visits multiplied by the fraction of determined maintenance checks per UAV in the fleet. Constraints 4.82 ensures that a maintenance check can only occur when the UAV visits the DC. The *ETSA-2* model is formulated in Section 4.3.2.2.

#### 4.3.2.2 Exact Two-Stage Approach – Stage 2

The *ETSA-2* receives each UAV’s finalized route from the *ETSA-1* with information about the route’s number of trips as well as each trip’s duration and energy requirement. The *ETSA-2* re-orders the sequence of trips within a UAV’s route without changing the sequence of stops within a trip with the objective to minimize total cost. The key method by which the model minimizes cost is by sequencing the customers and necessary maintenance checks such that the key cost components – number of UAVs required, total operating time, total distance traveled and total energy consumed – are minimized. Thus, it is fundamentally an assignment problem. Throughout the formulation in Equations 4.83–4.101, index  $i$  refers to trip  $i$  in the received UAV route whilst index  $j$  refers to a trip position that a trip ought to be assigned to.

In addition to Tables 4.1 through 4.3, Tables 4.4, 4.5 and 4.6 summarize additional sets, relevant model parameters and decision variables used to formulate the *ETSA-2* model, respectively. Note that  $w$  denotes total number of trips performed by a specific UAV’s route, hereon referred to as UAV  $k$ .

Set	Definition	
$W$	set of UAV trips	$\{1, 2, \dots, w\}$
$W^+$	set of UAV trips with final trip omitted	$\{1, 2, \dots, w - 1\}$
$W^-$	set of UAV trips with first trip omitted	$\{2, \dots, w\}$
$W_j$	set of UAV trips with trips beyond trip $j$ omitted	$\{1, 2, \dots, j - 1\}$

Table 4.4: *ETSA-2* set definitions.

$$\text{Minimize } c = c_d + c_t + c_w + c_e, \quad (4.83)$$

Parameter	Definition	Domain	Units
$A_i$	earliest start time of trip $i$	$\forall i \in W$	deci-time
$B_i$	latest start time of trip $i$	$\forall i \in W$	deci-time
$T_i$	trip $i$ flight duration	$\forall i \in W$	deci-time
$D_i$	trip $i$ distance traversed	$\forall i \in W$	km
$E_i$	trip $i$ energy consumed	$\forall i \in W$	kWh

Table 4.5: *ETSA-2* parameters.

Variable	Definition	
$x_{i,j}$	trip $i$ assigned to position $j$	binary
$p_j$	maintenance check activated after position $j$	binary
$q_j$	trip-count maintenance check activated after position $j$	binary
$t_j$	flight-time maintenance check activated after position $j$	binary
$e_j$	energy consumption maintenance check activated after position $j$	binary
$a_j$	position $j$ start time	continuous
$b_j$	position $j$ end time	continuous

Table 4.6: *ETSA-2* decision variables.

where

$$c_d = C_D^k, \quad (4.84)$$

$$c_t = C_T^k \sum_{i \in W} D_i, \quad (4.85)$$

$$c_w = C_W^k (b_n - a_1), \quad (4.86)$$

$$c_e = C_E^k \sum_{i \in W} E_i, \quad (4.87)$$

subject to

$$\sum_{i=1}^N x_{i,j} = 1, \quad \sum_{i=1}^N x_{j,i} = 1, \quad \forall j \in W, \quad (4.88)$$

$$M_u p_j \geq u_j, \quad \forall j \in W, \quad (4.89)$$

$$M_t p_j \geq t_j, \quad \forall j \in W, \quad (4.90)$$

$$M_e p_j \geq e_j, \quad \forall j \in W, \quad (4.91)$$

$$q_j \geq q_{j-1} + 1 - M_q p_{j-1}, \quad \forall j \in W^-, \quad (4.92)$$

$$t_j \geq t_{j-1} + \sum_{i \in W} T_i x_{i,j} - M_t p_{j-1}, \quad \forall j \in W^-, \quad (4.93)$$

$$e_j \geq e_{j-1} + \sum_{i \in W} E_i x_{i,j} - M_e p_{j-1}, \quad \forall j \in W^-, \quad (4.94)$$

$$q_j \geq 1, \quad \forall j \in W, \quad (4.95)$$

$$t_j \geq \sum_{i \in W} T_i x_{i,j}, \quad \forall j \in W, \quad (4.96)$$

$$e_j \geq \sum_{i \in W} E_i x_{i,j}, \quad \forall j \in W, \quad (4.97)$$

$$Q_j \leq Q^k, \quad t_j \leq T^k, \quad e_j \leq F^k, \quad \forall j \in W, \quad (4.98)$$

$$b_j = a_j + \sum_{i=1}^N x_{i,j} T_i, \quad \forall j \in W, \quad (4.99)$$

$$a_{j+1} = b_j + U_0 + U_0^+ p_j + U_0^- (1 - p_j), \quad \forall j \in W^+, \quad (4.100)$$

$$a_j \geq \sum_{j=1}^N x_{i,j} A_i, \quad a_j \leq \sum_{j=1}^N x_{i,j} B_i, \quad \forall j \in W, \quad (4.101)$$

with

$$M_u = w + 1, \quad M_t = B_0, \quad M_e = F^k. \quad (4.102)$$

Constraints 4.84, 4.85, 4.86, 4.87 capture the fixed, distance traversed, wage and energy costs of UAV  $k$ 's operation. Constraints 4.88 ensure there is an exclusive and exhaustive matching between trips and trip positions in the sequence. Constraints 4.89, 4.90 and 4.91 translate the trip-count, flight time and energy maintenance check trackers onto the cumulative maintenance check tracker. Constraints 4.92, 4.93, 4.94 ensure trip-count, flight time and energy between subsequent trip positions. Constraints 4.95, 4.96, 4.97 enforces that trip position  $j$ 's trip-count, flight time and energy are strictly greater than or equal to those dimensions of trip  $i$  assigned to trip position  $j$ . Constraints 4.98 ensure that the multi-trip trip-count, flight time and energy do not exceed their allowable capacity before a maintenance check must be activated. Constraints 4.99 simply fixes trip position  $j$ 's end time. Constraints 4.100 ties the end time and start times of subsequent trip positions. Finally, Constraints 4.101 ensure that trip position  $j$ 's start and end time are within the start and end time ranges permissible trip  $i$  assigned to trip position  $j$ .

### 4.3.3 Efficient Heuristic Solution Approach

Even in scenarios with a small number of customers to service, the *EA* and *ETSA* can take a prohibitively long time to reach optimality. Under real-world solution time constraints, a faster but potentially sub-optimal solution may be desirable. In this section, we develop a heuristics-based approach to solve the UAV routing problem as a tool to solve otherwise intractable demand instances whilst optimizing for the same cost function. The developed heuristic not only serves as a potential avenue to feasible, albeit sub-optimal solutions, but also as a naive warm-start tool for the *EA* and *ETSA*.



### 4.3.3.1 High-Level Heuristic Solution Approach

There are two steps to the heuristic solution approach: 1) a sequential insertion heuristic, the *I1* algorithm followed by the *Savings* algorithm; and 2) a series of pseudo-random improvement operator applications that, together, constitute a final solution improvement step. The high-level *HA* solution approach is covered in Algorithm 1.

The functionality captured in the `I1SavingsInsertion` function in Algorithm 1 is now discussed. Both the *I1* and *Savings* algorithms insert customers sequentially until no more customers are left un-served. At each insertion iteration, the most similar customer to the customers already on the UAV routes is selected with similarity defined simply the average customer geographic proximity to all the other customers on the route. The *I1* algorithm is specifically used for TW stops whilst the *Savings* algorithm is only employed after all the TW stops have already been inserted and only non-TW stops remain. In both algorithms, each customer is inserted in the sequence position as to minimize the overall fleet routing cost. If no insertion is feasible, then a new vehicle is created and this customer is assigned as the seed customer. The TW stops are first inserted ahead of the non-TW stops, since it is assumed that conflicting TWs without enough time for a vehicle to serve both stops and travel between the stops forces an additional vehicle to be dispatched to still meet that hard TW constraint. Thus, routing the TW stops first provides a lower bound for the total number of vehicles required, providing the *Savings* algorithm with as many insertion options as possible whilst minimizing the fixed UAV activation cost such that the *Savings* algorithm can efficiently minimize total fleet cost as it inserts remaining non-TW stops. This procedure is elucidated in Algorithm 2. Any more detail regarding the *I1* and *Savings* algorithms will not be included here and, instead, this thesis defers to the extensive literature on both algorithms (Bräysy and Gendreau, 2005; Clarke and Wright, 1964).

---

**Algorithm 1:** High level *HA* solution approach.

---

- 1 **Inputs:**  $l$ : a list of customers to be assigned to UAV routes.
  - 2  $R \leftarrow \text{I1SavingsInsertion}(l)$ ;
  - 3  $R \leftarrow \text{RouteImprovement}(R)$ ;
  - 4 **Outputs:**  $R$  a set of UAV routes filled with the stops from  $l$ .
- 

### 4.3.3.2 Insertion Feasibility

This section covers how insertion feasibility is explicitly evaluated at each step in the *I1* and *Savings* insertion algorithms across the various feasibility dimensions: time, distance, and energy. These feasibility checks are also leveraged in the route improvement step described in Section 4.3.3.3. Prior to any route-specific feasibility checks, an overarching service feasibility check is run to filter out any outright infeasible customers. Whilst the later feasibility functions would return these customers are

---

**Algorithm 2:** *HA I1* and *Savings* insertion logic.

---

- 1 **Inputs:**  $l$ : a list of customers to be assigned to UAV routes.
  - 2  $l_{TW} \leftarrow \text{getTWstops}(l)$ ;
  - 3  $l_{noTW} \leftarrow \text{getnoTWstops}(l)$ ;
  - 4  $R \leftarrow \text{I1}(l_{TW})$ ;
  - 5  $R \leftarrow \text{Savings}(l_{noTW}, r)$ ;
  - 6 **Outputs:**  $R$  a set of UAV routes filled with the stops from  $l$ .
- 

infeasible and the end-result would be the same, these customers would remain in the customer insertion for the duration of the insertion procedure substantially extending insertion run-times. Thus, the model proactively removes infeasible customers prior to insertion such that all customers provided to the insertion algorithms are fundamentally serviceable given the operational constraints.

**Service feasibility.** This feasibility check exists to filter out customers who exist in the provided demand set but are fundamentally infeasible to serve based on operational constraints, vehicle constraints or customer-specific constraints. The methodology is captured in Algorithm 3 with its functions described in more detail below.

---

**Algorithm 3:** Service feasibility logic.

---

- 1 **Inputs:**  $s$ : a set of customers that exist in the demand region.
  - 2  $s' \leftarrow \text{FilterInfeasibleGeography}(s)$ ;
  - 3  $s' \leftarrow \text{FilterInfeasibleCommodity}(s')$ ;
  - 4  $s' \leftarrow \text{FilterInfeasibleEnergy}(s')$ ;
  - 5 **Outputs:**  $s'$  a filtered set of customers that are strictly serveable by the pre-defined UAV fleet.
- 

The `FilterInfeasibleGeography` function identifies customers that geographically reside in regions that are deemed no-fly zones by the exogenous constraint scenario defined for the particular demand set. Also note that if the minimum altitude for a particular region is higher than the maximum flight altitude for the UAV, there is no feasible flight altitude in this region and all customers in this region are also considered infeasible.

The `FilterInfeasibleCommodity` function is built upon the assumption that if a particular customer is not serveable as a whole, its demand can be disaggregated to the package level such that each package or group of packages can be served individually. This disaggregation is done such that the total demand of each subset of packages served by the UAV is smaller than the UAV's capacity along that commodity. With that said, the disaggregation logic attempts to maximize the total demand of each package subset to minimize the need for repeated, unnecessary customer visits. If at the single package level the package exceeds the UAV's capacity along any of the commodity dimensions, that package is considered strictly infeasible to serve

and excluded from the demand set.

Finally, the `FilterInfeasibleEnergy` function validates if each customer, disaggregated at the package level, is serveable from the DC in a single point-to-point trip given the UAV's maximum available on-board battery capacity given any exogenous constraints that may exist between the DC and customer that may alter the flight trajectory taken to serve that customer. This also takes into account each package's weight and its impact on the UAV's energy consumption. If a UAV cannot serve a single package given these societal constraints and energy capacity, that package is considered infeasible and excluded from the demand set.

**Route feasibility.** The overarching feasibility function aggregates the other feasibility functions and is termed `IsValidFromScratch`. Its input is a list of customers and, customer-by-customer, the function incrementally appends the customer to a list of test customers and runs the full energy, timing and distance validation. This function is detailed in Algorithm 4. The algorithm first dissects the list of customers into trips by determining at which points in the sequence do the cumulative payload commodity totals exceed the UAV's carrying capacity and inserting a return-to-center at that point, captured in the function `InitialReturnsToCenter`. Then, starting from an empty customer list, it then iteratively adds a single customer to a test list and evaluates the energy feasibility of each new resulting trip. If any trip is considered infeasible, the most recent customer appended to the end is initialized separately as a new trip which should strictly be energy-valid. This procedure is captured in `BreakTrips`. At this point, the final set of return-to-center points is known. The final distance and time feasibility checks are then performed.

**Distance feasibility.** The *isDistanceValid* algorithm is detailed in Algorithm 5 and ensures the total distance traversed does not exceed the total allowable UAV travel distance.

**Time feasibility.** The *isTimingValid* algorithm is detailed here in Algorithm 6. This algorithm is also leveraged to keep track of the trips, flight time and energy accrued between maintenance checks, activating a maintenance check and the associated delays when one of the check criteria are met.

**Energy feasibility.** Finally, energy feasibility is only validated in the *BreakTrips* algorithm since it is at this point that every trip is either energy feasible or broken into smaller sub-trips to become energy feasible. Thus, the *BreakTrips* algorithm and *IsEnergyValid* algorithm used internally in the former are detailed below in Algorithms 7 and 8, respectively.

---

**Algorithm 4:** IsValidFromScratch logic.

---

```
1 Inputs:  $l$ : a potential sequence of customers to be served by a UAV.
2  $r \leftarrow \text{InitialReturnToCenter}(l)$ ;
3  $l_{test} \leftarrow []$ ;
4 for  $i$  in  $\text{range}(\text{len}(l))$  do
5    $l_{test}.\text{append}(l[i])$ ;
6    $t \leftarrow \text{GetTrips}(r)$ ;
7    $t \leftarrow \text{BreakTrips}(t, r)$ ;
8    $t, \text{valid} \leftarrow \text{isDistanceValid}(t)$ ;
9   if not valid then
10    | return False
11  end
12   $t, \text{valid} \leftarrow \text{isTimingValid}(t)$ ;
13  if not valid then
14    | return False
15  end
16 end
17 Outputs: True, provides sequence of customers represents feasible UAV
    route.
```

---

#### 4.3.3.3 Route Improvements

This section elucidates how the route improvement operators step is structured. The process consists of a set of operations to be performed, 1) internal to each UAV route, and 2) between UAV routes. The route improvement solution iterates through a fixed number of both operator repetitions. Naturally, inter-UAV improvement operators can only work if there exists more than one UAV route for the given solution. Whilst there exists a maximum number of total improvement operator iterations, the procedure can also be terminated if one of the following conditions is met:

- a user-defined number of operations has been performed with no improvement; or
- a user-defined number of operations has been performed with an improvement of less than a user-defined percentage.

At each iteration, the exact improvement operator is chosen pseudo-randomly and the probability of choosing the operator is based on an exponentially smoothed weight that is computed using the success rate of the operator and the ratio of average time per operation of that types to all other operators of that type that is updated at each iteration. The list of available operators and the operator weight update logic is not included in this section, but appears in Appendix B.

---

**Algorithm 5:** IsDistanceValid logic.

---

```
1 Inputs:  $t$ : a list of potential customer trips to be served by a UAV;  $r$ : return  
   to center indices;  $range_{max}$ : operator-set max UAV range.  
2  $d \leftarrow 0$ ;  
3 for  $i$  in  $range(len(t))$  do  
4    $d' \leftarrow \text{getTripDistance}(t[i])$ ;  
5    $d \leftarrow d + d'$ ;  
6   if  $d \geq range_{max}$  then  
7      $\text{return False}$   
8   end  
9 end  
10 Outputs: True, provides sequence of customers represents feasible UAV  
    route.
```

---

## 4.4 Analysis

### 4.4.1 Parameter Definition

This section discusses how vehicle parameter settings for the UAV fleet are chosen. Note, the UAV fleet is assumed homogeneous along these parameters even though the model supports heterogeneity. This chapter defines the median vehicle parameters, i.e. the parameters that the model benchmarking runs in Section 4.4 are run with. In Chapter 5, however, permutations to these median vehicle parameters are made to suit more realistic demand sets as well as to capture evolving UAV technology evolution as further discussed in Section 5.3.2.

Whilst this thesis could delve into the reasoning behind specific vehicle parameters choices, much of this discussion was done in conjunction with industry partners and stakeholders in the UAV-LMD industry with current and future UAV technological evolution in mind. Thus, this thesis does not detail the specific discussions behind parameters. Further, technological evolution is a dimension of sensitivity analysis in Chapter 5 and how this thesis projects such evolution along these vehicle parameters will be discussed in Section 5.3. The median vehicle parameters are quoted in Table 4.7. Note, the units `clicks` is a unit measure of time whereby there are 100 clicks in 1 hour.

### 4.4.2 Data and Problem Instances

This section covers the specific data and problem instances leveraged in this chapter to validate the three GURP models against one another and confirm their comparable performance. This thesis defines a demand set for this benchmarking exercise, denoted *Set A*, which is adopted from literature which, in turn, was gleaned from the commonly used Solomon instances (Cheng et al., 2018; Solomon, 1987). Within *Set A*, this thesis leverages two subsets, *Set A<sub>1</sub>* and *Set A<sub>2</sub>* which simply place the DC

either at the corner of the demand region or at its center, respectively. More detail on *Set A* definitions and assumptions is not included in this thesis but can be found in references (Cheng et al., 2018).

This thesis leverages two demand set types, *Set A<sub>1</sub>* and *Set A<sub>2</sub>*, to prove additional robustness of the GURP models against artifacts of the demand and DC locations relative to the demand. Within each subset, *Set A<sub>1</sub>* and *Set A<sub>2</sub>*, the number of customers increases from 10 customers in steps of 5 to 30 customers. For each customer size instance, there exists three randomly generated instances so that, when benchmarking models against one another in Section 5.4, any unexpected artifacts that exist in a specific instance do not skew results substantially.

Note, the only difference between *Set A* as defined by Cheng et al. (2018) and in this thesis is simply an extension of the set to include additional features, namely package count and volume dimensions to a particular customer’s demand. The customer’s package count and volume demand is based on a random sampling from the probability distribution derived from the existing distribution of demand in *Set A* but strictly confined between 0 and the maximum capacity of the UAV along that dimension. For the original demand in *Set A*, this probability distribution was defined such that 40% of customers draw their demand from a uniform distribution from [0.1, 0.7] and the remaining 60% of customers draw from a uniform distribution from [0.1, `maxcapacity_weight`], `maxcapacity_weight` being set to 1.5 kg in the case of Cheng et al. (2018). It is also assumed that customer pickups do exist at a 1/10 probability rate derived from real parcel demand data. Finally, it is then assumed that the assumed UAV fleet size,  $L$ , is calculated as:

$$L = \max \left( \left[ \frac{\sum_{i \in N'} P_i^+}{3P^k} \right], \left[ \frac{\sum_{i \in N'} W_i^+}{3W^k} \right], \left[ \frac{\sum_{i \in N'} V_i^+}{3V^k} \right], \right. \\ \left. \left[ \frac{\sum_{i \in N'} P_i^-}{3V^k} \right], \left[ \frac{\sum_{i \in N'} W_i^i}{3P^k} \right], \left[ \frac{\sum_{i \in N'} V_i^-}{3W^k} \right] \right),$$

which assumes that each UAV would perform three trips on average. As a reminder to the reader, the GURP formulations in this chapter are written to support a heterogeneous UAV fleet but this functionality is not exercised in this thesis. One important note is that since customer locations in the Solomon instances are not in the geographic coordinate system, this thesis assumes that the quoted distances amount to travel times that are exactly translated in seconds. This means that the quoted `fixed_speed` vehicle parameter goes unused since it is strictly used to translate arc distances into arc travel times; however, it will be used in the real-world problem instances of Chapter 5 since customer locations are in the geographic coordinate system.

### 4.4.3 Model Benchmarking Results

This section documents the comparative benchmark results obtained when comparing the models' key performance metrics between the three available GURP models, namely the *EA*, *ETSA* and *HA*. Figure 4-3 illustrates how this benchmarking exercise is performed. At a high level, each demand set, *Set A<sub>1</sub>* and *Set A<sub>2</sub>*, has four customer demand sets in it, 15, 20, 25 and 30 customers. In each of these customer demand sets there are three randomly generated instances such that when the models are run across all three instances and their performance metrics averaged, the likelihood that artifacts in the demand set yield inconsistencies in the results is reduced. Each GURP model is run on each of these instances; however, it is run multiple times based on the problem definition. This problem definition is varied with additional problem features added in individually for complexity, termed scenarios. These scenarios are also shown in the problem definition matrix in Figure 4-3. These are labeled as follows with their short form label also included in parentheses:

- Benchmark: the most simple problem formulation with no additional features other than multi-trip, multi-vehicle, weight-commodity capacity and weight-dependent energy consumption functionality;
- Maintenance Check (pf): the benchmark problem formulation with maintenance check and pre-flight check functionality included;
- Time Window (tw): the benchmark problem formulation with customer TW functionality included;
- Commodity (comm): the benchmark problem formulation with maintenance multi-commodity capacity functionality included;
- Full Feature (ff): the benchmark problem formulation with all other available functionality included;
- Full Feature + Valid Inequalities (ffvi): the full feature problem formulation with model valid inequalities and user cuts activated;
- Full Feature + Valid Inequalities + Warm Start (ffviws): the full feature problem formulation with model valid inequalities and user cuts activated as well as leveraging the *HA* as a feasible solution warm start.

Note, the *HA* does not have different model formulations for the Full Feature, Full Feature + Valid Inequalities, and Full Feature + Valid Inequalities + Warm Start scenarios since these additional model functionalities do not apply to a heuristic formulation. This, the quoted results for the *HA* are the same across these three scenarios.

