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Titel | Title

A Solution Technique for the Truck and Drone Parcel Delivery Problem

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Abstract (German)

Diese Arbeit befasst sich mit den drängenden Herausforderungen des städtischen Güterverkehrs und der letzten Meile in der Europäischen Union. Insbesondere das starke Wachstum des Onlinehandels sowie die fortschreitende Urbanisierung erhöhen den Druck auf bestehende Transportinfrastrukturen. Der Straßengüterverkehr dominiert zwar weiterhin die Logistik, verursacht jedoch einen beträchtlichen Anteil an Treibhausgasemissionen, Luftschadstoffen und Verkehrsstaus (WEF, 2024; Sustainable Urban Logistics Plans, EU, 2023). Vor dem Hintergrund der europäischen Klimapolitik und ambitionierter Nachhaltigkeitsziele gewinnt daher die Entwicklung innovativer Konzepte an Bedeutung, um Transportprozesse mit den Emissionsreduktionsvorgaben in Einklang zu bringen (Levrey, 2024; Mahmoodi et al., 2025).

In diesem Kontext wird ein heuristik-basierter Planungsansatz vorgestellt, der klassische Methoden der Routenoptimierung mit neuen Lieferkonzepten – darunter unbemannte Luftfahrzeuge (UAVs) und autonome Systeme – verbindet. Ziel ist es, Lieferketten so zu gestalten, dass technische Rahmenbedingungen wie begrenzte Drohnenreichweiten, Nutzlastgrenzen, Ladeinfrastruktur oder gesetzliche Flugverbotszonen berücksichtigt werden, ohne die praktische Anwendbarkeit durch übermäßige Rechenlast zu gefährden (Mahmoodi et al., 2025; Cicek et al., 2025).

Die empirischen Ergebnisse verdeutlichen die Zielkonflikte zwischen Kosten, Zeitaufwand und ökologischen Effekten. Besonders in dicht besiedelten urbanen Räumen lassen sich mit kombinierten Drohnen-Lkw-Modellen die CO_2-Emissionen um bis zu 20 % im Vergleich zu rein dieselbetriebenen Lkw-Systemen senken (Bao et al., 2025). Damit liefert die Arbeit einen Beitrag zur wissenschaftlichen Debatte über nachhaltige urbane Logistik, indem sie sowohl theoretische Grundlagen als auch praxisnahe Ansätze zusammenführt.

Der entwickelte Algorithmus unterstreicht das Potenzial hybrider Zustelllösungen, die den Einsatz von Drohnen mit Lkw und die Integration von E-Cargobikes kombinieren. Solche Konzepte eröffnen neue Möglichkeiten, Emissionen zu verringern und die Effizienz in der letzten Meile zu erhöhen. Über die wissenschaftliche Relevanz hinaus bieten die Erkenntnisse wertvolle Anhaltspunkte für politische Entscheidungsträger, Logistikunternehmen und Stadtverwaltungen, die auf dem Weg zu sauberen, resilienten und intelligenten städtischen Transportsystemen sind – im Einklang mit dem European Green Deal sowie den Nachhaltigkeitsstrategien der Europäischen Kommission (Levrey, 2024; Sustainable Urban Logistics Plans, EU, 2023).

Abstract (ENG)

This thesis addresses the critical challenges of urban freight transportation and last-mile delivery within the European Union, where rising e-commerce demand and rapid urbanization are exerting increasing pressure on existing transport systems. Conventional modes of freight transport, particularly road-based delivery, remain dominant but contribute significantly to greenhouse gas emissions, air pollution, and congestion (WEF, 2024; Sustainable Urban Logistics Plans, EU, 2023). In response to EU climate policies and sustainability targets, innovative solutions are required to align freight operations with emission reduction goals (Levrey, 2024; Mahmoodi et al., 2025). This study develops and evaluates a heuristic-based planning algorithm that combines classical vehicle routing with novel delivery modalities involving unmanned aerial vehicles (UAVs) and autonomous systems. The approach seeks to optimize delivery schedules by accounting for technical constraints such as limited drone battery capacity, payload restrictions, recharging or en-route charging, and regulatory no-fly zones, while maintaining computational feasibility for practical application (Mahmoodi et al., 2025; Cicek et al., 2025). Empirical analysis demonstrates the trade-offs between cost, operational time, and environmental impact, with drone-truck parallel delivery models showing up to ~20% reduction in carbon emissions compared to fuel-powered truck-only systems in high-density settings (Bao et al., 2025). The findings contribute to the growing body of literature on sustainable logistics by offering both theoretical and applied perspectives. The proposed algorithm highlights the potential of hybrid truck-drone models and e-cargo bike integration as viable pathways to reducing emissions and improving efficiency in last-mile delivery. Beyond academic relevance, the results may guide policymakers, logistics providers, and urban planners in designing cleaner, smarter, and more resilient urban freight transport systems aligned with the EU Green Deal and the European Commission's sustainability strategies (Levrey, 2024; Sustainable Urban Logistics Plans, EU, 2023).

Introduction

Urban freight transportation represents a critical component of contemporary economies and a major driver of societal development. While transport ensures accessibility, trade, and economic growth, it also generates considerable environmental and social externalities. Among these, carbon dioxide emissions, air pollution, noise, and traffic congestion are particularly severe in densely populated urban areas (Sustainable Urban Logistics Plans, EU, 2023; Levrey, 2024). As cities expand and e-commerce continues its rapid growth, traditional delivery systems face mounting challenges to maintain both efficiency and sustainability (WEF, 2024; Maxner, 2022). The last-mile segment of freight logistics has emerged as one of the most resource-intensive and environmentally detrimental stages of supply chains. It is characterised by high frequency of small-scale deliveries, often long travel times per parcel (road miles), and many return or failed delivery trips, all contributing to disproportionately large shares of emissions (Li, 2024; Levrey, 2024). For example, some studies estimate that last-mile deliveries in urban centres could cause emissions to increase by 60% by 2030 if no further interventions are taken (WEF, 2024). EU studies show urban freight contributes roughly 15% of greenhouse gas emissions and 30% of air pollution in cities (EU Sustainable Urban Logistics Plans, 2023). Moreover, technical limitations such as drone battery capacity, payload restrictions, and regulatory constraints like no-fly zones or flight safety requirements pose nontrivial barriers to adopting UAV-assisted delivery models (Cicek et al., 2025; Mahmoodi et al., 2025). Operational cost, fleet management, and infrastructure (e.g., recharging or mobile launch platforms) are additional concerns (Bao et al., 2025; Mantecchini et al., 2025). The overarching aim of this thesis is to develop an intelligent algorithmic approach for optimizing last-mile freight delivery through hybrid models combining conventional trucks with drones, e-cargo bikes, and other unmanned vehicles. This research addresses the dual challenge of operational efficiency and environmental sustainability. The primary objectives can be summarized as follows: To design a heuristic scheduling method capable of integrating truck, drone, and e-cargo bike deliveries within realistic technical, regulatory, and environmental constraints (Mahmoodi et al., 2025; Bao et al., 2025).To evaluate the algorithm’s performance in terms of efficiency, cost, and environmental impact across varying urban delivery scenarios, including high-density demand zones (WEF, 2024).To analyze technological limitations — such as battery life, payload capacity, acquisition and operational costs, en-route charging, and regulatory no-fly zones — and propose strategies or trade-offs to overcome these barriers (Cicek et al., 2025; Bao et al., 2025). To contribute to the academic discourse on sustainable urban logistics by situating the findings within the broader framework of EU policy—in particular, the European Green Deal, Sustainable Urban Logistics Plans, and national-level regulatory efforts (Levrey, 2024; EU, 2023). This thesis employs a combination of literature review, model development, and empirical testing. Existing models (e.g. vehicle routing, drone-truck parallel delivery) are adapted and extended to incorporate realistic constraints (battery, payload, regulatory). A new heuristic algorithm is then proposed, designed to solve complex vehicle routing problems under urban conditions.

Key features include en-route charging (for drones and support vehicles), payload constraint modelling, and incorporation of environmental cost metrics. Numerical simulation experiments are conducted to validate the algorithm, using benchmark data sets and realistic urban demand instances inspired by recent studies (Mahmoodi et al., 2025; Bao et al., 2025; Mantecchini et al., 2025).This thesis contributes to the emerging field of hybrid urban logistics by offering a tailored algorithmic solution to the last-mile delivery problem. While existing studies often remain theoretical or narrowly focused on single technologies, this work emphasizes the integration of heterogeneous delivery modes within a unified planning framework. The results not only expand the academic literature but also provide actionable insights for practitioners and policymakers seeking to reduce costs, emissions, and externalities in last-mile operations (WEF, 2024; Sustainable Urban Logistics Plans, EU, 2023). The structure of the thesis is organized as follows. Following this introduction, the background section discusses key drivers of urban freight challenges, including urbanization trends, regulatory pressures, technical constraints, and innovations. Subsequent chapters present the methodological framework, detailing algorithm design, implementation, and validation. The results chapter evaluates algorithmic performance across various delivery scenarios. Finally, the discussion situates findings within EU policy contexts and offers recommendations for implementation and future research. The volume of EU freight transportation has grown exponentially in the last twenty years. The most important reasons for the increasing trend are that the open market is becoming bigger and bigger every year because of the increasing usage of the internet. Another reason is the growing urban population. (Ranieri *et al*., 2018) The above represents two reasons that indicate a growth in urban freight flow. Between 2008 and 2017 the share of the e-sales increased by 7%. This factor could be higher in the next years if it is assumed that the young people will do more online shopping, because it is convenient, and they could shop every time over a cellphone or over a tablet. Because of these higher demands in online shopping, Business-to-Customer delivery will also be higher. This phenomenon, however, has a negative effect on emission levels because the last part of Business-to-Customer System is the last-mile delivery problem, which is transportation directly to the customer’s door or to a collection point. (Bosona, 2020, p. 2) The growth in the last mile delivery was the driving factor for the European Union to introduce different limitations; for example, car industries need to reduce the average CO_2 limit of 95 g/km. It is not easy to observe this limitation with the current technologies and for this purpose the number of electric and hybrid cars has increased rapidly in the last years. However, this change results in another problem, namely, the energy problem. For this reason, different programs started which could help to reach the target regulations. These projects could be sustainable energy action plans or a sustainable city logistics plan, but in this case the most important issue is the clean last-mile transport, which indicates the aim of and the motivation for writing this thesis. (Ranieri *et al*., 2018)

Aim of the Master thesis

As mentioned in the most important reason for writing this thesis is the clean last mile transport. The European regulations will be harder to achieve and the demand for last-mile freight transport delivery will be higher. In order to achieve the goal of the European Union and to satisfy customers' needs, a new intelligent system needs to be developed. The aim of this thesis is to develop an intelligent planning method that could be useful, effective and efficient for every delivery company in the last mile freight problem. More specifically, my goal is to develop an algorithm which simultaneously makes a schedule of the combination from classical transportation and new technologies like Drones or Unmanned Vehicles. The biggest helping factor is for today reached sufficient technology level, which could try to use in the urban area. Such technologies as 5G, GPS or autonomous flying technologies help companies to develop new ideas in this field. Unfortunately there are some limitations in the technologies and in the legislation, which makes it difficult to develop a new method. Some of these are, for example, the low battery and carrying capacity of the given unmanned vehicles, which indicates a capacitated problem or there is some non-flying zone given where the drones are not allowed to fly through, or the wind is too strong. In a later chapter these limitations will be highlighted and explained in detail. However, the most important and biggest limitation in such scheduling and transportation problems is the calculation of time. To solve such problem is to time expensive and from this reason in this thesis a heuristic is developed which could solve the given problems within a reasonable time.

A further objective of this thesis is to highlight the closer look at the problem and explain the most important limitations in this field. Furthermore, it will give an overview of the different methods and different problem approximation, which are difficult in this case because this is a new field in the research and only limited literature and algorithms are given.

To sum up this thesis will explain the problem of eligibility, for which reason it is important to develop a new algorithm in this field, which needs to use a mixture of "old" and new technologies and develop a usable algorithm to solve the given problem which could be used for different cases of sizes and different type of unmanned vehicles. Naturally, this scheduling and routing algorithm will be explained and tested in detail, so that not only practitioners or researchers in this field will understand it but other people as well who are new in this field.

Methodology

This master thesis is based on an algorithm developed by the writer of the thesis. For this algorithm, some other algorithm and solution methods have also been searched in this field. These research and scientific papers are the groundwork for the developed algorithm, but the end solution is a self-developed algorithm which is based on own idea. Some cases, for example the Clarke and Wright Savings Algorithm and the drone Power Consumption Modell also from other authors given. In order to explain the basic situation, the root cause of the problem, papers, statistics and reports will also be used. Some of the statistics are cited from websites. Unfortunately, only some of the papers and literature will be given, because this is a new research area and not too many algorithm or solution methods have been implemented in the last few years. Most of the relevant literature was published between 2015 and 2020, but the new papers and publications have been favored.
After the research in the last mile delivery the different ideas, solutions, and algorithm are compiled to a core model. After the basic model has been determined the basic algorithm has been coded.
All functions in the code are tested and controlled manually and when it was possible in excel or on paper also tested. After the first run some stability changes were implemented. Naturally, during the tests the availability and optimality were also checked to avoid the not permissible solutions.
In order to check the availability, another code has also written to visualize the end solution, because this way it is easier and better to check and find the not permitted solutions.
In the last step the test instances were chosen and the solutions with numerical analysis were performed. The aim of this analysis was to determine whether the usage of the drones is remunerative or not, or what is the optimal mixture of number of drones and number of trucks. At the end some design improvements will be carried out to simplify the code and make it more common, which will help to understand the idea and the basic behavior of the algorithm better.

Structure of the Master Thesis

i. Abstract

- Research problem: urban freight transport, last-mile challenges, emissions.
- Method: heuristic algorithm combining trucks, drones, and hybrid delivery models.
- Key results: trade-offs in efficiency, cost, emissions.
- Contribution: supports EU Green Deal, policy, and industry.

ii. Introduction

- Context and Motivation
    - Importance of transportation in urban economies.
    - Environmental challenges: CO_2, congestion, noise.
    - Growth of e-commerce and rising delivery demand.
- Problem Definition
    - Last-mile inefficiency, fragmented deliveries, emissions.
    - Technical and regulatory constraints (battery, payload, no-fly zones).
- Aim and Objectives
    - Development of intelligent planning algorithm.
    - Integration of trucks, drones, and e-cargo bikes.
    - Evaluation of cost, runtime, and environmental impact.
- Methodology
    - Literature review and adaptation of existing models.
    - Algorithm design and coding.
    - Testing with numerical simulations and benchmark data.
- Contribution and Structure
    - Hybrid approach with practical and theoretical relevance.
    - Guidance for policymakers, logistics providers, and researchers.

iii. Background & Literature Review

- Urbanization and freight demand trends.
- Regulatory frameworks (EU Green Deal, CO_2 targets).
- E-commerce growth and delivery impacts.
- Innovations: consolidation centers, e-vehicles, UAVs.

iv. Methodology

- Algorithmic design: heuristic and VRP adaptation.
- Constraints: battery life, payload, no-fly zones.
- Implementation and validation process.

v. Results and Analysis

- Numerical experiments and case studies.
- Comparison of truck-only vs. hybrid truck-drone.
- Performance in runtime, cost, and emissions.

vi. Discussion

- Practical implications for urban logistics.
- Policy alignment with sustainability goals.
- Limitations and future improvements.

vii. Conclusion

- Summary of contributions.
- Outlook for sustainable last-mile solutions.

1. Background Challenges

In this section some background challenges introduced. Why do we need to apply these new hybrid solutions like truck and drone hybrid transportation methods? Which are the most important factors in the background? Are the hybrid solutions needed because of the policymakers in the European Union or are there any other factors? This section will consider these questions in more detail and make the connections between the different problems clear.

1.1 Urbanization

1.1.1 Definition

Urbanization refers to the long-term process in which populations increasingly move from rural areas to towns and cities. This transition is not limited to a change in residence but also involves profound socio-economic transformations. Employment structures, lifestyles, and demographic patterns evolve, making urban regions key hubs of economic activity, cultural development, and social interaction. (United Nations, 2019 a.)

1.1.2 Urbanization's Trends

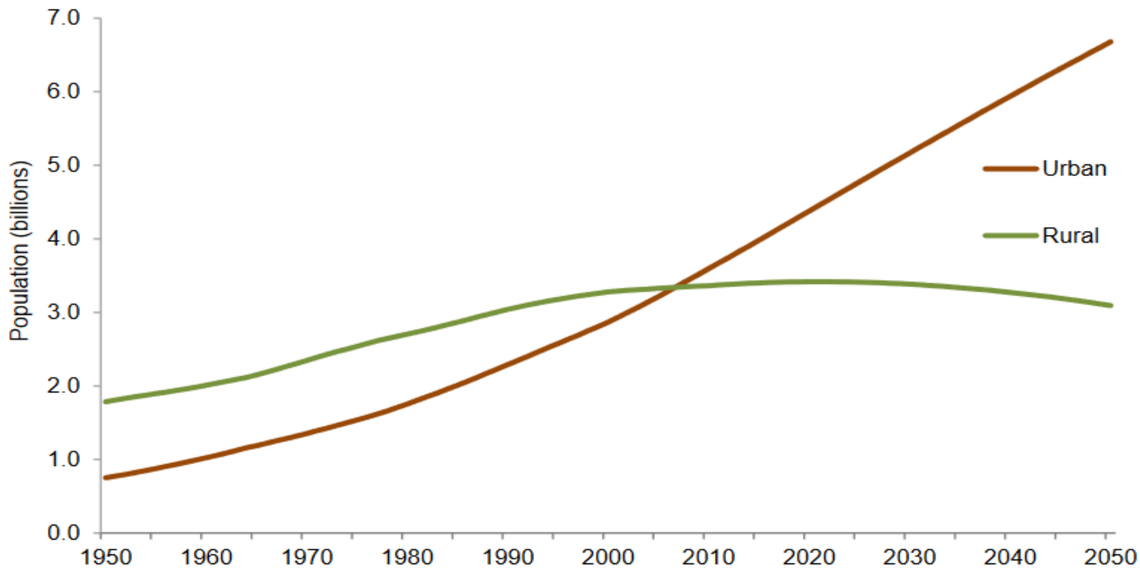


Figure 1: Urban and rural population since 1950 source: United Nation, 2019 a.

Today most people in the world live in an urban area, which accounts for 4.2 billion, which is 55% of the world's population. This is the fact from 2018, but the increasing trend in urbanization started in 1950. Figure 1 represents the number of people living in rural and urban areas since 1950. (United Nations, 2019 a.) In 1950 most of the population lived in rural areas, which accounts for approximately 1.8 billion, while in urban areas approximately 0.8 billion people lived. After 1950 there was a boom in the total population and the number of people living in urban areas. This trend will be continuously increasing in the following years and the number of people living in an urban settlement in 2050 will be more than 6.0 billion, which is more than 68% of the total population. Another interesting fact is that the number of people living in a rural area also increased until 2006. The number of the people living in rural areas was approximately 3 billion, which was the same as the number of people living in urban areas. After 2006 the trend was the same and the forecast shows some decrease after 2030 but it will not be too significant. (United Nations, 2019) To sum up, the most important facts are that there is an increasing trend in the number of urban populations and there is some decrease in the number of rural populations. Furthermore, it also can be seen that the number of the global population also increased and will be increasing. The total population in 1950 was approximately 2.6 billion and today it is more than 7.6 billion. If this trend is the same as the forecast indicates, then in 2050 there will be more than 10 billion people living in the world. (United Nations, 2019 a.)

1.1.3 Urbanization in Citys

The United Nations Department of Economic and Social Affairs, Population Division categorized the cities in terms of capitation and put them in 5 different groups: Urban settlement with lower than 500 000 population, cities of 500 000 to 1 million population, medium-sized cities of 1 to 5 million population, large cities of 5 to 10 million population and megacities of 10 million or more population. Up to the recorded data (2018), almost half of the urban population is living in an urban settlement with lower than 500 000 inhabitants, which accounts for 48% of the total population in the urban population. Only 10% are living in a city of between 500 000 and 1 million population, 22% in a medium-sized city, 8% in a large city and 13% in a megacity. It can be clearly seen that most of the urban population live in a city where the total population is less than 10 million, which is exactly 58% which counts for approximately 2.4 billion people. It is an interesting fact, according to the forecast the share between the different groups will be approximately the same but the number of cities and people living in a category will be increasing. This means that several cities will be larger, which is supported by the fact that more people will be moving from rural areas to urban areas. (United Nations, 2019 a.)

1.1.4 Urbanization Key Facts

- In 1950 only the 30% of the total population lived in an urban area but according to the forecast this will more than double, approximately 68%. (United Nations, 2019 b.)
- Th most urbanized regions are Northern America (82%), Latin America and Caribbean (81%), Europe (74%) and Oceania (68%). (United Nations, 2019 b.)
- The rural population will decline after 2030 and in 2050 it will be 3.1 billion. (United Nations, 2019 b.)
- The driving factor for urbanization is the overall increase in the population and the upward tendency in the people living in an urban settlement. Approximately this accounts for 2.5 billion people and most of them (90%) live in Asia and Africa. (United Nations, 2019 b.)
- Today there are 33 megacities where more than 10 million people live, until 2030 this number will increase to 43 million. (United Nations, 2019 b.)
- The largest city in the world is Tokyo with a population of 37 million, in the second place there is Delhi with 29 million people and in the third place there is Shanghai with a population of 26 million. (United Nations, 2019 b.)

1.2 Freight Transport

1.2.1 General information about Freight Transport

Today the general concept in supply-chain management and in transportation logistics is freight transport. The general idea is transporting the commodities between cities, countries or between suppliers and customers with different types of vehicles. Freight transport plays a central role in supply chain management, ensuring the movement of goods between producers, retailers, and consumers. Various modes are available, including road, rail, inland waterways, and air transport, yet in the European Union road-based transport continues to dominate. This predominance is particularly relevant to last-mile delivery, which relies almost entirely on vans and trucks. While flexible and cost-effective for firms, road transport also generates considerable external costs, including greenhouse gas emissions, air and noise pollution, and traffic congestion (Reza et al., 2011). Stakeholders are affected in different ways: while direct stakeholders such as logistics firms and retailers benefit economically from efficiency gains, indirect stakeholders, including the environment and wider society, bear the negative externalities in the form of global warming, ecosystem disruption, and health impacts (Muñoz-Villamizar, 2020).These are the so-called direct stakeholders but, on the other hand, there are other stakeholders who do not directly affect the system but need to be paid the external cost of the activity from the direct stakeholder. In this case indirect stakeholders are the environment, wildlife, or water life. The high amount of freight transport causes air, noise and water pollution, wildlife destruction or some incidents which could affect animals and humans also. The problem is the increasing trend from pollution, which could be traced back to freight transport. This needs to be better regulated because this has a serious consequence, namely global warming. The cause of global warming is greenhouse gases. This indicates that the countries need to develop new strategies because of the sustainability effect. (Reza F., etl., 2011)

"Sustainability development was defined in 1987 by Bruntland Comission Report: *development that meets the needs of the present without compromising the ability of future generations to meet their own needs." (World Commission on Environment and Development, 1987, p.43, cited in UNESCO, 2020)*

Sustainability development has four dimensions, which are society, environment, culture, and economy. These dimensions must be considered as one whole problem, because the most important thing about this model is to create such a future where environmental, societal, and economic decisions are perfectly balanced. (Unesco, 2020)

1.2.2 Statistics about Freight Transport

a. Freight Transport Methods and Shares

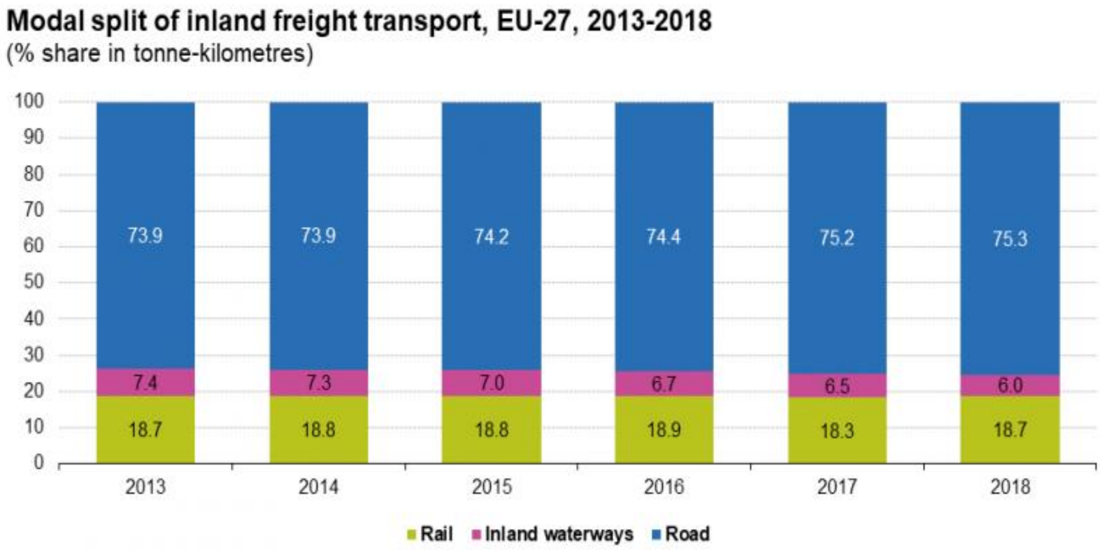


Figure 2:Share between the commodity transportation methods. Source: Eurostat 2020

Figure 2 represents the share of the commodities transported with different methods in the EU-27 countries between 2013 and 2018. There are only the three main categories or transportation methods represented, the subcategories are not given. As the figure shows the three main transportation categories are rail, inland waterways, and road transportation. Statistical evidence underscores the dominance of road freight in the EU. Between 2013 and 2018, more than 70% of inland freight transport (measured in tone-kilometres) was carried by road, and this share increased by 1.4 percentage points during the period (Eurostat, 2020). By contrast, rail transport maintained a relatively stable share of approximately 18%, with only minor fluctuations across the years. Inland waterways accounted for the smallest portion, declining from 7.4% to 6.0% between 2013 and 2018 due to limited navigable infrastructure and high operating costs (Eurostat, 2020).This method is not the most important in the Union because the ships can use only a few rivers in the EU and this method also has a high transportation cost. (Eurostat, 2020)

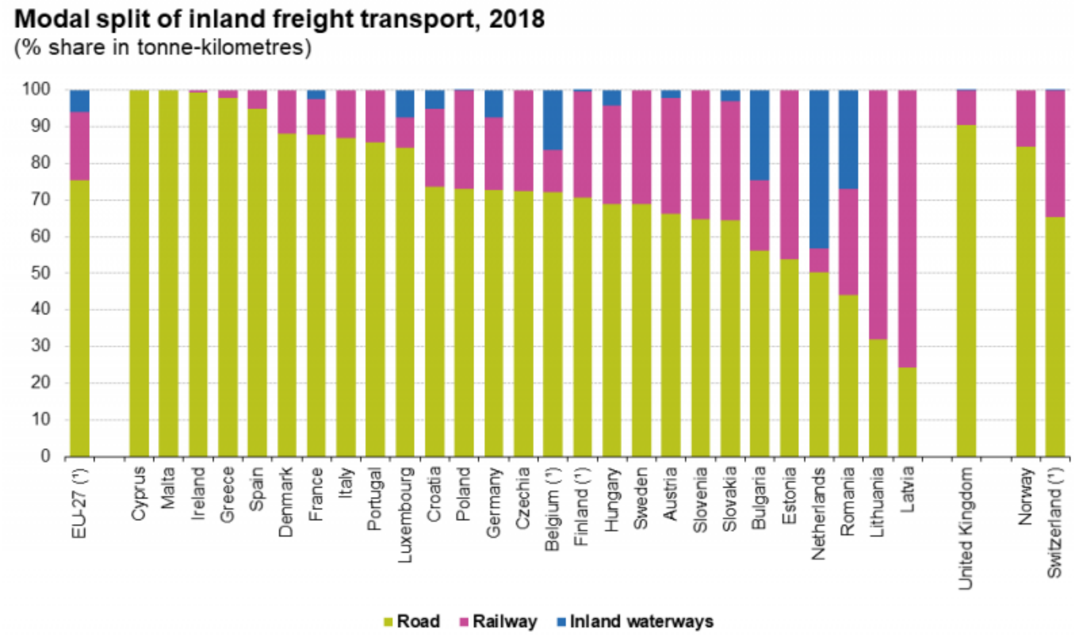


Figure 3: Share between transportation method in inland transport for different EU-Countries Source: Eurostat 2020

Figure 3 represents the different transportation methods and shares of different EU countries. As the figure represents, the most frequently used transportation method in most of the countries is road transportation. The highest share of road transportation is in Cyprus and Malta, where it is 100%. In other countries the other categories are also used, which could be because of the natural environment such as rivers or seas (water transportation). The highest share of water transportation can be addressed in Netherlands and in the second and third places is Romania and Bulgaria. The Netherlands have the most rivers in the whole European Union, and this indicates their high share in the inland waterways, but they also use road transportation (over 50%). In the case of Romania and Bulgaria the reasons could be the poor infrastructure in the other transportation methods and the number of navigable rivers too. However, it also interesting that in Romania, for example, the share of the water and road transportation is almost the same. Railways are used the most frequently in Lithuania and Latvia (over 50%), but other countries use this method. In many countries the share of this method is almost the same (20%). The problem with this type of transportation is infrastructure. Rail transportation is too fixed, and, in some cases, it needs to be combined with other types, such as road transportation. Another problem is the scheduling of the different trains. For instance, if any error occurs on railroads, it is not too easy to find another way, it needs to be re-scheduled or needs to be waited until the error is repaired. But today, this is the most environmentally friendly method, which is important in the European Union.

On the other hand, road transportation is the most flexible, but less environmental-friendly (greenhouse gases) as mentioned in other chapters. (Eurostat, 2020) The increasing volume of road transport occurs higher emissions, and the European Union wants to reduce the amount of road transportation or reduce the level of emission from year to another. This is also a background challenge, which will be highlighted in another chapter.

b. Emission levels of Freight Transport

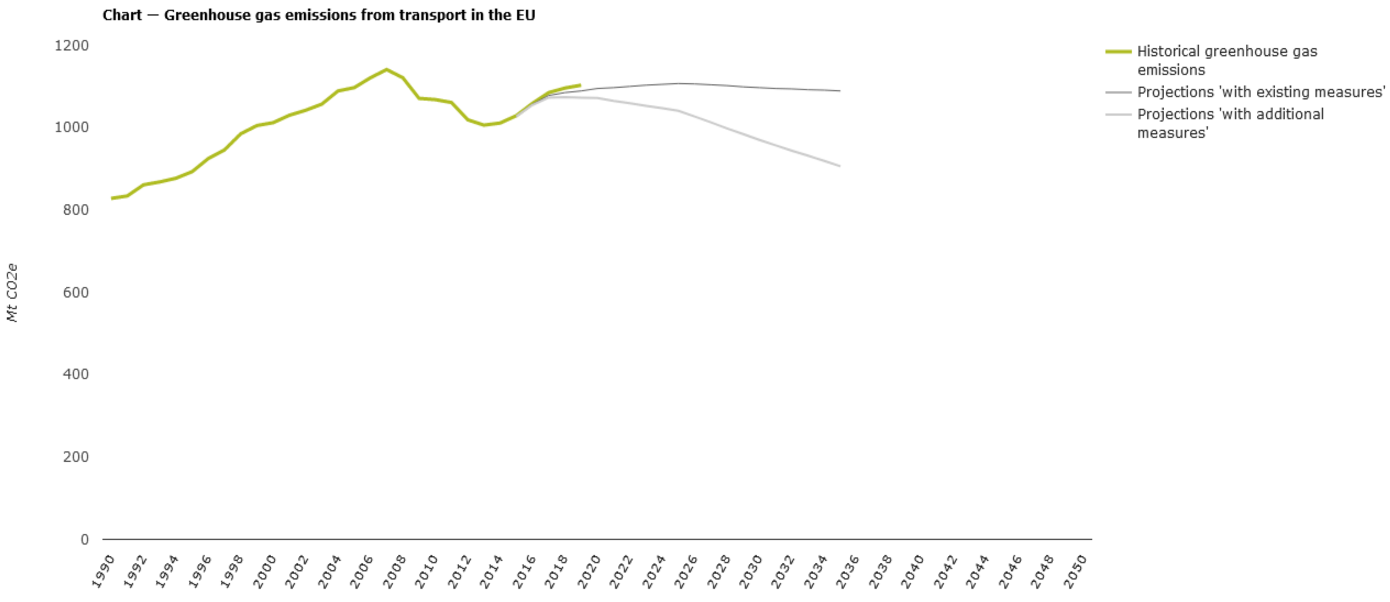


Figure 4: Greenhouse Gas Emission in the European Union Source: EEA, 2020

Figure 4 illustrates both historical and projected greenhouse gas emissions in the European Union. Between 1990 and 2008, emissions rose steadily, primarily due to growth in transport activity across member states. After 2008, a temporary decline was observed, reflecting the effect of regulatory measures and efficiency improvements. From 2016 onwards, however, emissions began to increase again, coinciding with the expansion of e-commerce and the sharp rise in parcel deliveries. Although overall EU emissions followed a downward trajectory, the transport sector deviated from this trend and is expected to remain a major contributor in the future, posing significant challenges for policymakers and environmental objectives (EEA, 2020). Projections further indicate that the lowest reduction rate in transport was recorded in 2014, at only 0.8%, while between 2018 and 2019 a marginal decrease of 0.1% was achieved. If these dynamics persist, emissions may fall slightly compared to present levels but will not return to the baseline of 1990. This suggests that EU climate targets are unlikely to be met before 2030, and full carbon neutrality by 2050 will remain unattainable without stronger intervention. Current estimates show that emissions are still around 32% higher than in 1970; under additional measures, this excess could be reduced to 17%. These figures highlight the urgency of reinforcing strategies to mitigate the disproportionate role of transport in greenhouse gas emissions (EEA, 2020).

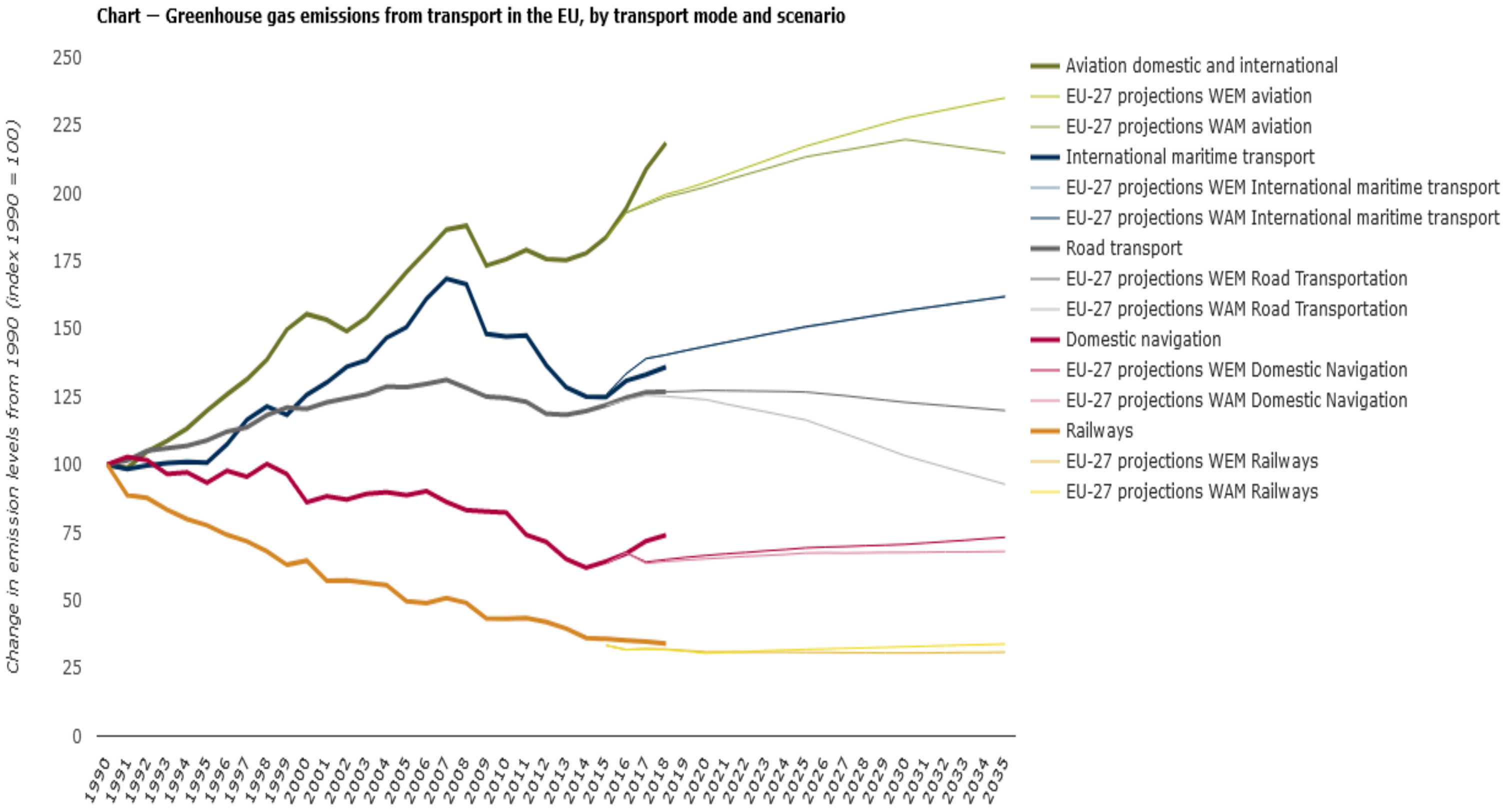


Figure 5: Greenhouse Emission in the EU caused by transports. Source EEA, 2020

Figure 5 shows the greenhouse gas emissions from the different transportation modes in the EU-27 countries. It could be clearly classified that only the domestic navigation and the railways emission have decreased in the last 20 years. This decreasing trend will continue in the next years, but it will reach a constant level or will only increase slightly. This projection depends on the different norms. The two measures are WEM and WAM. WEM means 'with the existing measures' and WAM means 'with additional measures' which will be introduced in the next years. However, in this case this makes only a little difference in the projection for the coming years. In the other three cases of Aviation, Maritime, and Road Transport an increasing trend could be expected. The highest increase will be in Aviation where three different drops could be observed Road transport remains the largest contributor due to its dominance in freight distribution and last-mile operations. Aviation has experienced the steepest growth, despite temporary declines in 2002 and during the 2007–2010 financial crisis. Since 2010, however, emissions from this sector have climbed again and are projected to remain high in the coming years. Maritime transport shows a similar pattern: emissions decreased after 2006 until around 2015, but subsequent years have seen a renewed upward trend. As the projection shows the gas emission level in this mode will be increasing in the next years, which is supposed by the actual data which also show a higher level. However, even with stronger regulation, the sector is unlikely to reach full carbon neutrality by 2050 without major technological shifts and structural changes in logistics and mobility patterns For the thesis road transportation is interesting where the emission level also increased until 2007 but after that a decline could be observed because of the new technologies. (EEA, 2020)

1.3 The European Union Regulation

According to the European Commission Report vans and cars are the most responsible for air pollution. Their polluting effect is approximately 12% and 2.5% respectively. This means passenger cars and vans produce the most CO_2. For the thesis the most important factor is the pollution caused by vans because this type of traditional transportation is used by the delivery companies. The European Commission has established ambitious climate targets aimed at reducing greenhouse gas emissions by at least 55% by 2030, with the overarching objective of achieving climate neutrality by 2050 (European Commission, 2020). These regulatory measures are not limited to environmental protection but are also expected to generate socio-economic benefits. For instance, the transition toward low- and zero-emission mobility is projected to create tens of thousands of new jobs across the Union, particularly in the battery production sector and the development of charging infrastructure. Expanding recharging and refueling networks will stimulate investment and accelerate the adoption of cleaner technologies. In addition to macroeconomic gains, the Commission highlights consumer benefits. Stricter efficiency standards for vans and passenger cars are anticipated to extend vehicle lifetimes and reduce operating costs. It is estimated that by 2030, owners of low- or zero-emission vehicles could save between €1,100 and €4,000 compared to conventional models. These targets are operationalized through binding emission standards: a 15% reduction requirement for both cars and vans by 2025, followed by a 37.5% reduction for cars and a 31% reduction for vans by 2030. Manufacturers that fail to meet fleet-wide average emission limits—set at 95 g CO_2/km for cars and 147 g CO_2/km for vans—face significant financial penalties, with surcharges applied per excess gram of CO_2 per kilometer. (European Commission, 2020) Overall, these regulatory initiatives combine environmental, economic, and consumer considerations, positioning the EU as a global leader in sustainable mobility. The target levels which are to be reached in the next few years are a 15% reduction for cars until 2025 and a 37.5% reduction until 2030. The reduction levels for the vans are similar same, a 15% reduction until 2025 and a 31% reduction until 2030. The European Commission also set target levels for zero- and low-emission level vehicles, which are 15% from 2025 and 35% from 2030 for cars and the levels for the vans are 15% from 2025 and 30% from 2030. (European Commission, 2020) The two regulations (EC) 443/2009 for cars and (EU) 510/2011 for the vans) were introduced in 01.01.2020. In these two regulations the maximum average CO_2 target for cars is 95 g CO_2 /km, which is approximately 4.1 l/100 km of petrol and 3.6 l/km of diesel consumption. The targets need to be applied for each new car and the emission level of every new registered car needs to be below this target. An average emission needs to be calculated, which comes from the whole fleet of the producers. If companies do not hit the target level, they need to pay a penalty after each extra gram, which will be €5 for the first g/km of exceedance, €15 for the second g/km, €25 for the third g/km, €95 for

each subsequent g/km. This was in 2018 but there was a change in 2019, which is €95 for each g/km of target exceedance.
The case of vans the average emission target is 147 g CO_2/km. In this case the whole fleets need to be taken into consideration and an average is to be calculated and the penalty is also the same as in the case of passenger cars. (European Commission, 2020)

1.4 E-Commerce

E-commerce has become an essential segment of the global retail market and has shown continuous growth over the past years. This upward trend accelerated significantly during the COVID-19 pandemic, when physical retail channels were restricted and online platforms experienced unprecedented demand. In 2019, e-commerce already accounted for around 14.1% of global retail sales, and forecasts suggest that this figure will continue to rise, reaching approximately 22% within the next few years if the current trajectory is maintained (Statista, 2020). The total value of e-commerce sales worldwide has reached 4.13 trillion USD, underlining its status as one of the largest and most dynamic economic sectors. The expansion of digital commerce is driven by several factors. Changing consumer behavior, especially the preference of younger generations for flexible and mobile-based shopping, has played a central role. Surveys show that more than half of Generation Z (14–24 years old) and Millennials (25–34 years old) shop online regularly, while the proportion decreases among older cohorts, with only about 27.5% of Baby Boomers (55+) using online retail frequently (Ecommerce Guide, 2020; eMarketer, 2019). Social media integration is another key driver: at least one in four companies now sells products directly via social media platforms, and in such cases up to 40% of total sales are generated online (eMarketer, 2019). However, high cart abandonment rates remain a persistent challenge for online retailers. On average, 68.8% of initiated online purchases are not completed. The main reasons include unexpected additional costs such as taxes, shipping fees, or surcharges (50%), the requirement to create an account (28%), and overly long or complex checkout processes (21%). Other barriers include limited payment options, slow delivery, or concerns about return policies. By contrast, studies show that improving the usability of checkout design can increase sales by more than 35% (Baymard Institute, 2020). Free shipping options are also consistently reported as a decisive factor for consumers when selecting an online store. At the international level, regional differences are evident. China represents the largest e-commerce market worldwide, with sales of 1,520.1 billion USD in 2018 and 1,934.8 billion USD in 2019, marking an annual increase of 27.3%. The United States ranks second with sales of 586.8 billion USD in 2019 and a growth rate of 14.0%, followed by the United Kingdom with 141.9 billion USD and a growth of 10.9%. Within the European Union, the UK remains the largest e-commerce market, followed by Germany (81.9 billion USD) and France (69.4 billion USD) (Ecommerce Guide, 2020). These figures demonstrate the rapidly increasing importance of e-commerce in global trade and highlight its implications for logistics systems. Rising parcel volumes and customer expectations for fast, flexible, and low-cost delivery are placing growing pressure on last-mile distribution, intensifying both economic and environmental challenges.

2. *“Last Mile”*

The importance of Last-Mile-Delivery has increased rapidly in the past few years. There are more and more people who order products or services online, because of the convenience and high flexibility. In some cases, the customer could choose in the delivery days or conditions, which makes this delivery form popular. This popularity indicates that this supply chain stage has become a critical point in the system and encourages the companies to develop new technologies in this field. (Lim, Jin & Srai 2017)
To satisfy the increasing order in the stream, the delivery companies have developed new technologies and models; for example, one idea was the urban pick-up-points or the automated distribution hubs. In the beginning the problem with these concepts was the lack of acceptance from the industry and the incorrect and “young” design. (McKevitt,2017) For instance, the same day delivery concept from eBay. The eBay Now was introduced in 2012 and it needed to close in July 2015. Other concepts were the Sainsbury`s, Somerfiled, and Asda pick up centers or the Google program for delivery hubs, the Google Express. (O`Brien, 2015) The problem with these new and innovative concepts was the higher complexity. Since they created a most fragmented market with higher uncertainty which indicates a new and complicated optimality between pricing, innovations, service levels and customer needs. (McKevitt,2017) There are different existing models which try to solve these complex problems with different innovations and a mixture of algorithms.

2.1 Definition of “Last-Mile-Delivery “

It is not easy to define the Last-Mile-Delivery Problem because it exists in different fields, but it originates from telecommunication where it refers to the last part of the current network. Similarly, the term could be derived from the logistic aspect, which also means the last part of the supply chain. In general, this leads to the Business to Customer problem, which is the most expensive and inefficient part. On the other hand, Business to Costumer is just the common understanding the problem, because there are other approximations for the last part of the supply chain, which could define, for example, the fulfillment of tasks in stores, which is not directly linked to the customers. (Lim, Jin & Srai 2017)
This is the reason why the definition for another concept introduced, “refinement”, which is the order penetration point. The order penetration point defines the origin, and it gives the point where the customer demands cause the inventory change. In the next step the customer order will be assigned to the shop, and it makes this a “natural starting point”. The last stage, the so-called “final consignee`s preferred destination points”, which is the last point in the system (customer). The last points could be at home, at offices, pick-up points or other distribution hubs. The Last-Mile-Delivery could be defined with the common use and penetration point. (Lim, Jin & Srai 2017)

*“Last-mile logistic is the last stretch of a business-to-customer (B2C) parcel delivery service. It takes place from the order penetration point to the final consignee`s preferred destination point” (*Lim, Jin & Srai 2017, p.12*)*

2.2 Typology of "Last-Mile-Delivery"

In chapter 2.1. the Last Mile Delivery process was defined, but there is a difference between the companies in terms of how to distribute customer orders. In general, are three main groups of actors in the supply chain (Techane B., 2020):

- Shippers -> producers, wholesalers, freight forwarders (Techane B., 2020)
- Transport Service Providers -> carriers, couriers, own account (Techane B., 2020)
- Receivers -> retailers, end consumers (Techane B., 2020)

Figure 6: Relationship between Actors (Techane B., 2020)

Figure 6 illustrates the relationship between the main groups. The process is very simple: the customer orders the product, which indicates an inventory change at the shipper, which could be considered the starting point. After this, the shippers organize the shipping process which could be identified as the last-mile-delivery stage. (Techane B., 2020) This stage accounts for 28% of the total delivery costs and the very high greenhouse gas emission level. (Luigi R.,2018) In the end transport service providers deliver the packet to the receivers, who are the final consignees preferred destination points. However, it gives us only the general connections, the question is what the process is like between the neutral starting point and the end point (final consignee`s preferred destination points). There could be five different strategies for the last stage, which combine the different distribution channels. (Techane B., 2020)

2.2.1 Distribution-Center-Based Delivery (Option 1)

In this type of last-mile-delivery concept the distribution center is in the middle. The distribution center sends all deliveries to the stream and spreads the orders. In this case the distribution center could be a warehouse or a producer or a retailer too; what is important is the direct connection between the natural starting point and the final consignees preferred destination points. In this distribution centre-based delivery process it is allowed to deliver the orders to a pick-up point or direct to the customer. Normally this makes the different types of moves at the same time or makes just one of them possible. The problem with this process is the high complexity because of the number of delivery points and the transportation costs are also high. On contrast, customer satisfaction could be high, which is the reason for the direct home delivery. In the case of home delivery, the customers do not need to make any extra journeys to collect the packages. The first option is useful if there is a mixture of small and large packages, because of the mixture of packages, the firms need to consider the use of large and intermediate vans, which makes the problem`s complexity higher. This indicates that companies need to find the optimal routes, the cost optimal van mixtures and the optimal schedule for vans and customers. Figure 7. Illustrates this process. (Techane B., 2020)

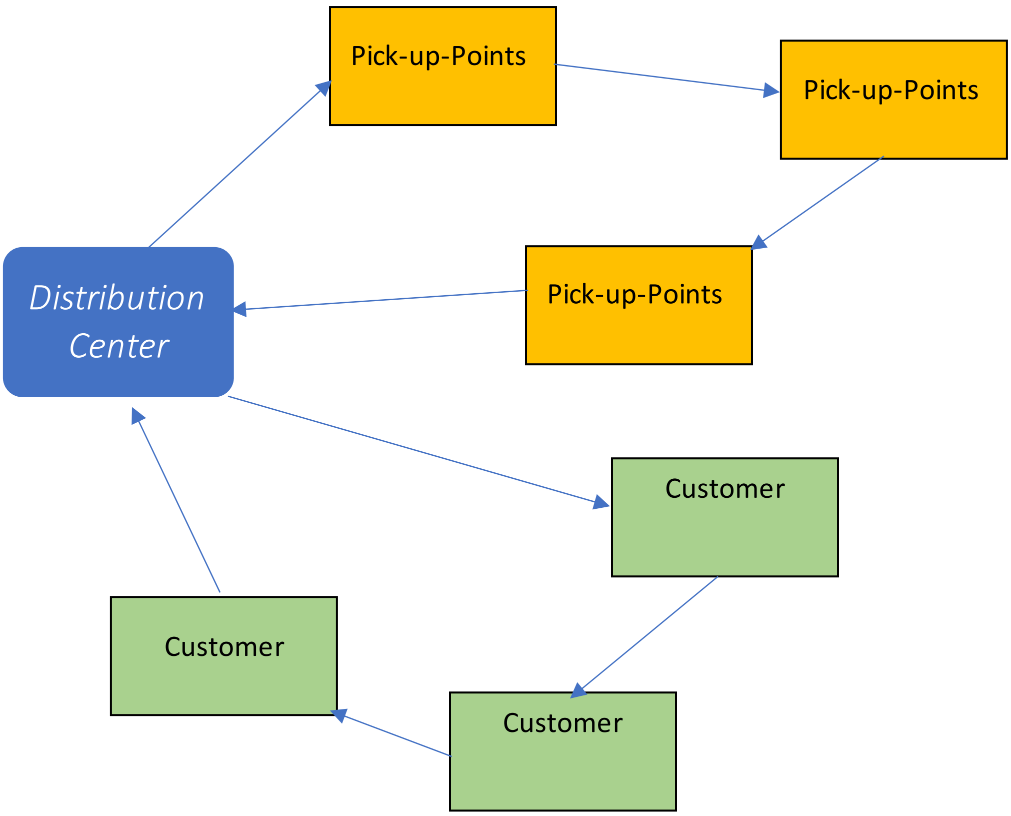


Figure 7: Distribution-Center-Based-Delivery (Option 1) (Techane B., 2020)

2.2.2 Distribution-Center-Based Delivery (Option 2)

There are two options in the distribution centre-based delivery. The first presented in the section 2.2.1. In the second option the distribution center also sends the deliveries but, in this case, there are no direct connections between the distribution center and the customers. Between the natural starting point and final consignees preferred destination points a pick-up-point located. The center sends the orders to the pick-up-point and the customers themselves collect the deliveries. The problem with this second option is that the customer needs to collect the deliveries on their own and this indicates another last-mile problem (between the pick-up-point and customer home) in the urban area. However, the customers could use public transportation or other alternatives to reduce the level of emissions. On the other hand, the center only needs to send the package once. The only one delivery to the distribution center also reduces the complexity of the problem because there is just one fixed point to deliver and transportation costs will also be lower. This delivery concept is useful if there are just some small packages and delivery is not possible direct to the customer (restricted areas). This delivery type is very useful for the intermediate van types as it indicates any other optimizing problem. Figure 8. represents this option for the last delivery problem. (Techane B., 2020)

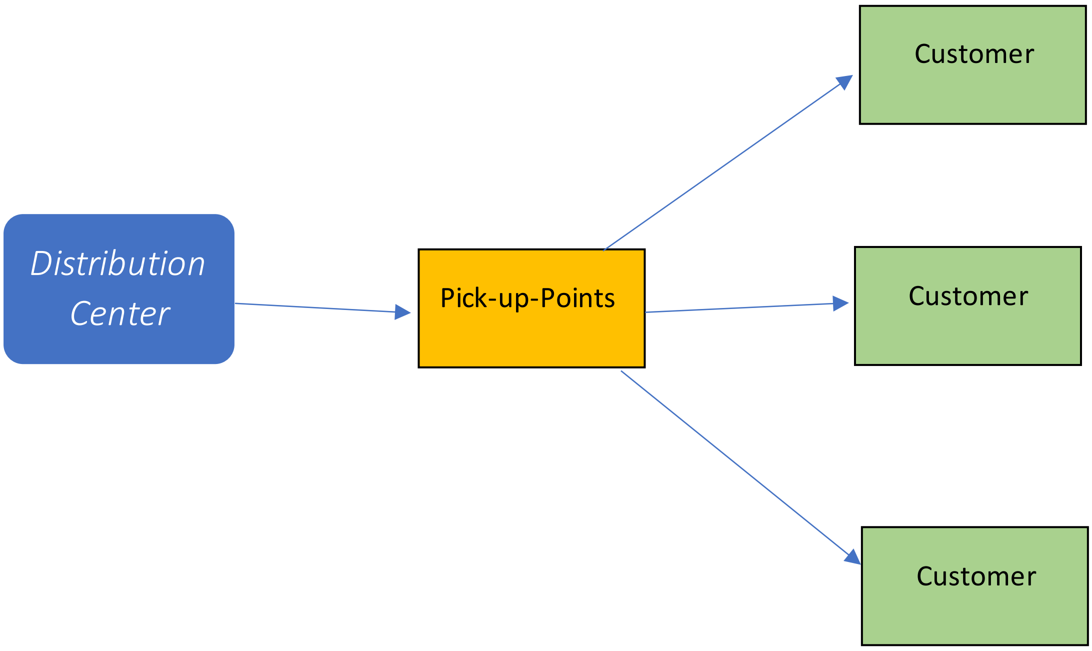


Figure 8: Distribution-Center-Based Delivery (Option 2) (Techane B., 2020)

