

TRUCK–DRONE COLLABORATIVE SYSTEMS FOR SCALABLE LAST-MILE PARCEL DELIVERY

DIDEM CICEK SIMSEK

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UNIVERSITY OF OTTAWA

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ABSTRACT

Truck–drone collaborative delivery (TDCD) has emerged as a promising approach to improve the efficiency and sustainability of last-mile logistics by combining the complementary capabilities of ground vehicles and unmanned aerial systems. Despite growing research interest, many existing studies rely on simplified operational assumptions, make limited use of empirically derived drone performance data, and give comparatively less attention to deployment conditions and user acceptance. This dissertation addresses these limitations through an integrated investigation of drone performance modeling, coordinated optimization, and behavioral adoption.

This thesis develops a comprehensive, data-driven framework for the design and optimization of TDCD systems. At the operational level, an optimization framework is proposed to jointly optimize truck stop selection, customer assignment, and drone fleet allocation under realistic constraints, including limited fleet size and energy capacity. To capture drone performance more accurately, regression-based models are developed to estimate delivery time and energy consumption, and are integrated into the optimization framework. The framework is evaluated using real-world route data derived from the Amazon Last Mile Routing Research Challenge dataset (2021), ensuring practical relevance.

Computational experiments and sensitivity analyses demonstrate that the proposed TDCD framework can significantly outperform conventional truck-only delivery systems, achieving substantial reductions in delivery completion time and total energy consumption while revealing diminishing returns beyond certain fleet sizes and infrastructure configurations. The results highlight the importance of coordinated decision-making across routing, resource allocation, and infrastructure design to maximize system performance and scalability.

Beyond operational optimization, this thesis examines the behavioral dimension of drone delivery adoption through a questionnaire-based study grounded in an extended UTAUT2 framework. The findings identify performance expectancy, social influence, and perceived risk as key determinants of Canadians’ adoption intentions. By integrating optimization modeling, performance evaluation, and user acceptance analysis, this research advances understanding of TDCD and provides practical insights for developing scalable and sustainable last-mile delivery systems.

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This thesis is dedicated to my daughter, Defne, and my son, Kerem, in the hope of showing them that it is always possible to restart, grow, and reinvent oneself.

AUTHOR CONTRIBUTIONS

This thesis is composed of original research conducted by the author under the supervision of the thesis supervisor and advisory committee at the University of Ottawa. The author was the primary contributor to all aspects of the research, including conceptualization, methodology development, model implementation, analysis, and manuscript preparation.

Specifically, the author developed the overall research framework for truck–drone collaborative delivery (TDCD), integrating optimization modeling with empirical performance estimation for last-mile logistics systems, and designed and conducted a questionnaire-based study to identify the key determinants of Canadians’ intentions to adopt emerging drone delivery services.

The thesis supervisor provided guidance on research direction, methodological rigor, and manuscript development, and contributed to critical revisions of the work. Advisory committee members provided feedback at key stages of the research. All work presented in this thesis is original unless otherwise cited. For chapters based on co-authored work, the author’s contributions remain primary and consistent with the description above.

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INTRODUCTION

The rapid expansion of e-commerce and on-demand consumer expectations has significantly transformed the structure and operational requirements of urban logistics systems. Over the last decade, last-mile delivery has emerged as one of the most critical and costly components of the supply chain, accounting for a substantial portion of total logistics expenditures with estimates suggesting that it can account for approximately 40–50% or more of total delivery costs, depending on the operational context, geographic setting, and definition of the cost base [1], while simultaneously contributing to urban congestion, environmental degradation, and operational inefficiencies. The accelerated growth of online shopping, further intensified during and after the COVID-19 pandemic, has placed unprecedented pressure on existing delivery infrastructures and exposed the limitations of conventional truck-based distribution systems [2]. As urban populations continue to grow and same-day delivery expectations become increasingly normalized, logistics operators are under mounting pressure to develop delivery systems that are not only operationally efficient, but also environmentally sustainable and socially acceptable [3].

Within this context, autonomous delivery technologies have attracted growing academic and industrial attention as potential solutions to the challenges of urban last-mile logistics [4], [5]. Among these technologies, truck–drone collaborative delivery (TDCD) has emerged as one of the most promising approaches due to its ability to combine the operational flexibility of unmanned aerial vehicles with the carrying capacity and routing capabilities of ground vehicles [6], [7], [8]. In TDCD systems, trucks typically serve as mobile depots or launch platforms from which drones perform localized deliveries before returning to the truck or designated rendezvous locations. This collaborative structure en-

ables drones to bypass road congestion, reduce delivery distances for trucks, and improve delivery responsiveness in dense urban environments.

From an industrial perspective, the potential applications of truck–drone collaborative delivery extend across parcel and e-commerce distribution, rural and remote delivery, healthcare and medical logistics, emergency response, and time-sensitive transportation services. In these settings, drones can complement conventional vehicle fleets by serving geographically dispersed or difficult-to-access customers while trucks provide the carrying capacity, mobility, and replenishment infrastructure required for larger delivery networks. These practical applications have motivated a growing body of theoretical research addressing vehicle–drone routing, launch and rendezvous synchronization, fleet configuration, customer assignment, endurance limitations, and coordinated scheduling. Collectively, these studies demonstrate that TDCD is not simply a variant of conventional vehicle routing, but a multi-resource coordination problem in which routing, scheduling, energy use, fleet allocation, and operational constraints interact in determining system performance.

The growing interest in TDCD has led to a rapidly expanding body of research focused on routing optimization, synchronization mechanisms, fleet sizing, energy management, and operational coordination. Early foundational studies such as Murray and Chu’s Flying Sidekick Traveling Salesman Problem (FSTSP) [9] introduced one of the first formal optimization frameworks for truck–drone coordination and demonstrated the potential efficiency gains achievable through synchronized aerial and ground delivery operations. Similarly, subsequent studies by Agatz et al. [10], Poikonen et al. [11], and Wang and Sheu [12] further extended drone-assisted vehicle routing formulations by incorporating drone

endurance constraints, launch synchronization, and operational scheduling considerations. These studies established the methodological foundation for drone-assisted logistics optimization and stimulated broader interest in collaborative autonomous delivery systems.

Despite the substantial progress in TDCD research, several important limitations remain in the existing literature. A large proportion of current optimization models continue to rely on highly simplified assumptions regarding drone operations, battery consumption, synchronization mechanisms, deterministic demand, and operational feasibility [13], [14], [15], [16]. Many studies approximate drone endurance using fixed manufacturer specifications or simplified distance-based battery constraints, while overlooking the complex relationships between payload, speed, flight distance, vertical takeoff operations, and energy consumption. Furthermore, most existing routing formulations primarily focus on theoretical routing efficiency without sufficiently integrating empirically grounded drone performance models or realistic operational constraints derived from actual delivery environments [17], [18].

Another significant limitation concerns the scalability and coordination realism of existing TDCD optimization approaches. While many routing studies investigate isolated delivery routes or single-truck scenarios [14], [19], comparatively fewer studies examine shared fleet allocation, coordinated multi-route operations, workload balancing, or infrastructure-aware deployment strategies under realistic operational settings. Explicit drone scheduling formulations often become computationally intractable as problem size increases, creating a trade-off between operational realism and optimization tractability. As a result, there remains a need for planning-oriented frameworks capable of capturing essential coordina-

tion dynamics while remaining computationally feasible for realistic large-scale delivery systems.

Beyond technical optimization challenges, autonomous delivery research also demonstrates substantial fragmentation across disciplinary domains. Operational optimization studies, sustainability analyses, user acceptance research, regulatory discussions, and infrastructure planning frameworks are frequently investigated independently despite their strong interdependencies in real-world deployment environments. Successful implementation of autonomous delivery systems depends not only on routing efficiency and operational feasibility, but also on public trust, perceived risk, environmental perceptions, pricing considerations, regulatory readiness, and broader societal acceptance. However, relatively limited research adopts a holistic systems-oriented perspective capable of integrating technical optimization with behavioral and societal dimensions of autonomous delivery adoption.

This interaction between operational feasibility and user acceptance provides the motivation for incorporating a behavioral study within this dissertation. Optimization models can identify technically efficient configurations for truck–drone delivery systems, but their practical value ultimately depends on whether consumers are willing to receive deliveries through such services. Factors such as perceived usefulness, convenience, risk, environmental benefits, social influence, and price may therefore affect the demand conditions under which optimized TDCD systems would operate. Examining consumer acceptance consequently complements the operational optimization studies by adding a demand-side perspective to the system-level assessment: while the optimization models investigate how truck–drone systems can be designed and operated efficiently, the behavioral analysis ex-

amines whether and under what conditions consumers are likely to accept the resulting service.

To address these gaps and advance understanding of autonomous delivery systems from both operational and societal perspectives, this thesis investigates three interrelated research questions. First, it examines whether truck-drone collaborative delivery can improve delivery efficiency relative to conventional truck-only operations. Second, it explores how a limited fleet of drones can be optimally allocated across multiple concurrent truck delivery routes to maximize system performance in TDCD networks. Third, recognizing that technological feasibility alone does not guarantee successful deployment, it investigates the factors influencing Canadian consumers' intentions to adopt drone delivery services. Together, these research questions provide a comprehensive framework for evaluating the technical, operational, and behavioral dimensions of autonomous last-mile delivery systems.

- Research Question-1: Can truck-drone collaboration improve delivery efficiency?
- Research Question-2: How can a limited fleet of drones be optimally allocated across multiple concurrent truck delivery routes in TDCD systems?
- Research Question-3: What factors influence Canadian consumers' intentions to adopt drone delivery services?

To address these research questions, this dissertation makes four primary contributions spanning empirical performance modeling, optimization, user acceptance analysis, and

systems-level planning. These contributions, together with the associated publications, are summarized below.

1. Development of empirically informed drone energy and delivery time regressors: This dissertation develops machine learning-based regressors for drone energy consumption and delivery time using empirical flight data collected from a DJI Matrice 100 multirotor UAV across varying payload, flight-distance, and speed conditions. By incorporating observed drone performance into the modeling process, the resulting regressors provide a more realistic alternative to simplified battery and endurance assumptions commonly used in the truck-drone collaborative delivery literature and serve as empirically informed inputs for the subsequent optimization studies. *Associated publication: Machine learning-driven truck-drone collaborative delivery for time-and energy-efficient last-mile deliveries (Chapter 3)*
2. Development of a data-driven MILP framework for coordinated truck-drone collaborative delivery: Building on the empirical drone performance models, this dissertation proposes a mixed-integer linear programming framework for coordinated truck-drone collaborative delivery optimization. The framework jointly optimizes truck stop selection, customer assignment, and drone fleet allocation across multiple concurrent delivery routes while incorporating operational energy constraints and shared fleet coordination. Using empirically informed delivery datasets, the framework advances the state of the art by emphasizing operational realism, scalability, and coordinated system-level resource allocation. *Associated publication: Data-Driven Optimization*

of Truck-Drone Collaborative Delivery with Shared Fleet Allocation (Chapter 4)

3. Investigation of Canadian consumer acceptance of drone delivery services: This dissertation examines the behavioral factors influencing Canadians' intentions to adopt drone delivery services using an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework and Partial Least Squares Structural Equation Modeling (PLS-SEM). The extended UTAUT2 framework provides the theoretical basis for identifying relevant adoption determinants, while PLS-SEM is used to assess the relationships among the proposed constructs and their effects on behavioral intention. The findings identify performance expectancy, social influence, environmental friendliness, perceived risk, and pricing considerations as important determinants of adoption, offering insight into the societal and behavioral conditions that may influence the successful deployment of autonomous delivery technologies. *Associated publication: Drivers and Barriers to Drone Delivery Adoption in Canada: Insights for Sustainable Last-Mile Logistics (Chapter 5)*
4. Development of a conceptual planning framework for scalable truck-drone collaborative delivery systems: This dissertation contributes a conceptual planning framework that distinguishes operational performance evaluation from scalability assessment in truck-drone collaborative delivery systems. The framework provides a structured foundation for analyzing launch infrastructure, fleet sizing, workload distribution, and system coordination under increasing operational complexity, thereby supporting the development of scalable and sustainable autonomous last-mile delivery net-

works. *Associated publications: Systems-Level Planning and Coordination of Truck-Drone Collaborative Delivery Networks (Chapter A), Green and intelligent planning of drone launch in truck-drone collaborative delivery (Chapter B)*

The following are the publications this PhD study produced:

1. “Machine Learning-Driven Truck-Drone Collaborative Delivery for Time and Energy Efficient Last-Mile Deliveries”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published in Electronics Journal in May 2025. Publisher: MDPI, DOI: 10.3390/electronics14102026.
2. “Data-Driven Optimization of Truck–Drone Collaborative Delivery with Shared Fleet Allocation”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published at the Drones Journal in June 2026. Publisher: MDPI, DOI: 10.3390/drones10070476.
3. “Drivers and Barriers to Drone Delivery Adoption in Canada: Insights for Sustainable Last-Mile Logistics”, co-authored by Didem Cicek and Burak Kantarci, and published at the Research in Transportation Business and Management in June 2026. Publisher: Elsevier, DOI:10.1016/j.rtbm.2026.101780
4. ”A comparative review of user acceptance factors for drones and sidewalk robots in autonomous last mile delivery” co-authored by Didem Cicek and Burak Kantarci, and published in Green Energy and Intelligent Transportation, in August 2025. Publisher: Elsevier, DOI: 10.1016/j.geits.2025.100310

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5. “Systems-Level Planning and Coordination of Truck–Drone Collaborative Delivery Networks”, co-authored by Didem Cicek and Burak Kantarci, and published in the proceedings of the Workshop on Network Architectures and Intelligence for Smart Mobility and Autonomous Systems (TRAVERSAL), held in conjunction with the IEEE High-Performance Switching and Routing (HPSR) Conference in June 2026. DOI: 10.1109/HPSR68369.2026.11615187
 6. “Green and Intelligent Planning of Drone Launch in Truck-Drone Collaborative Delivery”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published in the proceedings of the TRAVERSAL Workshop on Network Architectures and Intelligence for Smart Mobility and Autonomous Systems, held in conjunction with the IEEE World Forum on Internet of Things (WF-IoT) Conference in November 2024. DOI: 10.1109/WF-IoT62078.2024.10811216
 7. “Use of mobile crowdsensing in disaster management: A systematic review, challenges, and open issues”, co-authored by Didem Cicek, and Burak Kantarci, and published in *Sensors*, in February 2023. DOI: 10.3390/s23031699. *Note: The thesis took a different direction after this publication, but it formed the basis for systematic review methodology.*
 8. “Ai-driven attack modeling and defense strategies in mobile crowdsensing: A special case study on fake tasks”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published as a book chapter in *Mobile Crowdsourcing: From Theory to Practice*, in April 2023. DOI: 10.1007/978-3-031-32397-3_11. *Note: The thesis took*

a different direction after this publication, but the study provided the foundation for applying the Self-Organizing Feature Map machine learning technique to the TDCD problem.

The remainder of the dissertation is organized as follows. Chapter 2 reviews the literature on autonomous last-mile delivery, truck–drone collaborative delivery systems, drone energy modeling, and technology acceptance research. Chapter 3 presents the empirical machine learning-based drone energy and delivery time estimation framework. Chapter 4 introduces the MILP-based TDCD optimization framework and discusses the operational coordination methodology developed in this research. Chapter 5 presents the Canadian user acceptance study and its implications for autonomous delivery adoption. Finally, Chapter 6 concludes the dissertation by summarizing the main findings, discussing practical implications, and outlining open issues and future research opportunities for scalable and sustainable autonomous delivery systems.

In addition to the journal articles included in the dissertation, two IEEE conference workshop papers are provided in the Appendix to further support the evolution of the research framework. The first paper, *Green and Intelligent Planning of Drone Launch in Truck–Drone Collaborative Delivery*, presented at IEEE WF-IoT 2024, introduced an early AI-driven approach for dynamic drone launch location selection using Self-Organizing Feature Map (SOFM) algorithms under realistic delivery demand scenarios. This work contributed to the initial exploration of facility location planning and adaptive truck–drone coordination concepts that later evolved into the broader optimization and resource allocation

tion framework developed in the dissertation. The second paper, *Systems-Level Planning and Coordination of Truck-Drone Collaborative Delivery Networks*, presented at an IEEE HPSR 2026 workshop, extended the research toward a systems-oriented planning perspective by proposing a layered framework for scalability assessment, workflow orchestration, collaboration typologies, and operational coordination of TDCD systems. Together, these workshop papers document the progressive development of the dissertation research from early intelligent planning concepts toward integrated system-level TDCD design and scalability analysis.

LITERATURE REVIEW

2.1 PUBLICATION STATEMENT

Portions of the literature review presented in this chapter are based on the peer-reviewed publication "A comparative review of user acceptance factors for drones and sidewalk robots in autonomous last mile delivery" co-authored by Didem Cicek and Burak Kantarci, and published in Green Energy and Intelligent Transportation, in August 2025. DOI: /10.1016/j.geits.2025.100310.

This publication was developed during the early stages of the doctoral research and provides a comprehensive comparative review of questionnaire-based studies examining user acceptance of autonomous last-mile delivery by drones and sidewalk robots. The review synthesizes empirical evidence on the technological, behavioral, psychological, and societal factors influencing consumer adoption of autonomous delivery systems. The insights obtained from this work established the foundation for the present dissertation by identifying key research gaps and motivating the subsequent focus on drone delivery systems and truck-drone collaborative delivery.

2.2 EVOLUTION OF AUTONOMOUS LAST-MILE DELIVERY

The evolution of autonomous last-mile delivery has emerged from the convergence of rapid e-commerce growth, urbanization, sustainability concerns, and advances in automation and artificial intelligence. Early last-mile logistics research primarily focused on addressing in-

efficiencies in urban freight distribution, particularly congestion, high delivery costs, failed deliveries, and environmental externalities. Over time, the field evolved from traditional urban freight optimization toward increasingly automated and autonomous delivery ecosystems integrating digital platforms, robotics, drones, and intelligent transportation infrastructure. Initial research on urban logistics emphasized the operational and environmental burden of conventional delivery systems. Studies highlighted that the last mile represents one of the most expensive and inefficient segments of the supply chain, accounting for a substantial portion of logistics costs while contributing disproportionately to congestion and emissions [20]. Early sustainable logistics initiatives explored alternative delivery modes such as bicycles and cargo bikes. The CycleLogistics project demonstrated that a significant share of urban goods transportation could potentially be shifted from motorized vehicles to bicycle-based logistics, especially for short-distance deliveries under urban conditions [21]. These early studies framed last-mile delivery primarily as an urban sustainability and efficiency challenge. As e-commerce volumes accelerated, research attention shifted toward digitalization and automation within logistics systems. Automation began to transform warehousing, fulfillment, parcel handling, and distribution operations. McKinsey identified logistics and transportation as one of the sectors with the highest automation potential due to labor shortages, rising e-commerce demand, and technological advances in robotics and artificial intelligence [22]. Automation research initially concentrated on warehouse systems, robotic picking technologies, automated sorting, and parcel management. However, researchers increasingly recognized that fulfillment efficiency alone could not solve the growing complexity of urban last-mile operations. The need for integrated automation

across the entire logistics chain became evident. At the same time, self-service logistics innovations emerged as an intermediate step toward autonomous delivery ecosystems. Automated Parcel Stations (APS) gained attention as a technology-enabled alternative to conventional home delivery. Wang et al. examined consumer adoption of APS through innovation diffusion theory and demonstrated that perceived convenience, relative advantage, and favorable attitudes significantly influenced adoption intentions [23]. These systems represented an important transitional phase in last-mile automation because they introduced consumers to technology-mediated delivery interactions while reducing failed deliveries and enabling consolidated parcel distribution. Research during this period increasingly incorporated behavioral and user acceptance dimensions alongside operational efficiency. Parallel to developments in urban delivery systems, freight transportation research began examining autonomous trucking technologies. Studies investigating connected autonomous trucks (CATs) emphasized the potential benefits of reduced labor costs, fuel savings, increased safety, and operational efficiency [24]. Adoption studies based on diffusion-of-innovation theory suggested that the penetration of autonomous freight technologies would depend not only on technical maturity but also on organizational readiness, regulatory adaptation, and market acceptance. Similarly, research exploring automated trucking from the logistics industry perspective found that companies viewed full driver replacement, rather than partial automation, as the primary source of economic value [25]. These findings demonstrated that automation in freight transportation was evolving beyond driver-assistance technologies toward fully autonomous logistics operations. More recently, research has increasingly focused on autonomous last-mile delivery technologies such as delivery drones,

sidewalk robots, and robotic cargo systems. Systematic reviews of last-mile logistics literature identified emerging technologies and innovative delivery modes as one of the dominant themes shaping the field [20]. Drone delivery, autonomous robots, crowd logistics, and smart urban logistics platforms are now frequently positioned as core components of future city logistics systems. These technologies are driven by the need to improve delivery speed, reduce operational costs, support contactless delivery, and mitigate urban congestion and emissions. The COVID-19 pandemic further accelerated interest in autonomous delivery systems due to increased e-commerce activity and demand for contactless logistics services. The Canadian report *Robotic Cargo Transport: New Technologies, Novel Practices & Policy Readiness in Canada* emphasized that autonomous cargo delivery technologies are advancing faster than the regulatory environment governing them. The report [20] identified several opportunities associated with robotic delivery systems, including lower delivery costs, improved safety, decarbonization, and operational resilience, while also highlighting concerns related to privacy, accessibility, public trust, and regulatory uncertainty. This shift illustrates how the research agenda has expanded beyond operational optimization toward broader socio-technical and policy-oriented considerations. In parallel, advances in intelligent transportation systems and cooperative autonomous driving have further shaped the evolution of autonomous logistics. Infrastructure-vehicle cooperative systems now combine roadside sensing, edge computing, V2X communication, and autonomous vehicles to improve safety and traffic coordination [26]. Such developments indicate that future autonomous last-mile delivery systems will likely operate as interconnected cyber-physical ecosystems rather than isolated autonomous vehicles. Overall, the litera-

ture demonstrates a clear evolution from conventional urban freight optimization toward integrated autonomous delivery ecosystems supported by artificial intelligence, robotics, connected infrastructure, and advanced logistics platforms. While substantial progress has been made in vehicle technologies and operational modeling, several gaps remain. Existing studies often examine drones, robots, autonomous trucks, or logistics automation independently rather than as components of an integrated delivery network. Furthermore, challenges related to scalability, energy efficiency, regulatory harmonization, infrastructure readiness, and public acceptance remain insufficiently addressed. These gaps highlight the need for holistic frameworks capable of evaluating autonomous last-mile delivery systems from operational, technological, sustainability, and policy perspectives simultaneously.

2.3 DELIVERY DRONES AND USER ACCEPTANCE

Delivery drones, commonly referred to as unmanned aerial vehicles (UAVs) or unmanned aerial systems (UAS), have emerged as one of the most promising autonomous technologies for transforming last-mile logistics [27], [28]. These systems are designed to transport parcels autonomously or semi-autonomously between distribution hubs and end customers while reducing delivery times, operational costs, and environmental impacts associated with conventional ground-based delivery systems [29]. Recent growth in e-commerce, increasing urban congestion, labor shortages, and sustainability pressures have accelerated industry and academic interest in drone-assisted delivery operations. Major logistics and technology companies including Amazon Prime Air, Wing, Zipline, and Walmart have

already initiated pilot or commercial drone delivery programs in selected regions. Modern delivery drones rely on advanced navigation, sensing, and stabilization technologies to safely perform autonomous flight operations. Most commercial drone delivery systems utilize Global Navigation Satellite Systems (GNSS) [30], frequently enhanced through Real-Time Kinematic (RTK) positioning systems [31] that provide significantly higher location accuracy than conventional GPS-based navigation. RTK-enabled systems are currently employed by companies such as Amazon Prime Air and Wing to support precise navigation and landing operations. In addition to satellite positioning, drones incorporate onboard inertial measurement units (IMUs), gyroscopes, and accelerometers to maintain flight stability even during temporary signal degradation or environmental disturbances [32]. Advanced perception systems including cameras, LiDAR, radar, ultrasonic sensors, and computer vision algorithms further enable obstacle detection, altitude measurement, terrain awareness, and autonomous landing capabilities [33]. For example, Amazon’s latest delivery drones integrate multiple cameras, radar, and LiDAR sensors to support object detection and environmental awareness during flight operations. Despite rapid technological progress, commercial drone delivery operations remain operationally constrained by infrastructure, battery limitations, safety concerns, and regulatory restrictions. Current deployment models primarily target rural and suburban environments characterized by spacious landing zones, lower population density, and relatively unconstrained airspace. Urban operations remain substantially more challenging due to high-rise buildings, dense traffic environments, signal interference, safety risks, and strict aviation regulations. Regulatory agencies such as the Federal Aviation Administration (FAA) and Transport Canada

continue to impose strict operational constraints on commercial drone flights, particularly regarding beyond visual line-of-sight (BVLOS) operations, airspace integration, operational altitude, pilot certification, and safety compliance. In the United States, FAA Part 107 currently forms the primary regulatory framework governing commercial drone operations. Industry innovations continue to explore methods for improving the operational efficiency and scalability of drone delivery systems. Some companies have introduced hybrid operational mechanisms to reduce the energy-intensive takeoff and landing phases of drone flights. For instance, Zipline has implemented a delivery mechanism in which a small autonomous droid is lowered from the drone to the customer location, eliminating the need for full landing operations and reducing both energy consumption and delivery time. Docking and charging stations are also increasingly proposed as supporting infrastructure components that can be integrated into warehouses or distribution centers to facilitate automated charging, battery swapping, and fleet coordination. The economic potential of the drone delivery market has contributed significantly to the growing research interest in this field. Early industry reports anticipated rapid growth in the commercial drone sector, forecasting a multi-billion-dollar global market and widespread adoption across logistics and other industries. However, commercialization has advanced more gradually than initially expected, largely due to regulatory uncertainty, operational constraints, and the limited availability of routine BVLOS operations. Nevertheless, drone delivery continues to be recognized as a key enabling technology for future autonomous logistics systems due to its potential to improve last-mile delivery responsiveness, reduce urban traffic congestion, lower greenhouse gas emissions for suitable delivery scenarios, and complement existing ground-based

logistics networks rather than replace them [34], [35], [36]. Beyond technological feasibility and operational optimization, the successful implementation of drone delivery systems also depends heavily on societal acceptance and user willingness to adopt autonomous delivery technologies. While technical research on routing optimization, energy management, and airspace coordination has expanded considerably, public acceptance remains a critical determinant for the large-scale deployment of autonomous delivery systems [37], [38], [39].

As stated in the publication statement of this chapter, the author conducted a comprehensive comparative review examining user acceptance factors associated with autonomous last-mile delivery by drones and sidewalk robots [40].

The review paper synthesized findings from 20 questionnaire-based empirical studies conducted worldwide and represented one of the first comprehensive comparative reviews focusing specifically on user acceptance of autonomous last-mile delivery technologies. The study examined the behavioral, technological, psychological, and social factors influencing consumer adoption intentions for both drone and sidewalk robot delivery systems. The review further explored the theoretical foundations guiding user acceptance research, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT2), Diffusion of Innovation (DOI), Task-Technology Fit Model (TTFM), and Privacy Calculus Theory (PCT).

The findings (Figure 2.1) revealed that performance expectancy consistently emerged as the strongest positive predictor of user acceptance for both drone and robot deliveries. Across most reviewed studies, users demonstrated greater willingness to adopt autonomous

delivery technologies when they perceived clear benefits such as faster delivery times, convenience, contactless delivery, improved service efficiency, or operational reliability. In the context of drone delivery specifically, faster delivery expectations were repeatedly identified as a major contributor to user acceptance, particularly among frequent online shoppers and users already accustomed to rapid delivery services.

Social influence was identified as another important factor affecting behavioral intention to adopt autonomous delivery technologies. The review demonstrated that user decisions were often shaped by perceived social norms, peer opinions, and expectations from important social groups such as family members, friends, or coworkers. In addition, personal innovativeness and openness toward emerging technologies positively influenced acceptance levels, suggesting that technologically curious users were generally more willing to experiment with autonomous delivery methods. One particularly important finding of the review was the dominant negative role of perceived risk in shaping user acceptance decisions. Perceived risk was identified as one of the strongest barriers to adoption for both drone and robot deliveries. However, the nature of risk concerns varied depending on the delivery technology. In the case of drone delivery, privacy-related concerns emerged as especially significant due to the advanced recording and sensing capabilities integrated into drone systems. Users expressed concerns regarding surveillance, data collection, loss of privacy, safety risks, and the possibility of accidents or technological malfunction. Interestingly, some studies found that privacy concerns increased among users with greater technological familiarity, suggesting that awareness of drone capabilities may intensify concerns regarding surveillance and data security.

	DRONE DELIVERY		ROBOT DELIVERY
	Acceptance Factors		Acceptance Factors
P O S I T I V E	Performance Expectancy [24],[25],[41],[44],[49]	C O M M O N	Performance Expectancy [36],[38],[43],[46],[47]
	Social Influence [25], [42]		Social Influence [43]
	Innovativeness [42],[44]		Innovativeness [45]
	Environmental Concerns [37]		Environmental Concerns [45],[36]
	Hedonic Motivation [25]		Hedonic Motivation [46]
	Faster Delivery [37], [52]	S P E C I F I C	Positive Emotions (joy, surprise) [54]
	Trust in Delivery Company [24]		Optimism [45]
	Regulatory Framework [22], [24]		Task-Technology Fit [38]
	Online Shopping Frequency [53]		
N E G A T I V E	Perceived Risk [44], [52]	C O M M O N	Perceived Risk [43],[45],[46]
	Effort Expectancy [49]		Effort Expectancy [36],[47],[48],[54]
	Price Sensitivity [49]		Price Sensitivity [46]
	Privacy Risk [24], [53], [55]	S P E C I F I C	Negative Emotions (fear, anger) [54]
	Package Safety Concern [53]		Need for Human Interaction [45]
			Social Influence [56]
I n s i g n i f i c a n t	Effort Expectancy [25]	C O M M O N	Effort Expectancy [46]
	Environmental Concerns [49], [25]		Environmental Concerns [41], [48]
	Faster Delivery [25]		Price Sensitivity [43], [47]
	Technology Anxiety [37]	S P E C I F I C	Hedonic motivation [47]
	Technology Openness [52]		
	COMMON		SPECIFIC TO TECHNOLOGY

Figure 2.1: Comparative acceptance factors for drone and robot delivery

The review further identified several drone-specific acceptance factors that distinguished aerial delivery systems from sidewalk robots. Faster delivery expectations, trust in the delivery provider, confidence in regulatory oversight, and online shopping frequency positively influenced drone delivery acceptance. In contrast, package safety concerns, technology anxiety, privacy risk, and perceived operational uncertainty negatively affected adoption intentions. The review also highlighted that strict regulatory frameworks could positively influence user trust if they were perceived as ensuring safe and controlled drone operations.

An important conclusion emerging from the review was that user acceptance factors are strongly shaped by demographic and contextual conditions. Age, gender, education level, technology affinity, prior exposure to autonomous systems, and geographic location all influenced acceptance levels across different studies. Cultural differences were also found to significantly affect consumer expectations and risk perceptions regarding autonomous delivery systems. For example, pricing sensitivity varied substantially between countries, indicating that adoption strategies may need to be customized according to local market conditions and societal expectations.

Another important finding was that environmental sustainability, although frequently promoted as a major societal advantage of autonomous delivery systems, did not consistently emerge as a dominant driver of user acceptance. Several studies reported that environmental concerns or green image had only limited or statistically insignificant influence on users' adoption intentions for drone deliveries. This suggests that personal convenience, delivery speed, cost considerations, and perceived usefulness currently outweigh broader sustainability motivations in shaping consumer adoption behavior.

The review also identified important methodological trends within the autonomous delivery acceptance literature. Structural Equation Modeling (SEM), particularly Partial Least Squares SEM (PLS-SEM), was found to be the dominant analytical approach used across most empirical studies. Most reviewed studies relied on online questionnaire-based surveys targeting online shoppers, technology users, or urban consumers. The review noted that although the number of studies on autonomous delivery acceptance has rapidly increased in recent years, the majority remain exploratory and heavily dependent on hypothetical user scenarios rather than real-world operational experience.

The findings of this earlier review played an important role in shaping the broader direction of the present thesis. The comparative analysis demonstrated that although both drones and sidewalk robots offer promising alternatives for sustainable last-mile delivery, drone delivery systems attracted significantly greater research attention in areas related to operational scalability, routing flexibility, delivery speed, and logistics optimization. At the same time, the review highlighted that successful implementation of drone delivery systems depends not only on technical feasibility but also on societal trust, regulatory readiness, and operational realism. These observations motivated a transition in the author’s subsequent research toward drone-focused delivery systems and truck–drone collaborative delivery architectures, with particular emphasis on operational optimization, energy-aware resource allocation, scalability, and systems-level coordination.

As drone delivery technologies continue to mature beyond conceptual acceptance studies and pilot deployments, the research focus within the field has increasingly shifted toward the operational and optimization challenges associated with scalable implementation.

Consequently, the following sections examine the emerging literature on truck–drone collaborative delivery systems, routing optimization, drone resource allocation, energy-aware delivery modeling, and integrated operational coordination frameworks for autonomous last-mile logistics.

2.4 TRUCK–DRONE COLLABORATIVE DELIVERY SYSTEMS

2.4.1 DEFINITION OF TDCD

Truck–drone collaborative delivery systems (TDCD) refer to hybrid last-mile logistics systems in which trucks and drones operate cooperatively to complete parcel deliveries more efficiently than either mode operating independently [9], [27], [14]. In these systems, drones are typically integrated into truck-based logistics operations to extend delivery flexibility, reduce travel time, improve accessibility in congested urban environments, and enhance operational sustainability. Depending on the operational configuration, trucks may function as mobile depots, launch-and-retrieval platforms, charging stations, or primary delivery vehicles supported by drones. Rather than representing a single standardized architecture, TDCD systems encompass a broad family of collaborative delivery configurations characterized by different coordination mechanisms between ground and aerial vehicles. Existing studies classify these collaborative models into several major operational categories.

2.4.2 TYPES OF TRUCK–DRONE COLLABORATIVE DELIVERY SYSTEMS

Existing truck–drone collaborative delivery systems (TDCD) can be broadly categorized according to the degree of operational interdependence between trucks and drones, the delivery responsibility distribution, and the synchronization mechanisms used during delivery operations such as parallel delivery, mixed delivery, drone delivery with truck-assisting and truck delivery with drone-assisting.

Parallel Delivery

In parallel delivery systems, trucks and drones operate independently and simultaneously to serve separate customers within the same delivery network. The truck and drone fleets are coordinated at the planning level but execute deliveries on different routes without requiring continuous interaction during operations [41], [15], [42]. This configuration primarily aims to improve delivery efficiency through workload parallelization, reduced service times, and increased routing flexibility. A closely related subset of parallel delivery is sequential delivery, in which truck and drone operations become more tightly synchronized [15], [43]. In sequential delivery systems, the truck temporarily stops and waits while the drone completes its assigned delivery mission and returns to the truck before both vehicles continue the route together. Compared to fully independent parallel operations, sequential delivery introduces stronger temporal dependency between truck movement and drone scheduling, increasing synchronization complexity while potentially simplifying drone recovery and coordination requirements.

Mixed Delivery

Mixed delivery systems involve coordinated truck and drone operations along partially shared delivery paths. In these configurations, drones are launched and retrieved at designated truck stops while both vehicles continue operating within interconnected routes [44], [45]. Compared to fully parallel operations, mixed delivery introduces greater synchronization complexity due to the interdependence between truck movement and drone scheduling. One important variant within this category is relay-based truck–drone collaboration, in which delivery tasks are completed through staged hand-offs among multiple trucks and drones. In relay-based systems, a drone may be launched from one truck and recovered by another vehicle at a different location along the delivery network. This collaborative structure increases operational flexibility and may improve delivery coverage and routing efficiency in large-scale urban delivery environments; however, it also significantly increases coordination and scheduling complexity.

Drone Delivery with Truck-Assisting

In drone-centric collaborative systems, drones perform the majority of customer deliveries while trucks primarily serve supporting functions. In this configuration, trucks may operate as mobile depots, charging stations, battery-swapping platforms, or transportation carriers that reposition drones closer to delivery regions. This approach is particularly attractive for extending drone operational range and mitigating battery limitations in large service areas. Recent studies have also explored multi-drone and truck collaboration models, where multiple drones are simultaneously deployed and coordinated through one or more supporting trucks [46], [47], [48]. In such systems, trucks function as centralized operational hubs that transport, launch, recover, recharge, or manage several drones con-

currently. Multi-drone collaborative architectures aim to increase delivery throughput, improve service scalability, and reduce delivery completion times, particularly in high-demand urban environments. However, these systems also introduce additional challenges related to fleet coordination, scheduling, battery management, collision avoidance, and operational synchronization.

Truck Delivery with Drone-Assisting

In truck-centric collaborative systems, trucks remain the primary delivery mode, while drones are selectively deployed to support time-sensitive deliveries, remote customers, or operational bottlenecks. In such systems, drones may assist trucks in meeting strict customer time windows, improving responsiveness, or reducing delays caused by congestion and routing constraints. This configuration is often adopted when payload limitations, regulatory restrictions, or operational complexity prevent drones from functioning as the dominant delivery mechanism.

2.4.3 TRUCK-DRONE COLLABORATIVE DELIVERY SYSTEMS

Truck-drone collaborative delivery systems (TDCD) have emerged as a promising response to the increasing operational pressures associated with last-mile logistics, including rising delivery costs, urban congestion, growing e-commerce demand, and the operational limitations of truck-only delivery systems. Rather than representing a single standardized delivery architecture, the existing literature characterizes TDCD as a family of hybrid delivery models that integrate the line-haul efficiency of trucks with the speed and routing

flexibility of drones. Existing studies increasingly frame TDCD as a complex systems-level problem involving routing coordination, airspace utilization, congestion management, emissions reduction, and regulatory compliance, rather than solely as a vehicle-level optimization problem.

The literature presents a broad range of conceptual and operational frameworks for collaborative truck–drone delivery in urban environments. These frameworks range from policy- and regulation-oriented approaches to fully implemented optimization-based systems. However, despite the growing maturity of the field, no universally accepted unified framework has yet emerged. Instead, existing studies propose alternative collaborative structures depending on operational assumptions, delivery configurations, fleet coordination mechanisms, and urban operating conditions.

Several studies demonstrate that collaborative delivery systems become increasingly advantageous when demand density and service area size exceed the efficient operational range of either truck-only or drone-only delivery systems. She et al. [49] classify the field into four primary delivery configurations: direct drone deliveries from a fixed depot, drone deliveries launched from parked trucks, drone deliveries launched from moving trucks, and conventional truck-only home delivery used as the benchmark. Their findings indicate that collaborative delivery strategies become more favorable as customer demand and geographic coverage increase, primarily due to their ability to balance truck-based transportation efficiency with the flexibility of aerial delivery. Similar conclusions are reported in sustainability-oriented studies, which suggest that collaborative truck–drone systems can reduce both operational cost and environmental impact compared to conventional deliv-

ery fleets, although the magnitude of these benefits depends heavily on fleet composition, routing configuration, and operating conditions [50].

