Optimizing Last-Mile Delivery: A Bi-Objective Model for Cost Efficiency and Customer-Centric Distribution of Perishable and Non-Perishable Goods

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Preface

As my time as a student comes to an end, I find myself reflecting on the journey that has shaped me over the past two decades. From a young age, I was eager to explore the world and acquire knowledge. Now, as I complete my master's thesis, I see it not only as the culmination of my academic efforts but also as the foundation for the next chapter of my career.

I feel incredibly fortunate to have pursued my master's degree at TU Delft. The comprehensive education I received here has equipped me with the skills and insights needed to tackle future challenges. From traffic theories to supply chain management and logistics network design, I have gained invaluable knowledge developed by leading experts in the field. Moreover, I had the opportunity to apply these concepts during my internship, where I engaged directly with the logistics industry—optimizing delivery routes and enhancing customer experience. This hands-on experience has been instrumental in bridging the gap between theory and practice.

I would like to express my deepest gratitude to my parents, whose unwavering support has enabled me to complete this journey. I am also sincerely thankful to Professor Lori and Patrick for their invaluable guidance and constructive feedback, which have helped me refine my thesis step by step. Their insights and encouragement have been instrumental in shaping this work.

As I embark on this new chapter, I carry with me the knowledge, experiences, and friendships gained during my time at TU Delft. While this thesis marks the end of my student years, it also serves as the beginning of a lifelong journey of learning and growth. I look forward to the challenges and opportunities that lie ahead, ready to contribute to the ever-evolving world of logistics and transportation.

Luyang Cao
March 10, 2025

Summary

This thesis aims to address the challenges and opportunities in optimizing last-mile delivery in the e-commerce logistics chain. The research is focused on integrating customer preferences, including those related to perishable products, into the selection of pickup points, and parcel lockers, and the planning of delivery routes to enhance efficiency and customer satisfaction.

The proposal outlines the context of last-mile delivery optimization, highlighting the increasing consumer demand for personalized and convenient delivery options against traditional cost and time efficiency models. It discusses the emergence of pickup points and parcel lockers as cost-effective, flexible, and convenient alternatives to direct home delivery, addressing challenges such as failed deliveries and the need for 24/7 accessibility.

The main research question explores how the optimized delivery route planning that accommodates customer preferences for perishable products, can enhance the e-commerce logistics chain's efficiency and satisfaction. It sets out to analyze customer preferences, logistical challenges presented by perishable products, and methods to optimize pickup point and parcel locker selection and delivery routes.

Objectives include evaluating customer preferences, investigating logistical challenges of perishable goods delivery, determining the impact of integrating customer preferences into the logistics model and investigating the relationship between delivery method alignment with customer preferences and overall satisfaction and efficiency.

The scope is focused on the strategic and operational design of delivery routes for perishable and non-perishable items, leveraging the infrastructure provided by the company within the urban context of Rotterdam and Delft. It aims to balance minimizing delivery costs with maximizing customer satisfaction through a bi-objective optimization challenge. The methodology involves the Best Worst Method for modeling customer preferences and the Vehicle Routing Problem (VRP) model for optimizing delivery routes, considering additional constraints related to customer preferences and perishable goods.

Expected outputs include comprehensive optimization of delivery routes and pickup point selections that integrate customer preferences, detailed mathematical models, and algorithmic solutions aimed at reducing delivery costs and maximizing customer satisfaction. The proposal seeks to contribute to the logistics and supply chain management field by offering actionable insights for logistics companies and filling identified research gaps.

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1 Introduction

1.1 Research Context

In the field of logistics and transportation management, optimizing the last-mile delivery process has become a key focus for modern businesses. This phase of delivery, crucial in determining both operational effectiveness and customer contentment, involves the strategic selection of pickup points and meticulous route planning. Given the competitive nature of today's market, consumer expectations now extend beyond prompt delivery to include personalized and convenient service options. This shift in consumer demands calls for a reassessment of conventional route optimization strategies, which traditionally emphasize reducing costs and maximizing time efficiency, to align with the evolving landscape. This adaptation forms the central theme of this thesis proposal, exploring how these emerging requirements can be integrated into existing logistical frameworks.

Pickup points (PP) have emerged as a rapidly expanding alternative to traditional home delivery methods, now representing approximately 20% of household parcel deliveries in France, signifying a substantial customer base[1]. Cost-wise, utilizing pickup points for parcel delivery is more economical than direct-to-home delivery, regardless of the delivery area being urban or rural. The primary benefits include a higher density of deliveries per location and a significant decrease in the incidence of failed deliveries. Conversely, the frequent failures associated with home delivery can result in considerable financial losses and unnecessary transport distances.

Furthermore, the adoption of pickup points as a delivery option offers a flexible solution to the challenge of meeting diverse customer preferences. This method accommodates the varying schedules of recipients, allowing for parcel collection at their convenience, which significantly reduces the likelihood of missed deliveries. The strategic placement of these points in inaccessible locations, such as retail stores or dedicated collection hubs, further enhances this convenience, fostering a positive customer experience. Consequently, the incorporation of pickup points into delivery systems not only addresses cost and efficiency concerns but also aligns with the evolving expectations of consumers, who increasingly value flexibility and reliability in their delivery options.

Parcel lockers, a novel innovation in the realm of logistics and delivery services, provide an automated solution for secure and convenient package storage and retrieval. These self-service kiosks, strategically located in accessible public areas such as shopping centers, transport hubs, and residential complexes, enable customers to pick up their parcels at any time, offering unparalleled flexibility outside traditional delivery windows. This system addresses several logistical challenges by minimizing the need for direct recipient-to-delivery personnel interaction, thereby reducing the risk of failed deliveries and enhancing operational efficiency. Additionally, parcel lockers serve as a critical component in the optimization of last-mile delivery operations, offering a scalable and cost-effective alternative that caters to the modern consumer's demand for convenience, security, and 24/7 accessibility. Their integration into the delivery ecosystem represents a forward-thinking approach to meeting the evolving needs of both businesses and consumers in an increasingly digital and convenience-oriented market.

In the domain of last-mile delivery and e-commerce, three predominant order fulfillment methods have emerged: home delivery, pickup points, and parcel lockers. E-commerce and logistics entities often favor dispatching orders to pickup points or parcel lockers due to the reduced costs associated with these methods. Conversely, customer preferences for these fulfillment options vary widely. Individuals with work commitments may opt for parcel lockers or self-collection at pickup points, given their absence from home during weekday hours. In contrast, other consumers may choose home delivery for its convenience, eliminating the need to travel for package retrieval. This divergence in preferences between logistics providers, who prioritize cost efficiency, and customers, who seek convenience, frequently leads to a misalignment of interests.

Consequently, in the processes of route planning and the strategic selection of pickup point locations, incorporating customer preferences is pivotal for augmenting customer satisfaction. This consideration not only addresses the diverse needs and schedules of the end-users but also contributes to cost reduction by minimizing the incidence of unsuccessful home deliveries. By integrating consumer preferences into logistical decision-making, companies can tailor their delivery systems to offer more personalized and efficient services. This alignment between logistical strategies and customer expectations facilitates a more seamless and satisfactory delivery experience, fostering loyalty and potentially increasing the efficiency of the entire supply chain. Moreover, understanding and adapting to these preferences can lead to innovative logistics solutions that further optimize last-mile delivery operations, thereby enhancing the overall efficacy and sustainability of e-commerce and logistics industries.

Furthermore, the expansion of the e-commerce sector has facilitated the diversification of product types that can be distributed through logistics networks, including perishable commodities. Such items, encompassing foodstuffs, floral arrangements, and pharmaceuticals, necessitate stringent management of temperature conditions, expedited transit, and careful handling to preserve their quality from origin to destination. The proficient orchestration of perishable goods delivery is contingent upon a sophisticated infrastructure designed to meet these specialized requirements. Key components of this infrastructure include vehicles equipped with refrigeration capabilities, warehouses with climate control features, and the integration of technological solutions for real-time tracking and logistical oversight.

Additionally, the surge in consumer expectations for the prompt and fresh delivery of perishable products has been a driving force behind technological advancements within the logistics field. Innovations such as adaptive routing algorithms, which can recalibrate routes based on live traffic data, and predictive analytics tools for accurate demand prediction, are emblematic of the sector's evolution. These advancements not only enhance the efficiency and reliability of perishable goods delivery but also contribute to minimizing spoilage and optimizing supply chain operations, thereby aligning with sustainability objectives and elevating consumer satisfaction.

Companies must balance the urgency of delivery with the need for cost-effectiveness, all while ensuring product quality is uncompromised. As such, the successful delivery of perishable items not only enhances customer satisfaction and trust but also contributes to the reduction of waste and loss, aligning with broader sustainability goals within the supply chain. Thus, when companies are planning delivery routes and PP site selection, perishable products should also be taken into consideration.

1.2 Research Questions and Objectives

This research aims to optimize the order fulfillment ways, alongside delivery route planning, to accommodate customer preferences, particularly for perishable products, thereby enhancing efficiency and satisfaction in the e-commerce logistics chain. To achieve this, the following key research questions and objectives have been formulated:

Main Research Question:
How can the order fulfillment ways for customers, along with delivery route planning, be optimized to accommodate customer preferences, including for perishable products, to enhance efficiency and satisfaction in the e-commerce logistics chain?

Supporting Research Questions:

1. What are the predominant customer preferences regarding the delivery of perishable and non-perishable products through pickup points, parcel lockers, and direct home delivery, and how do these preferences vary across different consumer segments?

2. What specific logistical challenges arise when delivering perishable products through pickup points and parcel lockers, and what strategies can be implemented to ensure product integrity while optimizing cost and efficiency?

3. How can optimization methods be applied to improve the order fulfillment ways for each customer, and delivery routes in a way that integrates both customer preferences and the perishability constraints of products?

4. How does the alignment of delivery methods with customer expectations impact customer satisfaction, and the overall efficiency of last-mile delivery operations?

Research Objectives:

1. To evaluate customer preferences for the delivery of both perishable and non-perishable products, with a specific focus on the choice between pickup points, parcel lockers, and home delivery.

2. To identify and analyze the key logistical challenges associated with the delivery of perishable goods through different fulfillment methods and develop strategies to address these challenges while maintaining product quality and customer satisfaction.

3. To assess the impact of integrating customer preferences into logistics models, specifically in terms of efficiency, cost-effectiveness, and service quality in last-mile delivery.

4. To explore the relationship between delivery method alignment with customer expectations and the subsequent effects on consumer satisfaction, retention, and long-term loyalty in e-commerce logistics.

By addressing these research questions and objectives, this study seeks to provide actionable insights into improving last-mile logistics efficiency while meeting the diverse needs of e-commerce consumers. The findings aim to contribute to both theoretical advancements in logistics optimization and practical implementations that enhance service quality and operational performance.

1.3 Research theory and methods

In this study, the Best-Worst Method (BWM) is employed to model customer preferences and decision-making processes regarding delivery options. The BWM is particularly effective in capturing customer preferences by focusing on the most and least important attributes of different delivery methods[2]. This method allows the estimation of relative importance weights for each factor involved in the decision-making process, such as delivery time, location & distance, delivery fee, and freshness.

Vehicle routing problem will be the basement for this problem. Vehicle Routing Problem (VRP) model is particularly well-suited for modeling the complexities of delivery route optimization, including the assignments of order fulfillment ways, while considering customer preferences for both perishable and non-perishable products. The VRP's strengths in addressing this specific problem stem from its flexibility, comprehensiveness, and adaptability to various constraints and objectives. The VRP is inherently designed to optimize routes for a fleet of vehicles while considering multiple objectives, such as minimizing delivery costs and maximizing customer satisfaction. It can easily incorporate additional constraints related to customer preferences, delivery windows, and the specific needs of perishable goods (e.g., temperature control, and quick delivery).

Bi-objective optimization approach is utilized to model customer preferences for delivery options. It allows for the exploration of trade-offs between these two objectives by generating a Pareto front, which represents the set of non-dominated solutions where no solution can improve one objective without worsening the other[3]. Weight coefficients are used to reflect the relative importance of each objective, and the optimization process provides a set of optimal delivery strategies that balance both cost and satisfaction.

1.4 Research Structure

The thesis is structured to provide a comprehensive and systematic analysis of the research problem. It begins with the introduction, which presents the background, motivation, and research objectives. This is followed by the literature review, where relevant studies in last-mile logistics, customer preferences, and optimization methods are critically examined. The methodology section outlines the research design, data collection methods, and analytical techniques used to address the research questions.

Subsequently, the problem description and mathematical formulation section defines the problem and presents the mathematical models employed for optimization, followed by a solution methods chapter illustrating the methods used to solve the model. The results section provides a detailed analysis of computational findings and their implications. Finally, the thesis concludes with the conclusions and discussions, summarizing key insights, discussing their relevance, and identifying potential areas for future research.

2 Literature Review

2.1 Overview

The literature review serves as a foundational element of our research on optimizing delivery route planning, with a particular focus on incorporating customer preferences for both perishable and non-perishable products. This section aims to systematically synthesize existing research findings, theoretical contributions, and practical insights relevant to the topic. By doing so, it establishes a comprehensive understanding of the current state of knowledge, identifies prevailing trends and gaps in the literature, and justifies the need for the present study.

This literature review is designed to encompass a wide range of scholarly articles, industry reports, case studies, and conference proceedings published over the last 20 years. Special attention is given to works that specifically address the complexities of last-mile delivery optimization, the integration of customer preferences in logistic operations, the logistical challenges of perishable goods delivery, and the innovative use of pickup points and parcel lockers as alternative delivery solutions. By delimiting the scope to these areas, the review aims to capture the multifaceted nature of delivery route optimization in the contemporary e-commerce and logistics landscape.

The literature review pursues several key objectives and also has corresponding parts:

1. To map the evolution of delivery route optimization;
2. To explore the role of customer preferences in shaping delivery logistics;
3. To explore the specific challenges and solutions associated with the delivery of perishable products, recognizing the critical importance of timeliness and condition upon delivery.

2.2 Literature Review

2.2.1 Last-mile delivery analysis

Last-mile delivery, a pivotal phase in urban logistics, entails the transportation of goods to consumers' residences, striving for efficiency in cost, speed, and accuracy [4]. Despite its significance, scholarly investigations have illuminated the substantial costs and inefficiencies plaguing home delivery systems. Notably, Shashi's study underscores that last-mile delivery represents a staggering 53% of overall shipping expenses [5]. Furthermore, the economic impact of unsuccessful deliveries is considerable, with an average cost of $17.78 incurred for each failure, and a failure rate surpassing 5% for all last-mile deliveries [6]. These challenges, particularly the high incidence of delivery failures, have catalyzed the adoption of alternative delivery methodologies. Pickup points, for instance, have emerged as an efficacious solution, witnessing an increased uptake during recent epidemics as a strategy to circumvent the resource wastage endemic to traditional home delivery models.