These results serve to validate the comparable optimality, computational runtime advantage, and validity of the *HA* in comparison with the two exact models such that it can be deployed at scale in the case study analysis in Chapter 5. But specifically, with this available performance data, each model can be compared against one another for each combination of problem definition, demand set, and customer

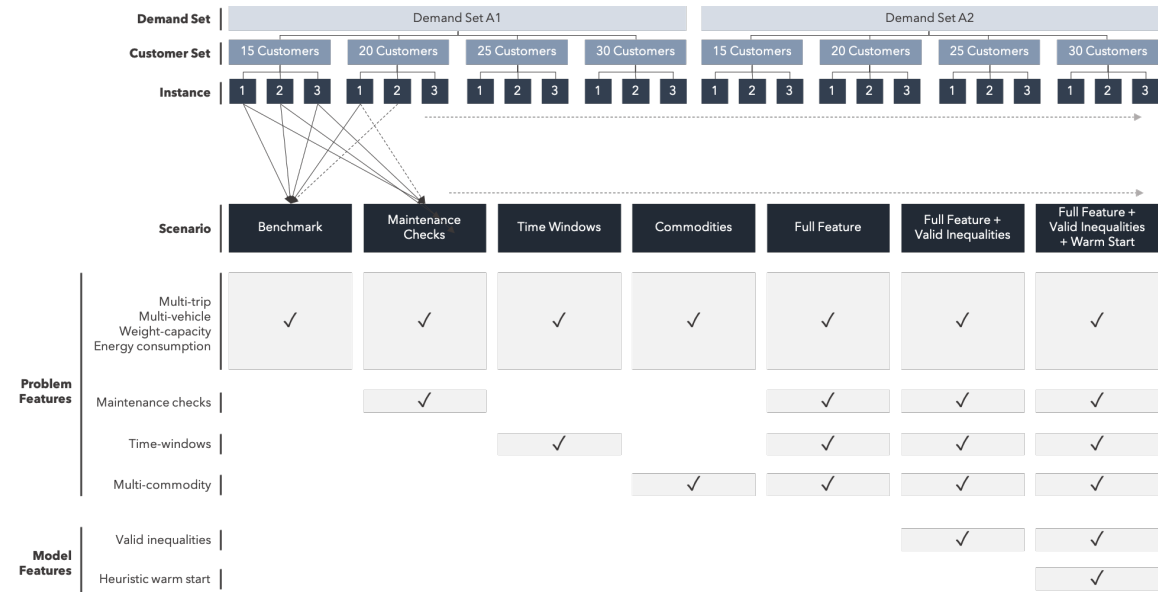


Figure 4-3: GURP model performance benchmarking methodology illustrated, totaling to 168 scenario-instance runs.

count demand set. This offers insight into: 1) the impact of additional problem complexity on the models’ performance metrics; 2) the performance differences between the three GURP models; and 3) the scalability of each model across increasing numbers of customers. Finally, the benchmark solves are run in the macOS terminal on Python 3.8 using a licensed optimization solver, Gurobi 9.1.1, with all parameters set to their default parameters. The experiments are performed on MacBook Pro 2.6GHz 6-Core Intel Core i7 with 16 GB of RAM on MacOS Big Sur 11.6.4.

The charts shown in this chapter are a subset of the results. This is to provide the reader a sufficient understanding of the insights and performance patterns between the three GURP models. To do this, this section only shows results for *Set A<sub>1</sub>* since the performance patterns across GURP models between *Set A<sub>1</sub>* and *Set A<sub>2</sub>* are similar and showing both would be a duplication of results. Additional charts for *Set A<sub>2</sub>* are included in Appendix C. The key performance metrics quoted are:

- *Termination [1/3]*: the total number of instances that are solved to optimality (measured as models that reached the termination criteria of 1% within the run-time limit of 7200 seconds);
- *Gap [%]*: the percentage gap between the upper bound (defined as the objective of the best known feasible solution) and the lower bound (defined as the best possible objective given a discrete variable domain relaxation) at model termination;
- *CPU [s]*: the total computation run-time required before model termination; and
- *UB [\$]*: the upper bound objective value at model termination.



The first set of results, shown in Figure 4-4, illustrates the impact of additional problem definition complexity on the GURP models' performance metrics. A subset of metrics are shown, namely *CPU [s]* and *UB [\$]*. The discussion is structured by analyzing each GURP model in turn followed by overarching takeaways:

- *Exact Approach:*

- *CPU [s]*: the most notable takeaway is the varying computation speeds of the various model formulations. Whilst the benchmark scenario lies in the middle of the other scenarios, the Time Window scenario is notably faster. This is likely because the inclusion of TWs constrains the overall solution space such that customers can only be visited at certain times of the day. Whilst for heuristic models, TWs typically increase computation time by requiring more feasibility checks to be performed, TWs improve *EA* computation time. Also noteworthy is the notable run-time improvements achieved when adding valid inequalities and warm starts to the Full Feature scenario.
- *UB [\$]*: It can be seen that compared to the Benchmark scenario, all other scenarios mean an increase in the *UB* which is expected since for each case, the problem definition is more tightly constrained than the Benchmark problem definition. Note that whilst the Maintenance Check and Time Window scenarios represent relatively small increases in the *UB*, the Commodity scenario results drives the *UB* significantly higher. It can be inferred that having multi-commodity capacity features is also what drives the Full Feature, Full Feature + Valid Inequalities and Full Feature + Valid Inequalities + Warm Start scenarios to the high *UB* shown in the chart. Finally, it can be seen that including Valid Inequalities into the *EA* model formulation results in a notable improvement on the *CPU [s]*. Furthermore, adding the heuristic Warm Start functionality greatly increases the *CPU [s]* performance.

- *Exact Two-Staged Approach:*

- *CPU [s]*: The *ETSA* exhibits similar *CPU* patterns to the *EA* with the exceptions that the Maintenance Check scenario takes the longest in compute time. This is surprising because the full-feature scenarios have additional complexifying problem features and one would expect them to take longest to solve. This thesis attributes this result to an artifact of the *ETSA* in that it may solve scenarios in a different manner to the *EA* because of its two-staged iterative approach.
- *UB [\$]*: The *UB* results, on the other hand, are very similar to that of the *EA*.

- *Heuristics Approach:*

- *CPU [s]*: Firstly, it can be seen that the *CPU* solve times are significantly lower than the two MILP-based models. It exhibits a similar pattern to the *ETSA* in that the Maintenance Check model takes the longest.
- *UB [\\$]*: The UB patterns between scenarios is also notably similar to the two MILP-based models with a little less consistency between the results of different customer counts. Otherwise, the Benchmark scenario provides a lower bound on the best overall solution cost with other scenarios until the Full Feature scenarios resulting in an increase in the UB.

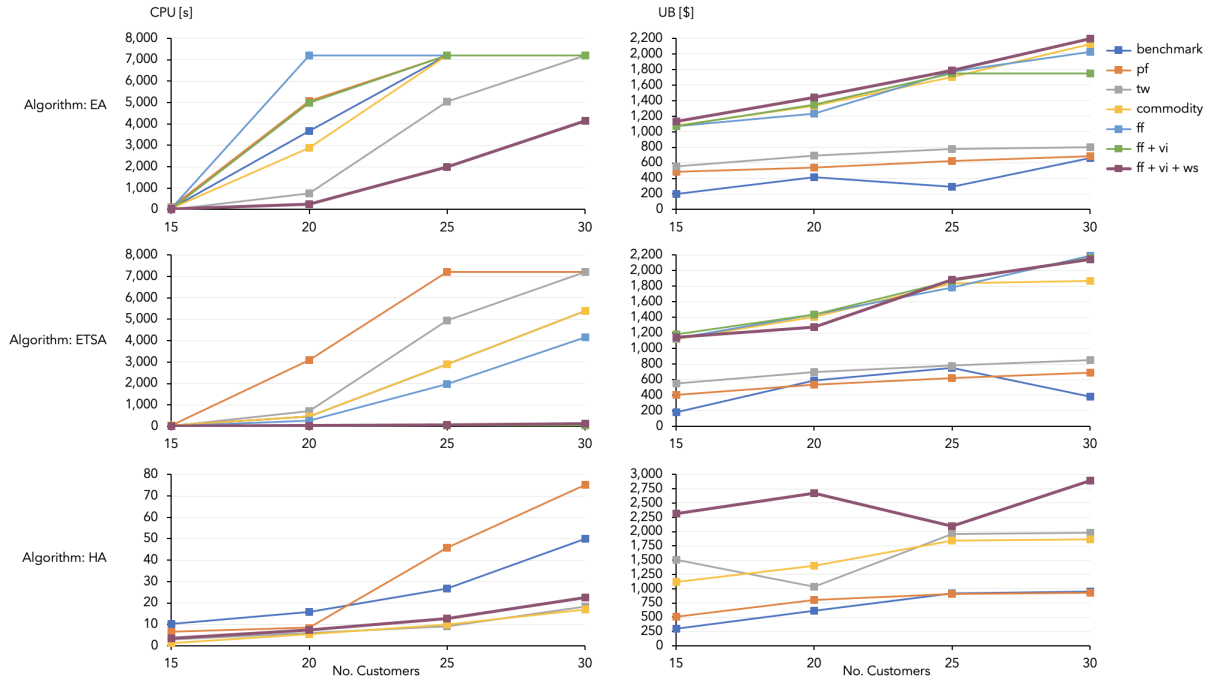


Figure 4-4: Demand Set A1: GURP model performance comparison across problem definition scenarios.

These results can be shown in a different way, comparing algorithms against one another for each performance metric for each scenario. The majority of these charts are included in Appendix C but the Full Feature + Valid Inequalities + Warm Start scenario results are included here, since this represents the full problem formulation of the GURP. Furthermore, the comparisons drawn between GURP models by analyzing the Full Feature + Valid Inequalities + Warm Start scenario can also be gleaned from analyzing the other charts in Figure 4-5. The key takeaways from these charts are as follows:

- *Term. [1/3]*: In general, the *EA* can solve to optimality for small numbers of customers but its ability to reach optimality within the 7200 second time limit is quickly lost as the number of customers is increased. The *ETSA* generally performs better on this front, more often reaching optimality before the time limit as the number of customers increases. Finally, the *HA* is quoted here to

always reach optimality. This is not strictly true because it is not solving an MILP-based optimization problem, but can be said to always terminate at what it discerns as the best solution.

- *CPU [s]*: The *EA* typically takes the longest to solve and very quickly plateaus at the run-time limit of 7200 seconds. The *ETSA* is notably faster and similarly gets slower as the number of customers is increased. Finally, the *HA* is orders of magnitudes faster with clear computational performance advantages over the MILP-based models.
- *Gap [%]*: The percentage optimality gap at termination reflects a similar pattern to that of the *CPU [s]* performance metric. The *EA* struggles to close the MIP-Gap, especially as the number of customers is increased. The *ETSA* shows strong performance however would likely increase just as the *EA* did at larger customers instances. Finally, the *HA* does not have a legitimate *Gap [%]* definition so is quoted at 0%.
- *UB [\$]*: Finally, the UB results show that the two MILP-based models typically reach similar UB results, highlighting the relative advantages of the *ETSA* over the *EA*. These models both significantly beat the *HA* which strictly finds less cost-optimal solutions than the two MILP-based models.

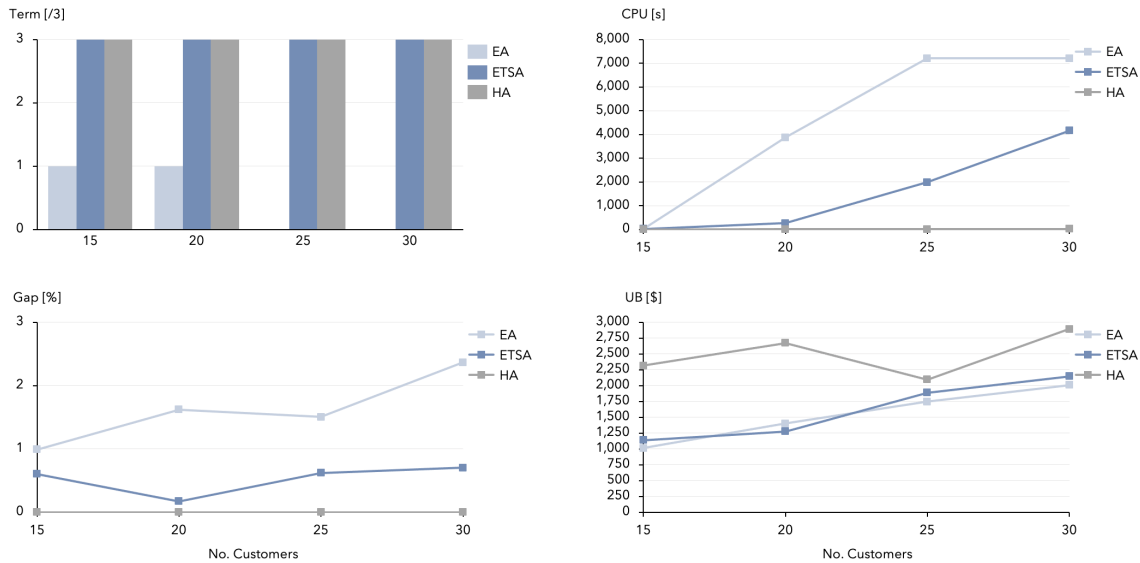


Figure 4-5: Demand Set A1: Full feature + valid inequalities + warm start scenario across customer demand sets and GURP models.

In summary, these results and discussion points highlight the following key insights:

1. Figure 4-4 shows that increasing the problem definition complexity by adding in additional features and constraints to the benchmark capacitated VRP results in: a) increases in compute times, and b) increases in the best operational cost for UAV-LMD operations;

2. Figure 4-5 shows that the *ETSA* can reach similar final operational cost solutions in better computational times than the *EA* and more often solve to optimality across the instances tested.
3. Figure 4-5 also shows that the *HA*, whilst finds solutions that are strictly worse in operational cost of the GURP, its computational run-time advantages are significant. This points to the *HA* as a valid and valuable model to be deployed in large-scale case study analyses to solve the GURP, as in Chapter 5.

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**Algorithm 6:** IsTimingValid logic.

---

```
1 Inputs:  $t$ : a list of potential customer trips to be served by a UAV;  $t_{departure}$ :  
   UAV fleet departure time;  
2  $n_{trips}, t_{trips}, e_{trips}, lvt_{prev} \leftarrow 0, 0, 0, t_{departure}$   
3 for  $i$  in  $range(len(t))$  do  
4    $t_{trip} \leftarrow GetTripDuration(t[i]);$   
5    $e_{trip} \leftarrow GetTripEnergy(t[i]);$   
6    $n_{trips} \leftarrow n_{trip} + 1;$   
7    $t_{trips} \leftarrow t_{trips} + t_{trip};$   
8    $e_{trips} \leftarrow e_{trips} + e_{trip};$   
9    $cust_{first} \leftarrow t[0];$   
10   $t_{to\_cust_{first}} \leftarrow GetTCenterToCust(cust_{first});$   
11   $t_{leave} \leftarrow cust_{first}.getSCT() - t_{to\_cust_{first}}$   
12   $lvt_{prev} \leftarrow \max(lvt_{prev}, t_{leave})$   
13   $valid, bvt_{prev} = IsTripTimingValid(t[i], lvt_{prev})$   
14  if not  $valid$  then  
15    | return False  
16  end  
17  if  $i < len(t)-1$  then  
18    |  $t_{next\_trip} \leftarrow GetTripDuration(t[i+1])$   
19    |  $e_{next\_trip} \leftarrow GetTripEnergy(t[i+1])$   
20    | if  $(n_{trips}+1 \geq n_{trips\_no\_pf})$  or  $(t_{trips} + t_{next\_trip} \geq t_{trips\_pf})$  or  $(e_{trips}$   
21    |    $+ e_{next\_trip} \geq e_{trips\_pf})$  then  
22    |   |  $n_{trip}, t_{trips}, e_{trips}, t_{depot} \leftarrow 0, 0, 0,$   
23    |   |  $t_{depot} \leftarrow t_{load} + t_{main}$   
24    |   | else  
25    |   | |  $t_{depot} \leftarrow t_{load} + t_{pf}$   
26    |   | end  
27    |   |  $lvt_{prev} = bvt_{prev} + t_{depot} + t_{load}$   
28  end  
29 Outputs: True, provides sequence of customers represents feasible UAV  
   route.
```

---

---

**Algorithm 7:** BreakTrips logic.

---

```
1 Inputs:  $l$ : a potential sequence of customers to be served by a UAV;  $t$ : a list
   of potential customer trips to be served by a UAV.
2 for  $i$  in  $\text{range}(\text{len}(t))$  do
3    $\text{valid} \leftarrow \text{IsEnergyValid}(t[i]);$ 
4   if not  $\text{valid}$  then
5      $t'_1, t'_2 \leftarrow t[i][:-1], t[i][-1:];$ 
6      $t.\text{remove}(t[i]);$ 
7      $t.\text{insert}(t'_1, i);$ 
8      $t.\text{insert}(t'_2, i+1);$ 
9   end
10   $r.\text{append}(l.\text{index}(t'_2[0]))$ 
11 end
12 Outputs:  $t$ : a list of potential customer trips to be served by a UAV  $r$ :
   return to center indices;
```

---

---

**Algorithm 8:** IsEnergyValid logic.

---

```
1 Inputs:  $t'$ : a single trip of customers being served by a UAV.
2 for  $i$  in  $\text{range}(\text{len}(t))$  do
3    $\text{valid} \leftarrow \text{GetTripEnergy}(t'[i]);$ 
4   if not  $\text{valid}$  then
5      $\text{return False}$ 
6   end
7 end
8 Outputs: True, trip represents feasible UAV trip;
```

---

Category	Parameter	Value	Units
<b>Capacity</b>	maxcapacity	4	[-]
	maxcapacity_volume	0.02	[ $m^3$ ]
	maxcapacity_weight	1.5	[kg]
	maxcapacity_energy	0.27	[kWh]
<b>Operational time</b>	departure_time	0900	[clicks]
	regular_shift_time	800	[clicks]
	clicks_loading	2	[clicks]
	clicks_maintenance	25	[clicks]
	clicks_preflight	5	[clicks]
	clicks_takeoff	1	[clicks]
	clicks_landing	1	[clicks]
	service_time_per_package_delivery	1	[clicks]
	service_time_per_package_pickup	2	[clicks]
	service_time_fixed_pickup	1	[clicks]
service_time_fixed_delivery	1	[clicks]	
<b>Operational cost</b>	cost_fix	2.00	[\$/day]
	cost_per_distance	0.10	[\$/km]
	cost_click_regular	0.50	[\$/click]
	cost_per_energy_kwh	0.1	[\$/kWh]
<b>Vehicle specifications</b>	power_auxiliary_kilowatts	0.01	[kW]
	power_efficiency_factor	1	[0-1]
	area_cross_section_vehicle	0.9	[ $m^2$ ]
	thrust_to_weight_ratio	1.3	[-]
	mass_vehicle	10	[kg]
	altitude_winch	0.004	[km]
	winch	True	[boolean]
	power_winch_kilowatts	0.01	[kWh]
	fixed_speed	40	[km/hr]
	fixed_speed_vertical	1	[km/hr]
<b>Pre-flight constraints</b>	max_trips_before_maintenance	5	[-]
	max_clicks_before_maintenance	100	[clicks]
	max_maintenance_energy_fraction	0.1	[0-1]

Table 4.7: Median UAV vehicle parameters for benchmarking analysis.

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# Chapter 5

## Operations Case Study Analysis<sup>1</sup>

### 5.1 Introduction

As a reminder, this thesis's research questions are defined as:

1. **Operational Constraints**: What are the key social, regulatory, technological and logistical constraints that would constrain real-world unmanned aerial vehicles for last-mile delivery (UAV-LMD) operations?
2. **Operations Modeling**: How can these novel operational constraints be captured in a generalized vehicle routing optimization model?
3. **Feasibility Analysis**: Given realistic demand data and operational parameters, is UAV-LMD financially profitable for service providers? Which constraints are key cost drivers? What are the social, operational and financial upshots of UAV-LMD?

This chapter addresses the final research question. This chapter serves to illustrate how the generalized unmanned aerial vehicle routing problem (GURP) routing models derived in Chapter 4 can be leveraged to explore the sensitivity of UAV-LMD operations to exogenous constraints, demand density and technology progression. These represent the three dimensions along which this chapter's sensitivity analysis is defined. To do this, this chapter explores:

- leverage a realistic demand data set to closely capture future UAV-LMD operations;
- adequately capture the per-day operational costs of UAV-LMD operations in a scalable model in tractable computation time;
- translate potential cost drivers into a sensitivity analysis from which insights can be derived as to which drivers are the most impactful.

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<sup>1</sup>This chapter contains content that is partially under review for publication in a peer-reviewed journal.

The value of this analysis is not in the results themselves but the holistic approach to solving the GURP that offers insights into the trade-offs that real-world constraints impose on UAV-LMD. Such an analysis is valuable to UAV-LMD operators and regulators to better discern which operational constraints are most significant in rendering UAV-LMD no longer economically viable.

## 5.2 Data and Problem Instances

This section details the specific data-sets employed and the key assumptions implicit to leveraging this data in this thesis’s analysis. The data used in the following case-study is artificially generated leveraging insights into demand pattern distributions from industry partners. The industry partner data available contains customer-level demand data over the course of one month in the greater Boston, MA, region with the following features below. The artificial data derived reflects each of these data features, engineering obfuscating features with various methods. These methods are also included below:

- *Customer ID*
- *Date*: the date that the customer demand was fulfilled;
- *Location (latitude, longitude)*: the specific geo-location of the customer;
  - Artificial obfuscation: the demand density loosely follows a two-dimensional normal distribution in all directions centered in downtown Boston. Thus, the artificial customer locations are sampled from this 2D normal distribution curve with an un-skewed covariance matrix. Locations sampled to be in non-land regions such as lakes, rivers and oceans are excluded and re-sampled until successfully sampled on land. Locations that are sampled beyond the allowable operational radius of the unmanned aerial vehicle (UAV) from the distribution center (DC) location of 6.25 km are also excluded and re-sampled.
- *Package Count*: the total number of package demand during drop;
- *Package-specific weight*: the weight of each package in the drop;
- *Package-specific volume*: the volume of each package in the drop;
- *Start commit time*: the earliest allowable fulfillment time;
- *End commit time*: the latest allowable fulfillment time;
  - Artificial obfuscation: for the package count, weight, volume, start commit times and end commit times, an empirical cumulative distribution function (ECDF) is derived for each demand dimension. ECDFs represent a cumulative probability that a variable sampled will take a value less than or equal to a specific value of that variable. The artificial data is then generated by sampling from these ECDF functions for each customer initialized.

- *Delivery or pickup*: whether the customer demanded delivery or pickup service.

Note, the model is defined on a operational per-day basis. Thus, this demand is segregated by the date that it is fulfilled. Also note that the total number of customers was the only input variable that was selected outside the scope of the industry’s historical demand data. This was simply because the allowable range of UAV operations is commonly artificially constrained in the literature and in industry practice. To reflect this, this thesis also constrains the range to 6.25 km and, thus, fixes the total number of customers in that range to a fraction of the total historical demand of the greater Boston region.