In parallel with routing and operational efficiency considerations, recent studies emphasize that TDCD systems cannot be evaluated independently from urban airspace and traffic-management constraints. Doole et al. [51] argue that widespread drone delivery adoption could generate air traffic volumes significantly exceeding current commercial aviation density within metropolitan regions, making urban traffic management and airspace capacity critical components of future delivery systems. Madani et al. [52] extend truck-drone collaborative delivery modeling by considering multiple customer visits together with multiple drone launch and retrieval locations, and propose an adaptive variable neighborhood search approach to address the resulting combinatorial complexity. Similarly, broader multimodal transportation studies position UAV-based delivery systems within integrated congestion-management and urban mobility frameworks, concluding that strategic urban traffic management (UTM) systems are essential for enabling scalable drone delivery operations while maintaining manageable congestion levels. Collectively, these studies suggest that large-scale TDCD deployment will require coordinated integration between routing optimization, urban airspace management, infrastructure planning, and regulatory oversight.

Methodologically, the TDCD literature is dominated by optimization-driven approaches. Numerous studies formulate collaborative delivery problems using mixed-integer linear programming (MILP), multi-objective optimization, heuristic algorithms, and simulation-based frameworks. Luo et al. [53] provide a comprehensive review of the mathematical

formulations and optimization models applied to truck–drone routing problems. For example, Mahmoodi et al. [7] propose a multi-objective mixed-integer optimization framework for hybrid RPAS-truck delivery systems and report improvements in delivery cost, delivery time, operational risk, and battery utilization relative to truck-only delivery approaches. Similarly, the sustainability-focused PDSTSP study combines mathematical optimization with life-cycle assessment and cost analysis, reporting approximately 20% lower carbon emissions compared to electric vehicle fleets and 20–30% lower operational cost relative to conventional fuel-based truck fleets [50]. These findings collectively demonstrate the significant potential of collaborative delivery systems; however, the majority of existing evidence remains model-driven, with conclusions primarily derived from simulation environments, continuum approximations, and optimization-based experiments rather than large-scale real-world deployment studies.

Overall, the existing literature suggests that TDCD systems are best understood as hybrid logistics architectures designed to balance truck transportation efficiency with drone-enabled delivery flexibility. While the field has evolved considerably beyond conceptual advocacy toward increasingly sophisticated optimization and coordination frameworks, several important challenges remain unresolved. In particular, limited consensus exists regarding standardized operational architectures, scalable coordination mechanisms, and integrated treatment of airspace constraints, operational uncertainty, and real-world urban demand variability. These limitations indicate that further research is required to develop more operationally realistic, scalable, and system-oriented TDCD frameworks capable of supporting large-scale autonomous last-mile delivery deployment.

2.5 RESEARCH GAPS

The literature on autonomous last-mile delivery has expanded rapidly over the past decade, evolving from early discussions of technological feasibility and user acceptance toward increasingly sophisticated operational and optimization-focused studies. Within this broader stream, truck–drone collaborative delivery (TDCD) has emerged as a promising last-mile logistics configuration because it combines the range and payload capacity of trucks with the speed and flexibility of drones. As summarized in Table ??, existing TDCD studies have made important contributions to routing optimization, delivery–pickup coordination, contactless delivery, multi-truck and multi-drone operations, time-window modeling, sustainability assessment, and alternative deployment architectures. However, despite these advances, the literature remains fragmented across operational routing models, sustainability-oriented assessments, and deployment-oriented concepts, with limited integration across these streams.

A major body of TDCD research focuses on routing and scheduling optimization. Foundational studies and their extensions have developed exact and heuristic approaches for classical truck–drone routing problems such as the FSTSP and TSP-D [54]. Other studies have expanded the problem setting by incorporating delivery and pickup services [55], contactless parcel delivery [56], medical-resource distribution [57], on-demand delivery with transshipment [58], time windows and service reliability [59], hybrid fleets of truck-carried and independent drones [60], multiple drone drops [61], and mobile drone station trailers

[62]. These studies demonstrate the potential of TDCD systems to reduce delivery time, improve routing efficiency, and increase operational flexibility. Nevertheless, many of them rely on simplified assumptions regarding drone endurance, travel time, service duration, and launch-and-recovery operations, which can limit their applicability to realistic urban delivery environments.

One important limitation concerns the modeling of drone energy consumption and operational time. In much of the existing TDCD literature, drone feasibility is represented through maximum flight range, endurance, or distance-based constraints rather than empirically grounded performance models. Some studies incorporate drone energy or endurance considerations [56, 60, 61], while sustainability-oriented work provides more detailed environmental and energy-related assessment [17]. However, these approaches are generally not based on empirical flight data that capture the effects of payload, flight distance, vertical movement, and operational conditions on drone delivery time and energy consumption. As a result, optimization models may overestimate drone feasibility or underestimate the operational constraints that would arise in practical deployment.

A second gap relates to drone resource allocation and fleet coordination. Several studies consider multiple trucks or multiple drones [56–60]; however, drones are often tied to specific trucks, predefined routes, fixed clusters, or a particular operating structure. Comparatively less attention has been given to shared drone fleet allocation across concurrent delivery routes originating from the same depot. This limits the ability of existing models to evaluate how drone fleet size, route-level drone assignment, truck stop placement, and workload balancing jointly affect delivery time, energy use, and system-level performance.

Therefore, integrated models that combine routing, energy-aware planning, and shared fleet allocation remain underdeveloped.

A third limitation concerns the separation between operational optimization and broader deployment considerations. Sustainability-focused studies assess emissions, cost, life-cycle impacts, or green routing benefits [17, 61], while recent deployment-oriented models introduce new operating concepts such as mobile drone station trailers [62]. These studies provide valuable insights into the environmental and practical feasibility of TDCD systems. However, public acceptance, regulatory readiness, infrastructure requirements, airspace coordination, and scalability are still often treated outside the core operational planning framework. This separation is problematic because successful TDCD deployment depends not only on route efficiency, but also on whether the system is technically feasible, socially acceptable, environmentally beneficial, and compatible with operational and regulatory constraints.

Overall, the reviewed literature shows that TDCD research has advanced significantly in areas such as routing optimization, drone scheduling, dynamic and time-window-based operations, algorithmic solution development, sustainability assessment, and alternative collaborative delivery architectures. However, much of this work remains concentrated on specific components of the problem, including route construction, drone dispatching, cost minimization, reliability, or emissions assessment, often under simplified operational assumptions. This creates an opportunity for complementary research that places greater emphasis on practical deployment conditions, including empirically informed drone performance, route-level operational data, coordinated fleet allocation, user acceptance, and

broader implementation constraints. Motivated by this perspective, this thesis adopts a systems-oriented and operationally grounded approach by combining empirical drone energy and delivery-time modeling with coordinated truck-drone optimization, shared fleet allocation across multiple routes, and analysis of behavioral and deployment considerations.

Table 2.1 further illustrates the diversity of methodological priorities across the literature. In several dimensions, prior studies provide deeper treatment than the present thesis, particularly in joint route optimization, dynamic service constraints, exact and metaheuristic algorithm development, hybrid delivery architectures, and comprehensive sustainability assessment. The contribution of this thesis is therefore positioned as complementary rather than superior, with particular emphasis on empirically informed UAV performance modeling, shared drone-fleet allocation across fixed truck routes, consumer acceptance, and system-level planning. These contributions are accompanied by limitations, including predetermined truck routes, largely static operating conditions, platform-specific UAV performance data, the absence of dedicated algorithmic development, and only partial treatment of sustainability beyond energy-efficiency considerations. Accordingly, the thesis views TDCD not solely as a routing problem, but as a broader cyber-physical logistics coordination system whose successful deployment depends on interacting operational, technological, infrastructural, behavioral, and implementation factors.

Table 2.1: Comparative positioning of selected truck–drone collaborative delivery studies

Study	Main focus	Real data	Empirical UAV	Routing/scheduling	Dynamic/time windows	Multi-route	Shared fleet	Algorithmic development	Sustainability	Deployment/adoption	Comparative note
Luo et al. (2023) [55]	Delivery–pickup routing and multi-objective optimization.	N	N	Y	N	N	N	Y	N	N	Strong multi-objective routing and evolutionary algorithm development; no empirical UAV calibration.
Zhen et al. (2025) [58]	On-demand truck–drone delivery with multiple routes and transshipment.	Y	N	Y	P	Y	P	Y	N	P	Strong multi-route and exact algorithmic treatment; limited empirical UAV modeling.
Wu et al. (2022) [56]	Contactless multi-truck, multi-drone parcel delivery.	P	N	Y	N	Y	N	Y	P	P	Strong multi-vehicle routing and heuristic development; drones remain truck-specific.
Lin et al. (2022) [57]	Medical-resource delivery using multiple trucks and UAVs.	N	N	Y	P	Y	N	Y	N	P	Strong emergency-routing and hybrid-algorithm focus; uses generated data.
Freitas et al. (2023) [54]	Exact and heuristic methods for FSTSP/TSP-D.	N	N	Y	N	N	N	Y	N	N	Strong exact and heuristic benchmarking; limited deployment scope.
Wang et al. (2019) [60]	Hybrid routing and scheduling with independent and truck-carried drones.	N	N	Y	N	Y	P	Y	P	P	Strong hybrid routing/scheduling and algorithmic focus; no empirical UAV calibration.
Baldisseri et al. (2022) [17]	Economic and environmental assessment of truck-based drone delivery.	P	N	P	N	N	N	N	Y	Y	Strong sustainability assessment; limited routing and shared-fleet optimization.
Shi et al. (2026) [62]	Truck–drone delivery using a mobile drone-station trailer.	N	N	Y	N	P	N	Y	P	Y	Strong deployment architecture and metaheuristic development; limited empirical UAV modeling.
Fu et al. (2025) [59]	Multi-objective TDCD with time windows and reliability.	N	N	Y	Y	Y	N	Y	N	P	Strong time-window, reliability, and algorithmic modeling; no shared-fleet allocation.
Zhu et al. (2025) [61]	Green TDCD routing with multiple drone drops.	N	N	Y	N	N	N	Y	Y	P	Strong sustainability-oriented routing, multi-drop modeling, and evolutionary optimization.
This thesis	Empirical UAV modeling, shared fleet allocation, adoption analysis, and system-level planning.	Y	Y	P	N	Y	Y	N	P	Y	Empirical UAV and shared-fleet focus; fixed truck routes and largely static operating conditions.

Notes: Y = explicitly and substantially addressed; P = partially addressed, indirectly considered, or addressed under restricted assumptions; N = not addressed or not central to the study. *Algorithmic development* indicates the development of a dedicated exact, heuristic, metaheuristic, evolutionary, or hybrid solution procedure, rather than the use of a standard optimization solver alone. *Sustainability* indicates explicit consideration of energy use, emissions, environmental impacts, or broader sustainability-oriented performance; P may denote partial consideration, such as energy-efficiency analysis without a comprehensive sustainability assessment. Classifications represent the primary scope of each study and do not imply an assessment of overall research quality.

Building on this positioning, the thesis investigates TDCD through complementary empirical, optimization, behavioral, and system-level perspectives, with particular attention to operational realism, coordinated resource allocation, and deployment scalability.

ARTICLE 1- MACHINE
LEARNING-DRIVEN TRUCK-DRONE
COLLABORATIVE DELIVERY FOR TIME
AND ENERGY EFFICIENT LAST-MILE
DELIVERIES

3.1 PUBLICATION STATEMENT

This chapter is based on the Journal article titled “Machine Learning-Driven Truck-Drone Collaborative Delivery for Time and Energy Efficient Last-Mile Deliveries”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published in Electronics Journal in May 2025. DOI: 10.3390/electronics14102026.

This article represents an important foundational component of the thesis by introducing the machine learning-based drone energy and delivery time models developed using real DJI Matrice 100 flight data. Unlike many previous TDCD studies relying on simplified battery assumptions, this work incorporated payload, horizontal and vertical flight distances, speed, takeoff, and landing effects into realistic drone performance estimation. The regression-based energy and time models developed in this study later became key inputs to the subsequent optimization framework of the thesis, where they were integrated into the MILP-based truck–drone collaborative delivery model using the Amazon Last Mile Routing Research Challenge dataset. In this way, the article established the empirical and operational foundation for the later resource allocation, truck stop selection, customer assignment, and fleet optimization studies presented throughout the dissertation.

3.2 INTRODUCTION

Autonomous delivery technologies; i.e delivery drones and robots have some constraints like range, speed or payload capacity. To mitigate these shortcomings, practical solutions including electric trucks as a carriage and launch platform is becoming more common. Modern supply chain networks utilize distribution centers or microdepots (alternatively microhubs) closer to customer locations to facilitate fast customer deliveries. This has also enabled to efficiently integrate drones and robots into existing logistics networks, considering factors like accessibility, cost, and operational feasibility [63]. In the context of collaborative delivery, trucks frequently function as mobile depots for carrying, charging, launching and recovering drones or robots [64]. Consequently, these vehicles can be regarded as mobile facilities, akin to relocatable drone depots.

Drones are emerging as a promising alternative for delivering e-commerce parcel deliveries. Major companies like Amazon, UPS, Zipline, and DHL are actively developing and testing drone delivery systems. Despite their potential, drones face challenges such as payload and battery limitations, and vulnerability to adverse weather conditions. Conversely, traditional truck delivery has its own drawbacks, including traffic congestion, carbon emissions, and dependency on road networks and conditions. The Truck-Drone Collaborative Delivery (TD CD) model addresses the limitations of each delivery mode, offering significant cost savings compared to using trucks alone [65]. By having trucks transport drones closer to customer locations, energy efficiency is improved, as drones rely on batteries. There has

been a substantial amount of research on truck-drone collaborative delivery, particularly in the last five years.

The Truck-Drone Collaborative Delivery Problem has been split into 2 main problems: Carried vehicle supporting drone delivery problem (CVSDDP) and simultaneous delivery problem of trucks and drones (SDP-TD) [66]. In the CVSDDP model, the truck acts as a mobile depot and platform for transporting the drone to the service area, where the drone then completes the delivery to the customer. Conversely, in the SPD-TD model, both the truck and the drone are capable of directly serving customers. In this study, we address the CVSDDP problem, where the truck serves as a support vehicle for the drone, without directly delivering to customers. Once the drone has visited all customers in its designated service area, the truck retrieves the drone and transports it to the next delivery center or back to the depot.

Synchronizing drone and truck routes in TDCD indeed poses significant challenges in collaborative delivery systems. Hence majority of the research focused on routing and scheduling problem. However, recent research has been increasingly addressing the emerging challenges of identifying the optimal truck locations for drone launches [66], [67], determining the optimal number of drones required to meet specific customer demands [68], [69], [70], [16], managing the battery power of drones [70] and making drone scheduling and routing decisions [68], [66], [71], [16]. This article takes a comprehensive approach and addresses the key challenges of TDCD in a coherent way using realistic data and proposing a machine learning driven Drone Energy Model to calculate drone delivery time and energy for fleet resource decisions over one week of delivery data. This holistic approach

to the problem, reinforced by process flowcharts, can enhance interdisciplinary researchers' understanding of the topic.

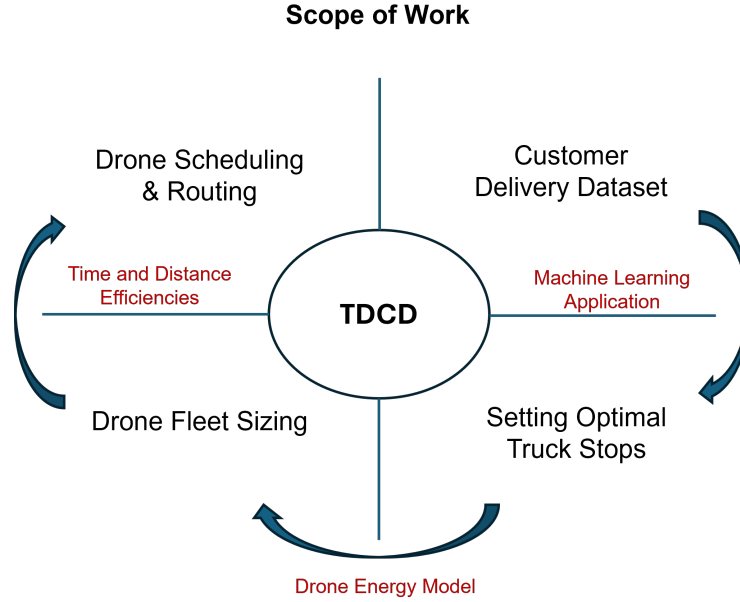


Figure 3.1: Scope of work in this study

Figure 3.1 provides a high-level overview of the scope of this work. This work builds upon the customer delivery dataset developed in previous work by the authors [72]. Utilizing machine learning techniques, optimal truck stop locations are identified as launch points for drones tasked with delivering packages to designated customer locations within the dataset. The truck stop and customer locations are incorporated into the proposed Drone Energy Model as distance parameters, enabling the assessment of energy consumption and informing strategic fleet sizing decisions. Additionally, time and distance efficiencies are systematically analyzed to optimize drone scheduling and routing, ensuring

operational effectiveness.

Previous research on collaborative truck-drone delivery for last mile parcel deliveries often relies on the drone range specified in the manufacturer’s guide to estimate battery power in problem formulation [73], [74], [75], [76]. Additionally, the vertical movement of drones (ascending and descending) and the impact of payload on energy consumption are frequently overlooked in these calculations. To address these gaps, we developed a realistic drone energy model using Machine Learning techniques that account for the effects of ascending, landing, and payload on drone battery consumption.

Most current studies utilize conceptual instances from previous research, such as randomized locations within a given area or a very limited number of customer locations. In contrast, our study employs a realistic dataset for online stochastic customer demand, assuming next-day delivery, as detailed in our previous work [72]. Furthermore, while existing research on truck-drone collaboration primarily focuses on time-inefficient optimization techniques, we applied a machine learning algorithm, the Self-Organizing Feature Map (SOFM), to identify distance-optimal launch centers within seconds based on online demand. Finally, our drone energy model aids in sizing the drone fleet according to the battery levels of available drones when there is no charging facility nearby.

The primary contribution of this work lies in the development of an AI engine that supports resource decision-making by integrating the SOFM algorithm with a Machine Learning-based Drone Energy Model using real drone flight data as also illustrated on the System Model in Figure 3.2.

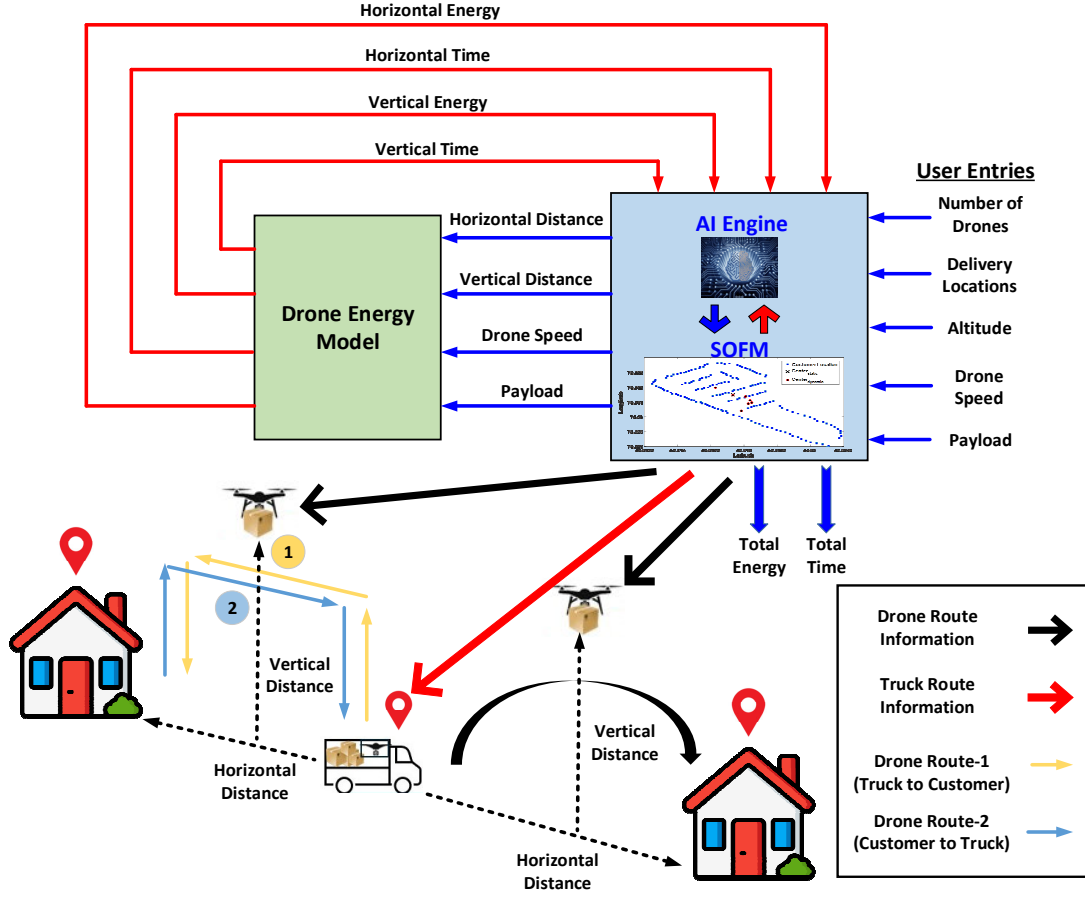


Figure 3.2: System model with block representations and input-output relationships

This paper is structured as follows: Section 3.3 discusses the previous works in the literature and highlights the novelty of this work. Section 3.4 details the research methodology. Section 3.5 presents the context and setting of the problem. Section 3.6 describes the drone energy model that is proposed in this work and the drone flight dataset that is used to build the energy model. Section 3.7 presents the findings on drone energy model and TDCD simulations with insights on resource allocation and energy management. Fi-

nally, Section 3.8 covers the concluding remarks for this work with directions for future research.

3.3 LITERATURE REVIEW

In the existing literature, numerous delivery network models have been proposed, considering variations in the number of vehicles, their distinct functions, and the differing numbers of depots. The first research on drone-assisted truck deliveries [9] formulates a flying sidekick traveling salesman problem and uses mixed integer linear programming to minimize the delivery time. In this joint delivery mode, first truck route is defined and then drone sub-routes are planned where drone merges with the truck after serving the customer onroute and where trucks can also deliver to customers when it is not feasible to deliver with drone. Researchers have extensively explored collaborative truck-drone delivery for last mile delivery (LMD), analyzing it through the frameworks of the traveling salesman problem and vehicle routing or scheduling problems [77], [78], [79], [80], [81], [82], [16] because synchronizing both drone and truck routes introduce a significant challenge to the collaborative delivery systems. [17] performs a comprehensive life cycle assessment analysis to estimate the greenhouse gas emission per parcel delivered and applies total cost of ownership model to understand cost performance of truck assisted drone deliveries. The study concludes that drone automation level and battery life cycle has significant cost impacts and that a delivery system combining an electric truck with a drone performs better than a diesel van or an electric van under varying customer densities or wind conditions.

Moreover in the recent years, identifying optimal facility locations for drone deliveries [83] has extensively been studied. A design case study concerning healthcare delivery throughout the Birmingham, Alabama (USA) area uses particle swarm optimization method to identify the optimal number and location of the drone stations for a truck-drone delivery and concludes that sorting the location of the drone stations improve the customer coverage but not necessarily improves the route distance [84]. The existing studies that deal with the facility location problem commonly use MILP (Mixed Integer Linear Programming) [83],[85], [65], MINLP (Mixed Integer Non-Linear Programming) [86] or other optimization algorithms like particle swarm algorithm [84]. There are some studies that aim to optimally locate the microdepots in the last mile delivery network without focusing on the TDCD problem [87],[88].

A qualitative comparison of this article to the existing and recent research is summarized in Table 3.1 and discussed in this paragraph. Bi et al. [68] have applied Reinforcement Learning, a type of agent based machine learning to the TDCD problem mainly to avoid drone collisions in a multi-drone environment. Wu et al.[66] applied Reinforcement Learning to solve the routing problem for both the truck and the drone, however mainly focused on the running time efficiency of the Machine Learning (ML) algorithm in comparison to two meta-heuristic algorithms. Figliozzi and Hadas [70] did not apply machine learning but applied distance-based policy in a dynamic stochastic demand environment to achieve energy efficiencies, and they discussed battery management in the context of charging infrastructure. Arishi et al. [71] used K-means clustering algorithm to identify the cluster of delivery locations and set the flight range constraint between the truck and each customer

as the maximum range of the drone. Bacanli et al. [67] investigated placement of parcel delivery centers for drones using machine learning and they have created synthetic data for training ML algorithm with distribution data. Chen et al. [69] investigates multi-fleet delivery problem through mixed-integer linear programming (MILP) model. Similarly, Thomas et al. [16] applies MILP model to the routing problem and analyzes the impact of drone utilization on the drone fleet size. While existing studies on TDCD have primarily focused on isolated aspects of the problem, our work bridges these gaps by integrating multiple critical components into a cohesive AI-driven framework. By addressing all the problems listed in the research gap table within a unified framework, this study significantly enhances practical feasibility, efficiency, and interdisciplinary insight for TDCD implementation.

Table 3.1: Research gap: Comparison of our work with the literature

Publication	Year	Realistic Delivery Data	Truck Stop Setting	Machine Learning	Drone Battery Management	Fleet Sizing	Drone Sched.& Routing
Bi et al. [68]	2024	X	X	✓	X	✓	✓
Wu et al. [66]	2023	X	✓	✓	X	X	✓
Figliozzi and Hadas. [70]	2025	X	X	X	✓	✓	X
Arishi et al. [71]	2022	X	X	✓	X	X	✓
Bacanli et al. [67]	2021	✓	✓	✓	X	X	X
Chen et al. [69]	2024	X	X	X	X	✓	✓
Thomas et al. [16]	2023	X	X	X	X	✓	✓
This Article	2025	✓	✓	✓	✓	✓	✓

3.4 METHODOLOGY

The methodology section discusses the datasets and machine learning applications used in this work and the process of integrating delivery information, drone energy model and the machine learning algorithm within the AI engine as shown in Figure 3.3. This figure clearly explains the steps followed in integrating the delivery information, drone energy model and the SOFM algorithm within the AI Engine. The axes indicate the inclusion of input parameters. The following subsections will detail the methodology and the flow of research work as guided by this flowchart.

3.4.1 DELIVERY DATASET

Realistic synthetic delivery data used in this work has been generated in our previous work [72] using actual customer addresses and realistic order patterns to simulate delivery scenarios. A neighborhood in Kanata, Ontario has been sampled with 191 customer locations. Online customer order data is generated for a period of one week (7 days) through randomization on MATLAB R2023a. 55% of customer locations place one order per week, while 45% do not place any online orders. Return (backhaul) orders or package collections are not included. The dataset included package delivery frequency (0 or 1 per week), package delivery day (Monday to Sunday), package delivery time (6am to 6pm) and package size (1-small, 2-medium, 3-large), however, only delivery day and delivery frequency features have been used in this work.

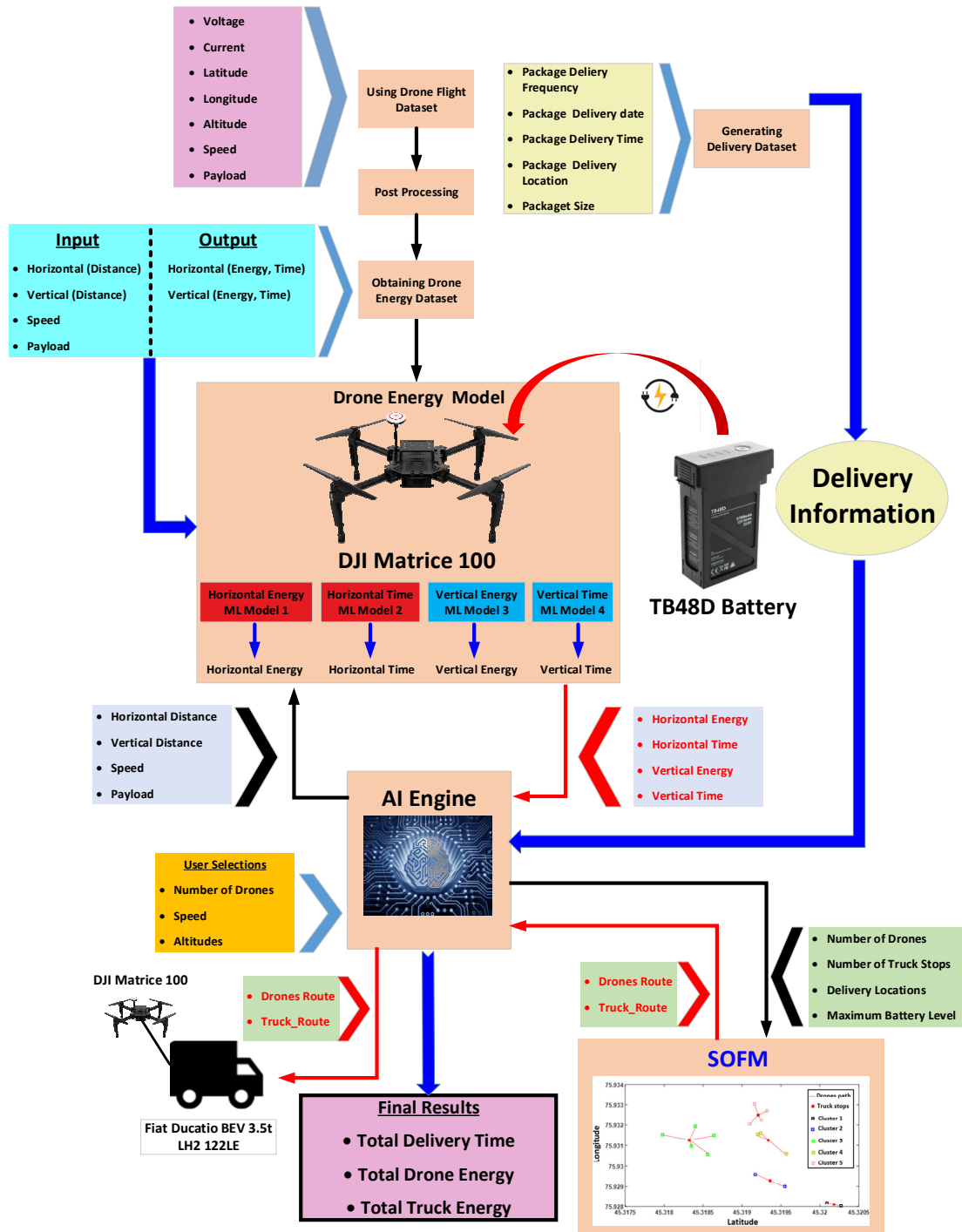


Figure 3.3: Integration of delivery information, drone energy model and SOFM algorithm within the AI engine

3.4.2 VEHICLE SPECIFICATIONS AND PARAMETERS

The truck used in this problem is an electric truck (e-truck) and the specifications for it is obtained from the work of Balassi et al. [89] with the factory parameters as noted on Table 3.2. Drone parameters, as noted on Table 3.3, are obtained from the work of Rodrigues et al. [90] and will be explained in subsection 3.4.3

Table 3.2: Truck vehicle specifications [89]

Truck Model	Fiat Ducatio BEV 3.5t LH2 122LE
Av Speed (per WLTP*)	46.6 km/hr
Operating distance (empty)	357 km
Operating distance (full)	317 km
Fuel tank/Battery capacity	79 kWh
Energy consumption (empty)	221.29 Wh/km
Energy consumption (full)	249.21 Wh/km
Payload capacity	764.1 kg
CO2 emission (empty)	0.083 kgCO2/km
CO2 emission (full)	0.094 kgCO2/km

Table 3.3: Drone vehicle specifications

Drone Model	DJI MATRICE 100
Weight	2431 g
Max Takeoff Weight	3600 g
Max Speed (no payload)	17 m/s (GPS mode)
Drone Battery Model	TB48D
Voltage	22.8 V
Capacity	5.7 A/hr
Energy	467.856 kJoule

3.4.3 DRONE FLIGHT DATASET

In order to use drone parameters in real-life settings and to build the drone energy model proposed in this work, we have used the previous work of Rodrigues et al. [90]. Their work has captured accurate operational metrics over 209 drone delivery test flights using a DJI Matrice 100 model ¹, for small package delivery. The battery used for DJI Matrice 100 is TB48D. The specifications of the drone and the battery is listed on Table 3.3. This in-flight

¹<https://www.dji.com/ca/support/product/matrice100/>

positional and energy use dataset of a DJI Matrice 100 is published and made available to public in 2021. In this dataset [90], a small quadcopter package delivery drone was tasked with completing 209 flights, each involving takeoff, flying a designated route, and landing, while varying operational parameters. The drone was outfitted with sensors such as GPS, IMU, voltage and current sensors, and an ultrasonic anemometer to gather detailed data on inertial states, wind speed, and power consumption. Parameters like commanded ground speed, payload, and cruise altitude were adjusted for each flight. This comprehensive data set, collected from April to October 2019, includes a total flight time of 10 hours and 45 minutes, covering around 65 kilometers. The data were validated by comparing flights with similar parameters. This dataset is very helpful for researchers who want to contribute to the field but lack comprehensive datasets to work with. We will elaborate on this issue under Section 3.6.

3.4.4 MACHINE LEARNING APPLICATIONS

In this work, an unsupervised machine learning algorithm, SOFM, is employed to identify the clusters of customer locations and to find the distance-optimal truck stops to launch the drones. This novel application of this method aims to minimize the vehicle travel distance and hence reduce energy consumption and environmental impact.

The SOFM algorithm, introduced by Kohonen (1990) [91], is a type of artificial neural network designed for unsupervised learning and dimensionality reduction. This algorithm represents multi-dimensional data using a two-dimensional grid of neurons. In SOFM, neu-

rons are interconnected through a predefined topology known as neighborhood connections [92]. The neuron that best matches the input data is referred to as the Best Matching Unit (BMU). The training process in SOFM is akin to the winner-take-all algorithm, utilizing vectorial distance-based competitive learning. During training, each data sample is compared to the weights of every neuron on the 2D hexagonal structure, and the Euclidean distance from each comparison is calculated independently. The BMU is then updated to minimize the distance between itself and the input data coordinates. Simultaneously, the neighborhood connections around the BMU are adjusted using a time-dependent radius function. This iterative process refines neuron positions, facilitating the formation of regional connections between neurons and input data coordinates. Training continues until a specified stopping criterion is met. SOFM has been widely applied in various domains, such as identifying mobility patterns and clusters of residents during the COVID-19 pandemic [93], and assessing cyber risks in mobile crowdsensing systems [94]. Shahbazi et al. compares the performance of SOFM with K-means, a distance-based clustering algorithm, and with DBScan, a density-based clustering in their work [95] and concludes that SOFM performs better than K-means and closer to DBScan. Since this work contains distance-based clustering, SOFM algorithm is used.

We utilize the concept of "AI engine", a code-based decision making agent, to optimize the scheduling and routing of drones, a topic commonly studied through optimization algorithms in the literature. The AI engine supports operational decision-making by assigning delivery tasks to drones, scheduling drone service for clusters of customer locations, and determining the drone fleet size required to satisfy delivery requirements. This engine is

fed with the delivery information from the delivery dataset and with the drone energy information from the Drone Energy Model. Additionally, the user inputs their selections for the number of drones, as well as their speed and altitude, into the engine.

Another key contribution of this work is the development of a Drone Energy Model using machine learning regression models, which is detailed in the following section 3.6.

3.5 PROBLEM SETTING

The problem is formulated as a truck assisting drone delivery problem in an urban residential setting. The truck is solely responsible for transporting and launching the drones; it does not charge the drones or deliver directly to customer locations. A residential neighborhood in Kanata, Ontario with 191 customer locations has been selected as the delivery area for this study. The polar coordinates (latitude and longitude) of these customer locations are obtained from OpenStreetMap ² to create the delivery area and plotted in Figure 3.4. The key assumptions of the problem are listed in below:

1. Truck is loaded at the distribution center with the parcels and the drones, and visits the delivery area selected for this problem. The distance between the distribution center and the delivery area is not considered in the calculations.
2. Truck goes to the identified stop (S_i), parks there and launches the drone. Parking restrictions are not considered in this residential setting.

²<https://www.openstreetmap.org/>

-
3. The truck can launch multiple drones (D_j) at each stop, based on the number of delivery locations and their distances from the truck.
 4. There is no nearby charging facility for the drones, and the truck lacks charging capacity. Therefore, it's crucial to utilize the drone's battery level (B_l) to the maximum.
 5. The drone visits each customer location (N_k) on the route, returns to the truck to re-supply with the next parcel. Truck stays in parking mode until all the delivery tasks assigned to the drone are completed.
 6. Drone energy and delivery time is calculated with payload on one way and without payload on the way back to the truck.
 7. Drone with higher battery power is scheduled first. Drone routes are planned starting from the farthest delivery location and progressing to the closer ones.
 8. Truck collects the drones and returns to the distribution center upon completion of the planned deliveries.

3.6 DRONE ENERGY MODEL

In recent studies addressing the energy consumption of delivery drones or investigating their battery limitations, the information has often been limited to the manufacturer's

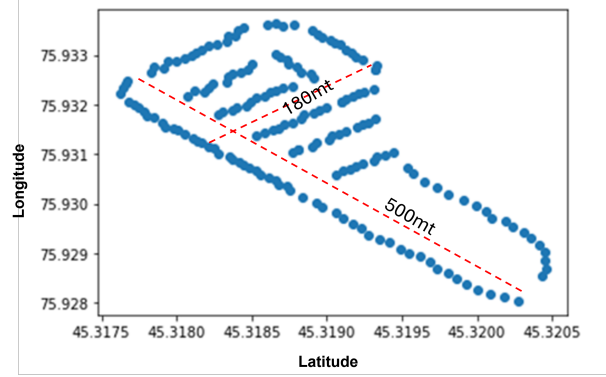


Figure 3.4: Simulated delivery area on OpenStreetMap

specification of the drone battery, neglecting critical factors such as vertical distance (altitude), speed and payload effects on the battery consumption. To bridge these gaps, we introduced an advanced drone energy model leveraging Machine Learning algorithms. This model provides a more accurate estimation of battery usage by incorporating the energy costs associated with ascending, descending, and varying payload weights, thereby offering a comprehensive solution for optimizing drone operations in real-world scenarios.