Wang's investigation into the efficacy of three predominant "Last mile" delivery methods—attended home delivery (AHD), reception box (RB), and collection-and-delivery points (CDPs)—reveals their varying suitability across different urban landscapes, particularly in areas of high population density. The study delineates that AHD and independent RBs are more effective in less populated areas or those with smaller order volumes. Conversely, shared RBs and CDPs excel in densely populated regions with substantial order quantities, with the optimal choice between them hinging on labor and facility costs [7]. Further research by Song et al., using West Sussex, UK, as a case study, corroborates the efficiency of self-pickup modes over traditional home delivery, highlighting significant reductions in transportation distances and delivery failure rates [8]. Cardenas introduces an innovative cost model focused on urban logistics efficiency, concluding that pickup points not only mitigate delivery failures but also enhance delivery density. This optimization leads to societal and logistical benefits, particularly when the volume of parcels to pickup points is sufficiently high, evidenced by a decrease in overall vehicle kilometers traveled (VKT) [1]. Subsequent analysis by Song assesses three home delivery frameworks: the traditional model, the PP (pick-up points) model, and the SDB (self-delivery boxes) model. This research determines that both PP and SDB models significantly lower the customer's collection costs—by 29.1% to 84%—especially when home delivery failures exceed 30%. Moreover, the SDB model is identified as superior in reducing express company delivery costs by 67.1% to 71.3% when missed deliveries range from 20% to 50% [9]. Punakivi took the Dutch food retailer industry as an example and concluded that transportation costs using the shared reception box concept are 55-66 percent lower in comparison with the current standard concept with attended reception and two-hour delivery time windows[10].

The reviewed literature underscores the critical challenges and inefficiencies in last-mile delivery, notably the high costs and failure rates of traditional home delivery systems. Research highlights the financial burden of last-mile logistics, prompting an exploration into alternative delivery methods like pickup points and reception boxes. Studies by Wang, Song et al., and others demonstrate that these alternatives can significantly enhance delivery efficiency and reduce costs, particularly in densely populated areas or scenarios with high delivery failure rates. The findings suggest a strategic shift towards these innovative delivery solutions could offer a more sustainable and cost-effective approach to last-mile logistics, tailored to specific urban demographics and consumer needs.

2.2.2 Incorporating Customer preferences in last-mile delivery

Considering customer preferences in last-mile delivery route planning and order fulfillment methods is crucial for several reasons. It directly impacts customer satisfaction by aligning delivery services with their expectations and convenience, such as preferred delivery times and locations. This alignment helps reduce failed deliveries and associated costs, improving operational efficiency. Additionally, understanding and integrating customer preferences can enhance the overall customer experience, leading to increased loyalty and competitive advantage in the market. It's a strategy that not only meets current consumer demands but also anticipates future trends and behaviors in e-commerce logistics.

Hayel considered customers' limited rational behavior and analyzed the effects of delivery mode delivery capacity, self-pickup mode processing capacity, and customer rationality level on the customer's choice of home delivery mode or self-pickup mode[11]. Luigi Guarino Neto investigated the willingness of consumers from developing countries to use the pick-up point structures and the viability of implementing them. They concluded that consumers from BOP(bottom of the pyramid) are the ones who intend to use the system when available to gain benefits, such as lower shipping costs, faster delivery, and convenience. Consumers from HIC regions were not so interested in the system and still prefer to receive their home-delivery purchases[12]. Yulia followed a focus group design and built on grounded theory to provide insights into customer value in relation to parcel lockers. They found that the use of parcel lockers in the last-mile delivery service algorithm results in social customer value. However, customer value in relation to parcel lockers is created in a dynamic, correlated manner, leading to both value creation and value destruction[13]. Xueqin et al. explored consumers' delivery mode preferences in omni-channel shopping, focusing on their willingness to exert physical, social, and attentive effort in the delivery process. Using multinomial logistic regression, it finds that preferences vary significantly based on the effort consumers are willing to contribute, with many favoring unattended delivery options to avoid social interactions and attentive effort. The research contributes to understanding how consumer logistics efforts influence delivery choices, offering insights for designing more effective omni-channel distribution systems[14]. Molin et al. investigated Dutch consumers' preferences for online parcel delivery methods, focusing on home delivery versus parcel locker (PL) use. By conducting a stated choice experiment, it identifies that even minor increases in home delivery costs, coupled with closer PL locations, could significantly shift consumer preference away from home delivery towards PLs. The findings suggest a potential strategy for reducing the dominance of home delivery by making PLs more accessible and economically attractive, highlighting the importance of delivery costs and convenience in consumer choice behavior[15]. The research by Amorim et al. examines customer preferences for delivery attributes in attended home delivery, with a focus on the grocery sector. It highlights the importance of speed, precision, and timing in delivery service choices and demonstrates how tailoring delivery options to specific customer segments could increase shipping revenue by about 9%. The study provides insights into customer behavior and service design for retailers[16]. Smeets's thesis explores customer preferences for pick-up points versus home delivery in online grocery shopping. Through a stated choice experiment, it investigates the impact of socio-demographics, psychographics, and general online shopping behavior on these preferences. The study finds differences in preferences between urban and rural areas, and across scenarios like weekly groceries and dinner parties. It suggests that retailers can enhance customer satisfaction and encourage the use of pick-up points by considering these preferences in their service offerings[17].

The collective research underscores the complexity of consumer preferences in last-mile delivery, revealing a nuanced landscape where choices are influenced by a myriad of factors including cost, convenience, effort, and socio-demographic profiles. These findings highlight the importance of adopting flexible, consumer-centric delivery solutions that cater to the diverse needs and expectations of customers. By integrating such insights into logistics strategies, businesses can enhance service quality, improve customer satisfaction, and navigate the evolving demands of the e-commerce landscape more effectively. While the discussed studies effectively analyze customer preferences for various last-mile delivery options, they notably do not integrate these preferences into the optimization of last-mile delivery routes and pickup point site selection. This gap suggests an opportunity for future research to develop comprehensive models that not only consider consumer willingness but also how these preferences can be systematically incorporated into logistical decision-making to optimize efficiency and satisfaction in the delivery process.

2.2.3 Delivery route planning and site selection considering customer preferences

Customer preferences in last-mile delivery focus on convenience, speed, flexibility, and reliability[15]. Consumers increasingly favor options that offer precise delivery windows, the ability to track shipments in real-time, and flexible delivery locations, including home delivery, pickup points, and parcel lockers. The choice often hinges on balancing cost with the convenience of delivery times and locations that fit into their daily routines, indicating a shift towards personalized delivery services that cater to individual lifestyle needs and expectations.

Zhang introduces a heuristic algorithm to address the Vehicle Routing Problem (VRP), incorporating customer service preferences into the routing decisions[18]. The authors develop a multi-objective mathematical model and propose a hybrid genetic algorithm enhanced by an insertion heuristic approach. The algorithm specifically accounts for the fuzziness of customer preferences by employing a modified push-bump-throw procedure. Computational analyses demonstrate the algorithm's effectiveness, showcasing improvements over existing methods. Christian introduced and analyzed the vehicle routing problem with delivery options (VRPDO), in which some requests can be shipped to alternative locations with possibly different time windows[19]. Alba built a model for delivery routing in a parcel-locker network taking into account receivers' preferences. It solved a routing problem in delivering parcels from a depot to parcel lockers with the aim of maximizing the utilities of the receivers going to the lockers. A Pareto frontier is obtained by optimizing these two objectives[20]. Guerrero-Lorente et al. present a mixed integer program (MIP) for redesigning the distribution network of a parcel carrier catering to omnichannel retailers, considering customer preferences for delivery and returns. It includes various facility types like city distribution centers, intermediary depots, and automated parcel stations, focusing on the impact of these facilities on consumer choice and transportation costs. The study proposes a heuristic approach that significantly accelerates the solution process, with a case study on a Spanish parcel carrier demonstrating potential improvements in network design for efficiency and customer satisfaction[21]. Abdulkader et al. introduced a new variant of the vehicle routing problem tailored for omni-channel retail distribution systems, where both retail stores and direct consumer deliveries are served from a single distribution center. It integrates retail store assignments and delivery routes into a comprehensive model, proposing two solution approaches: a two-phase heuristic and a multi-ant colony (MAC) algorithm. This study extends the capacitated vehicle routing and pickup and delivery problems by considering retail and online consumer demands, offering practical implications for omnichannel retail logistics optimization[22]. Peide Liu presents a comprehensive analysis of vehicle routing in omni-channel retail, exploring how to enhance logistical efficiency and customer satisfaction. Through mathematical modeling, it evaluates the impact of delivery mode capacities and consumer rationality on preferences between home delivery and self-pickup, highlighting the potential benefits of integrating various delivery methods. The study underscores the importance of considering consumer preferences in last-mile delivery to optimize routes and site selection for pickup points, suggesting a significant area for further research to directly link these preferences with logistical strategies for improved service outcomes[23].

Mateusz introduces a geometric approach to designing parcel locker networks, emphasizing sustainability in last-mile delivery by incorporating user preferences. The research, focusing on Lubusz Voivodeship residents, indicates that designing networks based on customer distance preferences can significantly enhance sustainability. Findings reveal that a triangular network covers a larger area with fewer parcel lockers than a square network, offering over 20% more efficiency. This geometric method, while specific to Lubusz Voivodeship, presents a universal model for improving parcel locker system design, balancing user convenience with environmental and operational efficiency[24].

The literature review illustrates a significant shift in vehicle routing problem (VRP) research toward customer-centric models. By incorporating customer preferences and leveraging innovative algorithms and mathematical modeling, these studies demonstrate a holistic approach to optimizing last-mile delivery. The emphasis on integrating consumer choices highlights the evolving focus of logistics optimization—balancing efficiency with enhancing customer satisfaction in an increasingly complex retail landscape.

While the literature makes significant strides in integrating customer preferences into route optimization for last-mile delivery, it reveals a research gap: none thoroughly explores a delivery network that combines home delivery, attended pickup points, and unattended parcel lockers. This oversight highlights an opportunity for future studies to design and assess a holistic delivery system that accommodates these diverse delivery modes simultaneously, potentially offering a more flexible and customer-oriented approach to last-mile logistics. The significance of customer preferences becomes even more critical for perishable products, as unattended parcel lockers lack refrigeration capabilities, which are essential for maintaining the freshness of these items. This limitation underscores the necessity of understanding and prioritizing customer desires to ensure the delivery method aligns with the specific needs of perishable goods, enhancing the overall satisfaction and convenience for the consumer.

2.2.4 Perishable product delivery

Integrating perishable product delivery within the broader context of last-mile logistics alongside non-perishable goods presents unique challenges and opportunities. This approach necessitates advanced planning and route optimization to ensure perishables are delivered within tight timeframes, maintaining product integrity. Combining perishable and non-perishable deliveries requires innovative logistic strategies, such as using multi-temperature vehicles and dynamic routing, to maximize efficiency while meeting diverse customer expectations. Emphasizing perishable goods introduces complexities in logistics but, when effectively managed, can significantly enhance service quality and operational sustainability in the evolving e-commerce landscape.

Liang et al. studied a supplier that delivers perishable goods to customers (home delivery) in a multiple-time-period planning horizon while simultaneously considering transportation cost and customer satisfaction. The perishable delivery problem is modeled as a bi-objective vehicle routing problem with multiple time periods, aiming to minimize the transportation costs and maximize customer satisfaction by minimizing the loss of perishable freshness[25]. Xuping presented a methodology for optimizing delivery schedules of perishable products to enhance customer satisfaction while minimizing delivery costs. It introduces a multi-objective vehicle scheduling optimization model that considers both the freshness of perishable goods and customer-preferred delivery times. A priority-based genetic algorithm (PB-GA) is developed to solve this model efficiently. Through numerical experiments, the approach demonstrates significant improvements in customer satisfaction and delivery efficiency compared to traditional methods, highlighting its potential for practical application in logistics for perishable products[26]. Byung presents a vehicle routing problem addressing the delivery of perishable food products using both refrigerated and general-type vehicles. It aims to maximize customer satisfaction by considering the freshness of delivered products. A nonlinear mathematical model and heuristic algorithm were developed to optimize vehicle routes, factoring in the vehicles' distinct capabilities to maintain product freshness. This approach seeks to balance the operational costs with the goal of delivering perishable goods in their optimal state, demonstrating the algorithm's effectiveness through numerical examples and sensitivity analysis[27]. Wang develops a multi-objective optimization model (MO-VRPMTW-P) to enhance perishable product distribution, balancing cost minimization with product freshness maximization. Utilizing a novel heuristic algorithm that combines variable neighborhood search and genetic algorithms, the research focuses on the spatiotemporal characteristics of fresh product orders. Demonstrated through computational experiments, the proposed method shows significant improvements in distribution efficiency and freshness preservation, indicating the value of incorporating spatiotemporal strategies in the logistics of perishable goods[28].

The literature emphasizes advanced approaches to optimizing perishable goods delivery, blending cost-efficiency with customer satisfaction by focusing on product freshness and preferred delivery timings. These studies introduce innovative models and algorithms designed to tackle the complexities of perishable logistics, showcasing the potential for significantly enhanced distribution efficiency and customer service. This collective research marks a pivotal step toward smarter, more responsive logistics systems capable of addressing the unique challenges presented by perishable products.

Existing research on perishable product delivery has predominantly centered around direct home delivery models, often neglecting alternative distribution channels such as self-pickup options, including parcel lockers and pickup points. This oversight represents a significant research gap. Self-pickup options could potentially offer greater flexibility for consumers who may not be home to receive deliveries, thereby reducing missed deliveries and enhancing overall customer satisfaction for perishable goods. These alternatives also typically allow for extended pickup hours, providing convenience that aligns better with varying consumer schedules.

Furthermore, there is a noticeable lack of studies that explore the simultaneous delivery of perishable and non-perishable items within the same logistical framework. This area presents a substantial opportunity for improving logistical efficiencies. Integrating the distribution of both perishable and non-perishable goods could lead to optimized delivery routes, reduced transportation costs, and lower carbon footprints. Such integration could also enhance customer convenience by consolidating multiple order types into single delivery events, thus reducing the frequency of deliveries needed per customer and streamlining the customer experience.

Below table 1 is the research gap table concluded from the literature research discussed above. The main research gaps for this topic can be concluded as follows:

1. Lack of exploration of delivery options integrating home delivery, attended pickup points, and unattended parcel lockers regarding delivery of perishable products;

2. Lack of comprehensive studies on customer preferences for a wide range of delivery options in a mixed product-type delivery network;

3. The absence of research on the simultaneous delivery of perishable and non-perishable items, considering customer preferences in delivery route and pickup point optimization

Table 1: Identified Research Gaps in Last-Mile Delivery Optimization

Research Area	Key Findings	Methodologies Used	Identified Research Gaps	Potential Impact of Addressing the Gap
Customer Preferences for Delivery Options	Focus on home delivery, limited insights into alternative options like parcel lockers and attended pickup points.	Surveys, discrete choice experiments, statistical modeling.	Few studies consider preferences across multiple delivery options, especially for perishable and non-perishable goods integration.	Better understanding can enhance customer-centric delivery services, improving satisfaction and logistics efficiency.
Delivery Route Optimization Incorporating Customer Preferences	Emphasizes benefits of customer-centric routing for efficiency and satisfaction.	Heuristic algorithms, multi-objective optimization, customer feedback analysis.	Lack of fully integrated models considering home delivery, attended pickup points, and lockers simultaneously.	More adaptive logistics solutions could enhance operational efficiency and service quality.
Perishable Goods Distribution Strategies	Research focuses on home delivery with an emphasis on cost and freshness.	Mathematical models, heuristic optimization, perishability simulations.	Minimal studies explore self-pickup (e.g., parcel lockers and attended pickup points) for perishable goods.	Exploring these options may improve flexibility, reduce delivery failures, and enhance freshness retention.
Integrated Delivery of Perishable and Non-Perishable Products	Most research separates perishable and non-perishable deliveries.	Mixed-integer programming, genetic algorithms, multi-modal optimization.	Limited studies on integrated logistics frameworks supporting both product types.	Optimizing mixed-order fulfillment could increase efficiency, lower costs, and improve customer convenience.