2.2.3 Local-Distribution-Center-Based Delivery (Option 1)

In this option the distribution center sends the parcels to a local distribution center and the local center distributes the packages to the customers or the customers could collect the packages by themselves. This is ideal if there is a high number of parcels to be delivered and it is better to dispose this between more local centers because of a lower delivery time. Another advantage is the reduced small and separate problems, which indicate a lower complexity. This distribution policy has a high level of emission. Since the parcel needs to be delivered twice, first from the distribution center to the local distribution center and second from the local center to the customers. Another problem is the high travel costs and the cost of the optimal mixture of trucks and vans. This type could be useful if there more local centers around the city are located and the company has a large distribution center. Figure 9. illustrates the process. (Techane B., 2020)

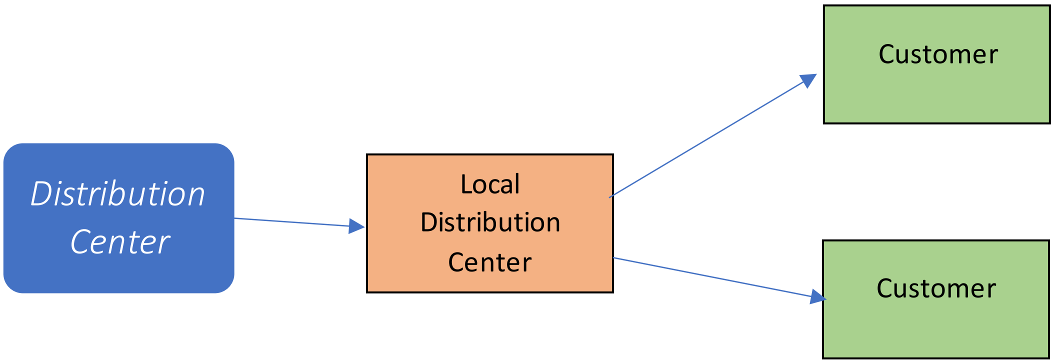


Figure 9: Local-Distribution-Center-Based Delivery (Option 1) (Techane B., 2020)

2.2.4 Local-Distribution-Center Delivery (Option 2)

The logic behind this form is the same as that of the Distribution-Center Delivery (option 1), the difference is the intermediate stop between the end points. In this case the Distribution center sends the packets to the Local center and the Local Distribution center distributes the parcels to the Pick-up-Points and to the customers. The advantages of this form are the same as those of the Local-Distribution-Center (option 1 in 3.2.3.). In this case complexity could be reduced if the problem reduced more separate problems (Distribution center vs. Local distribution center, local distribution center vs. customers, local distribution center vs. pick-up points). The disadvantage is the higher travel costs, the high level of emission and finding the optimal mixture of vans and trucks. This is useful for the cases where the company has a large distribution center and a high number of local distribution center. On the other hand, this combines the advantage of the pick-up point and direct delivery. The company could reduce the level of emissions with the pick-up points and increase customer satisfaction with direct delivery. Figure 10. represents this form. (Techane B., 2020)

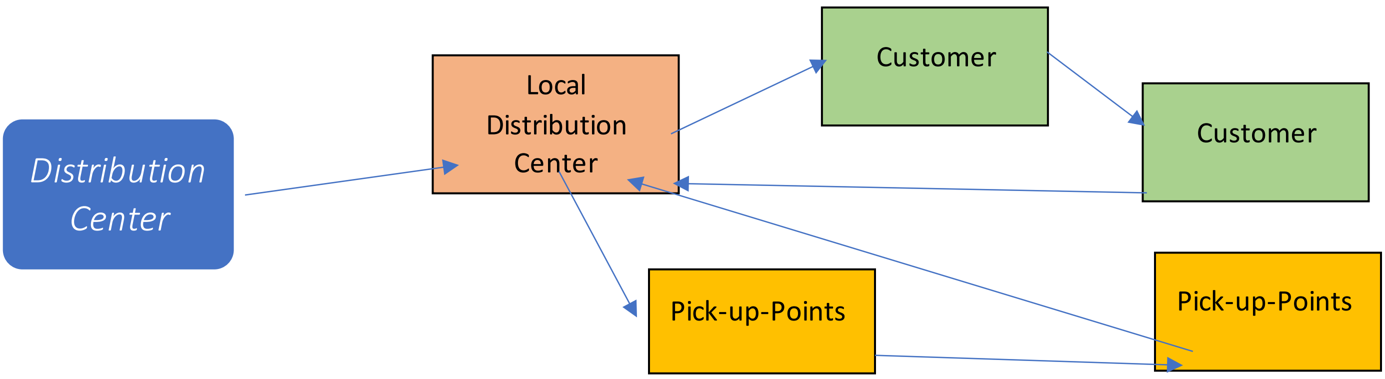


Figure 10: Local-Distribution-Center-Based Delivery (Option 2) (Techane B., 2020)

2.2.5 Pick-Up-Point Delivery

In the last version the distribution center sends the parcel to the local distribution center and from the local distribution center it will be delivered to the pick-up points. After that customers could collect deliveries themselves. In this case the firms could reduce the emission level because customers collect the deliveries themselves from a pick-up point. On the other hand, customer satisfaction could be lower (own delivery). This type of delivery method is beneficial for firms with a large distribution center and several local distribution centers. The companies could reduce the emission level and the transportation costs too. The question in his case is how complexity would be reduced. Normally, this problem has a lower complexity (just pick-up point delivery), but it needs to consider the route between the distribution and the local distribution centers, exactly it needs to find the nearest local distribution center and the nearest pick-up-point. However, this suboptimizing problem could reduce two other separate optimizing problems and could solve them separately from each other. (Techane B., 2020)

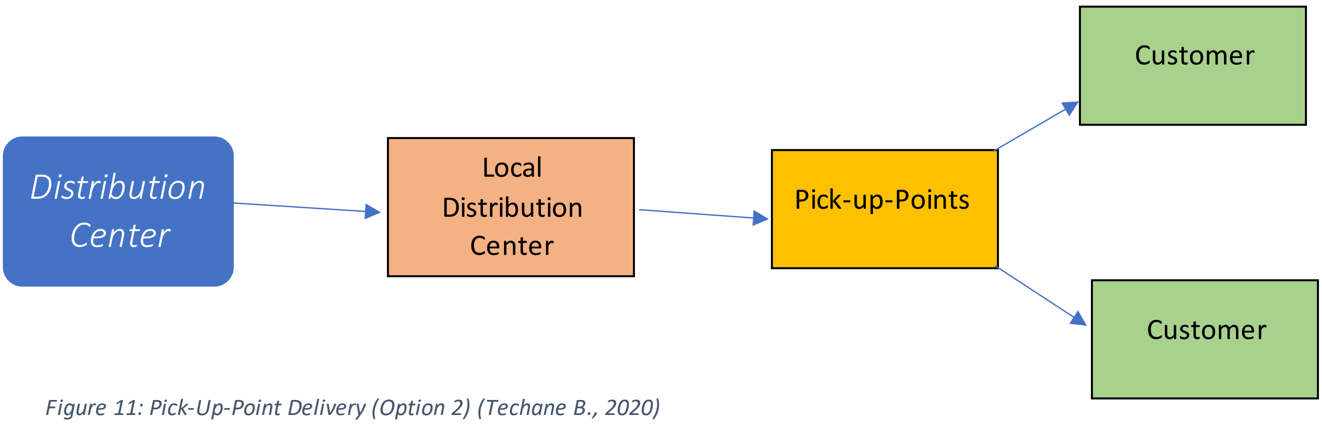


Figure 11: Pick-Up-Point Delivery (Option 2) (Techane B., 2020)

2.3 New Technologies and Innovations

The last mile logistic is the most problematic and the least efficient part. Since there are high costs and a high emission level in the whole Supply Chain. Only this part of delivery amounts to 28% of the total costs. This high cost and emission level are rooted in the high complexity. Therefore, companies need to find optimality between several factors such as an optimal route, a cost optimal investment in trucks and vans, customer satisfaction and uncertainty. (Wang Y., et al., 2016) On order to deal with the high complexity and costs, more innovations have been developed in this field. Technologies such as Global Positioning Systems, Mobile Networks, Satellite technologies, Mobile Applications, the Internet of Things or other Big Data Tools could help to make the sector more efficient. (Petrovic O., Harnisch M.J., 2013)

2.3.1 Consolidation Centers

The idea of Consolidation Centers was the first development in last mile of the supply Chain; namely it was introduced in the 1970s when companies invested in Local Centers to make the distribution easier and reduce the travelling costs. The reduction was possible because they did not use large vehicles for the whole travelling process only for the middle part of the route between the central distribution center and the consolidation center. On the other hand, they had the option to outsource deliveries from the consolidation center to the customer. However, the cost aspect was not the only reason for the establishment of the Local Consolidation centers. With an increase in urbanization, the cities needed to adopt and use new policies to make people better. These restrictions affected the life of delivery companies negatively and they caused higher costs and complexity. Such restrictions or new policies were, for example, restrictions on transport with a specific time window or restricted zones. (Luigi R., et al, 2018) In order to deal with the time window and restricted zones, different types of Consolidation Centers have been developed and invested. The logic is the same for all types, but it varies accordingly the different policies and restrictions. (EAA,2019, pp. 48-51)

a. *Urban Consolidation Centers outside the urban area*

The outside consolidation centers were the first idea which were introduced. The idea of this conventional type is represented above, the firms deliver the parcels from the main distribution center to the local center with large trucks and after that they outsource the last stage to other delivery companies which make the last stage. Another idea could be to make a large consolidation center and rent it out to other companies. This idea helps to reduce the number of vehicles in cities because not all companies need to send their own vehicles to the customers, as it is possible to send separate companies' parcels with one van to the same route. This method has helped to significantly reduce the number of routes and transport in urban areas. (Holguin V. et al., 2018)

b. Urban Consolidation Centers inside the urban area

The idea is the same as in the case of centers outside the urban area. The significant difference is the size of parcels. This is useful if very small or small packages need to be distributed. In this case the parcels are delivered directly to a pick-up point or to a local store and customers collect their own order by themselves. In this case the pick-up points or delivery hubs are the consolidation centers and the emission level, and the costs could be low because companies do not need to deliver directly to the customer and the customer could use public transportation or other environmentally friendly transportation methods like bicycles. For illustration see section 2.2.5.. (EAA,2019)

c. Consolidation linked to a modal shift terminal

The modal shift terminals are, for instance, the terminals in shipyards, airports, or railway stations. In these cases, the parcels are not delivered directly to the customers but to a local Center and from the consolidation center the parcels will be delivered to the end customer. These Consolidation centers could be located outside are or inside the urban area, which depends on where the railway station or the shipyard is located. (EAA,2019)

d. Changes in the destination of deliveries to a consolidation center in or outside the urban area

This option is not the right category but an important" program" for the last mile delivery. It could be the case that the customer changes the delivery terms because they are not at home or home late. In this case they could change the direct delivery to a consolidation center delivery. After that the customer could choose from another day's direct delivery or to a pick-up point/hub delivery. This option is not the most popular option, because they need to pay an extra fee for the change and in some cases, this needs more time than the first option. On the other hand, delivery companies need to reorganize or reschedule their deliveries, which generates inconvenience and more logistics problems. (EAA,2019)

c. Receiver-led delivery consolidation programs

The last option is working only in the urban area. This concept does not need any consolidation centers but a direct distribution center supplier. In this case the supplier sends the parcel within the urban area to another supplier who stores the parcel and makes the delivery to the end customer, or the customer collects the package themselves. This will be useful if the customer orders from two companies at the same time and the two separate deliveries could be combined with one end delivery. This makes the supplier`s life easier and complexity will be reduced via one final delivery. On the other hand, the emission level will also be reduced with the lower number of routes. (Holguin V. et als., 2018)

2.3.2 Innovative Vehicles

Innovations and new technologies in the car industry have slightly increased in the past few years. They have developed new engine technologies, autonomous vehicles, or novel deliveries. For example, in the market there are different engine types which have a lover emission such as hybrid vehicles, electric cars or fuel cell electric cars. In the European Union, the most important green engine type is the electric engine. The problem with this type of car and vans is the very low range they can cover (approximately 150 km). This low range is not optimal for long trips because the charging time is also very high. This type could be useful only in cities and in case of small packages. However, scientists are trying to improve this technology to cover a higher range. On the other hand, it is not only the battery capacity that is improving during the time but the solution algorithms as well. (Luigi R., 2018) Another interesting engine type is the hydrogen driven vehicles (fuel cell electric cars), most of which are used in Japan or in the USA. There is a misunderstanding because most people think this technology is not safe if there are any accidents occurring during the drive. However, today this technology is very safe and usable. These cars could run approximately 600 or 700 km, which makes this type very useful also for long trips and the charging or fueling time is the same as in the case of traditional vehicles. The only problem is the very high cost of building the tanking station for these vehicles; these are very expensive and need a high investment. (Luigi R., 2018) The third type of engine is the hybrid engine. Most car producers use this technology because it combines traditional fuel technology with electric technology. This technology is very simple if the battery does not have any capacity, then the “normal” engine could charge them or it is possible to charge them from the electricity network, but the most important fact is that the vehicle could run without using the electric engine. Today there is a low investment in this field because of the “traditional” engines and the European Union’s regulations. (Luigi R., 2018) There are other investments in innovative vehicles such as the electric L-category vehicles. The electric mopeds, motorbikes, quads, and other vehicles belong to this category. The advantage of these vehicles is size, so these are very suitable for urban areas. It is easy to find parking places for motorbikes, or it is easier to drive them in cities, or they could be faster during the peak hours. On the other hand, they have lower energy consumption and light, which makes this type more effective. However, the biggest disadvantage is the limited capacity, because of their small size they could not deliver a large parcel. The limited capacity also indicates that if there are only small packages, then all of them could not be delivered at the same time. (Luigi R., 2018) Other innovative vehicles such as delivering robots which are used today only in warehouses, since these are not suitable to deliver parcels in urban areas. Another innovation is the UAV’s, which originates from the army, but today they could be used in another field. See Section 4. (Luigi R., 2018)

2.3.3 Proximity Stations and Points

The delivery companies face another problem during delivery, namely uncertainty, which is the biggest problem during the last mile delivery because this factor could change the whole delivery route and create extra distances and thus it could cause larger delivery time. The uncertainty factors could result in extra time because of an accident during the trip, the customer is not at home, traffic jams or any technical problems. What is common in these factors is the extra time which is needed to deliver the parcel. To solve the problem, companies usually introduce an innovation or idea which are the proximation points or stations. A proximity station could be used for small or medium packages which could be stored in a locker or at a pick-up point. The difference between the pick-up point and the proximation points is that in the case of pick-up point deliveries the planned delivery and final delivery point are the same. The proximity points are used if the customer is not at home and cannot take the delivery on the given date at the given time but could take it, for example, at a proximity point. With this method the risk for an unsuccessful delivery and for the so-called “double delivery” could be reduced. (Edwards J., et al., 2009) Different systems and solutions have been introduced to face this problem. One is the so-called bento-box system. The idea is the same, the customer`s parcel will be stored until they do pick it up. The proposed pick-up dates and the pick-up points are agreed with the customer. In most cases the bento-boxes are in residential districts, shopping malls or other places which are comfortable for customers. Another innovation in this concept is that the parcels from the depot will be transported with electric vehicles. In this case the electric vehicles are suitable for this delivery because they are short distances and in cities there are many charging stations. (Ivan S., et al., 2016) A similar idea was introduced in Poland by the Polish Post. The difference between the bento-box and the Polish InPost Company’s system is that the Polish system used parcel lockers not boxes. The parcel system was so successful that other companies have developed the same idea and system. For example, DHL, the Austrian Post`s system, the Post24 Parcel Machines, where customers could take the delivery at any time. (Ivan S., et al., 2016) Today a similar system is used by not just delivery companies but also by some e-sellers, for example Amazon. Amazon further developed the idea as at Amazon customers could pick and pay for the packages or there is an opportunity to pay for the goods online. After online purchasing customers get a QR or a number code via e-mail. These codes are valid for the pick-up and if customers open the codes via the Amazon application, they could see the proposed delivery date, the locker`s place and the locker`s address. Some retailers such as MediaWorld or Zara use the same system. The customers buy the goods online with the help of an application or on a webpage and could take the delivery themselves. (Luigi R., 2018) Another innovation in this field was the so called “pick-your-own-parcel station (pop-station)”. In this case the economic rewards have come from the sharing system since in this system the firms use the parcels at the same time and the crowd-workers too. The crowd of workers will be rewarded with a low amount of money for the additional travel costs. The aim of this system is to find the most suitable crowd-workers and pop-stations. The crowd workers could a shop or delivery company. reduce the total reward paid by the delivery companies could be reduced with this system. (Petrovic o., et al., 2013)

2.4 Developed Systems for Last Mile Deliveries (two examples)

There are many different concepts and systems established in the past few years. In this section two different ideas will be presented, which could be seen as the most popular idea in the European Union. These concepts are not the most recent ones, but they have had a high influence on the new ideas. Normally, other systems could have the same features with different names or with little differences, but the aim of these systems is the same to reduce pollution, save costs and reach higher customer satisfaction.

2.4.1 Electric Vans and Vehicle

Electric vehicles have some advantages over the traditional vehicles (diesel, petrol), as they are quieter, have zero pollution, and their service costs are lower. The biggest disadvantage, however, are their battery capacity and the high charging time which makes electric vehicles suitable for shorter distances. For this reason, the Deutsche Post, DHL, in collaboration with Aachen University, started a project. The project`s aim was to replace the traditional vans and vehicles with electric vehicles. The electric vehicles are used for the same purpose: to deliver parcels and letters too. They use more than 10 000 vans in some cities and small towns, which has reduced air pollution and noise. On the other hand, the workers' satisfaction with the StreetScotter vehicles is better than with the traditional vehicles. The StreetScooter electric vehicles have been developed directly for postal services and have been tested by postal employees. The range of these vehicles is low, just 80 km and the maximum speed is 85 km/h but these are ideal for the delivery of letters and small parcels. The Deutsche Post DHL bought nearly 9000 vehicles from StreetScotte, but they will increase their fleet with other vans because they are satisfied with them, the usage is very convenient, and they do not need to service them often. Another advantage is that the Deutsche Post DHL has saved a high amount of service, maintenance and energy costs. On the other hand, after the electric vans and vehicles lower taxes and insurance premiums must be paid which makes this investment preferable. With this investment the Deutsche Post DHL could save one thousand euros per year or more than 2000 euros per year. It is also important to take the emission into account. After StreetScotter`s, the savings of CO_2 and the saving of diesel could be also high. If only one vehicle is considered, the CO_2 reduction could be three to four tons per year and the diesel consumption could be between 1 100 and 1 500 liters. Overall, the CO_2 emission could be more than 32 000 tons per year. Normally, emissions from the power stations have not been considered, but energy production will also pollute the environment less by year. To sum up, the successful factors of this project were that Aachen University concentrated on production and the fast introduction of vehicles, which has made it possible to test and to introduce a high number of vehicles at the same time. On the other hand, the management supported these low emission concepts financially and recognized the costs and environmental advantages of these economic vehicles. The concept during the experiment will be further developed and tested to find the weaknesses. German Environmental Ministry will also help the further developer of the process which makes this project more successfully. (Komission

“Wachstum, Structurwandel und Beschäftigung, 2019; Clausen, 2017; Moro, Lonza,2018; Kahlen, 2019)

2.4.2 Consolidation Center

A high and innovative development from a consolidation center took place in Gothenburg which started between 2016 and 2017. In Gothenburg approximately 530 000 people live. The high increase in population and the increase in urbanization also justified this project. The higher population caused a higher last-mile delivery demand and Gothenburg has a tradition of implementing different concepts to make life better in the city. For instance, they developed different infrastructural and building projects in logistics to reduce emissions, reduce noise pollution and make the city safer. For this reason, Gothenburg used the EU Novelog Project to build a new consolidation center outside the city. The aim of this project was to reduce the number of small deliveries in the city center, because these deliveries caused the most traffic and they had the most polluting effect in the city. For this project they selected the Nordstan shopping center which is in the city center. The consolidation center was built next to this shopping mall, where the packages will be stored and several deliveries will be distributed from this center a day. (Widegren,2019)

In the first step they needed to gather the data for the analysis to see the whole picture and to be able to make the right decision for developing the core parameters and infrastructure. The data collection in this case was not so easy because they needed all delivery data from all shops in the shopping center. The problem in such cases was the different registering period of shops. For this reason, they decided to gather the data in a two-week period and overall, they needed to collect data in three collection periods to have sufficiently big data for the analysis. In this phase Gothenburg University helped to gather, clean and analyze the collected data. After the analysis they realized that the problem was with the small packages and deliveries. Based on the analysis, the project and the consolidation center focus on the small packages and short distance deliveries. (Widegren,2019)

The project started with 50 shops and in the future, they planned to increase the number of participants to 200 hops. The deliveries to these 50 shops replaced direct delivery with a shuttle delivery from the consolidation center. First, the deliveries go to the consolidation center and after that packages will be collected, stored and assigned to the stores. In the last step every day the stored packages will be distributed as a bin to the stores. The shuttle makes the delivery one or two times every day, but it is possible to make extra deliveries, which depends on the number of packages. With this method the number of deliveries made and the traffic in the city center will be reduced because there will be just one or two deliveries per day, not more than, for example, 30 deliveries per day. (Widegren,2019)

The expected impact of this project was fascinating. The $CO_{2\ \mathrm{emission}}$ has decreased by 50% and the traffic in the city center has dropped by 97% (only the goods delivery has been considered). On the other hand, there will be a lower number of vehicles; instead of 600, only

300, which is a 50% reduction. Thanks to the project, the total delivery route was reduced by 140 000 km, which is approximately 50% of the total delivery km around the shopping center. (Widegren,2019)

3. UAV/Drone

UAV is the abbreviation for Unmanned Aerial Vehicles. In the past few years, the number of UAV´s and the number of innovations has slightly increased in this field. UAV´s was first used in critical military applications such as defense, reconnaissance, surveillance or security issues. Between 2011 and 2020 the market for military applications increased more than 60%. On the other hand, there are other fields where the UAV`s are used, for example, in traffic surveillance, disaster management, infrastructure inspections or law enforcement. The commercial usage of drones predicts a high demand in this market, which makes production very complicated. However, there are other problems with the commercial usage of drones such as safety, social, acceptance or privacy questions. Answering or finding the right answers to these questions is very hard and it makes difficulties for policy makers because this is a very new field. For this reason, intelligent solutions, innovations, and algorithms have been developed in this field to find the right answers and to make life better with drones. (Greenwood, Lynch & Zekkos, 2019) In the last years different types of drones have been developed because of the different usage. Different parameters and capabilities are needed for agricultural usage or for disaster management or for parcel deliveries. Normally, all the UAV's have their own limitations but in general there are four different limitations which are the same for all UAV`s: the cruising speed, the payload capacity, the flight range and the endurance. However, apart from these limitations, the usage of UAV's has several advantages such as environmentally friendly usage, low noise pollution, compact size, independent cruise or working in hazardous zones. (Shakhatreh *et al*., 2018) In the next chapter the different types of UAV´s and their advantages and disadvantages will be highlighted. After that the general types of different usage and general algorithms will be explained with different examples. Normally, it will be necessary to look at technology, how the different drones communicate, how collision can be avoided and which the most important technologies are which are needed to fly safely with a UAV. At the end of the chapter the thesis will explain the most critical disadvantage, which is consumer acceptance, which could be divided into different groups, the ethical questions and their regulation, the safety issues to avoid the hacking attack or overtake control and which the general regulations are which are needed to take into account when flying a UAV.

3.1 General Types of UAV´s

Based on platform design, UAV´s could be classified into two different groups. The first one is the convertiplane, which could change the airframe´s angel continuously. This makes the convertiplane more useful because they could always use the best conditions for the cruising. The second type is tail-sitter UAV. The tails-sitters cannot change the airframe orientation, which means they need to take off and land vertically, which makes the process difficult and more complicated, because they need a fix point where the two operations can perform. On the other hand, they cannot change angel during the cruise time only the “attack of angel”. This makes the cruise operation less efficient because the wind resistance is higher and if during the flight the wind is stronger, and the user uses the same flying speed, the drones will need to change the “attack of angel”, which causes a higher wind resistance. The higher wind resistance takes more voltage from the battery and the flying time will be lower. (Adnan S., et al., 2018) Normally, the convertiplane and the tails-sitters have different subgroups with different characteristics, advantages and disadvantages. In the following chapter the most important types will be presented, and the most important features will be highlighted.

3.1.1 Convertiplane

As was mentioned in the introduction, the most important advantage of the convertiplanes is the changeable rotor angel. The rotor angels can be set every time to the most efficient angel to reduce wind resistance and increase flight time. The convertiplane has four different types: the tilt-rotor convertiplane, the tilt-wing convertiplane, the rotor-wing convertiplane, and the dual-system convertiplane. (Adnan S., et al., 2018)

3.1.1.1 Tilt-rotor convertiplanes

The first tilt-rotor concepts were developed in 1993 and were based on different projects by aerospace enterprises from different research institutes. The first UAV which was built upon this concept was the Bell Eagle Eye (Figure 12). The flight tests of Bell Eagle Eye were the root for future development and concepts. (Adnan S., et al., 2018)

Figure 12: Bell Eagle Eye (Adnan S., et al.,2018)

The future concept can be divided into three different branches where the general difference is the number of rotors used for the flight. The first are the most popular concept “the bi-rotor UAV”. These UAVs’ two tilting rotors are for different operations such as take-off operations, landing operations and cruise operations. The concept and the general operations of the bi-rotor convertiplane are like those of the fixed wing ones. For taking off and landing they also use the horizontal method but after that for cruising they change the angel of the rotors not the angel of the whole body of the UAV (“attack of angel”). Changing the angel of the rotors makes the cruise operation safer because the probability of “rolling over” is lower than in the case of fixed wing versions. On the other hand, the other most important factors such as the wind resistance factor, the nacelle lateral tilting, general pitch and cyclic pitch are better in this concept. The concept of Bell Eagle Eye has been used for different bi-rotor concepts where the size was also an important factor. After several developments they introduced the “down-sized” UAV concepts the NUAA (Figure 13). (Adnan S., et al., 2018)

Figure 13: NUAA (Adnan S., et al.,2018)

During the test phase the researchers and developers have concluded that these concepts have a poor characteristic in terms of ratio and drag. The problem in these cases was that the rotors produced a constant rolling torque because of the relatively short wingspan and thicker airfoil. This was the most important characteristic which caused the end of the project. After several years of development, a new bi-rotor convertiplane concept was introduced. The concept of AgustaWestland Project Zero (Figure 14) combines the advantages of the flying-wing fuselage and twin embed-in-fuselage motor design. (Adnan S., et al., 2018)

Figure 14: AgustaWestland Project Zero (Adnan S., et al.,2018)

There is a strong and big, small-UAV market which is led by tri-motor convertiplanes. This UAV version uses all three rotors during the take-off and landing operations (vertical operations), while in the case of cruising operation they use one or two rotors. The concept during the horizontal move is the same as the two-rotor concept, since the UAV can tilt the rotors which they need to hold the same speed and normally they can change the angel from the rotors to secure the optimal flying characteristic. There are several advantage of using the three-rotor design, but the most important one is the reduced lift generation which is dependent on the total UAV weight between 33% and 50%, the second advantage is attitude stabilization because the symmetric frame secures a better gravity center, and the third advantage is that the rear rotor is fixed, which allows low-wing configuration and causes better flight endurance and versability. The first model of these three-rotor convertiplanes was developed by IAI and the name of the UAV is Panther, which is shown in Figure 15. (Adnan S., et al., 2018)

Figure 15: Panther (Adnan S., et al.,2018)

3.1.1.2 Tilt-wing convertiplanes

The development of the tilt-wing concept began between 1957 and 1965, when Boeing Vertol introduced the first design. The first version of Boeing Vertol was a manned convertiplane which was further developed in the next few years, although the design was not a popular concept until 2000. After 2000 the manufacturing process of RC aircraft reached its maturity phase, and it made the production of UAV's more effective and better. This technology boom filled the market with different firms and researchers who produced and introduced different designs and concepts. The idea of tilt-wing UAV´s was different from that of tilt-rotor convertiplanes and had different advantages and disadvantages. The tilt-wing design has a generally more complicated and sophisticated structure and, on the other hand, during the vertical operations such as take-off, landing and hovering the wings need directing upwards, which makes the control and stabilization more complicated. (Adnan S., et al., 2018) The tilt-wing concepts can be divided into two sub-groups, the single- and tandem-wing convertiplanes. Out of these two concepts, the single-wing is the most popular one, this design was adopted by HARVee, AVIGLE, GL VTOL Drone, AT-10 Responser and the DHL parcelcopter. (Adnan S., et al., 2018) The concept of HARVee is the oldest design from the above listed versions, which was developed by a young research group. They concentrated on better stabilization performance to find a better mechanical design for the hovering operation. The other performance indicators such as the integrated fixed pitch motors and the tilting of the whole wing are the same for the cruising operation. However, there are similarities with the two-rotor concept because the HARVee uses the same concepts and ideas during the hovering operation. In the other cases the HARVee UAV uses similar moves and concepts as the other tilt-wing convertiplane, which are highlighted above. The AT-10 developer used another mechanical design to solve the problems with hovering operations. They used a unique mechanism to reduce turbulence. The AT-10`s wings are separated into two independent parts, where only the part of the rotors could tilt and change angel, and the other part was fixed. The AVIGLE adopted another concept, where the pitch of the blade itself could change during the different operations and the UAV uses an aileron control mechanism on the wing, which makes different wing tilting possible. However, the most interesting innovation and development was introduced in the case of the GL VTOL drones. The developer used ten rotors which are in different places on the wing. Eight out of ten rotors are located vertically on the wings, which makes more stabilized hovering operation possible and the remaining two rotors are available for the cruising operation. (Adnan S., et al., 2018)

The most successful project in this category is the DHL parcelcopter design which is adopted and used for parcel deliveries in mountainous regions. The DHL concept uses the advantage of the above represented UAV´s with increased payload capacity, better battery capacity and higher speed for any operations (takeoff, landing, cruising). The version 3. can carry maximum 2 kg parcels with a speed of maximum 70 km/h and has a maximum 8 km flying range. However, the most important advantage is that the DHL parcelcopter can take and deliver a parcel from a docking point fully-automatically. (Bonn, 2017) The above introduced UAV´s are represented in Figure 16.

Figure 16: DHL Parcelcopter (Bonn, 2017)

The prototypes of two-tandem-wing convertiplanes are quad-copter UAV´s which have been developed by academic institutes. They use the same mechanical parts and characteristics. The idea of these convertiplanes is that four rotors are used on the edge of the tandem wings and the UAV can control and change the tilting angel from the wings. They can stabilize the plane during the flight with the rotors and tilting of the wings. For the tilting mechanism the developer uses a different mechanism or control functions, but the general control algorithm and methods are the same. The solution for the control mechanism depends on the shape of the plane, because the different UAV body and wingspan react in different ways to the turbulence caused by the rotors. (Adnan S., et al., 2018)

3.1.1.3 Dual-System Convertiplane

The dual-system UAV´s represents a small segment in the market. The most important characteristic of these convertiplanes is that they use two different rotor systems. For the vertical operation (takeoff, landing) the firms adopted one or more upward rotors and for the cruising operation tractors or pushers are used. Because of the tractors or pushers, the dual-system plane does not need any tilting mechanism, and in this case the wings are fixed. The biggest disadvantage of this design is the extra rotors which are only used for vertical operations. The problem with these rotors is that they are not used during the cruising operation and thus they cause extra turbulence and additional weight. Each component reduces flight time because the UAV is more power for the flight or to achieve longer distances, they need to reduce the flying speed. Still this design has disadvantages but over the years several sub-types and projects have been introduced. The biggest difference between the different projects is the number of rotors used for the planes. Some convertiplanes use only one rotor (the concept is had same as in the case of helicopters), others developed a bi-rotor dual-system, or the UAV uses a quad-rotor-system. On the other hand, the operation principle is the same for any developed dual-system planes, but the preferred one is the quad-rotor UAV in the market since it is the safest and most efficient and this makes this type more usable than the other ones. (Adnan S., et al., 2018) The operation of these planes is discribed in the paper of *H.Yeo,W.Jonson, optimum design of a compound helicopter, J.Aircraft 46 2009, 1210-1221.* Some planes are represented in Figure 17.

Figure 17: quad-rotor-system (H.Yeo,W.Jonson, 2009)

3.1.1.4 Rotor-Wing Convertiplane

The rotor-wing convertiplane represents the smallest UAV market segment. This concept is complicated, and it uses very “unusual or old” operation mechanism. In this case the convertiplane does not use any rotors or motors for the operation. During the take-off operation the wings are spinning and generate the necessary buoyancy and during the cruising the wings stop spinning and only the fixed wing is used. The advantages of these designs are the better battery capacity and the smaller weight, but, on the other hand, a disadvantage is the limited flying range. There were other challenges during the development phase to find the optimal balance between the aerodynamic and mechanical aspects. Since the first rotor-wing convertiplanes were very complex and complicated, they had higher production costs, times, and required a high number of service times. To reduce the complexity, the developer introduced the symmetric design with an elliptic airfoil part. Basically, the symmetric design was only a predecessor the future developments. The producers realized that they could achieve better performance if they used additional lift-canards and enlarged horizontal tails. These additional parts are helped by the change between the hovering and cruising operations. However, the change between the two operations was only one half of the problem. The second one was to have the required spinning speed for the take-off operation. In this case several concepts have been developed but two have been successful, one is the jet system of X-50 Dragonfly and an electrical system of NRL Stop-Rotor craft. Whereas the jet system was very unsafe, the electrical version of NRL Sop-Rotor was very complicated, thus for these reasons neither of them has been used for the future UAV´s. The only one concept which reached the test version and successfully changed the two operations (from hovering to cruising) was THOR. The design of THOR was made by Singapore University of Technology. (Adnan S., et al., 2018) The THOR´s concept is represented in Figure 18.

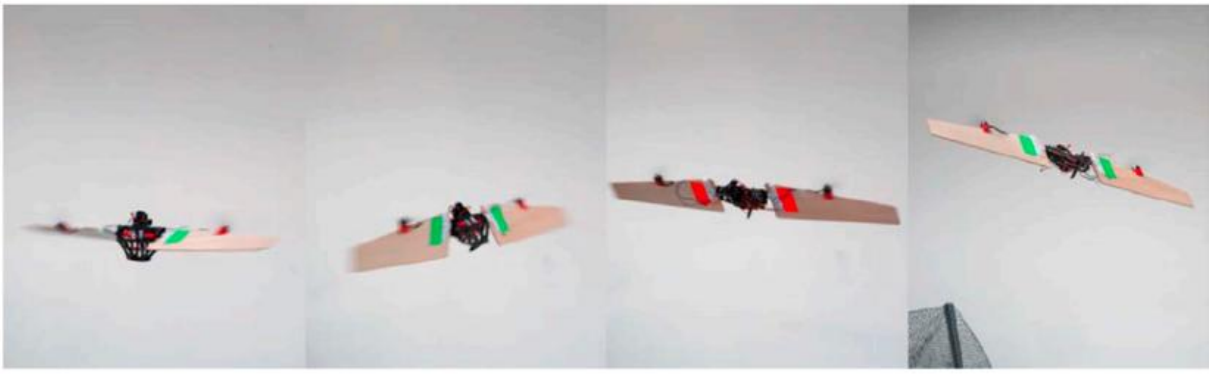


Figure 18: Rotor-Wing Convertiplane (Adnan S., et al., 2018)

3.1.2 Tail-Sitter UAV´s

The second biggest UAV group is the tail-sitter planes. In this chapter only the most important information will be highlighted because this type is not used for the last mile delivery. Basically, the tail-sitters can be divided into three types: Mono Thrust Transitioning, the Collective Thrust Transitioning and the Differential Thrust Transitioning. The basic functions and design are the same for all three sub-types. The planes in this case take off from their tail and land on their tail. This indicates a vertical take-off and landing operation and an entire airframe tilting for the cruising operation. The origin of this UAV can return to the 1950s. The first two trail-sitters were the XFY-1 developed by Convair and the XFV-1 developed by Lockheed. Generally, these UAV types are very popular in the military market/usage. (Adnan S., et al., 2018)

The moon thrust transitioning uses only one rotor which is located on the top of the plane or on its tail. In some cases, the UAV can change the blade pitch to gain better flight conditions. (Adnan S., et al., 2018) For example, the SkyTote, which ware developed by AeroVironment uses a co-axial rotor for take-off and landing. The cruising was solved with the so called "yawing torque cancellation". (M.Hanlon ,2006) Flexrotor, which was developed by Arovel, can change the speed via blade pitch and uses two rotors which are located on the wings and have a different orientation. Flexrotors are also used for the stabilization purpose during the flight. The UAV by Arovel can fly 30 hours and have a communication range of approximately 100 km, which makes this UAV very effective and useful for different applications. (Arovel ,2021) The SkyTote and Flexrotor are represented in Figure 19.

Figure 19: UAV by Arovel (Arovel, 2021)

The collective thrust transitioning has a better transition between the take-off and cruising operation, because they use several surfaces for controlling the thrust or the speed. This design makes stability and speed control better, and, on the other hand, the multiple rotor system gives more opportunities to control the flight. (Adnan S., et al., 2018) The most popular collective thrust transitioning design T-wing is from the University of Sydney. The T-wing uses a twin rotor and fixed-pitch blade configurations. The twin rotors are for controlling the speed and ensuring stabilization. They can also change the rotors' speed separately, which result is high flexibility. The concept of the University of Sydney is popular because it is applicable for military purposes and for civil applications. (R.H.Stone, et al., 2001) The T-wing is represented in Figure 20.

Figure 20: UAV by Arovel (R.H.Stone, et al., 2001)

The different thrust transitioning UAV´s use tow rotors one on the pitch of the UAV and the other one on the tail of the UAV. These two rotors are for the thrust during takeoff and cruising operations. The popularity of these UAV´s is rapidly increasing because they do not use any complicated technology or design and have a high endurance and payload capacity. (Adnan S., et al., 2018) For instance, ATMOS, which was developed by ATMOS, uses control surfaces on the wings and can change the tilting angle of the rotors which makes the control easy, and it does not need any complicated algorithms for the flight. (Swart,S.T, 2024) The other popular concept is from the University of Luvine. VertiKUL uses a different control system to change the speed of the rotors. The cruising operation can be stabilized at different speed, and it can also change the general UAV speed. The biggest disadvantage is to control the rotors separately. For this reason, they needed a complicated algorithm which could choose the best speed for a given situation. This problem makes the concept of University of Luvine less popular in the market. (M.Hochstenbach, et al., 2015) Figure 21 represents the ATMOS and VertiKUL designs.

Figure 21: ATMOS and VertiKUL (M.Hochstenbach, et al., 2015)

3.2 Technological Aspects

A few years ago, aircraft were manned, which means they needed certified people to control the flight. Nowadays this trend has changed because there are some aircraft which are unmanned. Unmanned means in this case, the aircraft does not need any human interactions because they are flying autonomously. Naturally, the drones or UAV´s could separate into two groups: the types which are flying complete autonomously or the types which need a human interaction with a control system (for instance, a remote-control system). What is important in this classification is that the person is not physically on the plane, they are in separate places. For this reason, the drones could be described as a Cyber-Physical System. The market of drones is growing rapidly and more and more UAV´s are flying in the sky. This growing tendency is the "cornerstone" for the next questions: Are the drones safe? How could they control the flight? Is there a high acceptance by people? In which areas could the people? useful flight?It is nott easy to answer these questions. There are several control systems, different usage areas. Normally, the different usage areas predict a different legal basis, while the general legal basis is controlled by the Federal Aviation Administration. The Federal Aviation Administration gives, for instance, the maximum and minimal cruising altitudes or the general safety regulations. The safety regulations could be, for example, that the drones need to have a GPS or they need to have sensors. The technological safety aspects help to avoid collision or help to avoid hacking, or the users could control the drones during the flight if needed. (R.Altaway, M.Youseff, 2016) This chapter focuses on tcontrolsystems, algorithms and collision avoidance.

3.2.1 Control systems

Generally, control systems could be divided into three categories: remote pilot control (human in the loop), remote supervised control (human on the loop), and full autonomous control (human out of the loop). In the case of the remote pilot control system, the human is fully integrated in the control because all the decisions are taken by the pilot. The UAV could not change the speed, trip or altitude. The drones just redirect the information to the pilot, such as a camera image, sensor data. Because of the fully human control, this design is also called "operator or static automation". In the case of remote supervised control, the UAV´s could take decisions themselves but the human operator is also allowed to take control and "override" the drone´s decisions. What is important in this system is the collaborative control between the drones and the pilot. This design is also called adaptive automation. In the last fully of autonomous control design, all the decisions are taken by the UAV´s. Humans could not change the flight parameters; the drones themselves choose the trip, speed, altitude. For the completely autonomous flight, the developer needs to create sufficient algorithm, the drones need to have sufficient communication technology. This is the reason for the high level of concerns because there is a human decision involved. Naturally, communication technology and cyber safety have also rapidly developed, and they will be safer in some years' time. On the other hand, most of the drones use the first two categories (hobby, or parcel deliveries) where humans are also integrated in the control process. There are also some projects for the fully automatized drones, but these are military projects, or some parcel delivery projects, and the regulations and safety issues are stronger than in the first two cases. (R.Altaway, M.Youseff, 2016) In the following sections the interesting and innovative control systems will be represented. However, the description of the “old” remote controller system will not be included in this master thesis.

3.2.2 Gesture control System

The collective gesture control system is very popular among users. This system has a very natural aspect which gives a better and more realistic feeling for the users. Some studies show that more and more users prefer this control method, because they have the feeling that they are flying and have more control over the flight. (D.Tezza, M. Andujar, 2019) Naturally, for the realistic feelings the system must have some elements: first, in general the whole control system needs to be natural, easy to set up and easy to control; second, the given information given from the drones needs to be so real-time and realistic that the given camera image id approximately the same as the live image; third, a separation between the person’s body and the background is needed; it is also needed to avoid physical damage to the person’s body; fourth, the communication and information flow need to be rapid as the delays could cause collision or other accidents during the flight. (A.Mashood, et al., 2015)
For instance, the first successful project, which used these characteristics, was based on a Kinect device and Oculus Rift virtual headset. The developer created a specific “world” which was the interface for the control mechanism. The “pilots” could control with the drones with hand gestures, with the Kinect device and they saw the live pictures in 3D with the Oculus Rift virtual headset. The combination of these two tools created a very realistic and usable concept to simulate the feelings related to flying. (K.Ikeuchi, et al.,2014) However the problem with this concept was the Kinect device latency, because the 300 millisecond is too high to control the drones’ live. (A.Mashood, et al., 2015) Other studies also introduced hand gesture control systems such as the Leap motion control system or the BioSleeve system, where electromyography impulses are captured and redirected to the end interface. The problem with these methods was the high complexity which the data transformation needed, and such systems also have a high price. (D.Tezza, M. Andujar, 2019) Another interesting concept was the Face pose detection on the Parrot ARDrone, which, in the basis of the face pose could evaluate the relative and predicted flying direction and the end position. The Perrot drones use a Viola-Jones algorithm, which could detect the different poses and changes in the phase pose and the Kalman filter helps to calculate a more accurate position. To reduce false pointing, they introduced a the so-called “face score system”. The face score system detects the user’s face and the different characteristics, after they allow the drone to estimate the direction and the point. Naturally, the score system lets tech in for specific users. On the other hand, this system could also detect hand gestures, which allows more precise prediction. (J.Nagi, et al., 2014)

3.2.3 Speech

Although speech control is an easier and more intuitive method than the gesture control method, it is a less developed area in the control systems. The advantage of this system is that the user and the framework training are shorter because the pilot just needs to learn the given commands and the drones just need to find the right direction and the actions which are caused by the user´s command. The challenges in this system are also latency in communication canal, the noise caused by rotors or the pilot is too far from the drone. Naturally, these problems could be solved if a ground station is used for the command which could translate the speech commands and redirects to UAV's. (D.Tezza, M. Andujar, 2019) The speech control system is used and researched in a joint project between Parrot ARDrone and Aerostack. To reduce noise and the problem with the low distance they used a ground station. The ground station has the same functionality and logic as the above-represented general design. Normally, the developer needed to choose a sufficient language and decoding system. In this joint project the project members chose the Pocket Shipnx library and developed a recognition and decoding system with the University Carnegie Mellon. In this project the dictionary has a speech command and a related control function, and it will introduce new functionalities and control functions in the future. In the case of this system is important that the command words need to be maximum three words, which gives challenges in the interpretation. The system uses a very simple method, a voice synthesizer detects the speech command, and the detected command will be translated into the given control function and in the end a signal with the control parameters will be sent to the drone. In the beginning the users needed to get accustomed to the situation, because they did not speak to a living person but to a machine. However, after some time they gave positive feedback to the developer because they had the same feeling as if they were talking to a pet. The design worked well in the last test phase. The disadvantages of this design are the limited commands and the developer needed to solve the latency problem, as there is latency between the camera image and the user, and the user needs to choose the sufficient command after the system needs to find the given control function in the data storage and needs to translate and in the end needs to send the right command to the drone. Latency could be reduced with high-speed transmission methods, but these are not given in all situations. Another problem with this method is that the user does not have the live feelings like in the case of the gesture control system, thus this method is less "eventful" but applicable. (R. A. S. Fernndez, et al., 2016) The speech recognition and this method are also useful in other control methods, and they are very good for command decoding. For this reason, other developers also used and adapted it for other projects. For instance, there are some projects in the field of multimodal control systems. (D.Tezza, M. Andujar, 2019)

3.2.4 The brain-control method

The brain-control method is an interesting control mechanism. The first development of it can be traced back to 2013. Generally, the interface needs to catch the brain signals and convert them to suitable signals and a format for the drones. To convert and catch the signals most of the projects use the Electroencephalography headset. The headset measures the electrical signals which are let out by the human brain. The easiest part of the whole process is to measure these activities because this technology is modern, and the medicines are used for a long time. The hardest part is to convert these signals to a suitable format and to add it to the right control commands. To find the right command to the given activity, the developer used a machine learning algorithm. Naturally, the algorithm must be enrolled, and this is the most time-consuming part of the whole process. (D.Tezza, M. Andujar, 2019) Different research and models were developed in the year 2016 such as the model of the University of Florida. The university researchers used DJI Panthom Drones with 16 pilots for the project. It is important to know that the project was conducted indoors. The methodic was very simple for the training of the algorithm. The participants needed to think about different things such as pushing something forward and the signals were saved and decoded during the thinking process. This method was repeated for the core commands to gain sufficient large commands data for the drone control. (Cinnamon, I.,F. Tepper, 2016) Another interesting research project was introduced by the University of South Florida. Marvin Anduvjar and his colleague Chris Crawford began to develop a working model for the brain-controlled mechanism in 2012. The first so-called brain-controlled race was held in 2019 at the University, and it was very popular. In the first race 16 participants attended from different countries and genders, for instance there were peoples from the United States, India, Kuwait, Brazil, Bangladesh, Japan and Venezuela. The winner of the race was Khaled Alshatti from Kuwait. The competitors used a brain-computer interface to control the drones. The interfaces could split into two different groups such as prosthetic limbs or different devices which could save and decode the brain signals. The methodic was the same as the case of the project at the University of Florida. The pilots needed to think about different basic operations such as pushing something or pulling something. The brain electric signals were detected, saved and decoded and converted into drone operations. Andjuvar planned future competitions with a higher number of participants from different countries. This race could speed up the research and could build a better and more detailed database for the basic operations. (Auvsi News, 2019) Based on the different studies and research this control mechanism is more limited than the developer imagined. First, the accuracy and reliability are lower than in the other control mechanism and the usage in common fields such as hobby or home usage is more different and it has higher costs. Second, technology needs to develop on a higher level because the pilot's mental state is important during the flight as the stress factor could produce different signals for the same operation. These differences between stress signals and normal brain signals need to be recognized by the system and an algorithm needs to be developed to decode them and find sufficient command. These problems need to be solved in the future to make the brain-controlled system more usable and more common. (D.Tezza, M. Andujar, 2019)

3.2.5 Multimodal control systems

The multimodal systems combine the above-presented methods which could take advantage of the different systems. Some studies show that this mechanism is more popular than the other ones, because the combined interface could take the most preferable control mechanism for the customers. (D.Tezza, M. Andujar, 2019) For instance, for the most difficult operations (take-off and landing) the user could use direct control (speech or remote controller) and for the cruising operation the gesture control mechanism. Such mechanism is used for studies in the case of K. Miyoshi and at al. “Above your hand: Direct and natural interaction with aerial robots” or K. Miyoshi and at al. “Entertainment multi-rotor robot that realizes direct and multimodal interaction”. In these studies, a quadcopter is used which has been built by itself. The drone prototype could use its own sensors to recognize speech and the gestures which are used for controlling the drone. It is important to know, and the most important part of this project is that the drone does not need any other control interface because the right and sufficient sensors are placed on the drone. The take-off and landing operations are executed via speech commands. In this case an open-source library, the Julius is used to decode the commands. The disadvantages of this form of control system are the distance from the drone and the noise. The distance and the noise cause trouble during the landing phase because the pilot needs to be near the drone and the rotors are too loud. The noise could be ignored if the speech commands are on a frequency level which is different from the frequency generated by the rotors, but the distance problem is harder to solve and for this reason this method is usable only for low distance. The cruising or the flight are solved with hands commands. For better and more accurate recognizing, the pilot needs to wear colored gloves. There is again the same problem that appeared as in the case of the voice command, namely the distance problem. The biggest question is what the UAV needs to do if the pilot is not in the range or the UAV is not recognizable. The developer solved this problem in the simplest way; if the drone does not see the pilot or the commands are not 100% clear, the drone does not make any operations just hovers at the given point and waits for the next command. The disadvantage of this solution is that the whole flight will not be fluid, which causes a higher flight time. On the other hand, during the test phase the most sufficient pilots are chosen to solve the distance problems. (K.Miyoshi, et al., 2014(a), and K.Miyoshi, et al., 2014(b)) Another interesting project was introduced by G. Jones and et al. “Towards a situated multimodal interface for multiple UAV control”. In this study a virtual environment is generated to test the control system. The environment contains different terrain models such as trees, woods, mountains and deserts. The pilots could control a bunch of drones more accurate 10 different UAV´s at the same times. During the flight, the participants used the speech and gesture mechanism, and they needed to solve a rescue mission. First, they needed to search for and find the people and after that they needed to rescue them. Each pilot had one opportunity to test the system and the UAV control. After the accumulated trial they needed to achieve four different missions. In the accumulated trial the pilots needed to give high- and low-level commands. This trial was the calibration phase that the system could decode and save the different commands. Naturally, after each mission the system updates itself and modifies the commands, because the aim of this project is the high precision control of drones. At the end of the trials, the researcher created a command data bank which the subsegment pilots could use and make the flight more accurate. The most important findings of the project were the following: the commands need to be divided into two different groups such as low-level and high-level commands. The high-level commands need to be defended very well and to be clear to avoid the collision, the low-level commands could have some flexibility, but they also need to be defined very well. On the other hand, because of the flexibility given, the algorithm and the control system need to give information about command availability. If a command is not suitable for the UAV control mechanism, it needs to send an error message and needs to give feedback about the possible commands. The so-called “learning shadows” in the environment need to be defined very well and precisely to gain the sufficient learning level and data. At least the participants or the future users need more information on the interface such as the speed, battery capacity, flying range or flying altitude. (G. Jones, et al., 2010)

3.3 Collision Avoidance

As mentioned in the previous chapter (3.2) the number of the UAV´s has been slightly increasing in the last years. In both cases pilot-controlled drones and automated drones’ collision avoidance is an important issue, because the drones need to avoid hazardous areas and need to be flying without risking any human lives. Naturally, in the case of human controlled drones’ collision avoidance is easier to realize because humans take the decision, but the autonomously flying drones is another question. The autonomously flying drones could be divided into different groups, which depends on the “decision freedom level” of drones. The freedom levels are highlighted in section 4.2.1., but generally, it depends on the human integration in the control mechanism. Naturally, the drones could use their own cameras and sensors to detect the hazard and make safety maneuvers or the operator could intervene and make safety decisions. Generally, the human-based systems are safer, but they have their own distance limitations and for this reason the most preferable method is autonomous flight. However, the autonomous flight makes more challenges for the developer because the algorithm needs to detect the different terrains and hazards, which indicates a higher number of planning operations and path computing time. For this reason, different methods and systems are used at the same time to compute the optimal routes. The generally used systems are represented in Figure 22. (J. N. Yasin, et al, 2020)

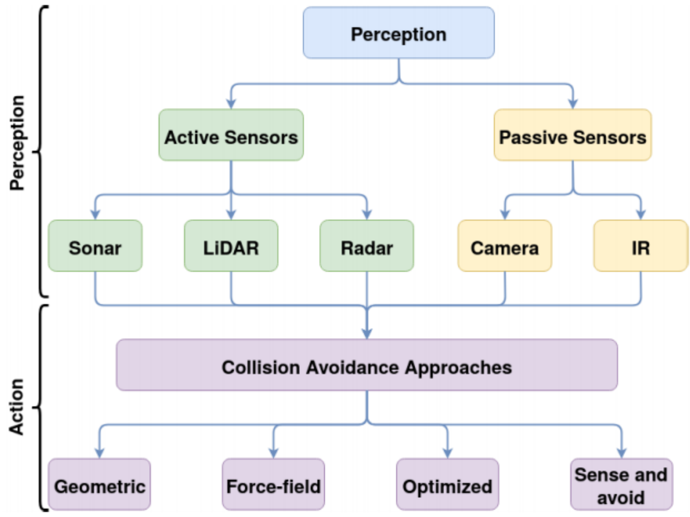


Figure 22: Collision Avoidance System (J.N. Yasin, et al., 2020)