The drone features of voltage, current, time, positional data, altitude, speed and payload are obtained from the in-flight positional and energy use dataset [90]. To enhance the compatibility of the drone flight dataset with machine learning models, several postprocessing steps were applied. Initially, the dataset reported voltage and ampere-hours for each flight. To better capture energy dynamics, we calculated the energy consumption per flight in kilojoules, incorporating delivery time as a key factor. Furthermore, the dataset lacked explicit tagging for drone movement direction—whether vertical or horizontal. To address this, new features were introduced: vertical distance and horizontal distance. These re-

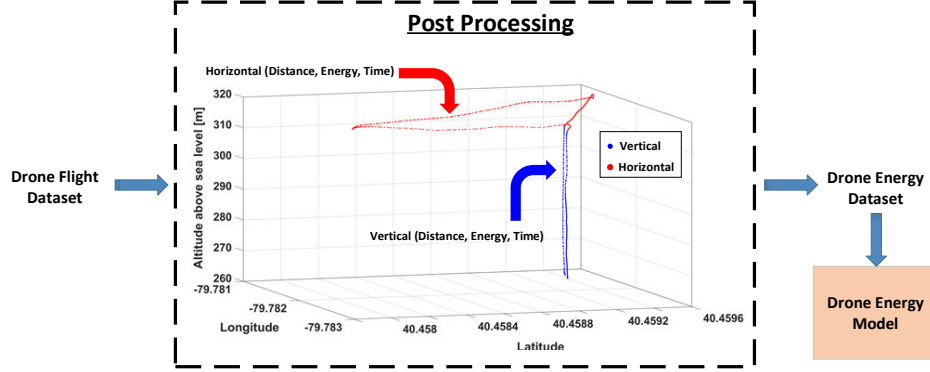


Figure 3.5: Drone trajectory sample at 50 meters altitude for postprocessing stage

finer features enable a more granular breakdown of energy consumption and delivery time, distinguishing between take-off/landing phases and cruise hovering. This segmentation ensures that energy and temporal characteristics are appropriately modeled for different flight operations, improving the dataset's effectiveness for predictive modeling. The horizontal and vertical distance along with the speed and payload selections are fed into the Drone Energy Model to ultimately produce the horizontal energy (HE), horizontal time (HT), vertical energy (VE) and vertical time (VT) as illustrated on Figure 3.6. The post processing of Drone Flight Dataset to create the Drone Energy Dataset that we worked on for this work is illustrated in Figure 3.5.

The energy consumption (kjoule) is calculated as below:

$$\text{Energy (kJ)} = \text{Voltage (V)} \times \text{Current (Ah)} \times 3600 \text{ (s/h)}/1000$$

The notations for the model parameters are defined in Table 3.4 and the mathematical illustration of the Delivery Energy (DE) and Delivery Time (DT) calculation of the model is given below. Since the formulation is derived from a machine learning model, the functional notations are used to capture the relationships encoded by the algorithm. Function-based notation preserves the flexibility inherent to the machine learning approach.

Table 3.4: Notation table

Notation	Description	Values
d_v	Distance_vertical	15m
d_h	Distance_horizontal	SOFM output
s_v	Speed_vertical	2m/s
s_h	Speed_horizontal	8m/s
w_0	Weight_empty	no load
w_p	Weight_loaded	250g
DE	Delivery Energy	Total energy to complete the delivery (kjoule)
VE	Vertical Energy	Energy for take-off and landing (kjoule)
HE	Horizontal Energy	Energy cruising to and from delivery location (kjoule)
DT	Delivery Time	Total delivery time (sec)
HT	Horizontal Time	Time spent to and from delivery location (sec)
VT	Vertical Time	Time spent for take-off and landing (sec)

$$\mathbf{DE} = VE + HE \tag{3.1}$$

Delivery Energy is calculated as the total of Vertical Energy (VE) and Horizontal

Energy (HE).

$$VE = (f_{VE}(d_v, s_v, w_p) + f_{VE}(d_v, s_v, w_0)) * 2 \quad (3.2)$$

Vertical Energy (VE) is determined by summing the energy consumption in two distinct cases: VE without payload (w_0), the energy required when there is no additional weight. VE with payload (w_p), the energy required when carrying a payload. Since the drone follows a two-way flight path—first traveling from the truck to the customer location with the payload, then returning to the truck without the payload—the total energy consumption for a complete flight cycle is doubled.

$$HE = f_{HE}(d_h, s_h, w_0) + f_{HE}(d_h, s_h, w_p) \quad (3.3)$$

Horizontal Energy (HE) is determined by summing the energy consumption in two distinct cases: HE without payload (w_0), the energy required when there is no additional weight. HE with payload (w_p), the energy required when carrying a payload. The distance parameter is not fixed as in the vertical energy and obtained from the SOFM algorithm.

$$\mathbf{DT} = VT + HT \quad (3.4)$$

Delivery Time is calculated as the total of Vertical Time (VT) and Horizontal Time (HT).

$$HT = f_{HT}(d_h, s_h, w_0) + f_{HT}(d_h, s_h, w_p) \quad (3.5)$$

Horizontal Time (HT) is determined by summing the delivery time in two distinct cases: HT without payload (w_0), the delivery time required when there is no additional weight. HT with payload (w_p), the delivery time required when carrying a payload. The distance parameter is not fixed as in the vertical time calculation and obtained from the SOFM algorithm.

$$VT = (f_{VT}(d_v, s_v, w_0) + f_{VT}(d_v, s_v, w_p)) * 2 \quad (3.6)$$

Vertical Time (VT) is determined by summing the energy consumption in two distinct cases: VT without payload (w_0), the energy required when there is no additional weight. VT with payload (w_p), the energy required when carrying a payload. Since the drone follows a two-way flight path—first traveling from the truck to the customer location with the payload, then returning to the truck without the payload—the total energy consumption for a complete flight cycle is doubled.

3.7 RESULTS

This section is split into two subsections to present the results obtained for the Drone Energy Model and TDCD simulations.

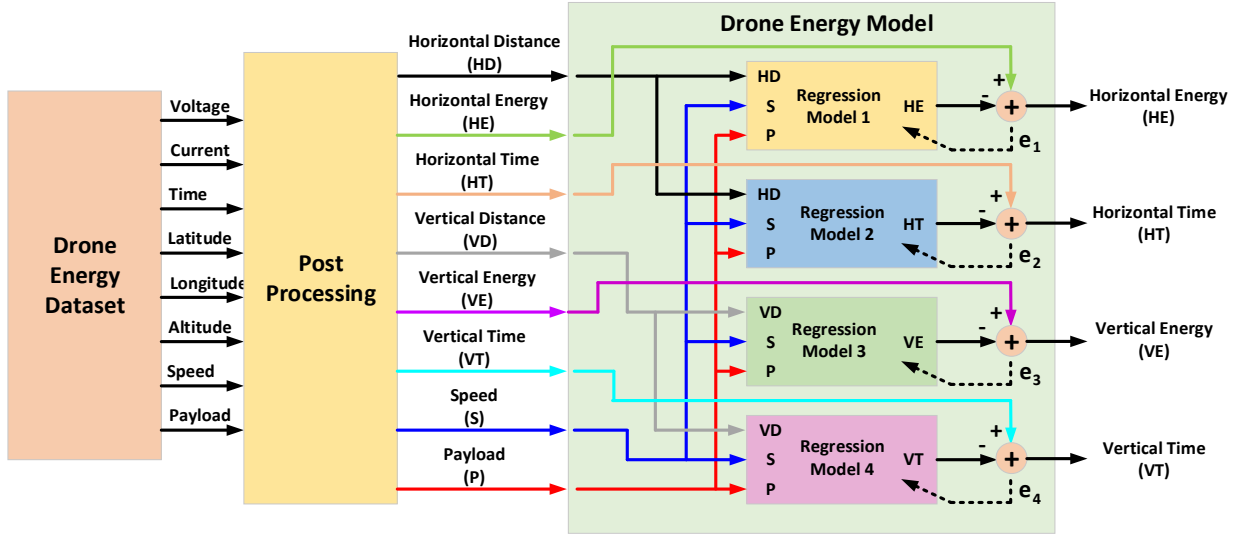


Figure 3.6: Drone energy model with data flow and input-output representations

3.7.1 DRONE ENERGY MODEL

The process of predicting the continuous output variables of Horizontal Energy (HE), Horizontal Time (HT), Vertical Energy (VE) and Vertical Time (VT) based on the input variables of Horizontal and Vertical Distance, Energy and Time, Speed and Payload is a Regression Problem. Several ML models have been trained to solve this problem and to come up with the best performing regression model. Out of all the trained ML models on MATLAB; linear regression models, regression trees, support vector machines, gaussian process regression, kernel approximation regression models, ensembles of trees and neural networks, the following models showed the best performance:

- Regression Model 1: Optimizable GPR outperforms other models for Horizontal

Energy (HE)

- Regression Model 2: Optimizable GPR outperforms other models for Horizontal Time (HT)
- Regression Model 3: Optimizable Ensemble outperforms other models for Vertical Energy (VE)
- Regression Model 4: Optimizable GPR outperforms other models for the Vertical Time (VT)

The optimized hyperparameters for the best performing ML Models that have been used to train the Drone Energy Model, where some of these variables are stated as "user selections" on Figure 3.3 are given on Table 3.5. Performance of these ML models can be found on Table 3.6. The model parameters for the input variables of the Drone Energy Model are noted on Table 3.7.

In a previous work [86], the battery consumption rate (BCR) was calculated using data from flight tests with the DJI Mavic 3, Heavy Lift Cargo, and Phantom 4 Pro+ drones. The rate at which battery charge decreases per minute during flight was measured and a linear relationship was found between battery charge decrease and payload increase. In this work, through the proposed Drone Energy Model, we calculate the required battery charge level of drones for completion of each delivery, taking into account the impact of payload as well as take-off and landing.

Table 3.5: Optimized hyperparameters for the best performing ML models to train the Drone energy model

Optimized Hyperparameters			
Optimizable GPR (HE)	Optimizable GPR (HT)	Optimizable GPR (VT)	Optimizable Ensemble (VE)
Basic Function: Constant	Basic Function: Linear	Basic Function: Linear	Ensemble Method: LS-Boost
Kernel Function: Isotropic Squared Exponential	Kernel Function: Non-isotropic Rational Quadratic	Kernel Function: Non-isotropic Matern 5/2	Minimum Leaf Size: 5
Kernel Scale: 0.0019163	Kernel Scale: 0.078043	Kernel Scale: 19.2427	Number of Learners: 63
Sigma: 287.3044	Sigma: 0.327	Sigma: 0.00035812	Learning rate: 0.26978
Standardize data: Yes	Standardize data: Yes	Standardize data: No	Number of predictors to sample: 3

Table 3.6: Performance of the ML models for the output variables

Performance of the ML Models		
Model Name	NRMSE_Train	NRMSE_Test
Optimizable GPR (HE)	0.0114904	0.0123111
Optimizable GPR (HT)	0.0073821	0.0079420
Optimizable GPR (VT)	0.0001387	0.1012344
Optimizable Ensemble (VE)	0.0202653	0.0328060

Table 3.7: Drone energy model parameters for the input variables

Model Parameters (Min-Max)		
Input Variable	Training Set	Test Set
Payload	0-500 gr	0-500 gr
Speed	4-12 m/s	4-12 m/s
Vertical Distance	4.63737m - 203.51263m	4.78525m - 202.1286m
Horizontal Distance	7.020779m - 364.1334m	7.12777m - 362.0462m

Results for the vertical energy and time calculations produced by the Drone Energy Model which is trained by the real data are provided on Figure 3.7a and on Figure 3.7b respectively. Likewise, the energy and time calculations for horizontal flights can be found on Figure 3.8a and on Figure 3.8b. The high accuracy of the model's performance is evident in these graphs, where the real data and model output align closely with minimal variations. Each response shown in these figures represents the ML model's output based on input parameters, including horizontal and vertical distances, horizontal and vertical

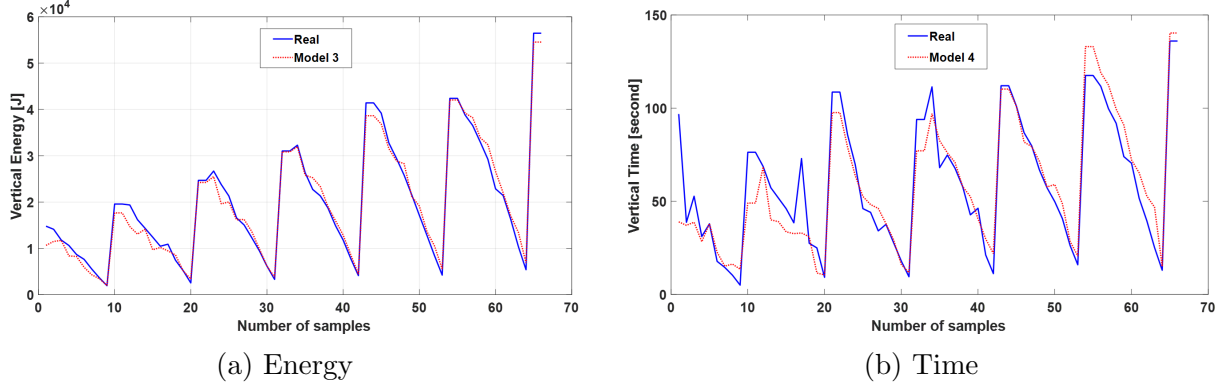


Figure 3.7: Vertical energy and time sample results

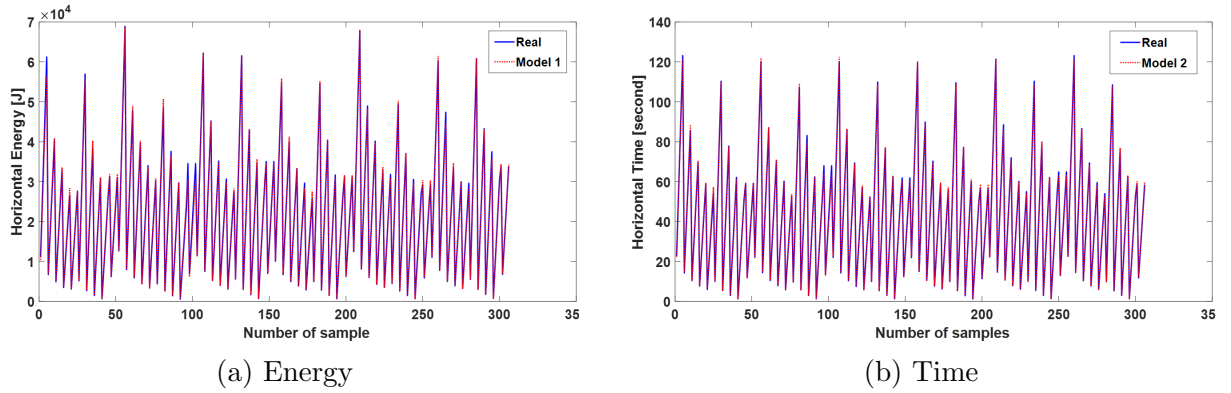


Figure 3.8: Horizontal energy and time sample results

speeds, and the presence or absence of a payload for package delivery. The difference between the real data and the ML model's predictions is quantified using the Normalized Root Mean Square Error (NRMSE) to enable meaningful comparisons in terms of real data values.

In the Drone Energy Model, a balanced strategy is employed to ensure equitable distribution of battery energy among the fleet of drones. This method prevents any single drone

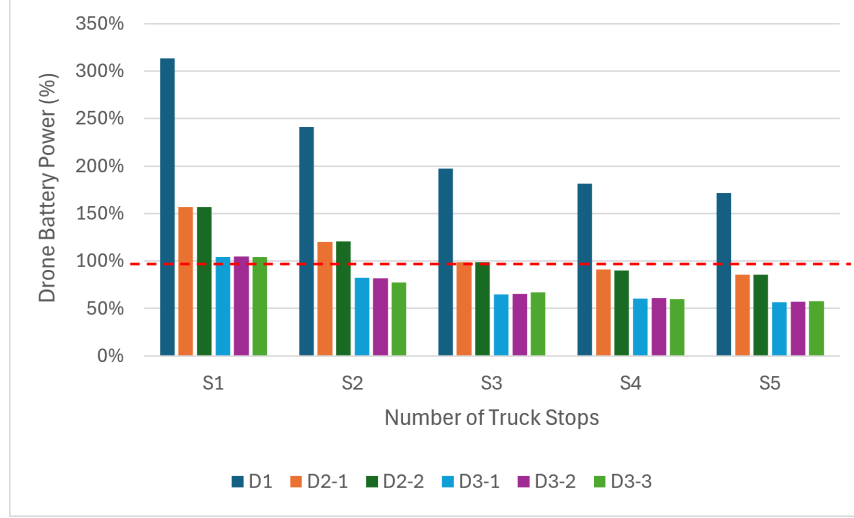


Figure 3.9: Required battery levels for drones to complete Tuesday delivery scenario

from depleting its battery while others still have excess energy, thereby optimizing overall fleet performance and longevity. On Figure 3.9 the required battery levels for varying number of drone fleet size and varying number of truck stops is calculated to complete the delivery plan for Tuesday which consists of 30 customer deliveries. The battery requirement over 100% is indicated as infeasible. Simulations for Tuesday indicate that delivering to all customer locations with a single drone is not feasible, regardless of the number of truck stops. Even when employing all three drones, their batteries deplete if the truck remains stationary at one stop. The approach of balancing battery use across multiple drones is evident on Figure 3.9 where drones D2-1 and D2-2 exhibit similar battery levels, while drones D3-1, D3-2, and D3-3 likewise maintain comparable battery levels.

3.7.2 TDCD SIMULATION RESULTS

A total of 93 simulation scenarios have been run on MATLAB for 7 days, for varying number of truck stops and for different fleet sizes. The simulation parameters are given on Table 3.8. The payload and horizontal speed are determined as the average of the minimum and maximum values specified in the drone flight dataset [90], while the vertical speed is chosen based on the value provided in the same dataset. The vertical distance, or altitude, is set to an energy-efficient level that ensures the delivery needs are met in a residential area characterized by the absence of high-rise buildings. The number of drones and truck stops is incrementally increased during the simulations to evaluate the delivery time and energy requirements for completing the daily delivery scenarios. Based on the size of the delivery area, it is observed that a maximum of three drones and five truck stops will suffice. There is only one truck used in the delivery simulations to keep the focus on the drone fleet. The number of customer locations is the total number of households that order online as assumed in the delivery dataset 3.4.1.

Table 3.8: TDCD simulation parameters

Simulation Parameters	Value
Payload (p)	250g
Horizontal speed (s_h)	8m/s
Vertical speed (s_v)	2m/s
Vertical distance (altitude) (d_v)	15m
Number of Drones (D_j)	$j \in \{0, 1, 2, 3\}$
Number of Truck Stops (S_i)	$i \in \{1, 2, \dots, 5\}$
Number of Truck (T_m)	$m=1$
Number of Customer Locations (N_k)	$k \in \{1, 2, \dots, 143\}$

Figure 3.10 shows the feasible and infeasible delivery simulations. The blank boxes on the table show the infeasible delivery scenarios given the distance of the truck stop to the customer delivery locations and the required battery levels of the drones, whereas the boxes with checkmarks show the feasible delivery scenarios for the given delivery plan of the day. 37 out of 93 scenarios (40%) were concluded as infeasible, meaning, drone battery level does not suffice the energy required for the delivery without a recharge.

Figure 3.11 presents the clusters, customer locations, truck stops plotted in polar coordinates for Monday delivery plan for total of 16 customer delivery locations. Figure 3.12 shows the path truck takes to visit the five distance optimal stops to launch the drones to the customer locations planned for Monday.

The results of the simulations conducted over a one-week period indicate a significant reduction in delivery time with the addition of an extra drone to the delivery fleet Figure 3.13. The introduction of a second drone reduces the delivery time approximately by 50% Figure 3.13a. However, the addition of a third drone yields a reduction in delivery time at a diminished rate of approximately 30%. Average delivery time for a single parcel ranges from a maximum of 101 seconds with one drone launched at one truck stop, to a minimum of 24 seconds with three drones launched at five stops Figure 3.13b.

The energy calculations are done for the total week's deliveries and for an average delivery. Only the delivery simulations, where the energy of the drone fleet would be sufficient to complete the delivery scenario, are considered in energy calculations. The plot for total energy consumption on Figure 3.14a presents the total of drone and truck

Day	# of deliveries	# of Truck stops	Drone Fleet		
			1 drone	2 drones	3 drones
Monday	16	1	☐	☒	☒
		2	☐	☒	☒
		3	☐	☒	☒
		4	☒	☒	☒
		5	☒	☒	☒
Tuesday	30	1	☐	☐	☐
		2	☐	☐	☒
		3	☐	☒	☒
		4	☐	☒	☒
		5	☐	☒	☒
Wednesday	19	1	☐	☒	☒
		2	☐	☒	☒
		3	☐	☒	☒
		4	☐	☒	☒
		5	☒	☒	☒
Thursday	31	1	☐	☐	☐
		2	☐	☐	☒
		3	☐	☐	☒
		4	☐	☐	☒
		5	☐	☒	☒
Friday	27	1	☐	☐	☒
		2	☐	☐	☒
		3	☐	☒	☒
		4	☐	☒	☒
		5	☐	☒	☒
Saturday	17	1	☐	☒	☒
		2	☐	☒	☒
		3	☐	☒	☒
		4	☒	☒	☒
		5	☒	☒	☒
Sunday	3	1	☒	☐	☐

Figure 3.10: Feasibility analysis of the TDCD simulation results

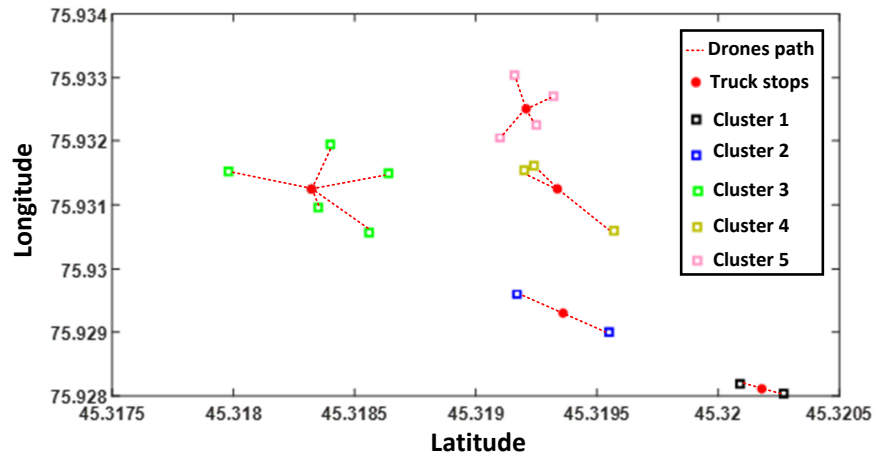


Figure 3.11: Clustering of Monday delivery locations

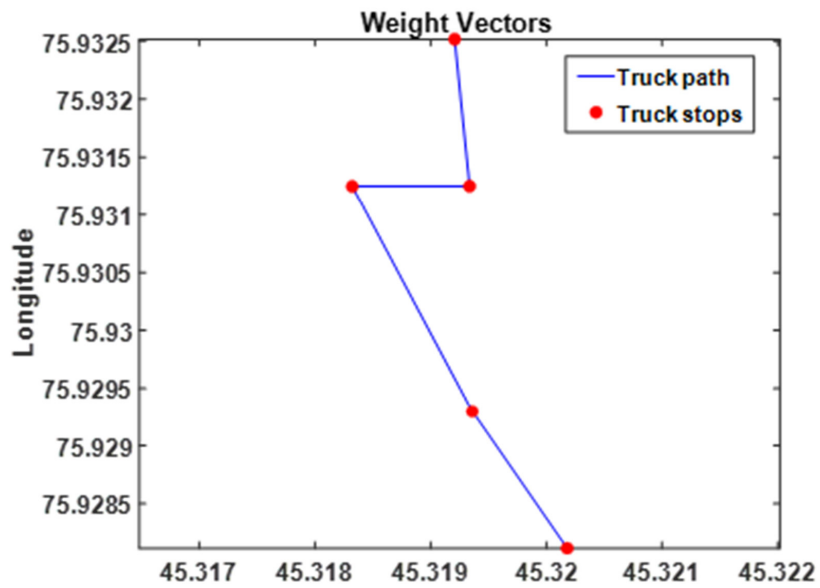


Figure 3.12: Truck route covering 5 stops on Monday

energy and it shows that delivery with 1 drone would not be possible unless truck visits 4 different stops to launch the drone. Delivery with 3 drones consume more energy at 2 truck stops and 3 truck stops, whereas it becomes more energy efficient compared to a 2-drone fleet at 1 stop, 4 stops and 5 stops. However, the linear increase in energy consumption with the increase in truck stops does not reflect the trend in individual delivery scenarios. The total delivery energy increases with the number of truck stops due to the coverage of more feasible delivery scenarios as the number of stops increases and size of the drone fleet expands. Figure 3.14b shows the average total energy (drone+truck) required to perform one delivery. Energy consumption of the truck is calculated through the distance measurements on Google Maps ³ and average speed and average energy consumption specifications of the Fiat Ducatio BEV model as stated under subsection 3.4.2. A specific delivery scenario for Monday delivery data is plotted in Figure 3.15 for better understanding of relationship of the energy consumption vs number of stops. We selected the Monday delivery scenario for representation because it features a reasonably complex structure, comprising 16 deliveries, 3 drones, and 5 stops. As seen on this plot, energy consumption declines with moving the truck to more stops and hence getting closer to the customer locations. In such case, truck travel distance is increased as plotted in the diagram.

Finally, energy efficiencies of multiple delivery scenarios are compared on Figure 3.16. Energy efficiency is calculated as total vehicle energy consumed to perform the total deliveries (of one week) over total time spent to complete the deliveries. This comparison allows the selection of the fleet resources to perform the most energy efficient delivery. Of

³<https://maps.google.ca/>

all the simulations conducted in this study, the scenario involving deliveries with 3 drones at 5 truck stops prove to be the most energy-efficient, consuming 5.2 kJoule/min.

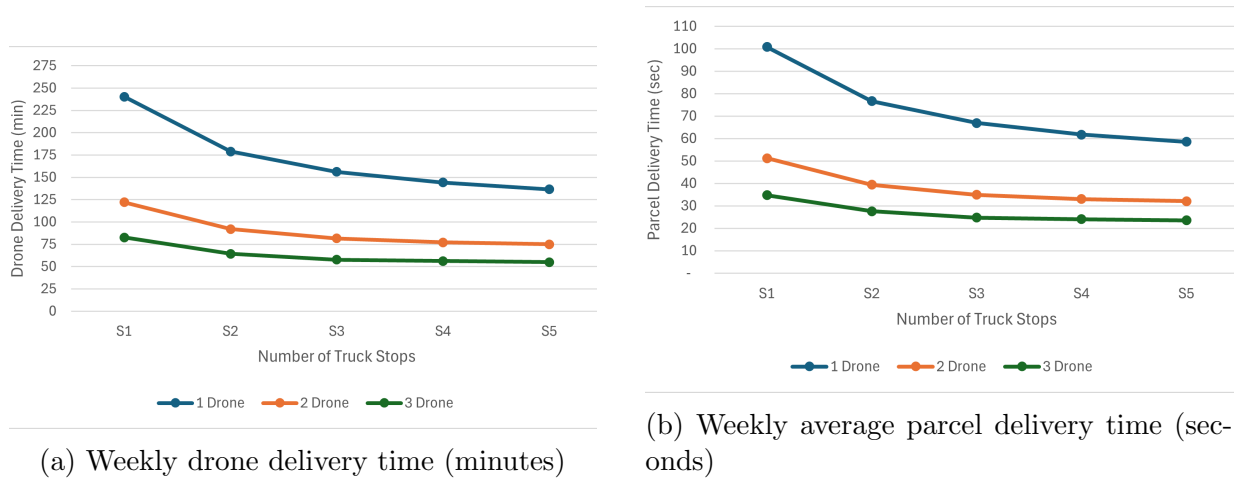


Figure 3.13: Weekly delivery time across different fleet sizes and truck stops

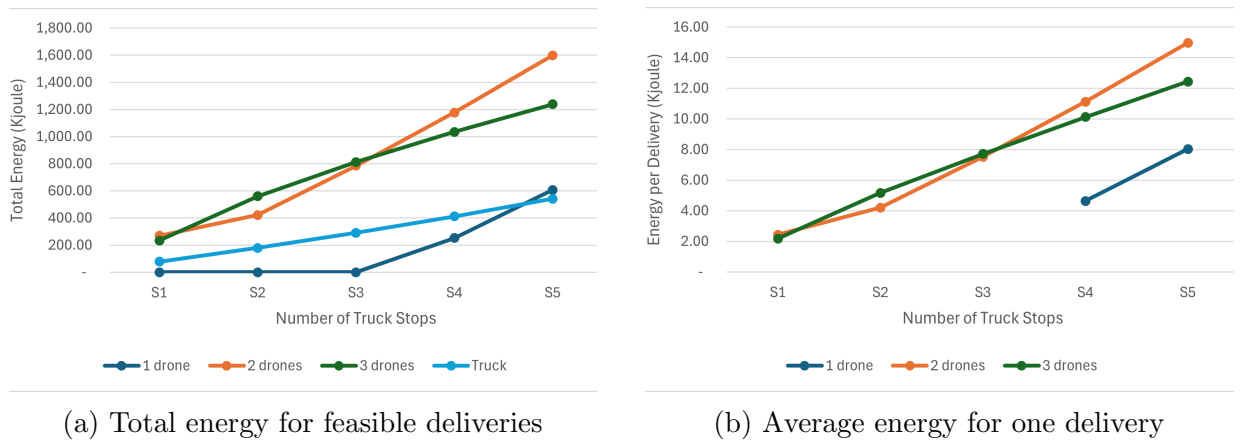


Figure 3.14: Energy consumption under varying fleet size and truck stops

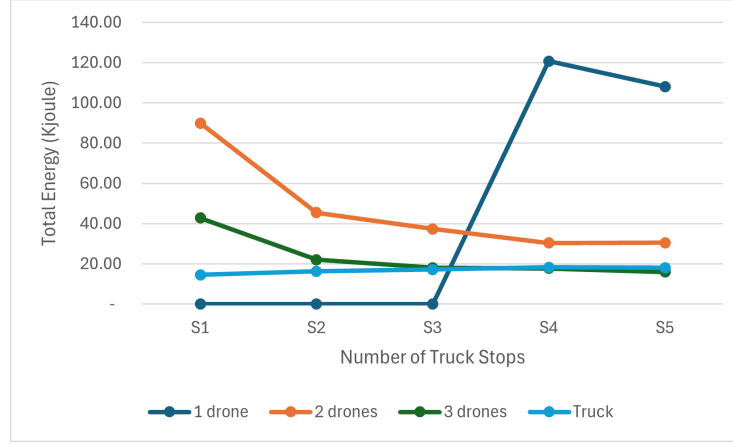


Figure 3.15: Total energy for Monday deliveries

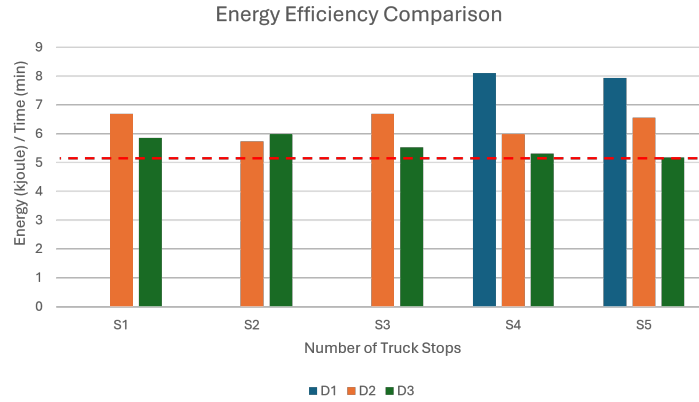


Figure 3.16: Energy efficiency comparison of varying fleet size and truck stops

3.8 CONCLUSION

This study presents a holistic and data-driven approach to truck-drone collaboration, bridging the gap between theoretical models and real-world applications. By leveraging machine learning and battery energy considerations, we offer an AI Engine framework that supports

operational decisions mainly on fleet optimization. By leveraging the SOFM machine learning algorithm, we have identified distance optimal truck stops for a residential setting with realistic synthetic delivery data. We then proposed a machine learning-based drone energy model that optimizes battery usage without the need for charging facilities to complete a delivery scenario and ran 93 delivery simulations on Matlab for one week’s data. Our comprehensive simulations identify delivery scenarios that would be infeasible without recharging the drones. Our findings demonstrate that deploying three drones at five truck stops results in the most energy-efficient delivery scenario, consuming 5.2 kJ/min, whereas deploying one drone at four stops yields the least energy-efficient outcome, consuming 8.1 kJ/min. However, it should be noted that the results are delivery-dependent, and the approach taken in this study represents the primary contribution towards achieving time and energy-efficient TDCD systems.

The immediate market adoption of this approach may face certain limitations, primarily due to the lack of consideration for complex urban environments. Factors such as parking restrictions, dynamic traffic patterns, and high-rise buildings could significantly impact the feasibility of implementation. Additionally, the absence of real-world operational logistics data may hinder the refinement of predictive models and decision-making processes, limiting the framework’s adaptability to practical deployment scenarios.

One promising direction involves scaling this approach to larger and more complex urban environments, where increased delivery density and dynamic traffic patterns may influence optimal truck stop placements and drone deployment strategies. Further studies could integrate real-world data from operational logistics networks to refine the AI Engine

framework, enhancing its adaptability to various delivery conditions. Additionally, incorporating advanced machine learning techniques such as reinforcement learning or deep learning could improve decision-making models, allowing fleets to autonomously adjust routes and energy consumption based on real-time demand fluctuations.

As autonomous logistics continues to evolve, developing intelligent, self-optimizing systems will be critical for improving sustainability, responsiveness, and cost-effectiveness in fleet management. The insights gained from this research have the potential to inform future advancements in drone-based logistics, enabling more adaptive and cost-effective delivery strategies. By expanding on the foundation set in this study, future work can push the boundaries of AI-driven logistics, making drone-assisted deliveries more viable and scalable in urban and rural landscapes alike.

ACKNOWLEDGMENT

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ARTICLE 2- DATA-DRIVEN
OPTIMIZATION OF TRUCK-DRONE
COLLABORATIVE DELIVERY WITH
SHARED FLEET ALLOCATION

4.1 PUBLICATION STATEMENT

This chapter is based on the Journal article titled “Data-Driven Optimization of Truck–Drone Collaborative Delivery with Shared Fleet Allocation”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published at the Drones Journal in June 2026. DOI: 10.3390/drones10070476.

This article represents the core operational optimization component of the thesis by developing a data-driven MILP framework for truck–drone collaborative delivery using real-world Amazon Last Mile Routing Research Challenge data. Building upon the empirical drone energy and time regressors developed in the previous study, this work integrates those machine learning-based performance models directly into the optimization framework to support realistic fleet allocation, customer assignment, and truck stop selection decisions under operational and energy constraints. Overall, this article establishes the main methodological and optimization framework of the dissertation and demonstrates how coordinated truck–drone operations can improve delivery efficiency and energy performance under a realistic delivery scenario.

4.2 INTRODUCTION

The rapid growth of e-commerce has intensified operational pressures on last-mile logistics systems, where delivery speed, cost efficiency, and environmental sustainability are often

conflicting objectives. In recent years, collaborative truck–drone delivery concepts have emerged as a promising mechanism to improve service levels while reducing operational energy consumption [6, 13, 17]. By enabling uncrewed aerial vehicles (UAVs) [96] to serve spatially dispersed customers in parallel with a ground vehicle, Truck–Drone Collaborative Delivery (TDCD) systems aim to reduce route completion time and enhance asset utilization. However, despite substantial academic interest, a persistent gap remains between conceptual modeling studies and real-world operational feasibility.

A large portion of the TDCD literature formulates routing and scheduling problems using synthetic customer distributions, stylized energy functions, and manufacturer-specified drone performance parameters [13, 97–99]. While these assumptions enable tractable modeling and algorithmic development, they frequently overestimate achievable operational performance. Manufacturer-declared cruise speeds, battery endurance, and payload capacities are typically measured under idealized test conditions, whereas field deployments encounter aerodynamic disturbances, payload-induced degradation, battery aging effects, and operational handling delays. As a result, time and energy savings reported under ideal assumptions may not accurately reflect deployable systems. This discrepancy highlights the necessity for empirically grounded optimization frameworks capable of capturing realistic drone performance and route-level operational constraints.

This study addresses this gap by developing a route-based Mixed-Integer Linear Programming (MILP) [100] framework informed by empirical drone performance data modeling with fleet-constrained operational planning. The central objective is to determine the optimal allocation of a limited drone fleet across predefined truck delivery routes in order

to minimize total route completion time and total energy consumption. Unlike models that assume unlimited drone availability or independently optimized routes, this framework reflects industry practice: logistics operators typically manage a fixed fleet of trucks and drones that must be strategically distributed across multiple routes departing from a common depot.

The proposed framework combines three key components. First, historical delivery route data derived from the Amazon Routing Challenge dataset [101] are used to represent spatially and temporally realistic urban last-mile demand. These routes preserve actual customer densities, travel distances, and service sequencing characteristics. Second, drone performance models are calibrated using empirical flight test data collected for a DJI Matrice 100 platform (<https://www.dji.com/ca/support/product/matrice100> Accessed: 31 December 2025). Rather than relying solely on nominal specifications, regression-based models estimate drone flight time and energy consumption as functions of payload, speed, and horizontal travel distance. This empirical modeling approach captures observed deviations from manufacturer-declared performance, thereby enhancing realism. Third, a fleet-constrained MILP formulation determines the optimal number of drones allocated to each truck route under minimum and maximum allocation limits while simultaneously minimizing a weighted objective combining makespan (maximum route completion time) and total energy use.

The contribution of this study is four-fold. First, the proposed framework explicitly models shared drone fleet allocation across multiple concurrent truck routes, addressing a planning problem that remains comparatively underexplored in TDCD literature. Second,

the study integrates empirically trained surrogate models for drone energy and flight time directly into the optimization workflow, enabling data-driven estimation of operational performance beyond manufacturer-declared specifications. Third, the formulation introduces a workload-based coordination abstraction that captures the effect of parallel drone operations while avoiding the computational burden associated with explicit batch-level scheduling formulations. Fourth, the framework is evaluated using real-world Amazon last-mile routing data, enabling assessment under realistic spatial and operational conditions.

Manufacturer-reported battery specifications are typically obtained under controlled laboratory conditions and tend to overestimate the achievable endurance of uncrewed aerial vehicles (UAVs) in real-world operations. Empirical studies show that UAV energy consumption depends strongly on payload mass, flight dynamics, and operational conditions, resulting in significant deviations from nominal performance values [102, 103]. To accurately capture these effects, this study adopts a data-driven modeling approach in which drone energy consumption and flight time are estimated using regression models trained on empirical flight data. By focusing on realistic drone degradation effects and constrained fleet allocation, this study moves beyond idealized demonstrations of TDCD feasibility and toward deployable planning tools for logistics operators. The framework enables evaluation of trade-offs between speed improvement and energy consumption under empirically observed performance levels. The results therefore contribute to bridging the gap between academic optimization research and industrial last-mile delivery planning, demonstrating that coordinated truck-drone operations can achieve up to 24% reductions in delivery makespan and 16% reductions in total energy consumption relative to conventional truck-

only delivery; however, these improvements are scenario-dependent and may vary with fleet size, route configuration, customer allocation, and operational constraints.

To preserve tractability for route-level fleet allocation decisions, several operational factors, including stochastic weather variation, dynamic traffic evolution, detailed battery degradation, and explicit drone sequencing, are intentionally abstracted in the proposed framework. Accordingly, the model is positioned as a strategic planning and resource allocation tool rather than a high-frequency operational dispatching or real-time control framework.

This paper is structured as follows: Section 4.3 reviews the prior work and compares their contributions versus this work. Section 4.4 discusses the problem setting with details on the system configuration and the key assumptions. Section 4.5 presents the Amazon 2021 Routing Challenge Dataset. Section 4.6 explains the research methodology detailing the clustering approach, energy and time regressors and the MILP formulation as well as the computational experiments. Section 4.7 presents the efficiency gains achieved relative to conventional truck-only delivery. It further provides a sensitivity analysis examining the impact of varying objective function weights, fleet sizes, and the number of truck stops. Finally, Section 4.8 presents the concluding remarks for this work with directions for future research.