3 Problem desciption and mathematical formulation

3.1 Overview

In the context of modern e-commerce and logistics, last-mile delivery is a crucial phase that has significant impacts on both operational costs and customer satisfaction. The challenge is particularly pronounced in densely populated urban areas, where ensuring timely and efficient delivery is essential for maintaining competitiveness and customer loyalty. The goal of this study is to optimize delivery operations by addressing the simultaneous problems of route planning, delivery mode selection, and facility location, with a focus on customer preferences and delivery of both perishable and non-perishable goods.

For the problem, it can be defined as a CVRP problem with a second objective along with its constraints. The problem is defined on a directed graph $G = (V, E)$, where the node set V containers all the set of customer I, attended pickup point J_A, unattended pickup point J_U and depot 0, while the arc set E is given by $\{(i, j) : i \in V, j \in V, i \neq j\}$. For each customer I, they can choose what kind of products they want to order, ambient, fresh or frozen items, or all of them. Customers who order only ambient (I_1) and customers who order both ambient and fresh or frozen (I_2) become the total set of customers $I = I_1 \cup I_2$. Customers have the option to choose between two order fulfillment methods: home delivery or pick-up points (attended or unattended). Attended pick-up points refer to locations where staff are available to assist with parcel collection. In contrast, unattended pick-up points, such as parcel lockers, are self-service facilities that operate without the presence of staff. Attended pickup point J_A and unattended pickup point J_U form the set of pickup points $J = J_A \cup J_U$. For customers purchasing fresh or frozen products, these items need to be properly stored in refrigerators or other temperature-controlled settings to maintain their quality. When customers choose attended pick-up points, these locations are equipped with refrigeration or freezing facilities that can keep the products properly preserved, ensuring the quality is maintained. However, unattended pick-up points, such as parcel lockers, lack such equipment, which can negatively impact the quality of fresh or frozen products.

The model is formulated as a bi-objective optimization problem with a focus on minimizing delivery costs while maximizing customer utility. The utility function considers key factors such as delivery costs, travel time, and freshness of products, with particular emphasis on quality preservation for perishable items. A set of constraints ensure the feasibility of the delivery routes, including vehicle capacity limitations, flow conservation, customer visit requirements, and preventing subtours.

3.2 Assumptions and Notations

3.2.1 Assumptions

Assumptions are essential in modeling complex real-world problems like VRP because they simplify the system, making it computationally feasible and easier to interpret. Several assumptions are made as follows:

1. **Customer Utility Maximization:** Customers are assumed to choose their delivery method based on the maximization of their perceived utility. This utility is influenced by factors such as delivery fee, delivery time, location proximity, and the freshness of

perishable goods. This assumption allows us to model customer behavior in a way that reflects economic decision-making processes and prioritizes customer satisfaction in the delivery service design.

2. **Static Travel Metrics:** It is assumed that the distances and travel times between all locations are predetermined and remain constant regardless of variables like traffic conditions or weather. This assumption simplifies routing logistics by treating the travel costs between nodes as fixed, enabling a focus on optimizing other aspects of the delivery network.

3. **Facility Capabilities:** We assume that attended pickup points are equipped with facilities necessary for storing perishable products, ensuring their freshness until customer pickup. Conversely, unattended lockers do not have such facilities. This distinction is critical for decision-making related to the routing of perishable vs. non-perishable goods and impacts the strategic placement and use of different types of delivery points.

4. **Initial Freshness:** Products are assumed to start at 100% freshness when they leave the depot. This assumption establishes a baseline for measuring the degradation of product quality over time and distance, which is vital for planning routes that minimize the time perishable goods spend in transit, thereby enhancing customer satisfaction with product quality.

These assumptions provide a foundation for developing a VRP model that is both manageable and aligned with the practical considerations of a typical delivery system. While they streamline the problem, it is important to recognize the potential for deviations in real-world applications, which may necessitate adjustments or extensions to the model.

3.2.2 Notation

In table 2, all parameters used in this model are summarized. And in table 3, all the determination variables are listed in the table.

Below are detailed explanations of how the parameters used in this model are defined. $D_{i,j}$ represents the straight-line distance between point i and point j, calculated using their geographic coordinates. The travel time $tt_{i,j}$ is determined by dividing the distance between points i and j by the average speeds in urban areas and highways, which are assumed to be 50 km/h. The parameter p_j reflects the type of pickup point (PUP). For attended PUPs, the fixed cost is set at €40, whereas for unattended PUPs, it is €20. The higher cost for attended PUPs accounts for labor costs associated with their operation.

The hourly cost of the delivery truck, h, is based on the market average price for a standard box van with a tail lift (3500 kg gross weight), estimated to be €45 per hour, inclusive of all operating expenses. The fixed daily cost, hd, incurred if the vehicle is utilized, is calculated as the monthly rental cost of the truck divided by 30 days, yielding approximately €30 per day. The service time at each point is derived from real operational data from the company, set at $\frac{1}{3}$ hour per stop. This value accounts for the time required for deliveries to both customer homes and pickup points, with the latter typically involving slightly more time due to the handover process with the PUPs. These parameter definitions ensure the model is grounded in realistic and practical assumptions.

Table 2: Input Parameters

Input parameter	Meaning
I	Set of all customers
I_1	Set of customers who only order ambient products
I_2	Set of customers who order both ambient and fresh frozen products
J	Set for all pickup points
J_A	Set of attended pickup points
J_U	Set of unattended pickup points
D	Set of depot
V	Set of all nodes
E	Set of all edges
K	Set of all vehicles
$D_{i,j}$	Distances between node i and node (km)j, $i, j \in V$
$tt_{i,j}$	Travel time between node i and node j , $i, j \in V$
w_i	Weight of products ordered by customer i , $i \in I$
$Pnum_i$	Number of parcels for customer i , $i \in I$
O_i	If products ordered by customer $i$contain odd size items or not , $i \in I$
Chd_i	Total cost of customer i if delivered by home delivery , $i \in I$
Cp_i	Total cost of customer i if delivered by pickup point , $i \in I$
q_i	Delivery Cost for customer i , $i \in I$
fcd_i	Cost value function of home delivery for customer i , $i \in I$
fcp_i	Cost value function of self-pickup for customer i , $i \in I$
fdd_i	Distance value function of home delivery for customer i , $i \in I$
fdp_i	Distance value function of self-pickup for customer i , $i \in I$
p_j	Pickup point open cost for pickup point j , $j \in J$
h	Hourly cost of vehicle
hd	Fixed day cost if vehicle is used
st	service time at each node
w_c	weight of cost objective
w_u	weight of utility objective

Table 3: Decision Variables

Decision variable	Meaning
$x_{i,j,k}$	Edge (i, j) is traveled by vehicle k or not ,$(i, j) \in E, k \in K$
$y_{i,i}$	If customer i chooses home delivery or not ,$i \in I$
$y_{i,j}$	If customer i chooses self-pickup by point j or not,$i \in I, j \in J$
z_j	Pickup point j open or not ,$j \in J$
$t_{i,k}$	Arrival time at node i by vehicle k ,$i \in V, k \in K$
v_k	Vehicle k is used or not , $k \in K$
u_i	Variable for sub-tour elimination ,$i \in V$
Wd_i	Arrival time of node i ,$i \in V$
f_i	Freshness of product for customer i when delivered ,$i \in I$
fdt_i	Utility of delivery time for customer i,$i \in I$
fcd_i	Utility of home delivery cost for customer i,$i \in I$
fcp_j	Utility of self pick up from pickup point j ,$j \in J$
$fdp_{i,j}$	Utility of distance for customer i picks up at pickup point j,$i \in I, j \in J$
$Vt_{i,i}$	Home delivery utility for customer i ,$i \in I$
$Vt_{i,j}$	Self-pickup utility for customer i by pickup point j ,$i \in I, j \in J$

3.3 Mathematical model

The model is detailed in the following, the first objective is delivery cost minimization problem.

$$Z_1 : Min \sum_{i,j,k} h \times tt_{i,j} \times x_{i,j,k} + \sum_{j} p_j \times z_j \tag{1}$$

$s.t.$

$$\sum_{j \in J} y_{i,j} + y_{i,i} = 1 \quad \forall i \in I \tag{2}$$

$$y_{i,j} \leq z_j \quad \forall i \in I \quad j \in J \tag{3}$$

$$y_{i,i} = \sum_{j \in V, j \neq i, k \in K} x_{i,j,k} \quad \forall i \in I \tag{4}$$

$$y_{i,j} \leq \sum_{m \in V, m \neq j, k \in K} x_{m,j,k} \quad \forall i \in I, \quad \forall j \in J \tag{5}$$

$$\sum_{j \in V, j \neq i} x_{j,i,k} = \sum_{j \in V, j \neq i} x_{i,j,k} \quad \forall i \in I/\{D\}, \quad k \in K \tag{6}$$

$$\sum_{i \in V, i \neq 0} x_{0,i,k} = \sum_{j \in V, j \neq 0} x_{j,0,k}, \quad \forall k \in K \tag{7}$$

$$u_i - u_j + N \times x_{i,j,k} \leq N - 1 \quad \forall i \in \{1, ...N\} \quad \forall j \in \{1, ...N\}, \quad k \in K \tag{8}$$

$$u_0 = 1 \tag{9}$$

$$\sum_{j \in J, k \in K} x_{i,j,k} \leq 1, \quad \forall i \in V, \quad i \neq 0 \tag{10}$$

$$t_{i,k} + tt_{i,j} + st \leq t_{j,k} + M \times (1 - x_{i,j,k}), \quad \forall i \in V, \quad \forall j \in V, \quad j \neq 0, \quad i \neq j, \quad k \in K \tag{11}$$

$$M \times v_k \geq \sum_{i \in V, j \in V} x_{i,j,k}, \quad \forall k \in K \tag{12}$$

Objective Function 1 minimizes the total travel cost, pick-up point open cost, and also truck usage cost. Constraint 2 requires the customer to choose either home delivery or self-pickup. 3 indicates the pickup point j needs to open if there is one customer who chooses this pickup point to pick up their parcels. Constraint 4 means if the customer i chooses home delivery, there must be a truck passing customer i. Constaint 5 is the same logic. Constraint 6 is flow conservation constraint. 7 requires the vehicle k has to back to depot if it leaves depot. 8 and 9 are sub-tour elimination constraints. 10 limits the visit times of each node to be maximum once. 11 calculates the arrival time of each node. 28 determines the usage of each truck.

$$Z_2 : Max \sum_{i \in I, j \in J} Vt_{i,j} \times y_{i,j} + \sum_{i \in I} Vt_{i,i} \times y_{i,i} \tag{13}$$

$s.t.$

$$wd_i \geq t_{i,k}, \quad \forall i \in V, \quad \forall k \in K \tag{14}$$

$$wd_i \leq 10 + 7 \times (1 - Z_1) \quad \forall i \in V \tag{15}$$
$$wd_i \geq 10 - 7 \times (1 - Z_2) \quad \forall i \in V \tag{16}$$
$$wd_i \leq 17 + 7 \times (1 - Z_3) \quad \forall i \in V \tag{17}$$
$$wd_i \geq 17 - 7 \times (1 - Z_2) \quad \forall i \in V \tag{18}$$
$$1 = Z_1 + Z_2 + Z_3 \tag{19}$$
$$fdt_i \leq 1 \times Z_1 + (1 - \frac{(wd_i - 10)}{7}) \times Z_2 \quad \forall i \in V \tag{20}$$

$$f_i = f_0 - \varphi \cdot (wd_i - 9), \quad \forall i \in I, \quad i \neq 0 \tag{21}$$
$$f_i = f_0 - \varphi \cdot (wd_i - 9), \quad \forall i \in J_A, \quad i \neq 0 \tag{22}$$
$$f_i = f_0 - \varphi \cdot (wd_i - 9 + T_{\mathrm{A}}), \quad \forall i \in J_U, \quad i \neq 0 \tag{23}$$

$$Vt_{i,i} = \beta_{\mathrm{dt1}} \cdot fdt_i + \beta_{\mathrm{c1}} \cdot fcd_i + \beta_{\mathrm{d1}} \cdot fdd, \quad \forall i \in I_1 \tag{24}$$

$$Vt_{i,i} = \beta_{\mathrm{dt2}} \cdot fdt_i + \beta_{\mathrm{c2}} \cdot fcd_i + \beta_{\mathrm{d2}} \cdot fdd + \beta_f \cdot f_i, \quad \forall i \in I_2 \tag{25}$$

$$Vt_{i,j} = \beta_{\mathrm{dt1}} \cdot f_{\mathrm{dt}}[j] + \beta_{\mathrm{c1}} \cdot fcp_i + \beta_{\mathrm{d1}} \cdot fdp_{i,j}, \quad \forall i \in I_1, \quad j \in J \tag{26}$$
$$Vt_{i,j} = \beta_{\mathrm{dt2}} \cdot fdt_j + \beta_{\mathrm{c2}} \cdot fcp_i + \beta_{\mathrm{d2}} \cdot fdp_{i,j} + \beta_{\mathrm{f}} \cdot f_j, \quad \forall i \in I_2, \quad j \in J \tag{27}$$

Objective Function 13 maximizes the customer utility. 14 calculates the arrival time of each node. 21 calculates the freshness when customers receive their parcels. 15 calculates the relative value of arrival time. 24 and 25 are the utilities for customers who choose home delivery, either they order only ambient or both ambient and fresh frozen. 26 is the utility function of self pickup.

These are the two objective functions of the model and their corresponding constraints.Since this model is a two-objective optimization problem, the computational process of the model needs to find a balance between the two objectives. So that the total objective synthesized by the two objectives is optimal. Objective 1 is a minimization problem while objective 2 is a maximization problem. Having combined the two objectives, the total objective to be optimized is:

$$Min \quad w_c \times Z_1 - w_u \times Z_2 \tag{28}$$

3.4 Modeling Customers' Satisfaction

In this research, the utility function is formulated to evaluate the effectiveness of different order-fulfillment methods based on multiple criteria that influence customer satisfaction. These criteria—such as freshness of products, delivery time, location and distance, and cost—capture the essential aspects of customer preferences. Each criterion is quantitatively modeled to reflect its impact on utility, enabling a structured and consistent evaluation of different order-fulfillment options. By incorporating these criteria into the utility function, the research aims to provide a comprehensive framework for optimizing customer satisfaction while balancing logistical constraints.

In this research, min-max normalization method is applied to model all four criteria in the utility function: delivery time, location and distance, cost, and freshness. For each criterion, a relative value between 0 and 1 is calculated to ensure consistency and comparability. This is achieved by normalizing the raw values, such as using the formula of subtracting the actual value from the maximum value and dividing it by the range (maximum minus minimum). This approach ensures that each criterion is represented on a uniform scale, facilitating their integration into the utility function and enabling an equitable evaluation of different order-fulfillment methods.

A separate notation table for modeling customers' satisfaction is shown below:

Table 4: Input Parameters for modeling customers' satisfaction

Input parameter	Meaning
Q_{min}	Minimum delivery cost customer can accept
Q_{max}	Maximum delivery cost customer can accept
W_{min}	Minimum delivery time customer can accept
W_{max}	Maximum delivery time customer can accept
R_{min}	Minimum (pickup) distance customer can accept
R_{max}	Maximum (pickup) distance customer can accept
ϕ	Deterioration rate per hour for fresh and frozen products
f_0	Start freshness of fresh and frozen products

When all four criteria have each been modeled, the entire model is complete. The specific modeling methodology for each criterion is described below:

3.4.1 Cost

$$fcd_i/fcp_i = f(q_i) = \begin{cases} 1, & \text{if} \quad q_i < Q_{\min} \\ \dfrac{Q_{\max} - q_i}{Q_{\max} - Q_{\min}}, & \text{if} \quad Q_{\min} \leq q_i \leq Q_{\max} \\ 0, & \text{if} \quad q_i > Q_{\max} \end{cases} \tag{29}$$

Formula 29 represents a piecewise function $f(q)$ that maps the cost q to a normalized score between 0 and 1 based on defined thresholds.