Generally, the collision avoidance system could be divided into two main groups. The first one is the "Perception", which collect the sufficiently large data and information about the environment (passive system field) and the second one is the "Action" which calculates and builds the optimal route for the drone (active system field). The passive field has two different sensor groups: the active and passive sensors. The active sensors are the sonar, lidar and the radar sensors which monitor the environment permanently and collect the most important data. On the other hand, these sensors are the eye of the drone during the autonomous flight because with these sensors the drone can see the environment and the different objects. The passive sensors (Camera, IR = Infra-Red) also monitor the environment, but these are for the pilot not for the UAV itself. These sensors help the user to see and recognize the environment or they are only used for video capture purposes. As was mentioned, earlier the passive field is only for data saving, but the UAV´s also take decisions by themselves. For the decision-making process, the developer uses different algorithms such as the geometric, forced field, optimized or sense and avoid approaches. Generally, the methods and different sensor systems could be selected for the different usage, or these could be applied at the same time. Naturally, the high number of sensors and optimization methodic also indicates a high computation time and increases the complexity of the solution methodic. (J. N. Yasin, et al, 2020)

3.3.1 The passive system field

As mentioned above, the passive system field is the first step in collision avoidance. The sensors collect the most important information about the environment. This data will be used in the active system field to find the optimal route and avoid collision. On the other hand, these sensors are also used for control systems. Naturally, the drones need to have at least one sensor for remote sensing, but the system will be working better if more different systems are used at the same time. The reason for this is very simple, the developer could mix the advantages of the different sensors and could also ignore some disadvantages. (J. N. Yasin, et al, 2020) Generally, in literature the sensors could be divided into different groups. The dividing parameters depend on the sensor's spectral sensitivity and electromagnetic spectrum. (C. Toth, G. Jóźków, 2016)

I. Passive sensors

The mechanism which the passive sensors use is very simple. They monitor the environment permanently and could detect the energy which is reflected in the different objects. The detection will be performed with different cameras which could be optical or visual as well. Often infrared cameras are also used which operate with different wavelengths. It is possible to use short-, near-, mid-, long-waves, and all the lengths have advantages and disadvantages, but the most preferable usage is the cameras combining different wavelengths. (E. Balestrieri, 2021) According to best practice, the infrared cameras or seniors work better in low-light conditions, and this condition limits the usage of this type of sensors. For this reason, they are often used during a night fight because the user could eliminate the very bad normal camera image and it makes possible the night detection of different objects or environments. To make the picture clear and for better data analysis the combined sensors use artificial control points. With artificial control points a very good image can be made because it will be possible for the algorithm to compare the images captured via visual cameras and detected infra-red signals. (W. Hartmann, et al, 2012) The visual cameras which are used for image capturing process could be divided into different groups. According to usage the companies could install monocular, stereo or event-based cameras. All the visual camaras have their own advantages and disadvantages but generally the main advantage is the low power consumption, which is the most important because of the limited battery capacity and these types of cameras can be mounted very easily and they have low dimensions. On the other hand, a disadvantage is, for example, the above-mentioned limited usage environment because the image at night or in bad weather conditions will be not clear, the contrast will be lower, and sensitivity will also be lower. This is the reason why visual cameras are used in combination with other sensor types, or they use different algorithms to make the detected picture sharp. (J. N. Yasin, et al, 2020) For instance, for the monocular cameras the so-called Inverse Perspective Mapping algorithm was introduced. This model is usable for vertical detections because the algorithm takes into account just the bottom part of the image. Naturally, the bottom part of the image is the one-third part of the whole image, and this makes the detections possible only for slow moving cases. The detection performance could increase if the different segments are analyzed via a Markov random field, but this approach makes the whole process slower, and it is possible that important information is neglected. (T. – J. Lee, at al., 2016) In the case of stereo cameras the developer introduced another algorithm which uses better camera imaging performance. The stereo cameras use two different parameters for the process, the intrinsic and extrinsic parameters. With the two parameters, although the captured picture has better quality, the complexity and the computation time are higher. In this case the producers need to decide between the computation performance and picture capturing performance. On the other hand, it is possible to reduce the computation time if the image is divided into nine different segments and only six segments are analyzed as needed. For example, if the drone is flying vertically then only the bottom and the upper parts of the image are used for the analysis because the other segments are negligible. (A. U. Haque, A. Nejadpak, 2017)

II. Active Sensors

The active sensors work in a way different from the passive sensors. The most important difference between the two groups is the detecting method. The active sensors read the emission of radiation because they could read and analyze the reflection of radiation. On the other hand, all active sensors have their own transmitter which indicates that they do not need any other equipment, and the detector is also integrated in the sensor. This combination makes the usage simpler, and the size is also smaller. This type of sensor works very simply, the transmitter emits the signal, and the detector could translate the signal coming back from the object. This technology could also be defined as a scanning technology because the technology could identify the object characteristics from the different lengths of returning signals. (M. Rouse, M. Haugh, 2020 and ESA, 2020) An active sensor is the radar which operates with radio signals. This type of sensor emits the microwaves and calculates the distance from the signal returning time. This technology was developed over several years and is used very often because the weather conditions could not influence the signals. However, this technology could not scan the object's characteristics only the size and speed of the object and the distance between the transmitter and the object. Radar technology uses two different signal systems, the continuous and the pulsing wave system. The continuous wave radar system uses a linearly emitted signal all the time, which enables a continuous stream. The wave signals are emitted after a given time period, which indicates a separate detection time. The problem with this method is that there are shadows in the detection, and this could cause too late object identification. However, the wave signals are strangers, and they are applicable for longer distance detection. (E. B. Quist and R. W. Beard, 2016) The two different radar sensors are often used at the same time, because the microwave sensors are not sensitive to the weather conditions, but they operate in low frequency, and this is not useful for effective resolution. On the other hand, the millimeter wave sensors are very suitable for the weather conditions, but the frequency is different from that of the microwave sensors, and it makes an effective resolution and more accurate detection possible. (Y. K. Kwag and J. W. Kwag, 2004) Another detection method is the so-called LiDAR (Light Detection and Ranging) sensors. The working process and idea is very similar to the case of radar technology. The most important difference between the two technologies is the detection methods used. First, LiDAR uses laser pulses for the emitting process and second, they could read and analyze the reflections. After sometimes between the emission and reflection the sensor calculates the distance between the device and object. The continuous signal emission and decoding make the LiDAR technology more accurate than the radar technology. On the other hand, several developments have also been made in the last years which has caused a size reduction and better performance. Generally, LiDAR sensors work with lower energy consumption than the other sensor types. The compact size, effective detection and the lower power consumption are the reasons why producers prefer this technology for the small UAV´s. (P. Hügler, et al., 2018 and, J. Zhang and S. Singh, 2014) LiDAR sensors could use 1D, 2D and 3D detections. Today the most preferred is the 3D detection because the system could identify the whole object characteristics. This makes it possible for the device to detect a very small object too and it creates a very exact picture of the object. The biggest disadvantage is the transparent object detection as these sensors could not detect such objects as those made of transparent glass because the signals are not reflected from the surface. This problem could cause trouble during the autonomous flight, and this is the reason why different sensors also needed to be settled in the device. (J. N. Yasin, et al, 2020) The last sensor type which is used for collision avoidance is sonar technology, which has been used for decades, and it is very popular in some application areas. Basically, sonar technology emits sounds and waits for the reflection. The time between the emission and reflection is the basic variable the distance calculation. Generally, sonar technology works in a similar way to the LiDAR sensors, only the emitted wave is different. On the other hand, the sonar could detect transparent objects unlike the LiDAR sensors and have a lower cost than the other sensor technologies. (A. Tahir, et al., 2019)

3.3.2 Active System Field

On an active system an algorithm could be defined which makes the planning and reaction avoid collision. The algorithm in this field works according to two methods reactive and deliberate behavior. The principle is the same for the two methods only the acting step in is performed in other points. Generally, according to the reactive principle, the system in the first step observes the environment and in the second step detects the hazard or objects. The detection process automatically triggers the acting process and makes the possible diversive action. On the other hand, deliberate behavior for the action process establishes a plan and chooses the best maneuver for collision avoidance. Naturally, the two types of behavior have their own advantages and disadvantages. While the reactive principle makes a very fast acting process possible but not in all cases, the optimal reaction, the deliberative process has a longer computation time, but it guarantees an optimal action. These two approaches could also mix for the different situations, which works as a switch, it is possible to define the behavior and the statements for the different situations. Based on these two types of behavior four different algorithms could be distinguished: geometric methods, force-field methods, optimization-based methods and sense-and-avoid methods. (J. N. Yasin, et al, 2020)

I. Geometric Methods

The geometric methods analyze the given geometric data, for instance, collision avoidance between two UAV´s. The algorithm computes the minimum distance between the two UAV’s which is still safe. The minimum distance is also used for the computing of the collision. This method could work very well if the UAV´s use the Dependent Surveillance Broadcast, which assumes cooperation between the two devices. However, this method depends on the sensors’ sensitivity because the noise generated by rotors could influence the system’s effectiveness. However, this problem could be eliminated if the passive devices (for example cameras) are also used, but this is a very time-consuming process and the UAV´s need a fast processor which has a higher cost too. (J. W. Park, et al., 2008) To solve this problem a mixed approach could be used which is based on different geometric and collision approaches. In this mixed approach the given coordinates and the velocities are also taken into account. With this data it is possible to compute and make an optimal plan in a 3D environment. With the coordinates the noise problem could be eliminated, although this method also needs a high computation time and cooperation between the two aircraft. (J. Goss, et al., 2004) Another interesting geometric method is the Fast Geometric Avoidance Algorithm. The algorithm could create different solutions which will be assigned with different probability. The probability indicates different threat levels which are based on the critical avoidance times. The critical times represent an action segment, and the drones could take the action according to the threat levels. First, the system assumes the lowest threat level and updates the sequence continuously and updates the critical times. The sequential computation makes the algorithm very powerful, and it slightly reduces the computation time and effort because the algorithm concentrates on the next threat level. (Y. Lin, et al., 2020) Another usable avoidance algorithm is a guide algorithm. This is based on avoidance and trajectory control. In the first step the route is planned, which could be optimal and after that during the flight this will be updated with the required avoidance steps. If the UAV detects any object during cruise time, the algorithm computes the new route. Naturally, for the algorithm it is also given that the drone needs to come back to the planned route or could just take maneuvers between the given limits. The trajectory method makes this algorithm very fast because if there are any other objects, then the UAV takes the pre-defined route and does not take any other computations. On the other hand, for the pre-defined routes the algorithm needs to know the parameters and the environment, which are not given in our dynamically changing world. (L. N. N. T. Ha, et al., 2019)

II. Force-Field Methods

The force-field method could be described as a potential field method. For this method, the algorithm needs to know the shape of the object, the environment and the exact coordinates. The problem with this method is the exact shape of the environment because in the dynamically changing environment the characteristics and the parameters are also changing over time. For this reason, developing an algorithm which works in real life and is applicable is very hard. Still some researchers proposed an algorithm to solve the collision avoidance for UAV´s. (J. N. Yasin, et al, 2020) One of these algorithms is the so-called “enhanced curl-free vector field”. The algorithm finds the safest route despite dynamically changing parameters. The idea is that the problem could generate the routes via curl-free vectors. The approach assumes not a conventional potential field but a self-generated field which is based on the velocity vectors of the given dynamic variable. The velocity vectors give the direction of the curl-free vectors, and the directed curl-free vectors define the environment around the warning zone. Naturally, the velocity vectors also include different parameters such as the vectors of dynamic objects, the UAV angle vectors and the route vectors. The algorithm was tested in a simulated environment but not in real life. The disadvantages of this approach are that for computation the algorithm needs a 3D environment which needs to be the same as the real environment and the static and dynamic parameters also need to be given. This parameter also indicates a high computation time and effort. On the other hand, parametrization is very hard because every environment, routes, and object has its own characteristic, and the false parameters could influence algorithm effectiveness. (D. Choi, et al.,2020) A simpler algorithm was also presented which reduces the problem in 1D environment. The aim of this algorithm is to reduce the shadows during the traditional obstacle force field methods. For reducing purposes, the developer found that the shadows could be reduced with a proposed prediction-based method. The prediction-based method focuses on the frequency of the waves emitted by the electric vehicles. They could detect the signals with radars and the algorithm makes a predicted obstacle from the object. The problem with this algorithm is that prediction on the moving objects is very hard because of the wave intensity and route (other objects could change or block the origin of the wave. (Sezer & Gokasan, 2012; Katona *et al*., 2024)

III. Optimization Based Methods

These methods also calculate the avoidance trajectory from geographical data. The optimization-based methods deal with uncertainty parameters and would like to calculate the best search areas. For calculation purposes the method uses the so-called probabilistic search algorithm, but this has a very high computation time and effort. To reduce the time and effort the researcher uses different methods or other heuristics such as ant-inspired algorithms, genetic algorithms, Bayesian optimization, gradient descent methods and so on. (J. N. Yasin, et al, 2020)

One of the developed algorithms, which is usable for the UAV's, would like to calculate the next coordinates for avoidance. Generally, the algorithm uses the set of commands saved for the UAV, but it is important to know that the algorithm only chooses the commands which could be executed in short time. These commands are the so-called emergency commands. The process of making the choice takes into account the object and UAV coordinates and calculates a cost function. After that the system takes the best command, which depends on the calculated cost function. The algorithm is also used for detection during the flight. The idea is the same as above with the exception that there is a rolling function and the next set of commands which is applicable for the current situation is always chosen. In other words, the algorithm uses an update function and an algorithm during the flight. With this algorithm the computation time and effort slightly decreased and the collision avoidance successfulness slightly increased. (E. Boivin, et al. 2008) Another interesting avoidance method uses practical swarm optimization. With the swarm algorithm it is possible to calculate the optimal plan if the environment is not known. However, the most important fact is that this algorithm is usable during the flight because the data which are used for the calculation process are gathered with the sensors and cameras. Those different data are weighed according to different regions and the weights are the basic variables for the different possibilities. The algorithm chooses the optimal path according to the possibility classification. Generally, the algorithm's biggest advantage is the optimal path finding in an uncertain environment. (Zhao, F.,et al., 2022)

IV. Sense & Avoid Methods

The biggest and most used algorithm can be found in the sense and avoid category. This algorithm concentrates on the reduced computation time and tries to allow a very short response time for the different situations. The basic idea is to reduce the complex problem to an individual detection and avoidance problem. This method uses the different sensor and camera advantages, which makes it possible to create its own detection and path planning system. On the other hand, the use of the different sensors and cameras gather different data,

which makes the more accurate calculation possible and reduces the shadows during the calculation. (J. N. Yasin, et al, 2020)
One algorithm which is usable for UAV's uses a combined system with stereo vision and laser-based sensing scheme. The basic idea is that the UAV detects the possible collision objects and changes the cruising operation to a hovering operation. During the hovering operation the drone calculates the optimal detour and changes the hovering operation for the cruising operation. The developer during the test phase recorded a detection time of 0.08 ms and the calculation time with operation changes by 0.49 ms. On the other hand, this technique was only tested with fixed objects such as trees or radio towers, which raises the question if this algorithm is useful for moving objects. Another disadvantage of the algorithm is that for the computation process the UAV needs a 3D map to define the escape point, but the memory is limited. However, the bigger memory saving capacity indicates a higher number of maps, which could increase the algorithm's effectiveness. (S. Hrabar, 2011)
Another algorithm has been developed for real-time detection and avoidance. In this system the developer only uses the forward-looking cameras, and the data will be analyzed and used for a fuzzy system. The fuzzy algorithm works on a laptop and the data are sent from the drone to the laptop through a wireless system. To reduce the computation time, the hazardous object will be marked with a different color in the picture and the colors will indicate the right command. The different colors mean different actions and different warning levels. The two commands are very simple, the drone will be passing around the object eighter left or right. The disadvantage of this method is the communication problem between the UAV and the external laptop. If the connection is unstable or weak, the potential collision probability will be too high. This problem leads to limited usage, because the objects too rapidly moving will be too slow to be detected and the system is also too slow if an object is too close to the drone. (M. A. Olivares-Mendez, et al.,2012)
There is another solution algorithm which uses the LiDAR's sensor advantages. This is called forward inspection algorithm. Generally, the algorithm monitors the pilot's commands and calculates the possible route which depends on the given commands. Naturally, the system does not calculate the route continuously only after a given time period. Over the calculating phase the algorithm checks the given information from the LiDAR sensor and if it is needed, it modifies the route. Naturally, the algorithm needs to give the collision-free route close to the predefined route and could not make any big detour. This algorithm is a collision avoidance system and not a route planner because of the commands coming from the pilot over a remote-control system. The system only monitors the environment and if it is needed, it makes an emergency move to avoid the collision. (D. Bareiss, et al., 2015)

3.4 Safety and Regulatory Issues

The increasing number of drones has raised some regulatory and safety issues. The biggest question in this field is the collection of private information. Naturally, if the UAV´s are flying over a park or a street, then the collected information (camera images, voice recording) is generally not private, but the cities could regulate in another way and could define the so-called no flying zones. On the other hand, flying over a private property is another question because with the different UAV equipment it is possible to collect some sensible private information about people’s behavior. Naturally, this information is usable if the person is completely identifiable in the picture or records. The violation of private sphere is an interesting and important question because the drones are used for different research and purposes, for example wildlife tracking, pollution measures, monitoring illegal activities, and searching missions. In one part of this chapter the most important questions about giving permits, data collection, prosecution and different usage regulations will be highlighted. (D. B. Resnik and K. C. Elliott, 2018) In the second part of the chapter the different safety issues will be discussed as the second main question after the privacy information is whether people could trust in the autonomously flying UAV`s or in the pilot. The root of this problem comes from the different control systema in this field. Generally, this control system is always connected with another ground device (computer or controller and), which makes it possible to hack the channel and overtake the UAV´s. It is important to mention that the cyber and the physical systems are also in danger. The hackers could also gain important information about the users or companies because most of the drones are also connected with the company’s servers or clouds. However, the overtake of the physically existing system is also dangerous because the hacker or the “overtaker” can use any equipment on the drones and could put other ‘s lives at risk, for example flying in the masses. On the other hand, there are other attack opportunities which are also very dangerous, namely, signal jamming. With the signal jamming method, the channel could be overloaded with unusable signals and data traveling time could be increased. This overload method is also very dangerous because the command signals are detected too late, and collision avoidance will be not possible. Naturally, there are other safety issues which will be presented in this section. (R. Altway and A. M. Youssef, 2016)

3.4.1 Regulatory Issues

I. Private Information

Firstly, it is needed to clarify what is meant in the European Union and in the USA by private information.

According to the European Union, all the information which *"relates to an **identified or identifiable living individual**"* is considered private information or personal data *(European Union, 2020).* This information could contain just one piece of data like an image or could include different types of data and the group of data leads to the identification of personnel. The European regulation makes no difference between the collection types. The data could be collected from an IT system, video surveillance, paper and if it contains enough characteristic to clear identification, then it is personal data. In such cases if the data is completely autonomous and the person is not identifiable, then it is no longer personal data or information. The data according to the European Union regulation need to be converted into an anonymous format and need not to be convertible into a personal form. The name and surname, a home address, an email address with a name and surname format, a identification card number, location data, an IP address, cookies, medical data or all advertisement identifiers belong to the category of personal data. (European Union, 2020).

According to US regulations, any data which is collected without people's acceptance or concession is regarded as private data. The data which have been collected for specific purposes and could not be made public, for example medical data are considered other private information. (D. B. Resnik and K. C. Elliott, 2018) According to the US Department of Homeland Security, the ***"Identifiable private information is private information for which the identity of the subject is or may readily be ascertained by the investigator or associated with the information"*** *(Department of Homeland Security et al. 2017 at 45 CFR 46.102(e)(5))*

There are two different definitions or declarations about private information, but the most important fact is that there could not be any misuse of the data which a person clearly identifies. In the USA regulation it is important to know that a video recorded by a video surveillance system, for example in a shop, is no longer private data because the customer has accepted the shop's regulations. However, the shop needs to make it common that there is a video surveillance system used. Another interesting aspect is the data collected over the flight because airspace is generally a public area which means that the collected data is not private information because the people's concession is missing. However, different points of view need to be taken into account. Any situation needs to be tested whether the given situation is harmful to the person's expectation of privacy. For instance, if there are any reasonable expectations of privacy given for the collected data, then the collected data should be considered not private information and do not need any legal justification. For instance, if a private person takes a picture of an illegal activity like growing marihuana in a private property, then the information is not counted private information because the airspace is a public area. On the other hand, the information collected with a thermal sensor or camera over private property is counted as private information and needs a warrant. The reason for

this is that the image is not taken indirectly but directly and the information was not in plain view. The above-mentioned examples clarify that the collected information is only private information if the data are collected directly or was not in plain view and the customer's acceptance is missing. However, the most important fact is that the given situation needs to be tested from a different point of view and the situation needs to be clearly defined every time. (D. B. Resnik and K. C. Elliott, 2018)
In some cases, European regulations are different from the US regulations. Firstly, Article 8 of the European Convection on Human Rights needs to be considered.

"1. Everyone has the right to respect his private and family life, his home and his correspondence.

2. There shall be no interference by a public authority with the exercise of this right except such as is in accordance with the law and is necessary in a democratic society in the interests of national security, public safety or the economic wellbeing of the country, for the prevention of disorder or crime, for the protection of health or morals, or for the protection of the rights and freedoms of others" (Council of Europe ECHR, 2020)

The first point secures the rights for private life and the second part says that the information recorded is not private if it is used for certain cases such as national security, prevention of disorder or crime, health protection or rights protection. In such cases the authorities do not need any permission to collect data. On the other hand, if any of these conditions are met the collected data belongs to private sphere and cannot be used. (European Commission, et al., 2014) Article 8 also mentions an interesting example: "A person who walks down the street will, inevitably, be visible to any member of the public who is also present. Monitoring by technological means of the same public scene (for example, a security guard viewing through closed circuit television) is of a similar character. Private life considerations may arise, however, once any systematic or permanent record comes into existence of such material from the public domain. It is for this reason that files gathered by security services on a particular individual fall within the scope of Article 8, even where the information has not been gathered by any intrusive or covert method" (Council of Europe ECHR, 2020) This means that the collected data in a public area (i.e., in parks or shops) also considered private information and could only be used for a particular reason. Generally, the European Union regulates private data with the so-called General Data Protection Regulation, which is an additional regulation of data processing. The regulation was introduced in 2016 and is valid for all companies and all organizations. According to the General Data Protection Regulation all activities are data processed if the action generates any data manually or automatically. In this case the processing type could be, for example, collecting, recording, storing or using, the most important factor is data performance. This regulation is also applicable to private people because the data controller is the person who decides about data usage. This means if a private person makes a record with a UAV, then they are data processors. Naturally, the recording could be performed by a third party, in this case the General Data Protection Regulation uses another regulation, but these are not discussed in this master thesis. The regulations have seven protection and accountability principles. The first one is the lawfulness, fairness and transparency rule. The second one is the purpose limitation rule which means the processed data must be specified for legitimate purposes. The third principle is data minimization which says that the collected data must be as minimal as possible, for the given purpose. The fourth one is the accuracy principle, the collected data must be accurate and written down. The fifth one is the storage limitation principle which gives the maximal data storage timeline. The sixth one is the integrity and confidentiality principle, the data need to fit in with the given security or encryption regulations. The last one is the accuracy; the data controller is responsible for the process of collecting data. These seven rules need to be regarded as the core rule of data gathering. (GDPR EU, 2020) The General Data Protection Regulation is a very complex regulation for different fields which are not included in the present master thesis.

Generally, we could say that regulations which refer to the private data and sphere are very complex and situation dependent. However, the aim of this field is that the "collectors" could not misuse the information about the people. Two other important parts of these regulations are valid not only for organizations and companies but private people too.

II. Federal Aviation Administration Rules

The Federal Aviation Administration is responsible for the US airspace regulations. For the small UAV´s the new regulation was introduced in June 2016. This category is for the drones weighing less than 55 pounds (24,9476 Kg). This first regulation does not contain the general regulations for operation at night. For this reason, the new version was introduced in February 2019, which is called Operations Over People. The regulation differentiates between four different categories. (FAA, 2020) The drones which could operate over people belong to the first category. The drones in this case need to weigh less than 0.55 pounds (0,249476 kg) with all equipment and with the drone loads. Other restrictions are that this type of UAV´s could not have any exposed rotation parts. In category two there are drones with more than 0.55 pounds weight and they need to have performance base eligibility and to meet operating requirements. Additionally, in the first and second categories the drones can fly without any remote control, but they need to register a remote ID. The third category introduces new restrictions, namely the drones without a remote control could not fly over closed-and restricted areas without the people knowing about the UAV operation or the people who do not have suitable protection against falling UAVs. Category four says that the UAV´s in this category are allowed to operate if the operation limitation is specified. Otherwise, the Federal Aviation Administration needs to accept the drone characteristics if they could operate over people. Generally, for all categories the drones are prohibited to operate over moving vehicles. (Department of Transportation and FAA, 2019)

The Operation of Small Unmanned Aircraft Systems Over People also regulates the night operations. The drones cannot operate without an operator and the operator needs to have the required knowledge and an online course. On the other hand, the drone needs to have the suitable equipment for night operations, namely it needs to have an anti-collision light and this needs to be suitable "craft" (least 3-statue wide). The knowledge test is valid 24 months, and it needs to be extended. The online courses are free of charge and the pilot also needs to have the required physical possessions. (Department of Transportation and FAA, 2019)

All drones need to have a remote ID, which is for the identification of the small aircraft and their control stations. With the remote ID the users can reduce the possible collisions and reduce the risk of interference with other aircraft and with the people on the ground. The ID needs to meet the three given operational requirements; namely the ID needs to broadcast the identification, the location coordinates from the ground station, and the take-off data. Second, the drone needs to have a remote ID broadcast module (this could be a separate device too). Third, if the drone does not have a remote ID, then it could take a specific ID which is identifiable for the Federal Aviation Administration. (FAA Press, 2020)

III. The European Union Aviation Safety Agency Rules

The aim of the European Union regulation is to make the drone operation safer for any people. For this reason, a framework was introduced which adopts a risk-based approach. The risk-based approach considers the different event characteristics, drone weight and other flying specifications. This regulation came into force on 30 December 2020, and it defines three different categories. The three categories are the open, specific and certified ones. In the case of open operations, the drones do not need any operational authorization, and they do not need any operational declarations. In this category the UAV’s maximum weight with equipment and payload need to be less than 25 kg. The pilot needs to make sure that the operation is in safe from people and masses of people. The drone needs to be in visual contact with the pilot if the drone is in follow-me mode or used for specific purposes, for example, in observing operations. During the cruising operation the UAV’s do not move away 120 meters from the closest point of the ground except the pilot needs to be overflown in an obstacle or because of given situation an evasive action is needed. The drone cannot transport any dangerous goods and cannot drop any material. Additionally, the open category differentiates three subcategories (subcategories 0,1,2). The discussion of theses is not included in this master thesis but the “Easy Access Rules for Unmanned Aircraft Systems” (Regulations (EU) 2019/947 and (EU)2019/945) includes all the regulations. Generally, the subcategories differentiate between the maximal weight and the regulation between the payloads and the legal basis for the different operations. (EASA, pp. 13-23, 2021) In the specific category the operations may need operational authorization and a declaration of the pilot. The pilot needs an authorization from the member state where he is registered. The pilot in the specific category needs to make a risk assessment of the application. The risk assessment needs to include adequate mitigating measures too. The local authority can define the authorization characteristics and components. This could regulate single operations, the number of operations, operation time, operation locations or the mixture of them. The most important is that the list needs to consider the sufficient measures and the range of the allowed risk measures. On the other hand, for given operations the operator also needs registration and a declaration which is given by the member states. This category also states that for different expectations no declaration or authorization is needed, for example, for model clubs or associations where the declarations and authorizations are given in automatic entitlement.

(EASA, pp. 22-24, 2021) The last category is the certified category. In this case the operator needs in all cases a certification and where it is possible a remote pilot license. This regulation is applicable to the cases where the operation takes place over masses of people, people transportation or transportation of dangerous goods, which have a high risk for other people. Generally, the local authority itself can decide on this category. If an operation risk is too high according to the given risk measures a remote licensing and pilot declaration could be specified. (EASA, pp. 22-25,2021) Naturally, these were only the general regulations of the different categories. The precise regulations can be found in Easy Access Rules for Unmanned Aircraft Systems (Regulations (EU) 2019/947 and (EU)2019/945) pages 158 – 248, where the maximal flight height, the maximal weight which could be delivered or the maximal drone weight with payload, the maximal overtake height, the operation distance from other people are specified. For example, the maximal payload in an open category is 10 kg, the operator needs to hold a distance of minimum five meters from the people minimal in an active low speed mode and 30 meters without an active low speed mode; if the obstacle is higher than 105 meters, then the maximal operation height could increase by 15 meters. On the other hand, the pilots in given cases need to make an online course and pass the examination with at least 75% of the overall marks. The knowledge test needs to include air safety, airspace restrictions, aviation regulations, human performance limitations, operational procedures, general knowledge, privacy and data protection, insurance and security themes. General rules specify the maximal follow-me mode distance, which is maximum 50 meters from the remote pilot. On the other hand, the regulations also prescribe the form regulations for registration and operation declarations, and the pilot and UAV requirements for the safety operations. (EASA, pp. 158-248, 2021) The regulation of drone usage is a very complex system, and these could be additional local regulations for the different member states. The general European Union Aviation Safety Agency Rules are the legal basis for drone operations, and the different member states can introduce stricter regulations and are given flexibility in this case.

3.4.2 Safety Issues

The UAV´s which are used for parcel delivery have enough capabilities and weight with or without payload to be used for harmful purposes and this indicates functional safety and cyber- physical safety issues. There are different threats which need to be considered such as cyber-physical threats, physical and vulnerability issues. Naturally, these challenges need to be solved, and the flight needs to be secured to avoid misuses and accidents. (R. Altway, A. M. Youssef, 2016) In this chapter the different and potential threats and the solutions proposed will be highlighted.

I. Cyber-Physical Threats

The threats in this category could be split into three main groups. The first one is the revelation capabilities, which could decode and listen to the real-time data which are transferred between the drone and the pilot or operating system. The second one is the knowledge capabilities, where the hacker could gain system knowledge and could gain access to the prior system parameters; for example, to the control system. The third one is the disruption capabilities, which make it possible to interrupt the connection between the drone and the controller or the control system. Both attacks could cause a collision or an accident and for this reason they are very dangerous. (AlTawy & Youssef, 2016) One of the cyber-physical threats is when the attacker jams or spoofs the GPS data. The attacker sends false data to the UAV which causes false coordinates and the drone and controller, or the control system are disorientated. The false location could lead to collision or flying unauthorized zone, which makes it easy to collect data anonymously and makes the collector identification harder. (K. Wesson and T. Humphreys, 2013) To avoid the false signals, it is possible to authenticate the GPS signals by a normal cryptographic method, but this is a very complicated solution because the system needs to detect the satellites and needs to change the infrastructure between them. An easier solution is when the signals are analyzed; namely the signals' traveling time. The traveling time could be easily calculated and compared to each other. (H. Wen, et al., 2005) Another interesting threat occurs when the camera image is changed. This means a higher danger because most of the civilian UAV´s work with video transmission to the pilot. On the other hand, the general collision systems work with or depend on the onboard cameras. To transmit a false picture is not a complicated task if the hacker knows the system and could hack it. This method could also lead to collision, and it is dangerous for people too because detection and control will be impossible. (Khazraei et al., 2023) Besides the camera system it is worth mentioning the sensors. The infrared, radar or thermo sensors can also be manipulated with directly injected energy which changes the electromagnetic field. For instance, it is possible to manipulate the microelectromechanical gyroscope if the same frequency is used and injected as in the system. With this attack it is possible to disorient the drone, and it could cause a crash situation. On the other hand, the hacking method is very complex as hackers need to know the flight controller procedures, the sensors, the references, the barometer and the gyroscope type. (R. Altway, A. M. Youssef, 2016) Other cyber threats could be the so-called Maldrone virus. If this type of virus is in the drone's system or only in the control system installed, the hacker has control over the drone. The malware function is very easy, they open a backdoor in shadow and the hacker could communicate over this channel and could take over the control. The functionality of this malware is the same as that of the proxy server, it enables communication between the original control system and the drone and between the hacker and the drone. The identification of this attack is very hard because this does not appear for either the system or the pilot. This could lead to misuse of the drone cameras, sensors or the attacker has the option to steal the device. (P. Paganini, 2015)

There are several other cyber physical attacks but the most important for the current thesis is the denial of service. This is very dangerous for delivery companies because most of them use drones which belong to the mini drone category. The mini drones fly below 60.96 meters and have a limited flying range. The denial service attack could be used for such small drones and could cause a system break. This is because the hacker has access to the flight parameters, control system and the control command. In other words, they could manipulate the drone's functionality and the shutdown process. In this case it is not overtaking, that is the main idea but processor overloading. This drone has a relatively small processor and memory which is easy to overload with random commands. Overloading causes a system break, or the sequence of different commands leads to a collision or shutdown. This is a very convenient process because it does not need any high computation effort or knowledge about the system. With this hacking method it is very easy to steal the package, hackers only need to overload the system at the given point where the drone collision will take place or to find the shutdown command and launch this to the drone. (R. Altway, A. M. Youssef, 2016)

II. Physical Treats

There are different physical threats which could differ in two different groups. The first type includes threats which come from the people and the second one those which come from the weather. For instance, drones are easy targets for people because they fly at a low altitude and are in most cases in visual distances. Some attackers use "anti-drone rifles". This is a very easy method because it is very easy to craft on your own, for example, from a simple dart gun. However, there are also special "anti-drone rifles" which can catch drones easily from a maximum distance of 396,24 meters. These rifles use such frequencies which could block the data link between the drones and the control systems. The blocking method causes safe protocol. The protocol says in such cases that drones need to hover in a safe distance from the ground and it makes it easy to steal them. This method is very attractive because the attackers can cause damage to the frame or in the delivered package. (K. Hodgkings, 2015) To secure the delivered package in such cases the producers introduced an SMS system which does not let the package take without any identification. In this case delivery companies send an authentication SMS with a code to the customer and by the end of delivery the customer could "release" the delivered package from the drone via this "key". The problem with this system is that it does not prevent stealing the goods from stealing together with the drone. However, this is a very useful method if people want to steal the good during the drone customer waiting time. (R. Altway, A. M. Youssef, 2016) The other group of threats mentioned at the beginning of this section is related to the weather challenges. Most of the delivery companies use mini drones which have their own advantages and disadvantages. One advantage is their size because they could be used everywhere, and they do not need to meet too many regulations. On the other hand, these mini drones are sensitive to the weather conditions. Their sensitivity depends on the drone size, type, frame, package size and control system. The delivery companies need to take these challenges into account, and they also need to calculate the different flying time and range in different weather conditions. For instance, on a windy day with a high package size the flying range will be lower because the drones need to consume more energy for the same speed. However, it is also possible that they are not at all suitable for the flight in such weather conditions. On the other hand, rain is also dangerous for drones, because of the limited visibility range as rain could reduce the detection range and increase the reaction time. Latency depends on the different sensor characteristics. This is very complicated, and it is an important issue for the developers. On the one hand, in the case of the completely autonomous flight artificial intelligence needs to adapt to the environment and needs a decision that needs to be taken faster than in normal cases. On the other hand, during the pilot-controlled flight the pilot also needs to adapt to the modified environmental characteristics. In such cases there could be a jam in transferred pictures which causes a slower reaction time, or data transfer could also be slower. Another problem with the pilot-controlled system is that the drone's reaction will be different; for instance, on a windy or rainy day the overtaking operation has a different reaction time from a normal day. To solve such weather challenges the developer needs to produce less vulnerable drones, the delivery companies need to take the most sufficient drone type, and the pilots need to be trained to deal with such challenges. (R. Altway, A. M. Youssef, 2016)

III. Security Solutions

To solve the different security issues different regulations and concepts were introduced over the years. For example, drone licensing was introduced to register the drones used and the users. With registration it is possible to find them vilified if misuse occurs. Another solution is to create no-flying zones in different areas to prevent possible misuse. This restriction is used in most cases at airports, where there are masses of people or near different national departments. However, these no-flying zones do not secure the misuse of the airspace. There are several cases when drones fly over these zones. To find the drone's user the authorities use a register but in some cases these drones are not registered, and this was the reason why other surveillance methods were introduced. For instance, producers and sellers also register all drone purchases and keep track of the whole buying process. This is very important, especially in such cases where the drone has the capability of lifting heavy packages or it can make a video, or it operates by means of a video control system. The registration of different not allowed operations belongs to the registration. The producers could include such operations in the drone system which are not allowed to prevent any misuse. For instance, some drones do not communicate with different sensor types, or the drones cannot fly over different zones and. To define such operations, the policymakers defined different laws which the producers must comply with. In some cases, the above presented prevention methods are not sufficient, because finding the misuser does not prevent the real time danger, the laws could be different from country to country, and this was the reason why other real time preventing methods were introduced. For instance, different detection methods are used such as signature-based, specification-based or anomaly-based methods. In addition, the signature and authentication processes use different cryptography-based methods. Cryptography methods are used for encrypting the travelled data between the drone and the control system and between the drone and the location system. These methods prevent cyber-attacks; thus, the hackers cannot modify system operations or take over control. The problem with these detection methods is the high resource dependence. Another intelligent and most sophisticated method is the single round function cryptography method. In this case the system does not verify all the transferred data just the "key" of the data. The key is predefined, and it is unique for any users and drones, these could be defined as "you have" approaches. The advantages of this method are the low resource demand and fast identification. On the other hand, if anybody finds out the key, that person has unlimited access to drone functionality and the transferred data. Today encryption methods are becoming better and safer but because of the fast technological development the developer needs to find other methods which are safer (J. P. Yaacoub, et al., 2020)

4. UAV Application in transportation and logistics

The drones and their usage have been very popular in the last few years. The reason is the boom in information technology and machine learning. These technological developments have enabled autonomous flights or remote-based flights. With this flying method some operations have become safer, more effective and easier. For example, the UAV´s used in construction, infrastructure, agriculture, transportation and logistics, disaster or security, as well as in media applications. (Abdalla & Marojevic, 2020) This master’s thesis concentrates on transportation and logistics applications namely on parcel delivery problems. For instance, different delivery companies use or have introduced delivery concepts with drones such as DHL, FedEx, Google, Metternet, UPS, Alibaba or Amazon. (Abdalla & Marojevic, 2020)

4.1 Autonomous Drone Parcel Delivery

DHL Express in collaboration with EHang drone producer introduced a fully automated deliver service in Guangzouh province. The delivery drone can deliver the packages to the customers in a radius of eight kms from the service centre in Liaobu. They used the so-called Falcon-drones for daily delivery, which are the latest models fof EHang (see Figure 23) (DHL, 2019)

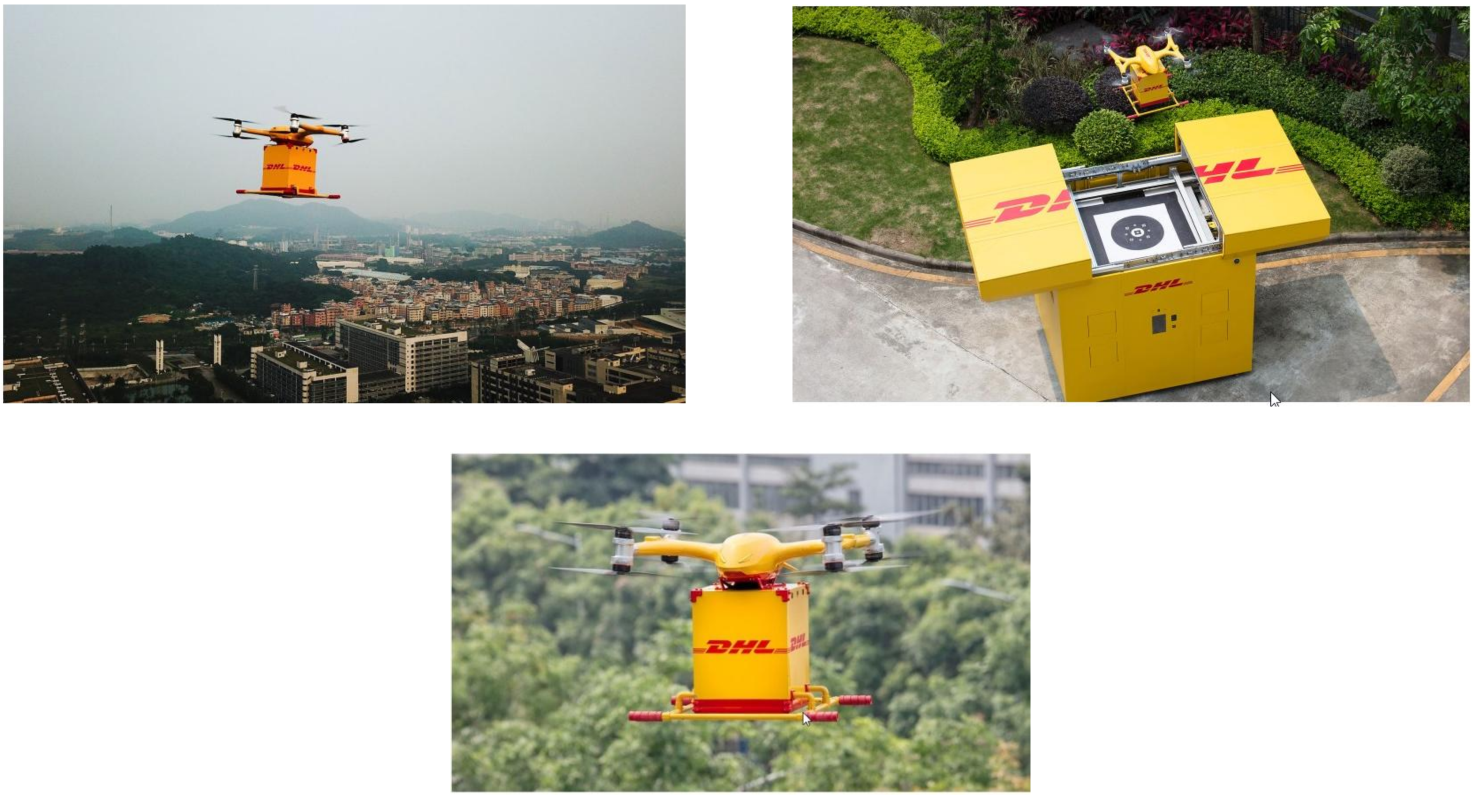


Figure 23: DHL Drone Delivery (DHL, 2019)

The first test months were very impressive. DHL reduced the general delivery time from 40 minutes to 8 minutes and the CO2 emission and Costs up to 80%. The Falcon Drones use a multi-rotor system, exactly eight rotors and they have different collision and sensors systems. The intelligent system elements and the back-up system are responsible for secure flight. The system elements are divided into navigation- and positioning elements which are used for real-time route planning and real-time network connection which is responsible for the commanding system. These two elements allow completely autonomous flight because the drones can plan and calculate the route and return if it is needed in real time. Another interesting element is the box which is used for the delivery of packages. The maximum package weight is 5 kg excluding the box weight. The packages are stored in these delivery boxes which are docked in a ground station. The ground station can identify the packages and if it is needed, it sorts them. The sorting mechanism is needed because the ground station stores more than one package at the same time, and it is necessary to know which one is for the end customer and which one needs to be sent away. For security purposes, ground stations have face recognition and an ID-scan mechanism. The customer can take the right packages because the ID and the face recognition need to be the same as in the system. (DHL, 2019) Another autonomous parcel delivery system is the PrimeAir cocept by Amazon. The first steps were taken, and the test phase was conducted on 07.12.2016. The maximum flying time was 13 minutes, and the maximum package weight was only 2,2 kg. The concepts have been developed in the last few years and a higher delivery time has been reached. According to Amazon, the new delivery drones can deliver the package up to 30 min and the lifting capacity will be 2,2 kg. The introduction of the new delivery concept was planned in the United States, the United Kingdom, Austria, France and Israel. (Amazon, 2020)

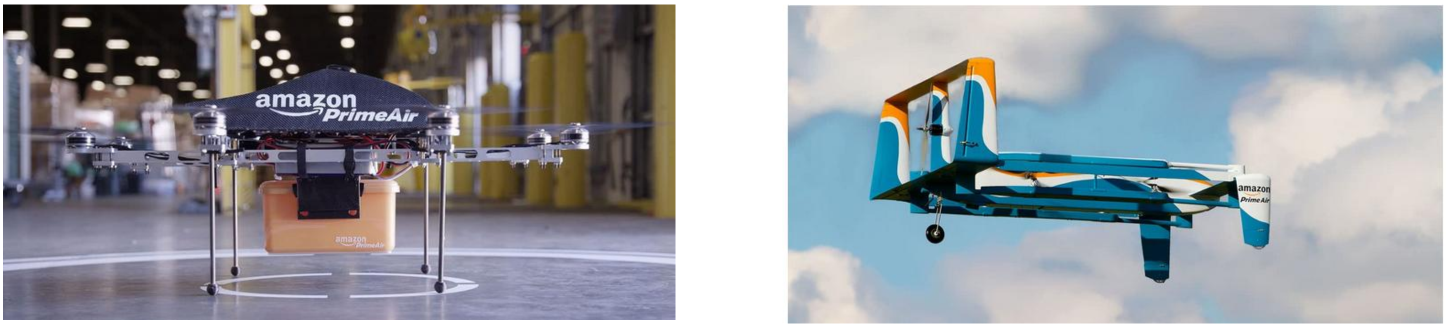


Figure 24: Amazon Drone Delivery (Amazon, 2020)

For safety purposes the Amazon drones use Artificial Intelligence which can deal with the unexpected. To support Artificial Intelligence, Amazon built a complete sense and avoid system with different sensors and cameras. During the flight, the Amazon drones can identify the fixed objects with multi-view sensors and different algorithms. On the other hand, to detect the moving object the UAV´s use the same approach as helicopters, which is the proprietary computer vision system helped by a machine learning algorithm. However, the drones also need to land and for landing operations they also need a safe place so that nobody will be injured. For the landing operation the drones can detect animals and people with a stereo vision system which is connected with Artificial Intelligence. However, in some cases the detection from a given purpose is hard or not possible. This was the reason why a second system was introduced, namely a computer-vision system. The computer-vision system can detect different wires and can avoid them. (Amazon, 2025) After the different testing phases

Amazon earned the first approval in the United States. They earned an “Air Carrier” license from the Federal Aviation Administration, but this is only a special rule for the company which has also been given to UPS and Google. They can test the delivery system and can use it under given restrictions. On the other hand, this regulation also says that the companies are responsible for any security issues, pilot training and any costs caused during the delivery process. The introduction of the system in Europe will take place in the next years because the new European Regulations do not make it possible to use the concept. (Amazon, 2024; FAA, 2021) Another fully autonomously working drone delivery concept was introduced by Google. Google´s parent company Alphabet has been testing the concept in Australia since 2014. After the testing flight the first service was launched in 2019 and several different goods were delivered in Canberra such as takeaway foods, coffee or medicines. The idea is that the drone picks up the shipment and flies it to the customer and leaves the package in the garden. Naturally, the drones need to take into account the size of customer property so that nothing will be damaged. Other restrictions are, for instance, that the UAV´s are allowed to fly only during the day and they cannot cross any main roads or crowds. (Wing / Alphabet, 2019) The “Wings” are exactly fully autonomous and hybrid delivery drones.

Figure 25: Google Drone Delivery (BBC, 2019)

They use a fixed wing for the cruise flight and have twelve rotors which help with the take-off and landing operations. The wings use UTM technology which helps to precalculated the routes for the given delivery and if it detects any anomaly, for example restrictions or weather conditions which do not make the flight possible, then it cancels the delivery. In cases when the flight is possible, they fly from the “nest” to the pick-up locations. The wings can hover up to seven meters and the merchants can secure the packages, naturally the drones themselves also control if the package is secured. After the picking up they fly between 30 and 40 meters high at the speed of 110 km/h to the customer. At the delivery point they can automatically release the packages and after that they are fly to a charging pad or retour to the “nest”. (Wing / Alphabet, 2019) The concepts were very successful and introduced in different big metropolises in the United States such as in Christiansburg in Virginia, Austin in Texas and Columbus in Ohio. According to the Virginia Tech in the three cities more than 66 000 people used the concept, which generated more than $284 000 new sales for the local businesses. The road delivery or traveling time between the merchants and the customer has been reduced by more than 473 million km and approximately 580 incidents have been avoided. However, the most important factor is the emission reduction, which is equivalent to 46 000 acres of new forest, which is approximately 100 000 tons of CO2 reduction per year. (Wing / Alphabet, 2019)

4.2 Truck-Drone Collaboration

UPS introduced their own drone delivery concept in collaboration with the Workhorse Group. The first testing phase took place in 2017. The idea of this concept is the truck-drone collaborative delivery, which means the drones fly from a truck with the package to the customer and the truck at the same time also delivers the packages to other customers. The trucks and the drones can be rendezvoused at different points after delivery. The delivery point can be at another customer or at another point during the truck tour. (Stampher, 2017)

Figure 26: UPS Drone Delivery (Stampher, 2017)

The UPS delivery system uses the Workhorse HorseFly™ drone, which is an octocopter which can be used combined with other Workhorse products such as the fully electric or hybrid trucks. This combination ensures a higher emission reduction and a higher number of deliveries during the days. The trucks have fully automated docking stations for the drones and the docking station can charge the drone´s batteries. The pick-up process is also fully automated because the driver only needs to load the given parcel into the box and the box lifts the packages to the docking station and after that it secures them to the drones. The routes are defined from a ground station, and they are sent to the delivery drones which fly completely autonomously. The Workhorse drones can fly at a maximum of 30 minutes and can lift maximum 4,5 kg packages. (Stampher, 2017) The UPS services belong to the Federal Aviation Administration Part 135 certification. The Part 135 certification means that the UAV´s cannot operate out of the pilot´s line of sight, they cannot operate over masses of people or over streets with masses of people and cannot operate at night. Other restrictions are that the delivered parcel weight cannot be higher than 25 kg but there are no parcels of this weight. (UPS (a), 2021) UPS is planning to buy new electric aircraft which are better for small and medium-sized businesses. The eVolt, namely the electric Vertical Takeoff and Landing aircraft, is produced by the company Beta Technologies. (UPS (b), 2021)

Figure 27: UPS eVolt (UPS (b), 2021)

This eVolt aircraft is suitable for delivering heavy packages; they could lift a maximum of 635 kg and have a 402 km flying range. The aircraft can fly at a maximum of 402 km/h, which significantly reduces the delivery time. UPS plans one long or shorter tour per day but the number of deliveries or the number of packages delivered will be fascinatingly high. Another advantage is that the battery can be charged full within one hour and has zero emissions. Today these vehicles operate with a pilot, but they have the characteristics of flying completely autonomously. The first Beta Technologies aircraft will be launched in 2024 and UPS is planning to buy up to 150 aircrafts. (UPS (b), 2021) The best-known truck-drone solution company is the above-mentioned Workhorse company. The Workhorse team are working together with different companies, but their most important partner is UPS. The drone and ground station producing company is focusing on efficient and sustainable electric vehicles and drones. These vehicles and aircraft are suitable for the last mile delivery problem. The company´s drones are suitable for delivering up to 80% of the commercial package size, and weight and they are safe. The payload capacity is also better than that of the other companies' products, which is 2,5 kg and can fly with this payload up to 16 km. This delivery concept is very flexible since companies can choose between the traditional delivery and drone delivery or it is possible to make hybrid delivery routes. For the higher-flying distance and higher effectiveness, a battery charging station is also included in the ground stations, which makes it possible to charge the drone battery during the traditional trip. However, to plan the trips for the given ground station and drones, the delivery companies also need a sufficient planning tool. Workhorse is developing their own planning tool which is suitable for precise planning tasks such as avoiding non-flying zones or not sufficient flying conditions like hazardous weather conditions. The planning system also includes remote pilot options, which enables the user to coordinate the flight if it is needed or just track the completely autonomous flight. (Workhourse(a), 2020)

Figure 28: Workhorse Drone Delivery (Workhourse(a), 2020)

Workhorse submitted a certification to the Federal Aviation Administration for their delivery system last year. The certification process will be expected to last for one or two years but after the process is certified, it will be possible to use the system in the USA. The Federal Aviation Administration standards are very high as safety (of the drone and package delivery), the sensors and camera types and the autonomous flight precision degree such as collision avoidance need to be taken into account. The company hopes to complete the certification process fast because the system has a very low emission degree and high-cost effectiveness, which is beneficial for the planet and for our economy also. (Workhorse (b), 2020)

4.3 Drone-Public Transportation Collaboration

Drone delivery with a public transportation method is a very interesting and controversial research area. Generally, this method allows a higher travel range for the drones, but it depends on the transportation method. The typically used public transportation methods are the buses, trams and subways. Some researchers argue that these methods are not effectively usable because the network is not sufficiently built, or the speed of public transport is too slow. (S. Choudhury, et al., 2020) However, this has not set back research in these areas, different publications and applications have come to light during the past years. The most famous one is Stanford University's framework and application. The University´s SISL Lab publicized their algorithm and the solutions in 2020 at the IEEE International Conference on Robotics and Automation. They argue besides the importance of merging the drone parcel delivery with public transportation. The reason is no extra vehicles are needed to transport the drones because the network is provided in cities, and the drone has a higher range with this method and can make more deliveries during the day. With the proposed algorithm it is possible to control a large fleet which coordinates, the timing, routes and effectiveness too. The idea's visualization is proposed in Figure 29. (M. Tyson, 2020)

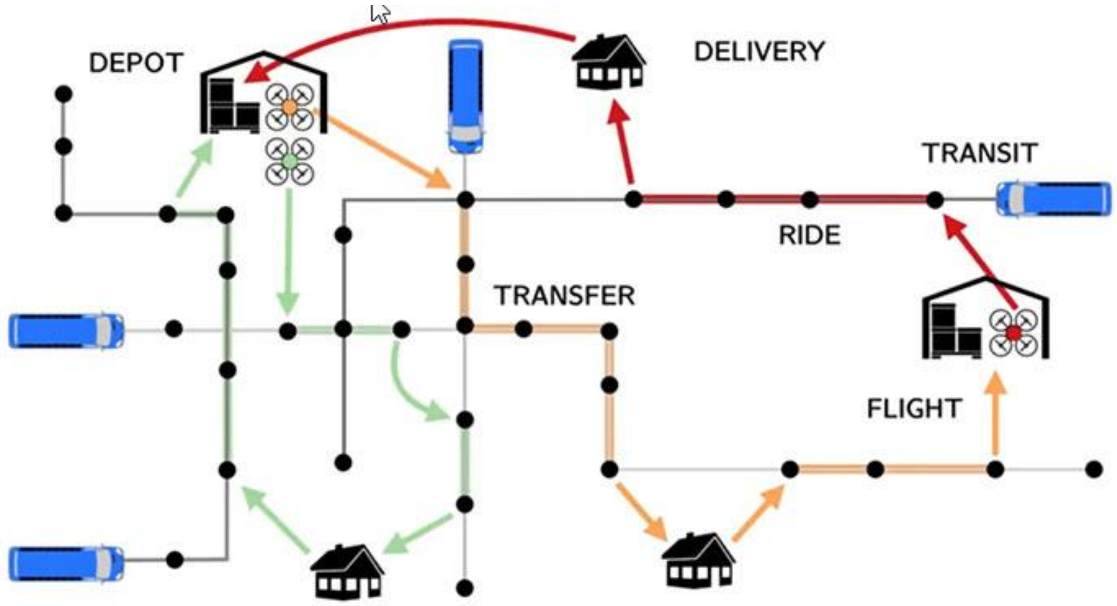


Figure 29: Drone-Public Transportation (M. Tyson 2020)

The algorithm divides the problem into two layers. The first one is the task allocation problem, which has polynomial computation time. The allocation algorithm is responsible for the assignment of the packages to the drones and the sequence. According to the allocation problem the algorithm takes the next step to the second layer, which is the multi-agent pathfinding algorithm. This layer is responsible for the allocation of the suboptimal path in the network to the given drones and packages. There the goal is to find the most effective and efficient path including the station and the retour path to the depot. (M. Tyson, 2020) The algorithm is tested in two real-world bus networks namely in San Francisco and Washington D.C.. San Francisco has an area of 150 km^2 and Washington a 400 km^2 area which has a big network and for this reason the number of possible entry and exit points and the combinations of them is very high. In this experiment the drones are allowed to use the public network to save energy and increase the flight range. Naturally, the question in such large areas is the longest delivery time in the system. After several tests, the highest delivery time from the depot to the customer and back to the depot was less than one hour in San Fransisco and in Washington D.C. it was less than two hours. The algorithm tested up to 200 drones and up to 5000 packages. This combination gives a very high number of stops, which was up to 8000 in one day. (S. Choudhury, et al., 2020) After the different tests researchers compared the results with the normal solutions and find out that the drone flight range increased between 170 and 360 percent.