4.3 RELATED WORK

The recent body of literature on TDCD has evolved significantly in terms of system configuration, optimization techniques, and operational realism. Early and foundational works such as the Flying Sidekick Traveling Salesman Problem (FSTSP) introduced by [42] established one of the first formal optimization frameworks for coordinated truck–drone delivery. In the FSTSP, a single truck and a single drone operate collaboratively, where the drone is launched from the truck to serve eligible customers and subsequently rejoins the truck at another location while the truck continues its route. The objective is typically to minimize overall delivery completion time through synchronized truck–drone routing decisions. This formulation extended the classical Traveling Salesman Problem (TSP) by incorporating drone launch, retrieval, and synchronization constraints, and it became a foundational reference for subsequent TDCD research. Later studies and extensions summarized in [18] further expanded these routing-centric formulations under variants of TSP and VRP structures, including multiple drones, heterogeneous fleets, endurance constraints, and synchronization policies, generally under controlled operational settings.

These studies predominantly rely on MILP models combined with heuristic or meta-heuristic approaches (e.g., VNS, LNS) and demonstrate notable improvements in delivery completion time compared to truck-only systems. In doing so, they establish a strong methodological foundation and provide valuable insights into the benefits of synchronized truck–drone routing under controlled assumptions.

More recent contributions attempt to enhance operational realism by incorporating additional decision layers. For instance, Ref. [98] integrates assignment, routing, and scheduling decisions under en-route drone operations, showing significant time savings through improved synchronization. Similarly, Ref. [99] advances the literature by allowing flexible launch and recovery locations and jointly optimizing key logistical decisions. These studies represent important steps toward capturing the complexity of real-world operations, particularly in terms of coordination and system design, and provide a basis for further exploration of integrated decision-making in TDCD systems.

Another important research direction focuses on improving energy modeling fidelity. Studies such as [13, 104] incorporate payload-dependent energy consumption, battery constraints, and even vertical (3D) routing considerations, highlighting critical trade-offs between delivery time, altitude, and energy usage. Also, Ref. [105] analyzes the energy consumption of drones under different weather conditions versus diesel and electric trucks. Despite these advancements, most works still rely on analytical or physics-based energy approximations and do not leverage empirical or data-driven models calibrated from real drone operations. Furthermore, while some studies (e.g., [97]) introduce real-world elements such as urban road networks, they primarily serve as comparative analyses of operational modes and do not integrate detailed energy modeling or fleet optimization. Some studies [17, 106] focus strongly on environmental benchmarking evaluating the carbon emission savings versus deliveries with diesel and electric trucks.

Despite the rapid growth of TDCD optimization research, as summarized in Table 4.1, several important limitations remain. First, many existing studies assume route-dedicated

or predetermined drone fleets, while a comparatively limited amount of work investigates system-level allocation of a shared drone fleet across multiple concurrent delivery routes. Second, although operational realism has improved in recent years, drone performance modeling in TDCD optimization remains largely dependent on analytical approximations, manufacturer specifications, or simplified endurance assumptions that may not accurately reflect empirical flight behavior under realistic operating conditions. Third, detailed synchronization-based formulations often introduce substantial combinatorial complexity and limit scalability for realistic route instances and lead to the need for computationally tractable planning-oriented abstractions.

These limitations are not merely differences in input data or parameter values. Existing formulations are typically built around fixed fleet assumptions, simplified drone performance representations, and explicit synchronization structures embedded within the mathematical model. Consequently, adapting such models to the context considered in this study would require substantial reformulation rather than minor modifications. In particular, the optimization of drone allocation across multiple routes, the integration of empirically derived drone energy and flight-time models, and the use of a workload-based planning abstraction introduce modeling requirements that are generally not supported by existing TDCD formulations.

This study addresses these limitations through a data-driven truck–drone collaborative delivery framework that combines empirically derived drone energy and flight-time models with fleet-constrained optimization. In contrast to prior studies, the proposed MILP formulation treats drone allocation as a decision variable and jointly optimizes resource

Table 4.1: Literature gap table

Paper	Primary Optimization Focus	Real Route Data	Data source	Energy and Time Inputs	Drone fleet optimization
[105]	Drone facility location and truck routing under service-time constraints	X	National Household Travel Survey 2017.	Literature-based energy equations.	X
[106]	Sustainability-oriented operational simulation of drone-assisted delivery	X	Synthetic / idealized case built on a city map. 15 stops and 150 customers in total.	Relies on idealized manufacturer specs and simulation assumptions.	X
[104]	Energy-aware truck-drone routing with time windows	X	Uses randomly generated customers, 35 customers in total.	Relies on idealized manufacturer specs and simulation assumptions; considers payload impact on energy consumption.	X
[17]	Environmental and economic assessment of truck-drone delivery systems	X	Synthetic / scenario-based. Customers are randomly distributed by density.	Relies on idealized manufacturer specs and simulation assumptions.	X
[99]	Collaborative truck-drone routing and scheduling with flexible launch/recovery	X	Synthetic test instances; 8, 25, and 50 customers across multiple area sizes.	Truck/drone travel times based on rectilinear vs. Euclidean distances. No empirical energy model.	X
[97]	Comparative analysis of truck-drone operational delivery modes	X	Mainly synthetic scenarios plus a real-world case study based on Beijing city road-network data.	Primarily delivery-time, range, speed, and geographic-distribution inputs. No explicit energy model.	X
[98]	Collaborative truck-multi-drone routing and drone scheduling	X	Synthetic generated instances (10, 20, 50, and 100 customers across multiple densities).	Travel-time and endurance based inputs with payload-dependent onward/return endurance. No explicit empirical energy model.	X
[18]	Hybrid truck-drone routing optimization and heuristic coordination	X	Mostly synthetic benchmark and case-study style instances.	Predominantly distance/time-based routing inputs considering capacity and limited payload effects.	X
[13]	Energy-aware truck-drone delivery optimization with battery considerations	X	Synthetic instances / generated experiments.	Advanced time-energy modeling: payload and battery capacity, vertical ascent/descent effects.	X
This Work	Shared fleet allocation with empirical energy/time modeling and workload-based coordination	✓	Amazon Last Mile Routing Research Challenge dataset; real route data and route-level case study.	Empirically trained time and energy regressors; route-level operational inputs.	✓

distribution, delivery completion time, and energy consumption across multiple delivery routes. The Amazon last-mile routing dataset is employed to evaluate the framework under realistic spatial and operational conditions, thereby supporting a more operationally representative assessment of truck–drone collaboration.

4.4 PROBLEM SETTING

We consider a real-world urban last-mile delivery system consisting of three battery-electric trucks operating from a common depot as shown on Figure 4.1. Each truck is assigned to a predefined delivery route derived from the Amazon Routing Challenge dataset. Each route comprises a fixed sequence of customer locations with known geographic coordinates, and the truck visiting order is assumed to be predetermined. Therefore, truck routing decisions are not part of the optimization problem.

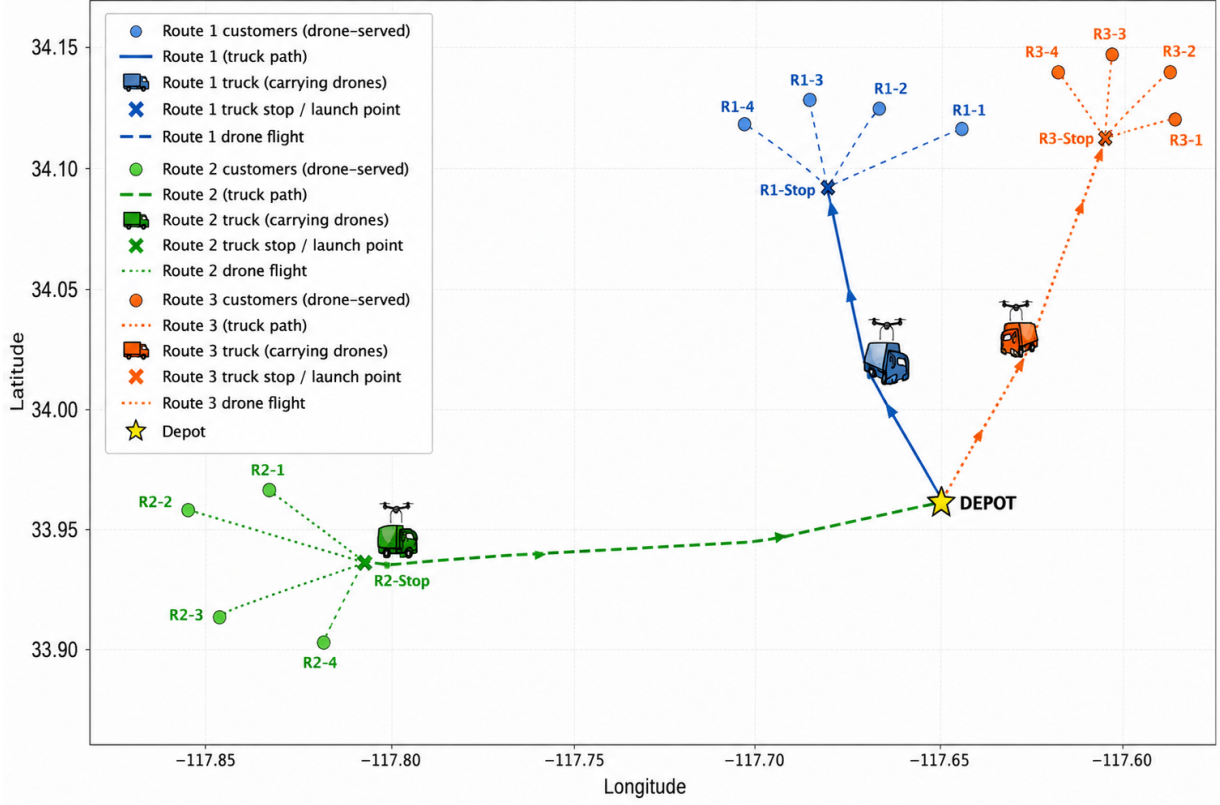


Figure 4.1: Overview of the delivery service area, truck routes, and drone service clusters.

A centrally managed fleet of homogeneous drones is distributed across the three routes. Let D^{tot} denote the total number of available drones. For each route $k \in \{1, 2, 3\}$, the number of drones assigned, D_k , must satisfy

$$D^{\min} \leq D_k \leq D^{\max}, \quad \sum_{k=1}^K D_k \leq D^{\text{tot}} \quad (4.1)$$

where $D^{\min}$ and $D^{\max}$ represent the minimum and maximum allowable number of drones

per truck, reflecting the physical capacity and operational coordination limits (see Table 4.2).

Trucks are modeled as battery-electric delivery vehicles (Fiat Ducato BEV (3.5t LH2 122LE)), while drones correspond to the DJI Matrice 100 platform. These platforms were selected because they provide experimentally validated and publicly documented operational specifications, including energy consumption, endurance, and battery-related performance parameters, which are comparatively difficult to obtain consistently for commercial delivery platforms. Their use therefore enables realistic calibration of truck and drone operational characteristics while maintaining transferability of the framework to alternative vehicle platforms through parameter adjustment. Drone missions are defined as round-trip sorties launched from truck stop locations to serve individual customers and return to the same launch point. The total drone travel distance includes both horizontal and vertical components. Specifically, each mission accounts for horizontal travel between the truck and customer locations, as well as vertical ascent and descent based on a fixed cruising altitude of 40 m. This altitude assumption reflects commonly adopted operational practices for drone deployment in suburban residential environments characterized by low-rise structures and minimal airspace obstruction. Given that this vertical profile is identical for every mission (i.e., fixed ascent and descent distances per takeoff and landing), the corresponding energy consumption and flight time associated with vertical movements are computed separately using the regression-based performance models and incorporated into the formulation as constant per-mission parameters (see Table 4.2). These vertical components are then added to the horizontal mission estimates within the MILP as exogenous

inputs, allowing the model to retain computational simplicity while preserving consistency with empirically derived drone performance. To preserve tractability within the planning-oriented optimization framework, several operational flight parameters, including cruising altitude, payload level, cruise speed, and service radius, are intentionally treated as fixed scenario parameters. Under these assumptions, the vertical ascent and descent profile remains identical across missions, allowing vertical flight energy and time contributions to be modeled as constant per-delivery operational terms without materially affecting relative assignment decisions. In contrast, horizontal flight distances vary significantly across customer–hub assignments and therefore remain the primary driver of energy-aware coordination and fleet allocation decisions.

Table 4.2: Model notation and parameters

Symbol	Description
Fleet Size and Allocation Limits	
K^{tot}	Number of routes
Tr^{tot}	Number of trucks
D^{tot}	Drone fleet size across all trucks
D^{min}	Minimum drones per truck
D^{max}	Maximum drones per truck
Vertical Flight Parameters (40 m Leg)	
E_v^{40}	Energy for one 40 m vertical leg
T_v^{40}	Time for one 40 m vertical leg
L^v	Vertical legs per delivery (up/down twice)
Drone Physics and Operational Parameters	
p	Drone payload capacity
T^{launch}	Drone launch overhead per package
v	Drone cruise speed
d^{max}	Maximum radial distance from stop to customer

Drone performance is represented using regression-based surrogate models that estimate energy consumption and flight time as functions of mission characteristics, including

travel distance, payload, and operational flight parameters. Unlike approximation-based approaches, these models are directly integrated into the optimization framework, and their outputs are evaluated exogenously for all feasible drone–customer assignments prior to optimization. The resulting energy and time estimates are then treated as deterministic input parameters within the model, ensuring both computational tractability and fidelity to empirically derived performance relationships. To ensure operational feasibility, a maximum service radius constraint of 10 km is imposed on drone missions, which effectively bounds the set of feasible drone–customer assignments. This threshold is defined as a conservative approximation of the effective operational range of the DJI Matrice 100 platform (see Table 4.2). The parameter values adopted throughout the study represent controlled scenario settings selected to isolate fleet allocation and coordination effects within the planning-oriented scope of the proposed framework.

Within each route, customers can be served either by the truck or by drones dispatched from selected truck stop locations. Truck stops are chosen from candidate locations (customer nodes), and selected stops are excluded from drone service. Drone operations are synchronized with truck movement, accounting for launch, recovery, and handling times within the delivery process.

The performance of each route is evaluated by its completion time (makespan), defined as the time required to complete all assigned deliveries. The system-level performance is

determined by the maximum completion time across all routes:

$$C_{\max} = \max_{k \in \{K\}} C_k \quad (4.2)$$

The optimization problem is formulated in Equation (4.5) as a weighted single-objective function that simultaneously captures operational efficiency and resource utilization. Although the proposed formulation includes assignment-related decision variables, the optimization problem extends beyond conventional static assignment-cost minimization commonly encountered in classical VRP formulations. In particular, the model jointly captures shared fleet allocation across concurrent routes, launch-stop activation decisions, workload-dependent drone coordination, and route-level makespan coupling. Unlike traditional VRP formulations where assignment costs are typically treated as fixed exogenous values, the proposed framework models workload scaling effects induced by parallel drone operations, where route completion times depend on the interaction between customer assignments, activated launch hubs, and the number of drones allocated to each route. Consequently, the optimization captures coordination dynamics and fleet-sharing effects that are not represented in classical assignment-based VRP formulations. Specifically, the objective minimizes a convex combination of total delivery time (makespan), total drone energy consumption, and the number of deployed drones, with respective weights of α_T , α_E , α_D adding up to 1. The selected weighting ranges were designed to illustrate trade-offs between delivery efficiency, energy consumption, and drone utilization under different planning preferences. To ensure comparability across these heterogeneous components,

each term is normalized as in Equation (4.3) using baseline performance metrics derived from conventional truck-only delivery operations in Amazon Routing Challenge Dataset. This normalization mitigates scale imbalances between time, energy, and fleet size, thereby enabling a balanced and interpretable trade-off within the objective function [107].

$$\min Z = \alpha_C \left(\frac{C_{\max}}{C_{\text{ref}}} \right) + \alpha_E \left(\frac{E_{\text{tot}}}{E_{\text{ref}}} \right) + \alpha_D \left(\frac{\sum_{k \in \mathcal{K}} D_k}{D_{\text{tot}}} \right) \quad (4.3)$$

Accordingly, the decision problem aims to jointly determine: (i) the allocation of a limited drone fleet across multiple routes, (ii) the selection of truck stop locations, and (iii) the assignment of customers to either a truck or drone service. These decisions are made to optimize overall delivery performance while respecting operational and energy constraints inherent to truck–drone collaborative systems.

In the proposed framework, the original Amazon route sequence is treated as a predefined truck traversal backbone rather than a routing decision variable. Customer locations along each predefined route are considered as candidate truck-stop locations. When a location is activated as a truck stop, the truck physically stops at that customer location and may launch drones to serve nearby assigned customers. Customers assigned to drone delivery are excluded from the truck-side service workload calculation, while customers not assigned to drones remain directly truck-served. The truck therefore follows the original predefined route structure, while the optimization model determines truck-stop activation, drone fleet allocation, and customer-to-drone assignment decisions. Additional operational overhead associated with drone launch and recovery activities at activated truck stops is

incorporated into the route completion-time calculation.

4.5 DATASET DESCRIPTION

The empirical analysis in this study is based on the Amazon Last Mile Routing Research Challenge dataset, a large-scale, historical dataset that captures detailed operational characteristics of last-mile delivery routes across multiple U.S. metropolitan areas [101]. The dataset contains 9184 historical delivery routes executed in 2018, divided into training and evaluation subsets, and includes rich information at the route, stop, and package levels. Unlike traditional benchmark datasets that rely on synthetic instances, this dataset reflects historical route data with representative operational constraints and driver behavior, making it particularly suitable for modeling operationally representative logistics scenarios. The original data are provided in structured JSON format, where each route is represented as a nested object containing route-level attributes (e.g., route identifier, departure time, vehicle capacity), a list of stops with geographical coordinates and sequencing information, and detailed package-level characteristics such as service times, dimensions, and time windows. To facilitate integration with the proposed optimization framework, the Json files were preprocessed and converted into tabular Csv formats. This transformation involved flattening hierarchical data structures, extracting relevant attributes, and constructing relational datasets linking routes, stops, and packages. Three delivery routes were identified from the Amazon Last Mile Routing Research Challenge dataset as originating from the same depot coverage region and were therefore selected for the

experimental case study. This shared-depot configuration was essential for evaluating the proposed shared drone fleet allocation framework across multiple concurrent truck routes operating within the same service area. Among the routes associated with the selected depot coverage region, thirteen candidate delivery routes were identified in the Amazon dataset. The average route size within this subset was approximately 157 delivery stops. The three routes selected for the case study exhibited customer counts (140, 151, 166) and route characteristics that were broadly consistent with this depot-level population while simultaneously satisfying the shared-depot requirement necessary for evaluating fleet-constrained drone allocation across concurrent routes. Consequently, the selected routes were not chosen as isolated examples but as operationally representative routes within the specific depot context considered in this study. The three route IDs (as stated on the dataset) selected for our problem are as follows: *Route1* – $ID_{b6cc07fea-86d2-41e4-9a58-cfc78956dcc7}$, *Route2* – $ID_{5486294a-503f-4346-b8a9-862e988cbe7c}$, *Route3* – $ID_{3f166f0e-fd2e-47ab-96a0-6cbc99cc6ee7}$.

Each Amazon delivery route is treated as a fixed truck path, where the visiting sequence is predetermined from operational data. The truck route itself is not optimized in the MILP; instead, the model optimizes the collaborative interaction between the truck and its onboard drones.

4.6 METHODOLOGY

Figure 4.2 presents the overall methodological workflow of the proposed planning-oriented truck–drone collaborative delivery (TDCD) optimization framework. The methodology integrates spatial clustering, empirically informed drone performance modeling, workload-aware coordination modeling, and MILP-based optimization to support coordinated truck–drone resource allocation and route-level delivery planning. The optimization model subsequently determines drone allocation, customer assignments, and activated truck launch hubs to minimize route-level makespan and energy consumption under coordinated TDCD operations.

The proposed formulation is intended as a planning-level resource allocation model rather than a detailed operational scheduling model. Consequently, several operational aspects commonly addressed in synchronization-based truck–drone formulations, including explicit drone sequencing, truck waiting decisions, detailed launch–recovery synchronization, and multiple drone sorties from the same launch location, are represented through aggregated workload approximations. This modeling choice was made to maintain computational tractability for realistic route instances while preserving the primary interactions between drone workload, fleet availability, and route completion times. The resulting framework is therefore most appropriate for tactical fleet planning and resource allocation decisions, whereas detailed operational scheduling remains an important area for future research.

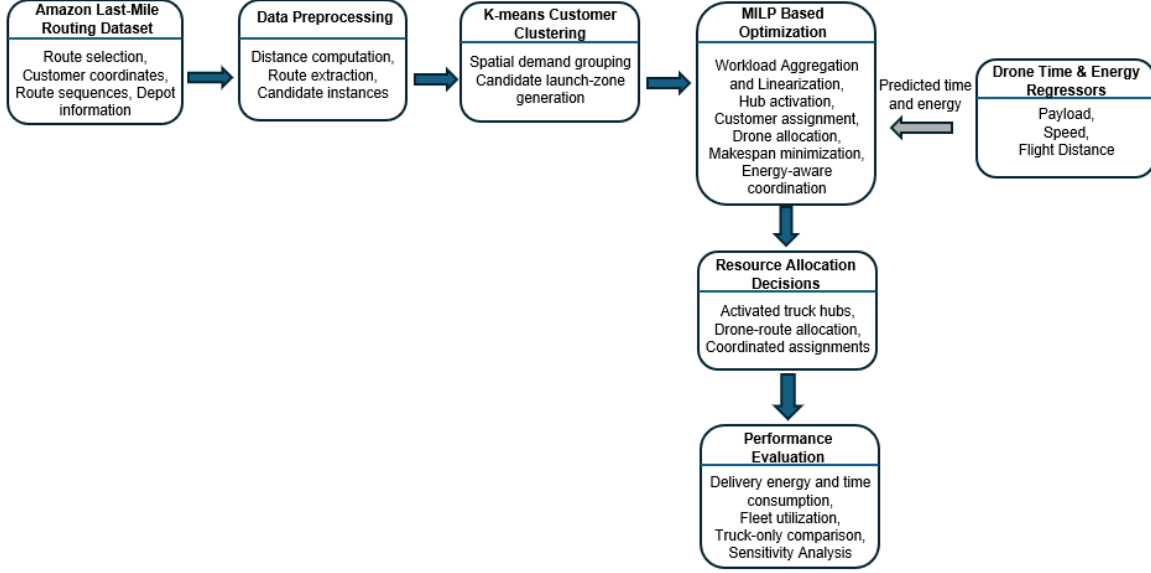


Figure 4.2: Methodological workflow of the proposed framework.

4.6.1 MACHINE LEARNING TOOLS

K-MEANS CLUSTERING

K-means clustering [108] is employed to partition customers into spatially compact service regions and, in doing so, to generate candidate truck-stop (drone launch) locations based on the spatial distribution of customer coordinates for each route. The clustering procedure acts as a preprocessing heuristic that reduces the candidate launch-location search space prior to MILP optimization. The cluster centroids are snapped to the nearest

actual customer locations, and the depot is always included as a candidate stop. Customers coinciding with selected truck stops are served directly by the truck, while remaining customers are eligible for drone delivery.

The final truck-stop (drone launch) coordinates are determined within the MILP by selecting from the set of candidate locations generated via K-means clustering, thereby endogenously identifying the most suitable stop positions for the optimization.

The drone battery range constraint is subsequently applied as a feasibility check to ensure that all customer–launch site distances within a cluster are operationally viable under the assumed drone endurance. Rather than driving assignment decisions across clusters, the battery constraint serves to validate the compatibility of the clustering structure with drone capabilities and to reveal situations where additional clusters or alternative service configurations may be required. Truck stops and drone launch sites are restricted to customer locations to preserve operational realism along the predefined delivery route, avoid introducing artificial stopping points that would require additional routing or feasibility modeling, and ensure that launch decisions remain consistent with the discrete stop structure observed in last-mile delivery operations.

At each truck stop, drone dwell time is modeled as the aggregate service workload assigned to that stop divided by the number of drones allocated to the corresponding route. This formulation approximates parallel drone dispatch under the assumption of balanced workload distribution across identical drones. Rather than explicitly modeling individual drone schedules or sequencing decisions, the total mission time at a stop is represented as

a function of cumulative assigned service time and available fleet capacity. This surrogate captures the synchronization constraint that the truck departs only after drone operations are completed while avoiding the combinatorial complexity of batch-indexed scheduling variables. Individual drone mission times are estimated using a trained regression model that approximates service duration under fixed operational assumptions.

Feasible drone assignments are restricted by (i) a maximum radial service distance of 10 km between customer and launch stop and (ii) a nearest-hub rule that limits each customer to at most two candidate launch stops. This pre-processing step reduces the combinatorial size of the assignment space and defines the feasible assignment set used in the optimization model.

Initially, the number of K-means-based truck stops was set to four per route to obtain a parsimonious partition with relatively even customer density across clusters, thereby supporting a balanced optimization structure. The number of candidate truck stops was not intended to represent a globally optimal clustering configuration. Instead, alternative cluster configurations were explored through sensitivity analysis in order to evaluate how truck–drone coordination behavior and fleet allocation decisions vary under different operational structures. The selected configuration provided a computationally tractable and operationally meaningful scenario for analyzing the interaction between delivery time, energy consumption, and shared drone fleet allocation.

ENERGY AND TIME REGRESSORS

The dataset used to train the drone energy and time regressors is taken from the work of Rodrigues et al. [90]. This large-scale dataset contains 209 flights, encompasses a total flight duration of 10 h and 45 min, spans the period from April to October 2019, and covers an aggregate distance of approximately 65 km. While extreme weather events (e.g., precipitation and high wind speeds) are avoided during data collection, care is taken to maintain a representative range of weather conditions and to prevent bias toward exclusively favorable weather. Flight data was collected at 25 m, 50 m, 75 m and 100 m with varying speeds of 4 m/s, 6 m/s, 8 m/s, 10 m/s, 12 m/s at different payloads of 0 g, 250 g, 500 g and 750 g.

The drone performance dataset, including voltage, current, flight time, positional data, altitude, speed, and payload, was preprocessed to ensure compatibility with the machine learning models. Specifically, raw electrical measurements were transformed into energy consumption metrics, and additional features such as horizontal and vertical travel distances, were derived from positional data to better capture distinct flight dynamics. These preprocessing steps enable a more structured representation of drone operations and support accurate prediction of energy and time consumption. Further details on the data processing pipeline and model development were provided in our previous work [109].

RandomForest Regressor is used for modeling time and energy consumption. For each

feasible customer–hub pair (i,s), horizontal flight time and energy are predicted as:

$$T_{is}^H = f_{\text{time}}(\text{payload, speed, distance}),$$

$$E_{is}^H = f_{\text{energy}}(\text{payload, speed, distance})$$

where payload and speed are fixed scenario parameters and distance corresponds to the horizontal Euclidean separation between the truck stop and customer. Vertical ascent and descent components are modeled at 40m altitude as fixed constants per delivery, contributing additional time (T^V) and energy (E^V). Instead of modeling separate handling time, a launch overhead parameter (30 s per delivery) is incorporated directly into each drone mission time, representing preparation and deployment activities.

The total drone energy consumption for both horizontal and vertical components is computed as follows:

$$E_{\text{tot}} = \sum_{(i,s)} (E_{is}^H + E^V) a_{is} \quad (4.4)$$

In this formulation, (a_{is}) is a binary decision variable that indicates the assignment of customer (i) to truck stop (launch location) (s).

To ensure the applicability of the regression models to the larger spatial scale considered in this study, the training dataset was extended to cover longer horizontal travel distances. In contrast to our previous work, where flight distances were relatively limited, the current problem involves drone missions of up to 4000 m. Accordingly, additional training samples were generated for both energy and time regressors at the selected cruise speed of 8 m/s and

for representative payload levels of 0 g and 500 g. This extension leverages the empirical observation that, for a fixed speed and payload, both energy consumption rate (Wh/km) and travel time rate (s/m or equivalently inverse speed) remain approximately constant over distance. Using these constant rates, synthetic data points were constructed by scaling energy and time proportionally with distance, thereby preserving the underlying physical relationships observed in the original dataset. This approach enables the regression models to generalize to longer-range missions while maintaining consistency with experimentally derived performance characteristics without requiring additional flight experiments. While this extrapolation preserves the dominant empirical relationships observed in the original dataset, the resulting long-range estimates should be interpreted as approximate operational projections rather than direct experimental measurements.

The results demonstrate two consistent and operationally meaningful trends in drone energy consumption, as shown in Figure 4.3. First, energy consumption per kilometer decreases as flight speed increases across all payload levels. This inverse relationship is particularly pronounced between 4 m/s and 8 m/s, where higher speeds improve aerodynamic efficiency and reduce energy expenditure per unit distance. Beyond approximately 10 m/s, however, the rate of improvement diminishes, indicating a region of diminishing marginal efficiency gains at higher speeds. Second, energy consumption increases with payload at all speed levels, reflecting the additional thrust and power required to sustain heavier loads. The effect of payload is systematic and shifts the energy curve upward without altering its overall shape, suggesting that payload primarily impacts the magnitude rather than the functional form of energy consumption. Together, these findings highlight

a trade-off between operational speed and payload weight, and support the identification of an efficient cruising regime, typically in the range of 8–10 m/s, where energy efficiency is optimized while accommodating varying payload demands.

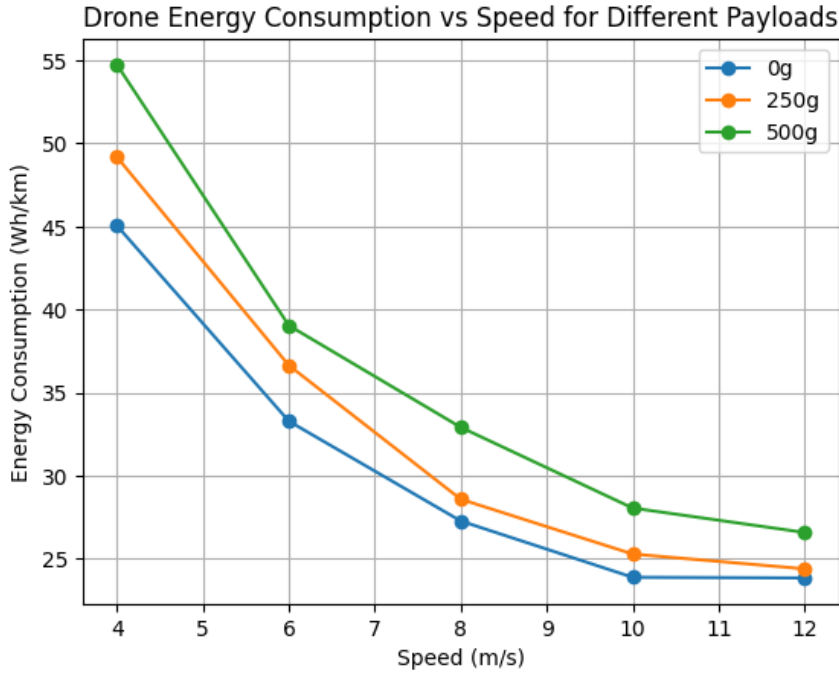


Figure 4.3: Drone energy consumption vs. speed for different payloads.

4.6.2 MILP FORMULATION

The TDCD problem is formulated as a mixed-integer linear program (MILP) that jointly optimizes drone fleet allocation, customer–hub assignments, and truck stop activation decisions under operational and energy constraints. The formulation adopts a decomposition between spatial candidate generation and operational decision-making to balance model

fidelity and computational tractability.

At the spatial level, candidate truck stop (drone launch) locations are generated exogenously using a route-specific K-means clustering procedure applied to customer coordinates. This preprocessing step defines a fixed set of potential launch hubs per route, capturing the spatial distribution of demand without imposing assignment decisions. The clustering stage therefore establishes the infrastructure layer of the system, i.e., the number and geographic placement of candidate stops, while deferring operational decisions to the optimization model.

At the operational level, the MILP determines (i) which candidate stops are activated, (ii) how customers are assigned to feasible hubs, and (iii) how a limited fleet of drones is allocated across routes. Importantly, customer-to-hub assignments are treated as endogenous decision variables rather than being fixed by the clustering outcome. As a result, customers may be assigned to non-nearest hubs when such reallocation improves system-level performance. This flexibility enables the model to balance service demand across hubs, reduce congestion effects, and mitigate route-level bottlenecks, in contrast to purely geometric clustering approaches that rely solely on spatial proximity.

To maintain computational tractability, the proposed workload-based synchronization formulation was intentionally designed as a planning-oriented approximation of coordinated truck–drone operations. Rather than explicitly modeling detailed drone dispatch sequences, batching decisions, or second-by-second synchronization events, the formulation aggregates drone service workload at activated launch hubs through an aggregate

dwelling time representation. This abstraction avoids the combinatorial complexity associated with explicit operational scheduling while preserving the dominant coordination effects influencing route completion time, including workload accumulation, launch preparation overhead, and synchronization-induced waiting behavior. Similar workload aggregation strategies have been widely adopted in vehicle routing and scheduling literature to approximate service operations and improve computational scalability. Accordingly, the objective of the formulation is not to replicate microscopic operational dispatch processes, but rather to provide a scalable system-level coordination representation suitable for strategic fleet allocation and infrastructure planning [110–112].

The objective function minimizes a normalized weighted combination of route makespan, total drone energy consumption, and fleet size, thereby capturing the trade-offs between delivery efficiency, energy usage, and resource deployment. The resulting formulation integrates data-driven drone performance estimates with system-level routing decisions in a unified optimization framework.

A key modeling choice in this work is the use of a surrogate dwell-time formulation to represent drone service operations at each hub. Earlier batch-indexed formulations, which explicitly model drone dispatching in discrete batches, introduce significant combinatorial complexity due to additional indexing dimensions and symmetry in equivalent batch configurations. This leads to weak linear relaxations and slow convergence of the optimality gap, even under extended solver time limits. The workload-based model, in which the surrogate dwell formulation aggregates drone service time at each hub into a continuous workload variable, was therefore adopted as a planning-oriented abstraction that preserves

route service burden while remaining solvable and decision-useful. This also suggests that explicit batch-level scheduling may be unnecessary for strategic fleet allocation in similar operating environments.

This modeling simplification yields a tighter and more computationally efficient formulation, enabling near-optimal or optimal solutions to be obtained within practical runtimes. By avoiding unnecessary combinatorial structure while preserving the essential operational dynamics of truck–drone coordination, the proposed MILP achieves a balance between realism and solvability suitable for real-world scale instances.

The truck delivery sequences are treated as predefined operational routes derived from observed Amazon delivery paths, allowing the optimization framework to focus specifically on drone fleet allocation and coordination decisions.

To formally model the TDCD problem, we define an MILP formulation that integrates fleet allocation, customer assignment, and hub activation decisions. The formulation is structured by first introducing the notation, followed by the objective function and constraints.

OBJECTIVE FUNCTION

The objective minimizes a normalized weighted combination of makespan, energy consumption, and fleet size:

$$\min \alpha_C \frac{C_{\max}}{C^{\text{ref}}} + \alpha_E \frac{\sum_{k \in \mathcal{K}} \sum_{(i,s) \in \mathcal{C}_k} (E_{is}^H + E^V) a_{is}}{E^{\text{ref}}} + \alpha_D \frac{\sum_{k \in \mathcal{K}} D_k}{D^{\text{ref}}} \quad (4.5)$$

The objective function in Equation (4.5) minimizes a normalized weighted combination of delivery time, energy consumption, and fleet size. Normalization of the objective function enables a balanced trade-off between time, energy, and fleet size, which are otherwise expressed in different units. This formulation therefore provides a computationally efficient yet operationally realistic framework suitable for large-scale, real-world instances.

The first term, $C^{\max}$, represents the system makespan, defined as the maximum completion time across all routes, thereby capturing the overall delivery efficiency of the system.

The second term aggregates the total drone energy consumption over all delivery missions. Specifically, E_{is}^H denotes the predicted horizontal energy required for a drone to serve customer i from launch stop s , while E^V represents the fixed vertical energy associated with ascent and descent. The binary variable a_{is} indicates whether customer i is assigned to stop s , ensuring that energy is only accounted for realized assignments.

The third term captures fleet utilization, where D_k denotes the number of drones allocated to route k . Unlike penalty-based formulations, fleet size is explicitly incorporated as a normalized objective component, allowing the model to directly trade off resource usage against time and energy performance.

The coefficients α_C , α_E , and α_D represent the relative importance of makespan, energy consumption, and fleet size, respectively. To ensure comparability across components with different units and scales, each term is normalized using the reference values C^{ref} , E^{ref} , and

D^{ref} . The values C^{ref} and E^{ref} are derived from the corresponding makespan and energy-performance measures of the conventional truck-only delivery scenario, whereas D^{ref} is set equal to the maximum allowable drone fleet size, which is 10 in the delivery scenario considered in this study.

Since truck routes remain fixed across scenarios, truck energy consumption primarily acts as a comparative baseline metric and is therefore not modeled as an endogenous optimization component.

Together, the objective function provides a unified performance measure that simultaneously captures system efficiency, energy consumption, and fleet utilization within a computationally tractable optimization framework.

CONSTRAINTS

Customer Assignment: Each customer must be served exactly once by a feasible stop:

$$\sum_{s \in \mathcal{S}_k : (i,s) \in \mathcal{C}_k} a_{is} = 1 \quad \forall i \in \mathcal{I}_k, \forall k \in \mathcal{K} \quad (4.6)$$

Stop Activation: Customer assignments are allowed only if the corresponding truck stop is activated:

$$a_{is} \leq y_s \quad \forall (i, s) \in \mathcal{C}_k, \forall k \in \mathcal{K} \quad (4.7)$$

Fleet Allocation Consistency: Let $\delta_{k,d}$ be a binary decision variable equal to 1 if route k

is assigned drone fleet level d , and 0 otherwise, where $d \in \mathcal{D} = \{1, \dots, 10\}$ represents the candidate number of drones assigned to a route. The following constraint requires each route to select exactly one fleet level, thereby ensuring a unique and internally consistent drone allocation for every truck route.

$$\sum_{d \in \mathcal{D}} \delta_{k,d} = 1 \quad \forall k \in \mathcal{K} \quad (4.8)$$

The number of drones assigned to each route is then determined by the selected allocation level.

$$D_k = \sum_{d \in \mathcal{D}} d \cdot \delta_{k,d} \quad \forall k \in \mathcal{K} \quad (4.9)$$

Total Fleet Constraint: The total number of drones allocated across all routes cannot exceed the available fleet capacity.

$$\sum_{k \in \mathcal{K}} D_k \leq D^{\text{tot}} \quad (4.10)$$

Stop Workload Aggregation: This constraint defines the total service workload at each stop as the sum of mission times for all assigned customers, including horizontal travel, vertical movement, and launch overhead.

$$\text{work}_s = \sum_{(i,s) \in \mathcal{C}_k} (T_{is} + T^{\text{vert}} + T^{\text{launch}}) a_{is} \quad \forall s \in \mathcal{S}_k, \forall k \quad (4.11)$$

Workload Linearization: The following constraints linearize the nonlinear relationship between workload and drone allocation by approximating the division of workload by the number of drones.