- If the cost q is less than the minimum threshold $Q_{\min}$, the score $f(q)$ is set to 1, indicating the best possible outcome.
- If the cost q lies between $Q_{\min}$ and $Q_{\max}$, the score is linearly scaled between 1 and 0, reflecting the relative desirability of the cost within this range.
- If the cost q exceeds the maximum threshold $Q_{\max}$, the score $f(q)$ is set to 0, indicating the least favorable outcome.

Q_{min} and Q_{max} are set at €2 and €6, respectively, as the acceptable range for delivery costs [15]. If the delivery cost is less than €2, the cost utility is assigned a value of 1, indicating that customers perceive the cost as highly favorable. Conversely, if the delivery cost exceeds €6, the cost utility is assigned a value of 0, reflecting the fact that customers are highly unlikely to choose home delivery at such a price. This range captures the critical thresholds for customer acceptance, where costs within the range gradually affect utility, while those outside the range lead to sharp shifts in customer behavior.

The actual delivery cost that customers need to pay, q, is defined by the company's pricing policy. Home delivery mode and self-pick up have different costs.

The home delivery cost structure is determined by a base rate with additional surcharges applied based on package specifications. The base at 4.80 euro per address. Additional charges include a dimension surcharge of 0.75 euro for packages classified as oversized and a non-standard surcharge of 4.95 euro for parcels exceeding 23 kg. The total cost for each customer is determined based on these criteria and the surcharges associated with their order.

The formula for home delivery cost per address is expressed as:

$$C_{home} = B_{home} + \begin{cases} S_{non-standard}, & \text{if } weight > 23kg \\ S_{dimension}, & \text{if package is oversized} \\ 0, & \text{otherwise} \end{cases}$$

where C_{home} is the total home delivery cost per address, B_{home} is the base rate (4.80 euro), $S_{non-standard}$ is the non-standard surcharge (4.95 euro), and $S_{dimension}$ is the dimension surcharge (0.75 euro).

For self-pickup, a tiered pricing structure is implemented. A standard base rate of 4.20 euro is applied for customers collecting more than three parcels, while a reduced base rate of 4.00 euro is provided for those with three or fewer parcels. Similar to home delivery, additional charges apply: a dimension surcharge of 0.75 euro for over-sized parcels and a non-standard surcharge of 4.50 euro for parcels exceeding 23 kg.

The formula for self-pickup cost per address is expressed as:

$$C_{pickup} = B_{pickup} + \begin{cases} S_{non-standard}, & \text{if } weight > 23kg \\ S_{dimension}, & \text{if package is oversized} \\ 0, & \text{otherwise} \end{cases}$$

where C_{pickup} is the total self-pickup cost per address, B_{pickup} is the base rate, which is 4.20 units if the customer has more than three parcels and 4.00 euro otherwise, $S_{non-standard}$ is the non-standard surcharge (4.50 euro), and $S_{dimension}$ is the dimension surcharge (0.75 euro).

Both delivery methods utilize an iterative approach to compute the total delivery cost for each customer, ensuring that pricing accurately reflects package characteristics and delivery conditions. The calculations take into account customer-specific data such as parcel count, package weight, and size classification to determine the final delivery charge efficiently.

3.4.2 Delivery time

$$fdt_i = g(wd_i) = \begin{cases} 1, & \text{if} \quad wd_i < W_{\min} \\ \dfrac{W_{\max} - wd_i}{W_{\max} - W_{\min}}, & \text{if} \quad W_{\min} \leq wd_i \leq W_{\max} \\ 0, & \text{if} \quad wd_i > W_{\max} \end{cases} \tag{30}$$

The calculation logic of the utility value for delivery time follows the same structure as the cost function, as shown in formula 30. This function evaluates the utility of different delivery time slots based on predefined parameters that reflect customer preferences and operational constraints.

In this function, the parameters W_{min} and W_{max} are defined according to the standard weekday working hours, ranging from 10:00 AM to 5:00 PM. These time boundaries are established to align with common availability patterns of customers while ensuring a balance between service efficiency and convenience.

The earliest possible delivery time is set at 9:00 AM, ensuring that deliveries occur within a reasonable timeframe and do not arrive too early, potentially disturbing the customer. The choice of 9:00 AM as the starting point allows for early morning deliveries while maintaining a respectful buffer before most people begin their daily routines.

Conversely, the latest acceptable delivery time is 5:00 PM, as the company operates on a next-day delivery promise. Delivering beyond this time would be considered late by customers who rely on the service for timely fulfillment of their orders. This cutoff is especially crucial for customers purchasing fresh produce, frozen items, or other perishable goods that may be needed for preparing dinner. If a delivery arrives later than 5:00 PM, it may cause inconvenience or disrupt meal planning, reducing customer satisfaction.

By structuring the delivery time utility function in this way, the company ensures that deliveries are conducted within an optimal time-frame, balancing logistical efficiency with customer convenience. The model accounts for both business constraints and consumer expectations, helping to enhance the overall delivery experience.

3.4.3 Distance

$$fdp_{i,j} = h(r_{i,j}) = \begin{cases} 1, & \text{if} \quad r_{i,j} < R_{\min} \\ \dfrac{R_{\max} - r_{i,j}}{R_{\max} - R_{\min}}, & \text{if} \quad R_{\min} \leq r_{i,j} \leq R_{\max} \\ 0, & \text{if} \quad r_{i,j} > R_{\max} \end{cases} \tag{31}$$

$$fdd_i = 1, \quad \forall i \in I \tag{32}$$

The calculation logic of the utility value for distance follows the same structure. But the function only applies to calculate utility for self pick-up at pickup point. As the utility of home delivery is also 1.

The parameters R_{min} and R_{max} are defined as 0.25 km(approximately a 3-minute walk) and 1 km (approximately a 12-minute walk), respectively [15]. These distance thresholds are used to assess the convenience of self-pickup locations relative to the customer's home address.

If a pickup point is located within a 0.25 km radius of the customer's address, it is considered highly convenient, as the walking distance is minimal. In this case, the utility value is assigned a maximum score of 1, indicating that the pickup location is optimally placed for customer accessibility.

As the distance from the customer's home increases beyond 0.25 km, the perceived convenience of the pickup point starts to decrease. This decline follows a linear function as we assumed, meaning that for every incremental increase in distance, the utility value proportionally decreases. This approach aligns with consumer behavior, as longer walking distances typically lead to lower willingness to pick up packages personally.

Once the distance surpasses 1 km, the pickup location is deemed too far for practical use, significantly reducing the likelihood that customers will opt for self-pickup. At this threshold, the utility value is set to, meaning that the pickup location is considered inconvenient and unsuitable for self-collection.

This utility function ensures that self-pickup locations are evaluated based on their practical accessibility, providing a structured approach to modeling customer preferences. By implementing a distance-based linear utility model, the system effectively differentiates between conveniently located and inconvenient pickup points, helping to optimize delivery and self-pickup logistics.

3.4.4 Freshness

The freshness function is designed to accurately represent the gradual decline in product quality over time, beginning from its initial state at the depot. This function plays a crucial role in modeling perishability, particularly for goods such as fresh produce, dairy, meat, and other time-sensitive products that degrade in quality as they remain in transit or storage.

At the moment of departure from the warehouse, the initial freshness value, denoted as f_0, is set to 1. This represents the highest possible level of product quality, assuming optimal storage and handling conditions at the point of dispatch. From this point onward, the freshness of the product decreases progressively over time, following a linear degradation pattern. The rate at which this deterioration occurs is governed by a predefined coefficient, represented by φ.

The coefficient φ serves as a measure of the product's sensitivity to time-related degradation. Different types of products exhibit varying levels of perishability, and this coefficient allows for the differentiation of such characteristics. A higher value of φ indicates that the product deteriorates more rapidly, meaning it has a shorter viable shelf life and must be delivered to the customer in a shorter time frame to maintain acceptable quality. Conversely, a lower φ value suggests that the product retains its freshness for a longer period, allowing for more flexibility in transportation and storage.

This function provides a simplified yet effective model for assessing the impact of time on product quality. By incorporating freshness deterioration into logistical planning, businesses can optimize delivery schedules, reduce waste, and ensure that customers receive products in the best possible condition. The linear nature of the function makes it computationally efficient while still offering a reasonable approximation of real-world perishability trends. In practice, the choice of φ depends on empirical data derived from studies on product shelf life, environmental conditions, and handling practices.

The freshness at a given point is calculated as:

$$freshness = f_0 - \varphi \times (wd_i - wd_0) \tag{33}$$

where $wd_i - wd_0$ represents the travel or delivery time to the customer's location. wd_0 is defined at the departure time of all the vehicles, which is 9 AM. This approach ensures that the impact of time on product quality is accurately incorporated into the optimization process, making it particularly suitable for perishable goods.

The parameter φ is derived from a real-world experiment designed to evaluate the preservation duration of frozen products under specific packaging conditions. In this experiment, the frozen products were packed in white thermal insulation boxes, each containing two packs of dry ice to maintain the internal temperature at an optimal level. The objective of the experiment was to determine the maximum duration for which the products remained in acceptable quality under these conditions.

To quantify freshness degradation, we assume an initial freshness level of 1 at the beginning of the storage period. The products are considered to have lost their acceptable quality when the internal temperature exceeds a predefined threshold, at which point the freshness level is assumed to reach 0. The experiment commenced at 12:00 AM, and by 8:00 PM on the same day, the internal temperature of the products had reached $0°C$, indicating a total preservation duration of 20 hours. Based on this observation, the freshness decay rate φ is estimated as 0.05 per hour. This value is subsequently used in the model to represent the rate at which frozen products lose their freshness under the specified packaging and environmental conditions.

4 Solution Method

The solution to this model primarily uses linear programming, starting with the formulation of decision variables, constraints, and objectives. Non-linear constraints and objectives are first linearized using techniques like auxiliary variables and big-M methods. A weighted sum approach is then applied to balance the two objectives—route optimization and utility maximization—by assigning appropriate weights. The linearized model is solved using Gurobi solver to find the optimal solution. Finally, the results, including route assignments, delivery or pickup decisions, and arrival times, are analyzed to evaluate performance metrics like cost, utility, and freshness, ensuring an efficient and feasible solution to the problem.

4.1 Linearization

From the model, it is evident that Objective Function 1 and all the associated constraints are well-defined and linear, forming the foundational structure of the problem. The non-linearity primarily arises from Objective Function 2, which focuses on maximizing customer utility, and its corresponding constraints. These non-linear components add complexity to the model, requiring linearization techniques to incorporate them into the overall optimization framework effectively.

Objective Function 2 is non-linear as it involves the product of two decision variables: one continuous and one binary. To address this non-linearity, an auxiliary variable a is introduced to linearize the product. This auxiliary variable represents the interaction between the binary and continuous variables, enabling the model to maintain linearity while preserving the relationship between the variables in the objective function. A big number M is also introduced to help the linearization process. Detail formulas are show below:

$$a_{i,j} \leq M \times y_{i,j} \tag{34}$$

$$a_{i,j} \geq 0 \tag{35}$$

$$a_{i,j} \leq Vt_{i,j} \tag{36}$$

$$a_{i,j} \geq Vt_{i,j} - M \times (1 - y_{i,j}) \tag{37}$$

The first constraint enforces that the variable $a_{i,j}$ takes a value of zero whenever $y_{i,j} = 0$, ensuring that the assignment of $a_{i,j}$ is contingent on the activation of $y_{i,j}$. The second and third constraints establish that $a_{i,j}$ remains within the bounds defined by $Vt_{i,j}$, thereby preventing infeasible values. The fourth constraint guarantees that when $y_{i,j} = 1$, the variable $a_{i,j}$ attains the exact value of $Vt_{i,j}$, enforcing a direct relationship between the two variables. Collectively, these constraints serve to effectively linearize the originally non-linear product term, maintaining computational efficiency and ensuring that the model remains solvable within a reasonable time frame. This linearization approach is particularly important for mixed-integer programming models, as it mitigates computational complexity while preserving the accuracy of the formulation.

The constraint 17 in objective function 2 is also non-linear as a multiplication of a continuous variable and a binary variable is involved. A same method as above is applied to linearize the constraint.

4.2 Coefficients Calculation of Customers' Choice

In order to model the customer's choice and satisfaction with the delivery service, the utility function is chosen. For delivery services, usually delivery time, distance, delivery fee, and product freshness (if the customer buys fresh products) are some of the main factors that customers consider.

The Best-Worst Method (BWM) was used in this research to derive weights for evaluating the importance of various criteria in selecting the most appropriate order-fulfillment method.

Best-worst method (BWM) is proposed to solve multi-criteria decision-making (MCDM) problems. In an MCDM problem, a number of alternatives are evaluated with respect to a number of criteria in order to select the best alternative(s)[29]. In this method, decision-makers first identify the best (most important) and worst (least important) criteria. Then, they provide pairwise comparisons between the best criterion and all other criteria, followed by comparisons between all other criteria and the worst criterion. By solving an optimization problem, BWM minimizes the inconsistency in the comparisons, providing a reliable set of criteria weights. This approach is particularly useful for ensuring consistency in decision-making and was employed in this research to quantify the relative importance of customer preferences, such as delivery costs, convenience, and product freshness.

To address the diverse nature of customer preferences, two separate BWM analyses were conducted: one for customers who only order ambient products, and the other for customers who order both ambient and fresh or frozen goods.

The Best-Worst Method (BWM) is applied in this research to determine the relative importance of criteria for evaluating customer utility in selecting order-fulfillment methods. Some example steps for how to model the coeffcients of customers who order both ambient and fresh & frozen are shown. The process involves the following steps:

1. **Determine the Set of Criteria:** Identify the criteria influencing customer preferences for order-fulfillment methods, including:

$$C = \{\text{Freshness, Delivery Time, Location \& Distance, Fee}\}.$$

   These criteria reflect the key factors impacting customer satisfaction, particularly for those ordering perishable goods.

2. **Determine the Best and Worst Criteria:** Decision-makers, such as customers or logistics experts, identify the most important criterion (**Best**, c_B) and the least important criterion (**Worst**, c_W). For example, customers ordering perishable goods might prioritize **Freshness** as the best criterion, while considering **Delivery fee** as the least important.

3. **Provide Pairwise Comparisons:**

   (a) Compare the **Best Criterion** (c_B) with all other criteria using a scale from 1 (equal importance) to 9 (extremely more important). The results are recorded in a vector A_B:

$$A_B = \{a_{B1}, a_{B2}, ..., a_{Bn}\},$$

   where a_{Bi} represents the importance of the best criterion (c_B) compared to criterion c_i.

   (b) Compare all criteria with the **Worst Criterion** (c_W) using the same scale. The results are recorded in a vector A_W:

$$A_W = \{a_{1W}, a_{2W}, ..., a_{nW}\},$$

   where a_{iW} represents the importance of criterion c_i compared to the worst criterion (c_W).