To capture demand density variations as part of the sensitivity analysis, this was done by simply increasing the total number of customers in the pre-defined demand area. Note, the package, weight and volume demand patterns per stop were not changed but preserved based on the distributions from industry data. This demand variation is shown pictorially in Figure 5-1. Within the confines of the demand distributions, radius and geographic constraints, the demand density is varied. defined as sparse (600 customers,  $D0$ ), moderate (800 customers,  $D1$ ), dense (1000 customers,  $D2$ ), and super-dense (1200 customers,  $D3$ ).

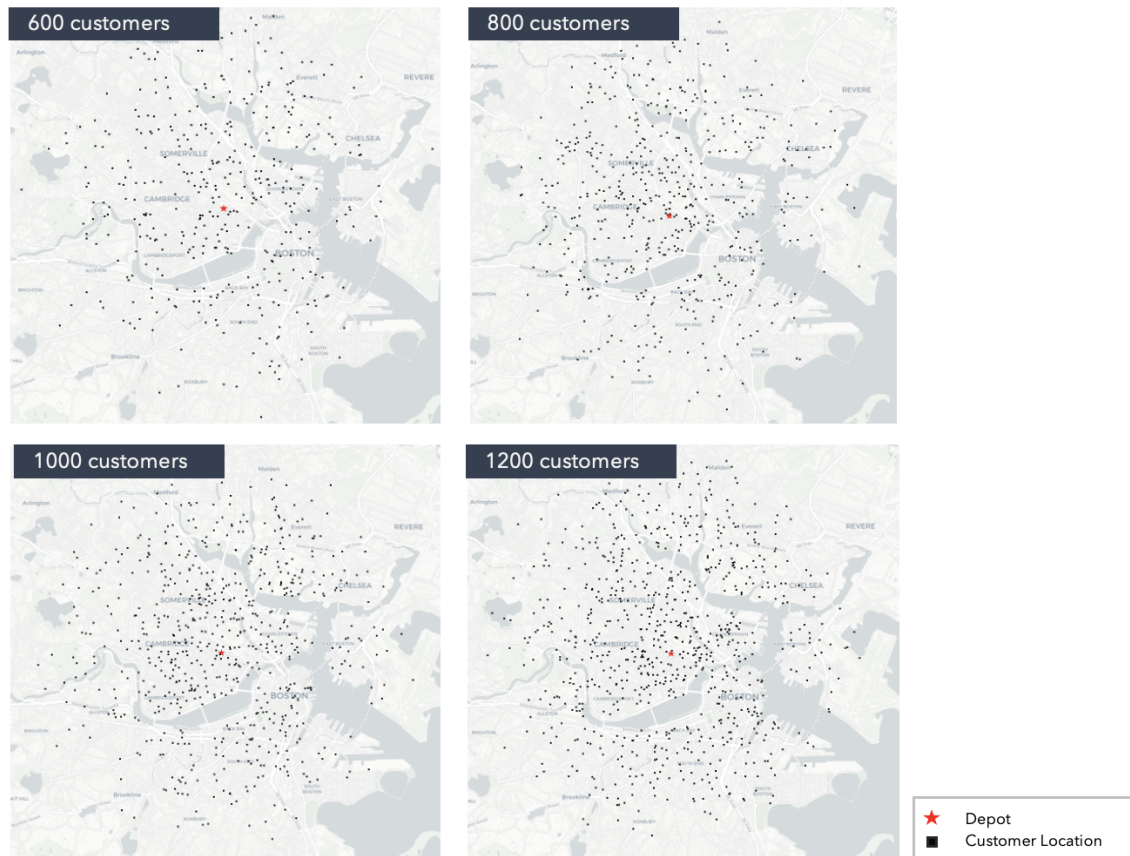


Figure 5-1: Illustration of demand density variation in Boston, MA.

## 5.3 Sensitivity Analysis Scenario Definitions

This section describes the sensitivity analysis this chapter undertakes in more detail by describing the specific constraint intensities, technological evolution, and demand density assumptions that form the building blocks of each unique scenario run. The goal of this analysis is to discern which dimensions – UAV technology or exogenous societal and regulatory constraints – have the most significant impact on UAV-LMD operational cost and, thus, economic feasibility.

This analysis is based upon 64 different scenarios that vary the three sensitivity factors (with their prefixes D, C, and T included since they are used as a taxonomy for defining a specific scenario). The final scenario sensitivity analysis matrix looks as per Figure 5-2.

1. D: demand density;
  - D0: Sparse (600 customers);
  - D1: Moderate (800 customers);
  - D2: Dense (1000 customers);
  - D3: Super-dense (1200 customers);
2. C: specific exogenous constraint intensities (see Figure 5-3 for details on what constitutes various exogenous restriction intensities);
  - C0: Baseline (no restrictions);
  - C1: Minimal;
  - C2: Moderate;
  - C3: Severe;
3. T: UAV's technological evolution (see Figure 5-5 for details on what vehicle parameters constitute each technology progression level):
  - T0: Today;
  - T1: 5 years;
  - T2: 10 years;
  - T3: 15 years.

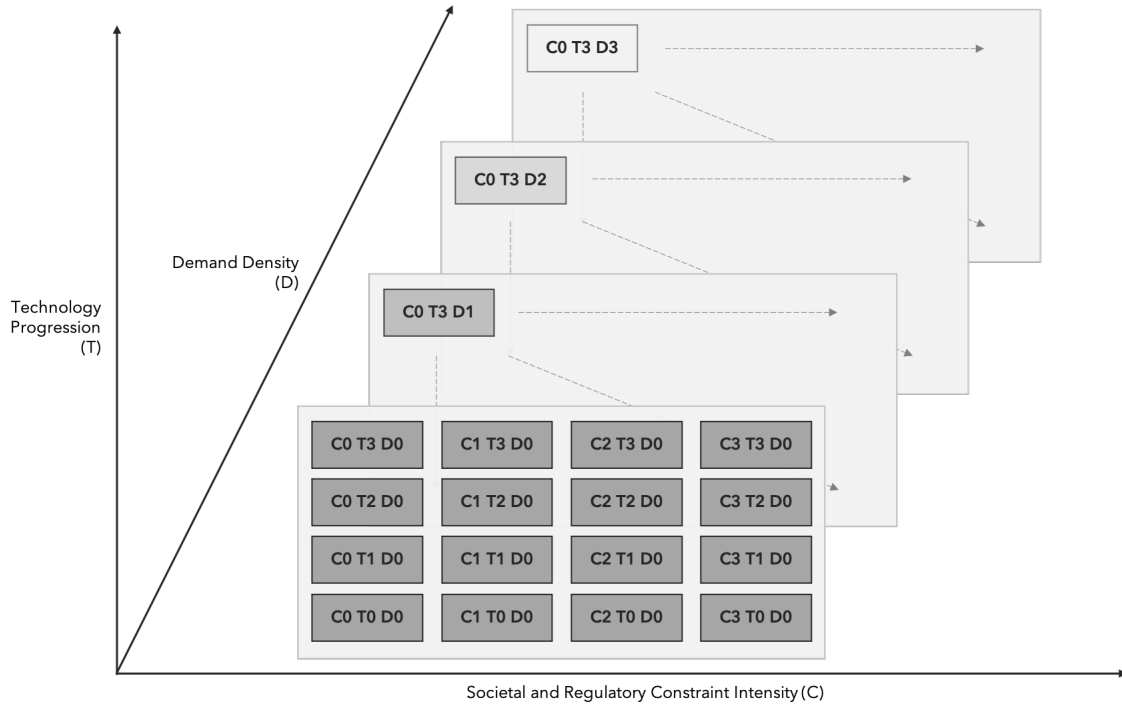


Figure 5-2: Summary scenario sensitivity analysis matrix.

### 5.3.1 Varying Societal and Regulatory Constraint Intensity

This section details the specific exogenous constraints modeled in the sensitivity analysis and how their intensities were varied to capture either less or more constraining exogenous constraint scenarios. This section builds off much that was described in Table 3.1 with pictorial examples of how the constraints were explicitly translated into model constraints. Note, this section also defines a baseline scenario against which all subsequent scenarios are benchmarked against. This baseline scenario should yield the least costly UAV-LMD deployment scenario from an operational perspective since it captures only the most obvious and already enforced exogenous constraints that are present today.

At a high level, the motivation behind this scenario definition approach is understand how increasing the intensity of exogenous constraints affects expected UAV-LMD and operating costs. To reduce the granularity and simplify the analysis, these exogenous constraints, derived from the exogenous analysis of Chapter 3, are not varied independently. Instead, they are varied together. For example, if the altitude constraints are made more stringent, so are the flight restriction constraints and the noise constraints. This can be understood via Figure 5-3.

	Baseline	Minimal	Moderate	Severe
<b>Regulatory</b>	Altitude Minimums and Maximums	200-400 ft. and maintain 50 ft. vertical and 200 ft. lateral separation from structures that exceed 200 ft.	200-400 ft. and maintain 50 ft. vertical and 200 ft. lateral separation from structures that exceed 200 ft.	200-400 ft. and maintain 50 ft. vertical and 200 ft. lateral separation from structures that exceed 200 ft.
	Operating Weight Constraints	MTOW 55 lbs.	MTOW 55 lbs.	MTOW 55 lbs.
	In-Air Vehicle Separation	No heading-based altitude stratification	Heading-based altitude stratification protocol as per §3.2.	Heading-based altitude stratification protocol as per §3.2.
	Flight-Zoning Restrictions	No flight restrictions	Prohibited Airspace: FAA, National park locations; High-rise above 400 ft.	Prohibited Airspace: FAA, National park locations; High-rise above 400 ft.; Boston Logan perimeter and flight paths; Prisons; Parks; Stadiums
	Safety-Related Procedures and Precautions	Maintenance check: 0 clicks; pre-flight check: 0 clicks	Maintenance check: 25 clicks; pre-flight check: 5 clicks	Maintenance check: 50 clicks; pre-flight check: 10 clicks
<b>Societal</b>	Misc. Regulatory Considerations	-	-	-
	Personal Protection	-	-	-
	Noise Concerns	0 ft. clearance above altitude stratification-derived minimum altitude over noise-sensitive areas	15 ft. clearance above altitude stratification-derived minimum altitude over noise-sensitive areas	30 ft. clearance above altitude stratification-derived minimum altitude over noise-sensitive areas
Environmental Concerns	Optimal routing, energy function, cruise minimum permissible altitude, visibility-graph trajectory	Optimal routing, energy function, cruise minimum permissible altitude, visibility-graph trajectory	Optimal routing, energy function, cruise minimum permissible altitude, visibility-graph trajectory	Optimal routing, energy function, cruise minimum permissible altitude, visibility-graph trajectory

Societal and Regulatory Constraint Intensity

Figure 5-3: Societal and regulatory constraint intensity sensitivity analysis by intensity level and constraint type.

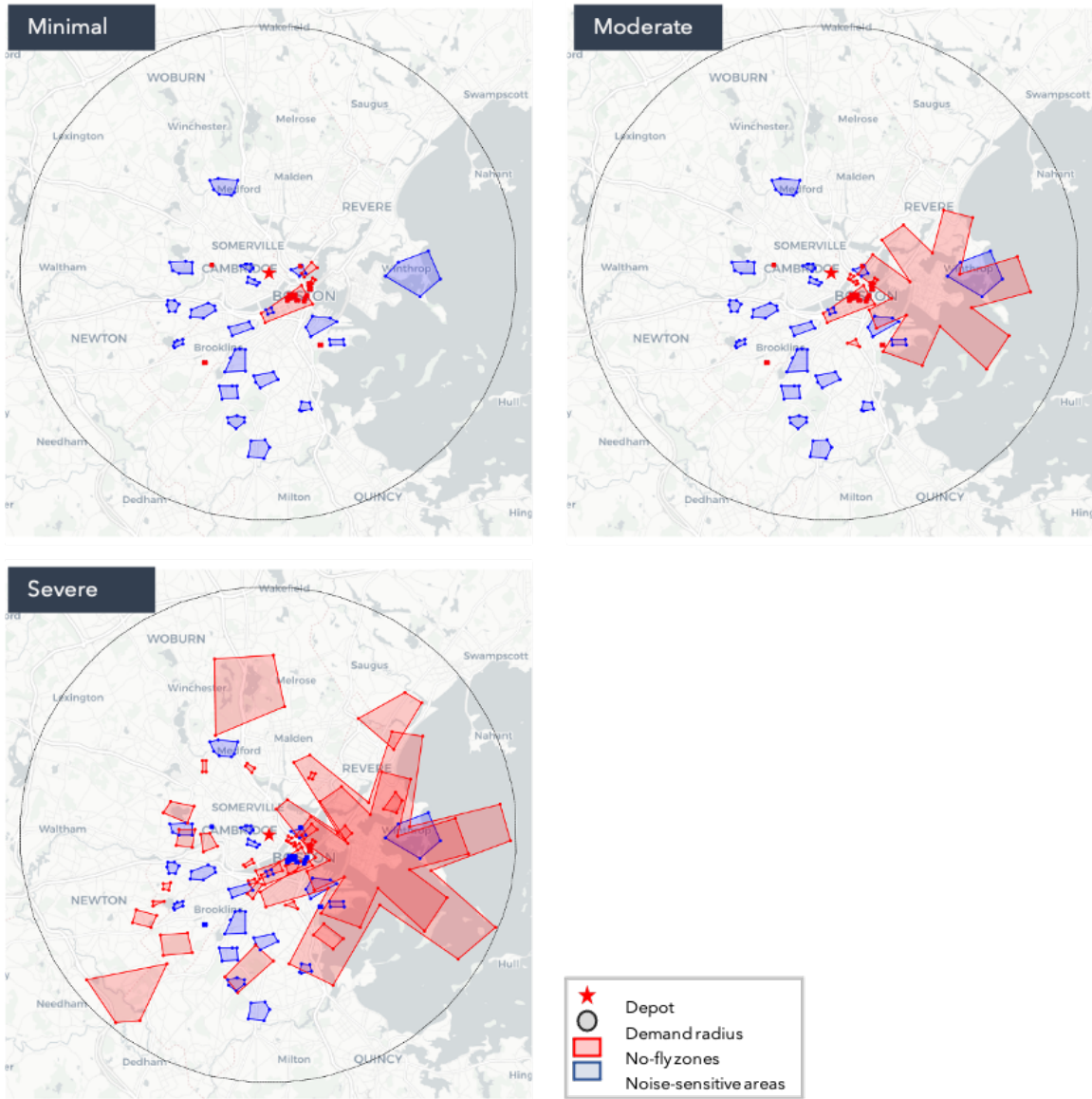


Figure 5-4: Illustration of minimal, moderate and severe exogenous constraint intensities, depicting no-fly zones and noise-sensitive regions as discussed in Figure 5-3. Note, baseline constraint scenario is no exogenous constraints and is not shown here.

### 5.3.2 Technological Evolution Projections

In a similar fashion to the intensity of the exogenous constraints applied in Section 5.3.1, to capture the effects of evolving UAV technology, specific vehicle parameters that are likely to advance in the coming years are assumed to change in parallel across four 5-year time periods. The parameters, their assumed technological progression, and the time-frames over which they progress derive from discussions with industry partners and insights gleaned from their UAV hardware research & development (R&D) efforts and technology roadmapping projections. It is beyond the scope

of this thesis to delve into the specific foundations of this technological progression since, at its core, this analysis seeks to understand if broad technological progression assumptions do, indeed, affect the overall operational cost solution. To achieve this, this thesis does not delve into details around the specific vehicle parameters other than to base them in ongoing industry research.

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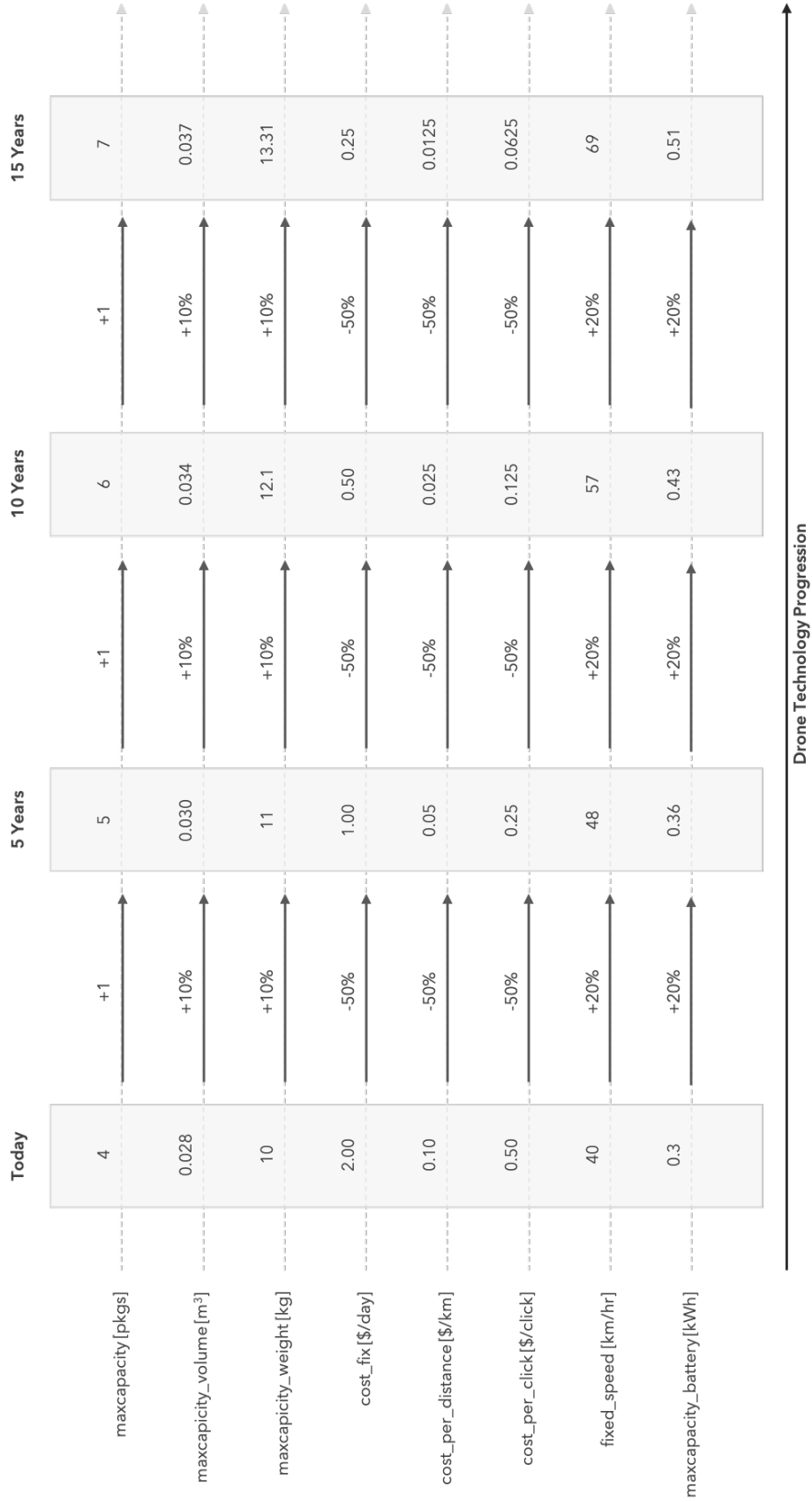


Figure 5-5: Technology evolution progression levels employed in sensitivity analysis by vehicle parameter.

## 5.4 Results

This section discusses the results from the 64 scenario runs completed as per the scenario sensitivity matrix illustrated in Figure 5-2. The comprehensive results data tables for these runs are included in Appendix D. Delving into specific key performance indicators (KPIs) from the case study scenarios, Figure 5-6 fills in Figure 5-2 with the cost-per-package results for each scenario whilst Figure 5-7 offers a deeper dive into the operational costs. Figure 5-8 shows the operational cost break-downs into its components averaged across demand densities but disaggregated by technology levels and scaled to 100%. Figure 5-9 is similar in that it also shows the operational cost break-downs into its components averaged across demand densities but disaggregated by exogenous constraint intensities. These cost components are as follows:

- *Fixed cost: (cf)*: the total fixed cost of operating a single UAV over the course of the day. It can be thought of as the asset depreciation cost of each UAV over its lifetime incurred on a single day.
- *Wage cost: (cw)*: The labor costs associated with operating the UAV fleet. It scales with the time each UAV remains in operation totaled across the whole fleet.
- *Distance cost: (cd)*: A proxy measure for additional distance-based costs that might be incurred with UAV operations such as damages, liabilities and repair and maintenance.
- *Energy cost: (ce)*: The cost of electricity to match the total energy consumed across all UAVs in the fleet, scaled by the cost of energy per kWh.

Finally, Figure 5-10 shows the average time UAVs spend at the DC across exogenous constraint and technology progression scenarios. Analyzing Figures 5-6 through 5-8 some key insights can be gleaned:

**Exogenous constraint intensity significantly impacts operational cost:** As the exogenous constraint intensity increases (along the x-axis in Figure 5-6), the cost-per-package fulfillment costs of UAV-LMD strictly rise across all demand density scenarios. This pattern can be clearly seen in Figure 5-7 as well. This confirms the hypothesis that increased societal and regulatory pressure does, indeed, increase the cost of UAV-LMD. This can be seen in Figure 5-6 since, independent of the demand density or technology progression level employed, the costs always increase as one moves to the right along each row of each matrix. Between the Baseline scenario and Severe scenarios for each demand density and the level of technology progression of UAVs today, the cost-per-package increases by, on average, 483% or more than four-fold, highlighting the severe impacts of increase exogenous constraints on cost-effective UAV-LMD operations.