First, the upper bound ensures that the scaled workload does not exceed the workload divided by the selected drone level.

$$v_{s,d} \leq \frac{1}{d} \text{work}_s \quad \forall s, k, d \quad (4.12)$$

Second, activation of each linearization segment is controlled by the drone allocation decision.

$$v_{s,d} \leq \frac{1}{d} \text{WorkUB}_s \delta_{k,d} \quad \forall s, k, d \quad (4.13)$$

Third, a lower bound ensures the tightness of the linearization using a McCormick-type formulation.

$$v_{s,d} \geq \frac{1}{d} \text{work}_s - \frac{1}{d} \text{WorkUB}_s (1 - \delta_{k,d}) \quad \forall s, k, d \quad (4.14)$$

The scaled workload is then reconstructed by aggregating across all allocation levels.

$$v_s = \sum_{d \in \mathcal{D}} v_{s,d} \quad \forall s, k \quad (4.15)$$

Dwell Time Definition: The dwell time at each stop is defined as the scaled workload,

representing the effective service time after accounting for parallel drone operations.

$$W_s = v_s \quad \forall s, k \quad (4.16)$$

Stop Activation Gating: The non-negative dwell-time variable ($W_s \geq 0$) is gated by the stop activation decision. When $y_s = 0$, the constraint enforces $W_s \leq 0$, which together with non-negativity implies $W_s = 0$. When $y_s = 1$, the dwell time may vary up to its prescribed upper bound WorkUB_s .

$$W_s \leq \text{WorkUB}_s y_s \quad \forall s, k \quad (4.17)$$

Makespan and Route Completion Time: To capture system-level performance under parallel route execution, the model distinguishes between route-level completion times and the overall mission makespan.

Makespan Definition: The makespan represents the maximum completion time across all routes and is defined as:

$$C_{\max} \geq C_k, \quad \forall k \in \mathcal{K}. \quad (4.18)$$

$C^{\max}$ denotes the mission makespan (in minutes), corresponding to the time at which all routes are completed. Equation (4.18) ensures that the makespan is at least as large as the completion time of each individual route. Consequently, minimizing $C^{\max}$ leads to minimizing the overall mission duration under parallel truck operations.

Route Completion Time: The completion time of each route is defined as the sum of truck travel time, truck service time, launch overheads, and drone service (dwell) time:

$$C_k = T_k^{\text{base}} + \sum_{i \in \mathcal{I}_k^{\text{truck}}} S^{\text{truck}} + \sum_{s \in \mathcal{S}_k} O^{\text{launch}} y_s + \sum_{s \in \mathcal{S}_k} W_s, \quad \forall k \in \mathcal{K}. \quad (4.19)$$

In this formulation, (C_k) denotes the completion time of route (k) (in minutes). The term (T_k^{base}) represents the precomputed truck travel time along the original route sequence derived from the dataset. The set $(\mathcal{I}_k^{\text{truck}})$ denotes the subset of customers served directly by the truck, and (S^{truck}) corresponds to the fixed service time required at each such stop. The parameter (O^{launch}) captures the fixed overhead associated with activating a drone launch operation at stop (s), which is incurred only if the stop is selected for drone operations (i.e., $(y_s = 1)$). Finally, (W_s) denotes the drone dwell time at stop (s), representing the total time required to complete all drone deliveries dispatched from that location.

Energy Feasibility: Equation (4.20) represents an optional mission-level energy feasibility constraint that can be used to restrict drone assignments exceeding available battery capacity. In the computational experiments reported in this study, operational feasibility was primarily enforced through a conservative maximum service-radius threshold and pre-processing of feasible customer-launch assignments rather than explicit battery-capacity enforcement.

$$(E_{is}^H + E^V) a_{is} \leq \bar{E} \quad \forall (i, s), k \quad (4.20)$$

In this formulation, customer assignments, hub selection, and drone allocation decisions are handled within a single integrated model, subject to operational constraints that reflect real-world conditions. Instead of explicitly tracking each drone’s dispatch sequence, drone activity at a given launch stop is approximated through a workload-based representation, where service effort is accumulated at the stop level. This modeling choice avoids introducing detailed scheduling variables, which would otherwise increase the problem size considerably. At the same time, it preserves the key effect of having multiple drones operating in parallel, without the associated computational burden.

The interaction between truck and drone operations is enforced through the makespan constraint (Equation (??)), which ensures that route completion time accounts for both truck travel and drone service activities. This reflects the tightly coupled nature of truck–drone collaboration, where delays at launch stops directly impact overall route performance.

A key feature of the formulation is the explicit modeling of workload sharing across drones. Constraints (Equations (4.12)–(4.15)) collectively provide an exact mixed-integer linear reformulation of the nonlinear relationship between service workload and drone fleet size. By discretizing drone allocation levels and employing a disaggregated linearization with auxiliary variables, the model captures the inverse dependency between service time and the number of available drones without introducing nonlinear terms.

This reformulation enables the model to approximate parallel drone operations while maintaining linearity, leading to significantly improved computational tractability com-

pared to detailed batch-based scheduling approaches. The proposed formulation intentionally balances operational fidelity and computational scalability by abstracting several detailed operational processes, including explicit drone sequencing, mission-level synchronization, waiting times, stochastic weather effects, dynamic battery degradation, and real-time dispatching behavior, through aggregate workload representations and fixed scenario parameters. While these abstractions may not capture all localized operational bottlenecks or mission-level imbalances, they preserve the dominant coordination and fleet allocation dynamics relevant to tactical planning of fleet-constrained truck–drone delivery systems across realistic route-scale instances.

4.6.3 COMPUTATIONAL EXPERIMENTS

From the processed data, several key inputs required for the optimization framework were derived. Customer locations were obtained from the stop-level latitude and longitude coordinates, which, despite being anonymized and slightly perturbed, preserve the spatial structure necessary for distance-based modeling. The observed stop sequences provided in the dataset were used to reconstruct the truck delivery paths for each route, serving as the baseline for conventional truck-only operations. Pairwise transit time matrices between stops were also utilized to compute travel times along these observed sequences, enabling estimation of route-level performance metrics such as total delivery duration. To construct the TDCD optimization instances, three delivery routes sharing a common depot region were selected from the dataset to represent concurrent suburban last-mile delivery

operations. The selected routes exhibit realistic customer densities, spatial diversity, and moderate-to-large customer counts suitable for evaluating shared drone fleet allocation and coordinated truck–drone operations. Candidate truck stop locations were generated from customer nodes through clustering-based spatial grouping while preserving the original route structure and depot assignments. These preprocessing steps enabled the construction of a consistent and computationally tractable optimization dataset while maintaining fidelity to realistic delivery dynamics and operational routing characteristics.

The proposed MILP formulation was solved on Python 3.10.18 using the Gurobi Optimizer version 11.0.3. (<https://www.gurobi.com/> Accessed: 31 December 2025), a state-of-the-art commercial solver for large-scale mixed-integer programming problems. Gurobi employs a branch-and-bound framework augmented with advanced techniques such as cutting planes, pre-solve reductions, primal heuristics, and symmetry detection to efficiently explore the solution space [113].

Given the combinatorial complexity introduced by center selection, binary assignment decisions, and integer drone allocation, the problem belongs to the class of NP-hard optimization problems and is computationally demanding. The model is formulated as a linear MILP, where nonlinear operational relationships (e.g., assignment-dependent time and energy contributions) are embedded through linear expressions and logical constraints. In particular, Big-M formulations [114] are used to enforce conditional relationships such as hub activation and assignment feasibility.

To balance solution quality and computational efficiency, a relative optimality gap of

1% was imposed. The optimization process was terminated when either (i) the relative optimality gap fell below this threshold or (ii) a maximum wall-clock time of 3600 s was reached. In Gurobi, the relative optimality gap is defined as the difference between the best incumbent (primal) solution and the best bound (dual bound), normalized by the absolute value of the incumbent objective.

The final optimization model contained 2619 constraints, 1077 variables, and 22,994 non-zero coefficients, including 929 integer variables of which 926 were binary. After pre-solve reduction, the model size decreased to 323 constraints and 565 variables. Gurobi explored a single branch-and-bound node and converged to an optimal solution within the specified tolerance in approximately 1.84 s, with a final MIP gap of 0.3167%. These results demonstrate that the workload-based coordination formulation remains computationally tractable for the considered multi-route planning instance while avoiding the substantially larger combinatorial complexity typically associated with explicit drone sequencing and batch-indexed synchronization models.

The HiGHS solver was also evaluated during preliminary analyses, but its solution quality and computational performance were comparable to those obtained with Gurobi.

4.7 RESULTS

4.7.1 PARAMETER SETTINGS

The experimental parameter settings used in this study are summarized in Table 4.3. The objective function weights are set to $\alpha_C = 0.50$, $\alpha_E = 0.40$, and $\alpha_D = 0.10$. This configuration prioritizes delivery time (makespan) as the primary performance metric while still incorporating energy efficiency and fleet utilization considerations.

The selected weights reflect the operational emphasis of last-mile logistics systems, where timely delivery is critical, but energy consumption and resource efficiency remain important secondary objectives. A sensitivity analysis of these parameters is conducted to evaluate the robustness of the solution with respect to different operational priorities.

Table 4.3: Experimental parameter settings.

Symbol	Value	Description
<i>Fleet Size and Allocation Limits</i>		
K^{tot}	3	Number of routes
T_r^{tot}	3	Number of trucks
D^{tot}	10	Drone fleet size across all trucks
D^{min}	1	Minimum drones per truck
D^{max}	10	Maximum drones per truck
<i>Vertical Flight Parameters (40 m Leg)</i>		
E_v^{40}	3.107 Wh	Energy for one 40 m vertical leg
T_v^{40}	40.408 s	Time for one 40 m vertical leg
L^v	4	Vertical legs per delivery (up/down twice)
<i>Drone Physics and Operational Parameters</i>		
p	500 g	Drone payload capacity
T^{launch}	30 s	Drone launch overhead per package
v	8 m/s	Drone cruise speed
d^{max}	10 km	Maximum radial distance from launch stop to customer
$\mathbb{K}^{\text{bat}}$	0	Battery feasibility enforced (0 = not enforced)

4.7.2 OPERATIONAL INTERPRETATION AND VALIDATION OF THE WORKLOAD-BASED APPROXIMATION

To further evaluate the operational realism of the proposed workload-based coordination approximation, the formulation was analyzed from a behavioral perspective rather than as a detailed real-time dispatch simulator. The surrogate synchronization mechanism aggregates drone service workload at activated truck hubs to approximate truck dwell requirements associated with launch preparation, coordination, and drone recovery operations. The resulting optimization behavior demonstrated several operationally realistic patterns. First, the results exhibited diminishing marginal improvements in makespan as additional drones were allocated, indicating the presence of synchronization and coordination bottlenecks rather than unrealistic linear scalability. Second, routes with higher assigned drone workload generated increased synchronization-related dwell contributions consistent with practical truck-drone coordination requirements. Third, the optimization allocated drones non-uniformly across routes (e.g., 3–4–3 allocation), suggesting adaptive resource balancing based on route workload characteristics rather than symmetric or arbitrary assignment patterns. Additionally, comparative analysis against a simplified coordination assumption without workload-dependent synchronization effects showed that ignoring truck–drone coordination requirements led to systematic underestimation of route completion times. This observation supports the importance of incorporating aggregate synchronization behavior within planning-oriented TDCD optimization models while preserving computational tractability.

4.7.3 SENSITIVITY ANALYSIS OF OBJECTIVE WEIGHTS

To evaluate the impact of objective function weighting on system performance, a sensitivity analysis was conducted by varying the relative importance of delivery time and energy consumption while maintaining a consistent modeling framework. The results, as shown in Table 4.4, reveal clear trade-offs between time efficiency and energy consumption, as well as structural stability in the optimal drone allocation.

Table 4.4: Objective weight sensitivity analysis: impact of time and energy priorities on system performance.

ID	α_C	α_E	α_D	Gap (%)	Makespan (min)	Energy (Wh)	Drone Allocation
1	0.0	1.0	0.0	0.0	863.9	12,033	1–4–1
2	0.2	0.7	0.1	0.0	405.3	12,033	2–3–3
3	0.4	0.5	0.1	0.0	357.9	12,033	3–4–3
4	0.5	0.4	0.1	0.0	357.9	12,033	3–4–3
5	0.6	0.3	0.1	0.0	357.9	12,033	3–4–3
6	0.8	0.1	0.1	0.0	358.1	12,037	3–4–3
7	1.0	0.0	0.0	0.0	357.9	14,961	3–4–3

When the objective function prioritizes energy minimization (0% time, 100% energy), the model yields the lowest total energy consumption of 12,033 Wh. However, this comes at the expense of significantly degraded service performance, with a makespan of 863.9 min.

The corresponding drone allocation (1–4–1) indicates a highly imbalanced and minimal deployment of resources, which limits parallelization and leads to prolonged completion times.

As the weight on delivery time increases, a substantial reduction in makespan is observed. Even a modest inclusion of time in the objective (20% time, 70% energy) reduces the makespan by more than 50%, dropping to 405.3 min, while maintaining the same total energy consumption. This demonstrates that time improvements can initially be achieved with negligible energy trade-offs.

Allocating more weight to delivery time results in only marginal gains. Starting from a 40% time weight, the makespan levels off at around 357.9 min, suggesting that the system has reached its efficiency limit under the current constraints. Interestingly, this plateau aligns with a consistent drone allocation pattern of (3–4–3), indicating that this configuration provides a well-balanced distribution of workload across the routes.

In contrast, when the objective function fully prioritizes time minimization (100% time, 0% energy), the makespan remains at its minimum value (357.9 min), but the total energy consumption increases significantly to 14,961 Wh. This reflects the model’s tendency to utilize more energy-intensive delivery patterns to achieve marginal time gains, highlighting a clear trade-off between speed and energy efficiency.

Overall, the results indicate that energy-focused optimization leads to substantial time penalties and time-focused optimization leads to increased energy consumption. A balanced weighting (40–60% time) achieves near-optimal makespan with minimal additional energy cost. The drone allocation stabilizes across a wide range of weights, suggesting

robustness in the optimal resource configuration.

4.7.4 SENSITIVITY ANALYSIS OF RESOURCE ALLOCATION: DRONE FLEET AND TRUCK STOPS

To further evaluate the robustness and operational implications of the proposed framework, a sensitivity analysis is conducted on two key decision variables: drone fleet size (Table 4.5) and the number of truck stops (Table 4.6). These parameters directly influence the degree of parallelization in last-mile delivery and the spatial configuration of the delivery network, thereby affecting both delivery makespan and total energy consumption.

Table 4.5: Impact of drone fleet size on system performance.

Metric	Number of Drones				
	6	7	8	9	10
Time (min)	502	484	405	382	358
Energy (Wh)	12,033	12,033	12,033	12,033	12,033

Table 4.6: Impact of number of truck stops on system performance.

Metric	Number of Truck Stops				
	3	4	5	6	7
Time (min)	374	358	352	345	336
Energy (Wh)	13,872	12,033	11,590	10,996	10,424

The number of drones determines the system’s service capacity and the extent to which deliveries can be executed concurrently, while the selection of truck stops governs the proximity between launch points and customer locations. Together, these factors define the trade-off between operational efficiency and resource utilization.

The reduction in total makespan with increasing drone count is driven by the model’s ability to exploit the parallelization of delivery tasks. As more drones are allocated to a route, multiple deliveries can be executed simultaneously from each truck stop, effectively reducing the dwell time associated with servicing assigned customers. Under the adopted workload-based formulation, the service demand at each stop is distributed across the available drones, resulting in shorter completion times and improved overall delivery efficiency.

However, this improvement exhibits diminishing returns beyond a certain fleet size. As observed in the results, the makespan reduction becomes marginal after approximately eight drones, with the curve approaching a plateau. This behavior arises because the system transitions from being resource-constrained to workload-constrained. Once sufficient drones are available to serve most deliveries in parallel, additional drones remain underutilized, as there are no remaining tasks that can be further parallelized. At this point, the makespan is primarily governed by the longest individual delivery times and residual synchronization effects across truck stops, rather than by fleet size.

In contrast, the total drone energy consumption remains largely invariant with respect to the number of drones. This is because the model operates on a fixed set of delivery tasks, where each customer is served exactly once, and the energy required for each mission

is determined by distance-based regression estimates and fixed vertical flight components. Increasing the number of drones does not reduce the number of trips or the energy required per trip; it only redistributes the workload across more resources.

Consequently, while a larger drone fleet reduces makespan through increased concurrency, it does not yield proportional energy savings. The total energy consumption is additive over all delivery assignments and independent of fleet size, reflecting a clear separation in the model between time efficiency (resource-driven) and energy demand (workload-driven).

The reduction in total makespan with an increasing number of truck stops (Table 4.6) is primarily driven by improved spatial proximity between launch locations and customers. As more truck stops are introduced, the service area is partitioned into smaller clusters, reducing the average distance between each customer and its assigned launch point. This leads to shorter drone travel times per mission and consequently reduces the dwell time required at each stop, resulting in a lower overall completion time.

In contrast to the drone count case, the total drone energy consumption also decreases as the number of truck stops increases. This is because energy usage is directly dependent on the travel distance of each delivery mission, and shorter horizontal distances lead to lower energy requirements. By enabling more localized service regions, additional truck stops reduce the average trip length, thereby decreasing the cumulative energy consumed across all deliveries.

Consequently, increasing the number of truck stops improves both time and energy

performance. This reflects a structural difference from fleet expansion, where resource parallelization affects only temporal efficiency. In this case, enhanced spatial configuration directly reduces the workload intensity per delivery, leading to simultaneous gains in operational efficiency and energy consumption.

4.7.5 AMAZON TRUCK DELIVERY PERFORMANCE AS A BENCHMARK

The benchmark performance of the conventional truck-only delivery system as shown in Table 4.7 is derived using transit and service times obtained directly from the Amazon Routing Dataset, while incorporating an additional 30 min break per route to reflect realistic operational conditions not captured in the dataset. A fixed 30 min break time is incorporated into the conventional truck-only delivery benchmark to account for driver rest requirements. In contrast, within the TDCD setting, operational dynamics differ, as periods of reduced driving workload during drone dispatch and service can partially accommodate rest or recovery activities. The transit time for each route is calculated based on the total travel distance, including both the forward route and return to the depot, assuming a constant average truck speed of 30 km/h, which represents a reasonable operating speed for delivery vehicles in residential suburban environments.

$$T_k^{\text{transit}} = \frac{d_k^{\text{route}} + d_k^{\text{return}}}{v_{\text{truck}}} \quad (4.21)$$

Table 4.7: Conventional truck delivery benchmark results.

Route	Distance (km)	Transit Time (h)	Service Time (h)	Break (h)	Total Time (h)	Total Time (min)	Energy (Wh)
Route 1	57.52	3.67	2.69	0.50	6.86	411.60	13,532
Route 2	86.96	4.51	2.47	0.50	7.48	448.80	20,458
Route 3	73.74	4.01	3.39	0.50	7.90	474.00	17,348
Total/Max	218.23	–	–	–	7.90	474.00	51,338

Service time is derived from empirical delivery data and reflects the average parcel handling time observed in the Amazon routing dataset. For each route, total service time is computed as the product of the number of parcels and the corresponding average service time per parcel. To account for operational constraints, a fixed 30 min break is added to each route.

$$T_k^{\text{service}} = n_k \cdot \tau_k \quad (4.22)$$

$$T_k^{\text{total}} = T_k^{\text{transit}} + T_k^{\text{service}} + T^{\text{break}} \quad (4.23)$$

The total delivery time is then obtained as the sum of transit time, service time, and break duration. The system makespan is defined as the maximum completion time across all routes, representing the overall delivery horizon for the fleet.

$$C_{\max} = \max_k \{T_k^{\text{total}}\} \quad (4.24)$$

$$e^{\text{truck}} = \frac{e^{\text{empty}} + e^{\text{full}}}{2} \quad (4.25)$$

$$E_k = e^{\text{truck}} \cdot (d_k^{\text{route}} + d_k^{\text{return}}) \quad (4.26)$$

Truck energy consumption is estimated using an average energy intensity value derived from the literature. Specifically, the energy consumption rate is calculated as the mean of empty and fully loaded vehicle conditions reported in [106], resulting in an average of 235.25 Wh/km. Total energy consumption per route is then computed by multiplying this rate with the corresponding route distance, including the return leg.

This benchmark serves as the baseline for evaluating the performance improvements achieved through truck–drone collaborative delivery in terms of both delivery time and energy efficiency.

4.7.6 SYSTEM-WIDE PERFORMANCE OVER CONVENTIONAL DELIVERY BENCHMARK

The performance of the proposed TDCD system is evaluated against the conventional truck-only benchmark in terms of both delivery time (makespan) and total energy consumption. As summarized in Table 4.8, a Pareto-optimal solution selected from the time–energy trade-off analysis achieves a substantial reduction in system makespan, decreasing from

474 min in the baseline scenario to 358 min under collaborative operations. This corresponds to an improvement of approximately 24.5%, indicating a significant enhancement in delivery efficiency through parallelization of last-mile operations via drones.

Table 4.8: Performance improvement of the truck–drone collaboration relative to the conventional truck-only benchmark.

	Truck-Only Baseline	Proposed TDCD Framework	Improvement (%)
Total time (min)	474	358	24.5%
Truck energy (Wh)	51,338	30,984	39.6%
Drone energy (Wh)	–	12,033	–
Total energy (Wh)	51,338	43,017	16.2%
Energy per delivery (Wh)	112.60	94.30	16.3%
Distance travelled (km)	218.23	578.80	–165.2%
Energy per km (Wh)	235.25	74.32	68.4%
# of Truck Customers	456	12	–
# of Drone Customers	–	444	–
Drone utilization	n/a	3–4–3	–

The total energy consumption reported for the truck–drone collaborative delivery system (43,017 Wh) represents the combined energy usage of both truck and drone operations. Drone energy consumption is optimized within the MILP formulation using regression-

based mission energy estimates for all customer–launch assignments, including both horizontal and vertical flight components. The optimized drone delivery component obtained from the MILP solution equals 12,033 Wh. Truck energy consumption is evaluated separately based on the customers and launch locations assigned to truck service under the optimized truck–drone collaboration strategy. Unlike the truck-only baseline, where the truck serves all customers along the original Amazon delivery route, the collaborative delivery scenario reallocates a portion of customers to drones. Consequently, the truck is required to visit only the remaining truck-served customers and selected drone launch locations, resulting in shorter truck travel distances and lower energy consumption. The resulting truck operational energy across the three routes is 30,983 Wh, calculated using the truck energy intensity formulation presented in Equation (4.25).

From an energy perspective, the collaborative system reduces total consumption from 51,338 Wh to 43,017 Wh, which corresponds to an improvement of about 16.2%. Although this reduction is smaller than the gain in delivery time, it reflects the expected trade-off between speed and energy use. In practice, deploying more drones helps complete deliveries faster, but also adds to overall energy consumption due to additional flight operations.

Taken together, these results show that the truck–drone framework can improve overall system performance by reducing both delivery time and energy use compared to a conventional truck-only approach. The benefits largely stem from coordinated resource allocation and the ability to serve customers in parallel, which supports the practicality of hybrid delivery systems in last-mile logistics.

It is also worth noting that these improvements are obtained using historical delivery routes and empirically derived drone performance models, providing an operationally representative evaluation environment.

4.7.7 SUSTAINABILITY PERFORMANCE

Electric vehicles do not produce tailpipe emissions during operation; however, carbon emissions are indirectly generated through the electricity used to charge their batteries [115]. These use-phase indirect emissions depend on both the amount of energy consumed and the carbon intensity of the electricity grid supplying that energy. In this study, energy consumption is explicitly modeled based on realistic operational conditions, allowing for a consistent comparison between conventional and TDCD scenarios.

As a result, any reduction in total energy consumption achieved through TDCD directly translates into proportional reductions in electricity-related carbon emissions. Nevertheless, assigning absolute emission values is challenging, as grid carbon intensity varies significantly across geographies and over time due to differences in energy-generation mixes. To maintain methodological transparency and avoid location-specific bias, this study focuses on relative energy and emission savings, acknowledging that absolute carbon impacts are contingent on the regional electricity context.

4.8 CONCLUSIONS AND FUTURE WORK

The data-driven optimization framework presented in this work for truck–drone collaborative last-mile delivery integrates historical delivery-route data with empirically derived energy and time models. Rather than relying on synthetic data or manufacturer specifications, this study uses the Amazon Last Mile Routing Dataset to build more realistic delivery scenarios, combined with regression-based estimates of drone performance. The problem is modeled as a mixed-integer linear program (MILP) that simultaneously determines truck stop locations, assigns customers, and allocates the drone fleet while accounting for operational and energy constraints.

The collaborative delivery framework shows clear improvements over a traditional truck-only approach. In the selected Pareto-optimal solution, delivery makespan decreases from 474 min to 358 min, an improvement of about 24.5%. Total energy consumption also drops from 51,338 Wh to 43,017 Wh, corresponding to a reduction of roughly 16.2%. Overall, these results demonstrate how coordinated truck–drone operations can improve delivery efficiency by enabling parallel service while still maintaining energy-efficient performance.

From an operational perspective, the proposed framework is intended as a tactical planning and resource allocation tool for logistics operators seeking to determine how limited drone fleets should be distributed across concurrent delivery routes prior to dispatch operations. Potential applications include evaluation of fleet-sizing strategies, identification of suitable truck–drone coordination structures, and assessment of trade-offs between delivery

efficiency and drone energy consumption under suburban last-mile delivery conditions.

While the proposed MILP framework demonstrates promising performance for planning-oriented truck-drone collaborative delivery coordination, several modeling assumptions and limitations should be acknowledged. First, the proposed workload-based dwell time approximation represents aggregate drone service workload at each truck stop as a function of allocated drone resources rather than explicitly modeling detailed drone sequencing, launch/recovery operations, or batch-level scheduling decisions. Although this surrogate formulation substantially improves computational tractability and captures high-level workload coordination effects, it does not guarantee a fully operationally feasible drone schedule. In particular, the model assumes relatively balanced workload distribution across homogeneous drones and does not explicitly capture launch pad congestion, drone reuse dependencies, queueing effects, synchronization delays, or truck-side operational conflicts that may arise during real-time deployment.

In addition, several operational parameters are treated as controlled planning assumptions to maintain tractability and isolate system-level coordination behavior. These include fixed drone cruising speed, payload, service altitude, and deterministic travel conditions. Weather variability, stochastic travel times, battery degradation effects, communication delays, airspace restrictions, and dynamic customer demand are not explicitly incorporated into the current formulation. The framework also faces scalability limitations as the size of the delivery network increases. Although the workload-based coordination approximation reduces combinatorial complexity compared to explicit scheduling formulations, the computational burden may still grow substantially for large-scale instances involving

hundreds or thousands of customers, routes, or drone resources.

Finally, the experimental analysis is based on selected routes from the Amazon Last Mile Routing Research Challenge dataset and controlled extensions of empirical drone performance data. While these datasets provide a valuable data-driven evaluation environment, the proposed framework should not be interpreted as a fully validated real-world operational deployment model.

There are several possible directions for extending this research. Incorporating more advanced routing and scheduling features such as dynamic vehicle routing, stochastic travel times, and time-window constraints would help better reflect real-world operations. In addition, integrating adaptive or learning-based methods, including reinforcement learning, could support more scalable and real-time decision-making in larger networks. Extreme operational conditions such as severe weather events, high wind conditions, or unexpected operational disruptions are not explicitly modeled and remain important directions for future research. The benefits of truck–drone collaboration are expected to diminish in scenarios characterized by sparse customer distributions, limited opportunities for drone dispatch, lower drone cruising speeds, stricter operational restrictions, or increased synchronization requirements between trucks and drones. Under such conditions, the additional complexity associated with drone deployment may partially offset the operational gains observed in this work. Future studies should systematically investigate these boundary conditions through broader scenario analyses and multi-depot evaluations. Finally, the framework could be expanded to capture practical considerations such as heterogeneous drone fleets, regulatory requirements, and weather-related performance variations.

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ARTICLE 3- DRIVERS AND BARRIERS TO
DRONE DELIVERY ADOPTION IN
CANADA: INSIGHTS FOR SUSTAINABLE
LAST-MILE LOGISTICS

5.1 PUBLICATION STATEMENT

This chapter is based on the Journal article titled “Drivers and Barriers to Drone Delivery Adoption in Canada: Insights for Sustainable Last-Mile Logistics”, co-authored by Didem Cicek and Burak Kantarci, which is accepted for publication as of June 2026 by the Research in Transportation Business and Management (Elsevier).

This article complements the thesis by introducing the societal and behavioral dimension of autonomous last-mile delivery adoption, with a particular focus on drone delivery acceptance in the Canadian context. While the core dissertation primarily focuses on operational optimization, resource coordination, and system-level planning of truck–drone collaborative delivery networks, large-scale deployment of such systems ultimately depends on public acceptance and willingness to adopt emerging autonomous delivery technologies. Accordingly, this study extends the broader research agenda of the dissertation by examining the human and societal factors that may influence the future implementation feasibility of drone-enabled delivery systems.

5.2 INTRODUCTION

The global surge in online shopping since the pandemic has left supply chain operators with the challenge of managing high parcel volumes and last-mile delivery pressures. The extra load on logistics and transportation networks worldwide has led to a rapidly expand-

ing delivery-fleet market, which points toward more delivery vehicles on the road, greater road-use, and thus added congestion and emissions pressures [116], [117]. According to a recent report by the World Economic Forum [118], if current trends continue, the global number of delivery vehicles is projected to increase by approximately 61% by 2030, leading to a 60% rise in carbon emissions from urban deliveries under a business-as-usual scenario. Despite ongoing electrification efforts, the approximately 50 million registered electric vehicles worldwide by 2024 represent only a small share of the global light-duty vehicle fleet exceeding one billion [119]; moreover, vehicle electrification alone does not alleviate traffic congestion.

The situation is not any different in Canada. Energy used for transportation accounts for more than one-quarter of Canada’s total GHG emissions [120]. As of 2022, around 23 million light-duty vehicles (94% of total) that ran on gasoline were on Canadian roads. Increasing vehicle numbers and heavy reliance on internal-combustion driving, puts Canada on a trajectory of rising congestion and elevated carbon emissions unless systemic changes are made.

Autonomous delivery systems represent a promising avenue for enhancing the operational effectiveness of last-mile delivery and mitigating its environmental impact. However, as the technology remains in its early stages, several technological and regulatory challenges continue to limit large-scale deployment [40], [4], [121]. From an operational perspective, recent research has increasingly focused on optimizing drone delivery systems under realistic constraints, such as heterogeneous fleet configurations [122], delivery time windows [123], and service efficiency considerations, highlighting the complexity of real-world deployment.

Despite these advances, broader challenges related to system integration, regulatory frameworks, and public acceptance remain unresolved. Nevertheless, a thorough understanding of user acceptance determinants is vital for guiding the design of future delivery technologies and shaping effective business strategies [124], [125]. The findings of the literature review on user acceptance studies [40] emphasize the importance of tailoring communication strategies for autonomous delivery to different user segments, providing valuable insights for both delivery organizations and researchers interested in testing or deploying automation technologies in last-mile operations.

5.2.1 PROBLEM STATEMENT

User acceptance is a crucial determinant of the successful deployment of autonomous delivery technologies, as it reflects consumers' willingness to adopt and integrate such innovations into their daily lives. High acceptance can stimulate market demand, justify investments in automation and logistics infrastructure, and contribute to environmental sustainability by enabling optimized, low-emission delivery routes. Conversely, low acceptance may impede large-scale implementation, undermining both the economic viability and the environmental potential of these emerging technologies.

While a growing body of research has examined user acceptance of autonomous delivery technologies across different countries, the extent to which these findings generalize to the Canadian context remains unclear. This gap is particularly important given Canada's distinct regulatory environment, geographic conditions, and national sustainability com-

mitments. Moreover, although extended versions of the UTAUT2 framework have been applied in related domains, there is limited empirical evidence on how these constructs perform in the context of drone-based last-mile delivery, especially among technologically proficient user groups. This raises important questions regarding the applicability and relative importance of established adoption factors in emerging delivery systems.

Accordingly, this study addresses an important gap in the literature by providing one of the first empirical examinations of Canadian users' behavioral intention to adopt autonomous drone delivery services. By understanding the psychological, technological, and social factors that influence user acceptance, the study aims to provide insights that can inform policy, guide sustainable logistics innovations, and support Canada's broader zero-emissions strategy.

Beyond its geographical focus, this study contributes to the literature by empirically validating an extended UTAUT2 framework within the emerging context of autonomous drone delivery. Rather than introducing new theoretical constructs, the study adopts context-specific extensions established in prior research and examines their applicability in a Canadian setting. The findings provide evidence that certain traditionally significant determinants, such as effort expectancy and facilitating conditions, may lose explanatory power in technologically proficient user groups, suggesting boundary conditions for established technology acceptance models. Furthermore, the results highlight the interplay between sustainability considerations and perceived risks, demonstrating that environmental benefits alone may not offset concerns related to safety, privacy, and cost. By also identifying moderating effects of age and technical expertise, the study contributes to a more

nuanced and context-sensitive understanding of user adoption behavior in autonomous delivery systems.

This study aims to examine the factors influencing Canadian consumers' intentions to adopt drone delivery services by applying an extended UTAUT2 framework. Rather than proposing new theoretical constructs, the study adopts and validates an extended model previously used in autonomous delivery research, assessing its applicability within a new geographical and technological context. The findings contribute to the literature by identifying the key drivers and barriers of adoption, highlighting potential boundary conditions of established UTAUT2 relationships, and providing context-specific insights into the role of sustainability perceptions, perceived risk, and pricing considerations in shaping user acceptance. These insights are intended to inform both future research and the practical deployment of drone delivery systems.

5.3 RELATED WORK

Drone delivery in last-mile logistics presents both an exciting opportunity and a significant challenge for online retailers and logistics firms since they have to offer the best customer experience [126]. However, drone acceptance is seen as a potential barrier to future transportation applications [127].

In the last five years, several research papers have been published worldwide to uncover the factors that could improve the user acceptance of drone delivery (Table 5.1). In most of

these studies perceived usefulness and performance expectancy of the solution stands out as the biggest positive contributor to acceptance [128], [39], [129], [130], [131], [132]. Users' high perception of risk associated with drones is widely recognized as a key barrier to the adoption of drone delivery services. Among various risk dimensions, privacy risk including concerns about surveillance and potential leakage of personal information emerges as the most significant negative factor influencing user acceptance in several studies [128], [133], [134], [135]. Interestingly, perceptions of privacy risk tend to increase among individuals who have previously used drones or possess a deeper understanding of their technical capabilities [39], suggesting that privacy-related discourse remains underdeveloped. A study conducted in Germany [38] further reveals that users are more strongly influenced by perceived risks than by anticipated benefits when forming their adoption intentions. This may stem from the perception that drone delivery is not yet an essential improvement to existing logistics systems, or from limited public understanding of the potential advantages offered by this emerging technology.

Most drone delivery pilot projects to date have been conducted within the medical sector. A recent study in China [136] examined medical personnel's perceptions of drone-based deliveries and emphasized that establishing a robust regulatory and policy framework should be the primary focus to foster higher acceptance. Once such foundations are in place, efforts can then be directed toward enhancing infrastructure and achieving greater cost efficiency.

User acceptance of drone deliveries has also been examined through the lens of urban-rural disparities in China [137]. The study found that urban users place greater em-

phasis on risk mitigation and the regulatory environment, while rural users generally exhibit lower awareness of drone delivery technologies. Consequently, increasing pilot demonstrations and investing in supporting infrastructure are deemed essential to enhance acceptance in rural areas.

Previous research shows that the acceptance of drone delivery practices is often deeply influenced by the societal norms and cultural values of the testing country [138], [39]. Hence, this research focuses on Canadian users to capture context-specific insights into their perceptions, attitudes, and behavioral intentions toward adopting drone delivery services within Canada’s unique cultural, regulatory, and technological landscape.

While prior studies provide valuable insights into the factors influencing user acceptance of drone delivery [37], [139], [38], the existing literature presents several inconsistencies and unresolved issues. Although performance-related benefits are frequently identified as strong positive drivers, the role of perceived risk remains context-dependent, with some studies suggesting it outweighs perceived benefits in shaping adoption decisions. Similarly, findings related to effort expectancy and facilitating conditions vary across countries, indicating that their influence may depend on user characteristics and levels of technological familiarity [129], [140], [141]. These variations suggest that the relative importance of acceptance factors is not universal but shaped by contextual, cultural, and technological conditions. As a result, there is a need for context-specific empirical validation of existing models, particularly in underexplored settings such as Canada, where regulatory frameworks, environmental priorities, and user profiles may differ from those examined in prior research.

Table 5.1: Previous user acceptance studies on drone delivery

Ref	Year	Country	Sample Size	Sample Population	Gender	Survey Platform	Guiding Theory	Statistical Method
[128]	2021	USA	617	Online shoppers	M-58% F-42%	Online- Amazon Mechanical Turk	TAM	PLS-SEM
[142]	2022	USA	83	Undergraduate Students	M-66% F-34%	Online-Not stated	PCT and PPM	PLS-SEM
[138]	2022	Pakistan	361	Restaurant customers	M-62% F-38%	Offline distribution	TAM	PLS-SEM
[37]	2023	India	323	Online shoppers with food delivery service app	M-53% F-45% Other- 2%	Online- Email&Social Media	UTAUT2	PLS-SEM
[143]	2023	Malaysia	305	Online shoppers	M-44% F-56%	Online-Not stated	TCV	PLS-SEM
[133]	2023	Lisbon	304	Residents	M-48% F-52%	Online- Social Media	TAM	PCA and cluster analysis
[144]	2023	Singapore	450	Residents	M-49.3% F-50.7%	Online- Survey Company	TAM, TTF, PCT	SEM
[139]	2023	Vietnam	602	Online shoppers of two big retailers	M-43.5% F-56.5%	Online-Not stated	DOI ¹ , TAM	SEM
[145]	2023	China	231	Urban residents	NA	Offline distribution	Binary logistic model & Fuzzy-ISM	Regression Analysis
[39]	2023	Germany	183	Residents	M-49% F- 50% Other- 1%	Online-Qualtrics	UTAUT2	SEM
[38]	2023	Germany	819	Residents	M-54% F- 46%	Telephone survey	TAM	SEM
[146]	2024	Malaysia	158	Consumers with drone knowledge	M-69% F- 31%	Online-Google Forms	TAM & DOI	Regression Analysis
[135]	2024	Portugal	155	Portuguese Citizens	M-42% F- 58%	Online-Google Forms	TAM & TACs ² & TECHCs ³	Statistical SPSS Analysis
[132]	2025	Portugal	1108	Portuguese Citizens	M-38% F- 61%	Online Distribution	TAM & TACs & TECHCs	PLS-SEM
[137]	2025	China	498	General Consumers (urban & rural)	M-45% F- 55%	Online-Star Offline Distribution	TAM & ELM ⁴	Regression Analysis
[136]	2025	China	289	Medical Personnel	M-51% F- 49%	Offline distribution in ED department & Online for experts	TAM & DOI	Regression Analysis & Delphi Method (n=35)
This Work	2025	Canada	156	Tech-Savy Urban Consumers	M-43% F- 57%	Online distribution	UTAUT2	PLS-SEM

5.4 THEORETICAL FOUNDATION: UTAUT2

The two theories that guide the empirical studies on the adoption of autonomous last mile delivery are Technology Acceptance Model (TAM) [147] and Unified Theory of Acceptance

and Use of Technology-2 (UTAUT2) [125] as noted in our prior research [40]. TAM defines attitude as a key indicator of intention to use towards using a technological artifact, shaping the actual system usage. As per TAM, users tend to adopt a technology more readily if they perceive it as enhancing their performance (perceived usefulness) and requiring minimal effort to use (perceived ease of use). Due to its broad applicability and lack of specific contextual requirements, this model is frequently cited in explaining user behavioral intention to adopt new technologies.