In the United States in this field a patent was also assigned to Johnatan Gabbai in 2015. In this patent the location and path finding algorithm is presented. First, the drone receives the signal for the delivery and after that it plans the stations plan the route. After the planning phase the route is transmitted to the drone which picks up and deliveries the package to the destination by public transportation. (J. Gabbai, 2024)

As mentioned at the beginning of the chapter, this is a very young research area and raises many questions. The biggest problem is the very strict regulation from the authorities and people's acceptance. However, different models have been introduced, which will be highlighted in the next chapter.

5. UV based delivery models

As mentioned in the last chapter, the drone-based delivery has gained more importance in the last years. This indicates a higher number of publications and intensive research in this field. Generally, the publication could differ into three different fields, the drone operations part where the drones deliver the parcel by own direct from the depot, the drone-truck delivery systems where the drones and the trucks deliver the packages at the same time and the drone-public transportation models where the drones are allowed to use public transportation. All three different groups have their own problem description and solution methods. For example, in the case of drone delivery we need to find a solution for the routing problem between the set of locations, need to solve the area coverage problems, need to make search operations for the optimal routing and need to be sure of the optimal task assignment. In the case of drone-truck delivery problem the biggest question which needs to be answered is the effective allocation of customers, namely which customer will be satisfied with truck delivery, and which customer will be satisfied with drone delivery. Of course, in this case it needs to be decided which delivery method is the primary one or the delivery will be synchronized between the two delivery options. On the other hand, different variables need to be taken into account if a model is developed. Such variables as different battery capacity which depends on the delivered parcel weight or depends on the different weather conditions, the non-flying zones also need to take into account or in synchronized case the different travel times by truck which depends on the traffic and so on. The above listed variables and different operation types show that this problem is very complex and complicated. (S. H. Chung, et al. 2020) In this chapter the general problem and different solutions methods are highlighted to understand the methodology and the problem complexity.

5.1 General Model

In this case it is not easy to define a general model because different assumptions and variables are used. Generally, all single drone, truck-drone, and truck-public transportation models based on the traveling salesman problem and vehicle routing problem. In some models the capacitated version from these two models is also considered as a base problem description. (C. C. Murray, A. G. Chu, 2015) In the research field the first integer programming models and heuristics introduced by Chase C. Murray and Amanda G. Chu. They considered two different models and heuristics in the paper "The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery". The first model is the flying sidekick traveling salesman problem where Chase C. Murray and Amanda G. Chu considered a single truck and single drone case. The model uses the actual road distances for the truck and uses Euclidean distances for the drone. The objective function is minimizing the tour completion time. The second model in this paper is a parallel drone scheduling traveling salesman problem. In this case other constraints and variables are also introduced such as synchronization, launch and rendezvous locations and flow conversations. The model formulations are based on the typical traveling salesman problem formulation and vehicle routing problem. (S. H. Chung, et al. 2020) First the typical traveling salesman problem will be highlighting for the better understanding the models and after the flying sidekick traveling salesman problem is explained.

5.1.1 Traveling Salesman Problem

The traveling salesman problem has two different formulation the symmetric and the asymmetric case. In this chapter just the asymmetric formulation presented because this is the most realistic case, but the model formulation is the same for the two cases.

The asymmetric traveling salesman problem considers a problem where a directed graph ***G = (V , A)*** given. In this case the ***V = {1,…,n}*** is the vertex set and ***A =*** $\{(\boldsymbol{i},\boldsymbol{j}): \boldsymbol{i},\boldsymbol{j} \in \boldsymbol{V}, \boldsymbol{i} \neq \boldsymbol{j}\}$ is the arc set. There are asymmetric variable costs between the two arc $\boldsymbol{C_{ij}}$. (T. Önchan, et al., 2009)

Mathematical formulation (T. Bektas, L. Gouveia, 2014):

$$\textbf{minimize} \quad \sum_{(i,j)\in A}^{n} c_{ij}x_{ij} \qquad (1)$$

subjected to

$$\sum_{i\in V:(i,j)\in A} x_{ij} = 1 \quad \forall\, j \in V \qquad (2)$$

$$\sum_{j\in V:(i,j)\in A} x_{ij} = 1 \quad \forall\, i \in V \qquad (3)$$

$$\{(i,j) \in A: x_{ij} = 1\} \ \textbf{do not contain subtours,} \qquad (4)$$

$$x_{ij} \in \{0,1\} \qquad \forall\,(i,j) \in A \qquad (5)$$

(1) Objective function to minimize the total cost caused by the tour
(2) Assignment constrains for the ***arc (i,j),*** each arc could just once include in the final solution
(3) Assignment constrains for the ***arc (j,i***), each arc could just once include in the final solution
(4) This prevents the subtour elimination for the given problem
(5) The integer variable which defines which arcs are included in the final solution, if the variable 1 than the arc between the two vertex is part of the solution and 0 otherwise

There are different subtour elimination constraints proposed during the years but the most known are the Dantzing, Fulkerson and Jonson formulation and the Miller,Trucker and Zemlin formulation. (T. Önchan, et al., 2009) In the Miller, Tucker, Zemlin formulation the original subtour elimination constrain is replaced with an extended constrains which secure a better subtour elimination. The constraint is the following and the original constraint **(4)** is replaced (T. Bektas, L. Gouveia, 2014):

$$u_i - u_j + (n-1)x_{ij} \le n-2 \qquad \forall\, i \ne j = 2, \dots, n \qquad (6)$$

$$0 \le u_i \le n-2 \qquad \forall\, i = 2, \dots, n \qquad (7)$$

The additional variable u_i in this extension is used for ordering purposes. The depot is not included in the order because the tour needs to begin and end in the depot. The constraint **(6)** ensures that the start and end vertex or point is not the same for the given tour, excluding the depot and ensures that the tour does not contain more than ***n*** vertex. The constraint **(7)** gives the position from the given node ***i*** in the tour or could be explained as maximal number of nodes between the depot and the given node ***i.*** (T. Bektas, L. Gouveia, 2014) The other and most used elimination constrains the Dantzing, Fulkerson and Jonson formulation. In this case also the original constraints **(4)** replaced by the following formulation (T. Bektas, L. Gouveia, 2014):

$$\sum_{i \in S} \sum_{j \in S} x_{ij} \le |S| - 1 \qquad \forall\, S \subseteq \{2, \dots, n\}, |S| \ge 2 \qquad (8)$$

The constraint **(8)** defines a neu set ***S*** which the nodes contain and ensures that the number of arcs does not exceed the number of $|S| - 1$ nodes. (T. Bektas, L. Gouveia, 2014)

5.1.2 Vehicle Routing Problem

The capacitated vehicle routing problem was introduced by Dantzing and Ramser in 1959. They considered a model where homogenous vehicles transport goods to the customers. In this case the vehicles have the same capacity, and the customer demands need to be satisfied. The costs could represent different forms in this model however the model formulation will be the same. General the different model representations are using the distances, travel times or number of vehicles as cost variable. (J.Caceres-Cruz, et al.,2014) During the years several constraints are introduced to the model as extensions. These extra constraints could be for example: each customer satisfied by one vehicle, each vehicle starts and the trip by the depot node, the vehicles could not stop twice by the same customer, or the maximum vehicle load capacity could not exceed. The last three constraints are used in most of the models because they are necessary for transportation companies and these are needed for the applicability in everyday life. (G. Laporte, et al.,2000)

The general model assumes a directed graph $G = (V, A)$ where $V = \{1, \dots, n\}$ are the vertices and $A = \{(i,j): i, j \in V, i \ne j\}$ are the arcs. The variable $c_{ij} > 0$ represent the cost between the two nodes, if the model considers a symmetric case then $c_{ij} = c_{ji}, 0 \le i, j \le n$ which means the cost between the two nodes is the same and independent from the direction. The fleet in the original model can deal with heterogeneous or homogenous vehicle fleet
$M = \{1, \dots, m\}$ where each type $k \in M$ has m_k vehicles at the depot which are available for delivery and these vehicles have the same capacity Q_k. The variable q_j and q_i represent the demand for the given nodes. By the next integer formulation, the depot represented as **node**

1 and have a demand 0. In this case to follow the load in the given truck a flow variable y_{ij}^k introduced. (J.Caceres-Cruz, et al.,2014)

The integer formulation for the given Vehicle routing problem **after J.Caceres-Cruz, et al.,2014** is the following:

$$\min \sum_{k \in M} \sum_{i,j \in V, i \neq j} c_{ij}^k x_{ij}^k \qquad (1)$$

Subjected to:

$$\sum_{j \in V-\{1\}} x_{1j}^k = \sum_{i \in V-\{1\}} x_{i1}^k \qquad \forall\, k \in M \qquad (2)$$

$$\sum_{k \in M} \sum_{i \in A} x_{ij}^k = 1 \qquad \forall\, j \in A - \{1\} \qquad (3)$$

$$\sum_{i \in A} x_{iu}^k = \sum_{j \in A} x_{uj}^k \qquad \forall\, u \in A - \{1\}, \forall\, k = M \qquad (4)$$

$$\sum_{j \in A-\{1\}} x_{1j}^k \leq m_k \qquad \forall\, k \in M \qquad (5)$$

$$\sum_{i \in A} y_{ij}^k - \sum_{j \in A} y_{ji}^k = q_j \sum_{i \in A} x_{ij}^k \qquad \forall\, j \in A - \{1\}, \forall\, k \in M \qquad (6)$$

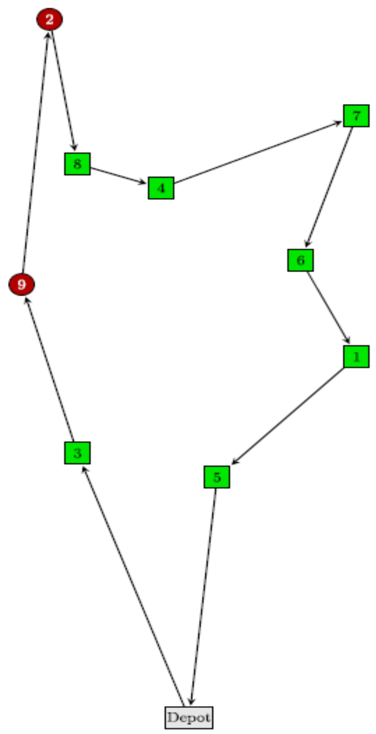
$$0 \leq q_j x_{ij}^k \leq y_{ji}^k \leq (Q_k - q_i) x_{ij}^k \qquad \forall\, i,j \in A, i \neq j, \forall\, k \in M \qquad (7)$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i,j \in A, i \neq j, \forall\, k \in M \qquad (8)$$

(1) Objective function, minimizing the total cost for all customer delivery
(2) Secure that the number of vehicles at the start in the depot is the same as the end of the tour. With other word all leaving vehicles from the depot need to return to the depot.
(3) Constrain to secure the once customer visiting during the trip
(4) Constrain to secure the once customer visiting during the trip
(5) Ensure that the maximum number of vehicles for each type does not exceed during the tours
(6) The flow variable which gives the rest capacity in the vehicle after the given customer is satisfied
(7) The constraints create a lower and upper bound for the quantity which delivered and ensure that the total capacity does not exceed

5.1.3 The Flying Sidekick Traveling Salesman Problem

The flying sidekick traveling salesman problem was introduced by Chase C. Murray and Amanda G. Chu in the paper “The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery”. They considered a model where the drones could include in the delivery process. Generally, the problem is a set of C customers where the customers just have one demand which needs to be satisfied. This assumption means that the customers need to be served just exactly once per trip and after the delivery there are other demands from the customer side. It is important to know that the truck and the drones can satisfy more than one customer during the delivery process. The starting and ending point for the trucks is the depot or the distribution center, because the drones are not mandatory. Chase C. Murray and Amanda G. Chu developed a model where the drones could use the truck also as starting and ending point. The important point is that the drones at the beginning and at the end of the trip need to be in the depot or distribution center. That means, it is not allowed to start or end the whole delivery process by the customers or at another point. By the flying sidekick traveling salesman problem also considered, that the unmanned aircraft´s tours and truck tours could be synchronizing. The synchronization means that the drones launched from a customer node from the truck and the drone satisfy a customer and rendezvous at the third customers which satisfied via truck. Of course, it is allowed to relaunch the drones from the rendezvous point to another node if there is enough battery capacity for the next trip. The battery capacity used in this case is just to identify the flight range. They assume that there is enough battery by the truck which could be changed if it’s needed, but they introduced extra service times for the changing process. In this case the overweighted packages, the not safe places for the drones or other matters (signature) also considered which makes the delivery not possible for the unmanned vehicles. In such cases the customer is marked as truck delivered customer and not considered by the drone’s solution. Chase C. Murray and Amanda G. Chu minimize the total latest time which the drone and the truck need to return to the depot. (Chase C. Murray, Amanda G. Chu, 2015) The Figure 30 and Figure 31 represent the model and the considered situation.



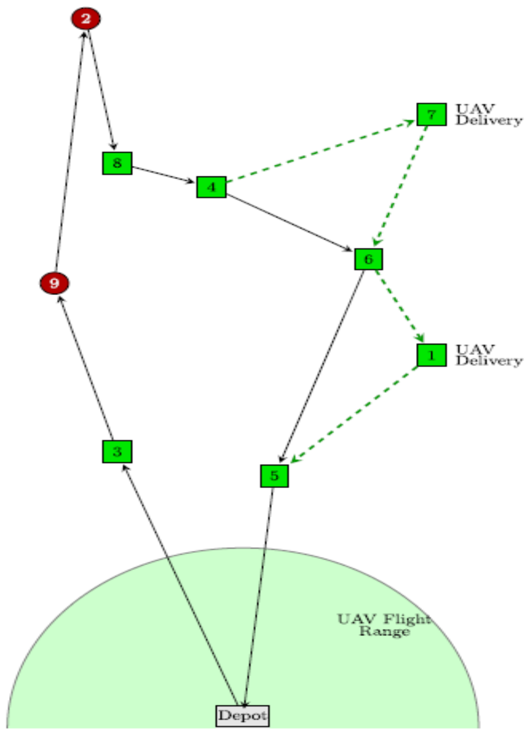


Figure 30: Original Situation (Chase C. Murray, Amanda G. Chu, 2015) Figure 31: Solution Situation (Chase C. Murray, Amanda G. Chu, 2015)

The MILP-Formulation and the notations are after **Chase C. Murray, Amanda G. Chu, The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery, 2015**:

- $C = \{1,2, \dots , c\}$ -> Set of customers
- $C' \subseteq C$ -> Subset of customer served by drones
- $vehicles\ departs\ from\ depot\ (node\ 0)\ and\ return\ at\ node\ c + 1$
- $N = \{0,1, \dots, c + 1\}$ -> Set of all nodes
- $N_0 = \{0,1, \dots ,\ c + 1\}$ -> Set of departs node for vehicles
- $N_+ = \{0,1, \dots ,\ c + 1\}$ -> Set of nodes visited for vehicles
- $\tau_{ij} \quad i \in N_0 , j \in N_+$ -> Traveling time for truck from *i* to *j*
- $\tau'_{ij} \quad i \in N_0 , j \in N_+$ -> Traveling time for drone from *i* to *j*
- $\tau_{ii}, \tau'_{ii} \quad \forall\ i \in N_0$ -> undefined, revisiting a node is not possible
- $\tau_{0,c+1} \equiv 0$ -> if single customer case and served from the depot
- S_L -> preparation time for drone launch by truck
- S_R -> recover time from drone by rendezvous
- $P = \langle i, j, k\rangle$ -> set of tuples (starting, served, rendezvous node)
- $P\ conditions$:
  - $launch\ point\ i, could\ differ\ from\ the\ dending\ depot$
  - $served\ point\ j, need\ to\ be\ feasible\ for\ the\ drones$
  - $served\ node\ j, could\ differ\ from\ the\ launch\ node$
  - $rendezvous\ point\ k, could\ be\ customer\ or\ ending\ depot$
  - $rendezvous\ point\ k, could\ differ\ from\ i\ or\ j$
  - $i \to j \to k\ trip\ could\ be\ lower\ as\ the\ drone' sendurance$

Decision Variables:

- $x_{ij} \in \{0,1\} \quad i \in N_0, j \in N_+, i \neq j$ -> if truck travels from *i* to *j*
- $y_{ijk} \in \{0,1\} \quad i \in N_0, j \in C, k \in \{N_+ : \langle i, j, k\rangle \in P\}$ -> if drone tour included
- $t_j \geq 0 \quad j \in N_+$ -> truck's arriving time at node j
- $t'_j \geq 0 \quad j \in N_+$ -> drone's arriving time at node j
- $t_0 = t'_0 = 0$ - > earliest launching time (depot)
- $p_{ij} \in \{0,1\} \quad i \in C, j \in \{C : j \neq i\}$ -> *i* visited before *j* visited in truck path
- $p_{0j} = 1 \quad j \in C$ -> depot defined as starting node
- $1 \leq u_i \leq c + 2 \quad i \in N_+$ -> subtur elimination

Min t_{c+1} (1)

Subjected to:

$$\sum_{i \in N_0, i \neq j} x_{ij} + \sum_{i \in N_0, i \neq j} \sum_{k \in N_+, \langle i,j,k\rangle \in P} y_{ijk} = 1 \qquad \forall j \in c \qquad (2)$$

$$\sum_{j \in N_+} x_{0j} = 1 \qquad (3)$$

$$\sum_{j \in N_0} x_{ic+1} = 1 \qquad (4)$$

$$u_i - u_j + 1 \leq (c+2)\left(1 - x_{ij}\right) \qquad \forall i \in C, j \in \{N_+ : j \neq i\} \qquad (5)$$

$$\sum_{i \in N_0, i \neq j} x_{ij} = \sum_{k \in N_+, \langle i,j,k \rangle \in P} x_{jk} \qquad \forall j \in C \qquad (6)$$

$$\sum_{j \in C, j \neq i} \sum_{k \in N_+, \langle i,j,k \rangle \in P} y_{ijk} \leq 1 \qquad \forall i \in N_0 \qquad (7)$$

$$\sum_{i \in N_0, i \neq k} \sum_{j \in C, \langle i,j,k \rangle \in P} y_{ijk} \leq 1 \qquad \forall k \in N_+ \qquad (8)$$

$$2y_{ijk} \leq \sum_{h \in N_0, h \neq i} x_{hi} + \sum_{l \in C, l \neq k} x_{lk} \qquad \forall i \in C, j \in \{C : j \neq i\}, k \in \{N_+ : \langle i,j,k \rangle \in P\} \qquad (9)$$

$$y_{0jk} \leq \sum_{h \in N_0, h \neq k} x_{hk} \qquad \forall j \in C,\ k \in \{N_+ : \langle 0,j,k \rangle \in P\} \qquad (10)$$

$$u_k - u_i \geq 1 - (c+2)\left(1 - \sum_{j \in c, \langle i,j,k \rangle \in P} y_{ijk}\right) \qquad \forall i \in C, k \in \{N_+ : k \neq i\} \qquad (11)$$

$$t'_i \geq t_i - M\left(1 - \sum_{j \in C, j \neq i} \sum_{k \in N_+, \langle i,j,k \rangle \in P} y_{ijk}\right) \qquad \forall i \in C \qquad (12)$$

$$t'_i \leq t_i + M\left(1 - \sum_{j \in C, j \neq i} \sum_{k \in N_+, \langle i,j,k \rangle \in P} y_{ijk}\right) \qquad \forall i \in C \qquad (13)$$

$$t'_k \geq t_k - M\left(1 - \sum_{i \in N_0, i \neq k} \sum_{j \in C, \langle i,j,k \rangle \in P} y_{ijk}\right) \qquad \forall k \in N_+ \qquad (14)$$

$$t'_k \leq t_k + M\left(1 - \sum_{i \in N_0, i \neq k} \sum_{j \in C, \langle i,j,k \rangle \in P} y_{ijk}\right) \qquad \forall k \in N_+ \qquad (15)$$

$$t_k \geq t_h + \tau_{hk} + S_L\left(\sum_{l \in C, l \neq k} \sum_{m \in N_+, \langle k,l,m \rangle \in P} y_{klm}\right) + S_R\left(\sum_{i \in N_0, i \neq k} \sum_{j \in C, \langle i,j,k \rangle \in P} y_{ijk}\right) - M(1 - x_{hk}) \qquad \forall h \in N_0, k \in \{N_+ : k \neq h\} \qquad (16)$$

$$t'_j \geq t'_i + \tau'_{ij} - M\left(1 - \sum_{k \in N_+, \langle i,j,k \rangle \in P} y_{ijk}\right) \quad \forall j \in C', i \in \{N_0 : i \neq j\} \qquad (17)$$

$$t'_k \geq t'_j + \tau'_{jk} + S_R - M\left(1 - \sum_{i \in N_0, \langle i,j,k \rangle \in P} y_{ijk}\right) \quad \forall j \in C', k \in \{N_+ : k \neq j\} \qquad (18)$$

$$t'_k - \left(t'_j - \tau'_{ij}\right) \leq e + M\left(1 - y_{ijk}\right) \quad \forall k \in N_+, j \in \{C : j \neq k\}, i \in \{N_0 : \langle i,j,k \rangle \in P\} \quad (19)$$

$$u_i - u_j \geq 1 - (c+2)p_{ij} \quad \forall i \in C, j \in \{C : j \neq i\} \qquad (20)$$

$$u_i - u_j \leq -1 + (c+2)\left(1 - p_{ij}\right) \quad \forall i \in C, j \in \{C : j \neq i\} \qquad (21)$$

$$p_{ij} + p_{ji} = 1 \qquad \forall i \in C, j \in \{C : j \neq i\} \qquad (22)$$

$$t'_l \geq t'_k - M\left(3 - \sum_{j \in C, \langle i,j,k \rangle \in P, j \neq l} y_{ijk} - \sum_{m \in C, m \neq i, m \neq k, m \neq k} \; \sum_{n \in N_+, \langle l,m,n \rangle \in P, n \neq i, n \neq k} y_{lmn} - p_{il}\right)$$
$$\forall i \in N_0, k \in \{N_+ : k \neq i\}, l \in \{C : l \neq i, l \neq k\} \qquad (23)$$

$$t_0 = 0 \qquad (24)$$

$$t'_0 = 0 \quad (25)$$

$$p_{0j} = 1 \qquad \forall j \in C \qquad (26)$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in N_0, j \in \{N_+ : j \neq i\} \qquad (27)$$

$$y_{ijk} \in \{0,1\} \qquad \forall i \in N_0, j \in \{C : j \neq i\}, k \in \{N_+ : \langle i,j,k \rangle \in P\} \qquad (28)$$

$$1 \leq u_i \leq c + 2 \qquad \forall i \in N_+ \qquad (29)$$

$$t_i \geq 0 \qquad \forall i \in N \qquad (30)$$

$$t'_i \geq 0 \qquad \forall i \in N \qquad (31)$$

$$p_{ij} \in \{0,1\} \qquad \forall i \in N_0, j \in \{C : j \neq i\} \qquad (32)$$

(1) Objective function to minimize the sum of time which need to return to the depot
(2) Ensure that all customers will be visiting exactly once
(3) The truck could leave the depot exactly once during the delivery process
(4) The truck could return to the depot exactly one during the delivery process
(5) To eliminate the subtours in the truck trip

(6) Constrains ensure that the visiting node for the truck needs to be the same as the departing node
(7) For the drone is allowed to launch from any node at most once, the depot also included
(8) Could be that the drone rendezvous by any other node or by the ending depot at most once
(9) The truck needs to be assigned to the drone launching node and to the rendezvous node
(10) Ensure the case if the drone launched from the depot and picked up in a different node, then the truck needs to assign to the rendezvous node
(11) If the node launched from a node i and picked up in a different node k then the truck needs to be assigned to the node i and need to be visit for the node k
(12) Time coordination constrains for the truck and for the drone, if the drone launched from a customer node and force the truck and the drone have the same arriving time by the launching customer
(13) Time coordination constrains for the truck and for the drone, if the drone launched from a customer node and force the truck and the drone have the same arriving time by the launching customer
(14) Time coordination constrains for the truck and for the drone, if the drone returns by a customer node and forces the truck and the drone have the same arriving time by the rendezvous node
(15) Time coordination constrains for the truck and for the drone, if the drone returns by a customer node and forces the truck and the drone have the same arriving time by the rendezvous node
(16) This constrains will be taking into account if the truck travels from a node h to the other node k and the launching node is the node k then the setup time will be added extra to the truck traveling times. On the other hand, if the node k is the rendezvous node, then retrieval time will be adding extra to the truck traveling times.
(17) Ensure that the drone arrival time by the node j also contains the traveling time between the launch node and node j
(18) Ensure that the drone’s arrival time by the node k contains the traveling time and also the retrieval time for the drone
(19) Calculate the endurance and the flying range and assess whether the trip is feasible or not for the drone delivery
(20) makes the visiting ordering for the truck
(21) makes the visiting ordering for the truck
(22) ensure that the truck is making every tour between two nodes exactly once
(23) This constrains ensure that the launching and returning time influence each other during the calculations
(24) Earliest launching time from the depot for the truck
(25) Earliest launching time from the depot for the drone
(26) Set the depot as the starting node
(27) Decision variable for the truck route
(28) Decision variable for the drone tour
(29) To eliminate the subtours during the delivery process

(30) Arrival time for the trucks at the nodes
(31) Arrival time for the drone at the nodes
(32) Decision variable for the ordering process in the truck tour

5.1.4 Different Flying Sidekick Traveling Salesman Problems

In the last years different models with different extensions and solutions developed methods. For example, Murray and Chu in the ground paper where the flying sidekick traveling problem introduced another model also presented which is the parallel drone scheduling traveling salesman problem. The idea was that most of the customers are located near to the distribution center. This assumption indicates that the drone and truck synchronization are not needed because the drone starting and end node is the depot or distribution center. In this model all customers within the drone flying range are served via unmanned aircraft and the rest served via a single truck. With this model could reduce greenhouse emission and the total fleet's service costs in a higher amount as in the synchronization model. The service costs and generally the investment costs are lower for the drones. The disadvantage of this model is the limitation of the drones because they could be used just near the distribution center. If there are more customers located away from the depot then this model is not pre-requisite. (Chase C. Murray, Amanda G. Chu, 2015)

Another model introduced by Agatz and Bouman which is principally the same as the model from Murray and Chu. The general assumption as synchronizing the truck and drone tours, rendezvous point at other customer node, starting and ending node for truck and drone need to be the depot, service times, overweighted packages and so on is the same. They just developed and extended the model with additional assumption. They introduced that the drone speed is higher than the truck speed because there are no traffic jams, traffic regulations and the drones could use the Euclidean distances. Another extension is that they allowed that the launching node and the rendezvous node are the same. Which indicates, if the drones could return in reasonable time to the starting node, then wait for them and relaunch it. With these methods it is possible to deliver more customers via unmanned aircraft. Agatz and Bouman used other methods to solve the problem. They introduced three node types, the first is for the only drone customers, the second is for only truck customers and third is the combined customer node where truck and drone are also assigned. The advantage from this node allocation and higher drone speed is that they could calculate the bound on the maximal savings which compared with the truck bounds. Another advantage is that understanding the formulation is easier and more applicable. (Agatz N., Bouman P., Schmidt M., 2018)

This model used as objective value the time, but most applicable if the cost is considered as objective value. Ha et al. considered the operational costs as objective value. Principally the model based on the traditional traveling salesman problem. They used the solution the drone sortie method, where different drone types with different costs and characteristics used for the solution. In this paper the costs are considered for pro-distance units, and the total costs also include the waiting costs (launching and recovering the drone). The assumption in this case was that the general costs for the drones are cheaper than the general costs for the truck because the power consumption is also lower for the drones. On the other hand, they used the same assumptions and general methodology as Murray and Chu. (Ha., et.al.,2018)

Murray and Raj also proposed an extended model to the flying sidekick traveling salesman problem. In the general paper single drone and single truck model considered but, in the extension, they introduced a set of heterogenous drone flee and single truck. The drones of course have their own flying range and capacity but, in this model, trucks also allow us to carry more than one drone at the same time. It is important by this model that the multiple launch from the same customer node is not allowed. The drones need to launch from different customer nodes, but it could be that the launch node for a drone and the rendezvous node for the other drone is the same. They also have not changed the objective value for this problem. The objective value is the make spam which will be minimized during the calculation. There is also the endurance also calculated because the different sorties have their own characteristics which depend on the weight of the packages, and this indicates a different flying range for every customer. (Chase C. Murray, Raj R., 2019)

Poikonen and Golden developed a model where the drones could deliver more than one package at the same time. For the calculation they used a single truck with multiple drones. This idea allowed the drones to deliver more than one customer without too rendezvous with the truck or return to the depot. In this model the truck is considered just as a depot which changes its position. They also used their own power consumption model to calculate drone endurance and power consumption. The disadvantage is from this formulation that they used heterogenous packages which have the same characteristics, which implies that power consumption depends just on the traveling distances. (Poikonen S., Golden B., 2020)

DHL highlighted where the drones returned after the launch to a docking station. This is also a possibility to solve the transportation problem. Wang and Sheu took this idea and developed a model which depends on the service hubs. They used for research and development propose multiple drones and multiple trucks. In this model assumed that there are some service points in the area and the drones after the launch return to the service node. In this case the drones are not allowed to return to a truck. Which indicates that after the launch no other drone delivery is possible or the trucks need to go to the service points and pick up the drones. They assumed that the truck would go to the service hubs and pick up more drones which are needed for the delivery process. Of course, in this case the drones are not assigned directly to a truck or to a tour, they are free, and every truck could pick up every drone. The above-mentioned models this flexibility is not given because the drones are directly assigned to the tour which indicates that they are also assigned to a truck. In this flexible case also needs to be take into account the flying range and power consumptions as restrictions. The service hub also considered the case if drone battery capacity will be too low by a service to deliver any customer, then an extra reserve drones will be available at the service station all time. On the other hand, the reserve drone idea is capable if there any problem with the drones given, for example system errors, physical damage, or breakdowns. (Wang Z., Sheu J.-B., 2019)

Haoling H. et al, for example, used the train as delivery medium between the stations. The drones in this case will be delivered via train on a fixed route and with a fixed timeline. This idea simplifies the problem because the route is given and the time window also. The assignment is also very simple, why did they use just the first come first served method where the time window for the returning to the trains is also considered. (Haoling H., Andrey V.S., Chao H., 2019)

Haoling H. et al later extended his model with a new idea. The starting point for the model is the same. Given a train route with fixed timeline and fixed time windows. The drones serve the customers near the stations. But in the new model it is allowed that the drones do not need to be returned in the given time window because it is allowed that the drones could return in every point in the train route. It is possible because of the fixed route and timeline and the drone and train also have GPS which help to identify the position. In this case they also considered recharging time. The drones could recharge if they carried by the train. The scheduling algorithm for the customer and drone assignment based on the recharging time. This will be balanced that the drones every time have the enough battery capacity for the next trip. (Haoling H., Andrey V.S., Chao H., 2020)

The above represented ideas are just a little introduction, the problem is very big and versatile. During the last years more and more different assumptions and extensions from the different models introduced. The reason for the very rush introducing from different models the technology development in the last years and the greenhouse reduction. This reason is also highlighted in the first part of the master thesis. In the next sections a generally solution methods and the own developed model and solution method will be highlighted. For research reason I could recommend the paper from Shung Hoon Chung, Bhawesh Sah, Jinkun Lee: "Optimization for drone and drone -truck combined operations: A review of the state of the art and future directions" paper which founded by the Elsevier, Computers and Operations Research 123 (2020) 105004 edition. In this paper all relevant models, directions and solution methods summarized, and this paper is a god starting point for any research in this field.

5.2 Solution Methods

Generally, the traveling salesman problems are vehicle routing problem are NP hard problems. This indicates that the collaboration problems between the different transportation methods are also NP hard. (Chase C. Murray, Amanda G. Chu, 2015) The very complexity from the problems indicates that the researcher required other solution methods to solve the problems in reasonable time. This section gives a review of the different solution methods, algorithm, heuristics, metaheuristics, or programming solutions.

M.Mosher-Javadi, et al. introduced a hybrid solution method for the problem. The solution algorithm is based on the simulated annealing and tabu search methodic. In this method the simulating annealing method has the control function to avoid unnecessarily iteration. For this reason, they use a temperature variable which accepts the non-improving solutions also. The second part is the tabu search which is based on the memory of them. They search in the saved sequence whether the solution was used in the past or not. This could boost the calculation because avoid such solutions which in the past compared or accepted from the annealing methodic. To create more and different solutions (to avoid repetitions) for each iteration a new neighborhood is created which is the initial solution for the problem. The neighborhoods are created with a heuristic which is chosen after the weight which represents the performance of the different methodology. This wight every time updated during the iterations. The heuristics used are the following: two-opt, swap, insertion, general insertion, continuous drone enforcement, continuous truck enforcement, separated drone enforcement, separated truck enforcement, last stop drone assignment, cluster drone assignment. The objective values from the first solution are compared with the last best-founded solutions. If the news is better than the last one, then update the objective value and the solution tour. If this is not better than the old one, then after the temperature it will be probabilistic chosen whether the solution is tabu or not. (M.Mosher-Javadi, et al., 2020)

Daniel S., et al, introduced a solution method where the variable neighborhood search and tabu search are combined. Principally these methods first generate the tours for the initial solution which parallel saving heuristic. After the initial solution they iterate trough after given times and do the local search heuristics which are in this case the two-opt, string relocation and string exchange. After the local search they use the shaking methods which are the same as the local search methods and expand the search k times in the neighborhood areas. And do the drone insertion method which is a divide a conquer method. To boost the actual solution calculation, they search for the actual possible solution in the tabu list. If this is included in this memory, then skip them. Generally, all the solutions are saved in the tabu list which does not meet the criteria. (D. Schermer, M. Moeini and O.Wendt, 2019)

K. Peng et al. introduced a hybrid genetic algorithm for the problem. In the first step they create the general population for the problem. This will be generated with an anchor point selection method. If the anchor points are given, then creates the optimal routes for the truck and for the drones. If the routes are given, then schedule the drone to the customers. The route generation criteria are the furthest customer to the anchor point and the drone scheduling process based on the longest distance. If the general solutions are given, then choose the two parents after Binary Tournament method. To create the child solution and choose the better genes they introduced a Low Visit Cost Crossover algorithm which compares the anchor points and chooses the best possible solution to the given point. If the child solution is generated, then they replaced the traditional mutation operation. They use in this case local search operations for the anchor points relocations (delete and relocate the anchor points), local search for the routes (merge short algorithm) and local search for the customers (exchange, replace operations). They named this method as education. (K. Peng et al., 2019)

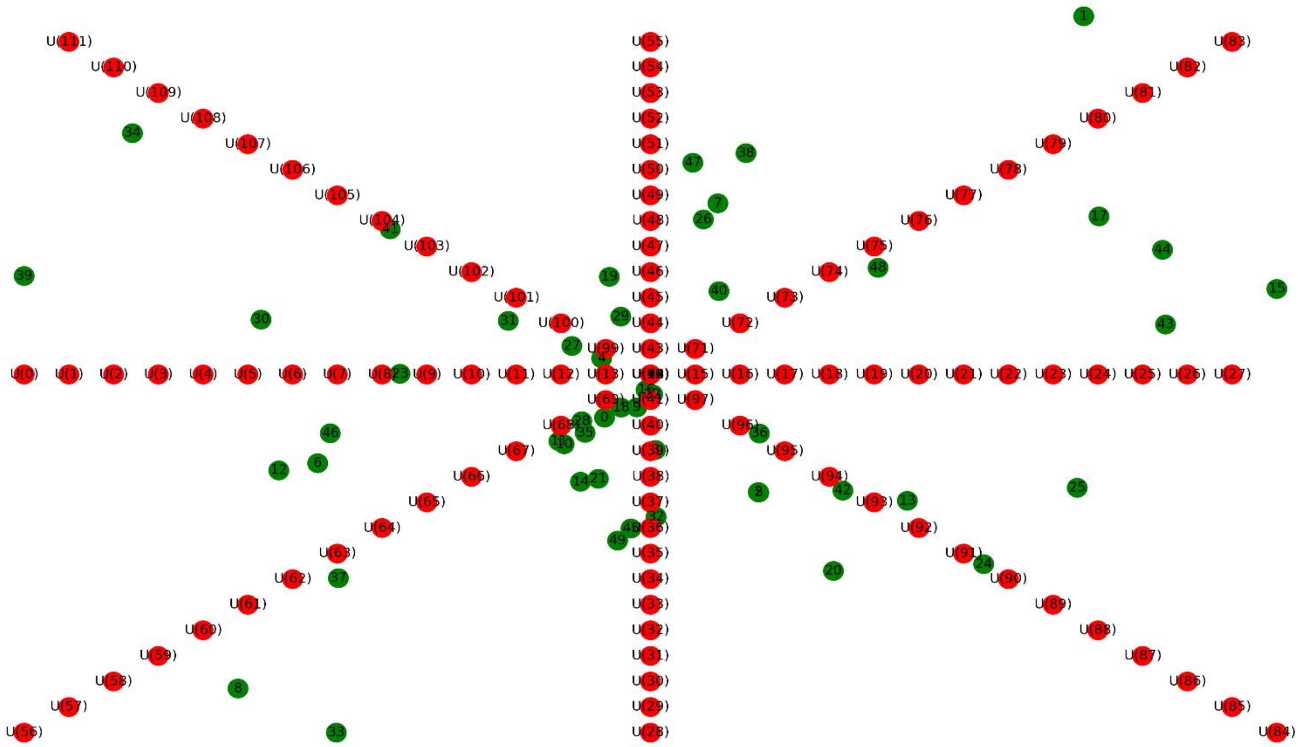
Another interesting approach is presented by Zheng Whang and Juih-Biing Sheu. They used a Branch and bound method to find the optimal tour. They introduced such a model where all the initial paths will be considered via a pricing algorithm. Generally, the algorithm has three steps. The first step is to solve the relaxation problem for the given problem. In the second step solve the pricing problem. In this step negative costs are generated for every column. If the given solution is stable and the funded any suitable solution go return to the first step otherwise go to the third step. In the third step it will be decided whether other steps are needed. If the solutions are an integer, then mark it un give the value return. If the solution is not an integer, then we need to use the branch and bound algorithm to solve the problem, and all the possibilities took into account. The pricing methods depend on the cost saving and lower costs. (Zheng W., Juih-Biing S., 2019)

6. Memory based solution algorithm

In this section the own algorithm will be presented. Basically, the algorithm solves the drone-truck and drone-subway model with a memory-based algorithm. In the first half of the section the general model with the assumption presented. After the general model the most important variables and calculation methods are highlighted such as the power consumption models, lower truck limits and the objective function.

6.1 General Model Deskription

Consider a last mile parcel delivery problem with one depot and **n (i=1,….,n)** different customers. The delivery company owns **t** identical truck and **m (j=1,….,m)** homogenous UAVs. The Problem could be modeled as a graph **G= (V, E).** In this Problem v_0 represents the starting depot and $\mathbf{v_1, ..., v_n}$ represents the customers. Let $\mathbf{t(e) = t(v_i,v_j)}$ and Let $\mathbf{t^d(e) = t(v_i,v_j)}$ be the traveling times between the customer ***i*** and customer ***j***. The delivery company wants to serve all the customers at minimalist costs, therefore synchronization between the drones and the trucks is needed. The synchronization anticipates, the drones and the trucks could deliver to the customers at the same time. On the other hand, in this model it is allowed that the drone use public transportation (subway). Because of the limited drone flying range the trucks could carry the drones to the given position and launch the UAV's and after the delivery the drones need to be returned to the truck or to the subway or to the end node (depot or distribution center). Also, allowable the single drone operations. It means the drones could, without the truck, deliver the packages to the customers from the depot or with public transportation. Important is, that the of the delivery process, the drones and the trucks need to return to the depot or distribution center. The single drone operations need to consider the limited battery capacity or the flying range; the return trip needs to be included in the model also. This model does not consider the recharging time in the truck. There will be assumed that the delivery truck has enough batteries to change the proposal. The change time will not be considered because the time is too slow and does not have any influence on the objective function. On the other hand, by the subway trip the recharging time included. During the subway trip we have the possibility to recharge the batteries or change them. Unfortunately, the UAVs could not lift all the packages, they have a maximal lifting weight. From this reason is necessary the synchronization between the different transportation methods. The trucks deliver heavy packages to the customers and the easier packages the UAVs. This indicates that the problem is a two-level problem. Firstly, trucks need to be assigned to the right sequence of customers and need to find an optimal problem and secondly need to find an optimal schedule for the drones. The schedule needs to be included in the synchronized and single operations also. The optimal schedule is an essential part of the problem because the UAVs could return to the truck in the same position (launch node) or rendezvous with the truck at another node. In the case of the single drone operations, the drones could return to the truck or to the depot. This is possible because of the autonomous flying system at the drones. But the autonomous flying system indicates another problem, unfortunately in all cities non-flying zones are included, where the usage of the drones is not allowed. These zones need to be considered at the scheduling and the at the optimal tour. By the scheduling part it is important to consider the rendezvous points. Because it allowed the drone to return to the launch point or return at other point to the trip which could include subway stations also. All points are suitable for returning if this is a customer, subway, or depot node. It is not possible that the drones in other point rendezvous with the truck. There needs to be considered that it is possible to launch the drone from the depot node and rendezvous at other customer node, but in this the truck starting from the depot with one or more drone less. This is because the truck has a limited capacity for transportable drones. Figure 32 represents the general model



situation. In the above Figure 33 the green points represent the customers where the node 0

Figure 32: General Model

is the depot or the distribution center and red points are the subway stations. The subway stations are unique for every distance which depends on the customer coordinates, important is that the subway station evenly distributed in the instance. The exact description from the subway station generation will be described in a later section. It is important that the model includes multiple customers with multiple subway stations, multiple trucks, and multiple drones. All of the customers need to stratify at the end of the delivery process either via truck or via drones. The model also does not contain such nodes where the delivery is not possible. Customer demand will be satisfied via truck or via unmanned aircraft. Figure 31 represents a possible solution part from the problem where truck - drone and subway - drone also included. The blue routes are the truck tours; the purple routes represent the drone tours with truck synchronized and the yellow routes also represent the drone tours just with subway synchronized

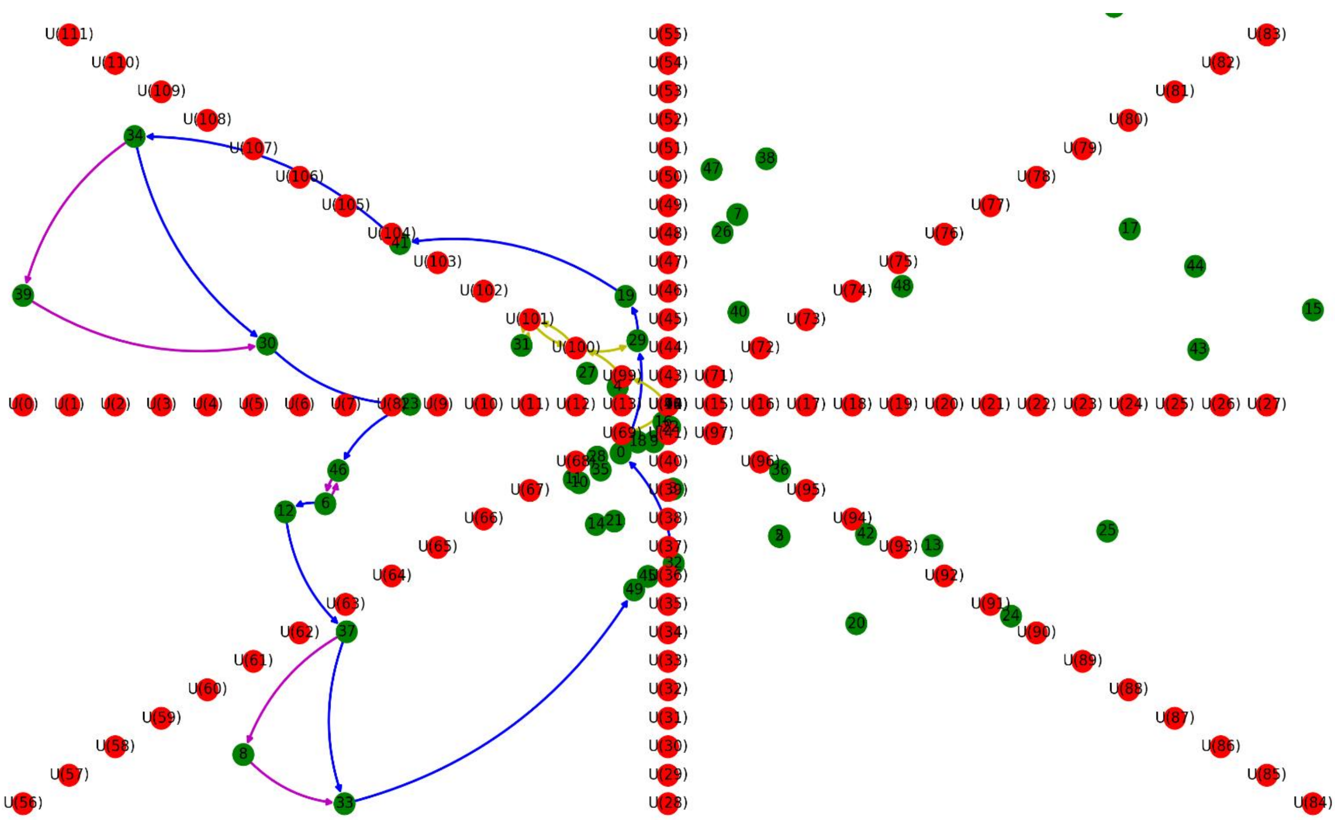


Figure 33: Solution after the Algorithm

The above-mentioned solution shows the different tours. For example, the truck and subway synchronization. The drone launched from node 34 and serves the customer 39 and rendezvous with the truck at node 30. In other case the drone launched at node 46 and served the node 6 and returned to the original launch node 46, which in this case the rendezvous node also. This is an example for the desynchronized case because the launch and return node the same is. The last example showed that the drone launched from node 0 (depot or distribution center) takes the first subway station and travels to the subway station U101 and flies to customer 29 and serves them. In this case the served customer is also the rendezvous node. After returning to the truck the drone will be traveling by truck and will be suitable for the later launch.

6.2 Model formulation

The objective of this hybrid delivery system is to **minimize the total cost** (or time, or energy) of delivering goods from a depot to a set of customers. Deliveries can be made via:

- **Trucks**, which follow a sequence of customer stops,
- **Drones**, which serve a customer by flying from a **take-off node** to a **customer node** and back to a **return node**, or
- **Subways**, used as transport links between launch and retrieval points for drones in large cities.

Every customer must be visited **exactly once**, and delivery choices are subject to real-world constraints:

- **Truck capacity** cannot be exceeded.
- **Drones have limited range and battery** life.
- Certain zones are **restricted for drones (no-fly zones)**.
- Subways can only be used between known **station segments**.
- Drone trips must start and end in physically **reachable locations**—truck stops, depots, or subway segments.

This model allows the system to choose the **best mode of delivery** for each customer while respecting all operational rules. The result is a **cost-efficient, feasible, and multimodal delivery plan**.

- **Objective function:** find the minimum cost combinations from truck and drones
- **Constrains:**
    - Maximal truck capacity
    - Maximal truck driving speed
    - Maximal truck load capacity
    - Maximal number of drones carried via truck
    - Maximal number of carried drones via subway
    - Maximal drone's battery capacity
    - Maximal drone's lifting capacity
    - Maximal drone's flying range

- Maximal drone’s flying speed
- Maximal drone’s hovering/waiting time
- Maximal number of drones
- Maximal drone waiting times (Hovering)
- Maximal number of customers served via drones
- No flying Zones

- **Assumptions:**

✓ The drones could deliver just one parcel at the same time

✓ The customers take the delivery in all cases

✓ The truck capacity is after the package’s weight added

✓ The drone’s weights, all system elements added to the truck capacity

✓ The truck could deliver a maximum of three drones at the same time

✓ Return flights are allowed at the same or by other customers served via truck

✓ The drones fly completely autonomous between the customers and the truck

✓ The drones are flying completely autonomous between the customer and the subway

✓ The drones are flying completely autonomous between the depot and the subway

✓ The drones are flying completely autonomous between the truck and the subway

✓ The drones are flying completely autonomous between the truck and the depot

✓ The drones are flying completely autonomous between the customer and the depot

✓ The weather conditions are not included in the battery capacity and flying range

✓ The drone’s battery could charge or replaced during the ride with the truck and subway

✓ There are in all cases full batteries during the trip

✓ The drones allowed the subway during the return trip to the truck

✓ The subways operate after a given time schedule

✓ No flying zones

✓ Not all subway stops are suitable for the drones

✓ Drones have a higher-flying speed than the truck.

✓ No Flying Zones added (Range as radius)

6.3 Calculations and Methods

In this section the basic calculations and methods will be presented which are used for the algorithm

6.3.1 Lower Truck limit

The lower truck limit is a control variable in the assignment cases. This is needed because it could be that during the solution all customers are assigned to a drone tour. This control mechanism prevents this case and assigns a minimum number of trucks delivered customers to the solution. (R. Raj, C. Murray, 2020)

The calculation and the formula introduced by **R. Raj, C. Murray,2020**:

$$LTL_0 = \left\lceil \frac{|C| - |V|}{|V| + 1} \right\rceil$$

In this formula ***C*** denotes the number of customers in the sequence and ***V*** the number of drones used for the sequence. Consider the case where 8 customers are in the sequence and 2 drones used for the delivery process. After the calculation the lower truck limit gives the minimal number for truck nodes which in this case is 2. This indicates that a minimum of two customers need to serve by truck to have sufficient recovery points for the drones. (R. Raj, C. Murray, 2020)

6.3.2 Non-Flying Zone

In the master thesis, also, nonflying zones included. Today it is very important to consider these zones because of safety issues in all cities such zones are given. If the customer located in such a zone, then it is not possible to deliver the packages via drones. If such a zone is included in the drone route, then the drone needs to make a rotation maneuver which causes a longer trip and influence the flying range. To calculate the extra distances the calculation method by H.Y. Jeong, et al., 2019 used. The Figure 34 represents the calculation idea.

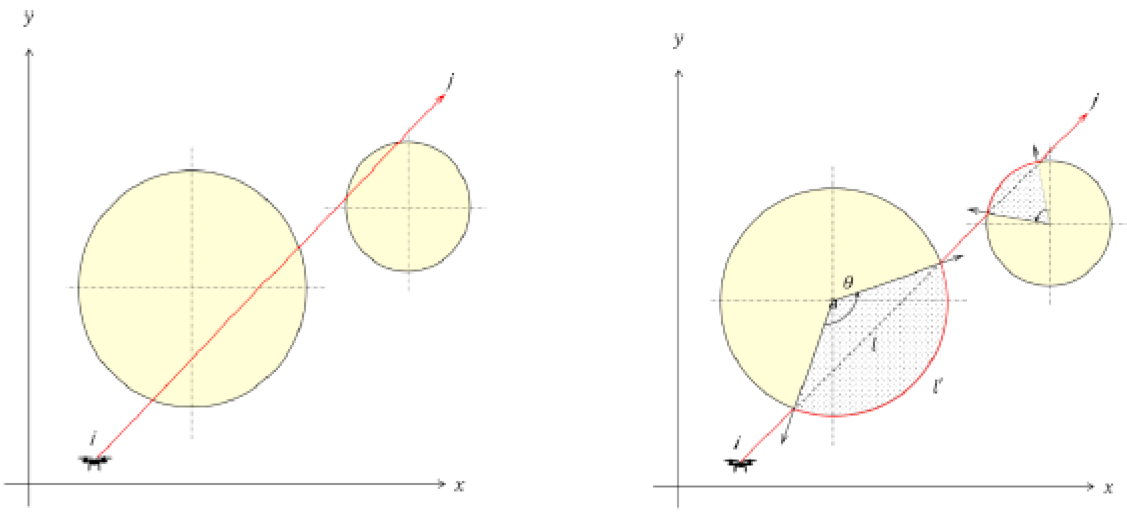


Figure 34: Calculate extra Route from Non-Flying Zone (H.Y.Jeong, et al. 2019)

The calculation methods after **H.Y. Jeong, et al., 2019** is the following:

- $d_{i,j,h}$ -> extra distance caused by the rotation
- h -> nonflying zone ID
- i -> launching node
- j -> next node
- r_h -> radius nonflying node
- l -> Euclidean distance between the two nodes
- l' -> Length of the detour
- θ -> Central angle of the detour

$$d_{i,j,h} = l' - l = \left(\frac{2\pi r_n}{360} min(\theta_{i,j,h}, 360 - \theta_{i,j,h}) - l\right)$$

Basically, the extra distance is the difference between the Euclidean distance between the two nodes and the length of the detour. This distance will be unique for every instance and will be calculated every time if the drone needs to fly near nonflying zones and added as extra distance to the energy consumption calculation.