Figure 5-8 shows how the costs break down, highlighting that much of the cost increase can be attributed to wage-cost increases. Even as technology progression

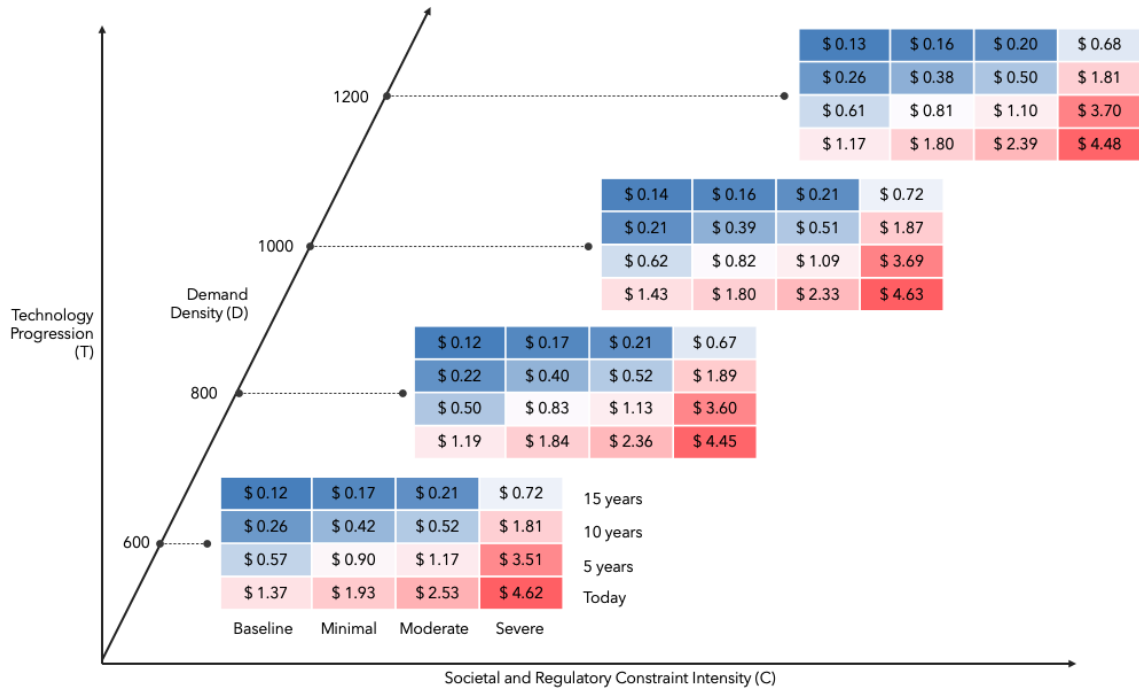


Figure 5-6: Daily operational cost-per-package fulfilled for each scenario across exogenous constraint intensity, technology progression and demand density sensitivity spectra.

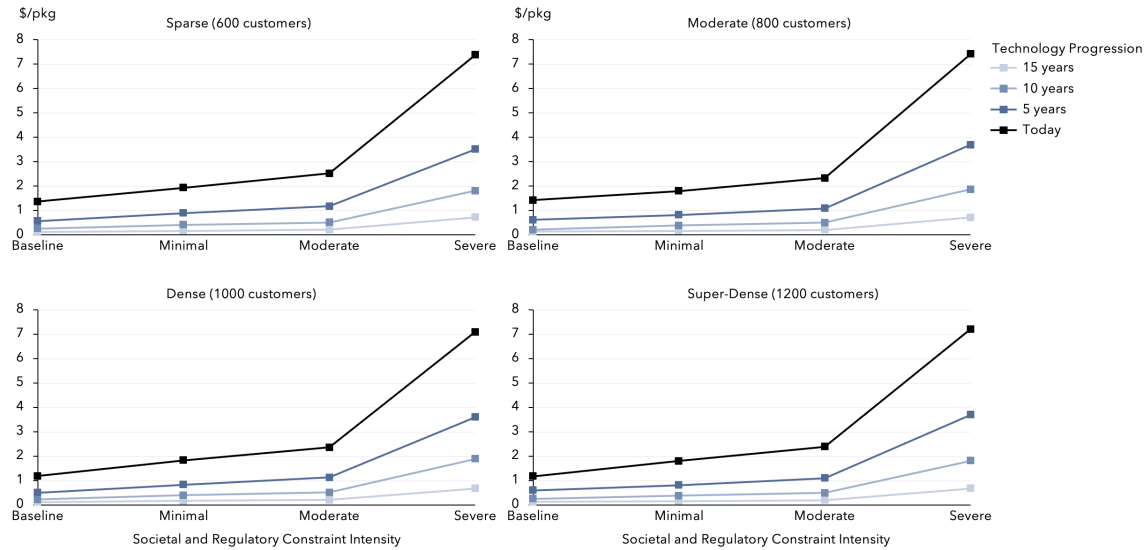


Figure 5-7: Daily operational cost-per-package fulfilled across exogenous constraint intensity and technology progression levels by demand densities.

advances and the total cost-per-package drops, the wage cost continues to be a more important cost driver. This is because the wage costs scale with the total operational time across all the UAVs in the fleet. As seen in Figure 5-10, the total time spent

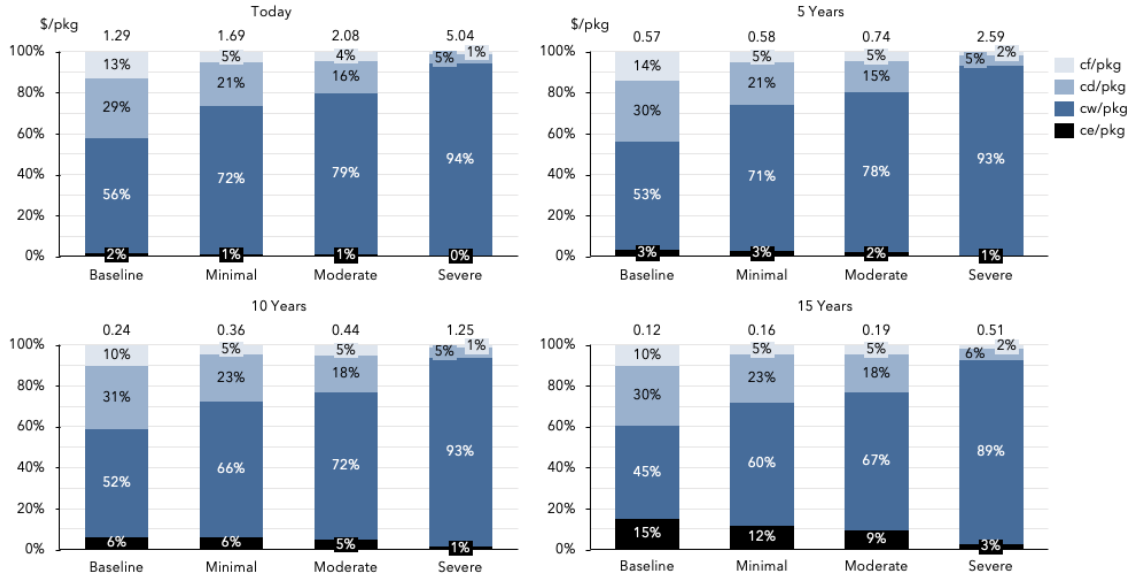


Figure 5-8: Daily operational cost-per-package break-down across exogenous constraint intensity by technology progression levels averaged across demand densities.

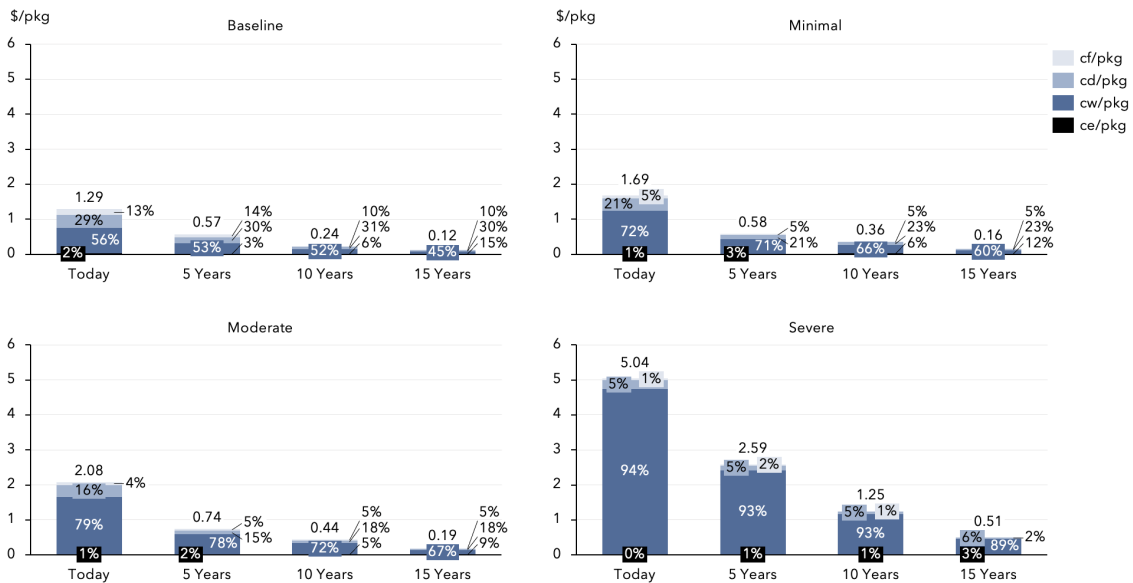


Figure 5-9: Daily operational cost-per-package break-down across technology progression levels by exogenous constraint intensity averaged across demand densities.

at the DC increases dramatically as the exogenous constraint intensity increases because of the increase in maintenance and pre-flight check delays the operators must incur. The majority of this increase is driven by the maintenance checks, which, as a reminder, must be performed if any of the `max_trips_before_maintenance`, `max_clicks_before_maintenance` or `max_maintenance_energy_fraction` parameters are exceeded.

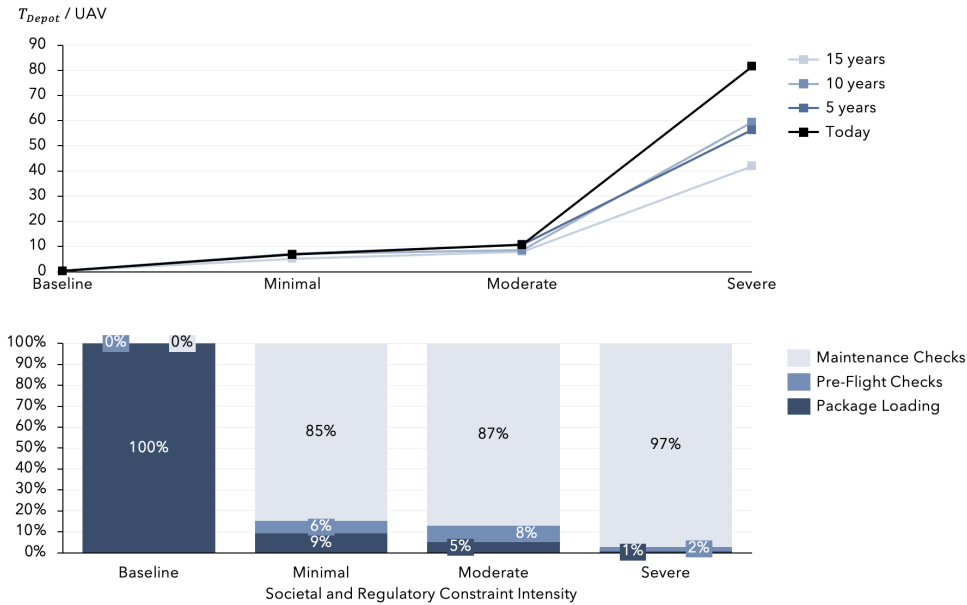


Figure 5-10: Average time a UAV spends at DC across technology progression levels and exogenous constraint intensity, averaged across demand densities.

It is interesting to note that this relationship holds independent of the demand density, which can often impact the efficiency of a last-mile modality, most often because higher densities can support larger drop sizes, thus, less time can be spent traveling between customers per package dropped. Note that the cost-per-package metrics seem to vary across demand densities without a clear trend either up or down. This thesis attributes this to the imprecision of the un-optimality gap between the *Heuristic Approach (HA)* and true optimality of the solution. This is discussed earlier in Section 5.4 and later in the thesis limitation in Section 6.3. Also note that this relationship holds independent of the technological progression level. With that said, the percentage increases between the Baseline and Severe scenarios is less pronounced at today's technology level compared to future technology levels at an average of 250%, 530%, 680%, and 480% for today's, 5 year, 10 year and 15 year technology levels respectively.

**Technology progression significantly reduces UAV-LMD operational cost:** In the opposite way to how introducing exogenous constraints increases UAV-LMD operational cost, as technology progression advances further into the future, it can be seen that the cost-per-package of UAV-LMD tends to decrease. This can be seen via Figure 5-7 in that cost-per-package curves strictly move closer to zero as the technology progresses. This occurs across all demand scenarios and exogenous constraint scenarios; the average percentage decrease in cost from today's technology to technology in 15 years is over 85%. This is consistent across all demand density scenarios with no discernable variation around the 85% cost reduction between

them. This precipitous reduction in cost is predominantly driven by reductions in the wage-cost, seen in Figure 5-9. The 50% reduction in wage-cost every 5 years of technological progression in Figure 5-5 is the key driver, based on the assumption that for every 5 years, a single laborer can manage double the number of UAVs over the course of the operational day.

**No discernable relationship between demand density and operational cost:** As mentioned above, demand density is often a key driver of operational cost for traditional ground-based last-mile fulfillment modes. This is because inter-customer drive times are significant relative to the total time spent out in the field and performing package drops. In the case of UAV-LMD, however, because travel times are not beholden on ground-based congestion and are point-to-point, UAVs time delays are predominantly driven by other time delays such as the maintenance and pre-flight checks. This underscores why additional societal constraints have such a large impact on UAV-LMD since the maintenance check time delays were increased by 100%, or doubled, between each exogenous constraint intensity.

Thus, naturally, the cheapest scenario is the Baseline constraint scenario (no exogenous restrictions) with technology available 15 years from now and the most expensive is the Severe constraint scenario with today's technology. A baseline cost-per-package for existing ground-based fulfillment methods is not an easily quotable number because it is driven by many factors: infrastructure circuitry, congestion, labor costs, demand density, average drop sizes and service level and timeliness promised. It is also beyond the scope of this thesis to delve into such an analysis. Whilst the data in Figure 2-1 quotes the cost-per-packages for existing last-mile incumbents, it is specifically for a 5 lb package serviced within a 10 mile radius. Experience with industry partners have suggested cost-per-packages as low as \$1.00 when demand densities are high, no unionized over-time labor is being utilized and drop sizes are large. The results in this section suggest that UAV-LMD can, indeed, exceed the inflection point at which it is not longer cost-optimal to use UAVs over traditional ground-based fulfillment modalities, especially if the demand conditions are favorable to ground-based vehicles. Furthermore, severe exogenous constraints have the ability to render UAV-LMD economically non-viable.

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# Chapter 6

## Conclusion

This thesis proposes solutions to the generalized unmanned aerial vehicle routing problem (GURP) in a holistic fashion, bringing together considerations that will guide the operational and technological development and deployment of unmanned aerial vehicles for last-mile delivery (UAV-LMD) operations. A systems-level analysis approach is adopted to discern the inter-relationships between competing dimensions that dictate the form that UAV-LMD operations take, namely the societal and regulatory constraints and vehicle routing considerations at the heart of traditional last-mile fulfillment literature and practice.

In Chapter 2, this thesis first explores the existing literature pertaining to UAV-LMD, identifying a literature and research gap in an inter-disciplinary approach to UAV-LMD that marries operations planning and vehicle routing with notions of societal and regulatory constraints in a holistic modeling framework. It also explores methodologies to formally model UAV-LMD operations based upon extensions to the traditional vehicle routing problem (VRP) literature. In Chapter 3, the thesis then performs a survey of apposite societal and regulatory constraints that currently and are likely to impact UAV-LMD operations. The thesis posits implementation pathways for specific societal and regulatory issues that do have notable historical cases of implementation in the unmanned aerial vehicle (UAV) domain or adjacent commercial aviation regulation. Following this in Chapter 4, the thesis explores three solution approaches to solving what it terms the GURP, an extension of the VRP specific to UAV routing to include operational and the set of exogenous constraints determined in Chapter 3. It identifies the computational run-time benefits of a heuristic-based approach to solving the GURP compared to traditional mixed-integer linear program (MILP)-based methods. Finally, in Chapter 5, this thesis deploys the heuristics-based GURP model on a set of demand scenarios in Greater Boston to discern the impact of varying levels of exogenous constraint intensity, technology progression and demand density on the operational cost of UAV-LMD.

## 6.1 Review of Thesis Research Questions

To conclude this thesis, this section revisits the original thesis research questions posed in Section 1.4 along with a succinct recapitulation of the relevant findings and results derived in this analysis.

**Operational constraints: What are the key social, regulatory, technological and logistical constraints that would constrain real-world UAV-LMD operations?** The key societal and regulatory constraints are identified to manifest in UAV-LMD operations via seven key operational modeling restrictions in the near- to medium-term. These constraints are identified based on the survey of academic and industry literature performed in Chapter 3. These are covered in Table 6.1.

This thesis notes that there are many pathways for regulators, both local and federal, to enact policies in the interest of protecting against any specific externality of UAV-LMD. Unless penned into law or proposed in currently deliberated bills in the United States (U.S.) Congress, there is little to no historical evidence as to which avenue will likely be adopted to protect against said externality. In this way, this thesis highlights the immense levels of regulatory uncertainty surrounding UAV-LMD. One potential source of regulatory inspiration this thesis identifies lies in the ways in which commercial passenger airlines are currently regulated and operationally constraint today. However, this thesis also uncovers that many of the regulatory frameworks that exist in the commercial airline domain today are not wholly reflected in apposite UAV-LMD regulation today. Thus, this indicates that there remains room for regulators to leverage existing commercial aviation regulation and draft similarly constraining policies for UAV-LMD in the coming years.

Of these societal and regulatory constraints quoted in Table 6.1, the most well delineated and patent constraints today are the altitude minimums and maximums, operating weight constraints, and flight zoning restriction which all exist in statute. The remaining constraints are amalgamations of tangentially apposite regulation or historical case law.

**Operations modeling: How can these novel operational constraints be captured in a generalized vehicle routing optimization model?** This thesis introduces a variety of novel constraints to the VRP that are modeled across the three GURP models formulated in Chapter 4. The key elements of this modeling approach are as follows:

**Capacitated multi-commodity routing model with time window (TW).** This is formulated as traditional VRP with multiple commodity dimensions captured as parallel flow conservation constraints (see Section 4.3.1.1).



Constraint Type	Description	Operational Constraint
<b>Regulatory</b>	Status Quo	Assume operational waivers granted for all restricting airspace classes
	Altitude Minimums and Maximums	Enforced operational altitude range with additional vertical and horizontal separation protocols from vehicles and obstacles.
	Operating Weight Constraints	Maximum max take-off weight (MTOW) limitations.
	In-Air Vehicle Separation Constraints	Static or dynamic altitude stratification logic with additional static or dynamic lateral vehicle separation protocols and on-board collision avoidance capabilities.
	Flight Zoning Restrictions	Temporary and permanent Federal Aviation Administration (FAA) issued flight restrictions.
	Safety-Related Procedures and Precautions	Regulated and enforced manufacturing, maintenance and operational safety practices.
<b>Societal</b>	Noise Pollution Concerns	Region- and time-specific restrictions to mitigate noise pollution with potential to further constrain operations based on flight frequency.
	Environmental Concerns	Optimal routing approach, energy cost objective function, adoption of minimum permissible cruise altitude, and minimum traversed distance approach to flight trajectory planning.

Table 6.1: Key societal and regulatory constraints to UAV-LMD and their high-level operational modeling restrictions.

**UAV-specific operational constraints.** These include weight-dependent energy consumption, flight time, trip count and maintenance check constraints that are all modeled as flow conservation constraints. In the case of energy consumption, a from-first-principles energy consumption model is derived and linearized (see Appendix A) and modeled as an asymmetric flow conservation constraint through each customer node. In the other constraints mentioned, they are also modeled as asymmetric flow conservation constraints in that they are only accountable as the UAV returns to and then leaves the depot node, not customer nodes.

**Valid-inequalities.** These include valid inequalities that are common and well known in existing VRP literature as well as novel constraints that are unique to the GURP defined. The key valid inequalities unique to this problem are those that pertain to UAV energy consumption between nodes and the pre-defined user-cuts that can be included in the model if a specific sequence of arcs and nodes traversed can be predefined as infeasible (see Section 4.3.1.3).

**Additional solution approaches.** The *Exact Two-Staged Approach (ETSA)* is formulated in this thesis to decompose the GURP into two more simple problems, both solved in tandem. This model yields notable run-time improvements on the benchmark *Exact Approach (EA)* whilst achieving near-optimal solutions. The *Heuristic Approach (HA)* is also formulated as a purely heuristic model to meet computational run-time scalability requirements for real-world case-study analysis of UAV-LMD as in Chapter 5.

**Feasibility analysis: Given realistic demand data and operational parameters, is UAV-LMD financially profitable for service providers? Which constraints are key cost drivers? What are the social, operational and financial upshots of UAV-LMD?** This thesis determines that the exogenous societal and regulatory constraints introduced into the GURP have a significant impact on the total cost of UAV-LMD operations and should not be ignored in future industry operations scoping efforts. Of these constraints, the most impactful to UAV-LMD's cost of operation are time delays because of safety and precautionary measures taken via regulation or self-imposed restrictions around maintenance and pre-flight checks. These drive up the wage-cost since it is assumed a certain amount of labor must tend to UAV-LMD operations.

UAV technology progression is also determined to be a key driving factor behind UAV-LMD's success. Because the wage-costs associated with UAV-LMD make up the bulk of the cost, advancements in autonomy or maximizing the number of UAVs per laborer are key operational practices that would help drive down the overall cost of operation. On the other hand, demand density seems to have little to no effect on the overall efficiency of UAV-LMD fulfillment network, likely because of the UAVs' ability to fly point-to-point, avoiding circuitous routes due to inefficiently designed infrastructure or ground-based congestion.

UAV-LMD's economic attractiveness and competitiveness is not explicitly defined in this thesis, in part, because defining a benchmark operational cost is not straightforward without an explicit modeling tool or set of continuous approximation equations to capture the nuances around demand densities, service levels, infrastructure circuitry and demand drop size unique to the problem instances leveraged in this thesis. Thus, whilst this thesis does not take a strict stance on the economic feasibility of UAV-LMD, it posits that a set of severely constraining societal and regulatory

constraints imposed on UAV-LMD operations with UAV technology available today could well render operations economically unattractive.

## 6.2 Additional Contributions

In addition to the insights this thesis provides to answer the specific research questions proposed, there exist other domains in which this thesis's analysis is valuable. These domains span across the policy, social and operations research dimensions of the UAV-LMD problem. Each of these contributions are discussed briefly below.