UTAUT2 evolved from UTAUT [148] by expanding its scope from employee adoption in workplaces to consumer adoption in voluntary settings, offering a richer understanding of technology use behavior through introduction of three new constructs for Hedonic Motivation, Price Value, and Habit. UTAUT2 proposes seven key determinants of user behavior: performance expectancy (expected benefits from switching to the new technology), effort expectancy (degree of ease in switching to the new technology), social influence (what significant others think about the new technology), facilitating conditions (user's perception on how ready the organizational and technical infrastructure for the new technology), hedonic motivation (playfulness or enjoyment found in the new technology), habit (the extent which the user performs behaviour automatically), and price value (user's cognitive trade-off between perceived benefits and costs of the new technology). UTAUT2 represents an extension of UTAUT [148], incorporating habit as a theoretical construct that directly influences technology use. This extension challenges the dominance of behavioral intention as the primary predictor of behavior. UTAUT2 distills the critical factors related to the prediction of behavioral intention to use a technology from several different theories/models

in the literature. It has strong explanatory power in predicting technology acceptance and use especially in consumer contexts and recently widely used in user acceptance research on Autonomous vehicles. It is a successful model in incorporating the impact of moderating factors of age, gender and experience and measuring both behavioral intention and actual use behavior through the integration of mediating factors (Figure 5.1).

Although UTAUT2 framework was originally developed to examine consumer technology acceptance of mobile internet, it has been applied to other contexts, such as cross cultural adaptation [149] or online education [150] studies in the cultural context of Canada. The present study will be the first in Canadian context that investigates user acceptance factors for drone delivery. UTAUT2 serves as the theoretical foundation of this study. However, given that autonomous last-mile delivery systems are still in their formative stages, investigating actual use behaviour is currently impractical. Therefore, the present research focuses on examining behavioral intention to use drone-based delivery services, rather than post-adoption or continued-use behaviours.

5.4.1 UTAUT2 CONSTRUCTS AND HYPOTHESES DEVELOPMENT

As autonomous delivery vehicles have not yet been widely commercialized, user acceptance studies typically consider behavioral intention as the most reliable predictor of actual use behavior. The present research aims to identify and analyze the factors influencing Canadian users' intentions to adopt drone-based delivery services as an alternative to conventional delivery modes such as truck deliveries. Building on UTAUT2, this study adopts

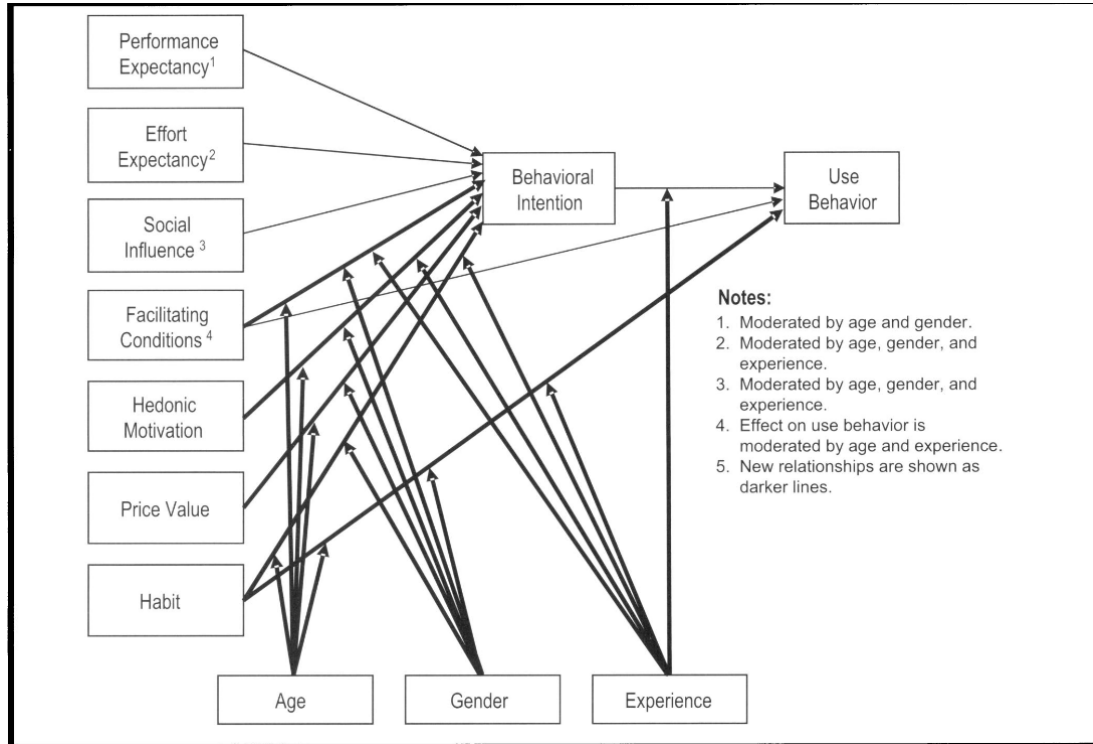


Figure 5.1: UTAUT2 Framework [125]

an extended version of the model that has been previously applied in the context of autonomous delivery systems. Rather than introducing new theoretical constructs, the model specification follows prior literature that incorporates additional context-relevant factors into UTAUT2. In particular, Perceived Risk and Price Sensitivity are included in line with the work of Kapser and Abdelrahman (2020) [129], who extended UTAUT2 to examine acceptance of autonomous delivery vehicles. Environmental Friendliness is incorporated based on more recent studies such as Schmidt and Saraceni (2024) [39], which highlight the growing importance of sustainability considerations in user acceptance of drone-based de-

livery technologies. Accordingly, this study applies and empirically validates this extended UTAUT2 configuration within the Canadian context of drone delivery adoption. Furthermore, the Habit and Hedonic Motivation constructs were excluded, as it is not yet feasible to evaluate these post-adoption behaviors for a technology that remains largely undeployed within the Canadian market. While the exclusion of Habit and Hedonic Motivation aligns with the early-stage nature of drone delivery adoption, it may have implications for the overall explanatory power of the model, reducing the model's ability to capture certain dimensions of user behavior. However, including these constructs in a pre-adoption setting could compromise measurement validity, as respondents would be required to speculate about habitual use patterns or experiential enjoyment without direct interaction with the technology. Consistent with prior studies on emerging technologies, the adapted model prioritizes contextual relevance and construct validity over theoretical completeness, ensuring that all included constructs can be meaningfully evaluated by respondents.

The drone delivery acceptance model that has been proposed and tested in this research can be found in Figure 5.2. Behavioral Intention to use drone deliveries (BI) is the endogenous (dependent) variable, while Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Perceived Risk (PR), Environmental Friendliness (EFR) and Price Sensitivity (PS) are the exogenous predictors feeding into BI.

Performance Expectancy is defined within the UTAUT2 framework as the degree to which individuals believe that using a technology will enhance their performance, efficiency, or overall outcomes. In the context of autonomous drone deliveries, this implies that users

are primarily driven by the perceived functional benefits of the technology, such as faster delivery times, increased reliability, and improved service convenience when forming their use intentions. Prior technology adoption research emphasizes performance expectancy (or perceived usefulness as per TAM model) as a key determinant of behavioral intention [128], [39], [129], [130], [131]. Therefore, the following hypothesis is proposed:

H1: Performance expectancy positively influences behavioral intention to use drone delivery.

Effort Expectancy is defined within the UTAUT2 framework as the degree of ease associated with consumers' use of technology. It captures users' perceptions of how simple, intuitive, and user-friendly a system is to operate. In the early stages of technology diffusion, when users have limited prior experience with the innovation, perceptions of ease of use become a crucial determinant of their willingness to adopt. Prior studies have reported contradicting results on the relationship between effort expectancy and behavioral intention in the context of autonomous last mile delivery, which may be attributable to country-specific dynamics. Studies in India [37], and Pakistan [138] reported positive impact of effort expectancy on intention to use, while a study in France reported lower behavioral intention to use drone delivery as effort expectancy (ease of use) increases. For Canadian context, a positive relationship is proposed with the following hypothesis:

H2: Effort expectancy positively influences behavioral intention to use drone delivery.

Social Influence is defined in the UTAUT2 framework as the degree to which an individual perceives that important others believe he or she should use the new system.

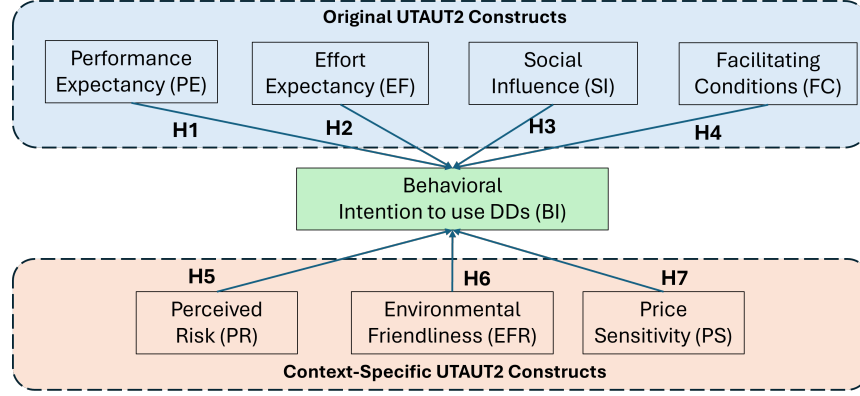


Figure 5.2: Proposed drone delivery acceptance model

It reflects the impact of social norms, peer opinions, and external pressures on an individual’s technology adoption decisions. In the context of emerging technologies, such as drone-based deliveries, social influence can play a particularly significant role, as individuals often look to trusted peers, media, or opinion leaders to shape their perceptions and reduce uncertainty regarding novel innovations. Prior studies have consistently demonstrated the positive relationship between social influence and behavioral intention in the context of autonomous last mile delivery [138], [39]. Therefore, the following hypothesis is proposed:

H3: Social influence positively influences behavioral intention to use drone delivery.

Facilitating Conditions is defined in the UTAUT2 framework as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology. This construct reflects users’ perceptions of the availability of resources, knowledge, and external support necessary to adopt and effectively use a new technology. In the context of drone-based delivery services, facilitating conditions

encompass factors such as technological readiness, regulatory frameworks, delivery network infrastructure, and user access to compatible devices or applications. Although prior research did not find strong correlation between facilitating conditions and behavioral intention in the context of autonomous last mile delivery, this construct was tested to see the impact for the Canadian users also with the newly created items that aim to test the importance of instant access to technical support and the role of ground vehicles to scale drone delivery. Therefore, the following hypothesis is proposed:

H4: Facilitating conditions positively influence behavioral intention to use drone delivery.

Perceived Risk, the hesitation users associate with technology use with the fear of loss while pursuing a desired outcome is proven to negatively influence the behavioral intention of German users to prefer autonomous delivery vehicles for last mile logistics [129]. In early stages of drone delivery systems, there can be technology and safety related risks perceived by Canadian users which will likely negatively influence their use intentions. Hence, the following hypothesis is proposed:

H5: Perceived risk negatively influences behavioral intention to use drone delivery.

Environmental friendliness favors sustainable and environmentally friendly solutions over traditional carbon emitting delivery solutions. Although environmental friendliness or environmental concerns ([40] is not one of the key constructs as outlined in the original UTAUT2 framework, it is increasingly being tested in user acceptance research [133], [142], [140]. Although previous studies have yielded mixed findings—showing that this construct

may either positively or insignificantly influence users’ intentions to adopt—the growing national focus on sustainability and Canada’s commitment to achieving net-zero emissions by 2050 are expected to strengthen the appeal of environmentally friendly technologies such as drone deliveries. Accordingly, the following hypothesis is proposed:

H6: Environmental Friendliness positively influences behavioral intention to use drone delivery.

The original UTAUT2 construct of “price value” was adapted into “price sensitivity” by Kapser and Abdelrahman [129], reflecting the extent to which consumers respond to price levels or changes in pricing. This modification is particularly relevant for autonomous delivery services, which remain in the early stages of market adoption and lack clearly established pricing structures. Understanding how sensitive Canadian consumers are to potential price differences between drone deliveries and conventional truck deliveries is therefore essential. It is proposed that Canadian users will negatively react to higher prices in line with prior research [141], [131]. Accordingly, the following hypothesis is proposed.

H7: Price Sensitivity negatively influences behavioral intention to use drone delivery.

5.5 METHODOLOGY

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) [151] to analyze the hypothesized relationships among the constructs of the extended UTAUT2

framework in the context of Canadian consumers' acceptance of drone-based last-mile delivery services. PLS-SEM is a variance-based structural modeling technique that simultaneously estimates the relationships between latent variables and their observed indicators while assessing predictive accuracy and explained variance. Unlike covariance-based SEM, which focuses on model fit and typically requires large samples and normally distributed data, PLS-SEM is particularly suitable for exploratory or predictive research and for models with complex relationships and small to medium sample sizes.

PLS-SEM's robustness in handling non-normal data distributions and its suitability for studies with limited sample sizes made it an appropriate analytical method for this research. The confirmatory approach was selected because the research model is grounded in a well-established theoretical framework. Most of the latent constructs (i.e performance expectancy, effort expectancy, social influence, facilitating conditions) have been extensively validated in prior literature, and their measurement was operationalized using established multi-item Likert scales. The dataset included 156 valid survey responses out of 205 total responses, exceeding the minimum sample size recommended by Hair et al. [152] based on the "10-times rule"—that is, at least ten times the maximum number of structural paths directed at any construct, which is seven hypothesized structural paths in our study.

All analyses were conducted using SmartPLS 4⁵, a dedicated software for variance-based SEM. The analytical process included running the PLS algorithm to estimate path coefficients and explained variance, followed by a bootstrapping procedure (5,000 subsamples) to test the statistical significance of the hypothesized paths. SmartPLS 4 was chosen

⁵<https://smartpls4.com/>

for its advanced visualization, user-friendly interface, and capability to perform multi-group analysis (MGA) to assess moderation effects such as age, gender, and user experience.

Confirmatory PLS-SEM (PLSc) allows for the simultaneous assessment of the measurement model (validity and reliability of latent constructs) and the structural model (strength and significance of hypothesized paths) which are elaborated more under subsections 5.5.3 and 5.5.4 respectively.

5.5.1 QUESTIONNAIRE DEVELOPMENT

This study adopts a quantitative research design, employing a cross-sectional field survey method with the objective to understand users' behavioral intentions to adopt drone delivery services for urban parcel deliveries in Canada. The cross-sectional design ensures that all independent and dependent variables are measured at a single point in time using a unified questionnaire, consistent with established survey research practices [153]. The questionnaire is designed to examine the influence of seven key constructs of the guiding theoretical framework UTAUT2; performance expectancy, effort expectancy, social influence, facilitating conditions, price sensitivity, perceived risk, and environmental friendliness on Canadians' intentions to use drone delivery services. Two UTAUT2 constructs, Habit and Hedonic Motivation, are excluded from the model as they are not yet applicable to this emerging technology. Habit formation assumes repeated use, which has not yet occurred, while hedonic motivation relates more to post-adoption experiences and marketing factors.

Each construct is measured by an average of three reflective indicators in the form

of statements derived from prior literature to ensure content and construct validity. The mapping of the indicators with the relevant constructs can be found on Table 5.2. The adopted sources are cited alongside each item in the survey, while newly developed items marked as “own development” address the collaborative delivery dimension specific to this study. The questionnaire also includes four multiple-choice questions to capture user preferences and expectations regarding drone delivery services.

The instrument is developed and administered through the Survey Monkey online platform⁶ (student version provided by the University of Ottawa Library) to ensure broad accessibility and cost-effectiveness. Questionnaire is made available both in English and French allowing users to take the survey in their preferred language. Participants are first presented with an informed consent form, followed by a brief introduction and an explanatory video about drone delivery operations⁷ to ensure contextual understanding. Three screening questions confirm that respondents reside in Canada, older than 18 years old and have previously made online purchases. Subsequently, seven demographic questions capture age, gender, education, employment status, technical expertise, familiarity with drones and the province of residence.

Prior to full deployment, the questionnaire has gone through pre-testing with 10 participants from academia and industry to refine wording, clarity, and reliability.

⁶<https://www.surveymonkey.com/>

⁷<https://youtu.be/YWwl-DVndH8>

Table 5.2: Constructs, hypotheses, questionnaire items, and adapted sources (*Note:*Drone delivery service is hereafter abbreviated as DDS.)

Construct	Item	Statement	Source
H1: Performance expectancy positively influences BI to use DDS.			
Performance expectancy	PE1	I would find DDS useful for parcel delivery.	[125]
	PE2	Using DDS would help me receive parcels faster.	[125]
	PE3	Using DDS would increase flexibility in my daily life.	[125, 129]
H2: Effort expectancy positively influences BI to use DDS.			
Effort expectancy	EF1	It would be easy for me to learn how to use DDS.	[125]
	EF2	My interaction with DDS via a mobile application would be clear and understandable.	[125]
	EF3	I have the technical skills required to use DDS.	Own development
H3: Social influence positively influences BI to use DDS.			
Social influence	SI1	People important to me would think I should accept drones for parcel delivery.	[125]
	SI2	If important people endorse DDS, I am likely to use it.	Own development
	SI3	Positive social media reviews increase my likelihood of using DDS.	Own development
H4: Facilitating conditions positively influence BI to use DDS.			
Facilitating conditions	FC1	I have the resources needed to receive parcels by drone, such as landing space and a smartphone.	[125]
	FC2	DDS would be compatible with technologies I use, such as smartphones.	[125]
	FC3	Instant technical support is important when using DDS.	Own development
	FC4	Ground vehicles carrying or recharging drones could expand DDS range.	Own development
H5: Perceived risk negatively influences BI to use DDS.			
Perceived risk	PR1	Overall, using DDS would be risky.	[129]
	PR2	Delivery drones might malfunction and damage parcels, people, or property.	[39]
	PR3	I am concerned about surveillance or privacy violations during drone delivery.	[39]
H6: Environmental friendliness positively influences BI to use DDS.			
Environmental friendliness	EFR1	I believe DDS is an environmentally friendly parcel delivery alternative.	[39]
	EFR2	DDS would allow me to receive parcels in a more environmentally friendly way.	[39]
	EFR3	Environmental quality improves when drones are used for parcel delivery.	[39]
H7: Price sensitivity negatively influences BI to use DDS.			
Price sensitivity	PS1	I would not mind paying more to try DDS compared with conventional delivery.	[129]
	PS2	I would be less willing to use DDS if it were expensive.	[129]
	PS3	Higher DDS cost compared with conventional delivery would not matter to me.	[129]
Dependent variable.			
Behavioral intention	BI1	I intend to use DDS in the future.	[125]
	BI2	I would try to use DDS when available in the future.	[125]
	BI3	I plan to use DDS frequently when available in the future.	[125]

5.5.2 DATA COLLECTION

The study employs a convenience sampling strategy, targeting individuals and organizations that are known to be interested in the topic and familiar to the researchers. These include the Faculty of Engineering, the Digital Transformation and Innovation Program, the Smart Connected Vehicles Innovation Centre, Association for Computing Machinery Women Student Chapter of University of Ottawa, Kanata North Business Association, Project Management Institute (PMI) Canadian Chapters, the Canadian Automated Vehicle Initiative (CAVI), Canadian Transportation Research Forum (CTRF) 2025 attendees, researchers from other provinces, and selected industry contacts. This approach enables the inclusion of diverse demographic groups while ensuring adequate representation from technology-oriented and innovation-focused communities across Canada.

Data collection was conducted between April 2025 and September 2025. The questionnaire was distributed through multiple channels, including email invitations, professional mailing lists, and online platforms associated with the aforementioned organizations. In some cases, the survey link was shared through internal communication channels and professional networks to reach participants with relevant background and interest in emerging technologies.

In accordance with the Ethics Review Board (ERB)⁸ approval obtained from the University of Ottawa, no monetary or material incentives are offered to participants. The target population comprises online shoppers in Canada, and it is anticipated that the topic

⁸University of Ottawa, Office of Research Ethics and Integrity, File number:H-02-25-11202

of drone delivery represents a relevant and engaging area of interest for this group. Consequently, participation is expected to occur on a voluntary and informed basis, motivated by personal curiosity and societal relevance rather than external rewards.

Following data collection, responses were screened for completeness and consistency. Incomplete responses were removed, resulting in a final dataset of 156 valid observations. All complete responses were further reviewed for plausibility and internal consistency; no additional responses were excluded, as no irregular or inconsistent response patterns were identified.

PARTICIPANTS AND DEMOGRAPHICS

A total of 205 individuals participated in the survey, of which 156 provided complete and valid responses, yielding a response rate of 76%. Screening questions ensured that only Canadian residents aged 18 years or older with prior online shopping experience could proceed with the questionnaire. The demographic characteristics of the respondents are summarized in Table 5.3. The majority of respondents were located in Ontario, reflecting the researchers' institutional and professional networks, as well as the concentration of technology and innovation hubs such as Kanata North. While this may introduce a regional bias and limit the generalizability of the findings to the entire Canadian population, Ontario also represents one of the most advanced provinces in terms of digital transformation and logistics innovation, making it a relevant context for early-stage investigations of drone delivery adoption. The sample was slightly skewed toward women (57%) compared to men (43%), which aligns with the 2021 Canadian census indicating a national gender distribu-

tion of approximately 51% women and 49% men. This over-representation of women in the sample likely reflects the characteristics of the convenience sampling approach employed. The educational profile of the respondents was notably high, with 93% holding a bachelor's degree or higher, suggesting a well-informed and digitally literate cohort. Moreover, respondents demonstrated substantial technological competence, with over 70% identifying as having intermediate to expert technical skills. This intentional inclusion of tech-savvy participants aligns with the exploratory nature of the study, as emerging delivery technologies such as drones are expected to gain earlier acceptance among digitally engaged consumers rather than traditional offline buyers. Overall, the sample represents a technologically aware, well-educated, and demographically relevant cross-section of Canadian online shoppers.

5.5.3 MEASUREMENT MODEL

Data are exported from the Survey Monkey tool and preprocessed before being uploaded into SmartPLS 4⁹. The preprocessing steps include the removal of incomplete responses from the PLS-SEM model input, coding of the indicators for each hypothesis and for the moderator variables (age, gender, technical expertise), and correcting the reversely coded constructs (PS1, PS3).

In PLS-SEM, the measurement model is evaluated rather than subjected to a traditional Confirmatory Factor Analysis (CFA) [154] as used in covariance-based SEM. The

⁹<https://smartpls4.com/>

Table 5.3: Descriptive statistics of the respondents

Category	Frequency (n=156)	Percentage (%)
Gender		
Man	67	43.2%
Woman	88	56.8%
Age		
18–24	14	9.0%
25–34	49	31.4%
35–44	62	39.7%
45–54	26	16.7%
55 and over	5	3.2%
Education		
High school or below	8	5.1%
College degree	3	1.9%
Bachelor's degree	56	35.9%
Master's degree	62	39.7%
Doctorate (PhD)	27	17.3%
Occupation		
Employed	86	55.5%
Student	46	29.7%
Self-employed	12	7.7%
Unemployed	7	4.5%
Homemaker	3	1.9%
Retired	1	0.6%
Province		
Alberta	6	3.8%
British Columbia	11	7.1%
Manitoba	4	2.6%
New Brunswick	4	2.6%
Newfoundland & Labrador	17	10.9%
Nova Scotia	3	1.9%
Ontario	100	64.1%
Prince Edward Island	1	0.6%
Quebec	9	5.8%
Saskatchewan	1	0.6%
Northwest Territories, Nunavut, Yukon	0	0.0%
Technical Expertise		
Basic	44	28.8%
Intermediate	41	26.8%
Advanced	43	28.1%
Expert	25	16.3%
Previous Experience with Drones		
Yes	78	50.6%
No	76	49.4%

reflective measurement model is assessed through indicator reliability (outer loadings), internal consistency reliability Cronbach's α , Composite Reliability, (ρ_c), convergent validity (AVE), and discriminant validity (HTMT). The measurement model consists of 8 constructs and 25 indicators measuring these constructs.

Internal consistency reliability is assessed using Cronbach's α [155] and Composite Reliability (ρ_c). Composite Reliability (ρ_c) is used as the primary indicator [152], as it provides the most stable and widely accepted estimate of reliability in PLS-SEM models. Both values are expected to exceed the recommended threshold of 0.70, indicating satisfactory construct reliability. The constructs Perceived Risk (PR) and Price Sensitivity (PS) demonstrated slightly lower values, yet both remained above 0.60, which is considered acceptable for exploratory research [152]. Convergent validity is measured through Average Variance Extracted (AVE), which is supposed to be greater than 0.5. The Price Sensitivity (PS) construct reported an AVE value of 0.489, which is slightly below the recommended threshold of 0.50. However, the construct was retained in the measurement model, as its composite reliability met the acceptable criteria. Regarding the factor loadings, four indicators from the Perceived Risk (PR) and Price Sensitivity (PS) constructs loaded below the recommended threshold of 0.70. While these indicators fall below the recommended threshold, they were retained after careful evaluation, as their removal did not substantially improve the composite reliability or AVE values, and they represent theoretically distinct aspects of the underlying constructs. This reflects a deliberate trade-off between strict statistical thresholds and preserving the conceptual breadth of the constructs in an exploratory research context [156]. The validity and reliability indicators of the measure-

ment model can be found on Table5.5.

Discriminant validity of the constructs is evaluated using the Heterotrait–Monotrait ratio of correlations (HTMT) to assess whether two constructs are empirically distinct. It is calculated as the average of the correlations across constructs over average correlations within constructs. As seen on Table5.4, all HTMT values were below the conservative threshold of 0.90, except for two construct pairs—Effort Expectancy and Facilitating Conditions (HTMT = 0.90) and Social Influence and Performance Expectancy (HTMT = 0.91). Given the theoretical relatedness of these constructs within the UTAUT2 framework and the satisfactory results from other validity assessment i.e cross-loadings (Table5.8), these minor exceedances are deemed acceptable. The observed proximity between Effort Expectancy and Facilitating Conditions may stem from their shared focus on usability and enabling resources. While Effort Expectancy reflects the perceived ease of using the system, Facilitating Conditions capture the availability of supporting infrastructure and resources. In practice, particularly among technologically proficient users, these aspects may be evaluated jointly, leading to partial conceptual overlap. Similarly, the association between Social Influence and Performance Expectancy may reflect the role of social context in shaping users’ perceptions of usefulness. Individuals often form expectations regarding the benefits of a technology based on the opinions and experiences of others, which can lead to a convergence between socially driven perceptions and performance-related beliefs. Despite this proximity, the constructs remain theoretically distinct and are retained in the model.

Table 5.4: Discriminant validity of the measurement model

HTMT-Matrix	BI	EF	EFR	FC	PR	PE	PS	SI
Behavioral Intention (BI)								
Effort Expectancy (EF)	0.471							
Environmental Friendliness (EFR)	0.597	0.337						
Facilitating Conditions (FC)	0.493	0.901	0.432					
Perceived Risk (PR)	0.400	0.228	0.240	0.224				
Performance Expectancy (PE)	0.702	0.755	0.607	0.786	0.218			
Price Sensitivity (PS)	0.312	0.289	0.244	0.354	0.214	0.274		
Social Influence (SI)	0.736	0.765	0.589	0.851	0.263	0.912	0.378	

5.5.4 STRUCTURAL MODEL

The PLS-SEM algorithm was first used to assess both the measurement and structural models, providing estimates of path coefficients, indicator loadings, and explained variance. Subsequently, bootstrapping with 5,000 resamples was conducted to test the statistical significance of the hypothesized relationships in the structural model. The path coefficients, along with their corresponding t- and p-values, were examined to evaluate the strength and direction of the hypothesized effects. The results revealed that while several relationships were statistically significant and supported the proposed hypotheses, the paths from Effort Expectancy (EF) to Behavioral Intention (BI) and from Facilitating Conditions (FC) to Behavioral Intention (BI) were not supported, as indicated by low path coefficients and non-significant t- and p-values. Collinearity among predictor constructs was assessed using variance inflation factor (VIF) values. As shown in Table 5.6, all VIF values were below the recommended threshold of 3.3, indicating no critical multicollinearity concerns among the constructs. In addition, Harman's single-factor test was conducted to assess the potential

Table 5.5: Validity and reliability of the measurement model

Constructs	Items	Factor Loadings	Cronbach's α	CR (rho_c)	AVE
Behavioral Intention (BI)	BI1	0.919	0.894	0.934	0.824
	BI2	0.882			
	BI3	0.922			
Effort Expectancy (EF)	EF1	0.891	0.791	0.876	0.703
	EF2	0.853			
	EF3	0.768			
Environmental Friendliness (EFR)	EFR1	0.922	0.895	0.934	0.826
	EFR2	0.926			
	EFR3	0.878			
Facilitating Conditions (FC)	FC1	0.711	0.797	0.868	0.624
	FC2	0.882			
	FC3	0.789			
	FC4	0.768			
Performance Expectancy (PE)	PE1	0.900	0.865	0.917	0.787
	PE2	0.874			
	PE3	0.888			
Perceived Risk (PR)	PR1	0.592	0.659	0.796	0.575
	PR2	0.695			
	PR3	0.944			
Price Sensitivity (PS)	PS1	0.971	0.601	0.704	0.489
	PS2	0.271			
	PS3	0.670			
Social Influence (SI)	SI1	0.876	0.824	0.895	0.741
	SI2	0.917			
	SI3	0.784			

presence of common method bias. The results showed that the first unrotated factor accounted for 35.02% of the total variance, which is below the commonly accepted threshold of 50%. This suggests that common method bias is unlikely to represent a major concern in this study.

The path graph for the structural model can be found at Figure 5.3. Further interpretation of the findings for each tested hypothesis is presented in the subsequent results

Table 5.6: Collinearity assessment using variance inflation factor (VIF)

Construct	VIF
Performance Expectancy (PE)	2.966
Effort Expectancy (EF)	2.286
Social Influence (SI)	3.129
Facilitating Conditions (FC)	2.790
Perceived Risk (PR)	1.064
Environmental Friendliness (EFR)	1.522
Price Sensitivity (PS)	1.099

Note: All VIF values are below the recommended threshold of 3.3.

section 4.7.

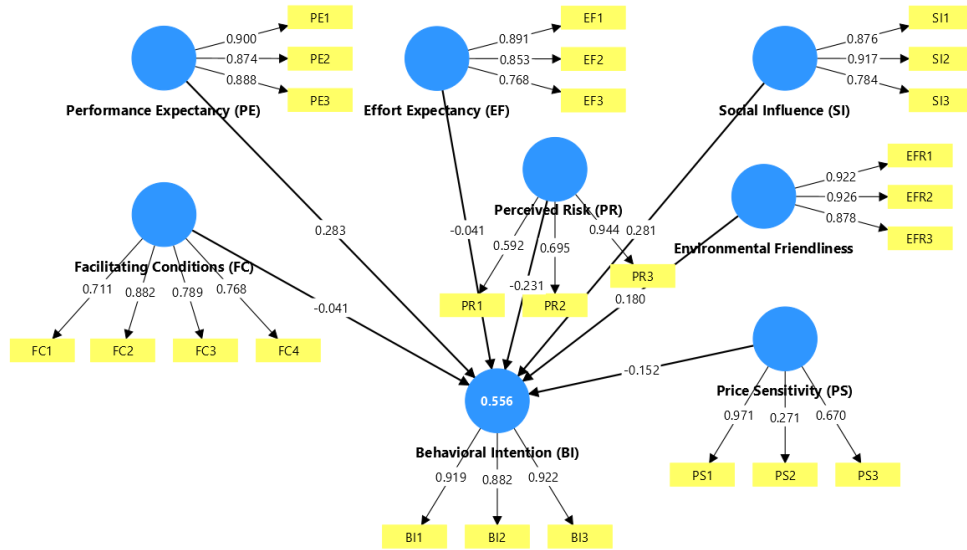


Figure 5.3: Path graph for the structural model

5.6 RESULTS

The hypothesis testing results revealed that five out of the seven proposed relationships were supported, indicating that most of the constructs in the modified UTAUT2 framework significantly influence users' behavioral intentions toward adopting drone delivery services. Performance Expectancy and Social Influence emerged as the strongest positive predictors, suggesting that respondents are more inclined to adopt drone deliveries if they perceive clear performance benefits and if such technologies are socially endorsed. Environmental Friendliness was also found to have a significant positive effect, highlighting the growing importance of sustainability considerations in shaping technology acceptance, especially in light of Canada's zero-emission targets. Conversely, Perceived Risk and Price Sensitivity negatively influenced behavioral intentions, reflecting users' concerns about safety, privacy, and cost implications associated with drone deliveries. The final evaluation of the proposed hypotheses can be found on Table 5.7.

However, the paths from Effort Expectancy (EF) to Behavioral Intention (BI) and from Facilitating Conditions (FC) to Behavioral Intention (BI) were not supported. This finding aligns with the respondent profile, which is characterized by a highly educated sample with approximately 70% demonstrating intermediate-to-advanced technical proficiency and over half having prior exposure to drone technologies. Such participants are less likely to be influenced by the ease of use or the availability of resources, as they generally possess sufficient skills and confidence to adapt to new systems. Moreover, the discrimi-

nant validity assessment revealed that the HTMT value between EF and FC was slightly above the recommended threshold, suggesting potential conceptual overlap between the two constructs. This implies that respondents may have evaluated both constructs similarly, perceiving them as part of a single underlying dimension related to practical ease and resource adequacy rather than distinct determinants of behavioral intention.

Table 5.7: Results of the tested relationships.

	Hypothesis	Path Direction	Path Coefficient	Standard Deviation	T statistics (≥ 1.96)	P values (< 0.05)	Result
H1	PE $\rightarrow$ BI	positive	0.283	0.121	2.344	0.019	Supported
H2	EF $\rightarrow$ BI	positive	-0.041	0.094	0.438	0.661	Not supported
H3	SI $\rightarrow$ BI	positive	0.281	0.116	2.420	0.016	Supported
H4	FC $\rightarrow$ BI	positive	-0.041	0.104	0.391	0.696	Not supported
H5	PR $\rightarrow$ BI	negative	-0.231	0.054	4.251	0.000	Supported
H6	EFR $\rightarrow$ BI	positive	0.180	0.074	2.418	0.016	Supported
H7	PS $\rightarrow$ BI	negative	-0.152	0.063	2.409	0.016	Supported

5.7 DISCUSSION

5.7.1 DISCUSSION OF THE KEY FINDINGS

Performance Expectancy emerged as one of the strongest predictors of behavioral intention, suggesting that users primarily evaluate drone delivery services based on their perceived

usefulness, efficiency, and practical advantages. This finding is consistent with prior studies on autonomous delivery technologies [39], [129], where operational benefits and perceived utility have frequently been identified as major drivers of adoption. The strong influence of this construct may reflect the utilitarian nature of last-mile delivery services, in which consumers tend to prioritize shorter delivery times, flexibility, and service effectiveness over the experiential aspects of technology use. In the Canadian context, this result may also indicate increasing openness toward innovative delivery solutions capable of addressing growing expectations for speed and convenience in e-commerce logistics.

Social Influence was also found to positively affect behavioral intention, indicating that perceptions of drone delivery adoption are shaped, at least partially, by the attitudes and opinions of others. This result aligns with previous research on emerging technologies, where social endorsement and peer perceptions often play a significant role during the early stages of adoption [148], [141]. Since drone delivery remains relatively unfamiliar to many consumers, individuals may rely on social cues and external opinions to evaluate the legitimacy, usefulness, and trustworthiness of the technology. The significance of this construct therefore highlights the role of collective perception and social acceptance in reducing uncertainty surrounding autonomous delivery systems.

In contrast, Perceived Risk demonstrated a significant negative effect on behavioral intention, suggesting that concerns related to safety, privacy, reliability, and operational uncertainty continue to represent important barriers to adoption. This finding is in line with prior studies reporting that users tend to approach autonomous and AI-driven delivery technologies cautiously when potential risks are not yet fully understood [133], [134], [135].

Compared to conventional delivery methods, drone delivery introduces additional concerns associated with autonomous navigation, technical malfunction, and data security, all of which may contribute to higher levels of perceived uncertainty. The persistence of these concerns emphasizes the importance of transparent communication, regulatory clarity, and trust-building measures in supporting wider public acceptance.

Price Sensitivity also appears to negatively influence users' behavioral intention toward drone delivery services, suggesting that economic considerations may represent a barrier to adoption, particularly during the early stages of commercialization. This result generally supports previous research indicating that consumers evaluate emerging delivery technologies not only in terms of convenience and innovation, but also through perceived economic trade-offs [129]. In this context, users may associate drone delivery with premium pricing or additional delivery costs, which could reduce willingness to adopt the service despite its operational advantages. However, given the relatively weaker measurement properties observed for this construct, the associated findings should be interpreted with appropriate caution and further validated in future research.

Environmental Friendliness was found to positively influence behavioral intention, reinforcing the growing view that sustainability considerations play an increasingly important role in the acceptance of emerging logistics technologies. This finding is consistent with recent studies suggesting that consumers evaluate delivery innovations not only on the basis of efficiency, but also according to their perceived environmental impact [39], [40]. In the context of drone delivery, users may associate electric and autonomous delivery systems with reduced traffic congestion, lower emissions, and more sustainable urban logistics

practices.

5.7.2 MODERATING IMPACT OF AGE, GENDER AND TECHNICAL EXPERTISE

For the 3 key categorical variables (age groups, gender, and experience groups) multi-group analysis (MGA) has been run on SmartPLS4 to see their moderating impact on the tested hypotheses and results are presented in this subsection. However, as formal measurement invariance testing was not conducted prior to the multi-group analysis, these findings should be interpreted as exploratory indications of potential group differences rather than definitive moderating effects.

AGE:

The multi-group analysis (MGA) revealed significant age-based differences in two structural relationships: Effort Expectancy $\rightarrow$ Behavioral Intention was significantly stronger among respondents aged under 35 years (difference = +0.473, $p < 0.05$), suggesting that younger users' adoption intentions are more strongly shaped by their perceptions of ease of use and technological simplicity. In contrast, Social Influence $\rightarrow$ Behavioral Intention was significantly stronger among respondents aged 35 and above (difference = -0.653, $p < 0.05$), indicating that older users are more affected by the opinions and social approval of peers, family, or colleagues when forming their intention to adopt drone delivery services. These findings highlight that distinct motivational factors drive adoption across age

cohorts, aligning with prior UTAUT2 evidence showing that younger consumers prioritize usability, whereas older consumers rely more on social validation in adopting emerging technologies [125], [152].