4. **Formulate the Optimization Problem:** The optimal weights ($w_1, w_2, ..., w_n$) for the criteria are determined by minimizing the maximum absolute differences between the pairwise comparisons and the derived weights. The linear programming model is formulated as:

$$\text{Minimize } \xi$$

   Subject to:

$$\left| \frac{w_B}{w_i} - a_{Bi} \right| \leq \xi, \quad \forall i,$$

$$\left| \frac{w_i}{w_W} - a_{iW} \right| \leq \xi, \quad \forall i,$$

$$\sum_{i=1}^{n} w_i = 1, \quad w_i \geq 0, \quad \forall i.$$

Here, w_B and w_W represent the weights of the best and worst criteria, respectively, while a_{Bi} and a_{iW} are pairwise comparison values.

5. **Calculate the Consistency and Optimal Weights:** The linear optimization problem is solved to obtain the optimal weights:

$$W = \{\text{Freshness: } w_1, \text{Delivery Time: } w_2, \text{Location \& Distance: } w_3, \text{Delivery fee: } w_4\}.$$

A consistency check is performed to ensure the reliability of the results, enabling the integration of customer preferences into the broader optimization framework for order-fulfillment selection.

The BWM implementation process began by designing two questionnaires. Each questionnaire consisted of a set of pairwise comparisons between criteria based on customers' preferences. For customers who only order ambient products, the criteria were Delivery Time, Location & Distance, and Delivery fee. For customers who order both ambient and fresh or frozen products, an additional criterion was added: Freshness. This consideration reflects the unique importance of product freshness for customers ordering perishable goods.

The questions for pairwise comparisons were constructed based on the previous analysis provided. Participants were asked to evaluate, on a scale from 1 to 9, how much more important one criterion was over another, with 1 indicating equal importance and 9 indicating extreme importance of one criterion over the other. The questions included comparisons such as Delivery Time vs. Fee, Freshness vs. Location & Distance, etc. The questionnaire for customers who order both ambient and fresh frozen is shown in appendix A.

The derived weights were then integrated into the broader optimization framework of the study, forming a fundamental part of the utility function for each customer segment. This differentiation allowed the vehicle routing and pick-up point selection models to accurately reflect customer preferences, ensuring that the solutions provided a balanced focus on both logistical efficiency and customer satisfaction.

4.3 Bi-objective optimization and weighted sum method

In optimization, real-world problems often require the consideration of multiple, potentially conflicting objectives. A bi-objective optimization problem is a type of multi-objective optimization that focuses on finding the best solutions for two conflicting objectives simultaneously. For example, in the context of last-mile delivery logistics, two main objectives may be minimizing delivery costs and maximizing customer satisfaction. These two goals are inherently conflicting because reducing costs often means reducing service quality, while improving customer satisfaction can lead to increased costs.

In such bi-objective problems, finding a single "optimal" solution becomes challenging due to the trade-offs between the objectives. Instead of one solution, the concept of a Pareto frontier (or Pareto front) is used to describe the set of optimal solutions where no one solution can be improved in one objective without compromising another objective. The Pareto frontier represents the boundary of all efficient trade-offs between the objectives [30] on the Pareto frontier are called Pareto optimal because they are considered equally good with respect to both objectives. In practice, decision-makers choose one solution from the Pareto frontier depending on the relative importance of the objectives [31]. This concept of the Pareto frontier is valuable in decision-making processes that involve multiple stakeholders with different priorities, such as balancing cost efficiency and customer satisfaction in logistics.

For this research, the bi-objective optimization problem is modeled to simultaneously minimize delivery costs while maximizing customer satisfaction through parameters like delivery time and product freshness. The Pareto frontier helps identify the best possible trade-offs between these objectives, providing an array of solutions that achieve efficient operational performance while ensuring high levels of customer satisfaction[32].

To solve the bi-objective problem, weighted sum method, which is one of the most commonly used approaches for solving multi-objective optimization problems is applied in this research. In this method, multiple objectives are combined into a single objective function using a weighted linear combination of the individual objectives. This approach is particularly suitable for problems with two objectives, as it allows for a straightforward trade-off analysis between the competing objectives.

Given two objectives Z_1 and Z_2 in this research, the combined objective function in the Weighted Sum Method can be expressed as:

$$Z = w_c \times Z_1 - w_u \times Z_2,$$

where Z_1 and Z_2 are non-negative weights ($Z_1, Z_2 \geq 0$) that represent the relative importance of the objectives and satisfy the condition $w_c + w_u = 1$.

The optimization process involves:

1. Selecting appropriate values for the weights w_1 and w_2, which reflect the decision-maker's preferences for the two objectives.

2. Solving the resulting single-objective optimization problem to find a Pareto-optimal solution.

3. Repeating the process with different weight combinations to explore the Pareto frontier, which represents the trade-off between the two objectives.

This method is widely applied in solving bi-objective optimization problems in logistics and supply chain management, including vehicle routing and order fulfillment optimization [32]. In this research, the Weighted Sum Method is employed to balance the trade-off between minimizing transportation costs and maximizing customer utility.

4.4 Max-Min normalization

Max-min normalization is a foundational data scaling technique widely applied in multi-criteria decision-making (MCDM) and optimization problems. It rescales data into a fixed range, typically [0, 1], to ensure comparability among criteria of differing magnitudes[33]. The normalization formula is given by:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{38}$$

where:

- x: The original value of the criterion,
- $x_{\min}$: The minimum value of the criterion,
- $x_{\max}$: The maximum value of the criterion,
- x': The normalized value scaled between 0 and 1.

In this research, max-min normalization is applied to the following criteria:

1. **Cost:** Represents the delivery cost.
2. **Delivery Time:** Reflects the time efficiency of order fulfillment.
3. **Freshness:** Critical for perishable goods.
4. **Location and Distance:** Measures the convenience of pickup points or delivery locations.

The utility function integrates these normalized criteria to provide a fair trade-off in the optimization process, enabling balanced solutions for logistical efficiency and customer satisfaction. Detail formulas for how to normalize each criteria are shown in 3.4.

In this research, normalization also plays a crucial role in handling the inherent differences in scale and magnitude between the two primary objectives: delivery cost and customer utility. These objectives are fundamentally different in both units and value ranges, with delivery cost typically measured in monetary terms and ranging in the hundreds or thousands, while customer utility is a dimensionless score typically ranging between 0 and 1.

Without normalization, directly combining these objectives using the weighted sum method would lead to disproportionate contributions to the overall objective function. The larger numerical scale of delivery cost would dominate the optimization process, effectively minimizing its value while neglecting the importance of customer utility. This imbalance would not accurately reflect the trade-offs intended by the decision-makers and could lead to suboptimal solutions.

To normalize cost and utility objectives Z_1 and Z_2, formulas below are applied:

$$Z_1' = \frac{Z_{1max} - Z_1}{Z_{1max} - Z_{1min}} \tag{39}$$

$$Z_2' = \frac{Z_2 - Z_{2min}}{Z_{2max} - Z_{2min}} \tag{40}$$

By using the formulas above, both objectives are converted a value from 0 to 1. This ensures the weights of two objectives to 1 instead of changing the weights two transfer them in a same magnitude.

To accurately apply this transformation, it is necessary to first identify the maximum and minimum values for each objective. This is typically achieved by running optimization processes separately for each objective, where the sole goal is to either maximize or minimize that particular objective without consideration for others. By doing so, one can capture the extreme values that the objective function can reach, which are then used as benchmarks for normalization.

Having normalized both objectives, the revised objective function becomes:

$$Z' = w_c * Z_1' + w_u * Z_2' \tag{41}$$

The problem is reformulated into a maximization problem by normalizing the objectives Z_1 and Z_2, resulting in Z_1' and Z_2'. Through normalization, the objectives are scaled such that higher values of Z_1' and Z_2' indicate closer alignment to their respective targets. As the normalization values increase, Z_1 and Z_2 progressively approach their desired objectives. Consequently, the final goal of the problem is to maximize the combined normalized objective, expressed as $\max Z'$.

5 Computational Results

5.1 Data set

The dataset used in this study consists of a set of geographic locations representing real customers and potential pick-up points. It has been carefully selected to reflect a realistic delivery and order-fulfillment scenario, typical of urban and suburban areas. This dataset forms the foundation for the computational experiments aimed at solving the vehicle routing and location selection problem in the context of the last-mile delivery. Sample data is shown below in table 5.

The dataset includes 44 locations, each defined by its latitude and longitude coordinates. These points represent both customer addresses and pick-up points, which are further categorized into attended and unattended types. The coordinates ensure precise positioning for route optimization, while the classification into attended and unattended types allows the model to capture the operational differences in these fulfillment methods. Points in this data set are plotted in a map shown in figure 1. Coordinates of actual customers are hidden to protect their privacy. As stated in figure's legend, point marked in pink is the depot where all trucks start from. Customers who order only ambient products and order both ambient and F& F are labeled as green and orange respectively. Attended pups and unattended pups(Locker) are colored in red and purple.

Each customer in the dataset is associated with specific attributes, such as parcel weight, number of packages, and whether they have special delivery requirements, such as perishable items requiring refrigeration. Similarly, pick-up points include attributes such as their capacity and availability of refrigeration facilities for storing perishable goods. For attended pups, refrigerated or frozen facilities are equipped in the store to keep the quality of goods, while parcel locks do not have the temperature-keeping function.

By using this dataset, the thesis aims to validate the applicability of the proposed model in achieving optimal routing and order-fulfillment solutions while maintaining a balance between cost-efficiency and customer utility.

Figure 1: Dataset visualization in Dutch Map

Table 5: Sample dataset

ID	Latitude	Longitude	Type	Weight (kg)	Parcel Count	Odd Size
1	51.98	4.44	Customer	20.96	2	Yes
2	51.99	4.35	Customer	5.20	1	No
3	52.00	4.38	PUP	0	0	No
4	51.99	4.36	Customer	2.90	1	No
5	51.99	4.35	Locker	0	0	No
6	52.01	4.35	Customer	36.97	1	No
7	52.01	4.36	Customer	40.20	3	Yes
8	51.99	4.48	Customer	7.80	2	No
9	51.98	4.35	Customer	11.90	1	No
10	51.98	4.44	Customer	4.50	1	No

5.2 Customer's perception

To enhance the reliability and validity of the study, the survey was meticulously designed and distributed to a carefully selected group of 100 participants. This sample size was chosen to ensure a broad representation of customer preferences and to gather sufficient data for robust statistical analysis. The participants were drawn from diverse demographics, reflecting varied consumption patterns and preferences within our customer base.

After collecting the initial responses, a rigorous screening process was applied to identify 50 responses that met our criteria for completeness and consistency. This step was critical to ensure the quality of the data, as incomplete or inconsistent responses could lead to skewed results and potentially misleading conclusions. The criteria for selection included checks for logical consistency in the answers and completeness of all required fields. The final set of 50 high-quality responses was then used for further analysis. This dataset formed the basis for deriving two distinct sets of weights using the Best-Worst Method (BWM)

These derived weights are crucial as they represent the relative importance of various customer service and product quality attributes, tailored to different customer segments. For the analysis, two groups were identified based on their purchasing patterns: those who order both ambient and fresh & frozen products, and those who only order ambient products. This distinction allowed us to tailor our strategies to meet the specific needs and preferences of each segment, potentially enhancing customer satisfaction and loyalty. The results for customers who order both ambient and fresh & frozen and only ambient are shown in the Appendix B and C.

For customers ordering only ambient products, the analysis results showed the importance of Delivery Time as the most crucial factor, with Location & Distance and Cost following in relative importance. For customers ordering both ambient and fresh or frozen products, Freshness emerged as the most important criterion, followed by Delivery Time, Location & Distance, and finally Cost. The aggregation of the responses allowed us to derive consistent weights for the decision model that represent typical customer preferences across different customer types.

The BWM analysis for customers who order both ambient and fresh or frozen products and customers who only ambient yield the results below:

Table 6: BWM Coefficients for customers who both order ambient and F&F

	Delivery time	Location & Distance	Delivery fee	Freshness
weight	0.13	0.08	0.065	0.71

Table 7: BWM Coefficients for customers who only order ambient

	Delivery time	Location & Distance	Delivery fee
weight	0.61	0.27	0.11

5.3 Calculation Results

With all data inputs ready, the proposed model is run with different combinations of w_c and w_u. As the weights of cost and utility change, the total delivery cost, the overall customer utility, the number of customers opting for self-pickup, and the delivery method chosen by customers purchasing fresh and frozen goods all exhibit significant variations. These results highlight the inherent trade-off between minimizing costs and maximizing customer satisfaction.

This analysis underscores the need for balancing these conflicting objectives to achieve an optimal solution that aligns with both operational efficiency and customer-centric goals, providing valuable insights for companies aiming to balance operational efficiency with customer-centric strategies. Companies can use this model to identify an optimal combination of cost and utility weights based on their specific business goals.

Table 8 presents the results obtained from running the optimization model with varying cost and utility weight combinations (w_c and w_u). The table includes key metrics such as the number of customers selecting home delivery and self-pickup, the total delivery cost, and the corresponding utility values. Additionally, it provides information on the computation time required for each scenario and the optimality gap achieved during the solving process. These results serve as the basis for evaluating the impact of different weight distributions on the overall optimization outcomes.

Table 8: Optimization results for different cost and utility weight combinations

W_c	W_u	# of home delivery	# of self pickup	Value of cost	Value of utility	Total objective value	Calculation time(s)	Gap
0	1	26	4	817.98	26.67	1	607	3.15
0.1	0.9	30	0	668.95	26.65	0.9569	181	4.8
0.2	0.8	12	18	477.77	25.98	0.915	86	4.93
0.3	0.7	7	23	288.45	24.63	0.886	115	3.32
0.4	0.6	1	29	142.33	22.65	0.8765	190	2
0.5	0.5	0	30	142.3	22.65	0.8865	1506	1.5
0.6	0.4	0	30	97.76	21.463	0.90446	190	1
0.7	0.3	0	30	97.76	21.463	0.92743	211	0.9
0.8	0.2	0	30	89.94	20.82	0.95255	215	0.9
0.9	0.1	0	30	89.94	20.82	0.97621	172	0.5
1	0	0	30	88.5	5.8	1	10	0

5.3.1 Trade-off Between Total Delivery Cost and Customer Utility

One of the key findings from the optimization results is the inherent trade-off between minimizing total delivery cost and maximizing customer utility. As the weight assigned to cost minimization (W_{cost}) increases, the model consistently reduces the overall cost of delivery by shifting from home deliveries to pickup points. However, this reduction in cost comes at the expense of customer utility.

When customer utility is prioritized ($W_{cost} = 0$), the model assigns 26 home deliveries and only 4 pickups, leading to the highest observed total cost of €817.98. In this scenario, customer utility is maximized at 26.67. As W_{cost} increases, the model gradually reduces the number of home deliveries, transitioning towards more cost-effective pickup points. This trend becomes particularly evident between $W_{cost} = 0.2$ and $W_{cost} = 0.4$, where total cost drops sharply from €477.77 to €142.33 while customer utility declines moderately from 25.98 to 22.65.

Beyond $W_{cost} = 0.4$, all deliveries shift to pickup points, effectively minimizing delivery cost but also leading to a steady decline in customer utility. At $W_{cost} = 1$, the total cost reaches its lowest value of €88.5, but customer utility drops significantly to 5.8, indicating the trade-off's critical impact on service quality.

These results highlight the importance of selecting an optimal balance between cost and utility. Businesses focusing solely on cost minimization may risk customer dissatisfaction, while those

Figure 2: Trade-Off Between Cost and Customer Utility. As the cost weight w_c increases, the total delivery cost decreases while customer utility declines.

prioritizing service quality must be prepared for higher operational costs. The findings suggest that an optimal balance exists around $W_{cost} = 0.3$ to $W_{cost} = 0.5$, where cost reductions are significant, but customer utility remains within an acceptable range.