1. The UAV-LMD literature review this thesis includes in Chapter 2 offers a comprehensive survey and review of apposite literature to what is a relatively new domain in operations research, last-mile logistics, aeronautic policy and urban-planning. The literature review focuses on routing-specific and society-specific literature, but covers the gamut of academic contributions since the inception of UAV-LMD as a commercial proposition.
2. In Chapter 3, this thesis visits areas of societal and regulatory constraint uncertainty that lie beyond the purview of commonly occurring operational constraints or constraints that can be inferred from historical aviation regulation. These domains include dynamic time-dependent regulation, the divergence of regulatory alignment between local and federal regulators, and the associated emergence of highly localized flight zoning restrictions. Whilst the latter most issue is not totally novel to the aviation community, it rarely surfaces in public regulatory dialogue and discourse, and could pose a significant operational and legal conundrum if imposed inconsistently or across a wide range of geographies.
3. This thesis offers potential protocols and approaches for translating the interest of society into regulations that directly constrain UAV-LMD operations and protect individuals from its potentially negative externalities. The key protocols put forward pertain to:
  - (a) In-air vehicle separation: the bearing-based altitude stratification protocol proposed in Section 3.1.1.3;
  - (b) Flight zoning restrictions: the visibility-graph-based trajectory planning logic proposed in Section 3.3;
  - (c) Safety-related procedures and precautions: the maintenance and pre-flight check scheduling optimization modeling approach discussed in Section 3.1.1.6 and formulated in Section 4.3.1.2.
  - (d) Noise pollution concerns: the noise pollution mitigation protocol broached in Section 3.2.2 and defined in Section 3.3 involving additional altitude clearance above noise-sensitive communities;
  - (e) Environmental concerns: the energy modeling and routing efficiency features included to help capture the environmental externalities in the GURP solution approach defined in Section 3.3.

4. This thesis puts forth a novel from-first-principles UAV energy consumption model across four generalizeable flight regimes. This model captures both fixed-wing and quadcopter vehicle configurations and included additional operational features such as utilization of a winch delivery system and auxiliary power requirements.

## 6.3 Limitations of Study and Future Work

UAV-LMD as a concept, business model, and area of operations and policy research is still in its infancy. As a result, there remain many domains of significant uncertainty surrounding various dimensions of UAV-LMD: UAV technology and technological progression, markets and a definitive use-case, infrastructure requirements and its impact on operations, regulation or societal acceptance to name but a few potentially derailing factors. In this light, the approach this thesis adopts is structured to maximize the generalizability of the insights derived and avoid areas of significant uncertainty. Whilst this approach by and large avoids areas that require significant assumptions to be made, simplifying assumptions are likely necessary in any holistic systems-level approach. This thesis acknowledges these limitations and includes them in the discussion below. These limitations are useful in that they also qualify as ripe grounds for future work.

1. In defining the geographic restrictions that pertain to noise-sensitive communities or no-fly zones for the case study analysis of the Greater Boston Region in Chapter 5, this thesis inherited data from existing noise-sensitivity research and dialogue on locations likely to be considered no-fly zones in the future. This is not a robust approach because: 1) whilst often present in case law, these locations are the opinion of researchers, industry players, and regulators but are not instituted in statute; and 2) restrictions over such areas will likely likely change and evolve in the coming decades as the demographics in those regions evolve and public acceptance campaigns are instituted. This thesis assumes a static state of the world in this regard. It could benefit from exploring a variety of different geographic restriction scenarios based on shared driving factors such as the regulatory motivation or historical patterns in how the local and federal regulators have collaborated to institute similar restrictions in the past.
2. Similarly, the broader societal and regulatory constraint analysis in Chapter 3 could be considered a snapshot of the current UAV-LMD landscape and does not take into account any public or regulatory evolution in any of the specific issues raised. The analysis did attempt to project each specific issue into the future but limited this effort because there are little to no literature or historical grounds to form such opinions. This thesis opted for a more measured approach to evaluating the potential societal and regulatory considerations because, in many ways, the motivation of this thesis is to uncover the value of a holistic, inter-disciplinary approach to UAV-LMD operations modeling and potential modeling and analysis avenues for future research.

3. Also pertinent to the societal and regulatory constraint analysis in Chapter 3, this thesis strictly excludes any dynamic, time-dependent constraints such as weather, presence of other aircraft, temporary flight restrictions or time-dependent geographic restrictions for noise or no-fly zones. This thesis would benefit greatly by including these operational features, but it would require an approach to solving the GURP that can capture dynamic changes in the constraints that govern the operations planning model. This is not an easy task and could require a simulation-based approach over the static MILP- or heuristic-based approach that is adopted in this thesis.
4. In developing models to solve the GURP in Chapter 4 and deploying the *HA* in the case study analysis of Chapter 5, this thesis accepts a level of un-optimality with the *HA* in exchange for improved computational run-times. This is a limitation worth mentioning not because the level of un-optimality is unacceptable but rather because there exists variation in the level of un-optimality when comparing the *HA* to the *EA* or *ETSA*. This underscores a level of uncertainty around the final key performance indicators (KPIs) shown in the case study results and analysis in Section 5.4. Such an analysis would benefit from either an improved *HA* that minimizes the optimality gap or a novel approach to leveraging the exact models, potentially in a divide-and-conquer approach when solving to fulfill a specific set of demand.
5. In the case study analysis of Chapter 5, not only are the demand distributions artificial, but they are based on a single industry partner's demand distributions and for a single metropolitan area. Such assumptions limit the generalizability of the analysis since UAV-LMD, like other last-mile fulfillment methods, are often significantly impacted by the geography and demand patterns of different demand regions. This thesis could benefit from multiple case-study analyses across multiple metro-areas to evince the generalizability of the results obtained.
6. Finally, this thesis strictly explores the pure-play UAV-LMD operational model, as defined by Moshref-Javadi and Winkenbach (2021), and not any adjacent UAV-LMD fulfillment methods that represent a number of industry player's current deployment strategies. For example, multi-modal UAV-LMD operations in parallel with traditional ground-based fulfillment modalities is what will most likely be seen in the coming decades. Other operational models such as the truck-and-drone system or a multi-echelon resupply multi-modal operational network are also popular strategies. This thesis isolates UAV-LMD as a single modality, thus losing the ability to provide insights on how UAV-LMD would change the operational KPIs of other operational models. This would be valuable to help glean any symbiosis inter-relationships between fulfillment modalities that cannot be explored in this thesis's isolated approach.

## 6.4 Final Thoughts

UAVs deployed to fulfill last-mile delivery demand stand to disrupt the status quo for how societies transfer goods across geographic landscapes and mega-cities. They have the potential to help make cities more environmentally sustainable, equitable and economically productive, unlocking what some term the sharing economy. Individuals, rich and poor, urban or rural, could have greater access to a breadth of goods and services unlike ever before in the history of our societies. This has implications for urban planners who could lessen the importance of having to design cities and their suburbs to support commutes or their proximity to infrastructure arteries. UAV-LMD has the potential to be a bastion of what some term the “internet of things.” Finally, it is on the cusp of disrupting the last-mile industry and offer service levels at costs that have historically been unreachable.

But for all of their technological promise to recast our cities and logistics industries, there remain some key questions that still remain unanswered, most notably: how will UAV-LMD be received by society and regulators and how will their reaction impact the economics and feasibility of such a service? Furthermore, could it negatively impact the communities amongst which it operates such that the economic benefits do not outweigh its negative externalities? Is it a net-benefit for the society and cities in which it is deployed? The past few decades have exemplified novel technologies being deployed at scale – from ride-hailing mobility to machine learning hiring algorithms – for which society has absorbed the toll of the “move fast and break things” strategy. In this way, could UAV-LMD also be a double-edged sword?

This thesis explores the peripheries of this question by tackling the first step in answering them: it marries the societal and regulatory considerations with UAV-LMD operations planning in an economic feasibility analysis. In doing so, it offers a multitude of in-roads for how to: 1) evaluate the societal and regulatory constraints, 2) model the the intersection of these constraints with traditional VRP operations planning, and 3) deploy models to explore the inter-dependencies between the key driving factors between UAV-LMD’s success.

Faced with these untold opportunities but set of challenges, the last-mile industry and its various stakeholders have an opportunity to define a future for UAV-LMD and its stakeholders. A more likely postulation is that the “last-mile” delivery problem is unabating and it will continue to pressure key industry players to innovate with new technologies, operational models or business models. The technology policy question will remain central to UAV-LMD in the coming years. But where there are problems, there are opportunities. Undoubtedly, societies, cities, regulators, and logistics players with a stake in solving the “last-mile” problem are in strong position to capitalize on its opportunities.

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# Appendix A

## Drone Power Consumption Equation Derivations

### A.1 Hover Flight

Thrust from a single propeller disk of the quadcopter can be written as

$$T = 2\rho A\bar{v}w, \quad (\text{A.1})$$

where  $T$  is thrust ( $N$ ),  $\rho$  is air density ( $kgm^{-3}$ ),  $A$  is the propeller disk ( $m^2$ ), and  $w$  is the induced velocity through the propeller disk ( $ms^{-1}$ ).  $\bar{v}$  is the resultant velocity ( $ms^{-1}$ ) and can be written as

$$\bar{v} = ((w - V\sin\alpha)^2 + (V\cos\alpha)^2)^{\frac{1}{2}}, \quad (\text{A.2})$$

where  $V$  is the speed of the quadcopter relative to the air around in ( $ms^{-1}$ ). We know that in hover,  $V = 0$ , therefore

$$\bar{v} = w. \quad (\text{A.3})$$

Therefore,

$$T = 2\rho Aw^2. \quad (\text{A.4})$$

In hover, the quadcopter thrust must be equal to its weight, therefore

$$4T = m_{tot}g = 8\rho Aw^2, \quad (\text{A.5})$$

where  $g$  is the gravitational constant ( $ms^{-2}$ ). The 4 exists since we have four propellers. Therefore

$$w = \sqrt{\frac{m_{tot}g}{8\rho A}}. \quad (\text{A.6})$$

Power consumed by as quadcopter is

$$P = DV + Tw, \quad (\text{A.7})$$

where  $D$  is the drag on the quadcopter ( $N$ ). Since we know in hover that  $V = 0$

$$P = Tw = m_{tot}gw = m_{tot}g\sqrt{\frac{m_{tot}g}{8\rho A}}. \quad (\text{A.8})$$

Therefore,

$$P_{hov} = \sqrt{\frac{(m_{tot}g)^3}{2\rho A}}. \quad (\text{A.9})$$

This power is calculated in ( $W$ ) and represents the energy consumed per unit second used by the quadcopter in hover.

## A.2 Horizontal Flight

In horizontal flight, the force equilibrium allows the following to be derived:

$$F_T \cos(\alpha) - F_d = m_{tot}\dot{v}, \quad (\text{A.10})$$

where  $\dot{v}$  is the rate of change of horizontal speed ( $ms^{-2}$ ). Therefore,

$$T \cos(\alpha) - \frac{1}{2}\rho C_D A_{eff} V^2 = m_{tot}\dot{v}, \quad (\text{A.11})$$

where  $C_D$  is the quadcopter drag coefficient and  $A_{eff}$  is the area of the Quadcopter facing forward incoming airflow ( $m^2$ ). We know that  $\dot{v} = 0$ , therefore

$$T \cos(\alpha) - \frac{1}{2}\rho C_D A_{eff} V^2 = 0. \quad (\text{A.12})$$

This can be written as

$$V_{hor} = \sqrt{\frac{2T \cos(\alpha)}{\rho C_D A_{eff}}}. \quad (\text{A.13})$$

We can use the definition of thrust-to-weight ( $TWR = \frac{T}{m_{tot}g}$ ) here as follows:

$$V_{hor} = \sqrt{\frac{2TWR m_{tot}g \cos(\alpha)}{\rho C_D A_{eff}}}. \quad (\text{A.14})$$

Now addressing  $A_{eff}$ , we know that

$$\sin\alpha = \frac{A_{eff}}{A} \approx \frac{m_{tot}g}{T} \approx \frac{1}{TWR}, \quad (\text{A.15})$$

therefore,

$$V_{hor} = \sqrt{\frac{2TW R m_{tot} g \cos(\alpha)}{\rho C_D \frac{1}{TWR}}}, \quad (\text{A.16})$$

$$V_{hor} = \sqrt{\frac{2TW R^2 m_{tot} g \cos(\alpha)}{\rho C_D}}. \quad (\text{A.17})$$

Finally  $C_D$  for a quadcopter can be approximated to that of a flat plate, which is as follows:

$$C_{D_{flat\ plate}} = 2C_f + 2\sin^2\alpha, \quad (\text{A.18})$$

where  $C_f$  is the skin friction coefficient and can be assumed to be zero. We know from equation (A.15) that  $\sin\alpha$  can be substituted such that the equation above reads as

$$C_{D_{flat\ plate}} = \frac{2}{TWR^2}. \quad (\text{A.19})$$

Thus,  $V_{hor}$  can be written as

$$V_{hor} = \sqrt{\frac{2TW R^2 m_{tot} g \cos(\alpha)}{\rho \frac{2}{TWR^2}}}, \quad (\text{A.20})$$

$$V_{hor} = \sqrt{\frac{TW R^4 m_{tot} g \cos(\alpha)}{\rho}}. \quad (\text{A.21})$$

Finally, assuming  $\alpha = 45^\circ$ ,  $\cos(\alpha) = \frac{1}{\sqrt{2}}$ ,

$$V_{hor} = \sqrt{\frac{TW R^4 m_{tot} g}{\rho \sqrt{2}}}. \quad (\text{A.22})$$

Power consumed in horizontal flight can be written as

$$P = TV_{hor}. \quad (\text{A.23})$$

This equation is true since energy ( $J$ ) is always equated to work done which is force ( $N$ ) multiplied by distance ( $m$ ). Since power ( $W = J/s$ ) is energy per unit time, power is equated to work done per unit second which is force multiplied by distance over unit time, or in other words, force ( $N$ ) multiplied by velocity ( $ms^{-1}$ ). Therefore,

$$P = TW R m_{tot} g \sqrt{\frac{TW R^4 m_{tot} g}{\rho \sqrt{2}}}, \quad (\text{A.24})$$

which finally reads as

$$P = TWR^3 \sqrt{\frac{(m_{tot}g)^3}{\rho\sqrt{2}}}. \quad (\text{A.25})$$

This power is calculated in ( $W$ ) and tells us the energy consumed in horizontal flight per unit second used by the quadcopter.

### A.3 Vertical Flight

In vertical flight, the force balance can be written as:

$$F_T - F_g - F_d = m_{tot}\dot{v}, \quad (\text{A.26})$$

where  $\dot{v}$  is the rate of change of vertical speed ( $ms^{-2}$ ) and can be assumed to be equal to 0 in a vertical ascent at constant velocity. Therefore,

$$T - m_{tot}g - \frac{1}{2}\rho C_D A_{eff} V^2 = 0. \quad (\text{A.27})$$

Rearranging to write  $v$  (i.e.  $v_{ver}$ ) in terms of thrust:

$$v_{ver} = \sqrt{\frac{2(T - m_{tot}g)}{\rho C_D A_{eff}}}, \quad (\text{A.28})$$

which can be written in terms of thrust-to-weight ratio (TWR) as:

$$v_{ver} = \sqrt{\frac{2m_{tot}g}{\rho C_D A_{eff}}} \sqrt{TWR - 1}. \quad (\text{A.29})$$

In vertical flight, the effective area associated with drag,  $A_{eff}$ , is equivalent to the total cross-sectional surface area,  $A$ . Furthermore, the power consumed is equivalent to the thrust multiplied by the vertical velocity as discussed in the section above. Therefore, the power consumed in vertical flight can be written as:

$$P = T \sqrt{\frac{2m_{tot}g}{\rho C_D A}} \sqrt{TWR - 1}, \quad (\text{A.30})$$

which can be written in terms of the thrust-to-weight ratio as:

$$P = TWR m_{tot}g \sqrt{\frac{2m_{tot}g}{\rho C_D A}} \sqrt{TWR - 1}, \quad (\text{A.31})$$

which can be simplified to

$$P = TWR \sqrt{TWR - 1} (m_{tot}g)^{\frac{3}{2}} \sqrt{\frac{2}{\rho C_D A}}. \quad (\text{A.32})$$

Finally, we know that the drag coefficient of a flat plate can be written as de-

scribed in (A.18). Again, we can assume the skin friction coefficient to be negligible, so the only drag component we are concerned about is form drag. Since the quadcopter is moving vertically upwards,  $\sin(\alpha)$  is equal to 1, and, therefore,  $C_D$  is equal to 2. Therefore, the final equation for power consumed in vertical flight can be written as:

$$P = TWR\sqrt{TWR - 1}(m_{tot}g)^{\frac{3}{2}}\sqrt{\frac{1}{\rho A}}. \quad (\text{A.33})$$

This power is calculated in (W) and represents the energy consumed in vertical flight per unit second used by the quadcopter.

## A.4 Power Consumption Linearization

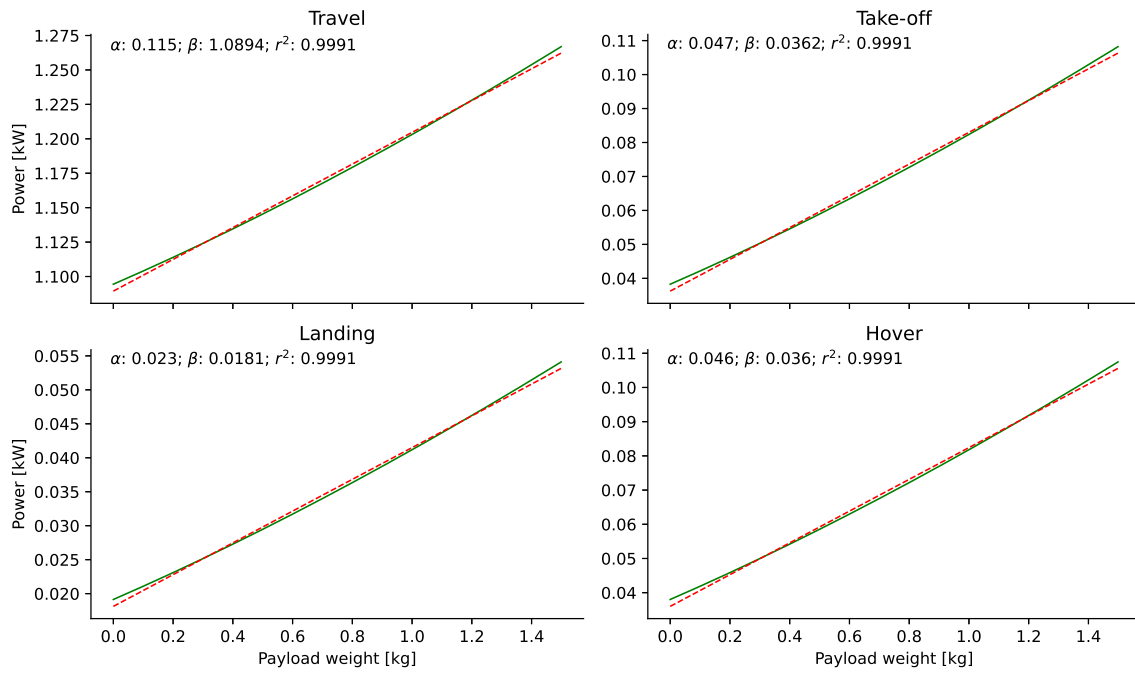


Figure A-1: Linearized power consumption functions for four modeled flight regimes.

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# Appendix B

## Route Improvement Operators

This section delves into the details of the route-improvement operator step of the *Heuristic Approach (HA)* described in Section 4.3.3. As a reminder, the route improvement process consists of a set of operations to be performed 1) internal to each unmanned aerial vehicle (UAV) route; and 2) between UAV routes. The route improvement solution iterates through a fixed number of both operator repetitions. Whilst there exists a maximum number of total improvement operator iterations, the procedure can also be terminated if one of the following conditions are met:

- a user-defined number of operations have been performed with no improvement; or
- a user-defined number of operations have been performed with an improvement of less than a user-defined percentage.

At each iteration, the exact improvement operator is chosen pseudo-randomly and the probability of choosing the operator is based on an exponentially smoothed weight that is computed using the success rate of the operator and the ratio of average time per operation of that types to all other operators of that type that is updated at each iteration. In general, there are three main categories of operators:

- *Random*: an operator for which all the inputs are chosen at random. Whilst computationally efficient, its success at improving the solution is unpredictable. It can, however, help solutions get out of local optima.
- *Greedy*: an operator for which the initial set of inputs is chosen at random, but the operator searches for the best possible operation to perform, given these initial inputs. Because of this approach, it is computationally inefficient but typically exhibits higher success rates.
- *Semi-greedy* an operator which, like the other two categories, is provided with random set of inputs and then, like the greedy operator, attempts to find the best possible operation. Unlike the greedy operator, however, the semi-greedy operator is limited to a specific number of possible operations before terminating and selecting the best potential operations from the list of operations it has

explored thus far. Such an operator brings together the best of the other two operator types. Whilst it is typically more computationally intensive compared to a random operator, it typically yields higher success rates, is faster than a fully greedy operator, and can help explore the solution space and avoid local minima.

The the list of available operators is included below, but the specifics of the operators themselves are not discussed. This is because these are common operators used in heuristic vehicle routing implementations in the literature. The author points readers to available resources, see Cordeau et al. (2002). The list of intra- and inter-route operators employed during this step are as follows:

- Intra-route:
  - Semi-Greedy Swap
  - Semi-Greedy Insertion
  - Random 2-Opt Exchange
  - Random 3-Opt Exchange
- Inter-route:
  - Random Exchange
  - Semi-Greedy Remove
  - Semi-Greedy Cross
  - Semi-Greedy Shift

The operator weight update logic, referred to as a roulette wheel, is formulated as follows: it is a strategy for choosing an item from a discrete probabilistic distribution. The weights of the operators are updated at each stage of the route improvement iterations, the objective being to adapt the probability of choosing the operators based on their success rate and their historical computational run-time.

The weights are initialized to:

$$w_i = \frac{1}{n\_operators} \quad \forall i \text{ in } I \quad (\text{B.1})$$

If  $t_{average}$  is the average time taken for all operators since last update and  $t_{i,average}$  is the average time taken for operations of type  $i$  since last update, then, letting  $M_i$  be a multiplier for the operator  $i$  such that:

$$M_i = \begin{cases} 1 & \text{if } t_{i,average} \leq t_{average} \\ \frac{t_{i,average}}{t_{average}} & \text{otherwise} \end{cases} \quad (\text{B.2})$$

The multiplier,  $M_i$ , will negatively affect the probability of choosing operator  $i$  if its average run-time is longer than that of the average run-time of all the other



available operators, making the weights adaptable both based on success and runtime. Then, the new weight for operator  $i$  is computed using an adapted exponential smoothing function:

$$w_{i,new} = (1 - \alpha)w_{i,old} + \alpha \frac{\sum_{k=a}^b S_k}{b - a} M_i \quad (\text{B.3})$$

where  $S_k$  is the success value of the operator for operation  $k$  and  $a$  and  $b$  are the beginning and end operation numbers, respectively, for the period under consideration.