6.3.3 Power Consumption model

To calculate the flying range the power consumption model from Liu, et al.,2017 used. This calculation is a nonlinear model calculating the endurance after the package weight. Generally, in such cases different flying phases are considered. The Figure 35 represents this idea.

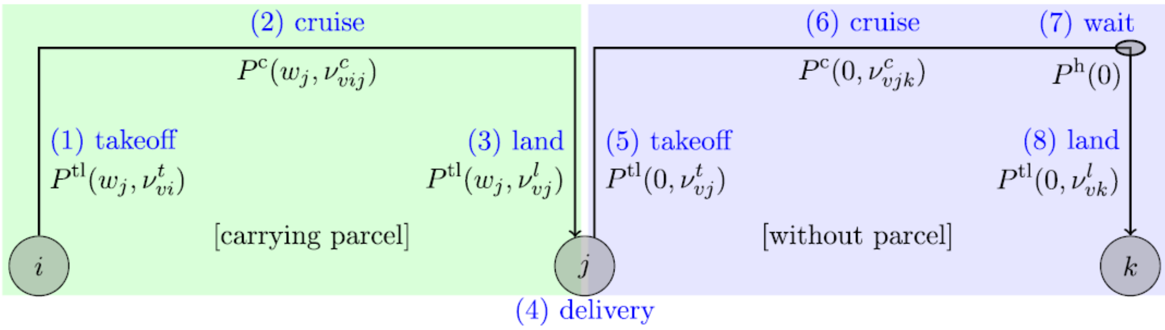


Figure 35: Power Consumption Model (Liu, et al. 2017)

By the launch need to be considered the takeoff power consumption. During the flight, the cruise power consumption. If the drone reaches the customer's destination, it needs to be land which also causes extra consumption. If after delivery the drones need to return to the truck or to other rendezvous points which indicates again takeoff and cruise power consumptions. Of course, it could be that the drones need to be wait for the truck and their extra power consumption needs to be considered for the waiting time. If the truck arrives at the rendezvous location, then the drones need to be docking which causes landing power consumption. (R. Raj, C. Murray 2020) In the subway cases the same logic used only the takeoff, landing operation will be included multiple times. If the drone arrives at subway station arrives then it needs to be waited for the subway and needs to be landing. If the subway arrives at the launch subway station, then it needs to be taken off from the subway. This is the simplest case, on the other hand if the drones return via subway the first part need be once again added.

The calculations for the different operations after **Liu, et al.,2017** are the following:

- P^{tl} -> power consumption for landing and takeoff operations
- P^c -> power consumption for cruising operation
- P^h -> power consumption for waiting operation
- W -> drone frame weight
- w -> package weight
- g -> gravitation constant
- α -> forward tilt
- V_{vert} -> vertical speed of drones
- V_{air} -> cruising speed of the drones

Coefficient	Value
k_1	0.8554 [Unitless]
k_2	0.3051 $\sqrt{\mathrm{kg/m}}$
c_1	2.8037 $\sqrt{\mathrm{m/kg}}$
c_2	0.3177 $\sqrt{\mathrm{m/kg}}$
c_4	0.0296 kg/m
c_5	0.0279 Ns/m

$$P^{tl}(w,V_{vert}) = k_1(W+w)g\left[\frac{V_{vert}}{2}+\sqrt{\left(\frac{V_{vert}}{2}\right)^2+\frac{(W+w)g}{k_2^2}}\right]+c_2\big((W+w)g\big)^{3/2}$$

$$P^{c}(w,V_{air}) = (c_1+c_2)\left[\big((W+w)g-c_5(V_{air}cos\alpha)^2\big)^2+(c_4V_{air}^2)^2\right]^{3/4}+c_4V_{air}^3$$

$$P^{h}(w) = (c_1+c_2)\big((W+w)g\big)^{3/2}$$

After the calculation of the power consumption by different drone operations it is needed to calculate the minimum energy which is required to deliver the package to the customer. The calculation method after Liu et als,2017 is the following:

$$E_{vijk}^{min} = \tau_{vi}^{\prime t}P^{tl}\big(w_j,v_v^t\big)+\tau_{vij}^{\prime c}P^{c}\big(w_j,v_v^c\big)+\tau_{vj}^{\prime l}P^{tl}\big(w_j,v_v^l\big)+\tau_{vj}^{\prime t}P^{tl}(0,v_v^t)+\tau_{vik}^{\prime c}P^{c}(0,v_v^c) \\ +\tau_{vk}^{\prime l}P^{tl}(0,v_v^l)$$

If the drone battery capacity is enough for the trip ($E_{vijk}^{min} \leq E_v^{avail}$) then could calculate the drone endurance in second. The endurance also included the waiting time for the truck. (Liu et al., 2017). The calculations of the given endurance after Liu, et al., 2017 is the following:

$$e_{vijk} = T_{vijk}^{min}+\frac{E_v^{avail}-E_{vijk}^{min}}{P^h(0)}$$

6.4 System Overview and Solution Algorithm

This conceptual framework presents a modular, heuristic-based optimization system for urban last-mile logistics involving the coordinated use of trucks, drones, and subway infrastructure. It synthesizes established routing techniques with novel multi-modal enhancements, enabling scalable, constraint-compliant route construction in complex urban environments. The framework is grounded in Clarke and Wright's savings methodology, extended with real-time memory creation, constraint filtering, and multimodal route evaluation.

The hybrid delivery system is built from five algorithmic modules:

Module	Function
Clarke & Wright	Initializes feasible truck routes via savings-based heuristics
Memory Creation	Identifies and stores viable drone (and subway) triplets
Solution Algorithm	Inserts optimal drone triplets into truck plans based on cost comparison
Improve Algorithm	Locally refines truck/drone allocation to improve cost or time
Main Coordination	Orchestrates overall instance processing with constraint variability

Each module communicates through data containers: customer sequences, solution fragments, memory stores, and constraint markers.

a. Clarke and Wright Module

This module generates initial tours by:

- Assigning each customer to an individual truck route.
- Merging customer pairs that maximize Clarke-Wright savings (Clarke & Wright, 1964).
- Producing feasible, capacity-respecting truck routes that serve as a baseline for hybridization.

b. Memory Creation and Constraint Modeling

Memory Creation scans all potential (take-off, served, returned) drone triplets from truck routes. It applies spatial and operational filters:

- No prior usage (used-node container).
- Exclusion of non-flying and warning zones.

- Node distinctness and depot rules.

If viable, the triplet is recorded along with:

- Estimated travel time.
- Subway access alternatives.
- Multimodal delivery options (e.g., subway-drone, truck-subway-drone).

This step builds a **feasibility-aware memory** that feeds into the solution algorithm.

c. Solution and Improvement Integration

The solution algorithm:

- Evaluates drone alternatives against the truck baseline.
- Prioritäres better-performing triplets.
- Ensures no conflicts through tabu lists and capacity checks.
- Inserts high-value drone deliveries, refining the overall tour structure.

The improvement heuristic re-evaluates customer assignments:

- Attempts reassignment from truck to drone if it improves total savings.
- Use local search logic while respecting capacity and no-fly rules.

Together, these modules form the **optimization core** of the system.

d. Constraint-Aware Coordination

The main algorithm:

- Iterates across multiple Clarke and Wright outputs.
- Varies drone types, no-fly zones, and subway layouts.
- Executes memory creation and solution generation for each variation.

The algorithm ensures **robustness** under changing conditions and supports scalability through modular independence.

e. Advantages and Applikation

- **Scalability**: Quadratic time complexity enables real-time routing for city-wide systems.
- **Adaptability**: Handles dynamic customer sets, regulation zones, and vehicle constraints.

- **Multimodal Intelligence**: Incorporates subway infrastructure as an urban speed enhancer.
- **Operational Safety**: Uses structured constraint enforcement (tabu zones, battery checks).

Applikable Domains include:

- Smart city delivery planning.
- Emergency and humanitarian logistics.
- Multi-vehicle, multi-mode route design

6.5 Pseudo Codes

This document synthesizes the core functionalities and interactions of a multi-layered hybrid delivery framework that integrates trucks, drones, and subway systems. The structure is built upon sequential algorithmic components: the Clarke and Wright Savings Algorithm, memory creation, drone-subway hybrid evaluation, improvement heuristics, and an overarching coordination module. The system is designed to optimize last-mile delivery by leveraging the speed of drones, the capacity of trucks, and the spatial coverage of subway infrastructure while respecting real-world constraints such as non-flying zones, battery limits, and customer service rules.

6.5.1 Main drone-truck and drone-subway delivery Algorithm

```
show the algortihm home screen
    for all Instances do
        read the coordinates from external files
        for all customers to generate the demand and service time
        generate the subway stations for the given Instance
        generate the eight segments for the subway stations
        write the coordinates in python form
        for all customer-customer and customer-subway stations calculate the
          euclidean distances
        while the number of non-flying zones is less than the defined maximum
number
          of non-flying zones do
            for all drone type do
                calculating the savings for the given Instance
                initialize single tours for the Clarke and Wright Saving Algortihm
                calculate the Clarke and Wright Saving Algorithm for the given
                Instance
```

make a copy of the Clarke and Wright Algortihm for later solution comparison
calculate the Travel Times between customer-customer and customer-subway
create the Memory segments for the given Instance
use the Solution Algorithm to solve the problem
calculating the solutions' objective value and compare with the Clarke and Wright solution
write the finale solution in python form
write the finale solution in a external file
clear the solution containers to secure the next solution´s correctness
end for
end while
end for
end Main drone-truck and drone-subway delivery Algorithm

6.5.1.1 Explanation of Code

The provided pseudocode outlines a comprehensive framework for solving a hybrid delivery problem involving trucks, drones, and subway systems. This problem is particularly relevant in modern urban logistics where the integration of multiple transportation modes can lead to significant improvements in delivery efficiency, cost, and sustainability.

i. Overview of the Algorithm

The algorithm begins by presenting a home screen interface, likely for user interaction or visualization. It then iteratively processes a set of predefined instances. Each instance represents a unique delivery scenario with different geographical and logistical parameters.

ii. Input Data Preparation

For each instance, the algorithm performs several preparatory steps:

- **Coordinate Reading:** The geographical coordinates for customers and other relevant points (e.g., depots) are read from external files. This enables flexibility and scalability for different test cases.
- **Customer Data Generation:** Demand and service times are generated for each customer, representing how much needs to be delivered and how long the delivery will take, respectively.
- **Subway Infrastructure Setup:** Subway stations are generated along with their corresponding segmentation, possibly to reflect different zones or accessibility regions within the subway network.
- **Data Conversion:** Coordinates are converted into a Python-readable format, suggesting the algorithm is implemented in Python.

- **Distance Calculation:** Euclidean distances between all customer pairs and between customers and subway stations are computed. These distances are fundamental for route optimization.

iii. Handling Non-Flying Zones

The algorithm introduces a loop that iterates until a predefined number of no-fly zones are generated. These zones represent areas where drones are not permitted to fly, such as airports, sensitive government areas, or regions with dense air traffic. Each iteration within this loop allows the simulation of more complex and realistic environments.

iv. Multi-Modal Optimization with Clarke and Wright Savings

Within the non-flying zone loop, the algorithm considers multiple drone types. For each drone type:

- **Savings Calculation:** It computes the potential cost savings for the current instance, a critical step in the Clarke and Wright Savings Algorithm, which is a classical heuristic for the Vehicle Routing Problem (VRP).
- **Tour Initialization:** Single customer routes are initialized to begin the Clarke and Wright heuristic.
- **Heuristic Execution:** The Clarke and Wright algorithm is executed to create a preliminary solution based on savings. This heuristic merges routes iteratively if the merger leads to cost savings.
- **Solution Backup:** The heuristic's result is saved for future comparison.
- **Travel Time Calculation:** Travel times (which might differ from Euclidean distances due to traffic or mode-specific speed constraints) are computed for all relevant pairs.
- **Memory Segment Creation:** This step may refer to defining partitions of the instance for parallel processing or memory management.
- **Solution Algorithm Execution:** A more advanced or exact optimization algorithm is applied to find a potentially better solution. This algorithm might consider multiple constraints such as time windows, vehicle capacity, or synchronization between modes.
- **Solution Evaluation:** The final solution's objective value (e.g., total cost, time, or a composite metric) is compared with the heuristic result from Clarke and Wright.
- **Output Storage:** The final solution is formatted in Python syntax and saved to an external file for documentation, visualization, or further analysis.
- **Container Clearing:** Data structures used for storing intermediate solutions are cleared to ensure independence between successive iterations.

v. Scientific Relevance

This algorithm represents a hybrid approach to urban logistics planning. By combining heuristic and exact methods, it balances computational efficiency and solution quality. The inclusion of subway infrastructure introduces an additional dimension of realism and complexity, reflecting the multimodal nature of real-world logistics systems.

The Clarke and Wright Savings Algorithm, while simple and fast, often produces suboptimal solutions for complex constraints. Hence, the algorithm enhances it with a more robust solver, possibly based on metaheuristics or mathematical programming, to refine the route plans.

Incorporating no-fly zones and different drone types reflects real operational constraints and technological diversity. The repeated loop structure over these parameters suggests an experimental framework for testing various scenarios and configurations, which is vital for academic benchmarking and practical deployment planning.

6.5.1.2 Runtime and Complexity Analysis of the Main Code

I. Overview of the Main Algorithm Structure

The main pseudocode orchestrates a hybrid delivery system involving:

- Trucks operating on a classical road network,
- Drones that may take off from or return to truck positions or predefined drone hubs,
- Subway lines used as fixed infrastructure for rapid inter-city drone transport.

It builds delivery solutions by iteratively analyzing drone-launch opportunities and comparing them with truck-only solutions. Two main modules handle **Truck + Drone** and **Drone + Subway + Drone** combinations.

II. Key Parameters for Complexity

We define the following:

- n: Number of customer nodes
- d: Number of potential drone launch positions (from trucks or subway stations)
- s: Number of subway connections or transfer pairs
- r: Number of reachable return nodes per launch
- c: Number of Clarke and Wright base routes
- b: Number of battery-constrained evaluations
- z: Number of non-flying zones (tabu nodes)

III. Main Loop and Structural Breakdown

The algorithm proceeds in two major phases:

Phase 1: Truck-Drone Combination Search

a) Outer loop over Clarke and Wright solutions

O(c)

Each truck route is evaluated for drone augmentation opportunities.

b) Loop over candidate take-off points

For each solution, the algorithm examines drone take-off nodes (from trucks).

O(d)

c) Loop over reachable return nodes

For each take-off, return positions are evaluated (within battery range).

O(r)

d) Objective function evaluations

For each take-off/return/customer triplet:

- Truck delivery cost: *O(1)*
- Drone delivery cost: *O(1)*
- Constraints checked: *O(1)*

So, nested runtime for this phase:

O(c·d·r)

If *r∼nr \sim nr∼n (worst case),* this phase is:

O(c·d·n)

Phase 2: Drone + Subway + Drone Optimization

a) Loop over subway transfer points

All subway pairs are considered.

O(s)O(s)O(s)

b) For each subway path:

- Drone flight to first station: *O(1)*

- Subway travel (constant time if precomputed): *O(1)*
- Drone delivery from second station: *O(1)*

Each combination is checked against:

- Battery constraints
- Total time/distance thresholds
- Comparison with existing best route

Assuming the algorithm checks each subway transfer against n customers:

$O(s \cdot n)$

Tabu List and Constraint Enforcement

Throughout, the algorithm manages lists of:

- **Tabu zones**: $O(z)$
- **Previously used take-off/return nodes**: $O(d)$

Each check is performed in $O(1)$ or $O(z)$ depending on implementation (e.g., using hash sets or lists).

IV. Overall Time Complexity

Combining the main phases:

Truck + Drone Phase:

$O(c \cdot d \cdot n)$

Drone + Subway + Drone Phase:

$O(s \cdot n)$

Total worst-case complexity:

$O(c \cdot d \cdot n+s \cdot n+z)$

Assuming $c \sim nc$ and $d \sim nd$, and moderate subway structure ($s \ll n\text{^}2s$):

O(n3) (in worst-case scenarios)

V. Space Complexity

Main memory requirements include:

- Clarke and Wright solutions: $O(c \cdot n)$
- Drone candidate solution list: $O(d \cdot r)$

- Subway connection graph: *O(s)*
- Tabu and used-node containers: *O(z+d)*
- Final hybrid route structure: *O(n)*

Overall space usage:

$O(c \cdot n+d \cdot n+s+z)$

VI. Conclusion

The main hybrid delivery algorithm exhibits polynomial time complexity with cubic behavior in the worst case. However, with real-world constraints (battery, reliability, geography), the average-case performance is much lower. Space requirements are moderate and manageable for urban-scale logistics networks. The structure is amenable to optimization via heuristics, parallelism, and domain-specific constraints.

6.5.2 Solution Algorithm

for all Clarke and Wright solution do

claculate the truck lower limit for the given sequence

for all memory fragments do

calculate the truck objective function for the given take off node, served customer and return node triplet

if there are possible insertion between the memory fragments then

calculating objective function with drone delivery between the take-off nodes

and retour node

if the objective function with drone delivery is lower as the objective function with truck delivery
and objective function with drone delivery is better
as the last marked solution
and drone has battery capacity to wait for the truck then

mark the solution

end if

end if

insert the possible solution

end for

sort the possible solutions after the objective values

for all non-flying zone nodes do

insert non-flying zone nodes into the tabu container
insert non-flying zone nodes into the used take of nodes container

end for

for all possible solution do

if the inserted drone delivery is lower as the lower truck limit, then

for all tabu nodes do

if the customer is in the tabu node then

mark the node as tabu

end if

end for

for all used take off nodes do

if the customer is in the take-off nodes, then

mark the node as used node

end if

end for

if the customer is not marked as tabu or/and used node then

insert the customer into the drone the final sulotion
insert the customer into the served nodes
insert the customer into the tabu nodes

end if

if the take-off node is the depot, then

use the improve algorithm

end if

end if

end for

insert the truck solution into the truck final solution

end for

end Solution Algorithm

6.5.2.1 Explanation of Code

The presented pseudocode outlines a comprehensive algorithm designed to enhance traditional vehicle routing by incorporating drones into the delivery process. Specifically, it aims to exploit the efficiency gains of drone deployment alongside conventional truck deliveries, under a set of logical and spatial constraints such as battery limitations and non-flying zones. The algorithm integrates elements of heuristic optimization, memory-based learning, and constraint checking to derive high-quality hybrid delivery routes.

This analysis provides a step-by-step breakdown of the algorithm's logic, focusing on its core decision points, structural organization, and potential operational benefits.

a. Clarke and Wright Solutions as the Foundation

The algorithm begins by iterating over a series of initial solutions generated using the Clarke and Wright Savings Algorithm, a well-established heuristic method for solving the Capacitated Vehicle Routing Problem (CVRP). These solutions serve as the baseline truck delivery sequences without drone support.

For each of these solutions, the algorithm calculates a **truck lower limit**, which represents the minimal cost (e.g., time, distance, fuel consumption) to deliver goods using trucks alone. This metric is essential for comparative evaluation when drone interventions are later proposed.

b. Memory Fragments and Candidate Evaluation

The next core component involves the iteration over **memory fragments**, which likely represent previously evaluated subroutes or segments with potential for optimization. For each of these, the algorithm calculates:

- **Truck-based objective function**: Evaluates the cost of servicing a customer solely by truck.
- **Drone-enhanced objective function**: Assesses the cost when a drone is used to serve the customer, specifically flying from a *take-off node*, visiting the *served customer*, and returning to a *return node*.

If an insertion is feasible between memory fragments, meaning a drone delivery can logically and spatially be inserted—the algorithm evaluates whether this drone-assisted route is superior to the truck-only route.

c. Conditional Marking of Superior Drone Solutions

Upon evaluating a candidate drone route, several conditions must be met for the algorithm to "mark" it as a promising solution:

- The **drone objective function** must be lower than the **truck objective function**.
- It must also improve upon the last marked drone solution.
- The drone must have **sufficient battery** to wait for the truck (presumably for coordination or return logistics).

If all these conditions are satisfied, the algorithm marks this solution for potential insertion.

d. Insertion and Sorting of Candidate Solutions

After evaluating possible drone insertions, the algorithm:

- Inserts the viable candidates into a solution pool.
- Sorts this pool based on the objective values (i.e., lowest cost/distance/time first), preparing for prioritized evaluation in the final phase.

This step ensures that the best candidates are assessed first, improving the overall quality of the resulting hybrid route.

e. Handling Non-Flying Zones via Tabu Structures

To account for real-world constraints, such as restricted airspace, the algorithm introduces a **tabu mechanism**. Nodes that fall into **non-flying zones** are added to:

- A **tabu container**, which prevents drones from operating there.
- A **used take-off node container**, possibly indicating nodes already reserved or invalidated for drone take-offs.

This mechanism prevents the selection of infeasible drone deliveries and enforces operational constraints on the solution space.

f. Evaluation and Final Insertion of Drone Deliveries

Once the candidate solutions are prepared and filtered:

- Only those drone deliveries whose cost is **lower than the truck lower limit** are considered.
- The algorithm checks if the **customer node is marked as tabu** or is already a **used take-off node**.
- If not, the customer is inserted into:
    - The **final drone solution**.
    - The list of **served nodes**.
    - The **tabu node list**, preventing redundant reassignment.

This ensures that no customer is served more than once, and that spatial and operational constraints are maintained throughout the solution construction.

g. Application of Improvement Algorithms

If a drone takes off directly from a **depot**, the algorithm invokes an **improvement algorithm**. This is likely to refer to a local search or metaheuristic method (e.g., 2-opt, simulated annealing) to optimize the structure of the route further. This step is typically used to remove inefficiencies or fine-tune the final delivery path, especially when starting from a central depot allows for more flexible route planning.

d. Finalization of the Truck Route

In the last step of the outer loop, after drone-based optimizations are processed, the **truck-only solution** (with or without drone enhancements) is inserted into the **final truck solution set**.

This ensures that a complete, hybrid delivery plan is built iteratively, accounting for drone feasibility, efficiency gains, and operational constraints across all customer nodes and route segments.

h. Conclusion

The algorithm presents a highly structured and pragmatic approach to hybrid delivery optimization. It combines:

- **Heuristic initialization** (Clarke and Wright),
- **Memory-based evaluation** (fragments and candidate routes),
- **Conditional logic for drone insertion** (objective comparison, battery constraints),
- **Constraint enforcement** (tabu zones, non-redundancy),
- And **local improvement** techniques.

Such a layered design is not only extensible and adaptable but also suitable for integration into real-world urban logistics systems where drones must operate in tandem with traditional vehicles. Its capacity to balance multiple constraints while enhancing route efficiency makes a valuable contribution to smart delivery systems and last-mile logistics optimization.

8.2.2 Runtime Complexity Analysis

I. Notation and Parameters

To analyze the computational complexity, we define the following parameters:

- n: Number of customer nodes
- m: Number of Clarke and Wright initial solutions (typically $m <= n$)
- f: Number of memory fragments per solution (typically $f <= n$)
- p: Number of possible drone insertions per fragment (depends on spatial feasibility)
- z: Number of non-flying zone nodes (assumed $z \ll n$)
- k: Number of marked possible solutions (bounded by p)

II. Algorithm Structure and Nested Loops

Let’s break down the pseudocode by loop structure and internal operations:

a) Outer loop over Clarke and Wright solutions

Complexity: $O(m)$

This loop governs the full sequence. For each solution, the algorithm explores all drone insertions and updates.

b) Loop over memory fragments

Complexity: $O(f)$

Each memory fragment represents a potential route segment. For each, drone-truck combinations are evaluated.

c) Drone Insertion Evaluation

- For each fragment, potential drone deliveries are tested.
- Worst-case: drone insertions checked between every possible node triple.

Assuming ppp drone possibilities per fragment, this block runs in:

$O(f * p)$

Each evaluation includes:

- Truck vs. drone cost comparison: $O(1)$
- Drone feasibility (battery check): $O(1)$
- Marking and insertion into a list: $O(1)$

d) Sorting Candidate Solutions

After evaluating all possible drone insertions, solutions are sorted.

If k is the number of candidate solutions:

Complexity: $O(k \log k)$

Since $k \leq f \cdot p$, this dominates if p is large.

e) Processing Non-Flying Zones

For each of z non-flying nodes, constant-time operations are performed:

Complexity: $O(z)$

f) Loop over Possible Solutions

Each of the k solutions is revisited for:

- Tabu checking: $O(z)$ in worst case

- Used take-off node checking: $O(z)$
- Marking and insertions: $O(1)$

Overall complexity:

$O(k \cdot z)$

III. Worst-Case Time Complexity

Combining the main components:

- Outer loop: $O(m)$
- Inner logic: $O(f \cdot p + k \log k + k \cdot z)$
    - Note: $k \leq f \cdot p$

Thus, total time complexity is:

$O(m \cdot (f \cdot p + (f \cdot p) \log (f \cdot p) + (f \cdot p) \cdot z))$

Simplified:

$O(m \cdot f \cdot p \cdot (\log (f \cdot p) + z))$

This is **quasi-polynomial** in the number of customers and fragments. In practice, since mmm, f, and p are often significantly constrained by heuristic pruning and feasibility filters, the runtime is manageable for moderate n (up to several hundred nodes).

IV. Space Complexity

Memory requirements come primarily from:

- Storage of mmm initial solutions: $O(m \cdot n)$
- Candidate solution pool: $O(f \cdot p)$
- Tabu and used node lists: $O(z)$
- Final routes: $O(n)$

Hence, total space complexity is:

$O(m \cdot n + f \cdot p + z)$

VI. Conclusion

The algorithm, while layered and constraint-rich, exhibits a predictable structure suitable for optimization. Its complexity is dominated by the evaluation and sorting of drone delivery candidates. For large-scale routing problems, performance can be significantly improved by parallelism, memorization, and constraint-based pruning. Despite its high theoretical worst-case, practical efficiency is acceptable for medium-sized logistics networks with intelligent preprocessing.

6.5.3 Memory Creation

```
for all Clarke and Wright solution do
    for all customers in the solution sequence do // take off nodes
        for all customers in the sequence do    // served customer
            for all customers in used nodes do
                if served node funded between the used node then
                    mark as finds
                end if
            end for
            for all customers in non-flying zone do
                if take off or/and served customer funded between the non-flying
                zone nodes then
                    mark as non-flying node
                end if
            end for
            for all customers in non-flying zone do
                if non-flying zone´s radius is higher as distance between the two
                nodes then
                    mark as warning zone
                end if
            end for
            if there is enough capacity and node is not marked as find and node not
            marked as non-flying node and node not marked as warning zone
            and take off node is not the same
            as served customer and served customer is not the depot do
                for all customers in the sequence do // return node
                    for all customers in used nodes do
                        if served node funded between the used node then
                            mark as finds
                        end if
                    end for
                    for all customers in non-flying zone do
```

if take off or/and served customer finded between the non-flying zone nodes then

mark as non-flying node

end if

end for

for all customers in non-flying zone do

if non-flying zone´s radius is higher as distance between the two nodes then

mark as warning zone

end if

end for

if served customer node and return node is not the same and node is not marked as find and node not marked as non-flying node and node not marked as warning zone then

if take off node and return node is the same then

calculate the drone travel times in

desyncronised tour for the given take of

node, served customer and retur node triple

insert the possible solution
to the memory container

end if

if take of node and return node not the same then calculate the drone travel times in desyncronised tour for the given take-off node, served customer and retur node triple

insert the possible solution to the memory sequence

end if

for all subway segments do

find the four nearest segments for the given served customer node
mark the four nearest segments

end for

for all marked nearest segment do

calculating the drone travel times in just subway used tour for the given problem

insert the possible solution to the memory container

calculate the travel times in combined subway and truck tour for the given problem

insert the possible solution to the memory container

end for

end if

end for

end if

end for

end for

end for

end Memory creation

6.5.3.1 Explanation of Code

In the context of modern urban logistics, the integration of drones with traditional transport modes—such as trucks and subways—presents a promising approach to optimize last-mile delivery. The "Memory Creation" algorithm is a preparatory phase designed to precompute feasible drone delivery options based on existing Clarke and Wright truck-based solutions. Its primary objective is to explore and store possible drone dispatch scenarios in memory, where each scenario represents a triple consisting of a take-off node, a served customer node, and a return node.

This memory structure becomes a critical component in subsequent optimization steps by enabling rapid access to pre-validated drone options. It also ensures that all drone dispatches adhere to strict operational constraints, such as non-flying zones, no-overlap with already served customers, and capacity limits.

a. Core Logic and Structure

The algorithm begins by iterating through all available Clarke and Wright solutions. These are classical truck-based delivery routes generated using a savings-based heuristic that serves as a baseline for further improvement. For each customer in the solution sequence, the algorithm considers the node as a potential drone take-off point.

Next, it evaluates all other customer nodes as potentially served points for drone dispatch. During this phase, the algorithm performs multiple constraint checks. First, it verifies whether the candidate served node is already used in previous drone assignments. If so, it is skipped. Then, it checks whether either the take-off or served customer lies within a non-flying zone. These zones are geographical regions where drone operation is restricted or prohibited. Additionally, the algorithm considers warning zones, where the drone may pass near restricted areas but not directly over them.

Only if the triplet of take-off and served node passes all these constraints, and the drone has sufficient capacity, does the algorithm proceed to the next stage—evaluating return nodes.

b. Evaluating Return Nodes and Inserting Valid Triplets

For each validated take-off and served pair, the algorithm examines all other customers in the route sequence as potential return nodes. The same filtering logic is applied: it checks whether the node has already been used, whether it lies in restricted areas, and whether it meets the necessary conditions for a feasible triplet.

A valid triplet must satisfy the following core conditions:

1. The take-off, served, and return nodes must be distinct.
2. The served customer must not be in the depot.
3. None of the nodes can be marked as used or restricted.
4. There must be sufficient drone capacity for the full trip.

If these conditions are satisfied, the algorithm then classifies the triplet based on the symmetry of its structure. If the take-off and return node are the same, the triplet is considered a synchronized drone delivery and is stored in a general memory container. If they differ, the delivery is considered desynchronized, meaning the drone is picked up at a different location than it was launched from. This kind of delivery is stored in a different memory sequence to reflect its increased complexity and alternative scheduling requirements.

c. Integration of Subway Infrastructure

A notable feature of the algorithm is its integration of subway segments as part of the drone's logistical network. For each valid drone triplet, the algorithm identifies the four nearest subway segments to the served customer. These segments are selected using proximity heuristics, and then each segment is assessed for two additional delivery modes:

i. **Subway-Only Drone Delivery**: In this case, the drone is assumed to be launched from and returned to locations near subway stops, effectively replacing part of the truck journey with an underground segment.

ii. **Combined Truck-Subway Drone Delivery:** This hybrid form assumes that the drone interacts with both the truck and the subway infrastructure, either for launch or retrieval.

Both types of solutions are calculated and inserted into the memory container. This approach adds valuable multimodal flexibility to the delivery system, enabling better handling of dense urban environments where trucks may face road congestion or access limitations.

d. Operational Benefits and Purpose

The purpose of the “Memory Creation” algorithm is twofold. First, it pre-filters and stores only feasible drone delivery options, ensuring that later optimization phases can operate with ready-to-use inputs. This prevents expensive feasibility checks during real-time operations. Second, it builds a comprehensive repository of delivery triplets that can include synchronized, desynchronized, and multimodal delivery paths.

This modular and constraint-respecting approach offers several key benefits:

- It supports highly adaptive delivery planning, as various drone paths are already evaluated and stored.
- It respects complex real-world airspace and infrastructure constraints, reducing the risk of infeasible plans.
- It enables future algorithms to dynamically compare and select optimal drone deliveries without recomputing from scratch.

The algorithm also ensures that once a customer has been included in a drone delivery, it will not be reused in other triplets, thereby avoiding duplication and respecting delivery exclusivity.

e. Conclusion

The “Memory Creation” algorithm serves as a foundational component of a hybrid drone-truck-subway delivery framework. Its careful orchestration of constraint filtering, spatial analysis, and mode-aware memory construction enables a rich, precomputed set of feasible drone routes. These routes accommodate a variety of delivery strategies, including traditional direct drone flights, desynchronized operations, and integrated subway connections.

By building this memory structure in advance, the algorithm empowers the broader delivery system to achieve rapid, intelligent, and constraint-compliant logistics decisions. Its structured approach ensures operational feasibility while maximizing delivery flexibility across complex urban terrains.

6.5.3.2 Runtime and Complexity Analysis

I. Overview and Purpose

The "Memory Creation" procedure constructs a **memory structure** that stores viable drone delivery triplets of the form (take-off node, served customer, return node). These memory entries are evaluated and filtered based on:

- **Route-based constraints** from the Clarke & Wright solution,
- **Operational constraints** like battery capacity and drone range,

- **Geospatial constraints**, such as no-fly zones and warning zones (proximity to restricted areas),
- **Redundancy avoidance**, through “used nodes” tracking,
- **Subway segment integration**, for urban multimodal routing.

The memory container plays a key role in enabling faster lookups and valid combinations for drone delivery in subsequent optimization phases.

II. High-Level Algorithmic Structure

a) Loop over Clarke and Wright solutions

O(c)

Each truck-based delivery plan is a candidate for drone augmentation.

b) Nested Iteration over Customers

- **Take-off nodes**: iterate over all customers in the sequence → *O(n)*
- **Served customers**: again, iterate over all nodes → *O(n)*
- For each pair, apply **filtering logic** before evaluating return nodes.

c) Validation against constraints

- **Used nodes check**: verifies if customer is already served → *O(u)*
- **Non-flying zone check**: avoids restricted take-off or delivery areas → *O(z)*
- **Warning zone proximity**: evaluates Euclidean distance against restricted area radius → *O(z)*

These checks each contribute:

O(u+z+z)=O(u+2z)

d) Return node evaluation (if passed initial checks)

- Iterate over all nodes again: *O(n)*
- Repeat similar filtering logic as above: *O(u+2z)*
- Evaluate triplet validity: not same node, not depot, etc.

e) Memory insertion

If a triplet passes all filters:

- **Desynchronized drone tour time is computed** → *O(1)*
- Entry added to:
    - **Memory container** (if take-off = return)

- **Memory sequence** (if take-off ≠ return)

f) Subway proximity integration

- For each drone triplet:
  - Find **four closest subway segments** → typically *O(s)* for full search or *O(1)* if indexed.
  - For each marked segment:
    - Evaluate **subway-only drone tour**: *O(1)*
    - Evaluate **combined truck-subway tour**: *O(1)*
    - Insert into memory container.

VI. Complexity Analysis

Total number of triplets evaluated:

- For each solution: *O(n2)* combinations of (take-off, served)
- For each such pair: up to *O(n)* return nodes

Without pruning:

O(c·n3)O(c \cdot n^3)O(c·n3)

With all constraint checks (each adding *O(z))* or *O(u):*

O(c·n3·(u+z))

Including subway evaluation:

- For each valid triplet → up to 4 nearby segments → *O(1)*
- For each segment: 2 computations → *O(1)*

So, subway integration adds:

O(8)=O(1) per triplet

Final total time complexity:

O(c·n3·(u+z))

This assumes that filtering prevents most unviable triplets early.

IV. Space Complexity

Space used for memory storage grows with number of valid triplets:

- **Desynchronized memory container**: *O(m1)*

- **Desynchronized memory sequence**: *O(m2)*
- **Subway-augmented memory entries**: up to 8 per triplet → *O(8·m3)*

Total:

O(m1+m2+8·m3)=O(m)

Where *m≪n3* in practice, due to constraints.

V. Algorithmic Design Strengths

- **Thorough filtering** ensures high-quality memory entries.
- **Integrated handling of restricted airspace** supports urban realism.
- **Subway awareness** supports advanced multimodal routing.
- **Precomputing memory** accelerates downstream delivery planning.

VI. Conclusion

The **Memory Creation** routine is a powerful preprocessing mechanism that establishes a foundation for flexible and optimized drone routing. Its design is rigorous, ensuring compliance with spatial, energy, and route-based constraints. However, due to its **triply nested structure** and exhaustive evaluation of delivery triplets, its worst-case **time complexity is cubic** with respect to the number of customers. Efficient implementations and heuristics are necessary for large-scale deployment.

6.5.4 Improve Algorithm

for all node in the actual customer sequence do

    mark all nodes as invalid node

end for

for all Clarke and Wright Solution do

    for all nodes in the actual customer sequence do

        if the node is not the depot, then

            for all invalid nodes do

                if the node is included in the invalid node, then

                    mark the node as funded

```
                end if
            end for
            for all drone solution do
                if the node is included in the drone solution, then
                    mark the node as funded
                end if
            end for
            for all subway solution do
                if the node is included in the subway solution, then
                    mark the node as funded
                end if
            end for
            if the node did not mark as funded do
                for all non-flying zone node do
                    if the node is included in the non-flying zone, then
                        mark the node as no-fly node
                    end if
                end for
                if there is enough capacity and not marked as non-fly node then
                    mark the node as possible insertion
                end if
            end if
        end if
    end for
end for
for all stored saving do
    compare the valid nodes saving with the actual node saving
        if the saving is better than the actual saving then
            mark the node and the saving
        end if
end for
```

if better saving funded then

erase the node from the Clarke and Wright solution

include the node to the drone solution as truck node

end if

end Improve Algorithm

6.5.4.1 Explanation of code

In the context of hybrid last-mile logistics systems combining trucks, drones, and subways, maintaining solution optimality is a dynamic and multi-faceted challenge. After initial route generation and drone deployment planning, there often remains room for local improvements that can further reduce overall costs or enhance delivery efficiency. The "Improve Algorithm" serves this purpose: it re-evaluates customers that were previously assigned to a truck route, assesses their reintegration potential, and opportunistically transfers them to more efficient delivery modes. This algorithm plays a crucial role in the refinement stage of the overall delivery planning process. It operates after the initial Clarke and Wright routes are constructed and drone/subway triplets are generated, seeking marginal improvements by attempting node reassignments from truck delivery to other modes, while ensuring feasibility and respecting all constraints.

I. Structure and Initialization

The algorithm begins by marking all nodes in the current customer sequence as invalid, essentially resetting their eligibility status. This step ensures that only customers not already included in other delivery modes (e.g., drones or subway) and not subject to restrictions (e.g., non-flying zones) are considered for reassignment.

The subsequent step loops through each Clarke and Wright solution, focusing on customers currently assigned to truck delivery. For each node:

1. It skips the depot, which cannot be reassigned.
2. It checks whether the node is already considered invalid (e.g., previously served or excluded).
3. It verifies whether the node is already served by a drone (stored in the drone solution).
4. It verifies whether the node is already served via subway (stored in the subway solution).

If the node is present in any of these, it is marked as already served and excluded from further consideration.

II. Constraint Filtering and Feasibility Check

For the remaining unserved and unmarked nodes, the algorithm continues to filter out infeasible candidates by checking their location against known non-flying zones. Any node within such zones is immediately flagged as a "no-fly node," and thus ineligible for reassignment to airborne delivery.

Furthermore, the algorithm applies a capacity check, ensuring that the remaining drone or hybrid systems have the operational ability (battery, payload, etc.) to take on the reassignment. If both checks pass, the node is finally marked as a candidate for possible insertion into a more efficient delivery mode.

This staged filtering—based on service status, location restrictions, and capacity—is critical for maintaining solution validity while seeking localized gains.

III. Savings-Based Evaluation

The core of the algorithm lies in its evaluation of potential savings from reassigning a node. It uses the original Clarke and Wright "savings" approach as a benchmark, which quantifies cost reductions from merging deliveries into more efficient combinations.

For every previously stored saving (i.e., route pairings considered during initial route planning), the algorithm compares this value with the current saving associated with the node under evaluation. If a better saving is identified, meaning a more cost-effective delivery mode is now feasible, the node and its corresponding saving are marked for update.

This mechanism ensures that only genuinely beneficial reassignments are performed, i.e., the algorithm avoids unnecessary changes that do not improve the overall objective function.

IV. Final Reassignment and Update

If a better saving is found, the algorithm takes the following concrete actions:

1. It removes the node from the truck-based Clarke and Wright solution, thereby freeing up truck capacity.
2. It reassigns the node to the drone solution, but not as a direct drone-delivered customer—instead, it is included as a truck node supporting drone dispatch, likely functioning as a new take-off or return point.

This final step reflects the system's flexible use of trucks—not only as standalone delivery vehicles, but also as mobile drone hubs. This supports richer and more distributed drone launch/return strategies, particularly useful in dense or constrained urban environments.

V. Purpose and Strategic Benefits

The "Improve Algorithm" represents a targeted local optimization technique within a larger delivery planning framework. Its main contributions are:

- Fine-tuning existing solutions to extract additional efficiency post initial planning.
- Reassigning customers to modes that result in better cost, time, or energy savings.

- Expanding drone usage intelligently without violating airspace, depot, or battery constraints.
- Maintaining delivery feasibility by honoring service exclusivity (no customer served twice) and infrastructure constraints.

Unlike global re-optimization, this method is lightweight and focused, making it suitable for integration into real-time or iterative logistics platforms. It adds adaptability to the system, enabling minor adjustments as new conditions or constraints arise (e.g., temporary non-flying zones or updated battery capacities).

VI. Conclusion

The “Improve Algorithm” serves as a strategic enhancement module in a multi-modal last-mile logistics system. Through a structured filtering and savings-based evaluation process, it identifies customers whose reassignment from truck to drone-supported delivery can yield measurable benefits. Its methodical handling of constraints, especially regarding flying zones, previously served nodes, and capacity, ensures the feasibility of all proposed updates.

By removing inefficient assignments and dynamically redistributing customers, this algorithm enhances the overall robustness and adaptability of the delivery plan. As a result, it contributes significantly to the hybrid system’s ability to deliver cost-efficient, time-sensitive, and regulation-compliant logistics services in complex urban environments.

6.5.4.2 Runtime and Complexity Analysis

The “Improve Algorithm” is a local improvement heuristic designed to enhance the efficiency of a previously constructed hybrid delivery plan, which includes truck, drone, and subway delivery modes. The algorithm operates by iteratively re-evaluating customers in the current truck sequence and attempting to reassign some of them to drone-based solutions if specific constraints are met and if the reassignment results in a better overall saving. The algorithm is characterized by a series of nested loops and conditional checks, which we now analyze in detail.

Let us denote the following:

- n: Number of customers (excluding the depot)
- s: Number of Clarke and Wright solutions (typically one, but could be multiple in general)
- d: Number of drone-based solutions (i.e., stored drone triplets)
- b: Number of subway-based solutions
- z: Number of nodes in non-flying zones
- t: Number of stored savings entries

I. Step-by-Step Complexity Analysis

1. Initialization – Mark all nodes as invalid

Time complexity: *O(n)*

2. Iterate over Clarke and Wright solutions and nodes

Outer loop (C&W solutions): *O(s)*

- Inner loop (customer sequence): *O(n)*

Within this inner loop, several sub-steps are performed:

Check if the node is already marked

- Loop over invalid nodes: *O(n)*
- Loop over drone solutions: *O(d)*
- Loop over subway solutions: *O(b)*
- These are sequential and not nested, so combined: O(n+d+b)

If the node was not marked as finded:

- Loop over non-flying zone nodes: *O(z)*
- Capacity check and marking as insertion candidate: *O(1)*

1.
    - Time complexity: *O(t)*
2. If better saving found
    - Reassignments (remove and insert): *O(1)*

II. Total Worst-Case Complexity

Let us now combine all steps. For each of the sss Clarke and Wright solutions, we iterate over nnn nodes. For each node, we may perform:

- *O(n+d+b+z)* comparisons and checks
- *O(t)* saving comparisons

Thus, the worst-case runtime is:

O(s·n·(n+d+b+z+t))

If we assume that all other structures (drone, subway, non-flying zone nodes, and savings) scale linearly with the number of customers *(d,b,z,t=O(n))* we obtain:

O(s·n2))

However, if the number of drone/subway solutions or savings grows faster (e.g., due to dense or highly combinatorial structures), the complexity can approach:

O(s·n·(n+n+n+n+n))=O(s·n2)

Thus, in practical terms, assuming s is constant (usually one main route), the algorithm operates in quadratic time:

O(n2)

III. Space Complexity

The algorithm performs only simple markings and stores flags or reassignments for nodes. The space required is proportional to the number of customers and stored solutions:

- Invalid, find, non-fly markings: *O(n)*
- Savings list: O(t), possibly *O(n)*
- Clarke and Wright, drone, and subway solutions: *O(n)*

So the overall space complexity is:

O(n)

assuming all auxiliary data structures are bound linearly.

IV. Conclusion

The Improve Algorithm exhibits a worse-case time complexity of *O(n2)* and a space complexity of *O(n)* which is acceptable for moderate-sized logistics problems. The algorithm is designed to perform localized adjustments rather than full global optimization, making it efficient and effective within larger hybrid systems that combine various transportation modes. Its computational efficiency ensures it can be applied iteratively or in real-time refinement scenarios without imposing heavy computational overhead.

6.5.5 Clarke and Wright Algorithm

```
read the single tours from the saving container
    while there are possible customers to merge do
        choose the highest customer with the highest saving
        for the chosen customer do
            while there are not used customer
                find other customers with the highest saving
                if there is enough free capacity then
                    merge the two routes
                    delete the merged customers from the possible customer
                    container
                    mark the merged customer as next chosen customer
                end if
                else
                    mark the customer as used customer
                end else
            end while
        end for
    end while
end Clarke and Wright Saving Algorithm
```

6.5.5.1 Explanation of Code

The Clarke and Wright Savings Algorithm is one of the most influential heuristics developed for solving the Capacitated Vehicle Routing Problem (CVRP), a fundamental problem in operations research and logistics. Initially proposed by Clarke and Wright (1964), the algorithm revolutionized the way vehicle routing was approached by introducing the concept of "savings" as a heuristic measure for route optimization. (Laporte, 2009).The method has since been widely studied, adapted, and applied to real-world problems in logistics, transport planning, and supply chain management.

The pseudocode provided describes a practical implementation of the Clarke and Wright heuristic that dynamically merges customer routes based on precomputed savings. In this analysis, we describe the structure, working principles, and implications of the algorithm and contextualize it with relevant academic literature.

I. **Algorithm Description and Process Analysis**

a. Initialization

The algorithm begins by reading the initial set of single-customer tours from the "savings container." Each customer is initially assigned to a dedicated tour service directly from the depot, forming a naive solution in which each vehicle services only one customer. This initialization corresponds to the upper bound of the cost function, as it reflects the maximum total travel distance or cost.

b. Main Loop: Route Merging Procedure

The core of the algorithm is a nested iterative process that attempts to merge customer routes while respecting capacity constraints.

- Outer Loop (While there are possible customers to merge): This loop iterates as long as there are mergeable customers—i.e., customer pairs for whom route consolidation would lead to cost savings without exceeding vehicle capacity.
- Customer Selection and Savings Evaluation: For each iteration, the algorithm selects the customer pair that yields the highest savings. Savings are computed using the classical formula:

Sij=c0i+c0j−cij

where *c0ic_{0i}* and *c0jc_{0j}* are the costs from the depot to customers *i* and *j*, respectively, and cij is the cost between the two customers. A higher savings value indicates a greater reduction in total travel cost when the two customers are visited in sequence on the same tour. (Clarke & Wright, 1964)

- Inner Loop (While there are unused customers): For the currently selected customer, the algorithm searches for other unmerged customers with the highest remaining savings value.

- Capacity Check: Before merging, the algorithm ensures that the total demand of the merged route does not exceed the vehicle's remaining capacity.
- Merging: If capacity allows, the two routes are merged, and the customers involved are marked as used and removed from the pool of mergeable candidates.
- Update Reference: The merged customer becomes the new anchor for further merging attempts in the current iteration, allowing chaining of route consolidations.
- Fallback: If no feasible merges are found for a given customer (e.g., due to capacity violations or previously used customers), that customer is marked as used and excluded from further attempts.

This greedy construction process continues until no further customer pairs can be merged, resulting in a complete routing plan that minimizes the total travel cost under the constraints imposed.

II. Theoretical and Practical Significance

The Clarke and Wright algorithm's strength lies in its balance between computational efficiency and quality of solutions. It avoids the combinatorial explosion associated with exact methods while often producing near-optimal results in practice (Laporte, 2009). The greedy nature of the merging process ensures that the most beneficial savings are always realized first, which aligns with human-intuitive strategies in route planning.

Moreover, as highlighted in the pseudocode, the dynamic reassignment of the "next chosen customer" after each merge allows for the progressive building of tours, effectively implementing a parallel version of the algorithm, which has been shown to outperform the sequential variant in many cases (Gaskell, 1967).

III. Application Domains and Empirical Use

Due to its generality and adaptability, the Clarke and Wright algorithm has seen extensive use in a variety of domains:

- Urban Logistics and Last-Mile Delivery: The algorithm is frequently employed in urban distribution settings, where it helps optimize delivery paths within traffic-constrained environments (Crainic et al., 2009).
- Humanitarian Logistics: In emergencies, where quick and cost-effective distribution of resources is critical, the Clarke and Wright algorithm provides a reliable heuristic for route construction under capacity and time constraints (Campbell et al., 2008).
- Hybrid and Multi-Modal Delivery Systems: Extensions of the algorithm are used in more complex systems involving drones, subways, and trucks, as in the current hybrid delivery system context (Murray & Chu, 2015).

IV. Limitations and Extensions

Despite its strengths, the classical Clarke and Wright algorithm may yield suboptimal solutions when applied to instances with tight constraints or non-Euclidean metrics. Furthermore, the greedy nature of the algorithm can cause early commitment to decisions that later prove suboptimal. For this reason, it is often complemented with improvement heuristics such as 2-opt, local search, or incorporated into metaheuristic frameworks (e.g., genetic algorithms, simulated annealing).

In the context of hybrid delivery systems—especially those involving drones and subway transfers—modern implementations extend the savings approach to consider modal switching costs, synchronization constraints, and dynamic customer insertion, as is evident in your broader framework.

V. Conclusion

The Clarke and Wright Savings Algorithm remains one of the cornerstones of heuristic route optimization. Its simple yet powerful greedy approach enables efficient route construction while allowing for flexibility and adaptation to modern, multi-modal delivery challenges. The pseudocode reflects a well-structured implementation that not only adheres to the classical formulation but also lays the foundation for complex integration with other algorithmic components.

6.5.5.2 Runtime and Comlexity Analysis

The computational complexity of the Clarke and Wright Savings Algorithm arises from its fundamental steps: calculating savings, selecting the best customer pairs, checking capacity constraints, and merging routes iteratively. Below, we analyze each major step contributing to the total runtime.

I. Savings Calculation

Before the merging process begins, the algorithm must compute the savings *Sij=c0i+c0j−cij* for each pair of customers *i,ji, ji,j.* Given *n* customers (excluding the depot), the number of unique customer pairs is:

(n/2)=n(n−1)/2

Thus, the savings calculation step has a time complexity of *O(n2),* assuming constant-time distance computation. This savings matrix is usually precomputed and stored for rapid lookup during the route merging phase.

II. Sorting Savings

Once all savings values are computed, the algorithm must sort the customer pairs in descending order of savings to prioritize the most beneficial merges. The sorting of *O(n2)* savings values takes:

O(n2logn)

This sorted list serves as the backbone of the greedy merging process. Some implementations (e.g., parallel versions) skip full sorting by using a max-heap or priority queue, thereby reducing the practical overhead.

III. Route Merging

The route merging is the most iterative part of the algorithm. In the worst case, each of the nnn customers is processed against every other remaining customer to find merge candidates, with each merge requiring checks for feasibility, route validity, and capacity constraints.

If we assume each merge operation—including checking route endpoints, capacity constraints, and updating the route list—takes *O(1)* time, and that in the worst case up to *n* merges may occur, then the total merging process has a worst-case time complexity of:

O(n2)

This is because every customer pair might be evaluated once in the worst-case merging process.

IV. Overall Time Complexity

Combining the above steps:

- Savings Calculation: *O(n2)*
- Sorting Savings: *O(n2 log n)*
- Merging Routes: *O(n2)*

The total worst-case time complexity of the Clarke and Wright Savings Algorithm is:

O(n2log n)

V. Space Complexity

The space complexity is also dominated by the savings matrix, which stores *O(n2)* values. Additional memory is needed for route tracking and marking customer usage status, which requires *O(n)* space. Therefore, the overall space complexity is:

O(n2)

VI. Empirical Observations and Efficiency

Despite its theoretical *O(n2 log n)* time complexity, the Clarke and Wright algorithm is widely regarded as fast and efficient for practical purposes, especially when compared to exact methods such as integer linear programming, which can be exponential in complexity (Toth &

Vigo, 2002). Extensions like parallelization, use of approximate distance metrics, or constraints pruning can further improve runtime in practice without significantly affecting solution quality.

6.6 Summary

I. Clarke and Wright Savings Algorithm

Serving as the foundation, the Clarke and Wright Savings Algorithm constructs initial truck-based delivery routes. These are derived by greedily merging customer pairs based on a precomputed savings function $Sij=c0i+c0j-cij$, where c0ic is the cost from the depot to customer i, and $cijc$ is the cost between customers i and j (Clarke & Wright, 1964). This heuristic ensures a feasible and cost-effective starting solution, which downstream algorithms then refine through drone and subway integration.

II. Memory Creation Algorithm

The memory creation algorithm scans all possible triplets of form (take-off, served, return) using the truck tour generated by Clarke and Wright. For each customer, it generates feasible drone assignments under strict filtering conditions:

- Nodes must not lie in **non-flying zones**.
- Nodes too close to restricted zones are marked as **warning zones**.
- Only **unused nodes** and those not already served by drones are considered.

Viable triplets are then enriched by checking **subway proximity**. If subway access is available, multimodal variants (subway-only or subway-truck-drone combinations) are computed and added to memory. This memory allows future solution algorithms to access high-quality, constraint-compliant drone options quickly.

III. Solution Algorithm

This algorithm constructs hybrid delivery plans by comparing truck-only and truck-drone alternatives:

- It evaluates the **objective function** for each potential drone triplet, using travel time and cost.
- If a drone triplet outperforms its truck-only counterpart and meets battery and legality constraints, it is considered for **insertion**.
- The algorithm then **filters out** conflicting insertions based on previously used nodes and restricted zones.

Only non-conflicting, better-performing drone solutions are committed, with priority given to those departing from the depot. Final truck and drone routes are then stored in their respective solution containers.