Figure 3 illustrates the Pareto front representing the trade-off between the two objectives: cost and utility. The plot shows how varying the weight coefficients for cost (W_{cost}) and utility (W_{utility}) affects the optimal values for both objectives. As the weight on cost increases, the value of cost decreases, but at the expense of utility, which simultaneously decreases as shown in the curve.

Each point on the Pareto front represents a solution where no other solution can simultaneously improve both objectives[34]. These points are considered Pareto optimal, meaning that, for a given solution, improving one objective would result in a sacrifice in the other. Specifically, the lower the value of cost, the lower the corresponding utility, demonstrating the inherent trade-off between minimizing cost and maximizing customer utility. The data labels on the plot provide the exact values of cost and utility for each weight combination, offering insights into the balance between these objectives for each solution.

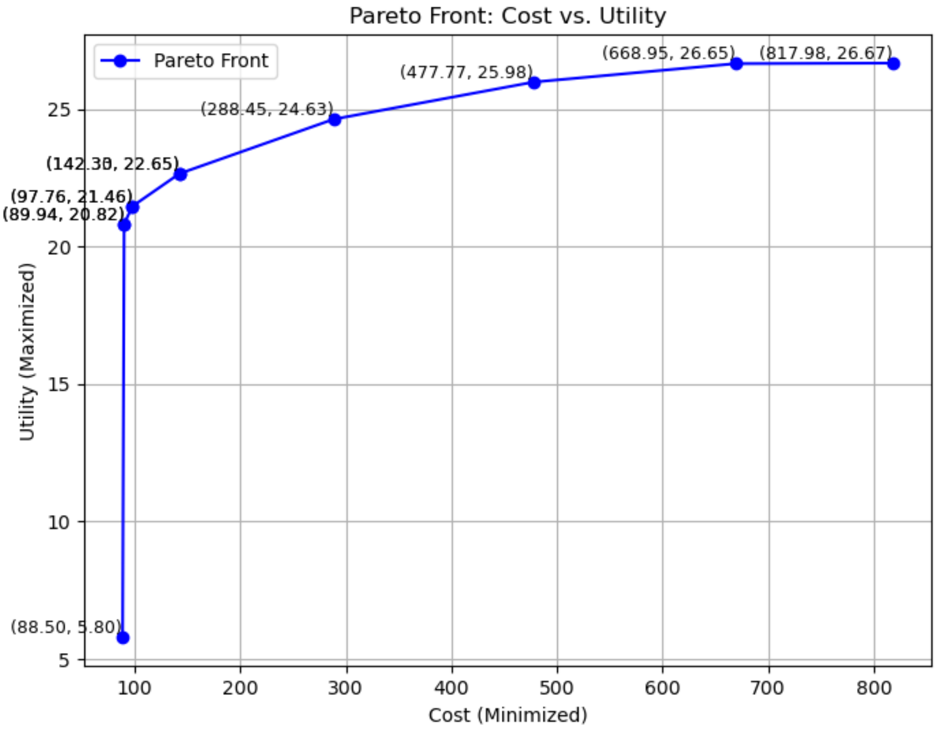

Figure 3: Pareto Front: Trade-off between Cost and Utility. Each point represents a Pareto optimal solution with the corresponding values for cost and utility.

5.3.2 Impact of Cost Weight on Delivery Choice

The cost weight (W_{cost}) significantly influences the delivery mode chosen by the model, affecting the distribution of home deliveries versus pickup point usage. At lower values of W_{cost}, the model assigns a substantial portion of deliveries to home delivery to maximize customer satisfaction, but as W_{cost} increases, the system increasingly favors pickup points due to their lower associated costs.

At $W_{cost} = 0$, home deliveries dominate with 26 home deliveries and only 4 self-pickups. This allocation reflects customer preference for direct-to-door deliveries when cost is not a concern. However, as soon as W_{cost} increases slightly ($W_{cost} = 0.1$), the model already begins shifting towards pickup points, with all 30 deliveries routed through home delivery. This early shift indicates that even a small prioritization of cost leads to significant changes in the delivery strategy.

Between $W_{cost} = 0.2$ and $W_{cost} = 0.3$, a transitional phase emerges where a mix of home deliveries and pickup point allocations are observed. In these cases, the model seeks a balance by assigning some deliveries to pickup points to reduce costs while still maintaining a level of home delivery for customer convenience. By $W_{cost} = 0.4$, however, the transition is complete, and all deliveries are routed to pickup points, signaling the model's preference for low-cost delivery modes when cost minimization is emphasized.

This shift is crucial for businesses considering cost-saving measures. If a company aims to reduce operational expenses without completely sacrificing customer service, an ideal operating

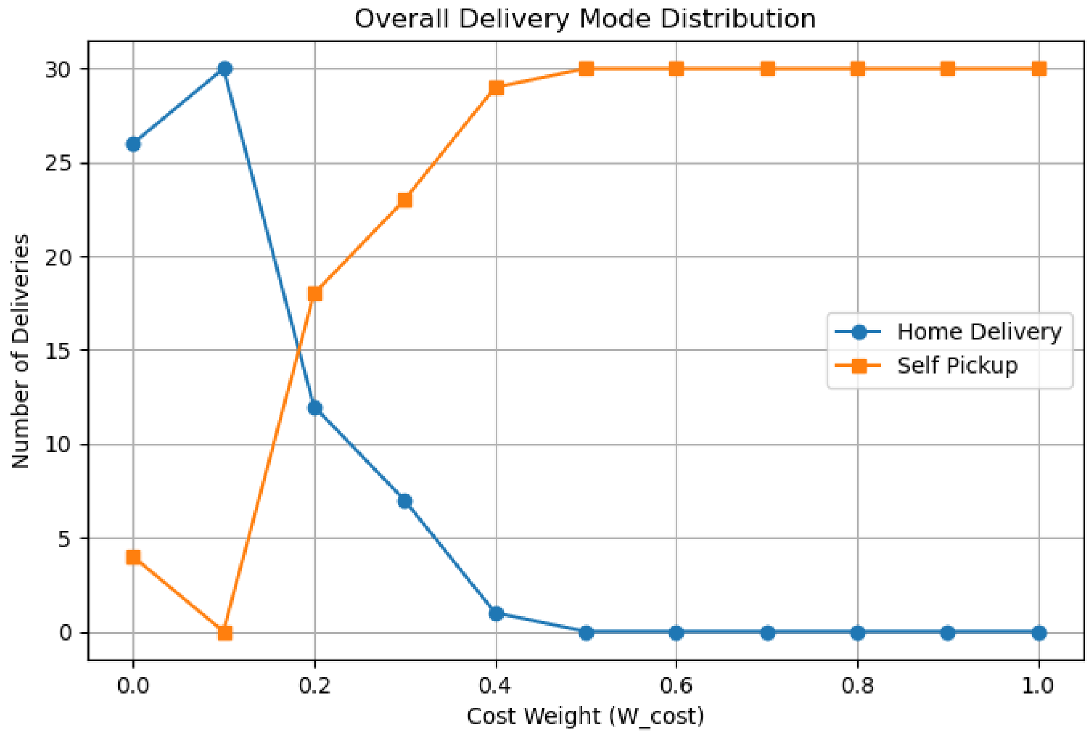

Figure 4: Impact Of Cost Weight On Delivery Choice

range lies between $W_{cost} = 0.2$ and $W_{cost} = 0.4$, where both cost and customer experience are balanced. Beyond this point, further prioritization of cost results in diminishing returns, as savings become marginal but customer utility continues to drop significantly.

This analysis reinforces the necessity for businesses to carefully decide how much weight to assign to cost minimization when designing delivery strategies. Overemphasizing cost reduction can lead to a complete elimination of home deliveries, potentially leading to customer dissatisfaction. Conversely, allowing for a more balanced approach ensures that customer preferences are still incorporated into the delivery model while achieving substantial cost savings.

5.3.3 Detailed Analysis of Delivery Mode Selection

The selection of delivery modes varies significantly across different cost-weight scenarios, reflecting the trade-offs between operational efficiency and customer preferences. The model results highlight how customers shift between home delivery, attended pickup points (PUPs), and lockers as cost minimization becomes more dominant. This section provides a more in-depth exploration of these shifts, analyzing how different customer segments respond to changes in delivery pricing.

At low cost weights ($W_{cost} = 0$), the vast majority of customers prefer home delivery. This preference is particularly strong among ambient-only customers, who do not face perishability concerns and prioritize direct-to-door service. However, as cost minimization becomes a stronger objective, home deliveries decline and eventually disappear by $W_{cost} = 0.4$. At this point, all customers transition to self-pickup, with a strong preference for attended PUPs among

Table 9: Home Delivery, Self Pickup, and Attended PUP Choices

W_cost	**W_utility**	**Home Delivery**	**Self Pickup**	**Total Attended PUP**	# of customers only order ambient	# of customers order both
0	1	26	4	4	2	2
0.1	0.9	30	0	0	0	0
0.2	0.8	12	18	4	0	4
0.3	0.7	7	23	16	10	6
0.4	0.6	1	29	20	12	8
0.5	0.5	0	30	21	12	9
0.6	0.4	0	30	20	12	8
0.7	0.3	0	30	20	12	8
0.8	0.2	0	30	20	12	8
0.9	0.1	0	30	20	12	8
1	0	0	30	20	11	9

W_cost	**Total Locker Usage**	# of customers only order ambient	# of customers order both
0	0	0	0
0.1	0	0	0
0.2	14	9	5
0.3	7	4	3
0.4	9	4	5
0.5	9	4	5
0.6	10	4	6
0.7	10	4	6
0.8	10	4	6
0.9	10	4	6
1	10	5	5

Table 10: Locker Usage Across Cost-Utility Weights

ambient-only customers and a mixed distribution between attended PUPs and lockers among fresh/frozen buyers.

For customers purchasing only ambient products, the transition from home delivery to self-pickup is particularly pronounced. At $W_{cost} = 0$, 14 out of 16 ambient-only customers use home delivery. However, as W_{cost} increases, home deliveries drop to zero by $W_{cost} = 0.4$, at which point all ambient customers have transitioned to self-pickup. Among self-pickup choices, attended PUPs dominate, with 12 customers choosing them over lockers.

The avoidance of lockers by ambient-only customers suggests that attend pups may have lower delivery time or short distance to customers. Unlike fresh/frozen customers, ambient buyers do not have perishability constraints, meaning their preference for attended PUPs likely stems from a desire for more convenient collection. The consistent lack of locker adoption across all cost-weight scenarios reinforces this hypothesis.

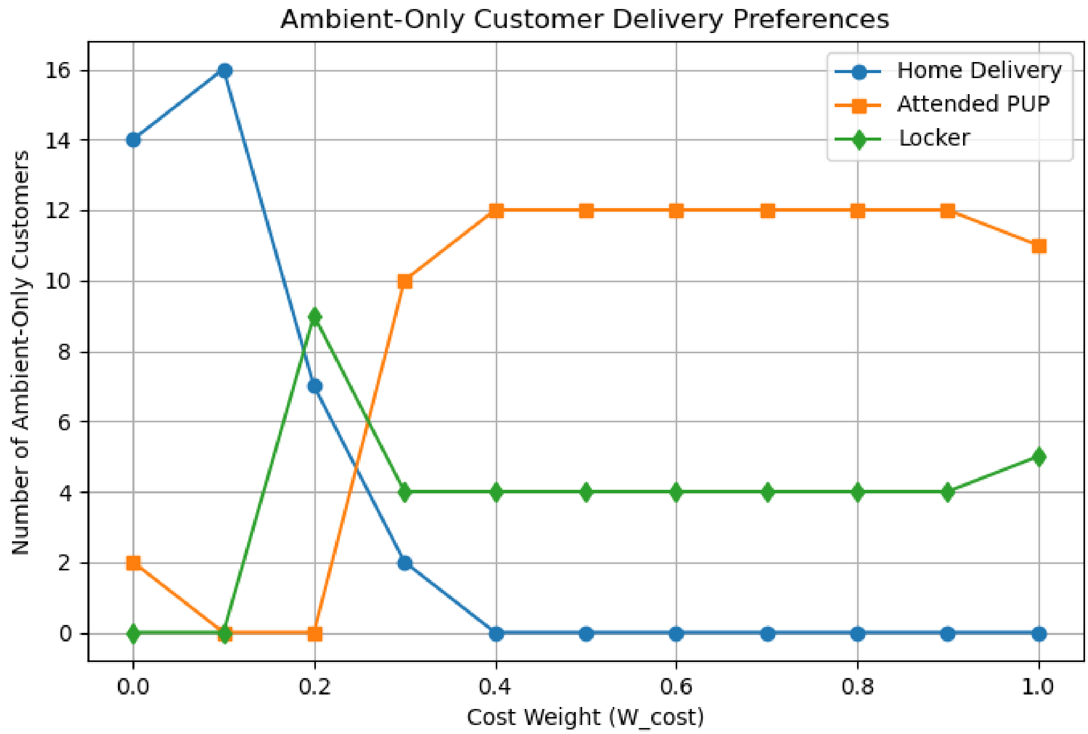

Figure 5: Ambient-Only Customer Delivery Preferences

Customers purchasing both fresh/frozen and ambient products display more diverse order fulfillment ways when transitioning from home delivery to self-pickup, assigned by the model. At $W_{cost} = 0$, 12 of these customers are assigned to home delivery. As cost weight increases, home delivery usage declines sharply, reaching zero at $W_{cost} = 0.4$. Unlike ambient-only customers, fresh/frozen buyers are not overwhelmingly assigned to attended PUPs. Instead, they are divided between attended PUPs and lockers, with a relatively stable proportion (5-6 customers) choosing lockers in all cost-weight scenarios.

The continued assignment of lockers by fresh/frozen buyers, despite the lack of temperature control, indicates that some customers prioritize convenience or proximity over freshness concerns. This finding suggests that while temperature-controlled storage is important, in order to reach a cost and satisfaction balance, it is not a universal requirement from company's view. Some may have short pickup-to-consumption times or alternative methods of maintaining product integrity, making lockers an acceptable trade-off under cost-minimization strategies.