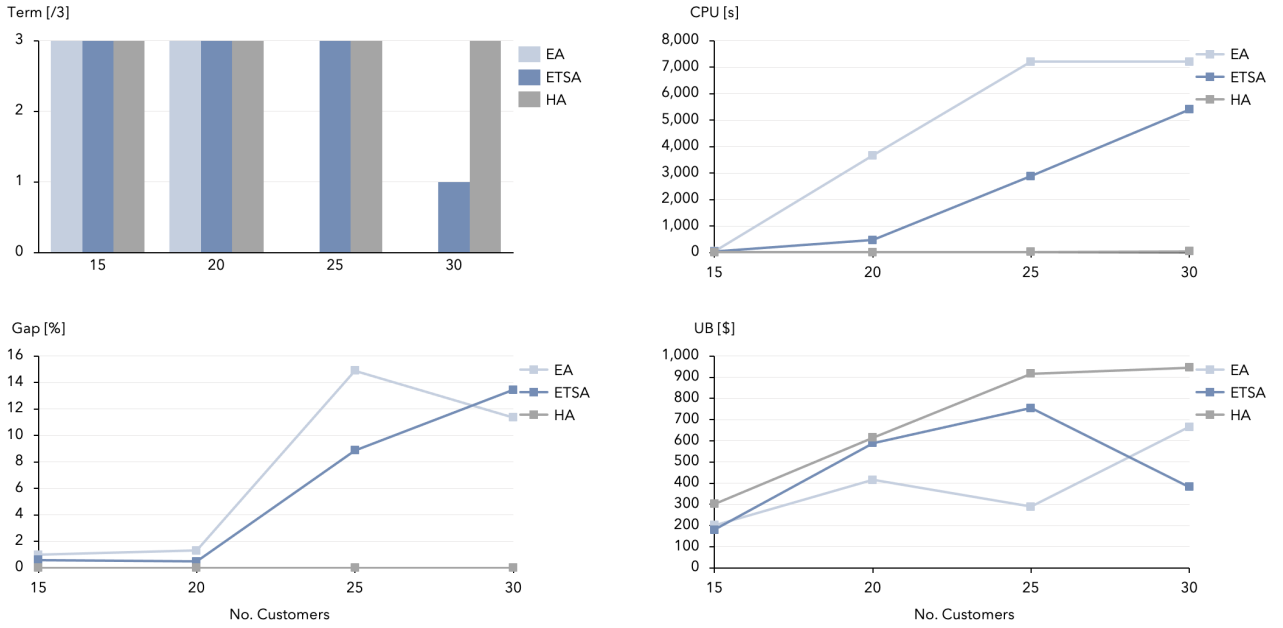
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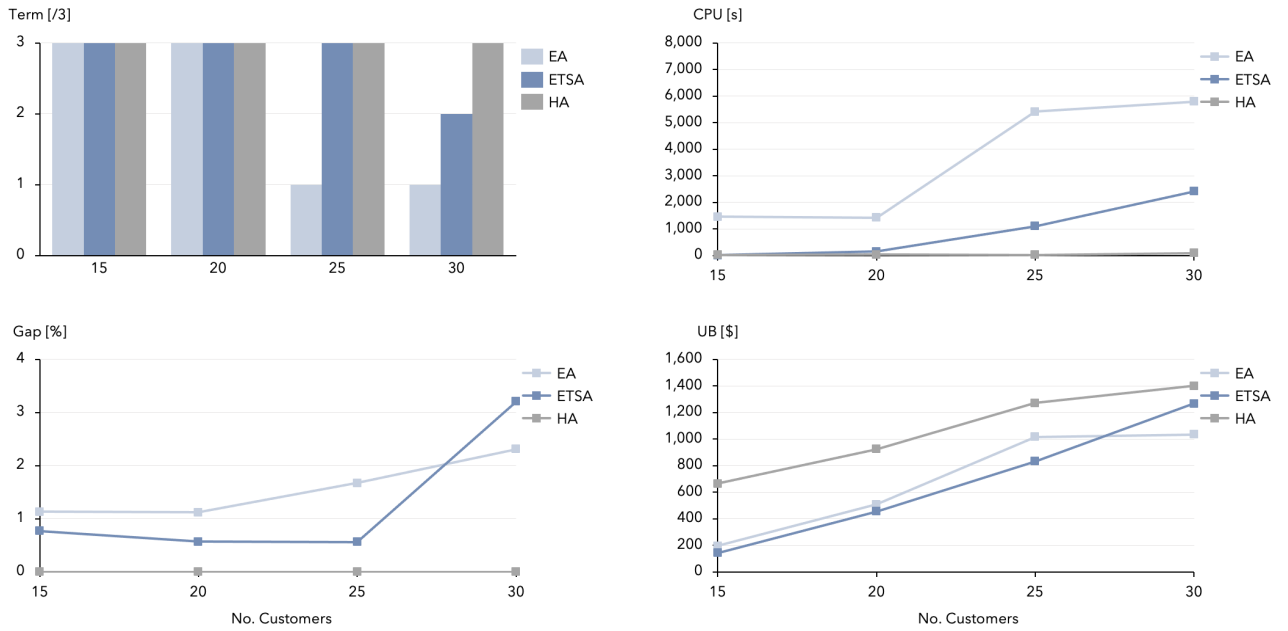
# Appendix C

## Algorithmic Benchmark Results

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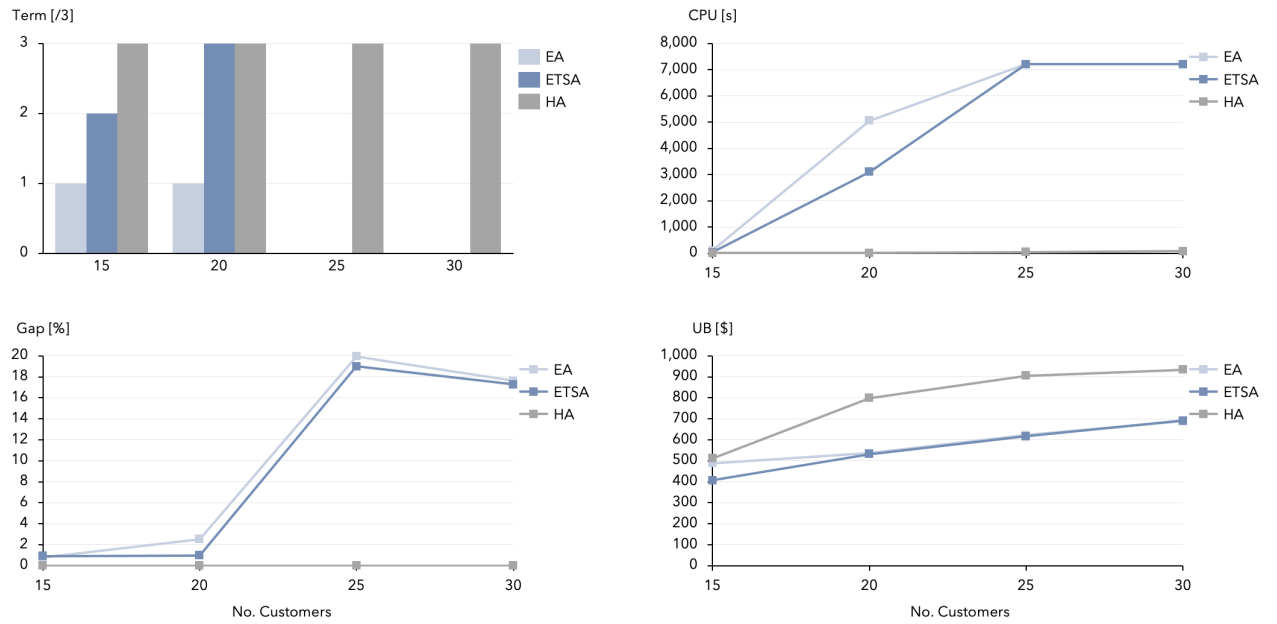


(a) Demand set A1.

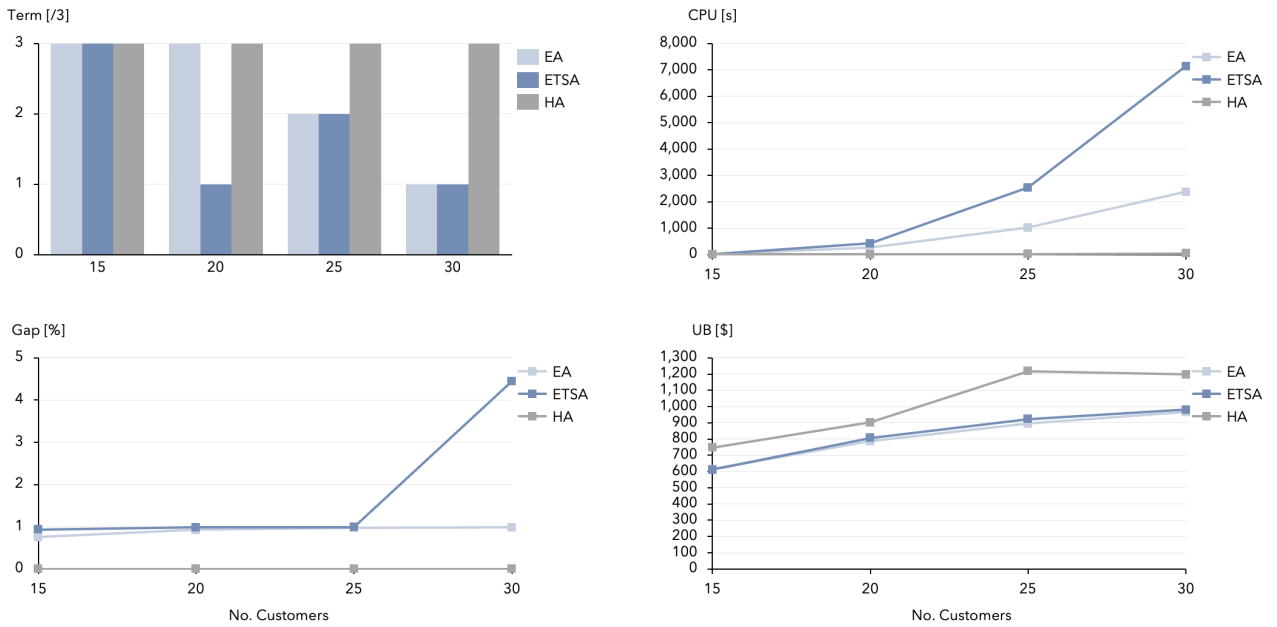


(b) Demand set A2.

Figure C-1: Benchmark runs varying number of customers and GURP model.

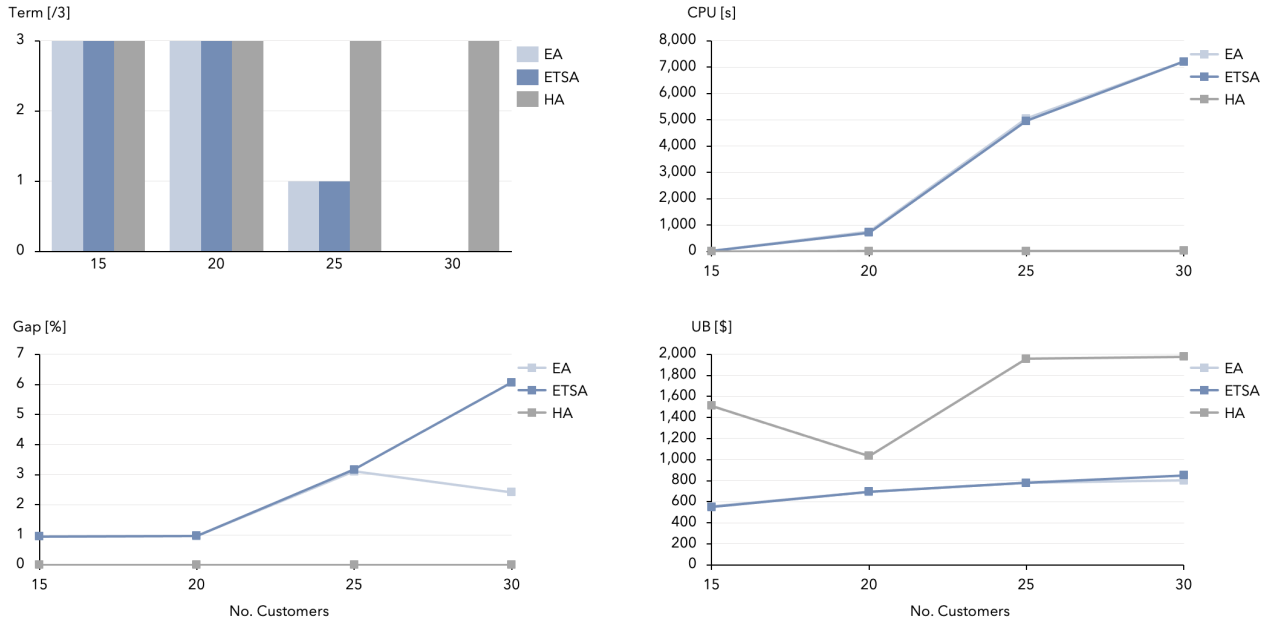


(a) Demand set A1.

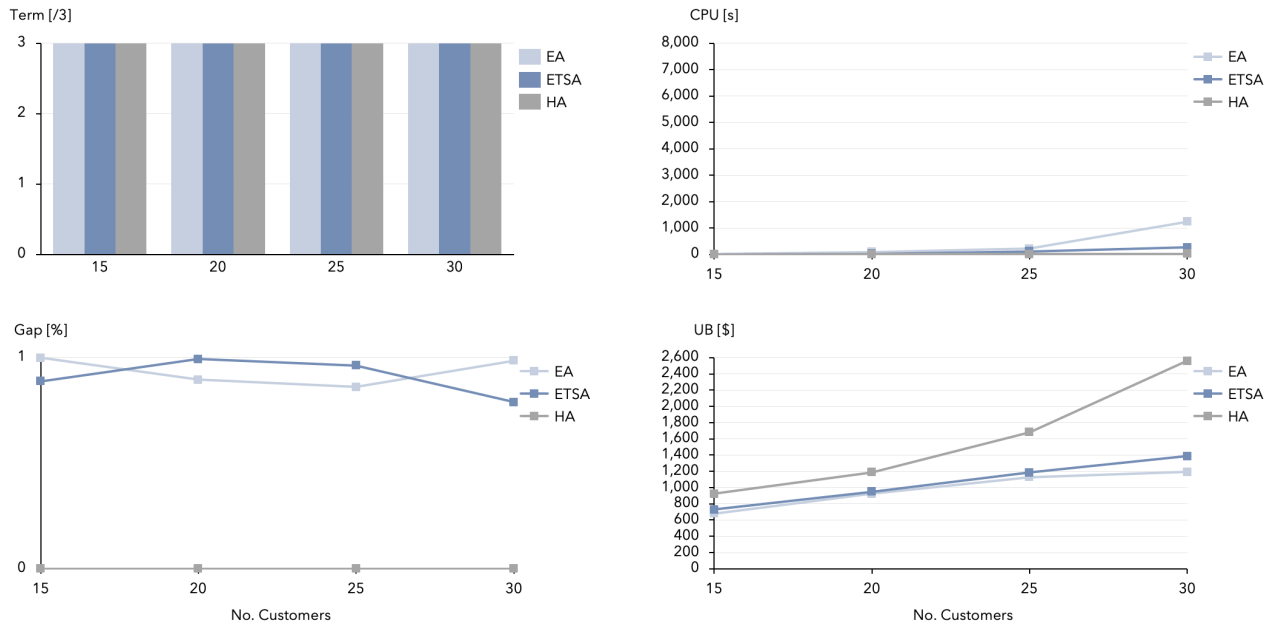


(b) Demand set A2.

Figure C-2: Benchmark pre-flight check runs varying number of customers and GURP model.

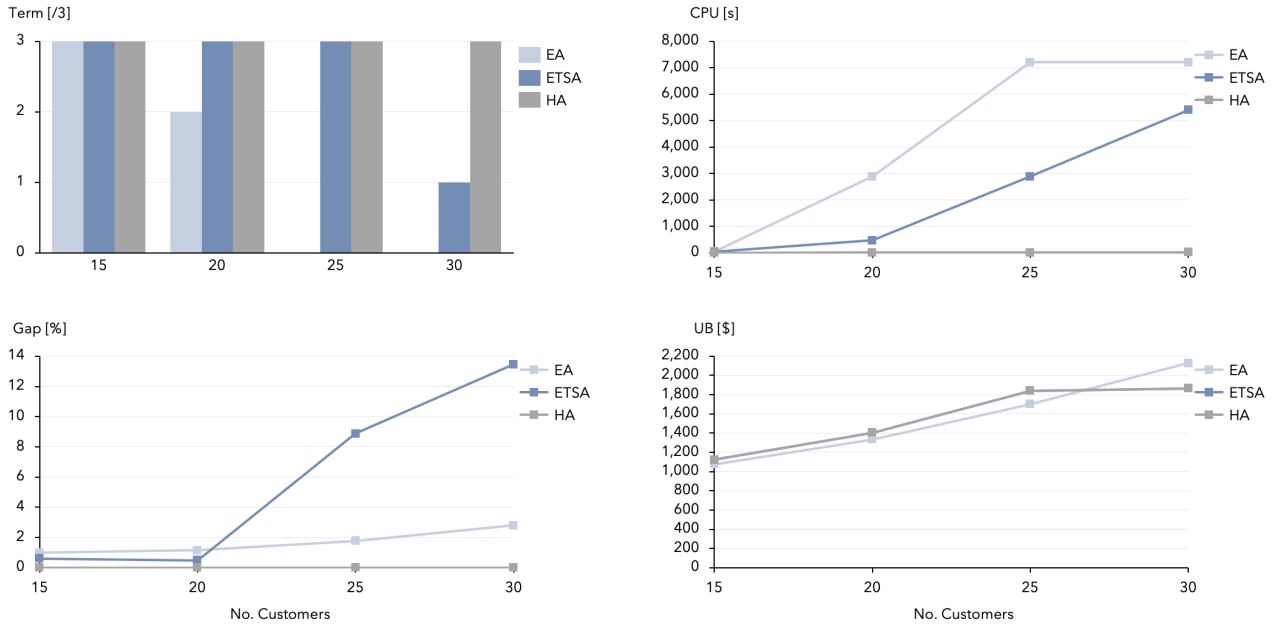


(a) Demand set A1.

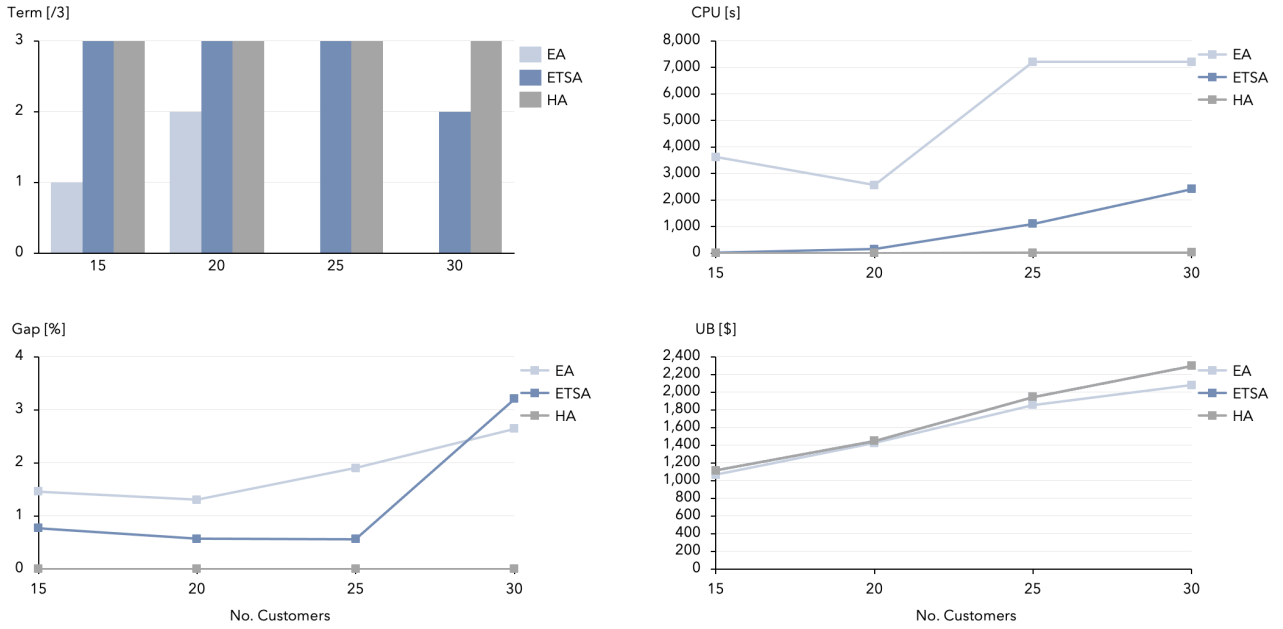


(b) Demand set A2.

Figure C-3: Benchmark TW runs varying number of customers and GURP model.

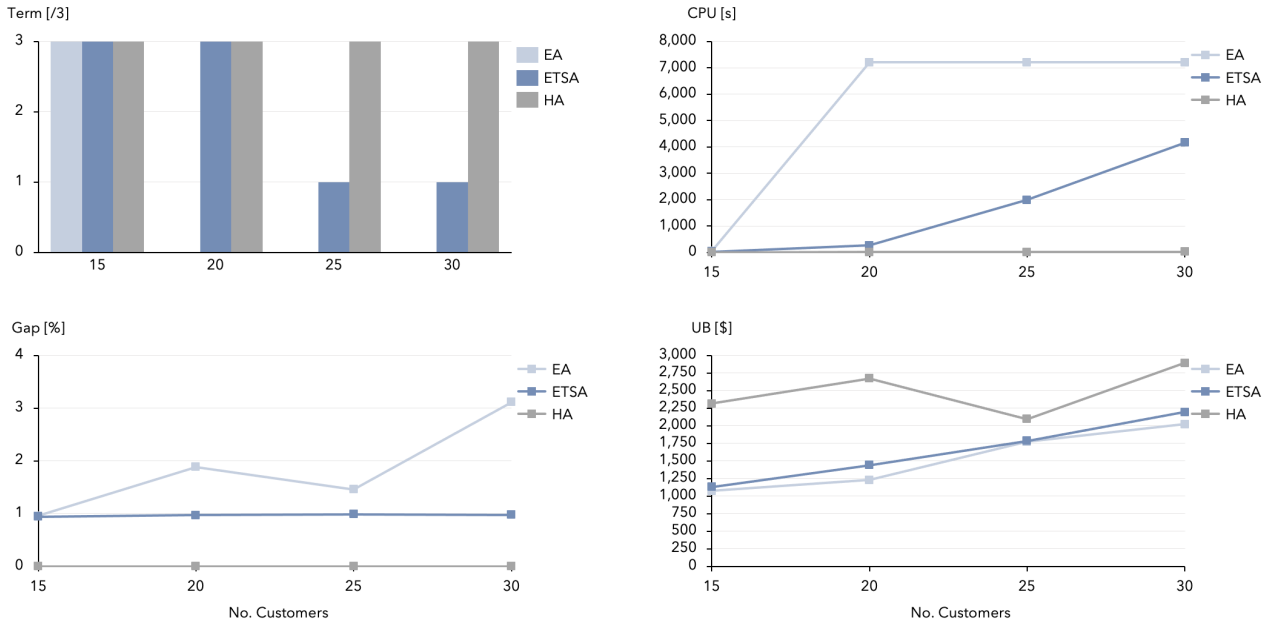


(a) Demand set A1.