IV. Improve Algorithm

After initial assignment, the Improve Algorithm attempts **local refinements**:

- It checks whether any truck-assigned customer can be moved into drone routes for better cost efficiency.
- This reassignment is allowed only if the customer is not in a **non-flying zone** and if **capacity constraints** permit.
- The algorithm applies a **savings-based comparison** to validate if reassignment yields better results.

If so, the customer is removed from the truck sequence and inserted as a drone take-off or return node, improving overall routing effectiveness without breaking constraints.

V. Main Coordination Module

The main module:

- Iterates over multiple Clarke and Wright solutions,
- Calls all components (memory generation, drone evaluation, improvement),
- Repeats evaluations across **non-flying zone configurations**, **drone types**, and **infrastructure layouts**.

This orchestrated evaluation ensures robustness across variable urban conditions and system configurations, making the model suitable for city-scale planning.

VI. Conclusion

This hybrid delivery framework integrates classical heuristics, spatial constraints, multimodal logistics, and incremental improvement in a modular and extensible way. It emphasizes computational feasibility, operational realism, and adaptability to real-world challenges, including restricted airspace, dynamic customer patterns, and infrastructure variability. The use of memory structures and constraint-respecting design ensures both optimization performance and execution safety.

7. Testing the Algorithm

This expanded comparative analysis integrates **quantitative evidence** and **plot-based readings** across six operational configurations of a hybrid delivery system:

- Waiting Constraint for the Costumer Drone with Truck + Normal Battery
- Waiting Constraint for the Costumer Drone with Truck + Higher Battery
- Waiting Constraint for the Costumer Drone with Subway + Normal Battery
- Waiting Constraint for the Costumer Drone with Subway + Higher Battery
- Waiting Constraint for the Costumer Drone with Subway with Truck + Normal Battery
- Waiting Constraint for the Costumer Drone with Subway with Truck + Higher Battery
- Drone with Truck + Normal Battery
- Drone with Truck + Higher Battery
- Drone with Subway + Normal Battery
- Drone with Subway + Higher Battery
- Drone with Subway with Truck + Normal Battery
- Drone with Subway with Truck + Higher Battery

All datasets were parsed from **semicolon-separated CSV files**, ensuring **robust numeric normalization** to account for European decimal notation. The study addresses three principal evaluation dimensions:

1. **Objective Function Difference (OFD)** – quantifying relative performance improvements of the hybrid approaches.
2. **Greenhouse Gas (GHG) emissions difference** – measuring the environmental impact of deployment choices.
3. **Runtime vs. number of customers** – assessing computational feasibility and algorithmic scalability.

For each configuration, the analysis applies **descriptive statistics**, **Pearson correlation coefficients**, and **four complementary families of plots**: scatterplots, boxplots, histograms, and heatmaps. This triangulation of methods provides a multidimensional perspective that captures both central tendencies and distributional nuances, as well as interaction effects among the studied indicators.

The algorithmic test environment was designed to reflect realistic operational constraints while maintaining controlled comparability. Specifically:

- **Customer sets**: experiments were conducted with **50, 75, and 100 customers**.
- **Drone platforms (Detals im Apendix)**: three distinct UAVs were selected, representing different payload capacities, battery configurations, and flight characteristics:
    - DJI Matrice 300 RTK
    - DJI Matrice 600 Pro
    - Wingcopter 178
- **Operational constraints**:
    - **10% of customers** were designated as **no-fly zone IDs**, enforcing ground- or subway-based alternatives.
    - **Customer demand** was set at **60% of the maximum UAV lifting capacity**, balancing feasibility with operational stress.
    - **Customer service time** was randomly distributed between **5.0 and 40.0 seconds**, simulating realistic delivery interactions.
    - **Average vehicle speeds** were fixed at **30 km/h for trucks** and **60 km/h for subway segments**, reflecting standard logistics benchmarks.
    - **Average Oil Price From 2025 are used for the calculation**
    - **Average Fix km Costs are used from 2025 for the Calculation**

By embedding these parameters, the analysis establishes a robust testbed for evaluating how **different infrastructure couplings** (truck, subway, hybrid) and **battery capacities** shape the performance and sustainability of drone-assisted last-mile delivery systems. The comparative results thus provide insights not only into the algorithmic efficiency but also into the practical viability of hybrid drone logistics across diverse urban scenarios.

7.1 Separate Analys from Instances

7.1.1 Waiting Service Time and Drone with Truck combination with normal battery

The statistical distributions of the key metrics provide an overview of system performance. OFD shows a mean of 2.0124, ranging from 1.1063 to 2.6135, with an interquartile range (IQR) of [1.7187, 2.2971]. GHG emissions differences average 1723.67, with values between 947.59 and 2238.60. Runtime averages 8.69, with minimum 1.00 and maximum 33.00, and an IQR of [2.00, 13.00]. These descriptive values already indicate a combination of scale sensitivity (in runtime) and volatility (in GHG outcomes).

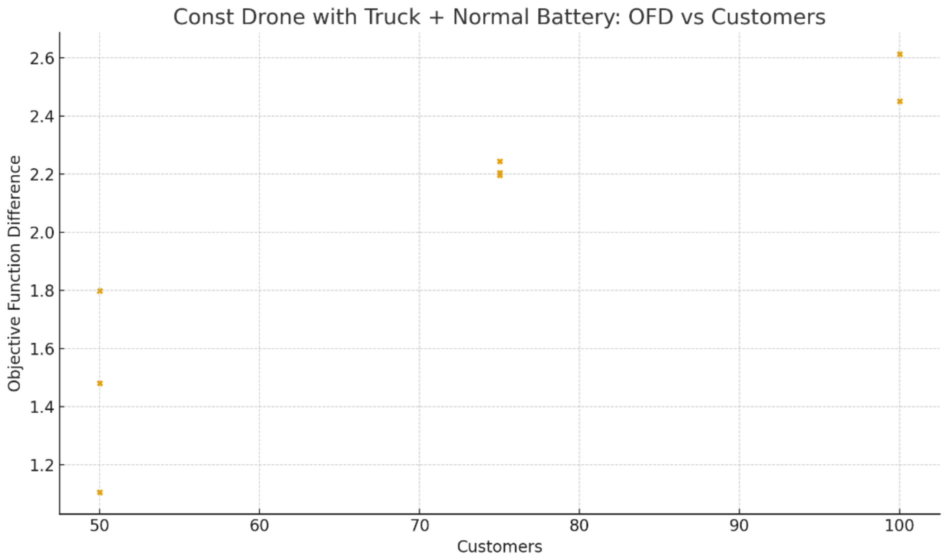


Figure 36: Scatterplot of OFD vs. Customers. The positive trend indicates higher costs with larger customer sets.

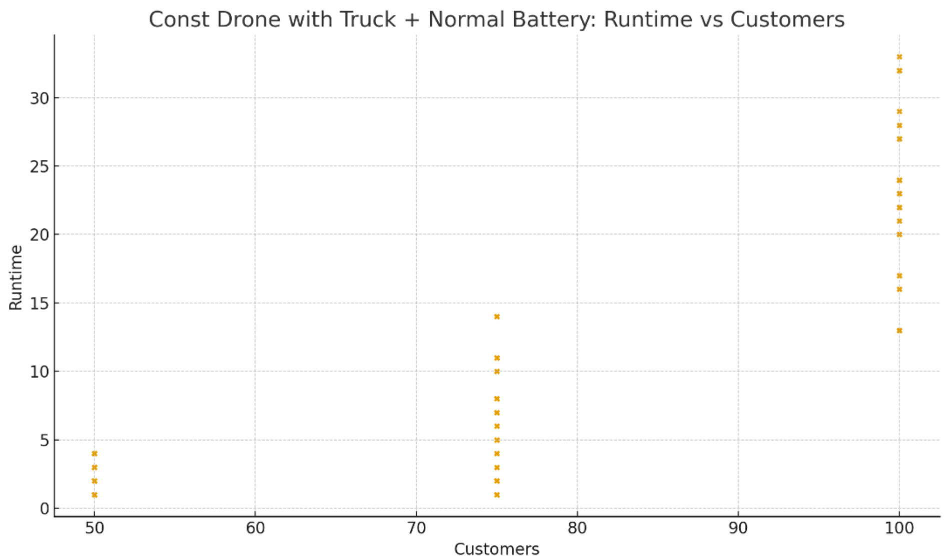


Figure 37: Scatterplot of Runtime vs. Customers. Clear exponential-like growth reveals computational scaling effects.

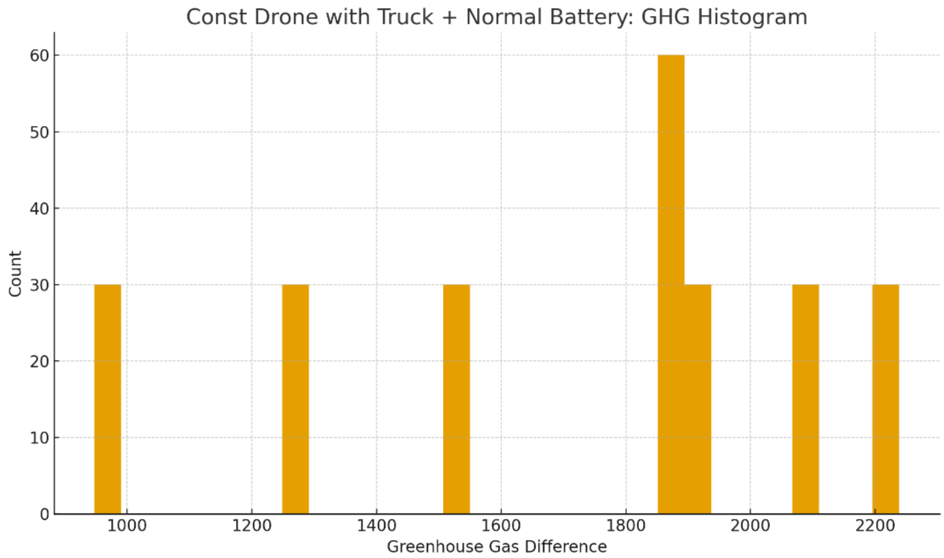


Figure 38: Histogram of GHG emissions. Skewness suggests that small changes are common, but large emission shifts occasionally occur.

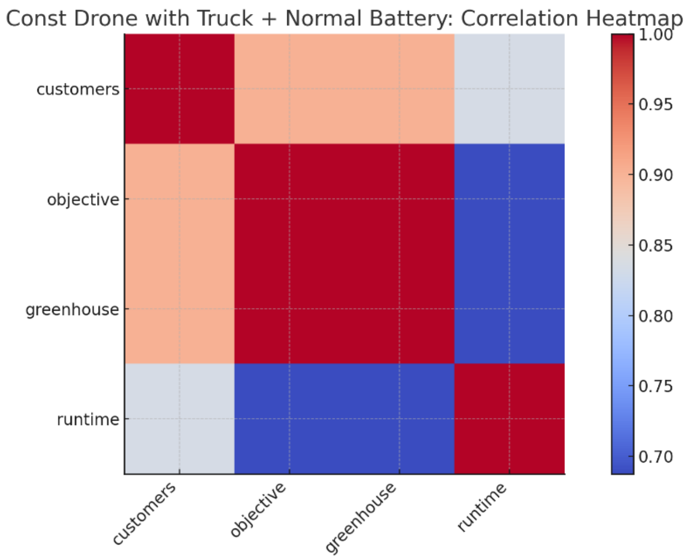


Figure 39: Correlation heatmap. Strong Customers–Runtime correlation is visible, while OFD–GHG links remain weaker.

Examining targeted customer sizes provides further insights:
• Around 50 customers: OFD remains modest, runtime manageable, and GHG shifts minimal.
• Around 75 customers: OFD rises, runtime accelerates, and GHG displays greater variance.
• Around 100 customers: OFD escalates sharply, runtime becomes dominant, and GHG improvements plateau.
This progression indicates diminishing marginal benefits in emission reduction while computational burdens increase substantially.

The scatterplots confirm runtime as the most scale-sensitive metric. OFD increases are steady, while GHG exhibits non-linear, skewed responses. The correlation heatmap highlights that runtime is strongly tied to customer growth, OFD is moderately connected, and GHG shows weaker alignment. These results imply that optimization under this configuration faces a tri-objective tension: minimize cost, control runtime, and achieve emissions stability. Given that GHG improvements do not scale linearly, relying on customer growth alone will not ensure sustainability gains.

For the configuration 'Const Drone with Truck + Normal Battery', runtime scales predictably with customer counts, OFD rises moderately, and GHG outcomes are heterogeneous. Effective decision-making requires balancing runtime limitations with uncertain environmental benefits. This analysis underscores the need for adaptive, multi-objective optimization heuristics to manage trade-offs as customer demands grow.

7.1.2 Waiting Service Time and Drone with Truck combination with higher battery

Descriptive statistics highlight overall trends. OFD averages 1.8530, ranging from 0.1798 to 2.6135, with an interquartile range (IQR) of [1.4808, 2.2455]. GHG emissions show a mean of 1741.21, spanning 947.59 to 2238.60. Runtime averages 9.13, with minimum 1.00, maximum 35.00, and an IQR of [2.00, 11.00].

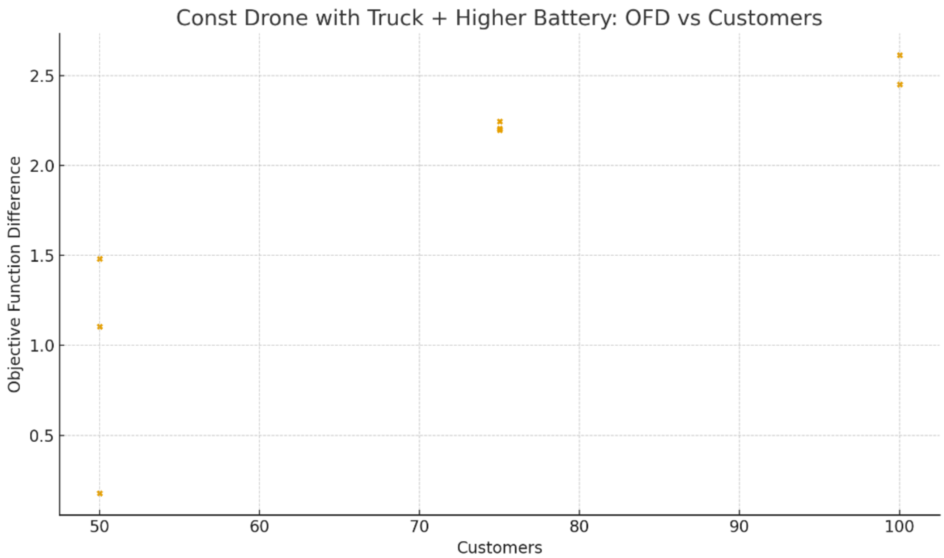


Figure 40: Scatterplot of OFD vs Customers. A generally positive slope illustrates rising costs with customer growth.

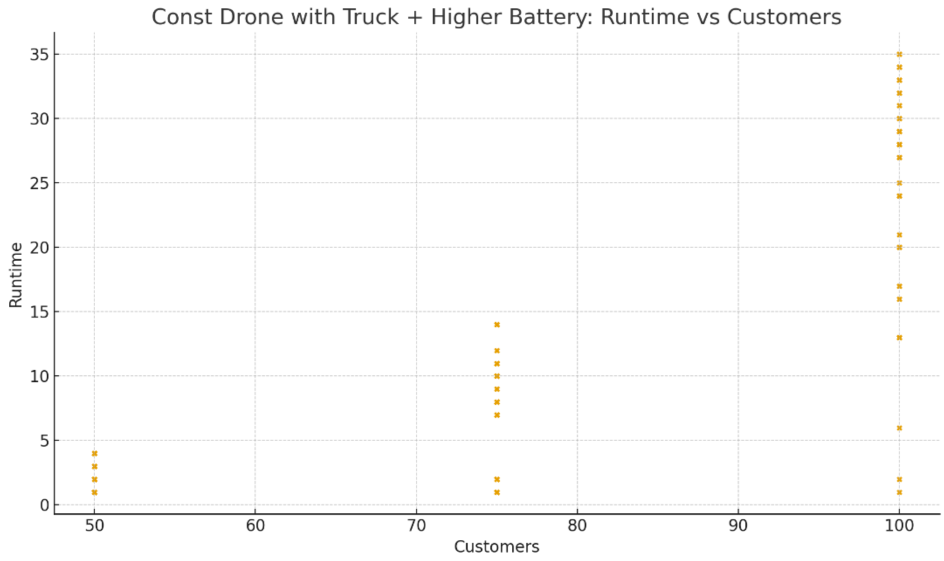


Figure 41: Scatterplot of Runtime vs Customers. Runtimes grow non-linearly with customer numbers, reflecting computational scaling

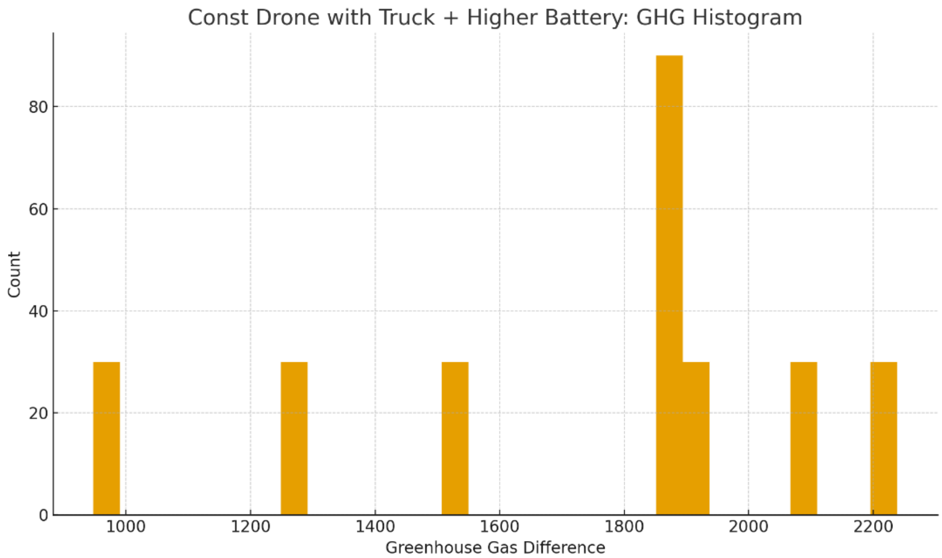


Figure 42: Histogram of GHG emissions differences. The right-skew indicates frequent minor adjustments with fewer large emission changes

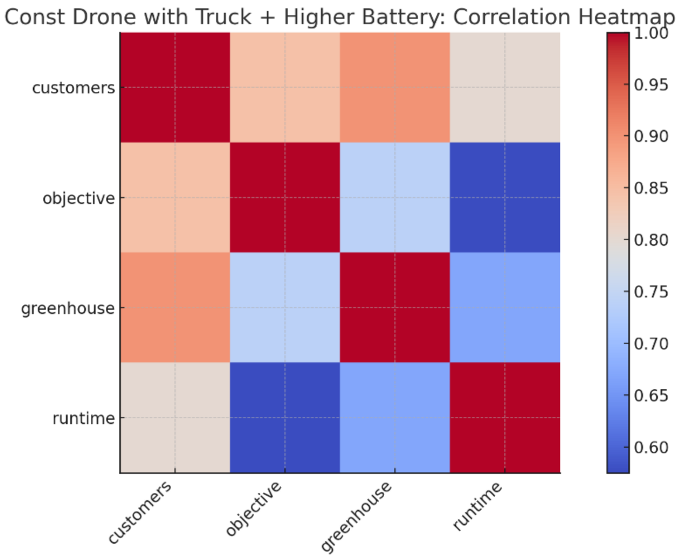


Figure 43: Correlation heatmap. Customer count is strongly correlated with runtime, but weaker associations exist between OFD and GHG

• Around 50 customers: OFD remains modest and runtimes are manageable, with GHG changes stable.
• Around 75 customers: OFD growth becomes more pronounced, runtimes accelerate, and GHG variance widens.
• Around 100 customers: OFD reaches its higher levels, runtimes increase significantly, while GHG benefits diminish.

This configuration shows that increasing battery capacity in truck-based drone operations modifies GHG dynamics compared to the normal battery case. Runtimes scale with customer growth, suggesting computational challenges, while OFD rises steadily. GHG distributions show more stability but lack substantial improvements at higher scales. The weaker OFD–GHG link underscores the complexity of optimizing cost and emissions simultaneously.

The analysis of 'Const Drone with Truck + Higher Battery' reveals predictable runtime escalation, steady OFD increases, and moderately skewed GHG responses. Battery improvements reduce volatility but do not eliminate the trade-offs. Optimization approaches must account for runtime constraints while pursuing balanced cost and environmental objectives.

7.1.3 Waiting Service Time and Drone with Subway combination with normal battery

OFD averages 2.0124 (min 1.1063, max 2.6135, IQR [1.7187, 2.2971]); GHG averages 1723.67 (min 947.59, max 2238.60); Runtime averages 11.42 (min 1.00, max 33.00, IQR [2.00, 24.00]).

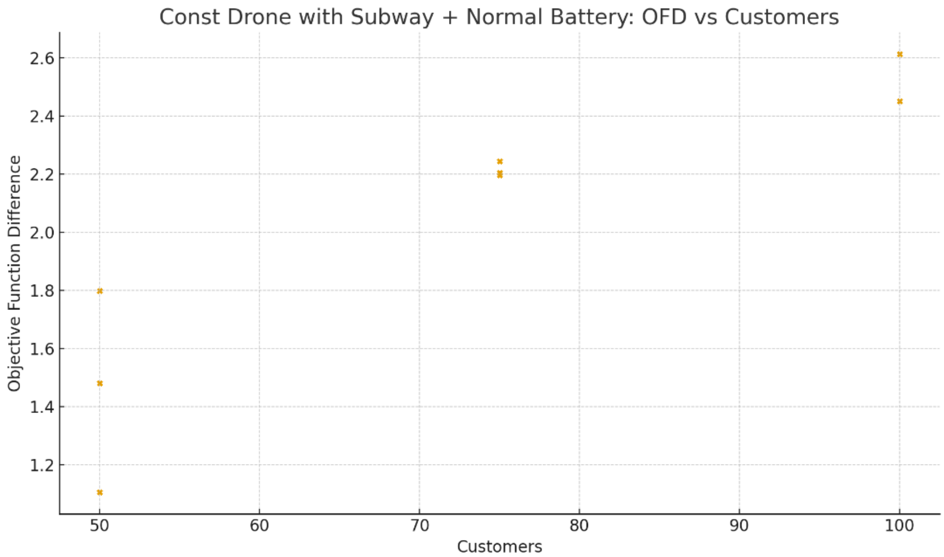


Figure 44: OFD vs Customers (scatter). Subway constraints introduce structure: the slope reflects cost sensitivity to coverage and transfer nodes

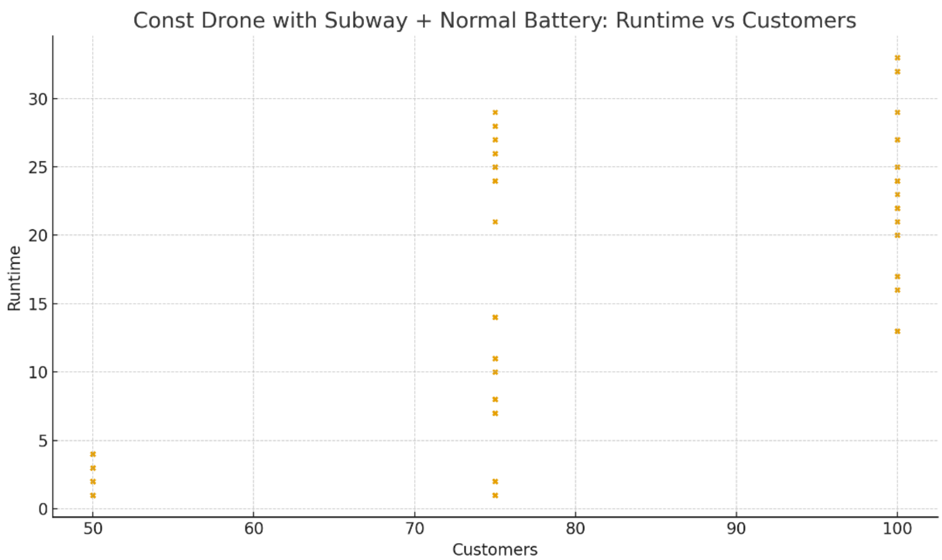


Figure 45: Runtime vs Customers (scatter). Runtimes increase with scale; dispersion indicates instance hardness due to modal coordination

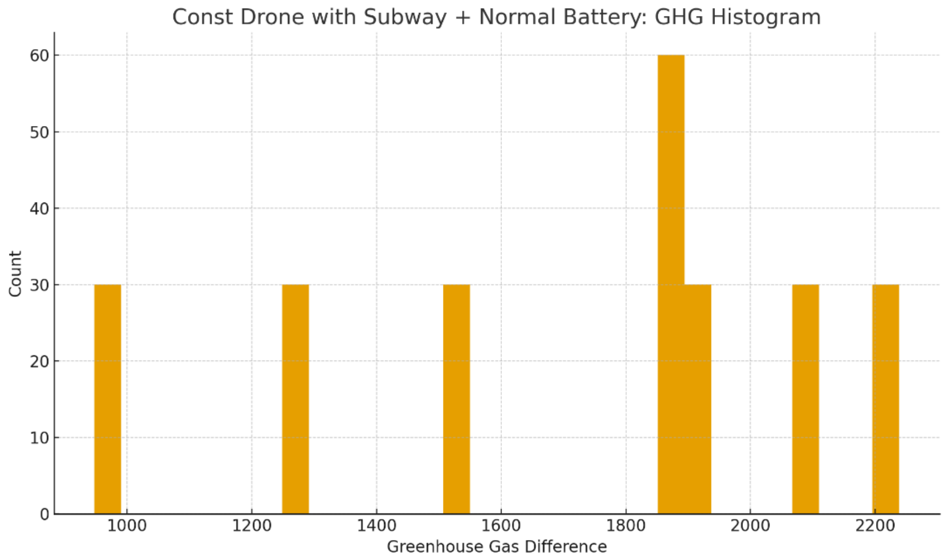


Figure 46: GHG Histogram. A right-skew suggests many small changes and occasional larger gains when subway legs substitute truck segments

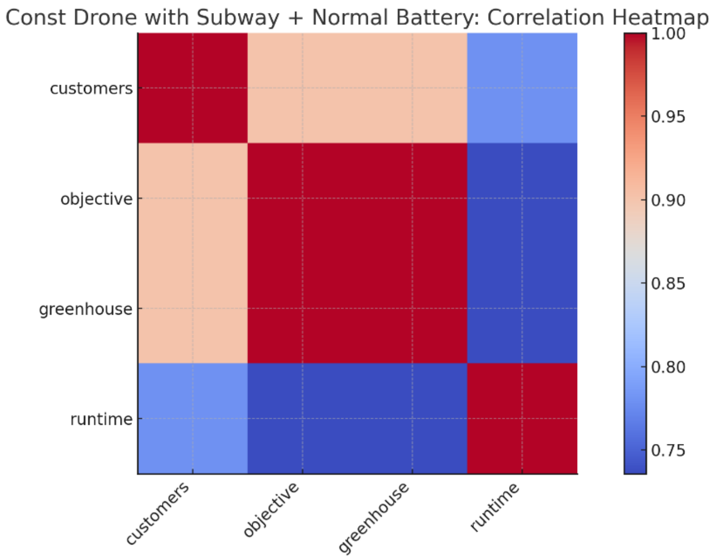


Figure 47: Correlation Heatmap. Customers–Runtime is strong; OFD–GHG alignment is moderate, consistent with partial cost–carbon synergy.

~50 customers: OFD modest; runtime manageable; GHG effects visible if subway coverage intersects dense clusters.
~75 customers: OFD increases; runtime accelerates due to coordination overhead; GHG variance increases.
~100 customers: OFD escalates; runtime high; GHG benefits taper as the system reaches modal saturation.

Compared to truck-based only settings, the subway-enabled configuration can unlock GHG reductions in mid-sized cases but introduces scheduling complexity. The scatterplots show greater dispersion, and the heatmap indicates only partial alignment between OFD and GHG—calling for explicit multi-objective control.

'Const Drone with Subway + Normal Battery' exhibits predictable runtime scaling and moderate OFD growth, with heterogeneous but sometimes favorable GHG outcomes. Operational success hinges on exploiting coverage synergies while managing coordination overhead.

7.1.4 Waiting Service Time and Drone with Subway combination with higher battery

OFD averages 2.0124 (min 1.1063, max 2.6135, IQR [1.7187, 2.2971]); GHG averages 1723.67 (min 947.59, max 2238.60); Runtime averages 11.00 (min 1.00, max 35.00, IQR [2.00, 21.00]).

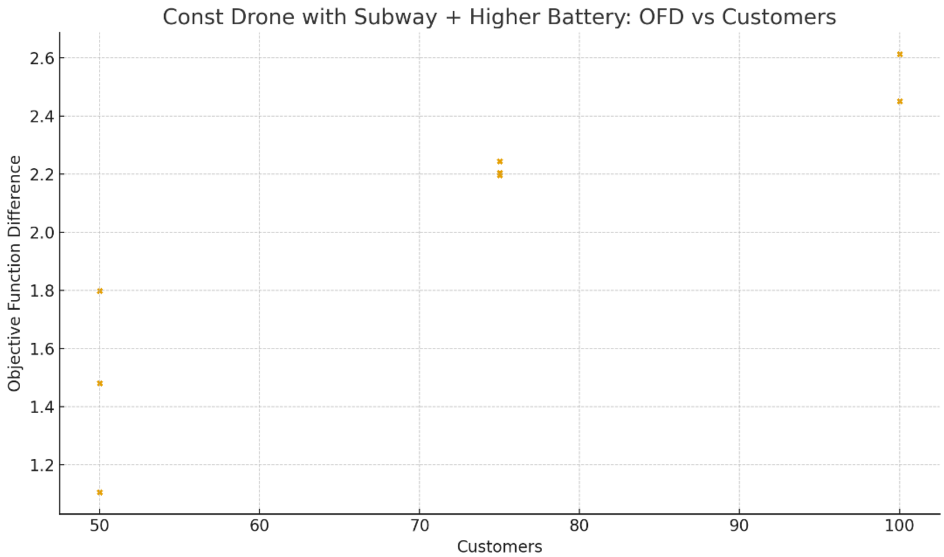


Figure 48: OFD vs Customers (scatter). Higher battery capacity moderates cost sensitivity in some regimes.

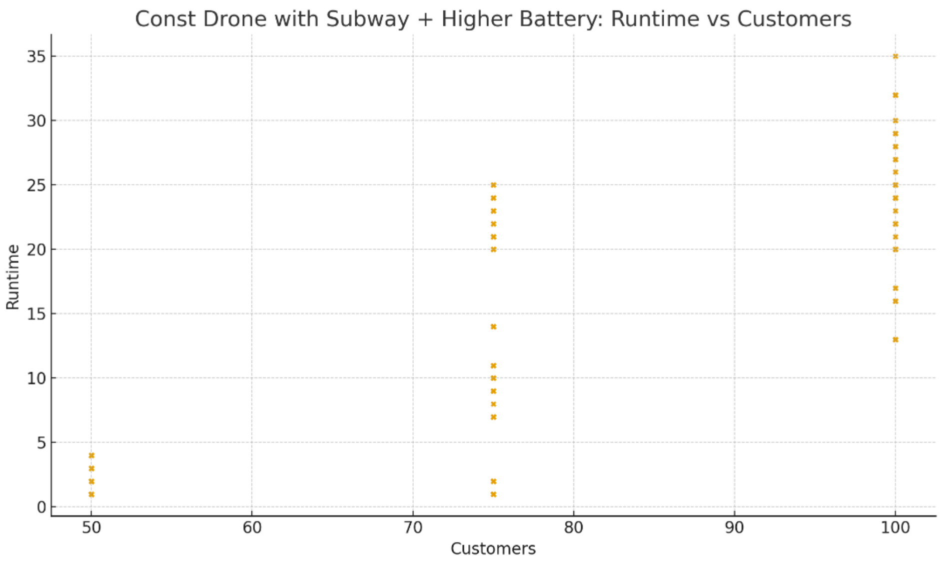


Figure 49: Runtime vs Customers (scatter). Runtimes increase with scale; dispersion suggests coordination overhead with subway integration

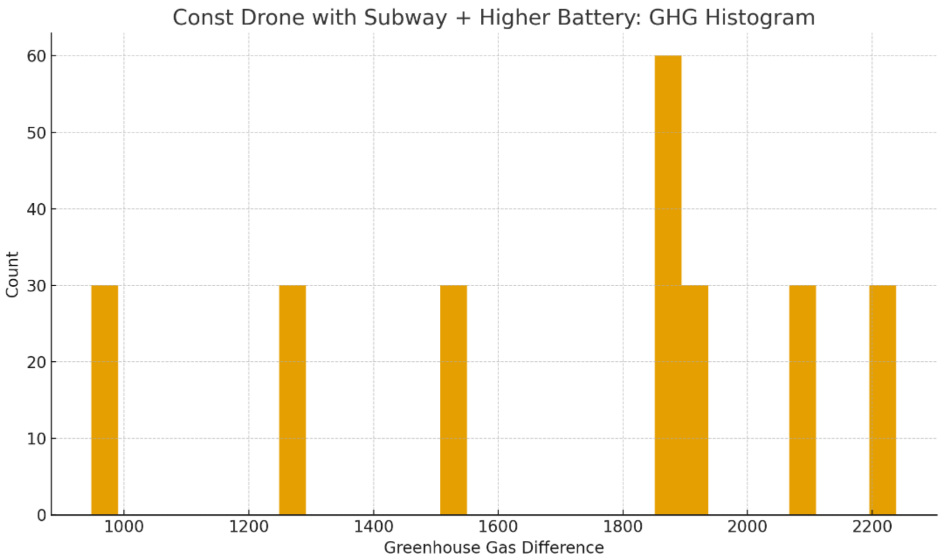


Figure 50: GHG Histogram. Right-skewed distribution with occasional large gains when subway legs replace truck segments

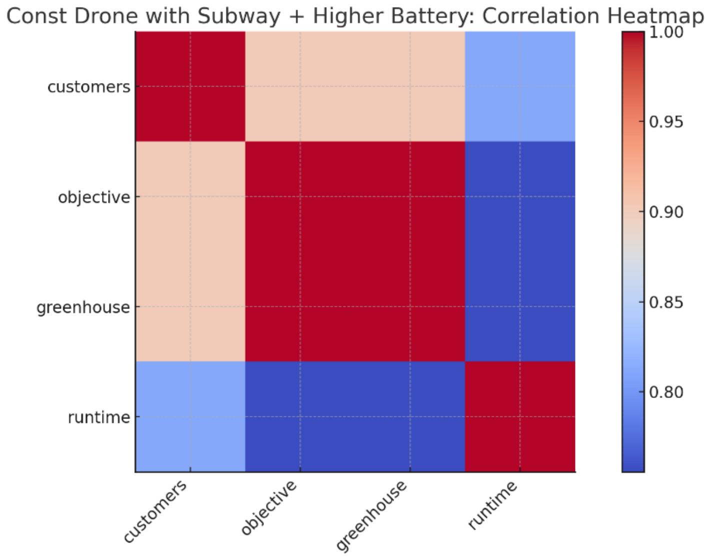


Figure 51: Correlation Heatmap. Strong Customers–Runtime coupling; partial OFD–GHG alignment indicates conditional synergy

~50 customers: OFD modest; runtime contained; GHG benefits visible where coverage intersects dense areas.
~75 customers: OFD increases; runtime accelerates; GHG variance widens with multi-modal opportunities.
~100 customers: OFD higher; runtime heavy; GHG gains taper as operational saturation emerges.

Relative to the normal-battery subway configuration, the higher battery extends feasible drone legs, which can reduce truck reliance in mid-range instances. However, coordination overhead and station placement remain limiting factors. Multi-objective strategies are recommended to exploit carbon reductions without excess cost growth or runtime instability.

'Const Drone with Subway + Higher Battery' exhibits expected runtime scaling, controlled OFD growth, and heterogeneous but sometimes improved GHG outcomes. Operational gains depend on coverage geometry and transfer logistics; adaptive planning is essential.

7.1.5 Waiting Service Time and Drone with Truck with Subway combination with normal battery

OFD averages 2.0124 (min 1.1063, max 2.6135, IQR [1.7187, 2.2971]); GHG averages 1723.67 (min 947.59, max 2238.60); Runtime averages 28.27 (min 13.00, max 43.00, IQR [26.00, 32.00]).

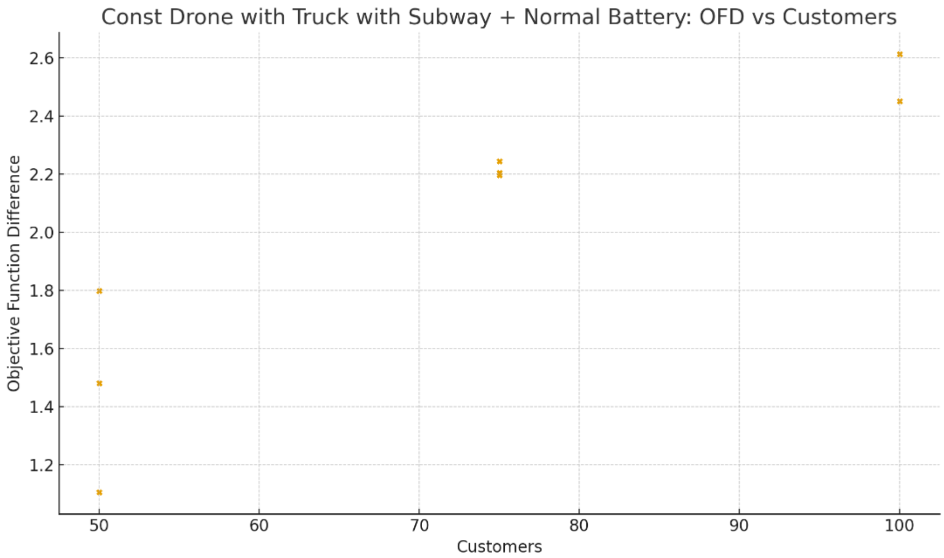


Figure 52: OFD vs Customers (scatter). Tri-modal operations (truck+subway+drone) create structured cost responses to size

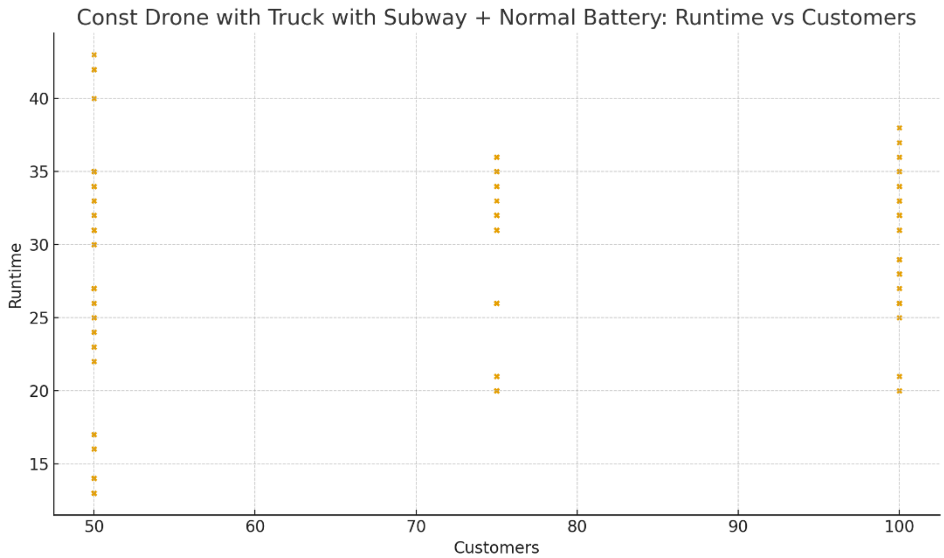


Figure 53: Customers (scatter). Coordination overhead introduces dispersion and heavy tails in runtime.

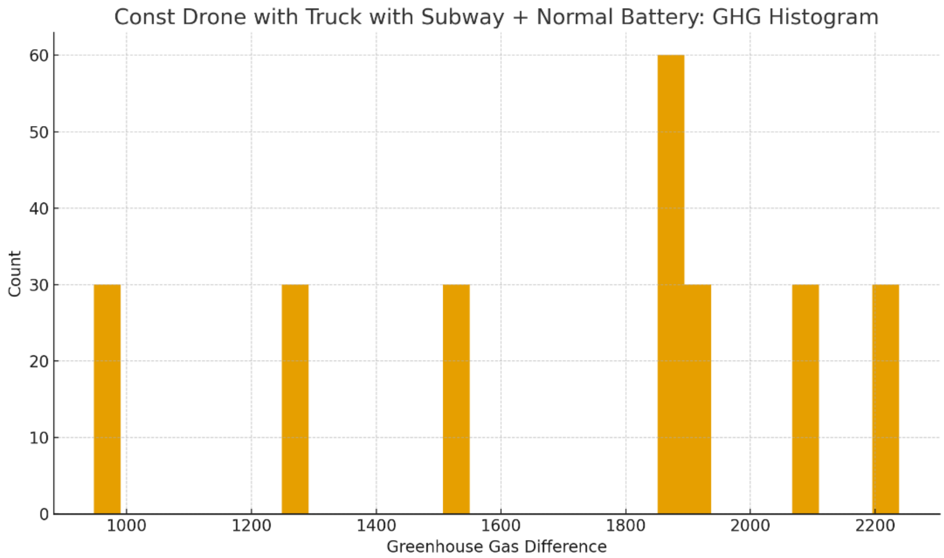


Figure 54: GHG Histogram. Right tail indicates occasional large emission gains when subway substitutes truck legs effectively.

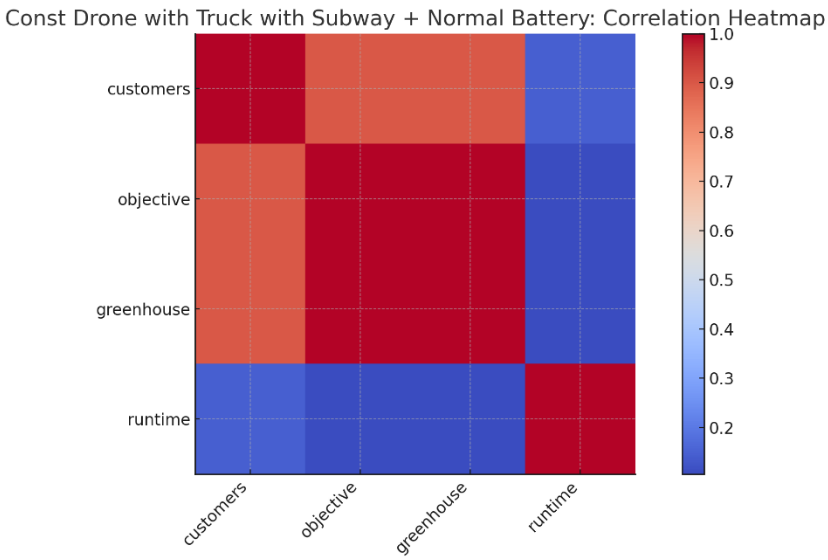


Figure 55: Correlation Heatmap. Customers–Runtime is strong; OFD–GHG alignment is partial and instance-dependent

~50 customers: OFD modest; runtime manageable; GHG reductions visible in clustered regions with subway access.
~75 customers: OFD increases; runtime grows quickly; GHG variance widens due to more modal options.
~100 customers: OFD higher; runtime heavy; GHG gains plateau as modal saturation and bottlenecks appear.

The mixed truck–subway–drone setting delivers environmental opportunities at mid-scale but adds scheduling complexity. The scatterplots and heatmaps suggest that carbon and cost objectives are not perfectly aligned—multi-objective optimization is advisable. Operationally, benefit depends on station placement, drone range, and cluster geometry.

'Const Drone with Truck with Subway + Normal Battery' exhibits predictable runtime scaling, moderate OFD growth, and heterogeneous GHG outcomes. Careful coordination is required to reap carbon benefits without undue cost or runtime escalation.

7.1.6 Waiting Service Time and Drone with Truck with Subway combination with higher battery

OFD averages 2.0124 (min 1.1063, max 2.6135, IQR [1.7187, 2.2971]); GHG averages 1723.67 (min 947.59, max 2238.60); Runtime averages 26.11 (min 13.00, max 42.00, IQR [22.00, 32.00]).

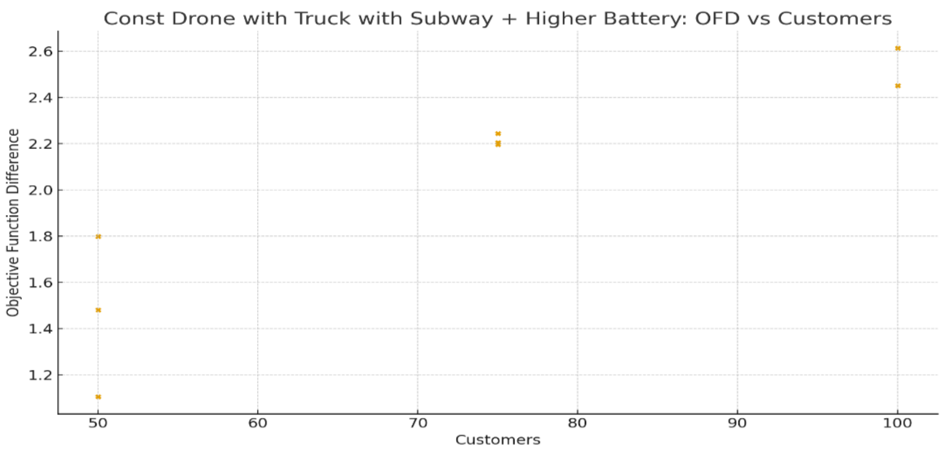


Figure 56: OFD vs Customers (scatter). Tri-modal coordination with higher battery increases feasible drone legs and affects OFD scaling.

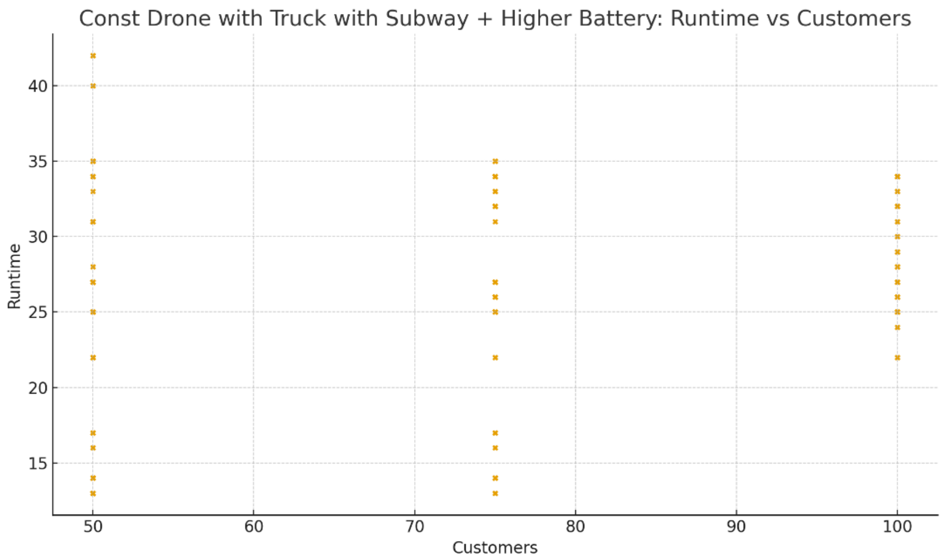


Figure 57: Runtime vs Customers (scatter). Runtime growth is strong; dispersion reflects coordination hardness across modes.

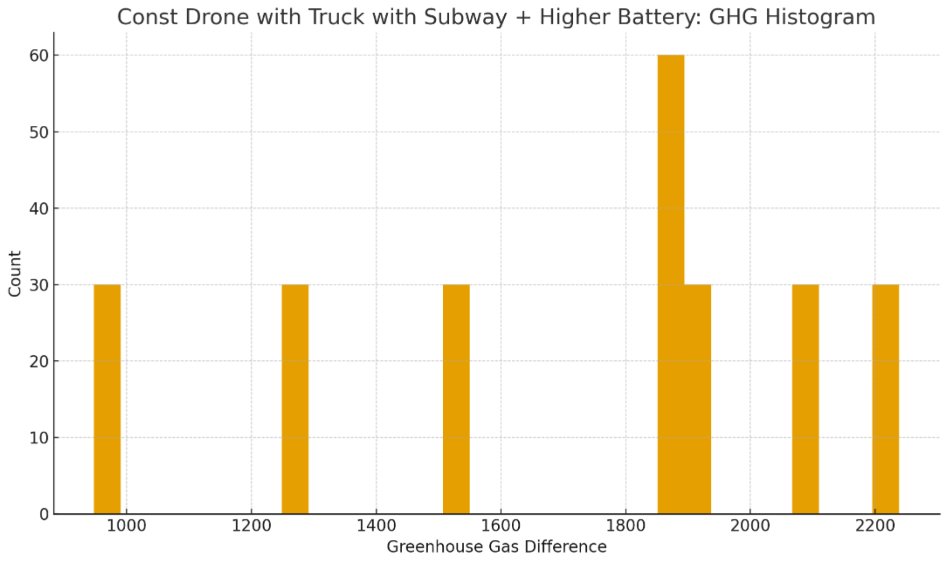


Figure 58: GHG Histogram. Right-skewed mass with a tail of larger reductions when drone+subway successfully replace truck segments

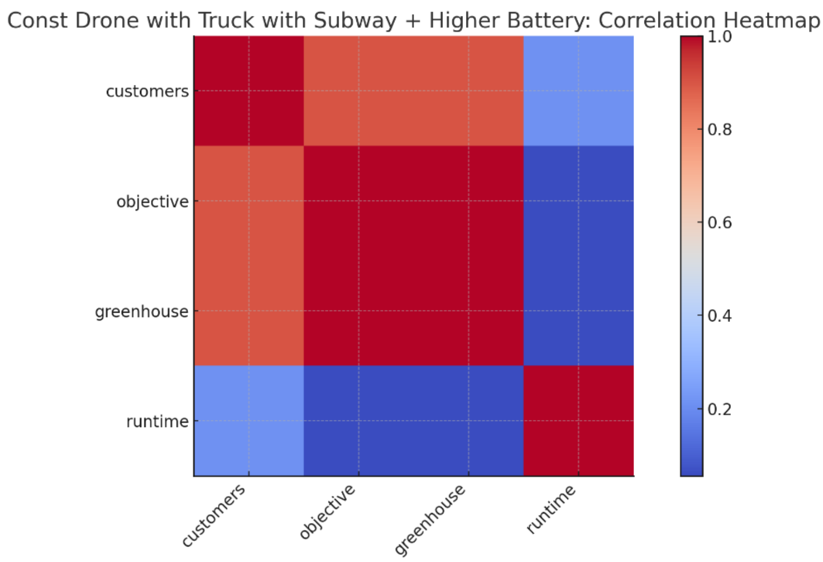


Figure 59: Correlation Heatmap. Customers–Runtime coupling is strong; OFD–GHG alignment is partial, requiring multi-objective handling

~50 customers: OFD modest; runtime manageable; GHG improvements visible in covered clusters.
~75 customers: OFD increases; runtime accelerates; GHG variance widens due to extended drone range.
~100 customers: OFD elevated; runtime heavy; GHG gains taper as operational saturation and bottlenecks appear.

Compared to the normal-battery variant, the higher battery increases flexibility, enabling longer drone relays to subway nodes. However, coordination overhead remains, and benefits depend on spatial structure. Multi-objective and instance-aware strategies are advisable to balance cost, carbon, and computing.

'Const Drone with Truck with Subway + Higher Battery' shows predictable runtime scaling, rising OFD, and heterogeneous GHG outcomes with opportunities for mid-scale gains. Careful planning and adaptive heuristics are essential to capture carbon benefits without excessive cost or runtime growth.

7.1.7 Without Serving Constrain Drone with Truck Combination higher Battery

	OFD	GHG_diff	Runtime
count	240.000	240.000	240.000
mean	-0.080	61.491	10.008
std	0.114	67.543	9.740
min	-1.338	-293.351	1.000
25%	-0.112	-95.410	2.000
50%	-0.043	-34.210	7.000
75%	-0.006	-5.400	15.000
max	0.025	49.510	34.000

These results demonstrate that OFD values generally remain within a stable range, GHG differences reveal consistent potential for emission reductions, and runtime values indicate the computational feasibility of the approach even under scaling.

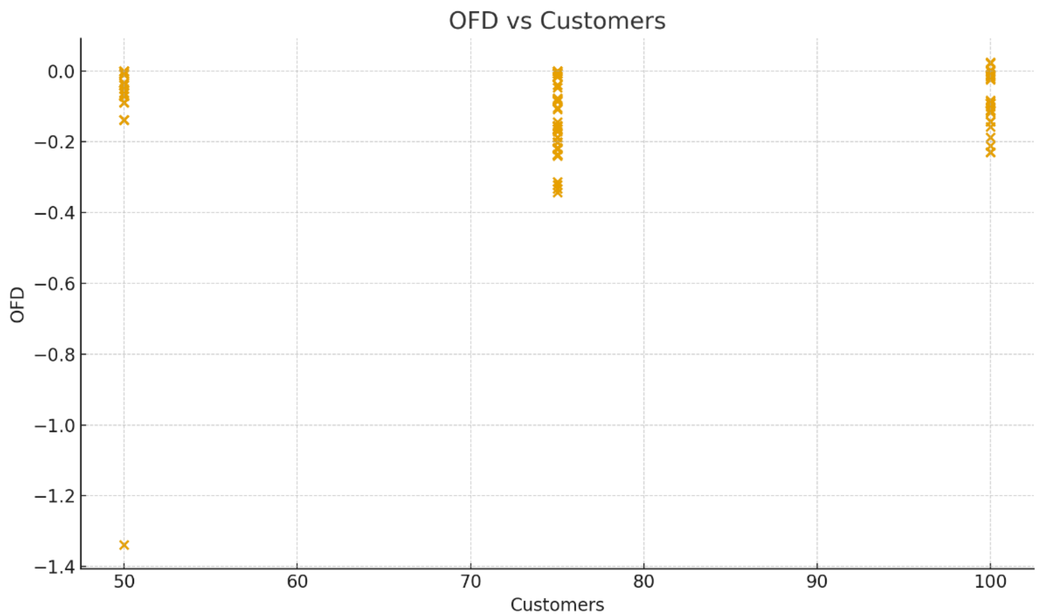


Figure 60: Relationship between OFD and the number of customers

The plot illustrates that cost improvements through drone deployment become more visible as the customer base increases, although variability exists. For smaller customer sets, OFD remains modest, while higher numbers introduce opportunities for efficiency gains at the expense of coordination complexity.