The results demonstrate a clear pattern: as cost weight increases, all customers transition from home delivery to self-pickup. However, the assigned self-pickup method varies significantly by customer type. Ambient-only customers overwhelmingly are assigned to attended PUPs, while fresh/frozen buyers exhibit a more balanced distribution between attended PUPs and lockers.
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The consistent use of lockers by a subset of fresh/frozen customers indicates that locker placement strategies should account for factors beyond temperature control. Proximity, accessibility,

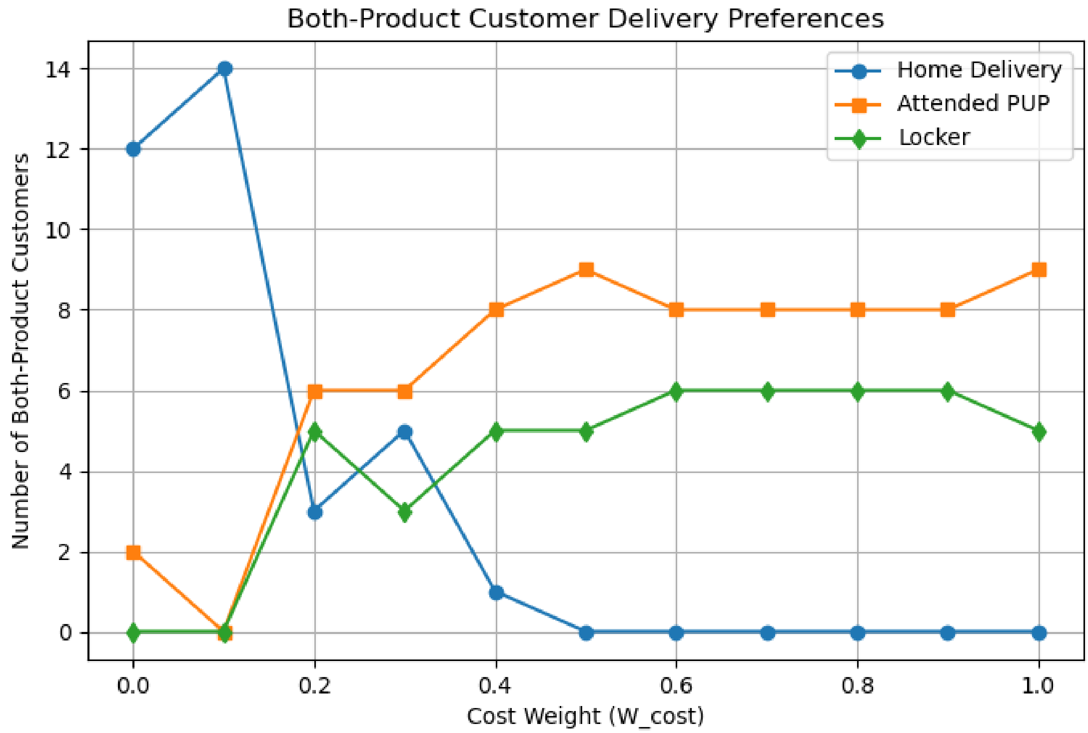

Figure 6: Both-Product Customer Delivery Preferences

and convenience may play a larger role in customer decision-making than previously assumed. To further refine these insights, future research could incorporate surveys or behavioral experiments to validate the model predictions.

5.3.4 Computation Time and Optimality Gap Analysis

The computation time and optimality gap results provide insights into the efficiency and convergence behavior of the optimization model.

As shown in Figure 8, computation time varies significantly depending on the cost weight W_{cost}. At lower cost weights ($W_{cost} \leq 0.3$), computation time fluctuates but remains below 200 seconds, indicating a relatively stable computational demand. However, at $W_{cost} = 0.5$, the computation time peaks at 1506 seconds, suggesting a more complex optimization landscape when cost and utility are equally weighted. Beyond this point, computation time stabilizes and decreases as the model favors cost minimization over utility.

The optimality gap follows a decreasing trend as W_{cost} increases. At lower values ($W_{cost} \leq 0.3$), the gap remains above 3%, indicating a less refined solution. However, for $W_{cost} \geq 0.7$, the gap consistently falls below 1%, showing that the solver achieves near-optimal solutions in these cases. The near-zero gap at $W_{cost} = 1$ confirms that cost-focused solutions are computationally simpler to optimize.

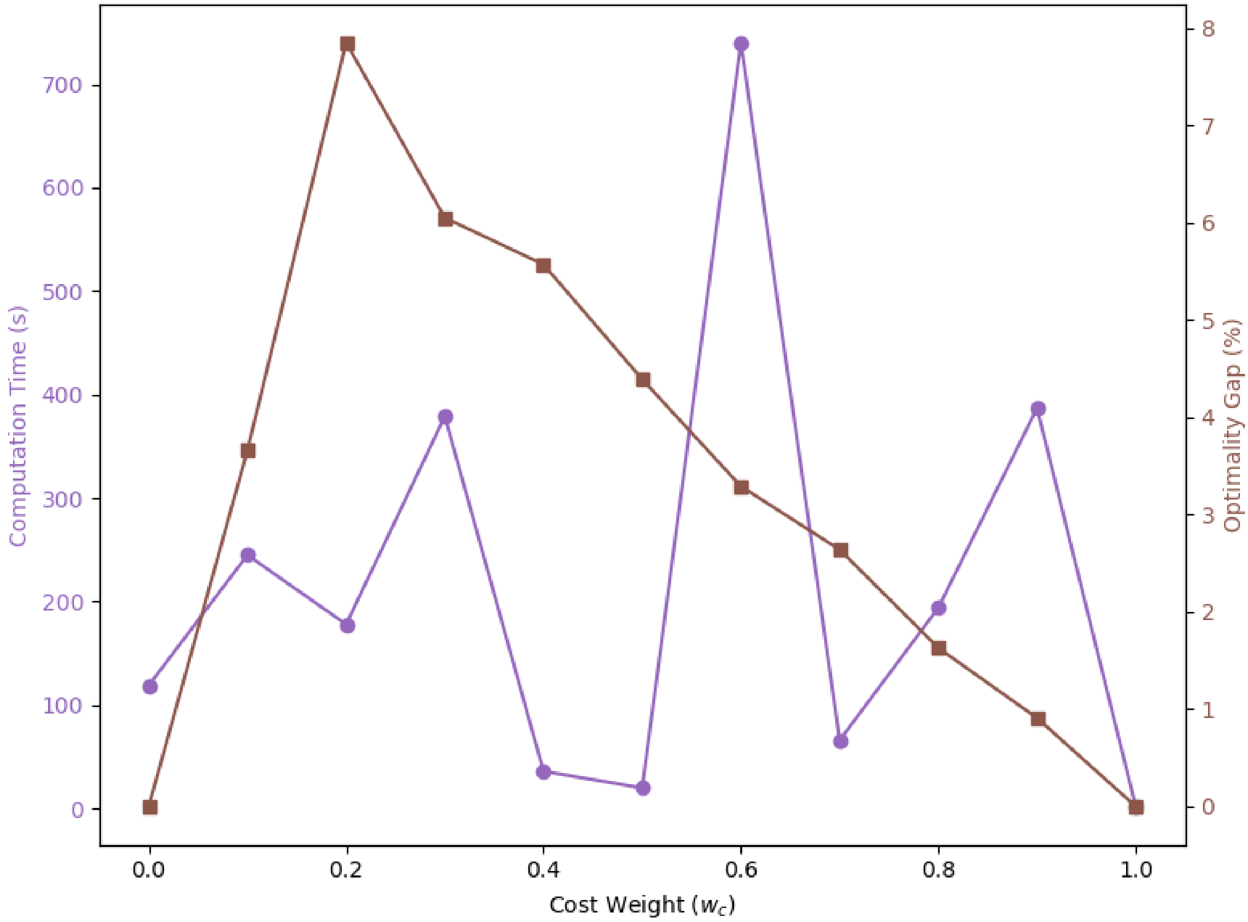

Figure 7: Computation Time And Optimality Gap Analysis

5.4 Delivery routes and Customers' Choices

To gain a deeper understanding of the trade-offs between cost minimization and customer utility, we select two key weight coefficient combinations that represent significant transitions in the cost-utility spectrum.

The selected cases are:

- Case 1: $W_{cost} = 0.2, W_{utility} = 0.8$ - This scenario maintains a strong emphasis on utility while beginning to incorporate cost considerations, providing insight into early-stage cost-saving effects.

- Case 2: $W_{cost} = 0.4, W_{utility} = 0.6$ - This setting reflects a more balanced approach, where cost efficiency becomes a more significant factor, leading to a noticeable shift in customer behavior.

These two cases are selected because they represent a moderate trade-off between cost efficiency and customer utility. Unlike extreme cases where either cost or utility dominates entirely, these combinations allow us to analyze the gradual shift in delivery cost structures and customer preferences. By examining these mid-range weight settings, we can observe the transition from a predominantly utility-driven model to one that strategically incorporates cost-saving mechanisms while still ensuring a reasonable level of customer satisfaction.

5.4.1 $W_c = 0.2, W_u = 0.8$

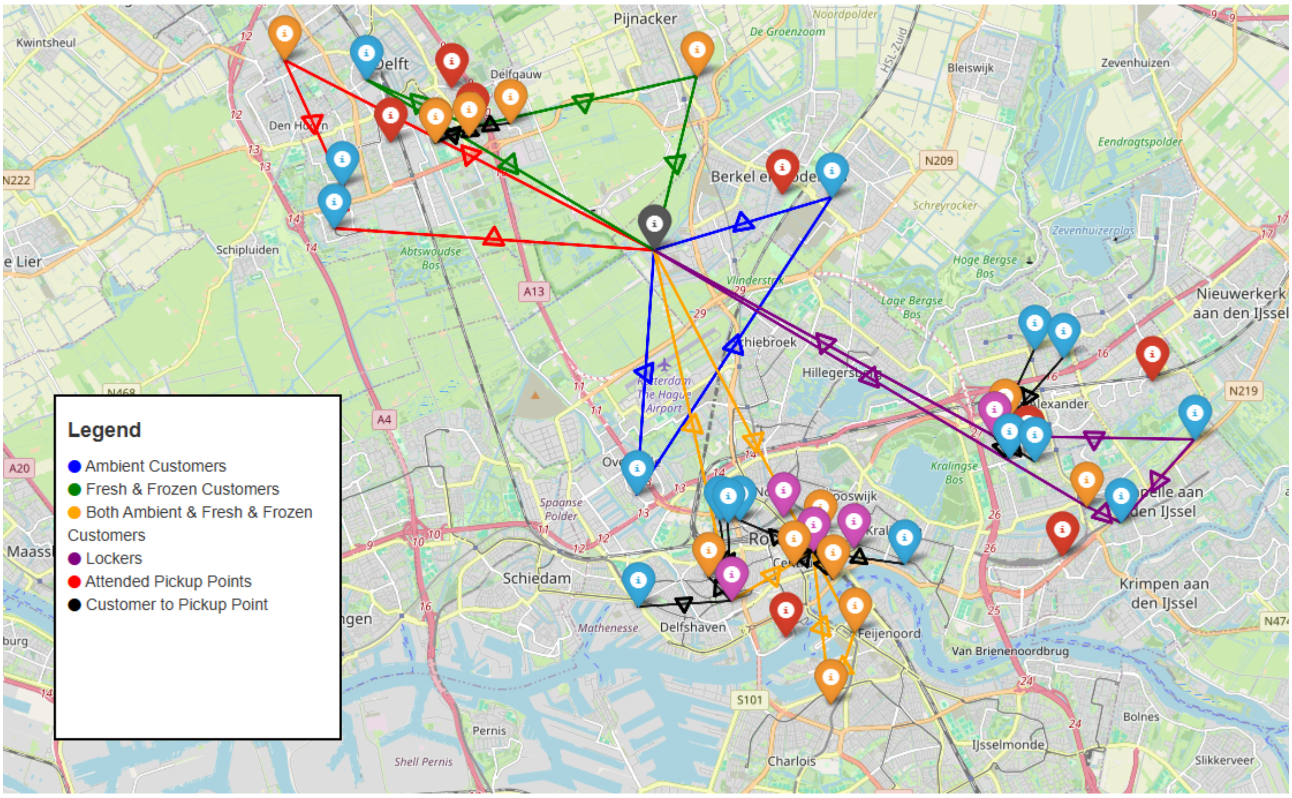

Figure 8: Delivery route and customers' choices when $W_c = 0.2$

To better understand the impact of different delivery choices, a visualization of the optimized delivery routes is presented. In the generated map, the gray dot represents depot location, which serve as the starting and ending points for delivery vehicles.

The black lines indicate the assignment of customers to specific pickup points. These lines originate from customer locations and point toward their selected pickup stations, representing self-pickup decisions. Customers who opted for home delivery are directly included in the vehicle routing without these black assignment lines.

Each colored route in the visualization corresponds to a unique delivery vehicle's actual travel path. Each color represents a different vehicle, illustrating how customer orders are efficiently grouped and distributed to minimize total distance traveled.

Table 11: Summary of Customer Delivery Choices when $W_c = 0.2$

Category	Customer Count	Customer IDs
Home Delivery	12	{7,9,10,12,13,14,16,18,19,23,25,30}
Self Pickup	18	{1,2,3,4,5,6,8,11,15,17,20,21,22, 24,26,27,28,29}
Self Pickup at Attended PUP	4	{20, 22, 27, 29 }
Self Pickup at Locker(39,40,41)	14	{1,2,3,4,5,6,8,11,15,17,21,24,26,28}

To understand the impact of cost and utility preferences on customer behavior, Table 11 presents the summary of delivery choices made by customers when $W_{cost} = 0.2$ and $W_{utility} = 0.8$. This weight setting represents a scenario where utility is prioritized while cost considerations start influencing decisions.

With $W_{utility} = 0.8$, the company aims to enhance customer satisfaction, which results in a relatively high number of home deliveries. Out of 30 customers, 12 opt for home delivery, indicating that direct-to-home service remains an essential part of the logistics model. While this enhances the overall customer experience, it also increases operational costs significantly due to the higher expenses associated with last-mile delivery.

At the same time, self-pickup has become the dominant mode of delivery, with 18 customers selecting this option. This shift suggests that even with an emphasis on utility, cost considerations begin to influence customer behavior, leading to a more balanced delivery distribution. The company's moderate focus on cost means that customers who are willing to engage in self-pickup still have the opportunity to do so, reducing overall delivery expenses while maintaining an acceptable level of convenience.

Within the self-pickup category, 4 customers utilize attended pickup points while 14 customers choose lockers. The lower number of attended pickup point users suggests that although these facilities offer higher service quality, their cost of operation, set at $20 per day, makes them a less attractive option compared to lockers. Despite attended pickup points having the capacity to serve up to 20 customers per day, their current underutilization implies that algorithm do not perceive a positive contribution to the overall objective in exchange for the higher delivery fee utility.

Lockers, on the other hand, attract a larger proportion of self-pickup users. With a lower daily operational cost of $10 per locker and a maximum capacity of 10 customers per day, lockers provide a more cost-effective solution for company which prioritize cost compared with home delivery. The fact that 14 customers rely on lockers highlights their role as a crucial component in reducing overall logistics costs while still allowing customers to retrieve their orders conveniently. However, the limited capacity of each locker means that if demand continues to rise, the company may need to invest in additional locker units or optimize their usage more effectively.

From an operational standpoint, this delivery choice distribution presents both opportunities and challenges. Home delivery remains in demand, emphasizing the importance of maintaining a well-functioning last-mile delivery network despite its high costs. At the same time, the growing reliance on self-pickup solutions indicates a potential avenue for cost reduction, particularly through optimizing locker allocation and improving the efficiency of attended pickup points. Given that attended pickup points have a higher service capacity than their current usage suggests, the company may consider adjusting pricing structures or offering incentives to encourage more customers to utilize these locations instead of defaulting to home delivery or lockers.

A key takeaway from this analysis is that while customer utility remains the primary objective under this weight setting, cost-saving mechanisms naturally emerge as a secondary consideration. The company may benefit from introducing targeted strategies that nudge customers toward self-pickup options without significantly compromising satisfaction levels. Enhancing the appeal of attended pickup points through pricing adjustments, promotional offers, or additional value-added services could help shift more customers away from expensive home deliveries, leading to a more balanced and cost-effective operational model.