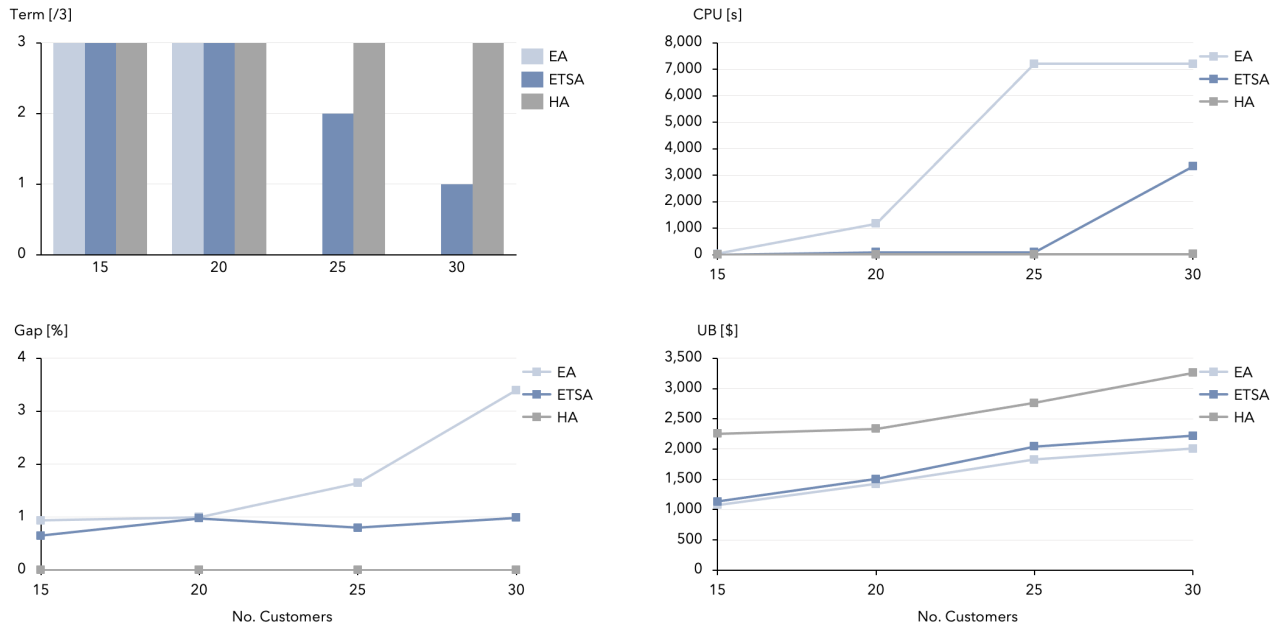


(b) Demand set A2.

Figure C-4: Benchmark multi-commodity runs varying number of customers and GURP model.



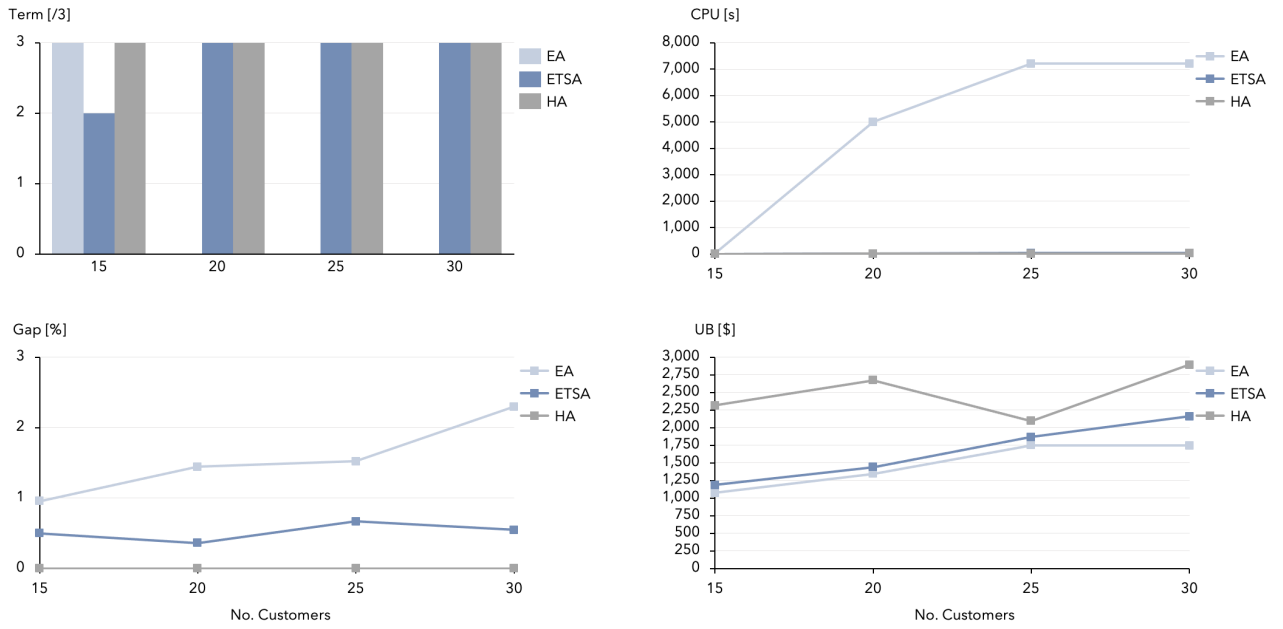
(a) Demand set A1.



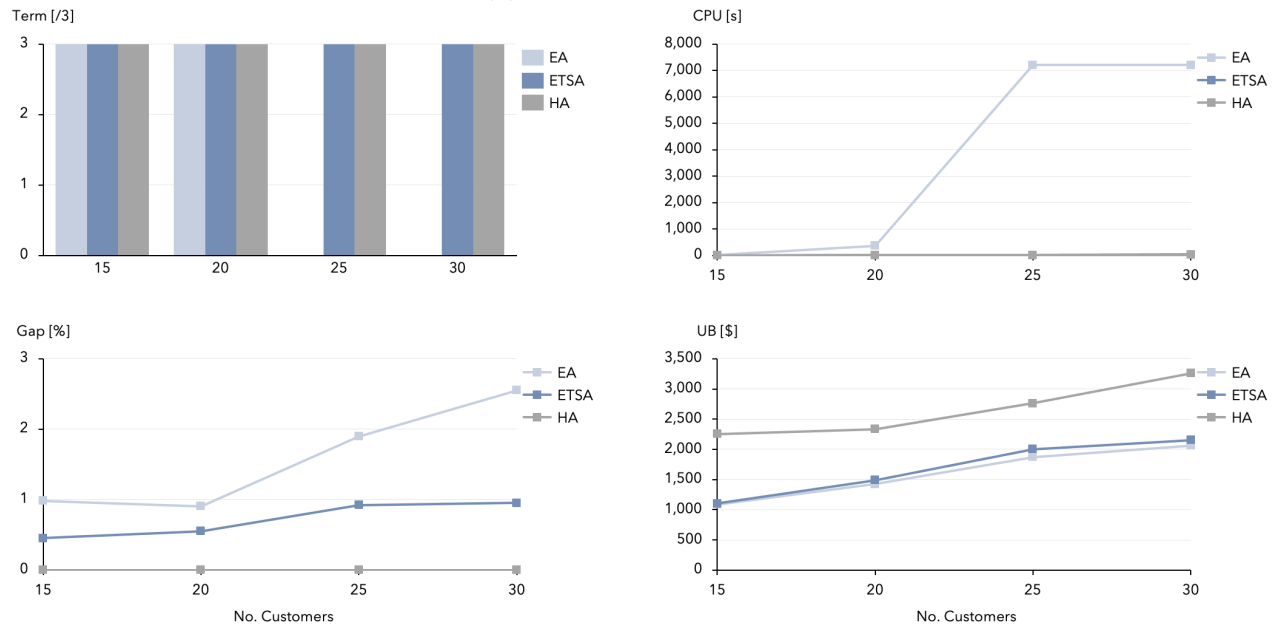
(b) Demand set A2.

Figure C-5: Benchmark full-feature runs varying number of customers and GURP model.



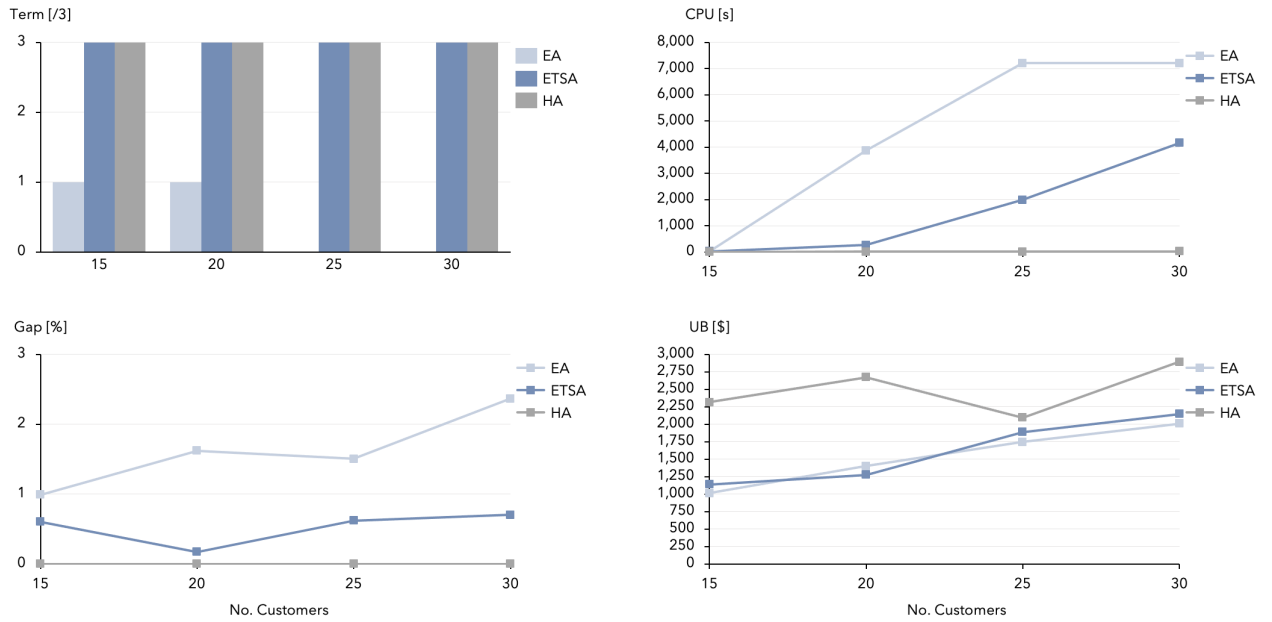


(a) Demand set A1.

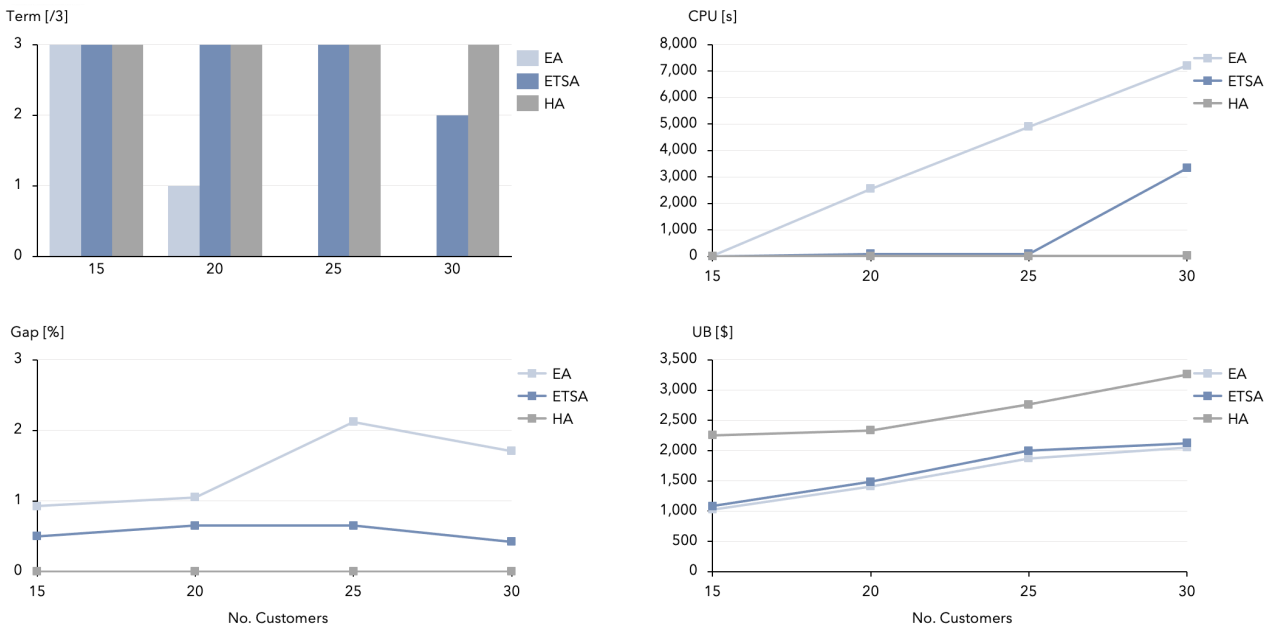


(b) Demand set A2.

Figure C-6: Benchmark full-feature and valid inequality runs varying number of customers and GURP model.



(a) Demand set A1.



(b) Demand set A2.

Figure C-7: Benchmark full-feature, valid inequality and warm-start runs varying number of customers and GURP model.

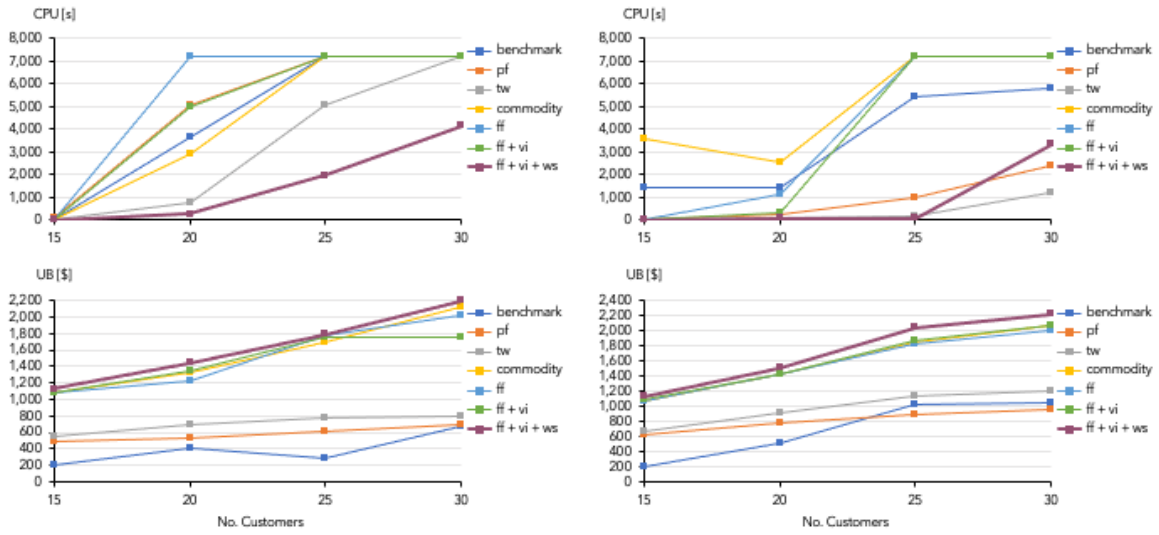


Figure C-8: Demand Sets A1 and A2: scenario performance comparison across customer demand sets for *EA*.

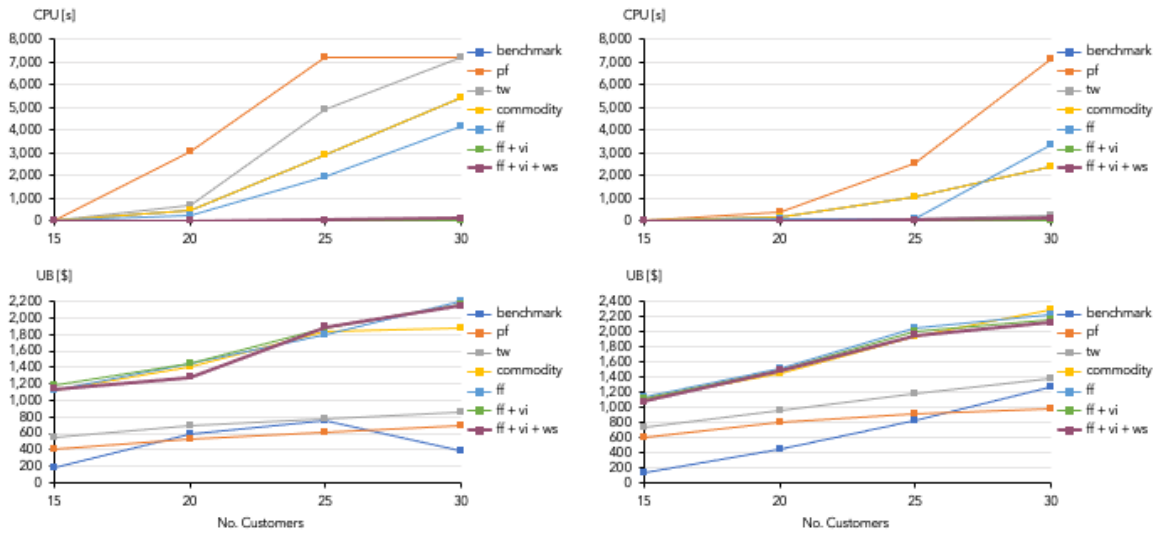


Figure C-9: Demand Sets A1 and A2: scenario performance comparison across customer demand sets for *ETSA*.

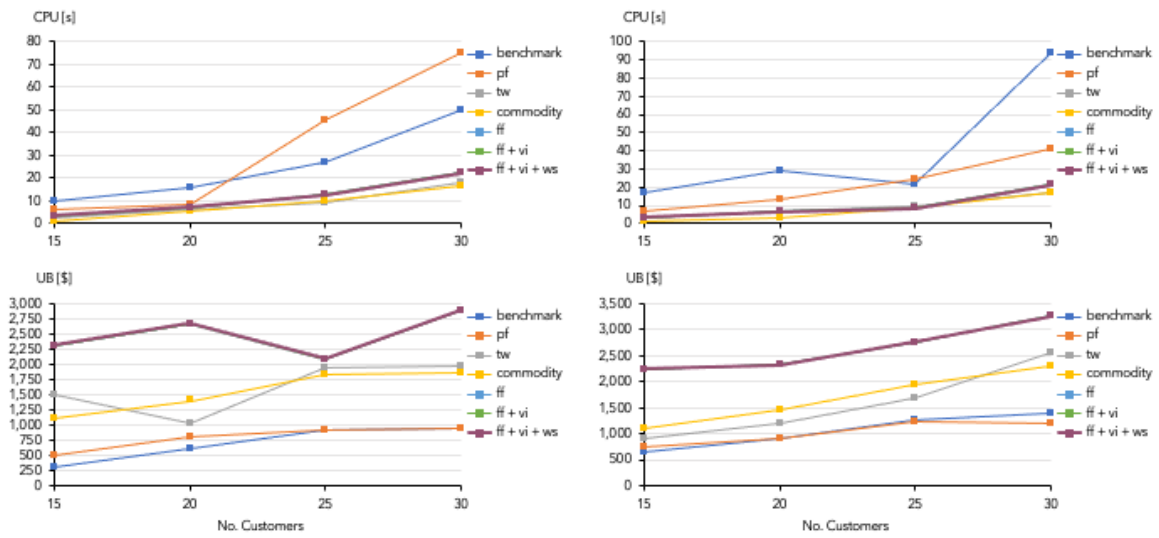


Figure C-10: Demand Sets A1 (left) and A2 (right): scenario performance comparison across customer demand sets for  $HA$ .

Table C.1: GURP model benchmarking results for Benchmark, Maintenance Check, Time Window and Commodities problem definition scenarios.