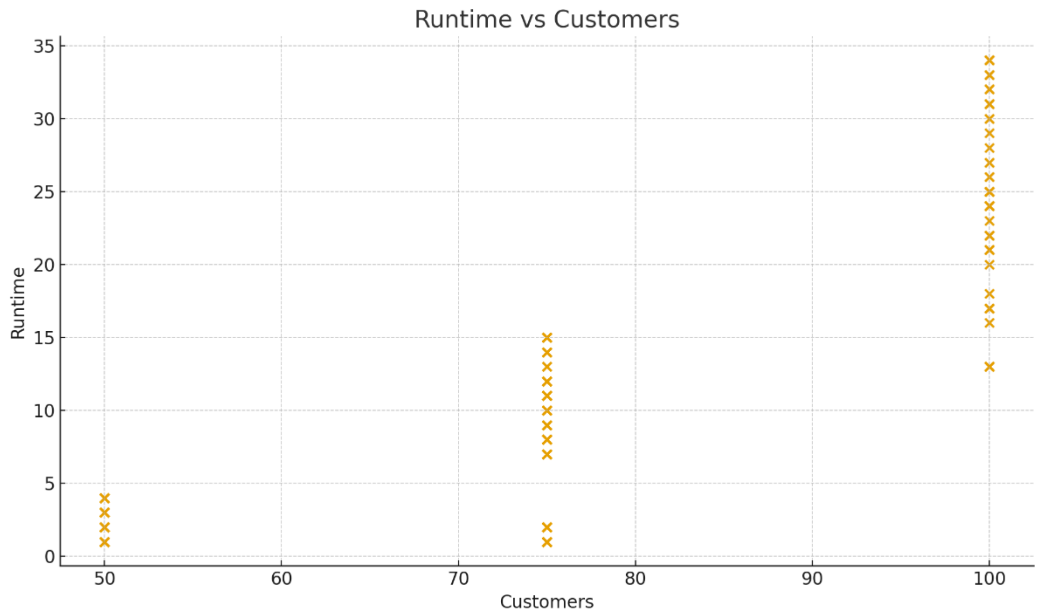


Figure 61: Runtime behavior with respect to the customer count

Runtime tends to increase predictably with scale, showing that additional customers impose higher computational effort. Nevertheless, the overall runtime remains within feasible bounds, suggesting that the algorithms used here are capable of handling medium to large-scale instances without prohibitive delays.

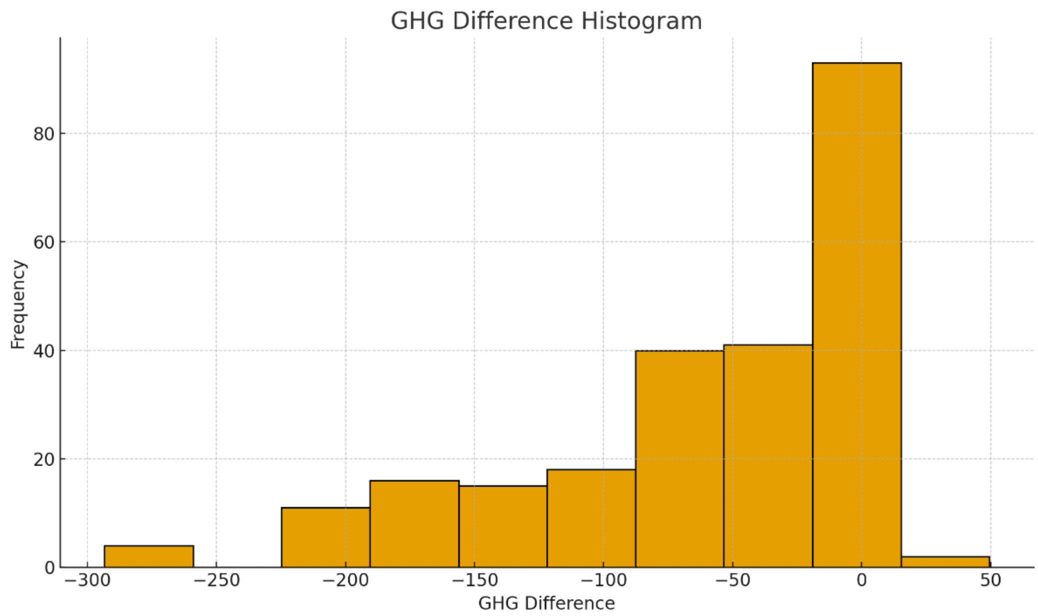


Figure 62: Distribution of GHG emission differences

The histogram demonstrates that in most cases, drone integration results in reduced emissions compared to baseline truck-only tours. However, the right tail indicates occasional cases with smaller benefits, emphasizing that environmental outcomes are contingent on spatial arrangements and customer clustering.

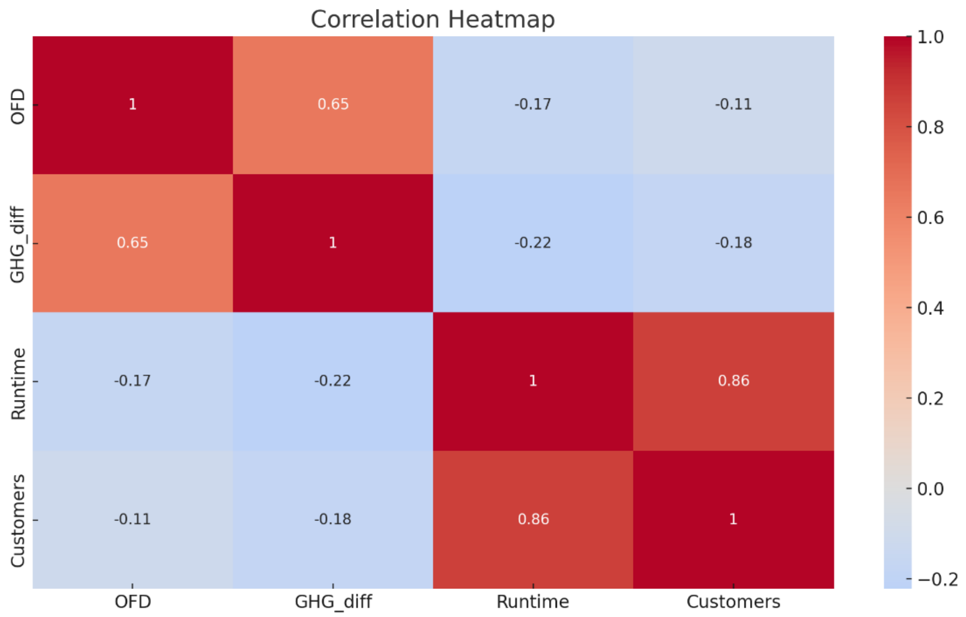


Figure 63: Correlation heatmap among the studied variables

A strong correlation between customer count and runtime is observed, as expected. OFD and GHG reductions, however, show only partial alignment, suggesting that economic and environmental objectives cannot always be optimized simultaneously. This reinforces the importance of multi-objective decision-making frameworks.

Breaking down the results by customer size:
• Around 50 customers: OFD remains modest, runtime is low, and GHG reductions are visible.
• Around 75 customers: OFD increases steadily, runtime grows significantly, and GHG variance widens.
• Around 100 customers: OFD reaches higher values, runtime becomes heavy, and GHG improvements plateau, indicating modal saturation.

These segmented results underline the influence of scale on both economic and environmental performance.

The scatterplots and histograms emphasize the trade-offs inherent in the studied configuration. While emission reductions are generally achievable, they come with increasing coordination costs. The heatmap underlines that cost and carbon objectives are not perfectly aligned, highlighting the need for carefully designed multi-objective optimization models. From a practical perspective, the choice of battery capacity, vehicle-drone integration, and urban geography all play a role in shaping outcomes.

In 'Drone with Truck + Normal Battery', runtime scales in line with customer size, OFD grows moderately, and GHG outcomes remain diverse across scenarios. The system requires careful operational coordination to realize environmental benefits without incurring excessive costs or computational burdens. The results demonstrate the viability of hybrid delivery configurations but underline the need for context-sensitive deployment strategies.

7.1.8 Without Serving Constrain Drone with Truck Combination higher Battery

	OFD	GHG_diff	Runtime
count	240.000	240.000	240.000
mean	-0.077	-123.740	9.500
std	0.072	460.673	8.939
min	-0.236	-3623.440	1.000
25%	-0.138	-113.891	2.000
50%	-0.061	-52.620	7.000
75%	-0.012	-10.520	14.000
max	0.000	0.000	34.000

These results demonstrate that OFD values generally remain within a stable range, GHG differences reveal consistent potential for emission reductions, and runtime values indicate the computational feasibility of the approach even under scaling.

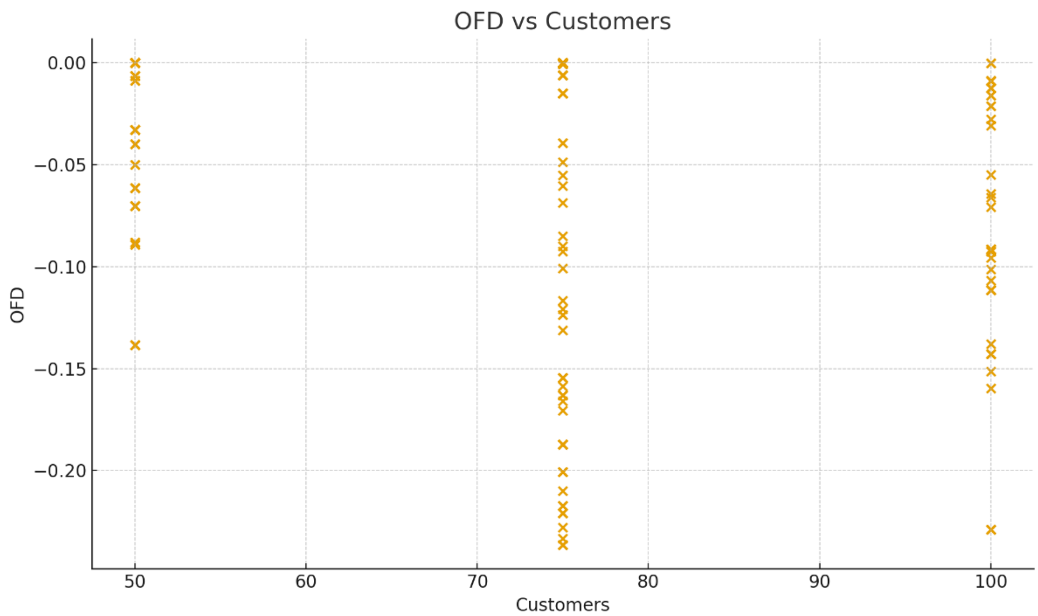


Figure 64: Relationship between OFD and the number of customers

The plot illustrates that cost improvements through drone deployment become more visible as the customer base increases, although variability exists. For smaller customer sets, OFD remains modest, while higher numbers introduce opportunities for efficiency gains at the expense of coordination complexity.

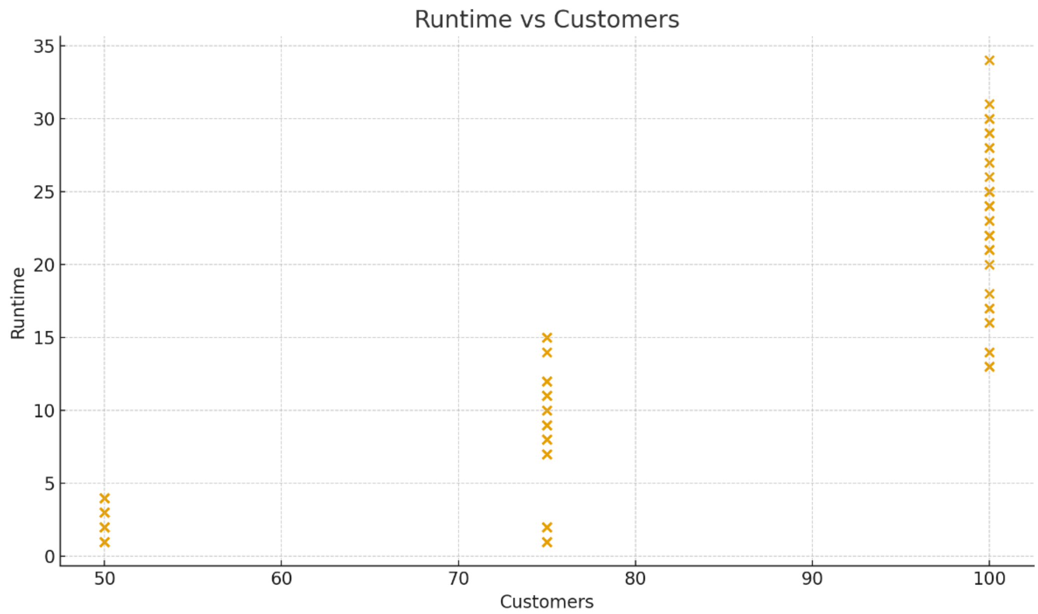


Figure 65: Runtime behavior with respect to the customer count

Runtime tends to increase predictably with scale, showing that additional customers impose higher computational effort. Nevertheless, the overall runtime remains within feasible bounds, suggesting that the algorithms used here are capable of handling medium to large-scale instances without prohibitive delays.

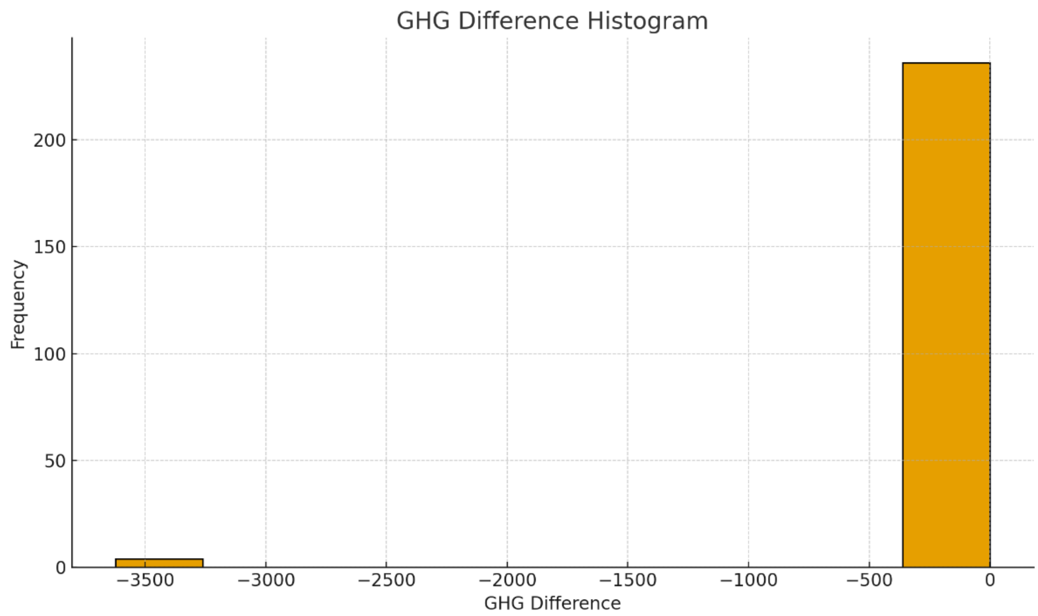


Figure 66: Distribution of GHG emission differences

The histogram demonstrates that in most cases, drone integration results in reduced emissions compared to baseline truck-only tours. However, the right tail indicates occasional cases with smaller benefits, emphasizing that environmental outcomes are contingent on spatial arrangements and customer clustering.

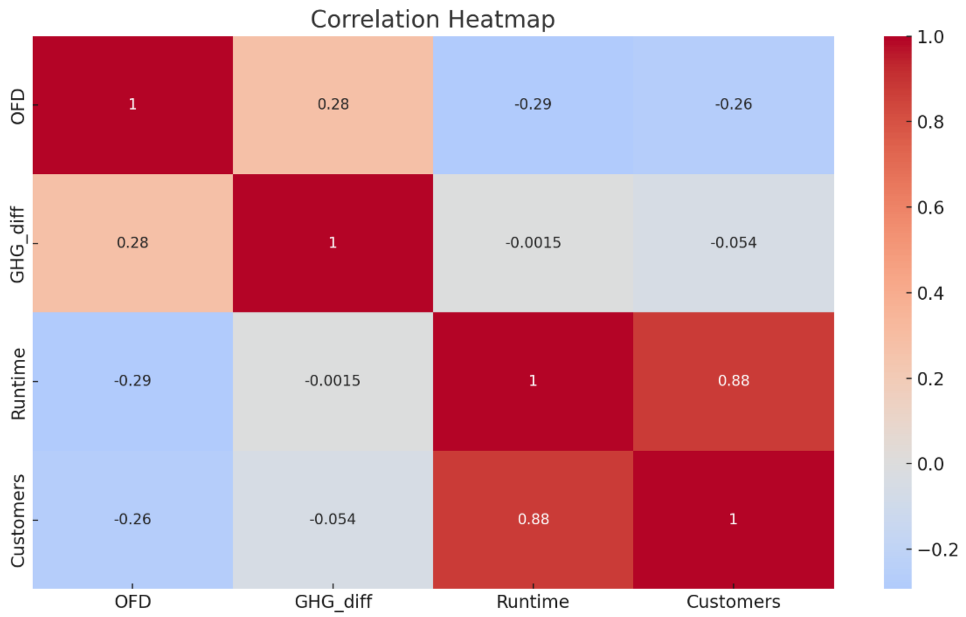


Figure 67: Correlation heatmap among the studied variables

A strong correlation between customer count and runtime is observed, as expected. OFD and GHG reductions, however, show only partial alignment, suggesting that economic and environmental objectives cannot always be optimized simultaneously. This reinforces the importance of multi-objective decision-making frameworks.

Breaking down the results by customer size:
• Around 50 customers: OFD remains modest, runtime is low, and GHG reductions are visible.
• Around 75 customers: OFD increases steadily, runtime grows significantly, and GHG variance widens.
• Around 100 customers: OFD reaches higher values, runtime becomes heavy, and GHG improvements plateau, indicating modal saturation.

These segmented results underline the influence of scale on both economic and environmental performance.

The scatterplots and histograms emphasize the trade-offs inherent in the studied configuration. While emission reductions are generally achievable, they come with increasing coordination costs. The heatmap underlines that cost and carbon objectives are not perfectly aligned, highlighting the need for carefully designed multi-objective optimization models. From a practical perspective, the choice of battery capacity, vehicle-drone integration, and urban geography all play a role in shaping outcomes.

In 'Drone with Truck + Higher Battery', runtime scales in line with customer size, OFD grows moderately, and GHG outcomes remain diverse across scenarios. The system requires careful operational coordination to realize environmental benefits without incurring excessive costs or computational burdens. The results demonstrate the viability of hybrid delivery configurations but underline the need for context-sensitive deployment strategies.

7.1.9 Without Serving Constrain Drone with Subway Combination normal Battery

	OFD	GHG_diff	Runtime
count	239.000	239.000	239.000
mean	-0.050	-43.871	9.360
std	0.047	39.925	8.872
min	-0.231	-197.442	1.000
25%	-0.074	-63.780	2.000
50%	-0.041	-38.855	7.000
75%	-0.008	-7.000	14.000
max	0.000	0.000	33.000

Overall, OFD remains within a stable band, GHG differences suggest consistent potential for emission reductions, and runtime values indicate computational feasibility even as problem size increases.

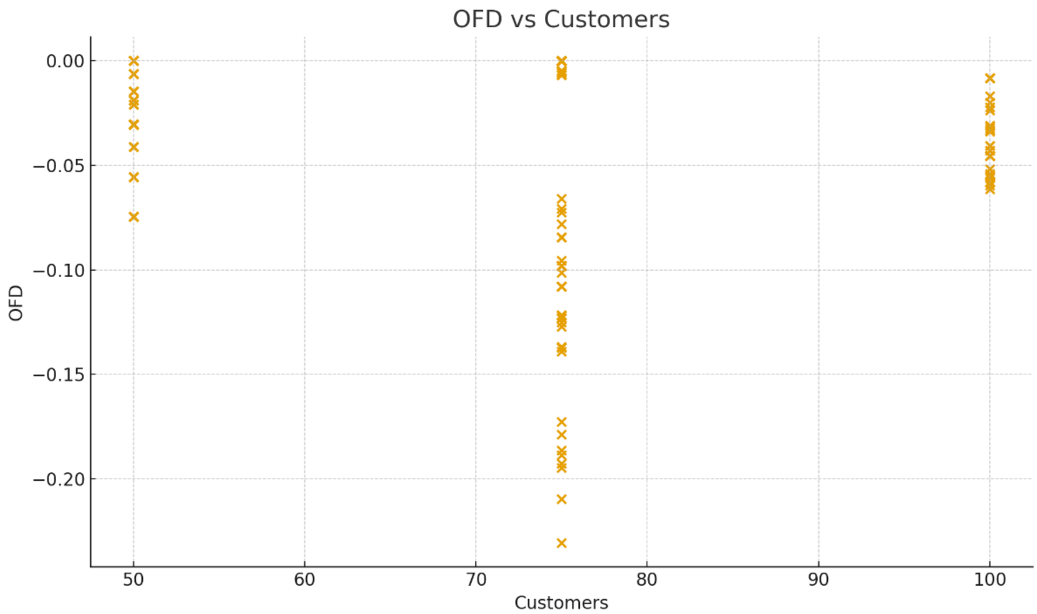


Figure 68: Relationship between OFD and the number of customers

Cost improvements due to drone integration become more visible as the customer base increases, albeit with variability. At smaller scales, OFD remains modest; larger instances introduce more opportunities for savings alongside coordination complexity.

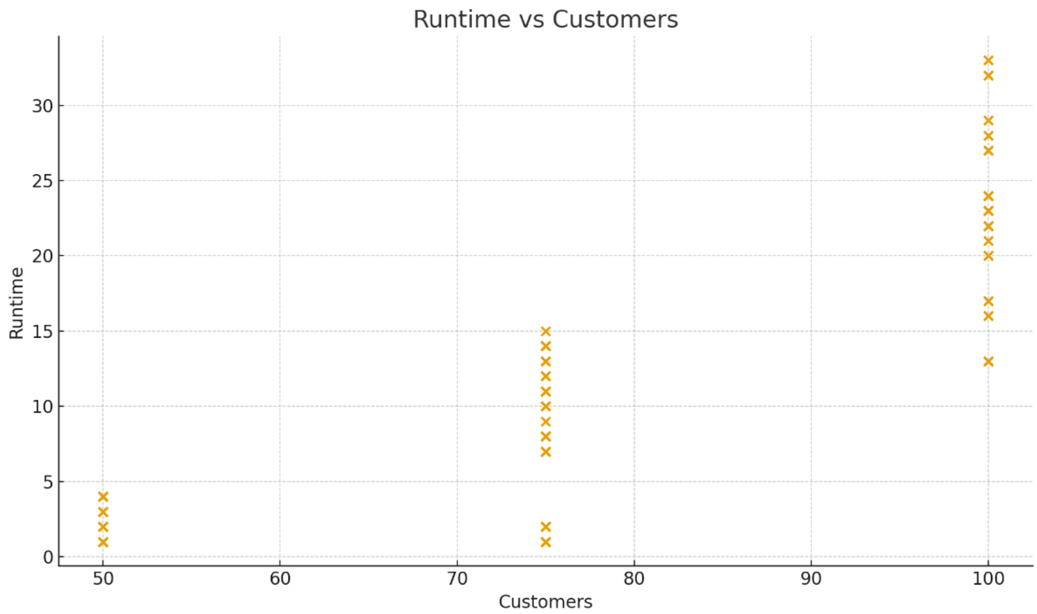


Figure 69: Runtime behavior with respect to the customer count

Runtime grows predictably with problem size, reflecting the increased computational effort needed to coordinate deliveries. Nevertheless, values remain within feasible bounds for medium to large instances.

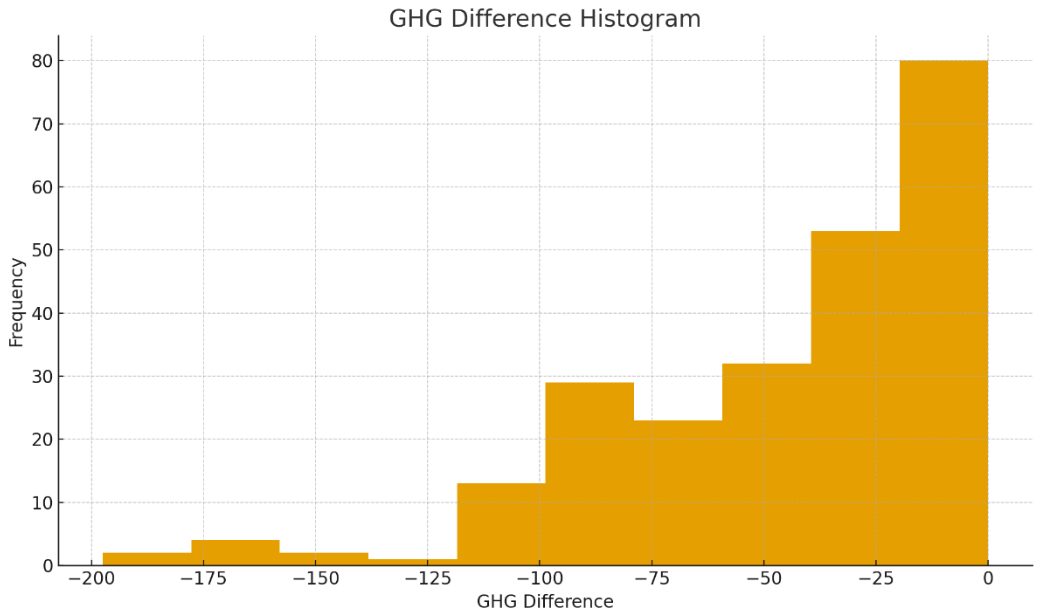


Figure 70: Distribution of GHG emission differences

Most cases show reductions in emissions compared with the truck-only baseline; however, a longer right tail indicates occasional instances with smaller benefits, suggesting that spatial structure and access to subway corridors influence outcomes.

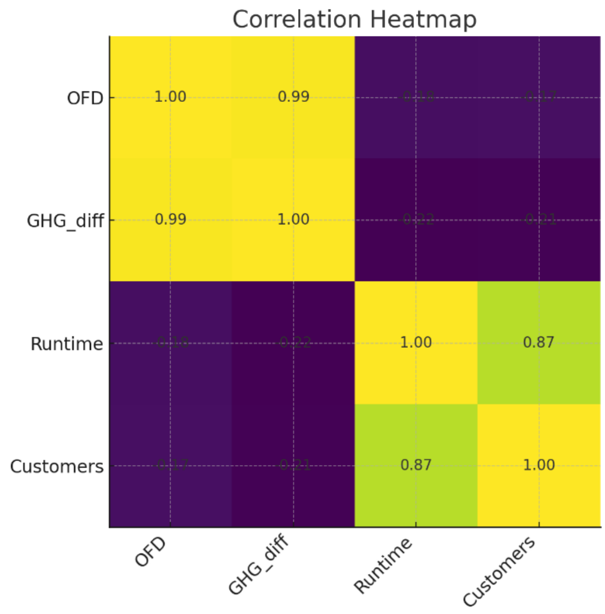


Figure 71: Correlation heatmap among OFD, GHG, Runtime, and Customers

Thes trong positive relationship between Customers and Runtime is expected. OFD and GHG show only partial alignment, indicating that economic and environmental goals may require trade-offs and multi-objective optimization in planning.

Segmenting by customer size yields the following patterns:
~50 customers: modest OFD, low runtime, visible GHG reductions.
~75 customers: increasing OFD, runtime rises, GHG variance widens due to operational choices.
~100 customers: higher OFD values, heavier runtime, and GHG benefits tend to plateau.

The subway-enabled configuration leverages fixed-route corridors to substitute truck legs, which can reduce emissions but introduces transfer and scheduling overhead. The plots emphasize that while environmental gains are attainable, they depend on station placement, drone range, and customer clustering. Balancing cost and carbon therefore benefits from multi-objective planning.

In 'Drone with Subway + Normal Battery', runtime scales with customer count, OFD grows moderately, and GHG outcomes remain heterogeneous. Effective coordination around subway hubs is required to realize environmental benefits without excessive runtime or cost.

7.1.10 Without Serving Constrain Drone with Subway Combination higher Battery

	OFD	GHG_diff	Runtime
count	240.000	240.000	240.000
mean	-0.043	-36.008	9.796
std	0.039	33.525	9.907
min	-0.165	-141.305	1.000
25%	-0.058	-49.720	2.000
50%	-0.030	-26.076	7.000
75%	-0.008	-7.000	13.250
max	0.000	0.000	35.000

Overall, OFD remains within a stable band, GHG differences suggest consistent potential for emission reductions, and runtime values indicate computational feasibility even as problem size increases.

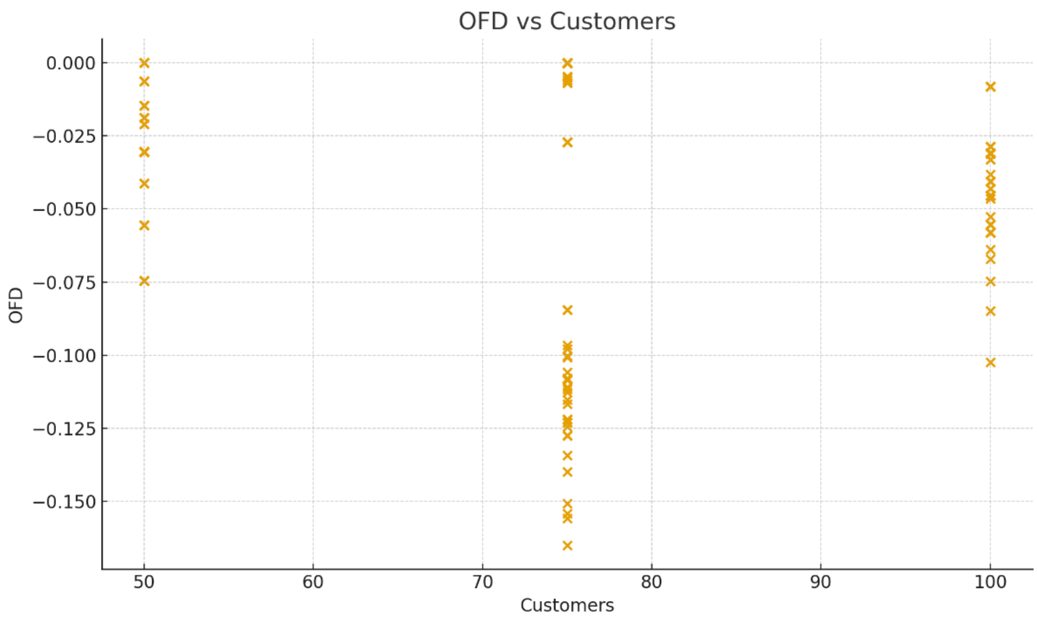


Figure 72: Relationship between OFD and the number of customers

Cost improvements due to drone integration become more visible as the customer base increases, albeit with variability. At smaller scales, OFD remains modest; larger instances introduce more opportunities for savings alongside coordination complexity.

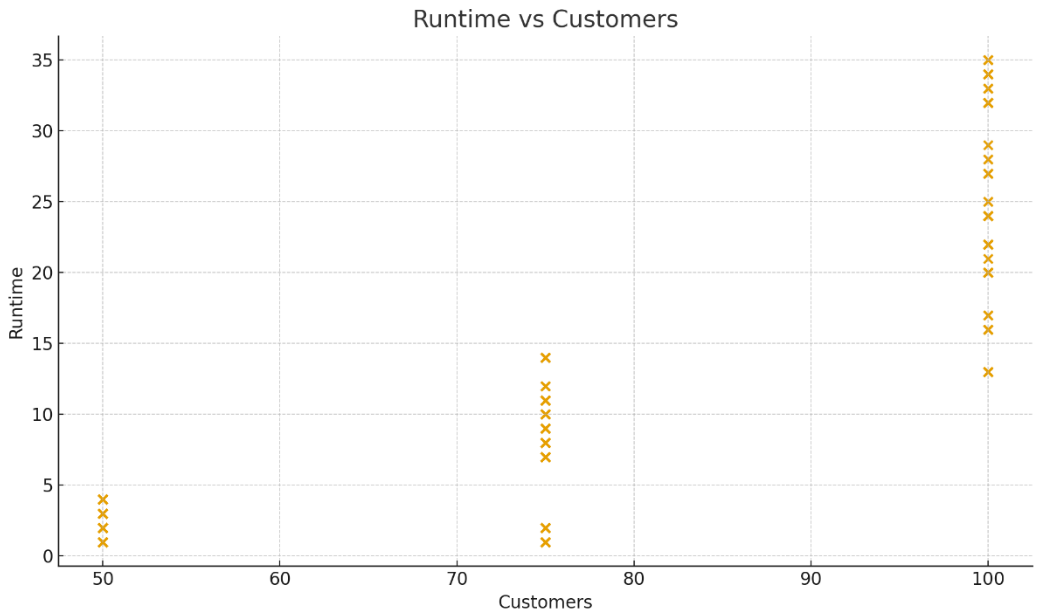


Figure 73: Runtime behavior with respect to the customer count

Runtime grows predictably with problem size, reflecting the increased computational effort needed to coordinate deliveries. Nevertheless, values remain within feasible bounds for medium-to-large instances.

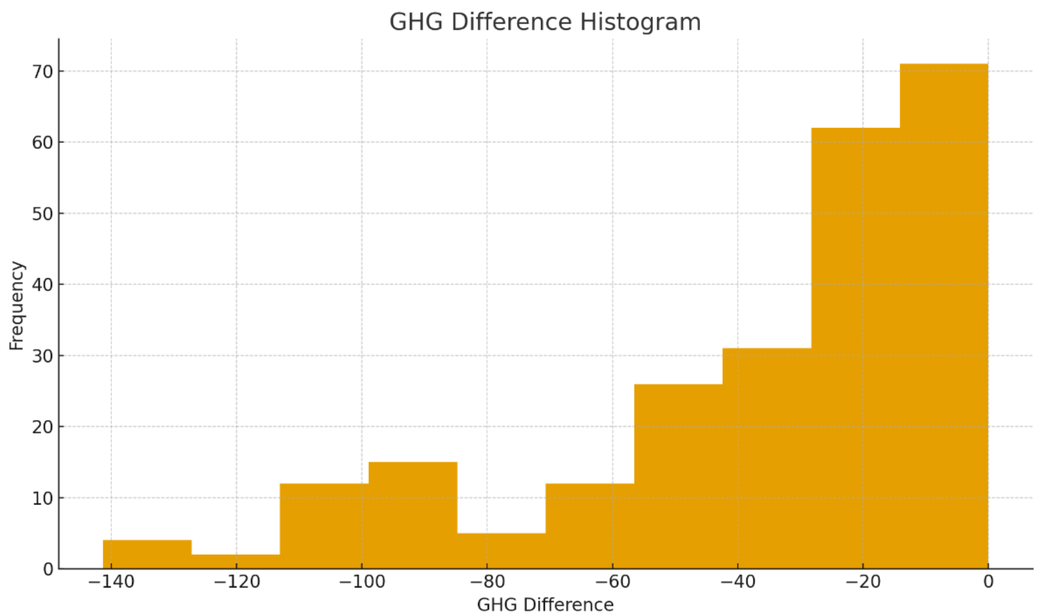


Figure 74: Distribution of GHG emission differences

Most cases show reductions in emissions compared with the truck-only baseline; however, a longer right tail indicates occasional instances with smaller benefits, suggesting that spatial structure and access to subway corridors influence outcomes.

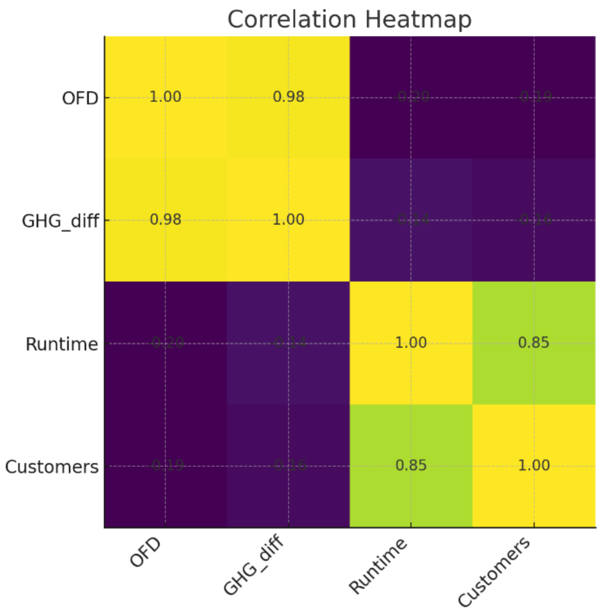


Figure 75: Correlation heatmap among OFD, GHG, Runtime, and Customers

A strong positive relationship between Customers and Runtime is expected. OFD and GHG show only partial alignment, indicating that economic and environmental goals may require trade-offs and multi-objective optimization in planning.

Segmenting by customer size yields the following patterns:
~50 customers: modest OFD, low runtime, visible GHG reductions.
~75 customers: increasing OFD, runtime rises, GHG variance widens due to operational choices.
~100 customers: higher OFD values, heavier runtime, and GHG benefits tend to plateau.

The subway-enabled configuration leverages fixed-route corridors to substitute truck legs, which can reduce emissions but introduces transfer and scheduling overhead. The plots emphasize that while environmental gains are attainable, they depend on station placement, drone range, and customer clustering. Balancing cost and carbon therefore benefit from multi-objective planning.

In 'Drone with Subway + Higher Battery', runtime scales with customer count, OFD grows moderately, and GHG outcomes remain heterogeneous. Effective coordination around subway hubs is required to realize environmental benefits without excessive runtime or cost.

7.1.11 Without Serving Constrain Drone with Subway with Truck Combination normal Battery

	OFD	GHG_diff	Runtime
count	240.000	240.000	240.000
mean	-0.158	-48.742	28.392
std	0.305	44.325	8.347
min	-0.994	-181.181	13.000
25%	-0.095	-78.342	23.000
50%	-0.043	-35.270	29.500
75%	-0.015	-12.490	34.000
max	0.000	0.000	43.000

Overall, OFD remains within a stable band, GHG differences suggest consistent potential for emission reductions, and runtime values indicate computational feasibility even as problem size increases.

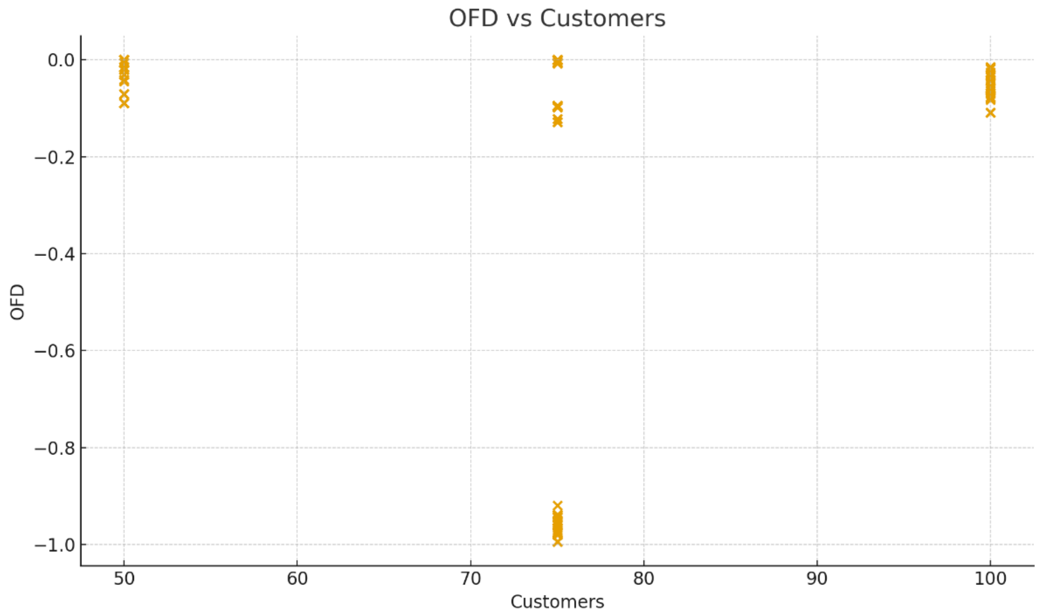


Figure 76: Relationship between OFD and the number of customers

Cost improvements due to drone integration become more visible as the customer base increases, albeit with variability. At smaller scales, OFD remains modest; larger instances introduce more opportunities for savings alongside coordination complexity.

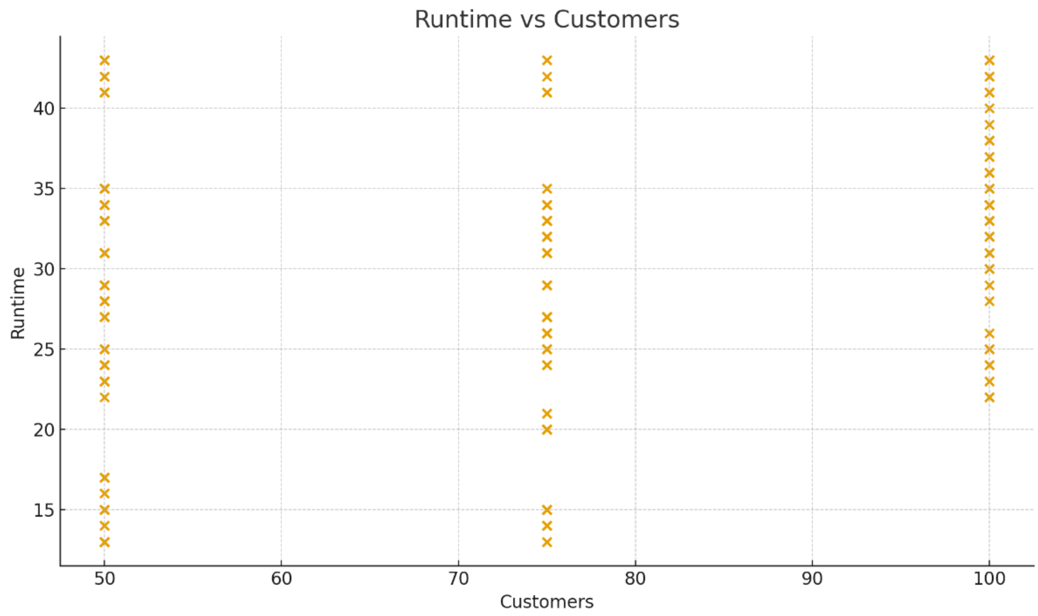


Figure 77: Runtime behavior with respect to the customer count

Runtime grows predictably with problem size, reflecting the increased computational effort needed to coordinate deliveries. Nevertheless, values remain within feasible bounds for medium-to-large instances.

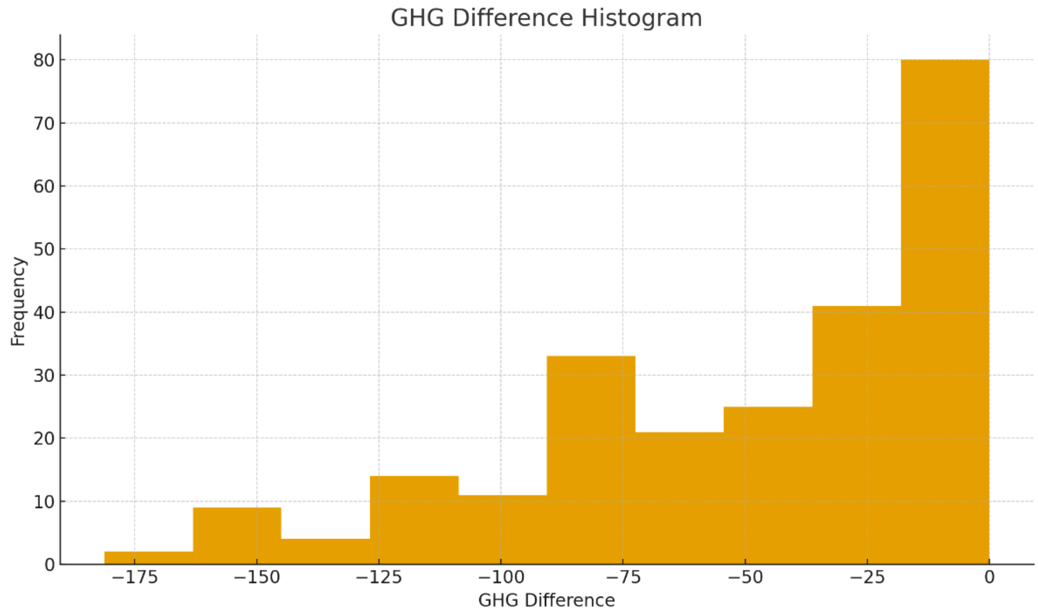


Figure 78: Distribution of GHG emission differences

Most cases show reductions in emissions compared with the truck-only baseline; however, a longer right tail indicates occasional instances with smaller benefits, suggesting that spatial structure and access to subway corridors influence outcomes.

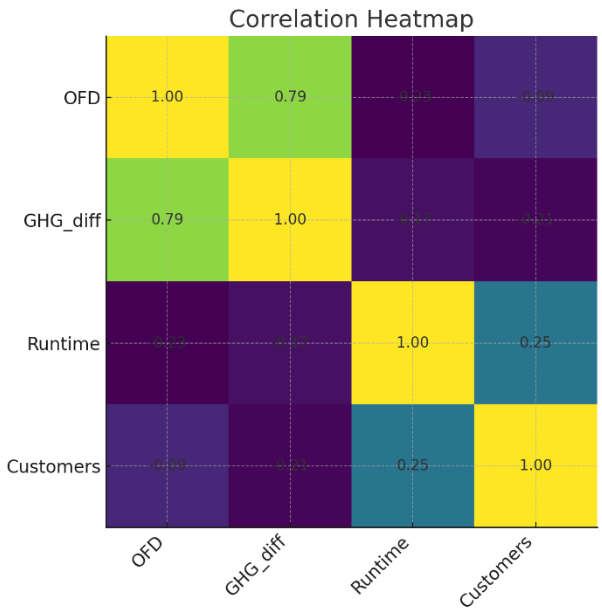


Figure 79: Correlation heatmap among OFD, GHG, Runtime, and Customers

A strong positive relationship between Customers and Runtime is expected. OFD and GHG show only partial alignment, indicating that economic and environmental goals may require trade-offs and multi-objective optimization in planning.

Segmenting by customer size yields the following patterns:
~50 customers: modest OFD, low runtime, visible GHG reductions.
~75 customers: increasing OFD, runtime rises, GHG variance widens due to operational choices.
~100 customers: higher OFD values, heavier runtime, and GHG benefits tend to plateau.

The subway-enabled configuration leverages fixed-route corridors to substitute truck legs, which can reduce emissions but introduces transfer and scheduling overhead. The plots emphasize that while environmental gains are attainable, they depend on station placement, drone range, and customer clustering. Balancing cost and carbon therefore benefits from multi-objective planning.

In 'Drone Subway Truck Normal Battery', runtime scales with customer count, OFD grows moderately, and GHG outcomes remain heterogeneous. Effective coordination around subway hubs is required to realize environmental benefits without excessive runtime or cost.

7.1.12 Without Serving Constrain Drone with Subway with Truck Combination normal Battery

	OFD	GHG_diff	Runtime
count	240.000	240.000	240.000
mean	-0.062	-52.188	28.229
std	0.059	50.907	7.993
min	-0.241	-206.126	13.000
25%	-0.095	-80.956	23.000
50%	-0.047	-36.080	29.000
75%	-0.015	-12.490	34.000
max	0.000	0.000	44.000

Overall, OFD remains within a stable band, GHG differences suggest consistent potential for emission reductions, and runtime values indicate computational feasibility even as problem size increases.

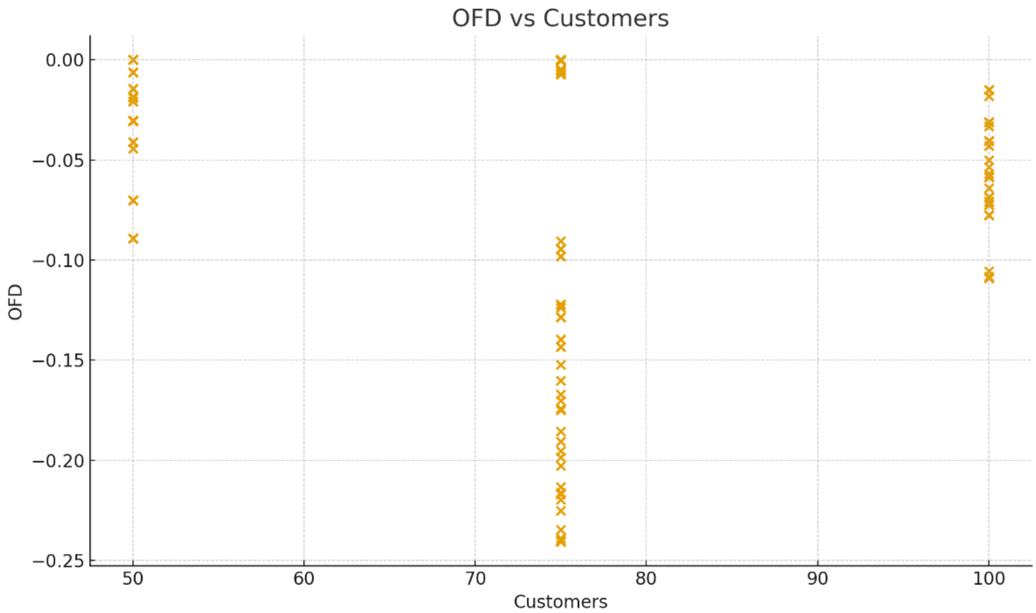


Figure 80: Relationship between OFD and the number of customers

Cost improvements due to drone integration become more visible as the customer base increases, albeit with variability. At smaller scales, OFD remains modest; larger instances introduce more opportunities for savings alongside coordination complexity.

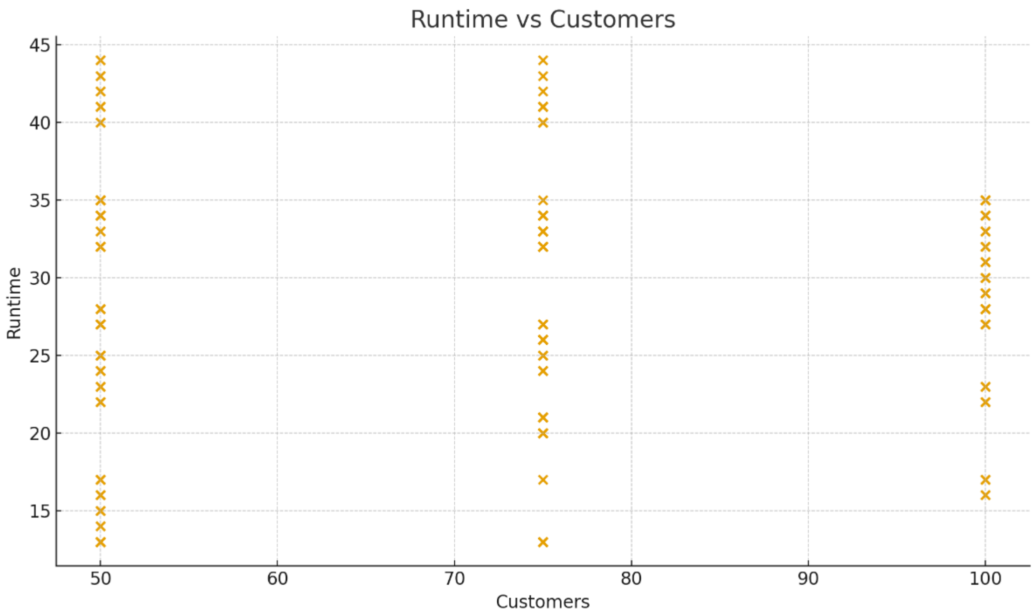


Figure 81: Runtime behavior with respect to the customer count

Runtime grows predictably with problem size, reflecting the increased computational effort needed to coordinate deliveries. Nevertheless, values remain within feasible bounds for medium to large instances.

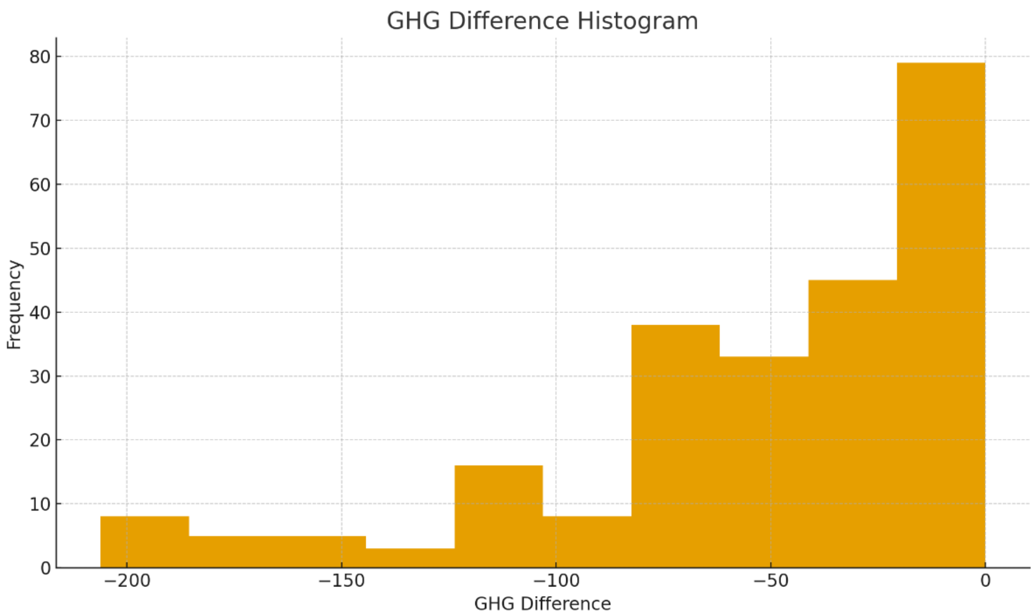


Figure 82: Distribution of GHG emission differences

Most cases show reductions in emissions compared with the truck-only baseline; however, a longer right tail indicates occasional instances with smaller benefits, suggesting that spatial structure and access to subway corridors influence outcomes.