GENDER:

The multi-group analysis (MGA) results indicated that gender did not have a significant moderating effect on any of the hypothesized relationships, suggesting that male and female respondents exhibited similar behavioral patterns in their intention to adopt drone delivery services.

TECHNICAL EXPERTISE:

The multi-group analysis (MGA) examining the moderating role of technical expertise revealed significant differences for two relationships: Performance Expectancy $\rightarrow$ Behavioral Intention and Social Influence $\rightarrow$ Behavioral Intention. The difference between low-moderate expertise (Basic & Intermediate) and high expertise (Advanced&Expert) was -0.500 for the PE-BI path and $+0.469$ for the SI-BI path, both significant at $p < 0.05$. These results suggest that respondents with higher technical expertise are more strongly influenced by performance expectancy, reflecting a greater appreciation of the functional and efficiency benefits offered by drone delivery technology. In contrast, less-experienced users rely more heavily on social influence, indicating that peer opinions and societal endorsement play a greater role in shaping their adoption intentions. This pattern aligns with prior technology adoption research [125], [157] which demonstrates that technically

experienced users tend to evaluate innovations based on instrumental value, whereas less experienced users depend more on social cues and external validation.

5.7.3 OTHER FINDINGS ON USER PERCEPTIONS

To contextualize respondents' overall attitudes toward drone delivery, the descriptive results for the behavioral intention items are examined. The mean score for the statement "I intend to use drone delivery service as a delivery option in the future" is 3.69 on a five-point Likert scale, indicating a moderately positive intention toward using drone deliveries. Similarly, the other two behavioral intention indicators — "I would always try to use drone delivery as a delivery option in my daily life when available in the future" and "I plan to use drone delivery service frequently when available in the future" receive mean scores of 3.37 and 3.54, respectively. These results suggest that, on average, respondents demonstrate a neutral-to-positive outlook toward adopting drone delivery services once they become available.

The questionnaire includes four additional items (Q37 – Q40) that fall outside the structural model but were designed to provide deeper insights into respondents' perceptions and preferences regarding drone delivery systems. These questions were optional to answer. The corresponding visual summaries are presented in Figure 5.4.

Q37 explored the current delivery methods respondents use for online purchases, allowing multiple selections. The responses from 154 participants indicate that home delivery remains the dominant mode, used by nearly all respondents (99%), followed by store or

curbside pickup (22%) and pick-up point delivery (22%). Although parcel lockers are still an emerging delivery option in Canada, their adoption by 13% of respondents suggests growing acceptance of this alternative. Only 11% of respondents reported preferring deliveries to their workplace or educational institutions.

Q38 examined the types of commodities respondents would consider ordering via drone delivery. Based on 154 responses, medical supplies and prescriptions ranked highest (55%), closely followed by food and groceries (51%). Houseware items (36%) and childcare products (32%) also represented notable categories. Interestingly, 14% of participants indicated they would use drone delivery for luxury goods. A small number of responses in the “other” category emphasized a preference for non-perishable and non-fragile items.

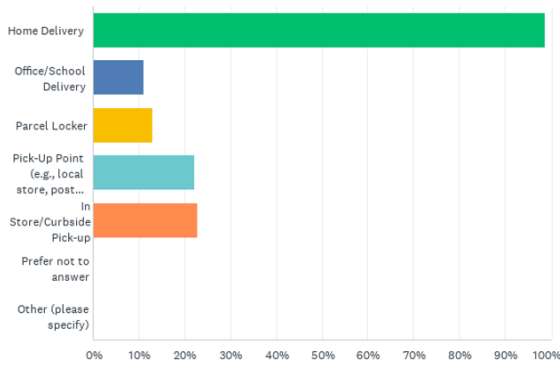
Q39 reveals 154 respondents’ expected timeline of drone delivery availability in Canada. The finding that 71% of respondents expect drone deliveries to become widely available in Canada within the next decade (with 32% anticipating this within 5 years and 39% within 5–10 years) likely reflects the sample’s high level of technological literacy and education. Given that 57% of participants hold a master’s or doctoral degree and 71% report at least intermediate technical expertise, it is reasonable to infer that they possess a stronger awareness of emerging technologies and innovation trends. This group may be more attuned to the rapid pace of automation and digital transformation in logistics, leading to more optimistic expectations regarding the timeline for drone delivery adoption in Canada.

Finally, Q40 investigated respondents’ perceptions of the key issues that may hinder the large-scale adoption of drone delivery in Canada by asking them to rank potential

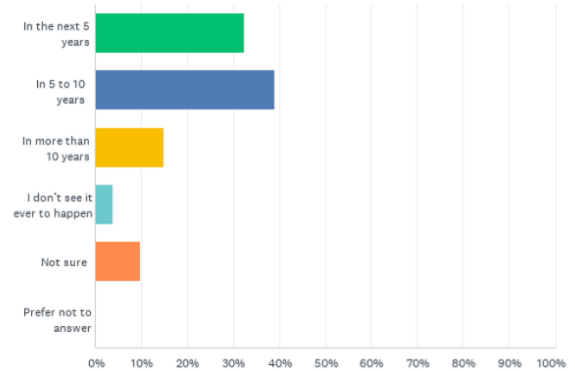
barriers in order of importance. Among 149 responses to this question, tough weather conditions emerged as the most critical concern, reflecting Canada’s challenging climatic environment, where factors such as snow, or extreme cold can significantly affect drone operations. Regulatory challenges were identified as the second most important issue, emphasizing the perceived complexity and uncertainty surrounding aviation regulations, flight permissions, and airspace management for unmanned aerial vehicles. Public safety and security ranked third, suggesting that despite growing technological optimism, concerns remain about accidents, misuse, and privacy violations. Other issues such as limited battery life and flight range, cost and economic viability, and infrastructure requirements were rated comparatively lower, though they continue to represent practical barriers to implementation. Overall, these results indicate that respondents tend to view environmental and regulatory constraints as the most pressing obstacles, while technological and economic challenges are perceived as more manageable over time.

5.7.4 PRACTICAL IMPLICATIONS OF THIS WORK

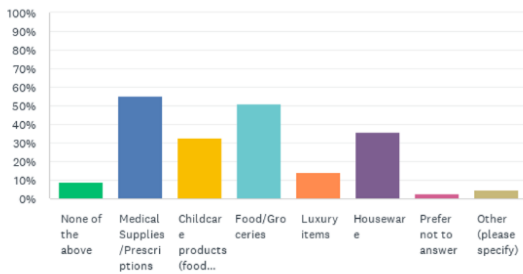
The findings offer several implications for stakeholders involved in drone delivery deployment. Performance Expectancy emerged as a key driver, indicating that users prioritize efficiency and convenience. Firms should emphasize faster delivery, reliability, and flexibility in their service design and communication. The negative effects of Perceived Risk and Price Sensitivity highlight the need for trust-building measures and competitive pricing strategies, particularly during early adoption stages. The non-significance of Effort



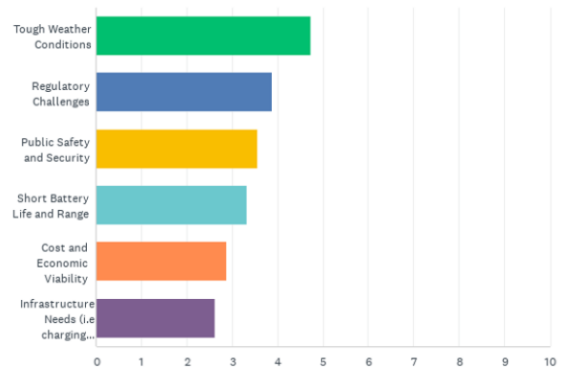
(a) Current preferences for parcel delivery



(c) When drone delivery may be widely available in Canada



(b) Commodity preferences for drone delivery



(d) Key issues that may prevent scaling in Canada

Figure 5.4: Survey results: (a) current delivery preferences and (b) commodity preferences; (c) availability expectations and (d) scale barriers.

Expectancy suggests that usability is less critical for technologically proficient users. Instead, development efforts should focus on system reliability, operational safety, and data security to address user concerns and enhance trust. The importance of Perceived Risk underscores the need for clear regulatory frameworks addressing safety, privacy, and airspace management. Promoting the environmental benefits of drone delivery and supporting pilot initiatives may further facilitate public acceptance. Overall, successful implementation requires aligning performance benefits with risk mitigation, pricing strategies, and regulatory clarity.

5.7.5 LIMITATIONS OF THIS WORK

While the study provides valuable insights into the behavioral intention to use drone delivery services in Canada, several limitations should be acknowledged. First, the use of a convenience sampling method, primarily targeting professional and academic networks in Ontario, resulted in a geographically skewed sample, which may limit the generalizability of the findings to the broader Canadian population. The sample is characterized by relatively high levels of education and technical proficiency, reflecting a technology-oriented user group. Ontario's dominance, however, also reflects its status as a national hub for technological innovation and early adoption, making it a relevant but context-specific case. Accordingly, the findings should be interpreted as representative of early adopter perspectives rather than the general population. Second, the younger (<25) and older (55+) individuals are underrepresented, potentially constraining the study's ability to capture

generational differences in technology acceptance. Third, although the study applied validated UTAUT2-based constructs and achieved acceptable reliability and validity metrics, self-reported survey data are inherently subject to common method bias and social desirability effects, which may influence the accuracy of responses. Fourth, the cross-sectional design limits causal inference; behavioral intention was measured at a single point in time and may evolve as drone delivery becomes more familiar or widely available. Finally, the relatively modest sample size ($n = 156$), while adequate for PLS-SEM analysis in exploratory research, further reinforces the need for caution when generalizing the findings, particularly given the concentration of respondents within technology-oriented communities. Future studies employing more diverse and representative sampling strategies would be valuable to validate and extend these findings across broader consumer segments.

In addition, certain limitations related to the measurement model should be acknowledged. The Price Sensitivity construct exhibited relatively weaker measurement properties, including lower indicator loadings and a slightly below-threshold AVE value, while some indicators within the Perceived Risk construct also demonstrated moderate loadings. Furthermore, HTMT results suggested partial conceptual proximity between certain constructs, particularly Effort Expectancy and Facilitating Conditions, as well as Social Influence and Performance Expectancy. Although the constructs were retained based on their theoretical relevance and acceptable reliability metrics for exploratory research, these limitations suggest that some relationships within the structural model should be interpreted with appropriate caution. Future research should further refine and validate these constructs using larger and more diverse samples.

5.8 CONCLUSION AND FUTURE DIRECTIONS

This study examined the factors influencing Canadian consumers' behavioral intention to adopt autonomous drone delivery services by applying an extended UTAUT2 framework in the context of last-mile logistics. Given the increasing operational and environmental challenges associated with conventional delivery systems, understanding user acceptance of emerging autonomous delivery technologies is an important step toward their successful implementation and broader societal integration.

The findings indicate a moderately positive intention among respondents toward the future use of drone delivery services. Among the seven hypothesized relationships, five were supported. Performance Expectancy, Social Influence, and Environmental Friendliness were found to positively influence Behavioral Intention, while Perceived Risk and Price Sensitivity demonstrated significant negative effects. In contrast, Effort Expectancy and Facilitating Conditions did not show significant relationships with Behavioral Intention. These findings suggest that users primarily evaluate drone delivery services based on their perceived usefulness, social acceptance, sustainability benefits, and potential economic and operational concerns.

From a theoretical perspective, the study contributes to the growing literature on autonomous delivery technologies by validating the applicability of an extended UTAUT2 framework within the Canadian context. In particular, the findings support the relevance of incorporating context-specific constructs such as Environmental Friendliness, Perceived

Risk, and Price Sensitivity when examining the adoption of emerging logistics technologies. The study also contributes to the limited body of empirical research focusing on user acceptance of drone delivery services in Canada.

The findings additionally provide several practical implications for logistics providers, technology developers, and policymakers. The strong influence of Performance Expectancy and Social Influence suggests that adoption strategies should emphasize operational efficiency, convenience, and positive public perception. At the same time, the negative effects of Perceived Risk and Price Sensitivity highlight the importance of transparent communication, trust-building initiatives, regulatory clarity, and cost-effective implementation strategies. The significance of Environmental Friendliness further indicates that sustainability-oriented messaging may positively support consumer acceptance of drone delivery systems.

Although the study provides meaningful insights into drone delivery adoption, several limitations should be considered when interpreting the findings. The use of convenience sampling and the concentration of respondents within technology-oriented and Ontario-based networks limit the generalizability of the results to the broader Canadian population. In addition, certain constructs, particularly Price Sensitivity, exhibited relatively weaker measurement properties, suggesting that some structural relationships should be interpreted with appropriate caution. Nevertheless, additional robustness assessments, including VIF analysis and Harman's single-factor test, did not indicate critical multicollinearity or major common method bias concerns.

Future research should employ larger and more representative samples across different provinces and demographic groups, while also incorporating longitudinal and real-world experimental approaches to better capture evolving consumer perceptions of drone delivery systems. Further studies may additionally examine the influence of regulatory, infrastructural, and operational variables on the broader adoption of autonomous delivery technologies.

APPENDIX

The cross loadings of the indicators are provided on Table 5.8 .

Table 5.8: Cross-loadings

	BI	EF	EFR	FC	PR	PE	PS	SI
BI1	0.919	0.390	0.505	0.413	-0.373	0.616	-0.332	0.621
BI2	0.882	0.298	0.517	0.314	-0.278	0.496	-0.319	0.516
BI3	0.922	0.413	0.451	0.407	-0.365	0.583	-0.240	0.588
EF1	0.398	0.891	0.278	0.601	-0.192	0.590	-0.128	0.576
EF2	0.344	0.853	0.247	0.643	-0.189	0.562	-0.124	0.554
EF3	0.259	0.768	0.195	0.567	-0.165	0.409	-0.057	0.425
EFR1	0.444	0.265	0.922	0.359	-0.151	0.466	-0.217	0.455
EFR2	0.456	0.240	0.926	0.302	-0.159	0.483	-0.203	0.432
EFR3	0.553	0.281	0.878	0.337	-0.257	0.516	-0.280	0.503
FC1	0.301	0.477	0.270	0.711	-0.203	0.476	-0.134	0.528
FC2	0.366	0.692	0.335	0.882	-0.174	0.563	-0.033	0.653
FC3	0.312	0.519	0.266	0.789	-0.077	0.457	0.040	0.456
FC4	0.339	0.560	0.284	0.768	-0.039	0.552	-0.073	0.522
PR1	-0.147	-0.018	-0.119	0.076	0.592	-0.050	0.138	-0.033
PR2	-0.148	-0.098	-0.102	-0.045	0.695	-0.029	0.003	-0.112
PR3	-0.420	-0.263	-0.221	-0.228	0.944	-0.259	-0.079	-0.275
PE1	0.565	0.609	0.513	0.633	-0.264	0.900	-0.122	0.726
PE2	0.483	0.606	0.433	0.591	-0.075	0.874	-0.167	0.643
PE3	0.602	0.478	0.488	0.515	-0.191	0.888	-0.271	0.680
PS1	-0.348	-0.154	-0.284	-0.106	-0.002	-0.263	0.971	-0.313
PS2	0.014	0.257	0.008	0.296	0.041	0.130	0.271	0.208
PS3	-0.112	0.043	-0.072	0.141	-0.068	0.053	0.670	-0.043
SI1	0.562	0.546	0.473	0.551	-0.214	0.699	-0.331	0.876
SI2	0.596	0.571	0.488	0.617	-0.225	0.685	-0.224	0.917
SI3	0.478	0.498	0.357	0.617	-0.157	0.607	-0.174	0.784

ACKNOWLEDGMENT

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CONCLUSIONS, OPEN ISSUES AND OPPORTUNITIES

6.1 CONCLUDING REMARKS

Advances in autonomous aerial systems and collaborative delivery concepts have created new opportunities for redesigning last-mile logistics beyond conventional truck-only operations. Among these approaches, truck–drone collaborative delivery (TDCD) systems have attracted considerable academic and industrial interest by combining the payload capacity and mobility of delivery trucks with the speed and accessibility of unmanned aerial vehicles. While this integration offers significant potential to improve delivery efficiency and resource utilization, large-scale deployment remains constrained by operational, technological, regulatory, infrastructural, and societal challenges. Operational constraints associated with energy consumption, fleet coordination, infrastructure utilization, and service reliability must be addressed alongside regulatory considerations related to airspace management, safety, and public acceptance. Moreover, the interconnected nature of these challenges requires moving beyond isolated routing and scheduling problems toward more comprehensive planning approaches that consider system-level interactions and long-term deployment requirements. Consequently, there is a growing need for integrated frameworks that support the effective planning, coordination, and scaling of truck–drone collaborative delivery networks.

This dissertation addressed this challenge through a comprehensive investigation of truck–drone collaborative delivery systems from technological, operational, planning, and societal perspectives. By integrating empirical modeling, optimization, user acceptance

analysis, and conceptual planning frameworks, the research contributes to a more holistic understanding of how TDCD systems can be designed, evaluated, and implemented within future last-mile logistics networks.

The first contribution of this dissertation was the development of empirical machine learning-based regressors for drone energy consumption and delivery time estimation using an empirical drone (DJI Matrice 100) flight dataset, presented in the journal article *Machine Learning-Driven Truck-Drone Collaborative Delivery for Time and Energy Efficient Last-Mile Deliveries*. Existing TDCD studies frequently rely on simplified assumptions regarding drone battery consumption, flight duration, and operational performance, often neglecting the complex relationships between payload, travel distance, and energy usage. The resulting machine learning models provided data-driven estimates of energy consumption and delivery times, enabling a more realistic representation of drone operations. The study demonstrated that integrating empirical drone performance models into delivery planning can improve the accuracy of operational assessments and provide a stronger foundation for optimization-based decision-making.

Building upon this empirical foundation, the second contribution focused on the optimization of coordinated truck-drone delivery operations using real-world delivery data. This work was presented in the journal article *Data-Driven Optimization of Truck-Drone Collaborative Delivery with Shared Fleet Allocation*. A mixed-integer linear programming (MILP) framework was developed to support coordinated fleet allocation and workload distribution across multiple truck routes served from a common depot. Unlike many previous studies that consider isolated truck-drone pairs, the proposed framework addressed

fleet-sharing decisions at the network level by allocating a common pool of drones among multiple delivery routes. Using delivery data derived from the Amazon Last Mile Routing Research Challenge dataset, the model demonstrated that coordinated fleet allocation can significantly improve overall delivery efficiency. The results showed substantial reductions in total delivery time (25%) and energy consumption (40%) compared with conventional truck-only operations while maintaining operational feasibility. Beyond the numerical improvements, the study highlighted the importance of treating drone resources as shared network assets rather than route-specific resources, thereby contributing a more realistic perspective to strategic and tactical planning for TDOD systems.

While technological and operational feasibility are essential for successful deployment, public acceptance remains a critical determinant of whether drone delivery systems can achieve widespread adoption. Consequently, the third contribution of this dissertation investigated the human and societal dimensions of drone delivery adoption through the journal article *Drivers and Barriers to Drone Delivery Adoption in Canada: Insights for Sustainable Last-Mile Logistics*. Using an extended UTAUT2 framework and survey responses 156 from Canadian consumers, the study examined the factors influencing behavioral intentions toward drone delivery services. The findings revealed that performance expectancy, social influence, and environmental concerns positively influenced adoption intentions, while perceived risk and perceived safety concerns acted as significant barriers. The study also identified differences across demographic and technology-experience groups, providing valuable insights for policymakers, logistics providers, and technology developers seeking to increase public acceptance of drone-enabled delivery systems. By addressing the

social dimension of innovation adoption, this research complements the technical contributions of the dissertation and emphasizes the need for balanced technological and societal considerations in future deployment strategies.

Recognizing that operational optimization alone cannot fully address the long-term challenges associated with large-scale TDCD implementation, this dissertation further explored system-level planning considerations through two complementary workshop papers. The first paper, *Systems-Level Planning and Coordination of Truck-Drone Collaborative Delivery Networks*, proposed a conceptual framework that distinguishes between operational optimization and scalability-oriented planning. The framework emphasized the importance of coordinating drone fleets, delivery routes, infrastructure requirements, and network-level decision-making as deployment scales increase. The second paper, *Green and Intelligent Planning of Drone Launch in Truck-Drone Collaborative Delivery*, investigated the role of intelligent launch-point planning in improving energy efficiency and operational effectiveness. Together, these studies expanded the research perspective beyond individual routing problems and introduced planning principles that can support future large-scale deployment of collaborative delivery networks.

Collectively, the findings of this dissertation demonstrate that the successful implementation of truck-drone collaborative delivery systems requires an integrated approach that combines realistic operational modeling, optimization-based decision support, user-centered adoption analysis, and strategic planning considerations. The research shows that significant improvements in delivery efficiency can be achieved when truck-drone operations are coordinated effectively and supported by empirical performance data.

From a practical perspective, the contributions of this dissertation provide several implications for industry stakeholders. Logistics operators can utilize empirical energy-consumption models to improve fleet planning and operational forecasting. Optimization frameworks developed in this research can support tactical decisions regarding drone fleet allocation, and resource utilization. Policymakers and regulators can leverage the findings from the adoption study to better understand public concerns and design policies that facilitate responsible deployment. Furthermore, the conceptual planning frameworks offer guidance for future infrastructure development and network design as drone-enabled logistics systems continue to evolve.

6.2 OPEN ISSUES AND FUTURE OPPORTUNITIES

Although truck-drone collaborative delivery has gained considerable attention as a promising approach for improving last-mile logistics efficiency, several open issues remain before such systems can be deployed at scale in real-world urban and suburban environments. The findings of this thesis highlight both the technical potential of coordinated truck-drone operations and the complexity of translating this potential into operationally reliable, socially acceptable, and regulation-compliant delivery systems.

One important open issue concerns the operational uncertainty associated with drone-based delivery. While this thesis incorporates more realistic energy and delivery-time estimation compared with simplified battery-based assumptions, drone performance in practice remains highly sensitive to external conditions such as wind, temperature, precipitation,

airspace restrictions, payload variability, communication reliability, and battery degradation over repeated use. These factors can influence flight range, service reliability, safety margins, and fleet availability. Future research should therefore move toward higher-fidelity operational models that integrate stochastic weather effects, dynamic battery behavior, maintenance requirements, and real-time system disruptions. A further limitation concerns the platform specificity of the empirical energy and delivery-time models developed in this thesis. The underlying flight data were obtained exclusively from a DJI Matrice 100 platform, and the resulting regressors therefore reflect the aerodynamic characteristics, propulsion system, payload range, battery configuration, and flight-control behavior of that particular multirotor UAV. Consequently, the models should not be assumed to generalize directly to heavier-payload drones or alternative airframe configurations such as hybrid fixed-wing UAVs. For deployment on other platforms, logistics operators should recalibrate the framework using platform-specific flight data collected across representative payloads, speeds, distances, vertical profiles, and environmental conditions. The same modeling structure can then be retained while re-estimating the energy- and time-prediction functions for the target UAV, thereby preserving the decision-support framework while adapting its empirical parameters to different vehicle classes and operating envelopes.

A second challenge relates to the coordination of truck and drone resources in larger and more dynamic delivery networks. The optimization models developed in this thesis provide a planning-oriented foundation for shared drone fleet allocation and workload coordination across multiple truck routes. However, real-world deployment would require additional consideration of dynamic order arrivals, time windows, traffic congestion, drone

sequencing, charging or battery-swapping operations, and interactions among multiple depots. As the scale of the system increases, computational complexity, synchronization requirements, and operational interdependence among trucks, drones, depots, and launch locations become increasingly important. Future extensions should also incorporate dynamic environmental and transportation conditions directly into workload estimation and routing bounds. Real-time wind speed and direction could be used to continuously update drone energy-consumption and flight-time estimates, thereby adjusting feasible delivery radii, workload limits, and reserve-energy constraints during operations. Similarly, live road-traffic information could be incorporated into truck travel-time parameters and synchronization constraints to reflect changing congestion levels and arrival times at candidate launch locations. These updates could be implemented through rolling-horizon optimization or digital-twin-based control, in which the model is periodically re-solved as new weather and traffic information becomes available. Such an approach would allow truck-stop selection, workload allocation, and drone fleet deployment decisions to adapt dynamically rather than relying solely on static precomputed bounds.

Another unresolved issue is the integration of truck–drone delivery systems with existing urban infrastructure and regulatory environments. Practical deployment requires more than routing efficiency; it also depends on suitable launch and recovery areas, drone landing zones, charging infrastructure, communication networks, airspace management, and local permissions. In addition, safety, privacy, noise, liability, and community acceptance remain central concerns for regulators, logistics providers, and the public. These issues suggest that truck–drone collaborative delivery should be studied not only as an optimization problem,

but also as a cyber-physical logistics system embedded within broader transportation, infrastructure, and governance frameworks.

The human and social dimensions of drone delivery also remain important areas for further investigation. The acceptance study conducted in this thesis shows that perceived usefulness, social influence, environmental concern, perceived risk, and privacy/security concerns can shape public intention to adopt drone delivery services. However, public attitudes may evolve as drone technologies become more visible, regulations mature, and pilot deployments expand. Future studies could examine acceptance across different regions, age groups, community types, delivery contexts, and levels of prior exposure to drone technologies. There is also an opportunity to connect behavioral acceptance models with operational planning models, so that deployment strategies account not only for cost and efficiency, but also for public trust, perceived fairness, and community readiness.

Finally, future work should further examine the environmental and economic trade-offs of truck-drone collaborative delivery under realistic deployment conditions. While this thesis demonstrates that coordinated truck-drone operations can reduce delivery time and energy consumption in selected scenarios, the broader sustainability impact depends on factors such as electricity sources, drone manufacturing and lifecycle impacts, infrastructure requirements, vehicle utilization, failed deliveries, and fleet maintenance. A more comprehensive assessment could integrate lifecycle analysis, cost-benefit evaluation, emissions modeling, and multi-stakeholder performance measures. Such work would help determine under what conditions truck-drone collaborative delivery can provide meaningful and scalable benefits compared with conventional delivery systems and other emerging last-mile

alternatives.

Overall, the open issues identified in this thesis suggest that the next stage of truck–drone collaborative delivery research should move toward more integrated, adaptive, and implementation-oriented frameworks. Future studies should combine operational optimization, empirical performance modeling, infrastructure planning, regulatory analysis, and public acceptance considerations. Addressing these dimensions together will be essential for advancing truck–drone collaborative delivery from promising experimental and planning models toward safe, scalable, and socially acceptable last-mile logistics systems.

APPENDICES

A

CONFERENCE PAPER 1- SYSTEMS-LEVEL
PLANNING AND COORDINATION OF
TRUCK–DRONE COLLABORATIVE
DELIVERY NETWORKS

A.1 PUBLICATION STATEMENT

In addition to the three journal articles that form the core of this dissertation, two peer-reviewed conference workshop papers are included in the Appendix as supporting contributions.

This chapter is based on the workshop paper titled “Systems-Level Planning and Coordination of Truck–Drone Collaborative Delivery Networks”, co-authored by Didem Cicek and Burak Kantarci, presented at the Workshop on Network Architectures and Intelligence for Smart Mobility and Autonomous Systems (TRAVERSAL), held in conjunction with the IEEE High-Performance Switching and Routing (HPSR) Conference in June 2026.

This paper proposes a systems-level planning and coordination framework for scaling truck–drone collaborative delivery networks. This work contributed a broader conceptual perspective that complements the optimization and empirical modeling contributions presented in the journal articles and helped position the dissertation within the wider context of autonomous delivery system design and deployment.

A.2 INTRODUCTION

The rapid growth of e-commerce and mounting concerns over traffic congestion, emissions, and heightened service expectations have led to the introduction of unmanned aerial vehicles (UAVs), commonly referred to as delivery drones, as a potential complement to

conventional truck-based logistics. Nevertheless, the widespread integration of drones into urban delivery networks remains limited by operational and regulatory constraints. Consequently, recent scholarship has increasingly turned toward hybrid truck–drone delivery systems, wherein drones function in coordination with ground vehicles rather than as independent agents.

Existing research has diverse frameworks to examine truck–drone collaboration. Collectively, these studies demonstrate that collaborative truck–drone configurations can outperform truck-only delivery, yielding reductions in delivery time, operational costs, and environmental impacts. However, no unified planning framework has yet emerged to systematically integrate these approaches and provide a road-map to scale these operations beyond pilot implementations.

This paper introduces a multi-layer planning framework for truck–drone collaborative delivery (FigureB.1). The framework explicitly differentiates between spatial readiness, collaboration design, operational coordination, performance evaluation, and scalability assessment. By synthesizing insights across regulatory, methodological, and operational domains, this study demonstrates the proposed framework through a case study based on a real-world routing dataset, evaluating the delivery performance of a truck–drone collaborative model for scalable urban last-mile parcel delivery.

This paper is structured as follows: Section B.3 discusses the related work and highlights the novelty of this framework. Section A.4 lays out the planning framework explaining the interdependent collaborative layers of the framework. A case study to demonstrate the

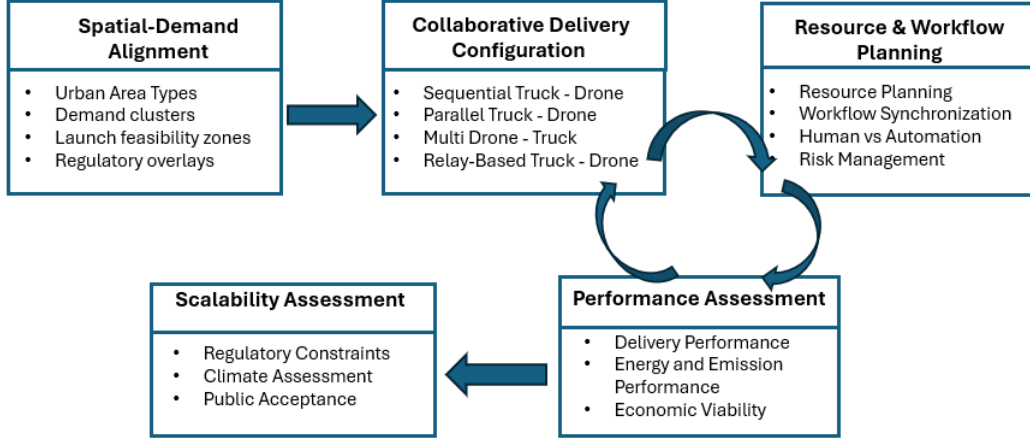


Figure A.1: Planning framework for scaling truck-drone collaborative delivery

framework is covered in Section A.5. Finally, Section B.7 presents the concluding remarks for this work with directions for future research.

A.3 RELATED WORK

Existing research on truck–drone collaborative delivery has predominantly focused on optimization-centric formulations, where the primary objective is to minimize delivery time, distance, or energy consumption under predefined operational assumptions. The majority of proposed frameworks adopt problem-specific mathematical models such as mixed-integer linear programming, heuristics, or metaheuristics tailored to a single collaboration mode, static demand conditions, or fixed fleet configurations. While these studies offer valuable algorithmic insights, they typically treat planning decisions, operational execution,

Table A.1: Comparative table: existing frameworks vs. proposed framework

Framework / Study	Primary Focus	Framework Type	Scalability Treatment	Key Limitations
[158]	Drone-based package delivery traffic density estimation	Methodological	Indirect (airspace capacity planning)	No truck-drone interaction
[8]	UAV supported last-mile delivery systems	Operational and optimization	Explicit computational scalability limits	Optimization becomes intractable at scale
[109]	ML-driven truck-drone resource decisions	Operational and optimization	Scenario-based scalability analysis	Framework focused on operational layer
[6]	Environmental and economic sustainability	Operational and optimization	Sensitivity-based scalability	Limited collaboration taxonomy
[7]	Hybrid RPAS-truck optimization	Operational and optimization	Explicit scalability evaluation	Algorithm-centric
[159]	Traffic Management and resource allocation	Batch Optimization	Computational scalability	More aviation oriented
[160]	Embedding drone deliveries in 5PL systems	Hybrid policy-operational	System-level scalability vision	High implementation complexity
This Paper	Truck-drone collaboration design and scaling	Planning	Explicit scalability assessment layer	Conceptual (intended to guide future implementation)

and performance evaluation in isolation, with limited consideration of end-to-end system design, workflow coordination, or scalability under real-world constraints. In contrast, the planning framework proposed in this paper adopts a holistic, multi-layered perspective that integrates collaboration typologies, resource and workflow planning, performance assessment, and scalability considerations within a unified structure. As summarized in the comparative table TableA.1, the proposed framework extends beyond optimization, addresses key limitations of existing approaches and enabling more transferable, decision-oriented insights for real-world deployment.

A.4 PLANNING FRAMEWORK

Urban last-mile drone delivery can scale only if drones operate collaboratively with trucks, which serve as mobile micro-depots, energy/charging hubs, and logistics synchronizers.

The proposed framework organizes this problem into five interdependent collaborative layers: A.4.1 Spatial–Demand Alignment, A.4.2 Collaborative Delivery Configuration, A.4.3 Resource and Workflow Planning , A.4.4 Performance Assessment and A.4.5 Scalability Assessment . Each layer builds on the previous one. Rather than assuming a strictly sequential process, the framework incorporates a circular feedback loop between the collaborative delivery configuration, resource and workflow planning, and performance assessment layers, recognizing that operational decisions and resource allocations must be iteratively refined in response to performance outcomes and evolving system conditions. The following sections describe each framework layer, outlining its scope and key analytical dimensions.

A.4.1 SPATIAL-DEMAND ALIGNMENT

This layer aims to understand the operational complexity involved and to identify where collaborative drone operations are most valuable. Urban environments differ in density, accessibility, traffic congestion, and flight restrictions. Scaling drones requires matching spatial opportunity with operational feasibility. Key analytical dimensions include: *Urban area types*: The delivery area is examined to identify spatial characteristics and is classified according to urban morphology, such as high-rise cores, mixed-use corridors, residential suburbs, and cul-de-sacs. *Demand clusters*: Geographic groupings of customer demand are identified through analysis of order data to assess where drone deployment can most effectively reduce truck delivery workloads, as performed in our previous work [19]. *Launch feasibility zones*: Areas are examined to determine where trucks can safely stop and drones

can take off and land. *Regulatory overlays*: Regulatory and policy constraints are overlaid onto the service area to delineate no-fly zones, restricted airspace around sensitive facilities, and privacy-related limitations governing drone operations.

A.4.2 COLLABORATIVE DELIVERY CONFIGURATION

While the literature presents numerous operational variants of truck–drone delivery, a consistent taxonomy remains absent. We propose four fundamental truck–drone collaborative models that capture the essential modes of synchronization, fleet scaling, and asset coupling observed in practice. More complex or adaptive strategies can be viewed as hybrid combinations of these baseline collaboration types.

Sequential Truck-Drone Collaboration

The truck and drone operate in a tightly synchronized manner, where the truck temporarily stops and waits for the drone to complete its delivery and return. During this time, the driver may perform auxiliary tasks such as parcel sorting or preparation. This corresponds closely to Traveling Salesman Problem with Drone (TSP-D) [15], [43] where the truck remains stationary at a parking node while the drone visits assigned customers and returns to the truck. This type of collaboration can help delivery in narrow streets or restricted access areas.

Parallel Truck-Drone Collaboration

The truck continues along its delivery route while the drone performs a delivery independently and rejoins the truck at a later location. Truck and drone operations are partially decoupled in time. This configuration also aligns with TSP-D where truck remains active instead of waiting for the drone to complete its delivery. Parallel Drone Scheduling TSP (PDSTSP) [41], and Flying Sidekick TSP (FSTSP) [15], [42] in the literature try to address the same problem. This type of collaboration mostly fits for suburban neighborhoods with moderate parcel density and predictable road networks.

Multi-Drone Truck Collaboration

A single truck functions as a mobile logistics hub capable of launching and recovering multiple drones, enabling simultaneous drone deliveries within a localized service area. This mode increases throughput but requires coordination among multiple airborne assets. This collaboration type has been referred in the literature as Multiple Flying Sidekick TSP (mFSTSP) [46], Flexible Drones TSP (FDTSP) [47] or TSP with multiple drones (TSP-mD) [48] model. This collaboration type can serve high parcel density clusters or peak-demand periods.

Relay-Based Truck-Drone Collaboration

Delivery tasks are completed through staged hand-offs among multiple trucks and drones. A drone may be launched from one truck and recovered by another, enabling extended operational reach beyond individual drone range limitations. This delivery type has the most operational complexity, hence studied the least by the scholars. Previous research

on this problem can be listed as [44], [45]. This delivery model can be used in large or spatially fragmented urban areas, or networks with strict drone range constraints.

A.4.3 RESOURCE AND WORKFLOW PLANNING

This layer defines how truck and drone resources coordinate to scale operations. Key analytical dimensions include: *Resource Planning*: Fleet composition and operational resource parameters are defined, including the number of drones and trucks, drone-to-truck allocation ratios, drone rotation strategies (e.g., charging cycles or battery-swap modules), and truck dwell-time policies. *Workflow Synchronization*: Operational workflows governing truck–drone interactions are specified, including launch and recovery protocols, package handover procedures, queuing arrangements between trucks and drones, supporting communication and positioning systems. *Human vs Automation role allocation*: The division of responsibilities between human operators and automated systems is specified. *Risk Management*: Risk mitigation measures ensure reliable and safe operations under uncertain conditions, including procedures for adverse weather (e.g., wind, precipitation, snow), compliance with urban safety constraints, and robust navigation capabilities.

A.4.4 PERFORMANCE ASSESSMENT

The objective of this layer is to evaluate the outcomes of alternative truck–drone collaborative delivery configurations across key performance metrics, enabling systematic comparison of operational effectiveness, environmental impact, and economic feasibility. Key

analytical dimensions with the proposed metrics include: *Delivery Performance*: Parcel throughput (the number of parcels delivered collaboratively over a given period or route), delivery time reduction relative to baseline, truck-only operations, and on-time delivery rate are important metrics to watch delivery performance. *Energy and Emission Performance*: Drone energy use per parcel, comparative emissions versus truck-only route and balancing the energy use during peak periods are the key metrics for this dimension. *Economic Viability*: From a capital cost and life-cycle perspective, delivery drones present a substantially lower upfront investment than electric delivery trucks often by an order of magnitude, yet their economic lifespan is predominantly constrained by battery degradation, which typically occurs on a much shorter replacement cycle than that of electric truck batteries, thereby necessitating a life-cycle-based rather than purchase-cost-based comparison of fleet assets.

A.4.5 SCALABILITY ASSESSMENT

This layer evaluates whether the collaborative model can scale and under what conditions. Key analytical dimensions include: *Regulatory Constraints*: Regulatory constraints capture the extent to which existing and evolving legal, aviation, and municipal frameworks enable or limit large-scale deployment of truck-drone collaborative delivery systems. *Climate Assessment*: Climate assessment evaluates the suitability and resilience of collaborative delivery operations under region-specific and seasonally varying climatic conditions. Unlike controlled pilot environments, large-scale deployment must contend with persistent

exposure to weather variability and climate-related extremes. *Public Acceptance:* Public acceptance reflects the perceived acceptability of widespread truck–drone delivery operations among stakeholders. Even when systems are technically viable and legally permitted, insufficient public support can significantly hinder large-scale adoption.