Set	No. Cust	EA					ETSA					HA							
		Opt [3]	Gap [%]	CPU	UB	LB	T/d	Opt [3]	Gap [%]	CPU	UB	LB	T/d	Opt [3]	Gap [%]	CPU	UB	LB	T/d
A1	15	3	0.99%	45.55	201.21	193.25	10.33	3	0.60%	37.77	179.73	176.22	6.33	3	0.00%	10.12	301.79	301.79	4.33
	20	3	1.31%	3664.78	414.95	402.21	10.20	3	0.48%	465.08	588.86	584.25	11.75	3	0.00%	15.70	614.63	614.63	4.00
	25	0	14.91%	7200.28	289.09	191.02	7.25	3	8.88%	2886.15	754.03	693.76	11.80	3	0.00%	26.63	917.06	917.06	5.67
	30	0	11.36%	7200.41	665.78	570.36	11.20	1	13.46%	5404.88	382.18	286.38	8.50	3	0.00%	49.89	946.01	946.01	6.33
A2	15	3	1.13%	1458.66	196.45	187.00	6.60	3	0.77%	6.51	142.02	136.28	5.50	3	0.00%	17.49	664.54	664.54	4.67
	20	3	1.12%	1423.21	507.35	494.26	9.67	3	0.57%	147.51	455.76	451.23	8.40	3	0.00%	29.55	923.65	923.65	6.00
	25	1	1.67%	5410.01	1015.88	987.04	15.25	3	0.57%	1102.14	832.02	826.03	12.00	3	0.00%	22.01	1271.92	1271.92	6.00
	30	1	2.31%	5790.05	1034.89	994.51	15.00	2	3.21%	2411.38	1266.21	1228.94	16.33	3	0.00%	93.89	1400.47	1400.47	8.50
A1	15	1	0.79%	99.12	487.98	484.11	3.00	2	0.93%	29.52	406.64	402.87	2.50	3	0.00%	6.46	512.02	512.02	3.00
	20	1	2.52%	5060.10	536.17	522.68	4.00	3	0.98%	3097.78	531.40	526.18	4.00	3	0.00%	8.38	798.58	798.58	4.33
	25	0	19.95%	7200.62	621.78	495.92	4.00	0	18.99%	7200.18	616.59	498.10	4.00	3	0.00%	45.70	905.73	905.73	5.67
	30	0	17.62%	7200.81	687.59	565.43	4.33	0	17.26%	7200.44	690.70	570.02	4.67	3	0.00%	75.13	934.01	934.01	6.33
A2	15	3	0.75%	8.25	614.51	610.10	3.67	3	0.94%	13.55	611.19	605.44	3.67	3	0.00%	7.03	747.54	747.54	4.67
	20	3	0.93%	279.74	785.59	778.32	5.00	1	0.98%	421.94	806.65	798.72	5.00	3	0.00%	13.46	902.65	902.65	6.00
	25	2	0.97%	1020.19	894.24	885.56	5.00	2	0.99%	2534.95	922.96	913.81	5.50	3	0.00%	24.38	1217.60	1217.60	8.00
	30	1	0.98%	2381.70	964.94	955.46	6.00	1	4.45%	7132.65	980.83	936.14	6.00	3	0.00%	40.69	1197.46	1197.46	8.67
A1	15	3	0.95%	7.36	554.31	549.04	3.33	3	0.95%	11.84	547.95	542.78	3.00	3	0.00%	2.89	1511.44	1511.44	3.67
	20	3	0.96%	746.25	692.93	686.27	5.00	3	0.96%	707.40	696.26	689.57	5.00	3	0.00%	5.90	1033.30	1033.30	7.33
	25	1	3.11%	5041.86	779.77	755.05	4.67	1	3.17%	4953.43	777.61	752.42	4.67	3	0.00%	9.05	1955.90	1955.90	7.67
	30	0	2.42%	7200.58	801.97	782.57	6.00	0	6.06%	7201.01	851.40	798.83	5.67	3	0.00%	18.31	1976.07	1976.07	10.00
A2	15	3	1.00%	5.68	678.49	671.72	4.00	3	0.89%	3.04	727.10	720.67	4.33	3	0.00%	3.05	921.18	921.18	5.00
	20	3	0.89%	87.87	921.64	913.34	7.00	3	0.99%	16.52	947.38	937.97	7.00	3	0.00%	6.82	1189.72	1189.72	9.50
	25	3	0.86%	211.82	1127.80	1117.97	7.33	3	0.96%	119.23	1184.66	1173.27	7.50	3	0.00%	9.74	1682.00	1682.00	10.33
	30	3	0.99%	1234.43	1191.27	1179.53	7.33	3	0.79%	260.33	1385.99	1375.17	10.00	3	0.00%	16.82	2559.62	2559.62	10.67
Commodities	15	3	0.99%	45.55	1075.07	1064.39	10.33	3	0.60%	37.77	1122.88	776.22	6.33	3	0.00%	1.23	1122.88	1119.85	10.33
	20	2	1.15%	2887.69	1334.13	1318.45	14.33	3	0.48%	465.08	1404.53	1184.25	11.75	3	0.00%	5.45	1404.53	1400.14	14.33
	25	0	1.77%	7200.53	1701.02	1670.93	17.00	3	8.88%	2886.15	1838.81	1293.76	11.80	3	0.00%	9.86	1838.81	1829.57	17.00
	30	0	2.81%	7200.35	2126.54	2066.90	21.00	1	13.46%	5404.88	1865.93	886.38	8.50	3	0.00%	16.99	1865.93	1850.03	21.00
A2	15	1	1.46%	3618.98	1064.35	1049.18	11.00	3	0.77%	6.51	1114.52	736.28	5.50	3	0.00%	1.62	1114.52	1104.63	11.00
	20	2	1.30%	2557.76	1423.71	1404.93	14.00	3	0.57%	147.51	1449.26	1051.23	8.40	3	0.00%	3.15	1449.26	1449.26	13.50
	25	0	1.90%	7200.15	1856.43	1820.90	18.67	3	0.57%	1102.14	1944.22	1426.03	12.00	3	0.00%	8.40	1944.22	1941.24	18.67
	30	0	2.65%	7200.28	2078.18	2022.80	21.00	2	3.21%	2411.38	2296.87	1828.94	16.33	3	0.00%	16.78	2296.87	2283.47	21.50

Table C.2: GURP model benchmarking results for Full Feature, Full Feature + Valid Inequalities + Full Feature + Valid Inequalities + Warm Start problem definition scenarios.

Set	No. Cust	EA					ETSAs					HA							
		Opt [3]	Gap [%]	CPU	UB	LB	T/d	Opt [3]	Gap [%]	CPU	UB	LB	T/d	Opt [3]	Gap [%]	CPU	UB	LB	T/d
A1	15	3	0.96%	48.32	1074.32	1064.01	10.33	3	0.94%	17.48	1130.92	1120.26	10.33	3	0.00%	3.54	2312.99	2312.99	11.33
	20	0	1.88%	7200.16	1229.09	1205.94	15.00	3	0.97%	261.90	1438.27	1424.33	14.67	3	0.00%	7.32	2673.31	2673.31	15.67
	25	0	1.46%	7200.09	1773.00	1746.75	17.00	1	0.99%	1981.87	1785.44	1767.82	17.00	3	0.00%	12.68	2092.79	2092.79	18.00
	30	0	3.12%	7200.11	2022.33	1957.34	21.67	1	0.98%	4153.77	2192.63	2171.24	21.00	3	0.00%	22.52	2894.02	2894.02	24.00
A2	15	3	0.94%	28.99	1076.39	1066.33	11.00	3	0.65%	3.75	1129.64	1122.02	11.00	3	0.00%	3.24	2253.87	2253.87	11.00
	20	3	1.00%	1175.03	1422.48	1408.27	14.00	3	0.98%	91.52	1504.55	1489.86	14.00	3	0.00%	6.79	2331.10	2331.10	15.00
	25	0	1.65%	7200.08	1826.27	1796.19	19.00	2	0.80%	86.72	2043.87	2027.41	19.50	3	0.00%	8.41	2760.21	2760.21	20.33
	30	0	3.40%	7200.23	2006.80	1940.32	21.00	1	0.99%	3332.38	2217.90	2195.98	20.00	3	0.00%	21.25	3260.21	3260.21	21.00
A1	15	3	0.96%	15.43	1074.33	1064.06	10.33	2	0.50%	0.86	1184.32	1178.34	10.50	3	0.00%	3.54	2312.99	2312.99	11.33
	20	0	1.44%	4997.84	1345.02	1325.87	14.67	3	0.36%	5.01	1438.27	1433.01	14.67	3	0.00%	7.32	2673.31	2673.31	15.67
	25	0	1.52%	7200.13	1748.17	1721.50	17.33	3	0.67%	31.40	1866.49	1853.80	17.33	3	0.00%	12.68	2092.79	2092.79	18.00
	30	0	2.30%	7200.21	1745.28	1705.18	22.00	3	0.55%	32.84	2160.17	2148.33	21.33	3	0.00%	22.52	2894.02	2894.02	24.00
A2	15	3	0.98%	13.86	1088.64	1077.96	11.00	3	0.45%	1.41	1101.81	1096.82	11.00	3	0.00%	3.24	2253.87	2253.87	11.00
	20	3	0.91%	364.37	1422.49	1409.65	14.00	3	0.55%	11.54	1486.43	1478.26	13.50	3	0.00%	6.79	2331.10	2331.10	15.00
	25	0	1.90%	7200.15	1871.40	1835.84	19.33	3	0.92%	9.30	2002.46	1983.98	19.00	3	0.00%	8.41	2760.21	2760.21	20.33
	30	0	2.55%	7200.19	2064.12	2010.13	20.67	3	0.95%	28.10	2150.84	2130.39	20.67	3	0.00%	21.25	3260.21	3260.21	21.00
A1	15	1	0.94%	17.48	1130.92	1120.26	10.33	3	0.60%	14.54	1139.94	1133.15	10.33	3	0.00%	3.54	2312.99	2312.99	11.33
	20	1	0.97%	261.90	1438.27	1424.33	14.67	3	0.17%	25.40	1276.61	1274.41	14.00	3	0.00%	7.32	2673.31	2673.31	15.67
	25	0	0.99%	1981.87	1785.44	1767.82	17	2	0.62%	61.51	1886.57	1874.68	17.50	3	0.00%	12.68	2092.79	2092.79	18.00
	30	0	0.98%	4153.77	2192.63	2171.24	21	3	0.70%	129.03	2147.24	2132.07	21.67	3	0.00%	22.52	2894.02	2894.02	24.00
A2	15	3	0.65%	3.75	1129.64	1122.02	11	3	0.50%	13.19	1078.88	1073.02	10.33	3	0.00%	3.24	2253.87	2253.87	11.00
	20	0	0.98%	91.52	1504.55	1489.86	14	3	0.65%	32.09	1481.54	1471.93	13.67	3	0.00%	6.79	2331.10	2331.10	15.00
	25	0	0.80%	86.72	2043.87	2027.41	19.5	1	0.36%	58.34	1956.15	1949.07	19.00	3	0.00%	8.41	2760.21	2760.21	20.33
	30	0	0.99%	3332.38	2217.90	2195.98	20	2	0.42%	130.99	2123.09	2114.53	21.00	3	0.00%	21.25	3260.21	3260.21	21.00

# Appendix D

## Case Study Analysis Results Data Table

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Table D.1: Case study scenario analysis results data for Dense (1000 customers) and Super-Dense (1200 customers) demand density.

No. Cust.	Tech	Exog. Const.	No. Pkgs.	No. In-feas.	No. UAVs	Cost [\$]	Cost/pkg Cost [\$]	Fixed Cost [\$]	Distance Cost [\$]	Wage Cost [\$]	Energy Cost [\$]	Distance [km]	t <sub>service</sub> [min]	t <sub>travel</sub> [min]	t <sub>depot</sub> [min]	t <sub>main.</sub> [min]	t <sub>preflight</sub> [min]	Energy [kwh]	
600	Today	Baseline	659	247	39	\$563.65	\$1.37	78	163.58	313.27	8.80	1635.76	17.30	40.89	4.46	0.00	0.00	88.02	
		Minimal	659	275	24	\$741.97	\$1.93	48	157.52	528.05	8.40	1575.21	16.13	39.38	4.20	44.25	1.65	83.97	
		Moderate	659	294	18	\$921.63	\$2.53	36	147.53	730.22	7.88	1475.33	146.04	15.32	36.88	4.04	87.00	2.80	78.82
		Severe	659	361	11	\$2,198.37	\$7.38	22	108.11	2062.39	5.87	1081.11	412.48	12.59	27.03	2.96	369.90	0.00	58.68
	5 Years	Baseline	659	154	30	\$288.41	\$0.57	30	91.10	157.97	9.34	1822.04	63.19	21.05	37.96	4.18	0.00	0.00	93.36
		Minimal	659	307	19	\$316.19	\$0.90	19	66.54	221.31	9.34	1330.81	88.52	14.77	27.72	3.78	41.00	1.25	93.37
		Moderate	659	322	18	\$395.46	\$1.17	18	61.86	306.84	8.77	1237.17	122.73	14.12	25.77	3.54	77.00	2.30	87.65
		Severe	659	290	26	\$1,296.52	\$3.51	26	69.46	1194.23	6.83	1389.13	477.69	15.43	28.94	3.12	423.75	6.45	68.34
	10 Years	Baseline	659	122	35	\$139.40	\$0.26	17.5	43.24	70.14	8.52	1729.66	56.11	22.32	30.03	3.76	0.00	0.00	85.25
		Minimal	659	165	23	\$207.45	\$0.42	11.5	48.79	134.60	12.56	1951.59	107.68	20.52	33.88	4.48	47.00	1.80	125.60
		Moderate	659	195	28	\$239.59	\$0.52	14	43.05	171.29	11.25	1721.95	137.03	19.26	29.89	3.98	80.00	3.90	112.46
		Severe	659	292	18	\$663.58	\$1.81	9	31.97	614.28	8.34	1278.82	491.42	15.32	22.20	3.00	446.25	4.65	83.36
15 Years	Baseline	659	99	10	\$66.48	\$0.12	2.5	21.18	32.16	10.64	1694.11	51.46	23.25	24.51	3.70	0.00	0.00	106.44	
	Minimal	659	125	13	\$90.00	\$0.17	3.25	21.19	54.92	10.65	1695.28	87.87	22.14	24.53	3.60	35.75	1.85	106.46	
	Moderate	659	156	15	\$107.43	\$0.21	3.75	20.23	73.38	10.07	1618.32	117.41	20.84	23.41	3.46	65.50	4.20	100.70	
	Severe	659	243	23	\$299.32	\$0.72	5.75	17.98	266.99	8.59	1438.52	427.19	17.28	20.81	3.00	378.75	7.35	85.89	
800	Today	Baseline	872	324	23	\$650.55	\$1.19	46	200.42	393.13	11.01	2004.22	78.63	22.98	50.11	5.54	0.00	0.00	110.05
		Minimal	872	378	27	\$906.74	\$1.84	54	191.41	651.01	10.32	1914.09	130.20	20.69	47.85	5.16	54.50	2.00	103.19
		Moderate	872	406	27	\$1,098.92	\$2.36	54	173.45	862.02	9.45	1734.54	172.40	19.48	43.36	4.86	100.50	4.20	94.49
		Severe	872	497	18	\$2,658.01	\$7.09	36	129.36	2485.50	7.15	1293.60	497.10	15.60	32.34	3.66	445.50	0.00	71.52
	5 Years	Baseline	872	205	18	\$335.60	\$0.50	18	109.13	196.98	11.49	2182.64	78.79	27.90	45.47	5.42	0.00	0.00	114.86
		Minimal	872	415	17	\$379.03	\$0.83	17	77.44	273.39	11.20	1548.79	109.36	19.10	32.27	4.74	51.75	1.50	111.98
		Moderate	872	435	24	\$492.88	\$1.13	24	74.54	383.55	10.79	1490.85	153.42	18.24	31.06	4.62	95.50	4.00	107.88
		Severe	872	400	25	\$1,699.71	\$3.60	25	86.47	1579.65	8.59	1729.42	631.86	19.62	36.03	4.26	562.50	9.45	85.94
	10 Years	Baseline	872	167	14	\$156.94	\$0.22	7	51.82	87.67	10.45	2072.82	70.14	29.37	35.99	4.78	0.00	0.00	104.49
		Minimal	872	238	22	\$254.62	\$0.40	11	59.13	169.08	15.40	2365.32	135.26	26.47	41.06	5.58	60.25	1.90	154.03
		Moderate	872	275	37	\$309.87	\$0.52	18.5	55.61	221.35	14.42	2224.40	177.08	24.86	38.62	5.20	103.00	5.40	144.16
		Severe	872	399	23	\$895.32	\$1.89	11.5	42.50	830.33	10.99	1699.95	664.26	19.62	29.51	4.18	603.75	7.20	109.93
15 Years	Baseline	872	134	14	\$86.47	\$0.12	3.5	27.43	41.94	13.85	2174.08	67.10	30.71	31.45	4.94	0.00	0.00	138.55	
	Minimal	872	174	22	\$117.83	\$0.17	5.5	27.43	71.08	13.83	2194.56	113.72	29.03	31.75	4.84	45.00	3.10	138.26	
	Moderate	872	218	31	\$138.07	\$0.21	7.75	25.55	92.08	12.70	2043.69	147.33	27.12	29.57	4.64	78.50	7.50	126.95	
	Severe	872	343	41	\$356.93	\$0.67	10.25	21.29	315.00	10.39	1703.16	504.00	21.92	24.64	3.84	442.50	11.10	103.90	

Abbreviations: No. Cust.: Number of Customers; Exog. Const.: Exogenous Constraints; No. Pkgs.: Number of Packages; Infeas.: Infeasible; No. UAVs: Number of UAVs; t: time; t<sub>main.</sub>: time-maintenance.



Table D.2: Case study scenario analysis results data for Sparse (600 customers) and Moderate (800 customers) demand density.

No. Cust.	Tech	Exog. Const.	No. Pkgs.	No. In-feas.	No. UAVs	Cost [\$]	Cost/pkg Cost [\$]	Fixed Cost [\$]	Distance Cost [\$]	Wage Cost [\$]	Energy Cost [\$]	Distance [km]	t-service [min]	t-travel [min]	t-depot [min]	t-main. [min]	t-preflight [min]	Energy [kwh]	
1000	Today	Baseline 1106	403	472	112	\$1,004.21	\$1.43	224	258.75	507.13	14.33	2587.46	29.42	64.69	7.32	0.00	0.00	143.33	
		Minimal 1106	472	508	25	\$1,143.42	\$1.80	50	241.71	838.53	13.18	2417.06	26.58	60.43	6.60	72.00	2.10	131.83	
		Moderate 1106	508	631	27	\$1,391.13	\$2.33	54	219.53	1105.57	12.03	2195.32	22.11	54.88	6.18	130.00	4.90	120.31	
		Severe 1106	631	257	18	\$3,524.05	\$7.42	36	165.00	3313.85	9.20	1650.01	662.77	20.04	41.25	4.78	596.70	0.00	92.00
	5 Years	Baseline 1106	257	520	110	\$524.65	\$0.62	110	143.69	255.96	15.00	2873.88	102.38	35.37	59.87	7.14	0.00	0.00	149.97
		Minimal 1106	520	546	29	\$482.23	\$0.82	29	97.83	341.03	14.37	1956.56	136.41	24.41	40.76	5.84	63.50	1.90	143.68
		Moderate 1106	546	506	34	\$608.35	\$1.09	34	90.69	470.24	13.41	1813.80	188.10	23.39	37.79	5.62	116.50	4.80	134.11
		Severe 1106	506	208	31	\$2,214.66	\$3.69	31	110.25	2062.32	11.10	2204.94	824.93	25.25	45.94	5.24	738.75	9.75	111.00
	10 Years	Baseline 1106	208	297	19	\$191.85	\$0.21	9.5	61.96	107.67	12.73	2478.20	86.13	37.23	43.02	5.88	0.00	0.00	127.26
		Minimal 1106	297	336	31	\$313.90	\$0.39	15.5	71.44	208.09	18.86	2857.78	166.47	33.56	49.61	7.00	73.50	2.80	188.61
		Moderate 1106	336	501	39	\$390.61	\$0.51	19.5	68.20	285.00	17.90	2728.10	228.00	32.00	47.36	6.84	134.50	7.30	179.02
		Severe 1106	501	167	34	\$1,131.59	\$1.87	17	52.84	1047.90	13.85	2113.48	838.32	25.27	36.69	5.36	761.25	9.75	138.52
15 Years	Baseline 1106	167	220	89	\$129.23	\$0.14	22.25	35.36	54.06	17.55	2828.92	86.50	38.87	40.93	6.70	0.00	0.00	175.55	
	Minimal 1106	220	267	29	\$144.45	\$0.16	7.25	33.21	87.03	16.96	2656.88	139.25	36.68	38.44	5.98	54.00	4.15	169.60	
	Moderate 1106	267	434	39	\$172.69	\$0.21	9.75	31.69	115.36	15.90	2534.93	184.57	34.78	36.67	5.92	97.00	10.20	158.97	
	Severe 1106	434	486	27	\$483.01	\$0.72	6.75	26.73	436.52	13.01	2138.22	698.43	28.08	30.93	4.92	622.50	12.00	130.07	
1200	Today	Baseline 1328	486	551	34	\$988.80	\$1.17	68	304.97	598.91	16.91	3049.70	119.78	76.24	8.44	0.00	0.00	169.14	
		Minimal 1328	551	588	28	\$1,399.64	\$1.80	56	298.73	1028.72	16.18	2987.34	205.74	32.37	74.68	8.14	87.75	2.80	161.85
		Moderate 1328	588	749	45	\$1,768.54	\$2.39	90	279.43	1383.88	15.23	2794.28	276.78	30.84	69.86	7.88	161.00	7.20	152.31
		Severe 1328	749	293	16	\$4,174.07	\$7.21	32	192.35	3938.93	10.79	1923.47	787.79	24.02	48.09	5.58	710.10	0.00	107.94
	5 Years	Baseline 1328	293	634	118	\$626.34	\$0.61	118	176.71	313.18	18.45	3534.28	125.27	42.96	73.63	8.68	0.00	0.00	184.54
		Minimal 1328	634	656	25	\$564.20	\$0.81	25	116.34	405.86	17.00	2326.74	162.34	28.77	48.47	7.00	75.75	2.35	170.01
		Moderate 1328	656	589	29	\$739.60	\$1.10	29	111.27	582.98	16.34	2225.45	233.19	27.87	46.36	6.96	146.50	5.50	163.45
		Severe 1328	589	244	33	\$2,731.27	\$3.70	33	133.60	2551.19	13.47	2672.04	1020.48	30.48	55.67	6.58	915.00	12.75	134.74
	10 Years	Baseline 1328	244	329	100	\$277.04	\$0.26	50	78.25	133.10	15.69	3129.85	106.48	44.78	54.34	7.36	0.00	0.00	156.92
		Minimal 1328	329	389	29	\$383.51	\$0.38	14.5	89.38	255.86	23.77	3575.17	204.69	41.34	62.07	8.48	89.50	3.30	237.69
		Moderate 1328	389	583	44	\$465.80	\$0.50	22	81.93	340.16	21.70	3277.37	272.13	38.79	56.90	8.14	159.50	8.80	217.01
		Severe 1328	583	198	37	\$1,348.25	\$1.81	18.5	64.73	1248.07	16.95	2589.26	998.45	30.65	44.95	6.50	903.75	12.60	169.51
15 Years	Baseline 1328	198	252	79	\$142.13	\$0.13	19.75	39.60	62.38	20.40	3168.28	99.81	46.59	45.84	7.38	0.00	0.00	204.01	
	Minimal 1328	252	314	46	\$174.71	\$0.16	11.5	39.27	103.88	20.05	3141.89	166.22	44.37	45.46	7.14	64.25	5.00	200.53	
	Moderate 1328	314	504	40	\$204.38	\$0.20	10	37.24	138.28	18.86	2979.40	221.24	41.74	43.10	6.80	119.50	10.10	188.59	
	Severe 1328	504	486	36	\$556.27	\$0.68	9	30.95	500.97	15.35	2475.84	801.56	33.80	35.82	5.64	712.50	13.80	153.51	

Abbreviations: No. Cust.: Number of Customers; Exog. Const.: Exogenous Constraints; No. Pkgs.: Number of Packages; Infeas.: Infeasible; No. UAVs: Number of UAVs; t: time; t-main.: time-maintenance.