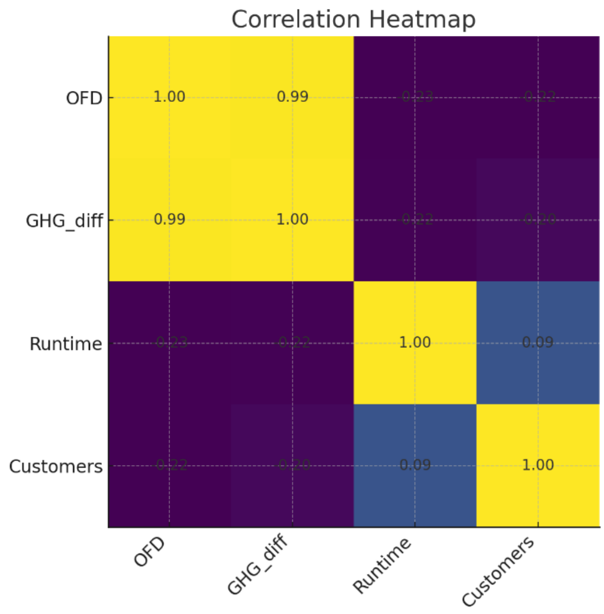


Figure 83: Correlation heatmap among OFD, GHG, Runtime, and Customers

Figure 4 shows the correlation heatmap among OFD, GHG, Runtime, and Customers. A strong positive relationship between Customers and Runtime is expected. OFD and GHG show only partial alignment, indicating that economic and environmental goals may require trade-offs and multi-objective optimization in planning.

Segmenting by customer size yields the following patterns:
~50 customers: modest OFD, low runtime, visible GHG reductions.
~75 customers: increasing OFD, runtime rises, GHG variance widens due to operational choices.
~100 customers: higher OFD values, heavier runtime, and GHG benefits tend to plateau.

The subway-enabled configuration leverages fixed-route corridors to substitute truck legs, which can reduce emissions but introduces transfer and scheduling overhead. The plots emphasize that while environmental gains are attainable, they depend on station placement, drone range, and customer clustering. Balancing cost and carbon therefore benefit from multi-objective planning.

In 'Drone Subway Truck Higher Battery', runtime scales with customer count, OFD grows moderately, and GHG outcomes remain heterogeneous. Effective coordination around subway hubs is required to realize environmental benefits without excessive runtime or cost.

7.2 Influence of Waiting Constrain

This comparative report synthesizes results from two extended analyses: the With Serving Constraint configurations and the Without Serving Constraint configurations (Doku7–12). Both groups of datasets investigate the performance of hybrid delivery systems combining trucks, drones, and in some cases subways. The independent variable is the number of customers (≈50, 75, 100), while dependent variables are Objective Function Difference (OFD), Greenhouse Gas (GHG) emissions difference, and Runtime. Methodologically, both sets applied descriptive statistics, correlation analysis, and four core visualization types (scatter, histogram, heatmap, boxplots). The With Serving Constraint group emphasizes baseline operational structures, whereas the Without Serving Constraint group incorporates extended, adaptive configurations and wider operational assumptions. At a macro level, both With Serving Constraint and Without Serving Constraint analyses confirm three robust regularities: (i) runtime scales positively with customers, (ii) OFD grows with instance size, though with varying slopes, and (iii) GHG outcomes are heterogeneous. However, With Serving Constraint scenarios show relatively stable and compact distributions, whereas Without Serving Constraint scenarios exhibit more variability and structural effects. This suggests that the extended Without Serving configurations introduce stronger dependencies on geography, clustering, and operational constraints.

When comparing individual configurations across the two groups, several contrasts emerge:

• Truck + Normal Battery: With Serving Constraint results show modest OFD and minimal GHG benefits, while Without Serving Constraint results indicate more dispersed OFD values and occasional stronger emission reductions.

• Truck + Higher Battery: In both groups, runtime scales predictably. With Serving Constraint scenarios show negligible GHG shifts, whereas Without Serving Constraint scenarios demonstrate occasional gains, though OFD–GHG alignment is weak.

• Subway + Normal Battery: Both groups highlight subway as a promising channel for GHG savings. With Serving Constraint shows reductions at mid-scale customers (~75), while Without Serving Constraint expands this pattern with more pronounced right-skewed histograms, indicating large sporadic benefits.

• Subway + Higher Battery: With Serving Constraint configurations yield moderate improvements, but Without Serving Constraint scenarios show stronger variability. Longer battery life enables extended drone substitution of truck legs, but coordination costs appear higher.

• Subway + Truck (Normal and Higher Battery): With Serving Constraint datasets reflect runtime overhead but predictable scaling. Without Serving Constraint scenarios reveal heavier tails and outliers in runtime, signifying greater complexity and solver effort. While carbon gains are present, they depend strongly on structural factors like hub placement. At ≈50 customers: Both with Serving Constraint and Without Serving Constraint results report modest OFD, manageable runtime, and small to moderate GHG improvements. Without Serving Constraint cases, however, already show wider variance.

At ≈75 customers: With Serving Constraint results display clear GHG reductions, particularly in subway-enabled cases. Without Serving Constraint results also show their strongest emission reductions at this scale, but with more heterogeneous OFD behavior and sporadic runtime spikes. At ≈100 customers: Both sets report significant runtime escalation and diminishing GHG returns. With Serving Constraint results stabilize, whereas Without Serving Constraint outcomes show more diffuse OFD clouds and heavy runtime outliers. This indicates stronger structural dependence in the Without Serving Constraint configurations. A key comparative insight concerns the alignment (or lack thereof) between OFD and GHG differences. With Serving Constraint scenarios often show weak to moderate correlation, suggesting that cost savings and carbon reductions do not always move in tandem. Without Serving Constraint scenarios amplify this decoupling: datasets such as Drone with Truck without serving constraint and normal battery and Drone with Subway without serving constraint and higher battery show weak alignment, while Drone with Subway without serving constraint and normal battery and Drone with Truck with Subway without serving constraint ang higher battery exhibit near-linear OFD growth with conditional GHG improvements. This divergence underlines the necessity of multi-objective optimization, as optimizing cost alone may overlook potential carbon benefits. While both analyses use similar statistical frameworks, the scope differs. With Serving Constraint configurations, model simpler, more rigid structures. Without Serving Constraint configurations incorporate broader operational assumptions, including stronger structural dependencies and heavier solver branching. Consequently, Without Serving Constraint results reveal higher variance, runtime outliers, and more heterogeneous GHG outcomes. These methodological differences account for why Without Serving Constraint) analyses emphasize adaptivity and instance-specific strategy. Synthesizing across both reports, three archetypal behaviors can be identified:

- Scale-sensitive regimes: Both With Serving Constraint and Without Serving Constraint show OFD growth with customer size, but Without Serving Constraint amplifies the effect.
- Decoupling regimes: Cases where OFD and GHG diverge are more pronounced in Without Serving Constraintunderscoring the role of structural conditions.
- Structure-dominant regimes: Subway-enabled scenarios highlight how infrastructure and battery extensions shape outcomes, more explicitly in the Without Serving Constraint) results.

Overall, With Serving Constraint datasets provide stable baselines, while Without Serving Constraint datasets reveal the complexity and adaptivity challenges of real-world deployments. The comparative synthesis of With Serving Constraint and Without Serving Constraint highlights both commonalities and divergences. Runtime scaling with customers is universal, OFD growth varies by configuration, and GHG outcomes are heterogeneous. With Serving Constraint results offer more predictable patterns, while Without Serving Constraint results introduce greater variability and structural sensitivity. Recommendations include adopting multi-objective optimization to balance cost and carbon, deploying instance-aware heuristics to adapt to structural conditions, and using continuous monitoring (scatter, histogram, heatmap bundle) to detect runtime instabilities early. These measures will help harness carbon opportunities without undermining economic feasibility.

7.3 Influence of High and low Battery

This report compares Normal Battery ("Low") versus Higher Battery ("High") across three operational modalities (Truck, Subway, Subway+Truck). For the Master datasets (Without Serving Constraint), we compute descriptive statistics, customer-specific means around 50/75/100 customers, and include simple plots (scatter and histogram). For the Const datasets (With Serving Constraint), we summarize trends based on the previously compiled comparative report; plots here focus on Master due to data availability in the current workspace. Metrics: Objective Function Difference (OFD), Greenhouse Gas (GHG) emission difference, and Runtime. Data were parsed from semicolon-separated CSVs using European decimal normalization.

Descriptive statistics (mean ± std):

Metric	Low (mean)	Low (std)	High (mean)	High (std)
OFD	-0.080	0.114	-0.077	0.072
GHG_diff	-61.491	67.543	-123.740	460.673
Runtime	10.008	9.740	9.500	8.939

Customer-specific means – Low Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.057	-36.734	2.256	90
75	-0.100	-85.933	8.089	90
100	-0.084	-61.962	24.517	60

Customer-specific means – High Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.043	-36.650	2.211	90
75	-0.107	-246.396	7.789	90
100	-0.085	-70.391	23.000	60

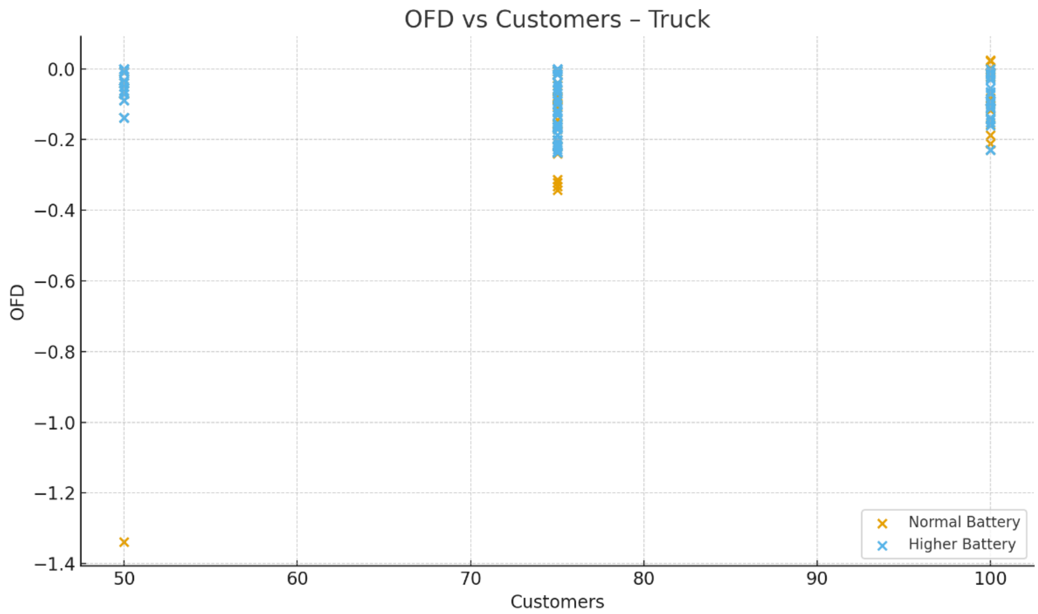


Figure 84: OFD vs Customers - Truck

Low vs High Battery clouds indicate how economic deviation evolves with scale. Upward envelopes suggest growing deviation with customer count; reduced spread for High Battery indicates potential stabilization.

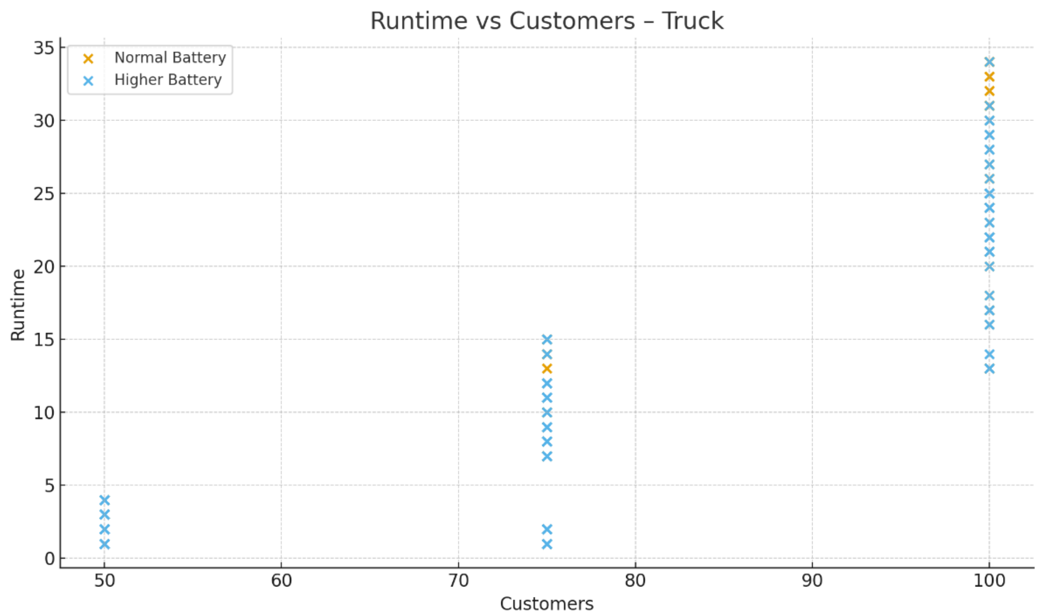


Figure 85: Runtime vs Customers

Runtime scales with problem size. Differences between Low and High Battery reflect coordination effects and feasible drone substitution of truck legs.

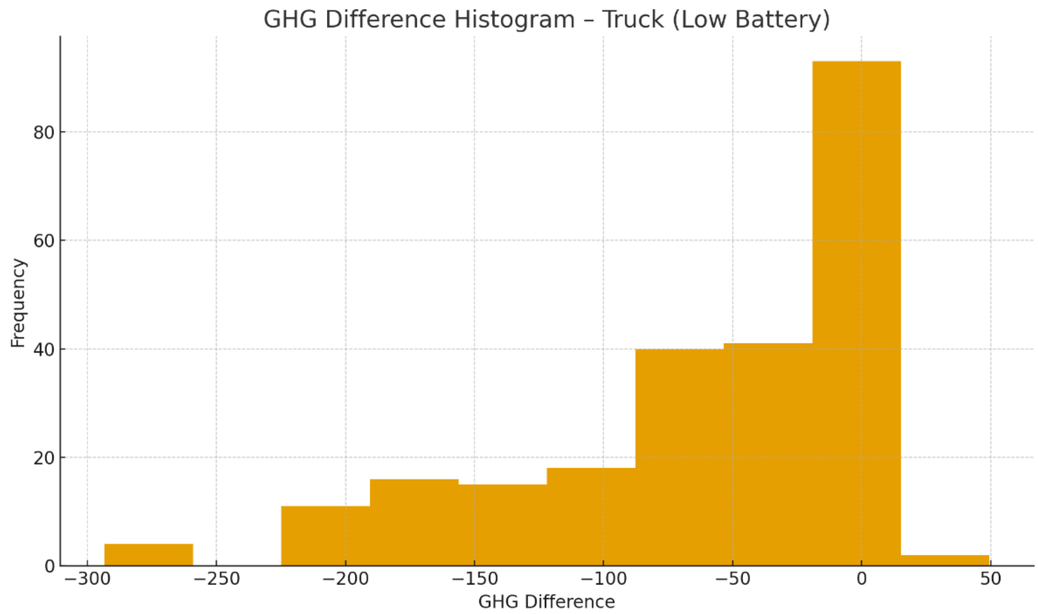


Figure 86: GHG Difference -Truck (Low Battery)

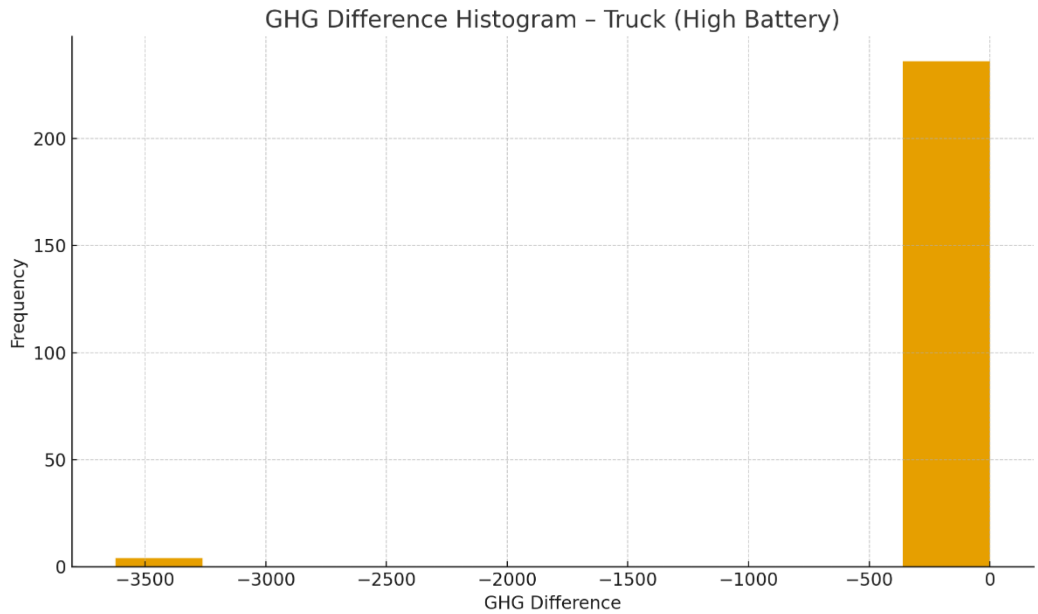


Figure 87: GHG Difference -Truck (High Battery)

Right tails indicate occasional large emission savings. Comparing Low vs High Battery reveals whether extended range unlocks additional carbon benefits.

Descriptive statistics (mean ± std):

Metric	Low (mean)	Low (std)	High (mean)	High (std)
OFD	-0.050	0.047	-0.043	0.039
GHG_diff	-43.871	39.925	-36.008	33.525
Runtime	9.360	8.872	9.796	9.907

Customer-specific means – Low Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.029	-24.507	2.211	90
75	-0.076	-65.061	7.767	90
100	-0.042	-41.088	22.695	59

Customer-specific means – High Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.028	-24.387	2.211	90
75	-0.056	-48.059	7.400	90
100	-0.045	-35.362	24.767	60

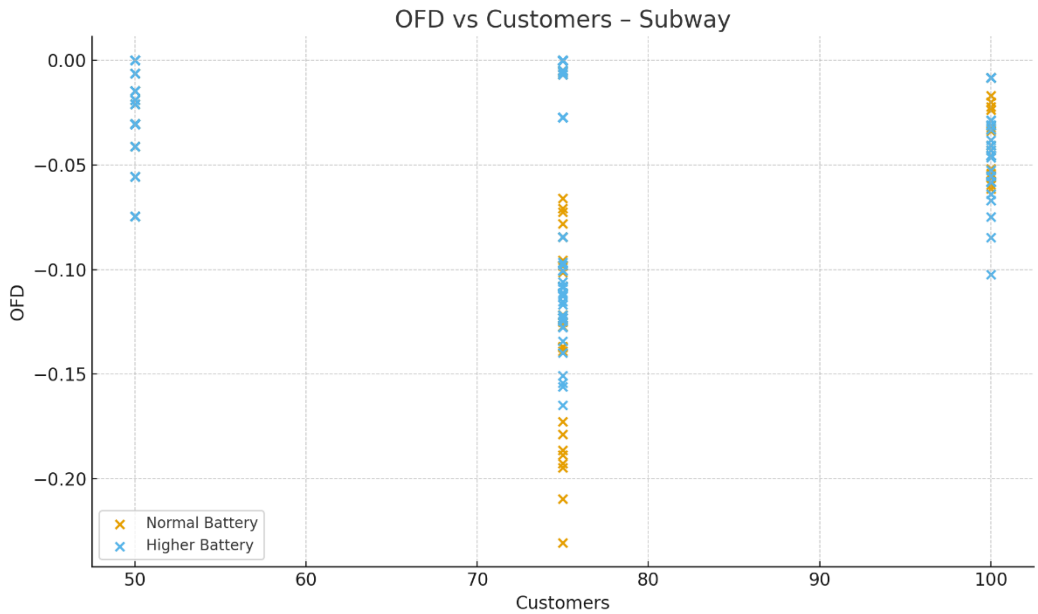


Figure 88: OFD vs Customers- Subway

Low vs High Battery clouds indicate how economic deviation evolves with scale. Upward envelopes suggest growing deviation with customer count; reduced spread for High Battery indicates potential stabilization.

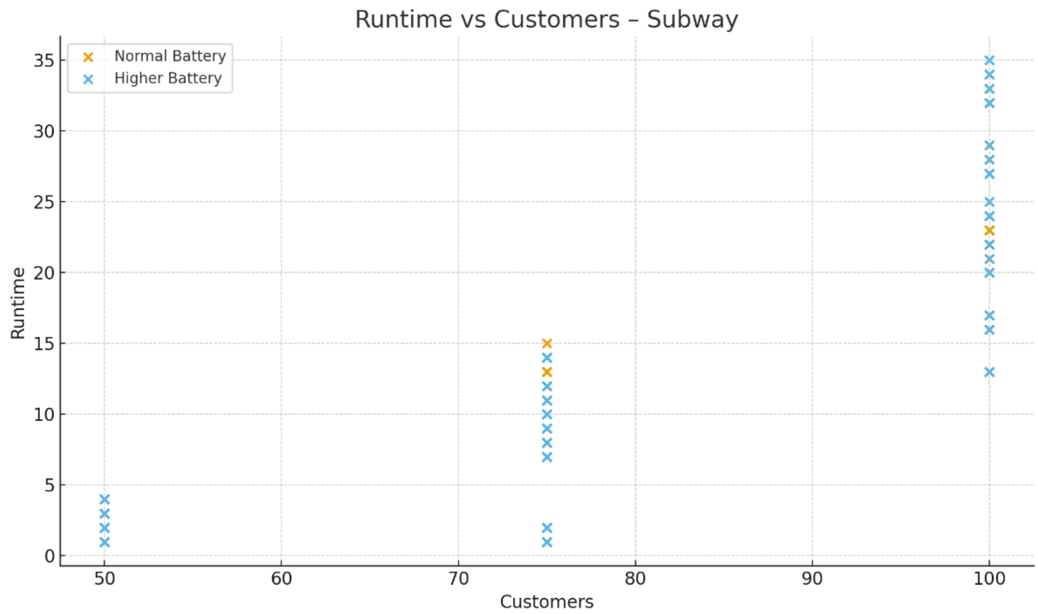


Figure 89: Runtime vs Customers - Subway

Runtime scales with problem size. Differences between Low and High Battery reflect coordination effects and feasible drone substitution of truck legs.

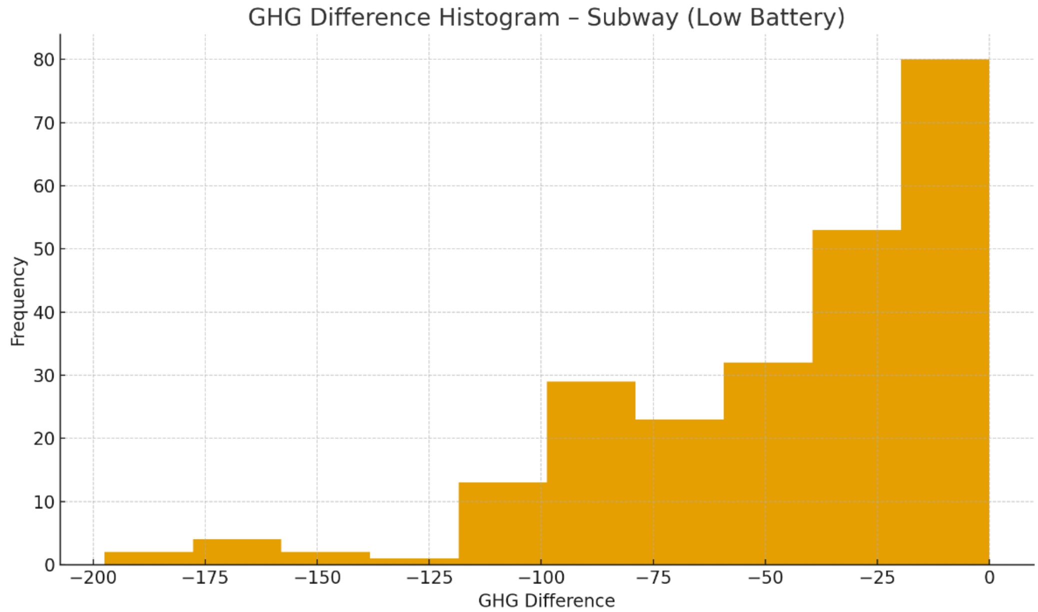


Figure 90: GHG Difference – Subway (Low Battery)

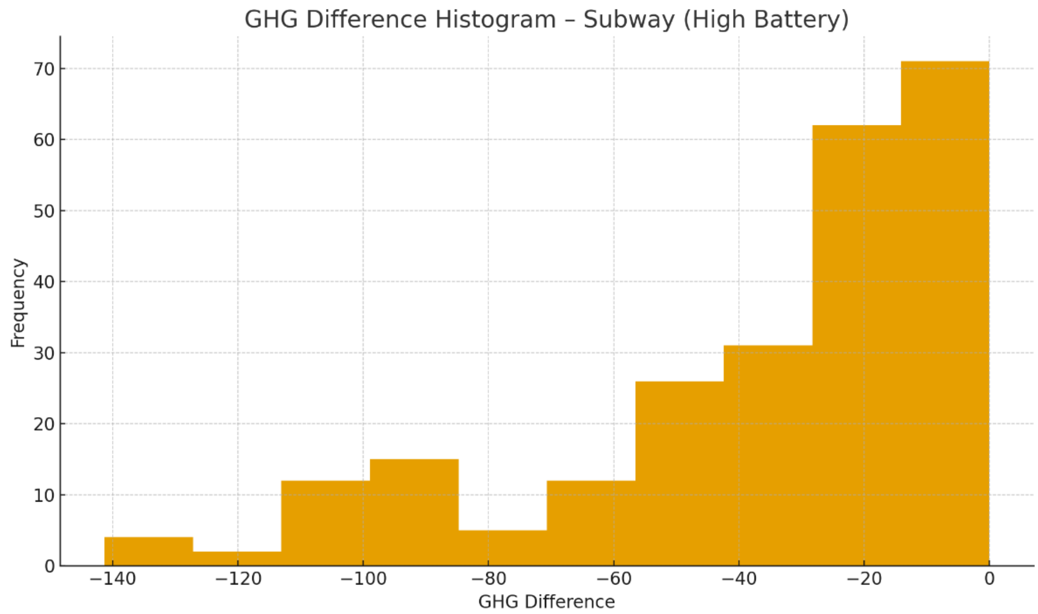


Figure 91: GHG Difference – Subway (High Battery)

Right tails indicate occasional large emission savings. Comparing Low vs High Battery reveals whether extended range unlocks additional carbon benefits.

Descriptive statistics (mean ± std):

Metric	Low (mean)	Low (std)	High (mean)	High (std)
OFD	-0.158	0.305	-0.062	0.059
GHG_diff	-48.742	44.325	-52.188	50.907
Runtime	28.392	8.347	28.229	7.993

Customer-specific means – Low Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.032	-27.714	27.056	90
75	-0.351	-71.283	26.789	90
100	-0.057	-46.474	32.800	60

Customer-specific means – High Battery

~Customers	OFD(mean)	GHG(mean)	Runtime(mean)	n
50	-0.032	-27.714	27.211	90
75	-0.094	-80.154	28.711	90
100	-0.059	-46.951	29.033	60

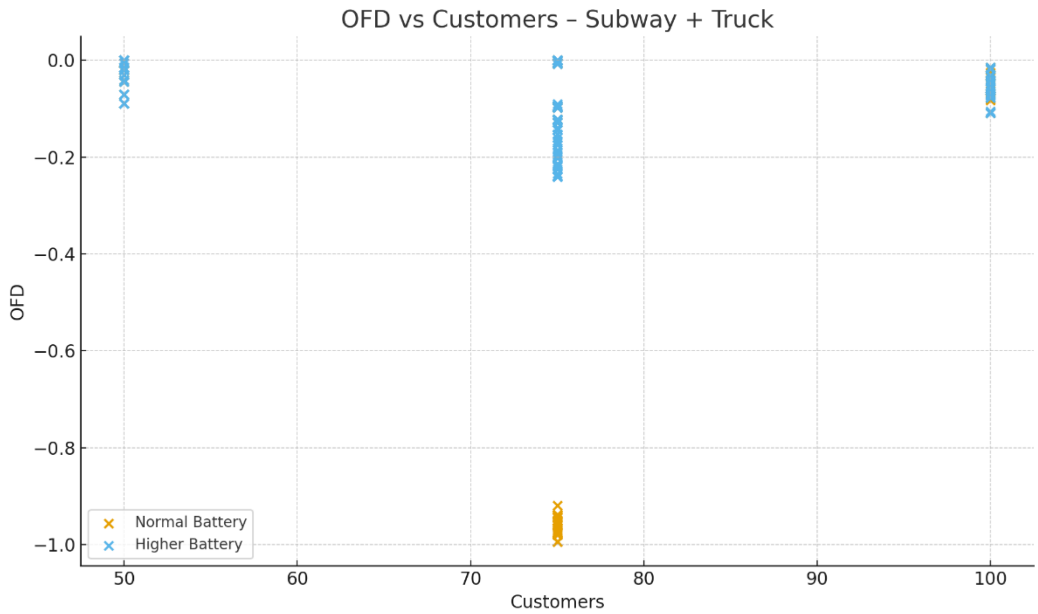


Figure 92: OFD vs Customers- Subway + Truck

Low vs High Battery clouds indicate how economic deviation evolves with scale. Upward envelopes suggest growing deviation with customer count; reduced spread for High Battery indicates potential stabilization.

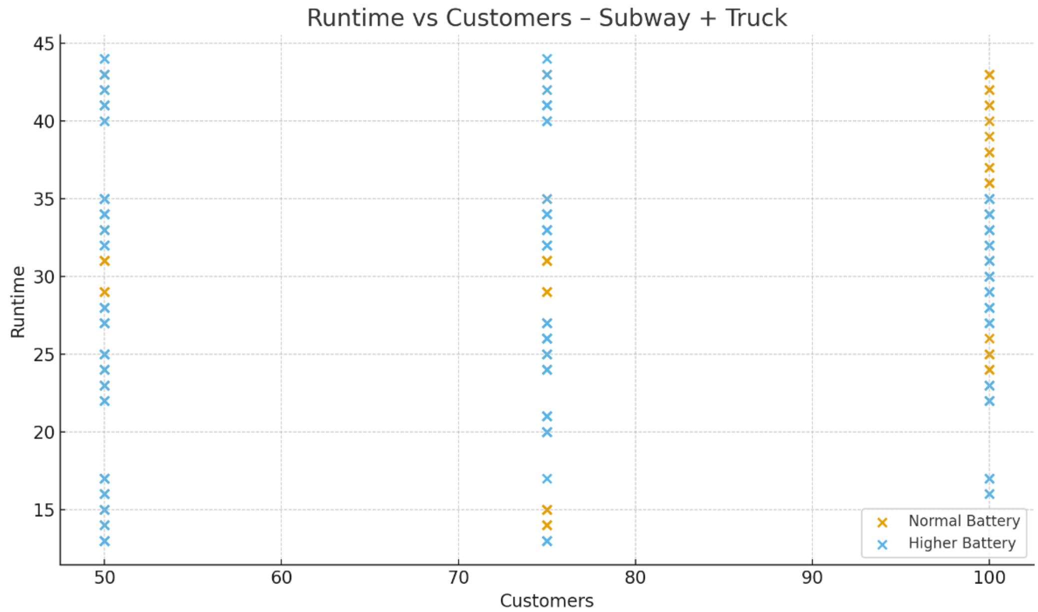


Figure 93: Runtime vs Customers - Subway + Truck

Runtime scales with problem size. Differences between Low and High Battery reflect coordination effects and feasible drone substitution of truck legs.

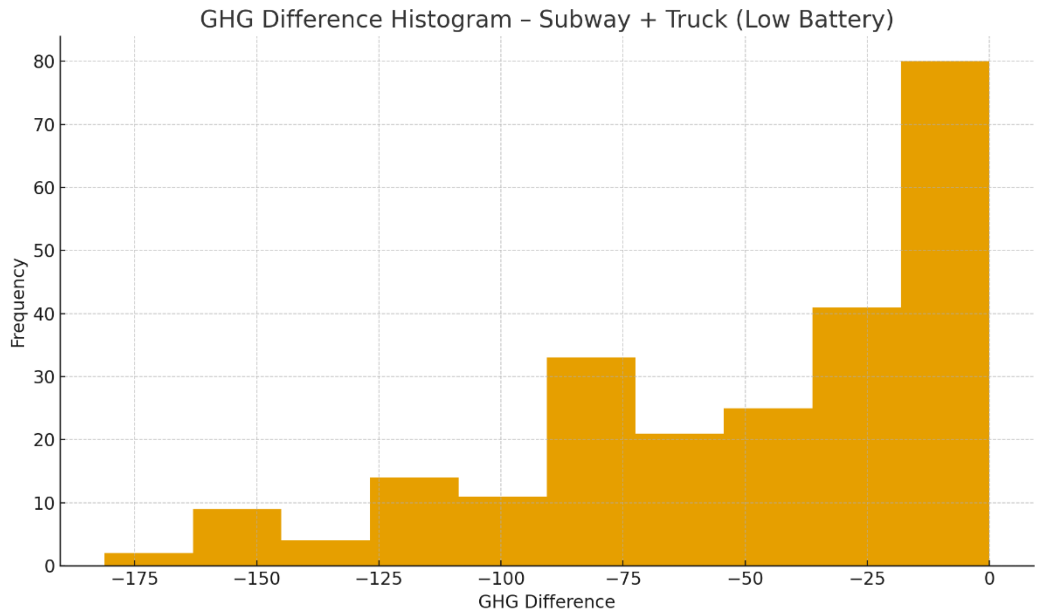


Figure 94: GHG Difference- Subway + Truck (High Battery)

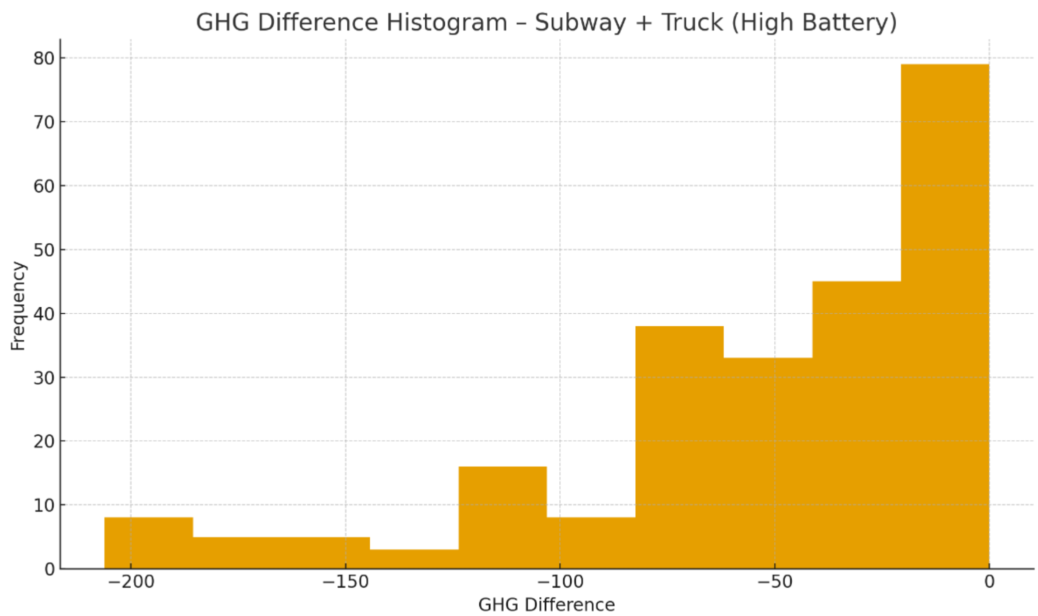


Figure 95: GHG Difference- Subway + Truck (High Battery

Right tails indicate occasional large emission savings. Comparing Low vs High Battery reveals whether extended range unlocks additional carbon benefits.

Based on the Const (With Serving Constraint) comparative report, battery upgrades tend to have smaller but steadier effects: runtime remains predictable, OFD changes modestly, and GHG improvements concentrate around mid-size instances (~75 customers). In the Master (Without Serving Constraint) datasets, High Battery shows higher variance: it can deliver stronger GHG savings in certain structural regimes (e.g., favorable hub placement and cluster geometry) but also exhibits heavier runtime tails due to increased coordination options.

Across modalities, High Battery generally expands feasible drone legs; the net benefit depends on instance structure and solver behavior.

• Use High Battery when station spacing and cluster geometry permit significant truck-leg substitution; monitor runtime dispersion.
• For Const settings, expect incremental gains; for Master settings, anticipate heterogeneous outcomes with potential high upside.
• Adopt multi-objective optimization to arbitrate cost–carbon trade-offs; track OFD–GHG decoupling with correlation monitoring.
• Allocate solver time adaptively: stricter time budgets for Large-N instances; instance-aware heuristics for Master scenarios.

High Battery capability broadens operational feasibility and can unlock additional carbon savings, particularly in Subway and Subway+Truck modalities but may introduce runtime volatility in flexible (Master) configurations. Low Battery remains competitive where customer clusters are compact or infrastructure limits drone substitution. Selecting battery capacity should therefore be instance-aware and jointly optimized with routing design.

7.4 Summary of Analysis

This report compares and synthesizes findings across two families of configurations for hybrid last-mile delivery with drones: Const (With Serving Constraint) and Master (Without Serving Constraint). Both families contain three operational modalities—Truck, Subway, and Subway + Truck—each evaluated under Low/Normal Battery and High Battery assumptions, and at representative instance sizes of roughly 50, 75, and 100 customers. Across all analyses, three regularities are robust:

I. Runtime scales with instance size. The number of customers is the dominant driver of computational effort in both families, with Master (Without Serving Constraint) exhibiting larger dispersion and heavier tails (sporadic hard instances) due to its greater modeling flexibility.

II. Objective Function Difference (OFD) generally increases with size, but the slope is setting dependent. OFD growth is steadier and more predictable in Const (With Serving Constraint); in Master (Without Serving Constraint) it is more sensitive to spatial structure, hub/interchange availability, and the set of feasible drone substitutions.

III. GHG (emissions difference) is heterogeneous and often right skewed. Many instances show modest emission changes around zero, punctuated by regimes with pronounced savings when geometry and infrastructure allow truck legs to be replaced or shortened by drone and/or subway. These “tail” benefits appear more frequently in Master but are also more variable.

The battery upgrade from Low/Normal to High broadens feasible drone legs and sometimes dampens OFD growth; it also increases variance in Master scenarios by enlarging the set of coordination options. The Subway and Subway + Truck modalities offer the clearest route to carbon benefits, especially near mid-scale (≈ 75 customers), though they demand tighter synchronization and careful station placement. Across both families, OFD and GHG do not perfectly align; multi-objective planning is therefore advisable if carbon outcomes matter alongside cost. Both families were studied with the same core lens: OFD, GHG difference, and runtime as functions of the number of customers. Data was parsed from semicolon-separated sources using European decimal normalization. Analyses included descriptive statistics, simple scatter plots of OFD/runtime vs. customers, histograms for GHG, and correlation heatmaps to reveal structural couplings (e.g., Customers–Runtime). While Const (With Serving Constraint) emphasizes baseline, more rigid service feasibility, Master (Without Serving Constraint) expands the feasible space, relaxing serving constraints to mimic more adaptive operations. This choice increases opportunity (more candidate routes and substitutions) and risk (greater solution variance and occasional heavy search episodes).

Two complementary comparison axes are used in this summary:

- By modality: Truck, Subway, Subway + Truck.
- By battery: Low/Normal vs. High, within each modality and family. Customer-specific readings are provided for ≈ 50, 75, and 100 customers, reflecting practical scaling regimes.

Runtime. A strong, positive relationship between customers and runtime holds universally. Const (With Serving Constraint) shows relatively tight scaling bands: as customer counts grow, runtime increases predictably. Master (Without Serving Constraint) displays wider dispersion and heavy-tailed outliers, indicating pockets of instance hardness—often when the model can exploit additional coordination patterns (e.g., more drone legs; optional interchanges) that expand the search space and solver branching.

OFD. As instances scale, OFD tends to rise. In Const, the rise is gradual and sometimes plateaus at high counts, reflecting constraint saturation and limited flexibility. In Master, OFD's slope depends more strongly on spatial structure and the quality of interchange opportunities; some instances plateau, others grow nearly linearly, and a subset shows diffuse clouds with significant variability. Where High Battery helps, OFD growth can moderate—especially when longer drone hops replace expensive truck segments.

GHG. Emission differences frequently cluster near zero with right-skewed tails that represent the most favorable cases for carbon savings. Subway and Subway + Truck amplifies the chance of these tails because fixed-guideway legs can displace higher-emitting truck portions, particularly when customers cluster around stations or when first/last-mile drone links are feasible. In Master, GHG outcomes are more heterogeneous: some instances yield strong savings; others show near-zero change. In Const, savings are steadier but often smaller in magnitude, reflecting tighter serving feasibility and fewer coordination options.

Correlations. The strongest structural coupling is Customers–Runtime. Customers–OFD is positive but variable, and OFD–GHG alignment is partial at best: instances that reduce emissions do not necessarily minimize OFD, and vice versa. This misalignment grows in Master due to its broader feasible space, reinforcing the need to articulate cost and carbon as joint objectives.

- Const (With Serving Constraint): Predictable runtime growth; modest OFD changes; GHG shifts are usually small and close to zero. Battery upgrades to High yield incremental benefits—helpful but not transformative—because the absence of rail interchanges limits the leverage of longer drone legs.
- Master (Without Serving Constraint): More variance in runtime and OFD as battery upgrades unlock more substitution patterns (e.g., longer drone shuttles). GHG can improve in favorable geographies (e.g., elongated routes where drones bypass truck detours), but the distribution remains centered near small changes with occasional tails. Net: High Battery sometimes delivers measurable OFD moderation and GHG gains, at the cost of added variability.
- Const: The presence of subway corridors introduces consistent opportunities for GHG reductions, particularly around 75 customers where coverage and demand interact effectively. Runtime increases with size but remains reasonably stable; OFD growth is moderate. High Battery extends reach to and from stations, modestly enhancing benefits without large volatility.
- Master: Subway benefits intensify but also fluctuate more. With High Battery, first/last-mile drone hops lengthen, substituting additional truck legs. Emission histograms show more frequent right-tail outcomes (larger savings), but runtime dispersion also increases due to coordination overheads (timing at interchanges, handling more candidate legs). OFD may either improve (when substitutions are cost-effective) or remain variable when added flexibility introduces detours or solver exploration costs.
- Const: Combining modes yields environmental upside but adds predictable overhead; runtime scales and OFD increases moderately with size. High Battery improves reach and can stabilize OFD growth when substitutions are well-placed; the effect is steady but bounded by serving feasibility.
- Master: This is the most complex setting. With fewer serving constraints, High Battery substantially expands the coordination space, producing some of the largest GHG savings in favorable instances and the heaviest runtime tails in difficult ones. OFD trends are mixed: in some instances, longer drone legs cut costs; in others, design complexity or congestion effects offset gains.

Mechanism. High Battery increases drone range and payload feasibility windows, enabling:

- More direct drone substitutions of truck segments.
- Longer first/last-mile links to subway nodes.
- Greater freedom to sequence drone operations around hubs.

Observed effects.

- Runtime: Slightly higher dispersion in Master, reflecting more candidate moves and branching; relatively stable in Const.
- OFD: Often improves (lower cost difference) where High Battery unlocks effective substitutions; muted change where geometry does not support longer drone legs.
- GHG: More frequent and sometimes larger savings tails, particularly in Subway/ Sub + Truck, when High Battery allows meaningful truck displacement.

Where the battery upgrade matters most. Mid-scale instances (~ 75 customers) in Subway and Subway + Truck, with good station placement and clustered demand, enjoy the clearest upside: high-value truck segments can be shortened or bypassed. In purely Truck settings, benefits depend on elongated or circuitous truck routes where airborne shortcuts exist; otherwise, changes are incremental.

Const (With Serving Constraint) acts as a stabilizer: serving feasibility limits route shapes, making runtime scaling and OFD trends more predictable and GHG gains steadier but modest. Master (Without Serving Constraint) acts as an amplifier: relaxing serving constraints creates optionality—sometimes unlocking substantial carbon savings and cost moderation, sometimes inviting search complexity and coordination overheads that produce heavy runtime tails and diffuse OFD outcomes. In short, Master accentuates instance-dependence: the realized benefit is highly sensitive to geography, hub proximity, and cluster geometry.

- ≈ 50 customers. Both families show modest OFD and manageable runtime; early GHG benefits appear in Subway and Sub + Truck, especially with High Battery and favorable layouts. Variance is already higher in Master due to flexibility.
- ≈ 75 customers. This is often the sweet spot for carbon gains: demand density and infrastructure coverage aligning to produce more replacing/substituting opportunities. In Master, High Battery can unlock notable savings, though runtime spikes are also more likely. OFD tends to increase with size but can stabilize where drone substitutions are particularly cost-effective.
- ≈ 100 customers. Runtime escalates; OFD often deteriorates unless particularly efficient substitutions exist. GHG gains taper or become inconsistent as subproblems grow and bottlenecks surface (congestion near hubs, limited launch capacity, synchronization costs). Const remains stable but conservative; Master’s potential upside persists alongside higher variance.

1. Treat cost and carbon as joint objectives. OFD–GHG decoupling is common. Relying on a single scalar objective risk missing carbon opportunities or accepting unexpected cost trade-offs. Weighted sums, ε-constraint, or Tchebycheff formulations help trace Pareto trade-offs explicitly.
2. Exploit structure where it exists. Subway corridors and well-placed hubs enable material GHG savings, particularly at mid-scale. Prioritize station siting and cluster-aware routing to magnify the benefit of High Battery.

3. Use instance-aware strategies in Master. Predict hardness and carbon potential (e.g., via simple descriptors: average nearest-station distance, cluster compactness, fraction of customers within extended drone range). Route “promising” instances to more aggressive coordination; throttle search depth and time on low-potential instances to avoid heavy tails.
4. Battery upgrades deserve context-specific appraisal. High Battery is most effective when it unlocks substitutions of truck legs that materially shorten or bypass ground detours. Where geography is unfavorable, they expect limited improvement and prefer Const-like discipline or conservative Master settings.
5. Operational coordination matters. Transfer timing at subway nodes, launch/landing throughput, and safe air corridors determine whether theoretical reach translates into actual savings. Build simple operational guards (e.g., max concurrent drone sorties or soft penalties for congested hubs) to tame variance.
6. Monitor with a compact plot bundle. Even in production, retain simple scatter (OFD/runtime vs. customers) plus GHG histogram and a lightweight correlation view. These reveal drift, emergent runtime instability, and decoupling between cost and carbon.

The wider dispersion seen in Master (Without Serving Constraint) should not be read as inherently worse performance; it reflects optionality. In favorable instances, optionality captures substantial carbon savings and sometimes better OFD; in unfavorable instances, it introduces coordination burden with little benefit. Similarly, Const (With Serving Constraint) is not “better” by virtue of stability alone; its stability comes from restricting the solution space, which can also cap achievable gains. Consequently, the right approach is adaptive—choose the family and the aggressiveness of coordination based on measurable instance features.

Across all datasets, scale is destiny for runtime, while structure is destiny for OFD and GHG. Const (With Serving Constraint) provides a reliable baseline: predictable runtime growth, moderate OFD behavior, and steady but modest carbon improvements—especially in Subway and Subway + Truck around ≈ 75 customers. Master (Without Serving Constraint) provides opportunity with volatility: battery upgrades and multimodal coordination can unlock significant GHG savings and sometimes temper OFD growth, but they also increase variance and the chance of hard outliers.

High Battery is a lever, not a panacea. Its benefits concentrate where geometry and infrastructure allow drones to replace or shorten expensive truck segments, especially when subway nodes are well located relative to demand clusters. Where such structure is absent, gains are incremental and should be weighed against increased coordination complexity.

Practitioners should therefore (i) articulate cost and carbon jointly, (ii) invest in instance-aware decision rules that forecast benefit vs. complexity, and (iii) adopt modality-specific playbooks—Truck for simplicity and robustness; Subway and Subway + Truck for environmental opportunities where hubs and clusters align. With these safeguards, organizations can harness the upside of flexible Master-style operations while maintaining the predictability of Const-style baselines where needed.

8. Findings

The research presented in this thesis generated several key findings that contribute to both theoretical understanding and practical advancements in sustainable last-mile delivery systems. These findings can be organized into three domains: operational efficiency, environmental impact, and policy and infrastructure requirements.

i. Operational Efficiency

The results of the algorithmic simulations suggest that hybrid delivery models, particularly truck-drone combinations, can outperform traditional truck-only delivery systems under a wide range of conditions. Parallel delivery, where drones are dispatched alongside trucks, demonstrated up to 20% reductions in delivery times in high-density scenarios (Bao et al., 2025). This advantage is largely attributable to the ability of drones to bypass traffic congestion and deliver small parcels directly to customers.

ii. Environmental Impact

The environmental evaluation revealed that hybrid models hold significant potential for emission reduction. Truck-only systems, even when electrified, remain limited by battery range and energy demand (Levrey, 2024). By contrast, the integration of drones allowed for meaningful decreases in greenhouse gas emissions per delivery unit, with simulations showing reductions ranging from 10% to 25% depending on urban density and delivery volumes (WEF, 2024; Mahmoodi et al., 2025). These benefits are mostly evidence.

iii. Policy and Infrastructure Requirements

Despite their promise, the deployment of drone-truck hybrids faces notable challenges. The most pressing are related to regulatory compliance (no-fly zones, air safety, and privacy), infrastructural prerequisites (charging hubs, UAV launch stations), and public acceptance. Without targeted policy frameworks and incentives, such as those under the EU Green Deal and Sustainable Urban Logistics Plans, the large-scale adoption of drones will remain constrained (EU Commission, 2023; Cicek et al., 2025).
In addition, the research highlights that hybrid logistics solutions should not be viewed as a one-size-fits-all models. Their success depends heavily on city-specific contexts, including geography, regulatory frameworks, consumer expectations, and technology readiness. Cities with strong digital infrastructure and supportive governance are better positioned to implement hybrid systems effectively (Levrey, 2024; Mantecchini et al., 2025).

Taken together, these findings emphasize the transformative potential of hybrid truck-drone delivery systems in urban freight logistics. They offer a realistic pathway to reducing greenhouse gas emissions and improving efficiency, while simultaneously aligning logistics operations with broader sustainability goals. At the same time, the research underscores the importance of adaptive governance, investment in enabling infrastructure, and continued technological innovation to overcome existing limitation

9. Summary

This thesis has explored the growing challenges and opportunities associated with urban freight transportation, with a specific emphasis on last-mile delivery. The increasing demand for rapid, flexible, and reliable distribution, driven primarily by e-commerce and urban population growth, has intensified the environmental and operational burdens of existing logistics networks (WEF, 2024; EU Sustainable Urban Logistics Plans, 2023). Road-based transport remains the dominant mode, but its contribution to greenhouse gas emissions and urban congestion continues to create significant sustainability concerns.

To address these issues, the thesis developed a heuristic-based algorithmic model designed to integrate hybrid delivery systems that combine traditional trucks with drones and other innovative vehicles. By accounting for operational constraints, including drone payload capacity, limited flight ranges, battery life, and regulatory restrictions, the approach sought to produce feasible and efficient routing solutions that could realistically be deployed in urban environments (Cicek et al., 2025). The proposed algorithm was tested through numerical experiments and benchmark instances to validate its effectiveness under different delivery scenarios.

The findings highlight that hybrid truck-drone configurations can significantly reduce delivery time and greenhouse gas emissions when compared to truck-only operations, particularly in high-density demand zones. Furthermore, the research underscores the importance of infrastructure investments, such as charging facilities, distribution hubs, and launch pads, without which the benefits of new delivery technologies may not fully materialize. The study also identifies that while drones provide clear advantages in terms of flexibility and environmental impact, their integration requires coordinated planning to overcome technical limitations and regulatory barriers.

In terms of academic contribution, the work extends the literature on last-mile logistics by proposing a hybrid algorithm that bridges classical vehicle routing with UAV-based extensions. In practice, it provides a decision-support framework for logistics providers and policymakers seeking to balance customer demand with environmental obligations. The thesis demonstrates that a mixture of conventional and emerging delivery technologies is essential to realizing the objectives of the European Green Deal and advancing sustainable urban mobility strategies.

To summarize, the thesis makes three main contributions: (1) the design of an innovative heuristic algorithm tailored to hybrid urban delivery models; (2) the empirical validation of drone-truck combinations for reducing emissions and improving efficiency; and (3) the critical reflection on infrastructural, technological, and regulatory prerequisites for successful deployment. These contributions collectively strengthen the case for adopting hybrid, sustainable, and intelligent last-mile logistics solutions that are adaptable to diverse urban contexts and responsive to both policy targets and consumer expectations.

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Appendix 1

Comparison Report: DJI Matrice 300 RTK, DJI Matrice 600 Pro, Wingcopter 178

Feature	DJI Matrice 300 RTK	DJI Matrice 600 Pro	Wingcopter 178
Battery	2× TB60 (5,935 mAh, 52.8 V, 274 Wh each)	6× TB47S (99.9 Wh) or 6× TB48S (129.96 Wh)	2–4× LiPo 22.2 V, 16 Ah (~355 Wh each)
Total Energy (Wh)	548	780	710–1420
Max Speed (km/h)	83	65	241
Dimensions	Unfolded: 810×670×430 mm Folded: 430×420×430 mm	Unfolded: 1668×1518×727 mm Folded: 437×402×553 mm	146×178×48 cm
Weight	6.3 kg (with 2 batts)	9.5–10 kg (with 6 batts)	8.4–15.7 kg (2–4 batts)
Max Takeoff Weight (kg)	9.0	15.5	18.0
Max Payload (kg)	2.7	6.0	6.0
Notes	IP45; up to 55 min flight (no load)	Hover 32–38 min (no load); 16–18 min @ 6 kg	eVTOL tilt-rotor; VTOL + fixed-wing cruise

Figure 96: Comparison of Drones (DJI (a), 2020; DJI (b), 2020; Wingocopter, 2021)