A.5 CASE STUDY

The proposed framework is applied to a truck–drone collaborative delivery scenario using a single delivery route selected from the 2021 Amazon Last Mile Routing Research Challenge [101]. The dataset released for the Amazon Last Mile Routing Research Challenge contains route-, stop-, and package-level attributes for 9,184 historical delivery routes executed by Amazon drivers in 2018 across five major metropolitan areas in the United States. The case study in this paper focuses on a single route in Palatine, Illinois, located within the Chicago metropolitan area, comprising 192 customer locations and spanning an operational service area of approximately 18 square kilometers (RouteID_{15baae2d-bf07-4967-956a-173d4036613f}). The delivery area as mapped on GoogleMyMaps¹ can be found on FigureA.2. The delivery truck is assumed to be a Battery Electric Vehicle (BEV) with a driver onboard. The objective of this demonstration is to operationalize each framework layer by outlining the key steps that support informed decision-making in the design of scalable, efficient, and economically viable TDCD models for urban last-mile delivery.

¹<https://www.google.com/maps/about/mymaps/>

A.5.1 LAYER 1: SPATIAL-DEMAND ALIGNMENT

The selected delivery area is a residential suburban fabric dominated by single-family neighborhoods, local streets, schools and churches as seen on the aerial imagery. Due to relatively predictable curb environments and no-hard parking restrictions, the area is good to scale truck-drone collaborative delivery. Although drone operations must comply with Federal Aviation Administration (FAA) regulations, local and district-level rules must also be satisfied prior to deployment. Customer demand, assumed to be known in advance, is then analyzed to identify spatial groupings using proximity-based features. The K-means clustering algorithm is applied to the dataset, resulting in seven distinct demand clusters, as shown in FigureA.3. Each cluster consists of 30 customers on average, except for one cluster (C7) with 8 customers. Then the centroids of each cluster is calculated as a guidance for selecting potential truck stops to launch the drone FigureA.4. The centroid is just a mathematical point and may not directly translate into an actual location; further investigation of the location is required considering the building and road infrastructures.

A.5.2 LAYER 2: COLLABORATIVE DELIVERY CONFIGURATION

The selection of a truck drone collaborative delivery configuration is governed by the interaction between key decision variables including delivery fleet scale reflecting operator resource capacity, feasible launch and recovery locations along the truck route, and customer allocation between truck and drone service, and a set of operational constraints en-

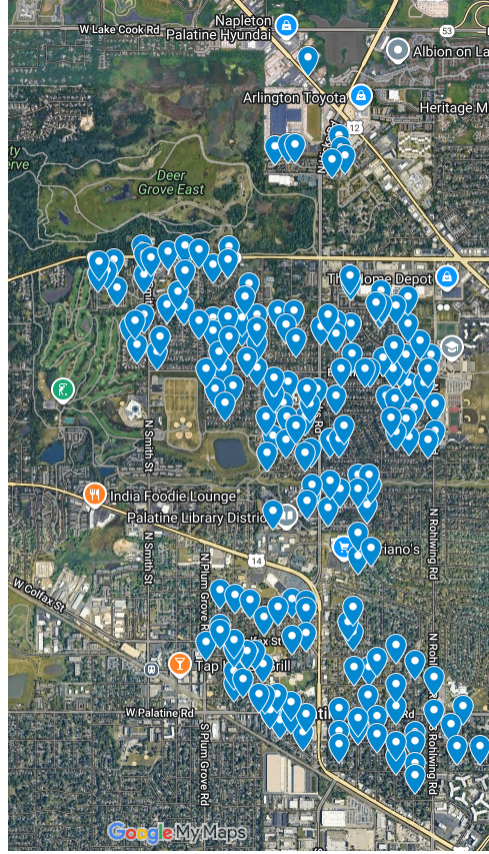


Figure A.2: Delivery area used for the case study

compassing drone energy limits, flight range, truck and drone synchronization and safety requirements, and regulatory restrictions such as controlled airspace and permit required zones. Given the clustered suburban morphology of the Palatine case area and the close spatial proximity of customers within each identified demand cluster, a multi-drone truck collaboration operating mode is selected as the baseline configuration to minimize delivery completion time.

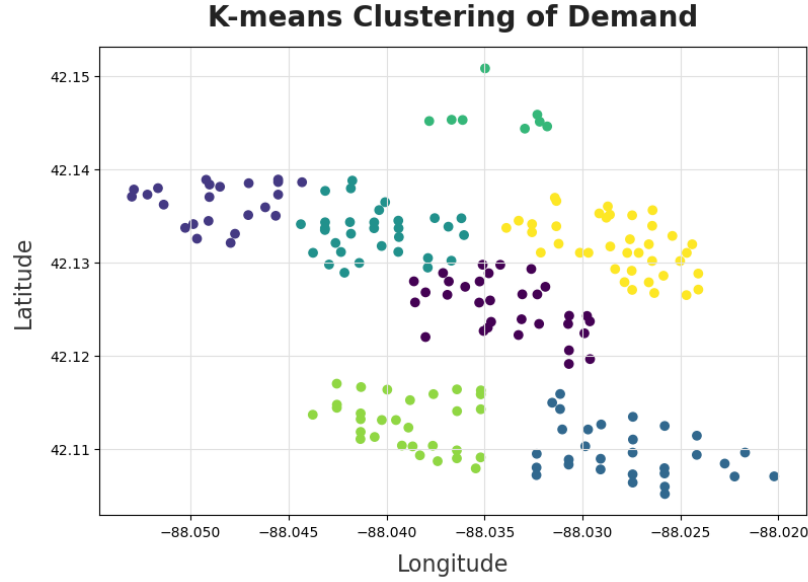


Figure A.3: Clusters of delivery demand

A.5.3 LAYER 3: RESOURCE AND WORKFLOW PLANNING

At this operational layer, this case study adopts a set of simplifying assumptions to enable a transparent demonstration of coordinated truck–drone operations. The delivery fleet consists of one truck carrying three drones, representing a moderate but realistic operational scale for a suburban service area. Each drone is assumed to carry one parcel per sortie, with no mid-flight handoffs or batch deliveries. Drone batteries are assumed to be swapped on the truck by the driver, implying human-in-the-loop ground operations and eliminating the need for automated charging or robotic handling infrastructure. Truck is acting mainly as a mobile depot and not used for parallel delivery. Weather conditions are assumed to be favorable, with no wind, precipitation, or visibility constraints affecting

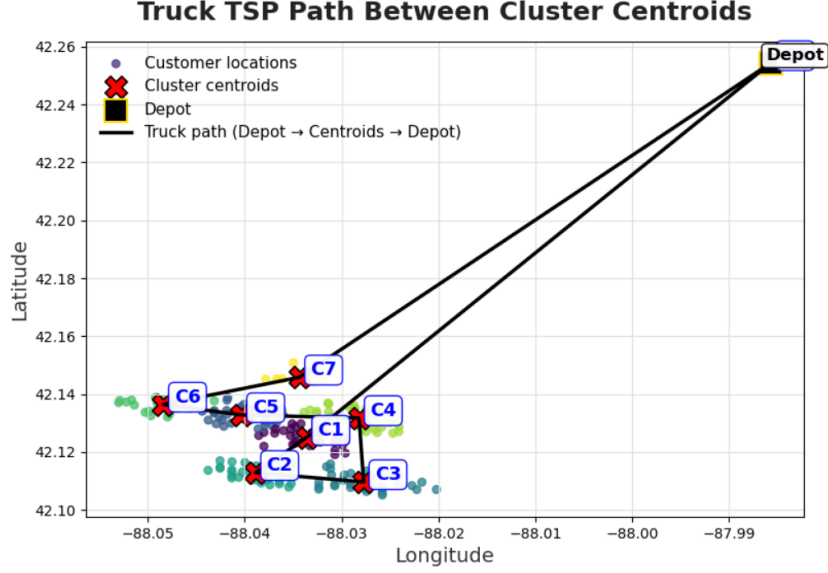


Figure A.4: Truck TSP path and potential truck stops

flight performance. All drones are modeled as DJI Matrice 100 equipped with TB47D battery ², with a payload of 500 gr and a constant horizontal flight speed of 8m/sec over the Euclidean distance at an altitude of 40 meters. The truck is modeled as a Fiat Ducatio BEV 3.5t [106] and assumed to operate at an average cruising speed of 30 km/h on suburban residential roads.

A.5.4 LAYER 4: PERFORMANCE ASSESSMENT

Delivery performance of a baseline truck-only route, formulated as a Traveling Salesman Problem (TSP) and solved using a greedy heuristic is compared against a multi-drone

²<https://www.dji.com/ca/support/product/matrice100>

Table A.2: Delivery time comparison of multi-drone truck collaboration vs truck-only delivery

	Truck only	Multi-Drone Truck
Truck travel distance-km	63.10	20.93
Truck speed-km/hr	30	30
Drone travel distance-km	-	161.5
Drone cruise speed (m/s)	-	8
Drone ascending speed (m/s)	-	3
Drone descending speed (m/s)	-	2.5
Drone cruising altitude (m)	-	40
Drone handling time (sec)	-	30
Total delivery time (min)	451.80	260.3
Delivery time reduction	-	-42.4%
Delivery time/parcel (min)	2.4	1.4

truck collaborative delivery scenario in terms of delivery time and energy considerations. Amazon Routing Dataset contains daily routes of average 150-200 stops. The total delivery time for the truck-only scenario on the selected route, comprising 192 customer locations, is reported as 204.7 minutes for transit, 222.7 minutes for package service (i.e handling, delivery to doorstep), 24.4 minutes for return to depot, amounting to total 451.8 minutes (7.5 hr) delivery time. In the multi-drone truck–drone collaboration scenario, total delivery time is computed as the sum of the truck’s travel time between cluster centers (using exact TSP), drone loading time, drone flight time based on Euclidean distances between cluster centroids and customer locations, and vertical ascent and descent times. The simulation has been run on Python (v 3.10.18) and the results show that collaboration model led to 42.4% reduction in total delivery time TableA.2. It is important to note that the magnitude of the reported savings is highly sensitive to the assumptions adopted in this study regarding cruising altitude, drone speed, payload, and parcel loading time.

For drone energy calculations, we use a hover endurance of 19.5 min (average of no-

payload and 0.5 kg payload hover specifications to reflect loaded outbound and unloaded return legs) and assume an 30% battery degradation factor to conservatively account for mission power variation across forward flight and vertical phases. This conservatism is motivated by prior endurance models showing speed-dependent power in forward flight and different power requirements in ascent/descent relative to hover [161]. The simulation shows 44.2% saving in total vehicle energy given the parameters as define on TableA.3. Vertical energy consumption is modeled as time-based power usage with operational vertical speeds of 3 m/s for ascent and 2.5 m/s for descent, selected conservatively below manufacturer limits to reflect realistic delivery conditions. The lower descent speed results in a longer descent duration and therefore higher energy consumption per unit vertical distance when expressed in Wh/km.

As both vehicles are electrically powered, tailpipe emissions are absent; however, upstream emissions arise from the electricity generation mix. A comparative assessment of CO₂ emissions between a Fiat BEV truck and a DJI Matrice 300 RTK drone is reported in [106], indicating that the drone produces approximately 17% of the truck’s emissions.

A.5.5 LAYER 4: SCALABILITY ASSESSMENT

All customer orders on the selected Amazon route are assumed to be drone-eligible, and customers are assumed to prefer drone delivery when available. However, only 64% of the parcels fall below the 5 lb payload threshold commonly cited for urban drone delivery operations, and public acceptance of drone delivery services remains uncertain. To

Table A.3: Energy consumption comparison of multi-drone truck collaboration vs truck-only delivery

	Truck-only	Multi-Drone & Truck
Drone Battery-Model		TB47D
Drone Battery-Energy		99.9 Wh
Hovering Time-No payload		22 min
Hovering Time-500gr payload		17 min
Hovering Time-Average		19.5 min
Battery Degradation Factor		30%
Max cruise range at 8m/s		6.55 km
Drone Energy at cruise		15.25 Wh/km
Drone Energy at ascend		40.66 Wh/km
Drone Energy at descend		48.79 Wh/km
Drone Total Energy		3.37 k WH
Truck Energy consumption	235.25 Wh/km	235.25 Wh/km
Truck Total Energy	14.845 kWh	4.92 kWh
Total Vehicle Energy	14.845 kWh	8.29 kWh
Energy Saving vs Truck-only	-	-44.2%
Energy per parcel	77.32 Wh	43.18 Wh

examine the sensitivity of system performance to adoption levels, the case study simulates a reduced-demand scenario by randomly removing 50% of customer orders from the routing dataset. In response, the delivery configuration is re-optimized by reducing the number of clusters from seven to three while preserving comparable customer densities per cluster (approximately 30 customers per cluster) and maintaining a fleet of three drones. Under this reduced-demand scenario, the optimized system achieves a 29.8% reduction in total delivery time relative to the traditional truck-only delivery model. At the same time, total drone energy consumption decreases by 33.5% compared with the full-demand scenario. The results indicate that although operational benefits remain significant under partial adoption, greater efficiency gains are realized as demand and user adoption of drone delivery increase.

A.6 CONCLUSION AND FUTURE WORK

This paper has addressed a gap in the truck–drone collaborative delivery (TDCD) networks literature by presenting a layered planning and coordination framework that separates system-level performance evaluation from scalability considerations. This distinction is critical in networked cyber-physical systems, where coordination strategies that perform well at limited scale may not remain effective as fleet size, traffic density, or operational constraints increase.

We have evaluated this framework using a realistic urban last-mile delivery scenario based on an Amazon delivery route. The results show significant reductions in total delivery

time (up to 42.4%) and energy consumption (up to 44.2%). It should be emphasized that the present simulation abstracts from several real-world operational dynamics such as stochastic weather conditions, wind disturbances, and drone aerodynamics incorporates these effects only through a uniform 30% battery degradation factor; therefore, actual field deployment may result in longer service times, an aspect that will be systematically investigated in future research through higher-fidelity operational modeling and real-world validation.

Our ongoing work focuses on extending the framework toward larger-scale and more realistic deployment scenarios, including environmental uncertainty, battery aging effects, and airspace capacity constraints.

ACKNOWLEDGMENT

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B

CONFERENCE PAPER 2- GREEN AND
INTELLIGENT PLANNING OF DRONE
LAUNCH IN TRUCK-DRONE
COLLABORATIVE DELIVERY

B.1 PUBLICATION STATEMENT

This chapter is based on the workshop paper titled “Green and Intelligent Planning of Drone Launch in Truck-Drone Collaborative Delivery”, co-authored by Didem Cicek, Murat Simsek and Burak Kantarci, and published in the proceedings of the TRAVERSAL Workshop on Network Architectures and Intelligence for Smart Mobility and Autonomous Systems, held in conjunction with the IEEE World Forum on Internet of Things (WF-IoT) Conference in November 2024 DOI: 10.1109/WF-IoT62078.2024.10811216.

This paper explored the use of artificial intelligence techniques for identifying optimal truck-based drone launch locations in truck–drone collaborative delivery systems. Using a realistic customer-order dataset and a Self-Organizing Feature Map (SOFM) algorithm, the study demonstrated how dynamically selected launch locations can reduce vehicle travel distance, energy consumption, and emissions compared with static deployment strategies. This work represents an early investigation into the spatial planning dimension of truck–drone collaborative delivery and provided foundational insights into the role of facility location decisions within collaborative delivery networks.

B.2 INTRODUCTION

In the context of parcel delivery, drones are recently being explored as an alternative delivery method. Several major companies, including Amazon, UPS, Zipline, and DHL,

have been actively developing and testing drone delivery systems. However, drones have payload and battery limitations, and are susceptible to adverse weather conditions. On the other hand, traditional truck delivery has its own flaws like contributing to traffic congestion, carbon emissions or being limited by road networks and conditions. Truck-Drone collaborative delivery (TDCD) model compensates for each sole delivery mode's shortcomings and delivers considerable cost savings versus sole truck delivery scenario [65]. As drones are dependent on batteries, having a truck transport them closer to customer locations can be energy efficient. Researchers have extensively studied collaborative truck-drone delivery in the context of last mile delivery (LMD) through the lens of the travelling salesman problem and the vehicle-routing or scheduling problem [77], [78], [79], [80], [81], [82], [16] because synchronizing drone and truck routes indeed poses significant challenges in collaborative delivery systems.

Modern supply chain networks utilize distribution centers or microdepots (alternatively microhubs) closer to customer locations to facilitate fast customer deliveries, which also enables drone deliveries. Over the past five years, researchers have shown a growing interest in identifying optimal facility locations for drone deliveries [83]. This focus arises from the need to efficiently integrate drones into existing logistics networks, considering factors like accessibility, cost, and operational feasibility. In the context of TDCD, trucks frequently function as mobile depots for carrying, charging, launching and recovering drones. Consequently, these vehicles can be regarded as mobile facilities, akin to relocatable drone depots. Building upon this concept of truck as a mobile drone depot, we explored the idea of selecting distance-optimal drone launch locations applying AI algorithms and assessing

the delivery efficiency gain.

Majority of the AI applications in Supply Chain uses supervised Machine Learning (ML) techniques. Unsupervised techniques like clustering algorithms appear as an emerging area of application mainly in inventory management or supply chain planning [162]. This study explores the use of Self-Organizing Feature Map algorithm (SOFM) [163], an unsupervised Machine learning technique, in finding the optimal truck locations to launch the drone to minimize the travel distance for both the truck and the drone. The task involves geo-locating drone launch locations in a two-dimensional and discrete space, optimizing drone route between the truck and the customer locations, serving each customer while minimizing the total distance traveled. The general framework for the proposed truck-drone collaborative delivery is illustrated in FigureB.1. The study pertains only to the delivery of the parcels to the customers; parcel returns or collections from the customers are excluded from consideration.

The study has two main contributions: firstly, it introduces a novel dataset for orders to build realistic delivery scenarios; and it employs an artificial intelligence algorithm to address the problem of determining optimal locations. This research proposes that by dynamically adjusting the optimal drone launch location based on customer orders, rather than relying on a fixed central location, significant reductions in vehicle travel distance, energy consumption, and CO2 emissions can be achieved.

This paper is structured as follows: Section B.3 discusses the previous works and highlights the novelty of this study. Section B.4 lays out the methodology pursued conducting



Figure B.1: General framework for truck & drone collaborative delivery (Photo credit: Google Earth)

this research. Section B.5 presents the order dataset that is generated and used in the simulation study. Section B.6 presents the problem formulation under subsection B.6.1 analyzes the findings under subsection B.6.2 and finally, Section B.7 presents the concluding remarks for this work with directions for future research.

B.3 RELATED WORK

There is immense amount of research in truck-drone collaborative delivery especially published in the last five years. In the existing literature, numerous delivery network models

have been proposed, each accounting for variations in the number of vehicles, the distinct functions of those vehicles, or the varying number of depots. Although extensive research has addressed routing and scheduling problems involving truck-drone collaborative delivery (TDCD), we have encountered only a few papers that analyze optimal facility location setting for drone launch.

The existing studies that deal with the facility location problem commonly use MILP (Mixed Integer Linear Programming) [83],[85], [65], MINLP (Mixed Integer Non-Linear Programming) [86] or other optimization algorithms like particle swarm algorithm [164] and to the best of our knowledge, none of them have applied SOFM algorithm to find the optimal drone launch location that minimizes the vehicle travel distance. There are some studies that aim to optimally locate the microdepots in the last mile delivery network without focusing on the TDCD problem [87],[88]. Finally, majority of the current research use conceptual instances used by the previous research [80] or very limited number of customer locations [85]. This study aims to fill the gap in the literature through working on real customer address coordinates with dynamic order patterns and introduces the application of an AI algorithm to the optimal location setting problem.

B.4 RESEARCH METHODOLOGY

Self-Organizing Feature Map (SOFM) [91] algorithm is a type of artificial neural network used for unsupervised learning and dimensionality reduction where multi-dimensional data can be represented by two dimensional neurons. In a Self-Organizing Feature Map, neurons

are interconnected through a predefined topology known as neighborhood connections [92]. The neuron that best matches the input data is called the Best Matching Unit (BMU). The training process in Self-Organizing Feature Maps (SOFM) closely resembles the winner-take-all algorithm. SOFM utilizes vectorial distance-based competitive learning. During training, each sample is compared to the weights of every neuron on the 2D hexagonal structure, and the Euclidean distance resulting from each comparison is computed independently. During training, the BMU is updated to minimize the distance between itself and the task coordinates. Simultaneously, the neighborhood connections around the BMU are adjusted using a time-dependent radius function. The iterative process adjusts neuron positions, enabling the creation of regional connections between neurons and task coordinates. Training continues until a specified stopping condition is met. SOFM has been frequently applied by researchers in different domains; to identify mobility patterns and clusters of residents during Covid19 pandemic [93], or to assess cyber risks in mobile crowdsensing systems [94].

Eq.(B.1) displays the distance function for two-dimensional inputs and weight vectors.

$$Dist(X, W) = \sqrt{[x_{lat} - w_1, x_{lon} - w_2] \times \begin{bmatrix} x_{lat} - w_1 \\ x_{lon} - w_2 \end{bmatrix}} \quad (B.1)$$

where X is the current 2D input vector and W is 2D node's weight vector.

$$BMU_X = \underset{w}{argmin} \|Dist(X, W^j)\| \text{ for } j = 1, \dots, m \quad (B.2)$$

where BMU indicates best matching neuron y to the input x as shown in Figure B.2.

$$W^i = BMU_{X^i} \quad (B.3)$$

where W in Eq.(B.2) indicates BMU for i th input X . During the learning phase of SOFM, the area of the neighborhood that is represented by the radius shrinks according to the number of epochs. More details on SOFM methodology can be found in a previous study [93].

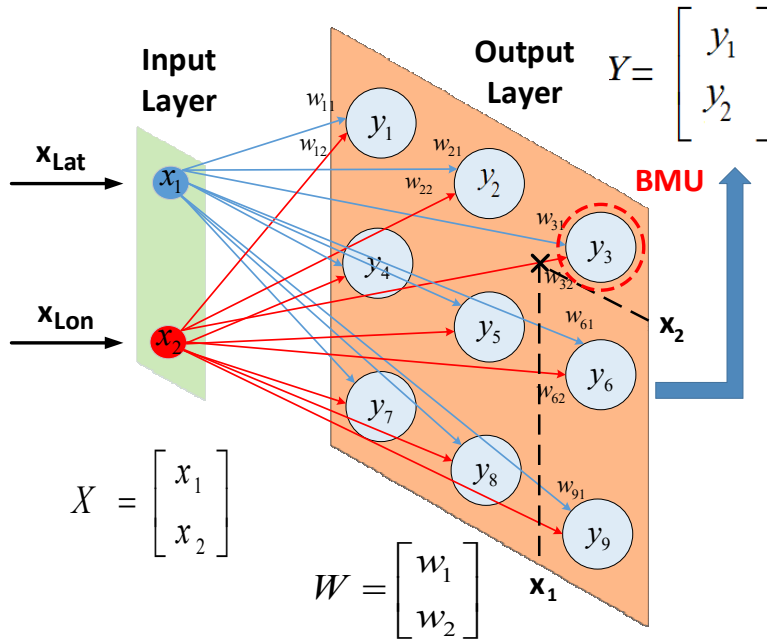


Figure B.2: SOFM general structure

The research methodology followed in this work is summarized in a process flowchart as illustrated in FigureB.3. Initially, a residential delivery area has been decided and mapped

on OpenStreetMap website ¹ . Then a delivery dataset has been generated on MATLAB (R2023a) tool. Further details on the dataset are explained in Section B.5. Then SOFM algorithm is applied to two different scenarios with static and dynamic optimal launch centers. Finally, the location of the optimal drone launch center that minimizes the total vehicle distance has been determined.

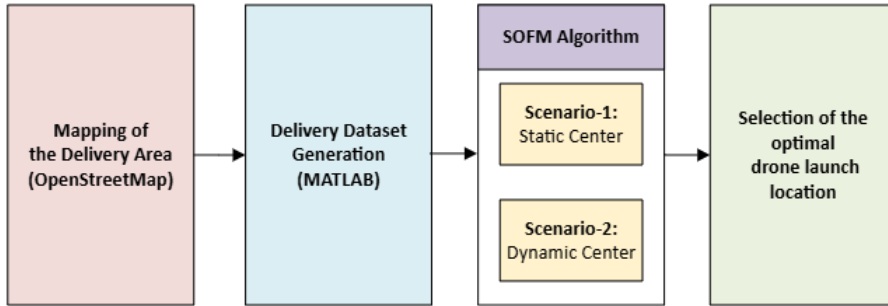


Figure B.3: Research methodology

B.5 DATASET GENERATION AND ASSUMPTIONS

Given the scarcity of a realistic customer data in the academic literature, a dataset has been proposed in this study for experimenting with various delivery scenarios. A residential neighborhood of 191 house addresses in Kanata, Ontario is sampled. The latitude and longitude coordinates of these addresses (customer locations) are obtained from OpenStreetMap (<https://www.openstreetmap.org/>).

¹<https://www.openstreetmap.org/>

The key assumptions made in the dataset, which are supported by publicly available statistics are listed below:

1. One week (7 days) of customer order data is generated.
2. Every order is an online order.
3. Every delivery is a drone delivery with truck-assisting.
4. 55% of the customer locations place 1 order per week, 45% places no online order. [165]².
5. Return (backhaul) orders (or collection of packages) are excluded.

The dataset includes extensive data features beyond the scope of this research, intended to support future investigations. Data features are generated using probabilistic distribution and random sampling on MATLAB R2023a tool. The features and the associated probabilities are given in TableB.1. However, for this study, only a limited number of features are used such as polar coordinates, order frequency and estimated delivery days.

The dataset will be made publicly available once the extensions of this study have been completed.

²Average Canadian user places 25 online orders per year as of 2022. 15% growth in e-commerce is estimated until 2024, hence 28.7 online orders/year is estimated, which translates into 55% of customer locations placing an online order per week (calculated as 28.7 orders/52 weeks)

Table B.1: Data generation probabilities

Features	Probabilities
Cutomer Locations	191
Priority Order	No: 80% Yes: 20%
Order Frequency/week	No order:45% 1-Order: 55%
Delivery Day/order	uniformly distributed (1/7 for each day)
Package Size/order	small: 4/7, medium: 2/7, large: 1/7
2* Delivery time slot	1:(6am-10am), 2:(10:01am-2pm), 3:(2:01pm-6pm) uniformly distributed (1/3 for each slot)
Delivery time	exact times are randomly generated

B.6 LOCATION SETTING FOR DRONE LAUNCH IN TD CD

As per the TD CD literature, the delivery model used in this exercise is named as drone delivery with truck assisting model [166]. However, to keep the focus of the study, we will continue using the term TD CD model.

As this study focuses on the comparison of dynamic versus static setting of the optimal drone launch locations based on the daily customer orders to minimize the total vehicle travel distance, and does not deal with routing or scheduling problems, a simple version of a truck-drone collaborative delivery (TD CD) model has been proposed as illustrated in FigureB.4.

A single round trip of the TD CD model defined in this work consist of the following steps as also noted on FigureB.4.

1. Truck is loaded at the distribution center with the parcels and the drone, then truck enters the delivery area.

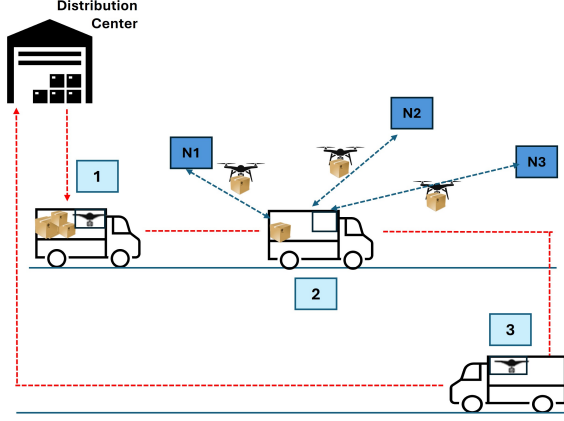


Figure B.4: Truck-drone delivery model

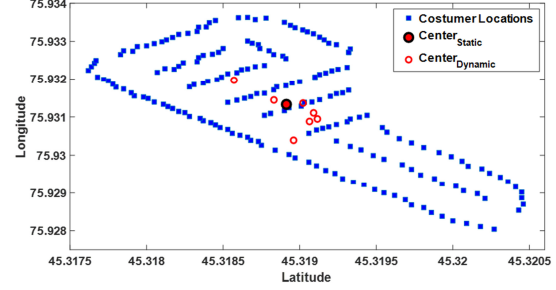


Figure B.5: Static and dynamic centers

2. Truck goes to the pre-selected location, parks there and launches the drone. The drone visits each customer location (N_j) on the route, returns to the truck to re-supply with the next parcel. Truck stays in parking mode until all the delivery tasks assigned to the drone are completed.
3. Empty truck (and drone) returns to the distribution center.

The high level assumptions made in this study are listed as below:

- Truck is a Battery Electric Vehicle (BEV).
- Each truck is equipped with a single drone.
- Drone routing or scheduling and delivery completion time is kept out of scope, hence single drone is assumed in calculations.
- Each order is ready for delivery in the distribution center.

-
- Selected optimal drone launch centers are available for parking.
 - The route between the distribution center and the delivery area is assumed to be fixed and excluded from the distance calculations.
 - The models and factory parameters of the vehicles used in this study can be found in (TableB.2)

Table B.2: Factory parameters [89]

	TRUCK	DRONE
Model	Fiat Ducatio BEV 3.5t LH2 122LE	DJI 300 RTK
Av Speed (per WLTP*)	46.6 km/hr	16.6 km/hr
Operating distance (empty)	357 km	15 km
Operating distance (full)	317 km	8.45 km
Fuel tank/Battery capacity	79 kWh	548 Wh
Energy consumption (empty)	221.29 Wh/km	36.54 Wh/km
Energy consumption (full)	249.21 Wh/km	64 Wh/km
Payload capacity	764.1 kg	2.70 kg
CO2 emission (empty)	0.083 kgCO2/km	0.014 kgCO2/km
CO2 emission (full)	0.094 kgCO2/km	0.024 kgCO2/km

B.6.1 PROBLEM FORMULATION

Two scenarios have been implemented for this exercise. Scenario-1 assumes a fixed center location for the truck to launch the drone, whereas Scenario-2 assumes varying center locations according to daily customer orders scheduled for delivery. It is important to note that both scenarios are configured as discrete event simulations and that the orders are

Table B.3: Notations table

Notation	Description	Range
C <i>i</i>	Set of centers (static and dynamic)	[<i>i</i> ∈ 0, 1, . . . , <i>K</i>]
N <i>j</i>	Set of customer locations	[<i>j</i> ∈ 1, 2, . . . , <i>M</i>]
C _e	Entrance of the delivery area	e=constant value
C _s	Static center	C _s =C <i>i</i> , [<i>i</i> =0]

not continuous, meaning there is a cut-off time for the incoming orders to be scheduled for transportation.

Scenario-1 DRONE LAUNCH AT THE STATIC CENTER

This scenario assumes that the truck travels to a central location every day and launches the drone from there. The drone flies to the assigned delivery locations and returns back to the truck. The truck in this scenario almost functions like a microdepot, which is strategically located to optimize drone delivery networks in modern supply chain models [167]. In this scenario, SOFM algorithm applied to the whole delivery area with all 191 customer locations, ignoring the order data, meaning whether or not the customer is scheduled for a delivery. The algorithm produced the distance based optimal center of the delivery area with optimal promixity to each customer location. This center is called "static center" since it is generated solely based on distance and is not variable according to the delivery locations.

$$D_d = 2 \cdot \sum_{i=0}^K \sum_{j=1}^M X_{ij} \cdot C_{ij} \quad (\text{B.4})$$

D_d denotes the total distance for drone travel, X_{ij} is the binary decision variable that equals 1 if the drone travels between center (i) and customer location (j), and 0 otherwise.

$$X_{ij} = \sum_{j=1}^M X_{ij} = 1 \quad (\text{B.5})$$

C_{ij} is the distance travelled between center (i) and customer location (j) and calculated as below:

$$C_{ij} = \|C_i - N_j\| \quad (\text{B.6})$$

D_t denotes the total distance for truck travel and calculated as the distance that the truck travels between the entrance point of the delivery area and the static center every day for seven days.

$$D_t = 2 \cdot \sum_{i=1}^K \|C_i - C_e\| \quad (\text{B.7})$$

D_v denotes the total distance for all vehicle travel and calculated as the total of drone travel distance D_d and truck travel distance D_t .

$$D_v = D_d + D_t \quad (\text{B.8})$$

Scenario-2 DRONE LAUNCH AT DYNAMIC CENTERS

This scenario assumes that the truck travels to a different center every day which are dynamically selected based on customer order locations. SOFM algorithm has been applied to the daily customer order data iteratively for seven days of the week and optimal "dynamic centers" have been calculated based on the delivery locations. The truck then launches the drone at those dynamic centers, the drone flies to the assigned customer locations and returns back to the truck. These dynamic center locations are calculated closer to the customer delivery locations, hence it shortens the vehicle travel distance D_v for both the truck D_t and the drone D_d . The visual illustration of the static center vs dynamic centers of the simulated 7 days can be found in FigureB.5.

$$D_d = 2 \cdot \sum_{i=1}^K \sum_{j=1}^M X_{ij} \cdot C_{ij} \quad (\text{B.9})$$

D_d denotes the total distance for drone travel, X_{ij} is the binary decision variable that equals 1 if the drone travels between center (i) and customer location (j), and 0 otherwise.

$$\sum_{j=1}^M \sum_{i=1}^K X_{ij} = 1 \quad (\text{B.10})$$

C_{ij} is the distance travelled between center (i) and customer location (j) and calculated as below:

$$C_{ij} = \|C_i - N_j\| \quad (\text{B.11})$$

D_t denotes the total distance for truck travel and calculated as the distance that the truck travels between the entrance point of the delivery area and the static center every day for seven days.

$$D_t = 2 \cdot \sum_{i=1}^K \|C_i - C_e\| \quad (\text{B.12})$$

D_v denotes the total distance for all vehicle travel and calculated as the total of drone travel distance D_d and truck travel distance D_t .

$$D_v = D_d + D_t \quad (\text{B.13})$$

After the dynamic centers for the truck to launch the drone are identified for each delivery day, then the drone flies to each delivery location scheduled for the day. As indicated in the problem formulation, the solution is concentrated on the total travel distance minimization. Since time and cost efficiency is not measured, it is assumed in this study that only one drone visits all delivery locations and return back to the truck to be loaded with the next customer order. The paths for the drone that is launched from the dynamic truck launch center to the customer delivery locations is illustrated for Friday deliveries in Figure B.6. Friday is chosen as a sample delivery day since the delivery locations are scattered around the delivery area which offers a better visual representation.

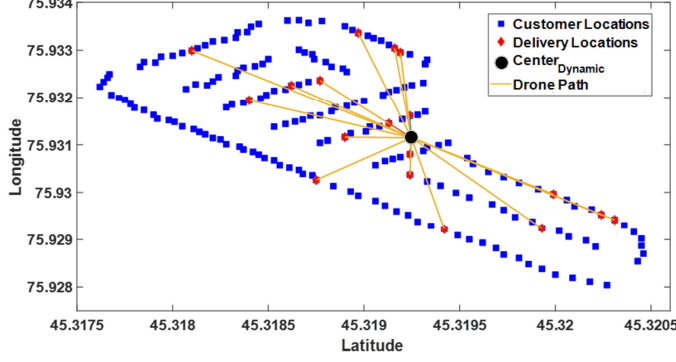


Figure B.6: Friday delivery locations

Table B.4: Drone comparative results (scen.1 vs scen.2)

	One way route (km)	Drone (Full)		Drone (Empty)		Total Drone Travel		
		gCO2	Energy (Wh)	gCO2	Energy (Wh)	Distance (km)	gCO2	Energy (Wh)
(Dd)-Scen.-1	15.71	377.15	1,005.73	220.00	574.21	31.43	597.15	1,579.94
(Dd)-Scen.-2	15.03	360.76	962.02	210.44	549.25	30.06	571.2	1,511.28
Efficiency-value	0.68	16.39	43.71	9.56	24.96	1.37	25.95	68.66
Efficiency-%	4.35%	4.35%	4.35%	4.35%	4.35%	4.34%	4.35%	4.35%

Table B.5: Truck comparative results (scen.1 vs scen.2)

	Distance (km)	gCO2	Energy (Wh)
(Dt) - Scen.-1	4.31	381.15	1,013.18
(Dt)- Scen.-2	4.26	376.83	1,001.69
Efficiency-value	0.05	4.32	11.49
Efficiency-%	1.13%	1.13%	1.13%

B.6.2 RESULTS

In Scenario-1, the total distance traveled by drone (D_d) is calculated from the static center where the truck launches the drone to the customer delivery locations over 7 delivery days. The one-way route between the truck and the customer delivery location that the drone

travels throughout the simulated 7 days measures 15.71 km. The total distance traveled by the drone is calculated as twice this amount, 31.43 km, as the drone covers the same distance twice - once with the parcel (full) and once without the parcel (empty).

In Scenario-2, the total distance traveled by drone (D_d) is calculated from the dynamic centers where the truck launches the drone to the customer delivery locations for a total of 7 days. The one-way route is measured as 15.03 km, round trip is measured twice this amount at 30.06 km. The results show that the distance traveled by the drone in Scenario-2 is reduced by 4.35% compared to the Scenario-1. The reduction in drone travel leads to 25.95 gCO₂ less CO₂ emission and 68.66 Wh less energy consumption (equivalent of 247.2 KJoules). The comparative results can be found in Table B.4.

Additionally, the total truck travel distance (D_t) is calculated in both scenarios. The truck travel routes were set on Google Earth in order to accurately calculate the distances for both scenarios, also given the manageable size of the route. Truck travel is measured from the delivery area entrance point to the drone launch location (static or dynamic). It is noted that the truck's travel distance is almost same in the two scenarios with a 1.13% reduction in truck travel distance in the dynamic scenario, which is negligible considering the real life driving conditions. The comparative results can be found in Table B.5.

The results of our two scenario analysis using the SOFM algorithm on the facility location problem for a truck-drone collaborative delivery model demonstrate significant benefits of using dynamic launch centers for reducing travel distance for both the truck and the drone. Overall, 1.41 km of vehicle travel distance, 30.28 gCO₂ and 80.16 Wh

(equivalent of 288.58 KJoules) has been saved.

B.7 CONCLUSION AND FUTURE WORK

This work has introduced the application of Self-Organizing Feature Map (SOFM) Algorithm to facility location setting problem in Truck-Drone Collaborative Delivery (TD CD) models with a simplistic experiment. The results suggest that the dynamic setting of optimal drone launch locations based on customer orders, rather than using a static central location, has significant benefits. By adapting to customer demand, this approach reduces total vehicle travel by 3.96% which in return leads to a saving of 30.28 gCO₂ emission and 80.16 Wh energy consumption (that translates into 288.58 KJoule). These savings contributes to planning of efficient last mile delivery strategies.

In the future, SOFM approach can be applied for drone scheduling problem as well. Additionally, a realistic dataset has been generated to be further expanded for future investigations on the time and cost efficiencies of sustainable deliveries with or without collaborating vehicles.

Table B.6: Total comparative results (scen.1 vs scen.2)

	Distance (km)	gCO ₂	Energy (Wh)
(Dv) - Scen.-1	35.74	978.31	2,593.12
(Dv)- Scen.-2	34.32	948.03	2,512.96
Efficiency-value	1.41	30.28	80.16
Efficiency-%	3.96%	3.09%	3.09%

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