5.4.2 $W_c = 0.4, W_u = 0.6$

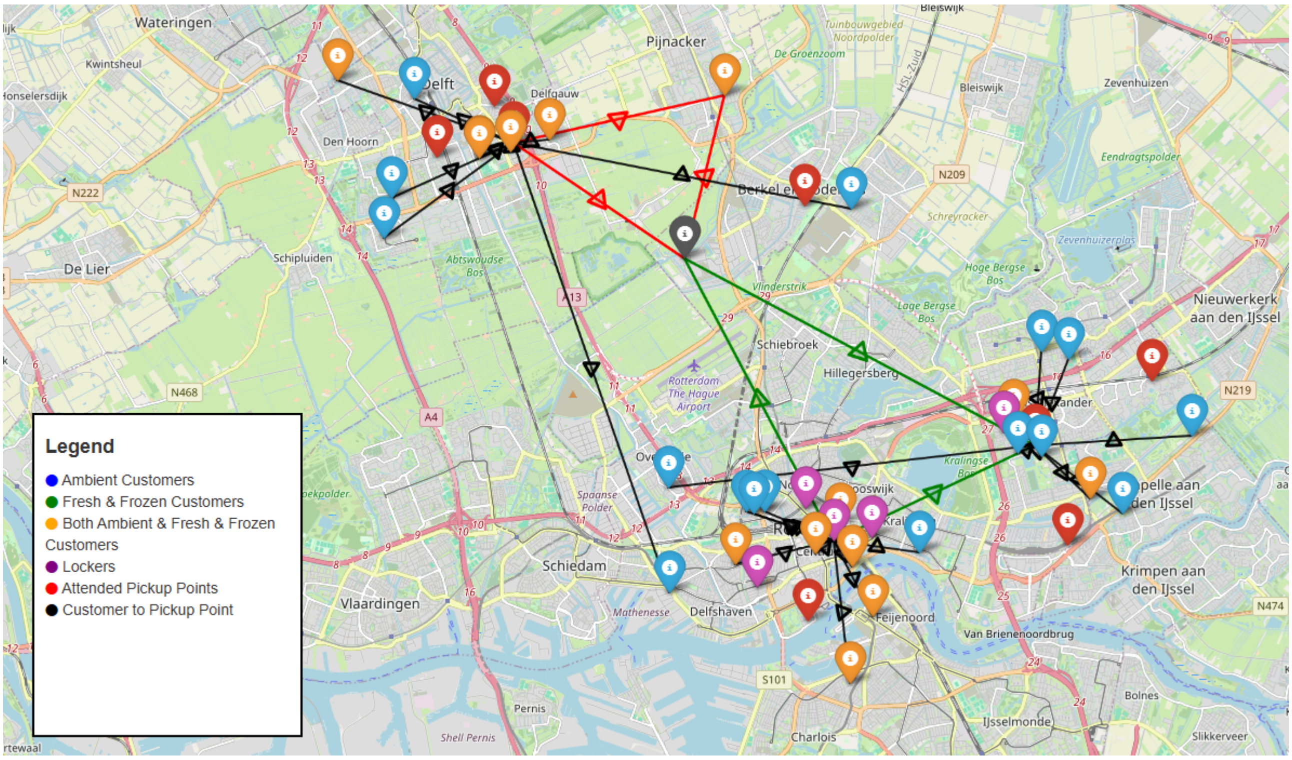

Figure 9: Delivery route and customers' choices when $W_c = 0.4$

Table 12: Summary of Customer Delivery Choices when $W_c = 0.4$

Category	Customer Count	Customer IDs
Home Delivery	1	19
Self Pickup	29	{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15, 16, 17,18,20,21,22,23,24,25,26,27,28,29,30}
Self Pickup at Attended PUP	20	{ 1,2,3,6,7,9,10,11,12,13,14,15, 16,20,21,22,25,27,29,30,}
Self Pickup at Locker	9	{4,5,8,17,18,23,24,26,28 }

With $W_{cost} = 0.4$, the company significantly reduces the number of home deliveries, with only one customer selecting this option. This outcome suggests that the company has successfully optimized cost efficiency by encouraging alternative delivery methods. Unlike the scenario at $W_{cost} = 0.2$, where home delivery remained a substantial portion of the model, the cost-conscious approach here minimizes high-cost home deliveries, transferring most customers to self-pickup locations.

Self-pickup has become the dominant delivery mode, with 29 customers opting for this method. This shift reflects the company's strategic approach to reduce last-mile delivery expenses while still maintaining customer convenience. The slight priority given to utility ensures that customers can still access reliable and structured delivery options without compromising service quality.

Within the self-pickup category, a significant change is observed in the preference for attended pickup points. Out of the 29 self-pickup users, 20 customers select attended PUPs. This indicates a more efficient utilization of attended pickup facilities compared to previous scenarios, where they were underutilized. Attended PUPs, which have a daily operational cost of \$20 and a capacity of 20 customers per day, are now operating at full capacity. This utilization maximization enhances cost efficiency by ensuring that attended PUP infrastructure is fully leveraged, reducing per-customer service costs and optimizing resource allocation.

Lockers remain a viable pickup option but are selected by only 9 customers. Lockers, while still economical at \$10 per day, have a restriction of serving only 10 customers per day. The relatively lower locker usage compared to attended PUPs indicates that when cost considerations become more pronounced, company may favor attended pickup points due to their higher service capacity.

From an operational perspective, this optimization presents significant cost advantages. The near-elimination of home deliveries substantially reduces high last-mile delivery costs. The full utilization of attended pickup points ensures that their operational expenses are justified, making them a cost-effective solution within this model. Lockers, while still useful, remain under their full capacity, suggesting an opportunity to further optimize their placement or adjust incentives to increase their usage.

The transition from home delivery to self-pickup solutions, particularly the shift towards attended PUPs, reflects a well-balanced strategy. This balance ensures that cost savings do not come at the expense of customer experience. While attended PUPs require a slightly higher fixed cost compared to lockers, their ability to serve a larger customer base makes them a more efficient investment under these conditions.

5.5 Customer's Satisfaction

This chapter presents the results of the bi-objective optimization model, examining how different weight coefficients (W_{cost} and $W_{utility}$) influence customer choices and utility distribution. The goal is to evaluate the trade-offs between cost and customer utility to understand their impact on delivery location selection, cost efficiency, and the overall service experience. The study explores correlations between weight coefficients and different utility components, including delivery fe, distance, delivery time, and freshness.

To provide an overview of the dataset used for analysis, Table 13 presents a simplified version of the original dataset. This table includes key attributes such as the weight coefficients, customer IDs, chosen delivery locations, and the different utility values associated with each decision.

Table 13: Sample Customers' Utility Data Table

W_{cost}	$W_{utility}$	Customer ID	Chosen Location	Total Utility	Delivery fee Utility	Distance Utility	Time Utility
0.0	1.0	1	1	0.914	0.500	0.922	1
0.0	1.0	2	2	0.892	0.1125	1.000	1
...	...	...	...	...	...	...	...
0.2	0.8	10	10	0.913	0.3	1	1
0.5	0.5	15	37	0.777	0.5	0.0	1
...	...	...	...	...	...	...	...
0.8	0.2	22	38	0.569	0.5	0.00	1
1.0	0.0	30	41	0.389	0.312	0.302	0

This table presents a representative subset of the dataset, highlighting how different weight coefficients influence the selected delivery location and the resulting utility values. It provides a compact yet informative summary of key decision-making patterns.

5.5.1 Impact of Weight Coefficients on Chosen Locations and Total Utility

In this bi-objective optimization problem, we analyze how different weight coefficients, w_{cost} and $w_{utility}$, influence the company's decision-making process regarding the selection of delivery and pickup locations, as well as the resulting total utility experienced by customers. These weight coefficients represent the company's strategic prioritization: a higher w_{cost} signifies a focus on cost minimization, while a higher $w_{utility}$ reflects an emphasis on maximizing customer satisfaction and service quality.

When w_{cost} is dominant, the company prioritizes low-cost fulfillment strategies, which often result in customers being routed to more economical pickup points such as lockers or shared attended pickup locations rather than home delivery. This leads to lower operational expenses but may come at the expense of customer convenience. Conversely, when $w_{utility}$ is prioritized, the company optimizes for service quality, leading to an increase in home delivery selections and attended pickup locations that offer enhanced facilities such as temperature-controlled storage.

The total utility observed in this analysis is strongly influenced by the weighting strategy adopted by the company. The data indicate a clear positive correlation between $w_{utility}$ and total utility, suggesting that prioritizing customer satisfaction results in better overall service experiences. However, excessive emphasis on cost minimization ($w_{cost} \rightarrow 1$) leads to a significant decline in total utility, as customers may face longer distances, reduced freshness for perishable goods, and suboptimal delivery times.

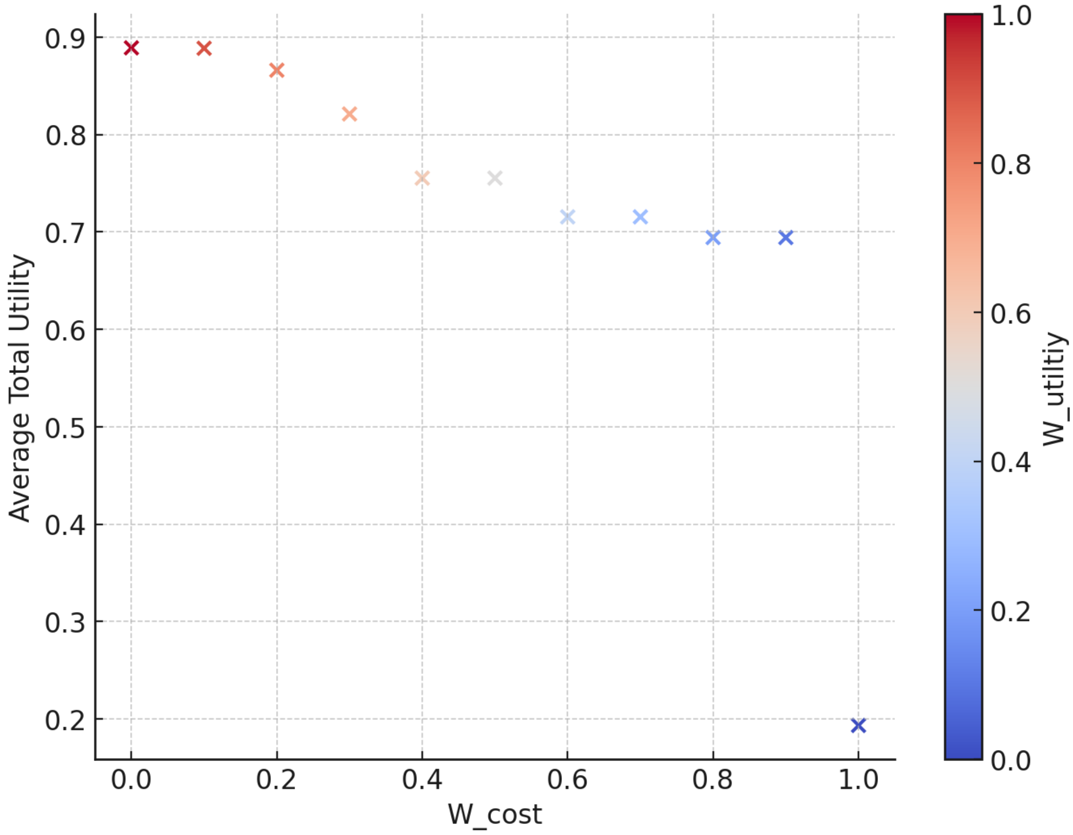

Figure 10: Impact of W_{cost} and $W_{utility}$ on Customer's Utility

5.5.2 Correlation Between Weight Coefficients and Customer Utility Components

To further analyze the implications of the company's strategic weighting of cost versus utility, we examine how w_{cost} correlates with different utility components, including delivery fee utility, distance utility, delivery time utility, and freshness utility. The heatmap in Figure 11 visually represents these relationships, providing insights into the trade-offs faced in decision-making.

The correlation matrix reveals that cost prioritization negatively impacts other utility components. Specifically, distance utility and delivery time utility show moderate negative correlations with w_{cost}, indicating that as cost minimization becomes the dominant objective, customers are required to travel greater distances or experience longer delivery times. This is particularly relevant for customers who rely on convenience-based services.

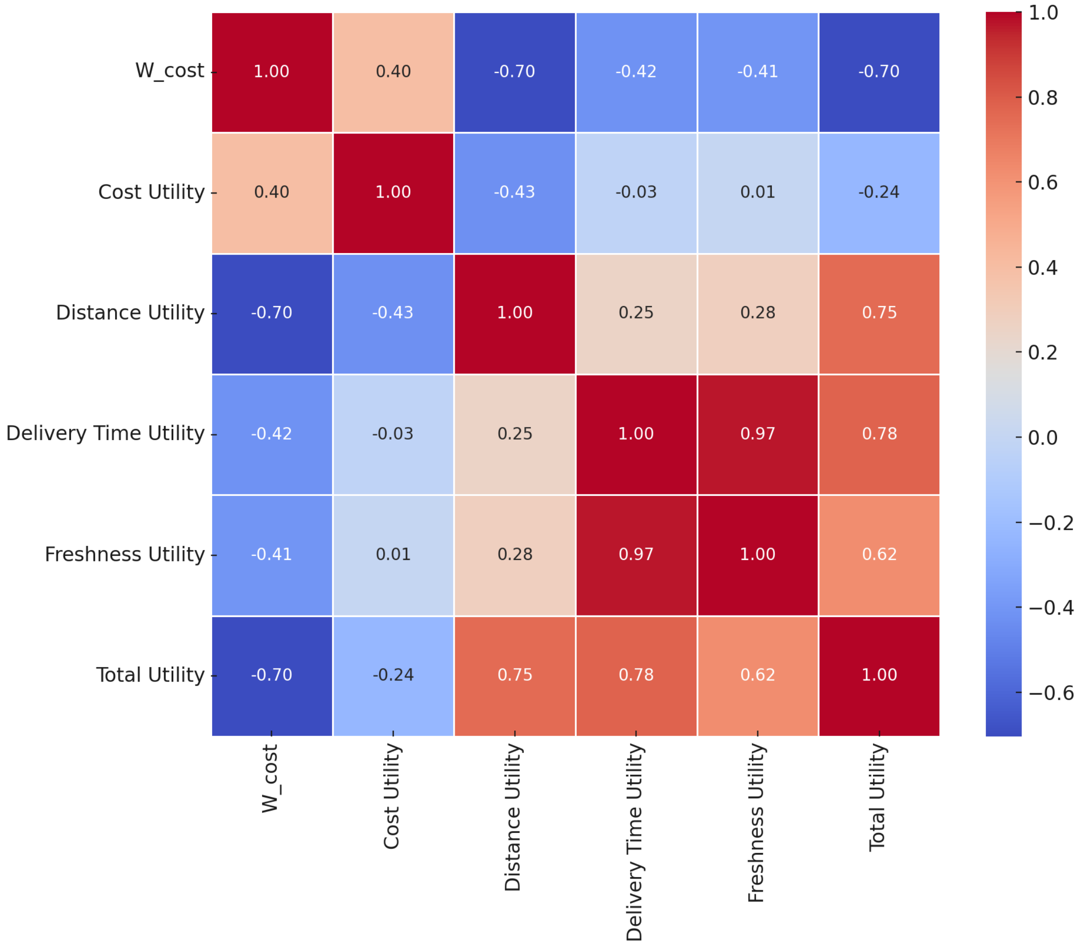

Figure 11: Correlation heatmap

For customers purchasing fresh and frozen products, freshness utility demonstrates a clear negative correlation with w_{cost}. This suggests that when cost minimization is the primary focus, customers are less likely to be routed to attended pickup points with temperature-controlled storage, increasing the risk of product deterioration. On the other hand, when $w_{utility}$ is given more weight, customers receive services that ensure higher freshness levels, leading to improved satisfaction.

Additionally, total utility exhibits a strong negative correlation with w_{cost}, reinforcing the notion that aggressive cost-cutting strategies undermine the overall customer experience. These insights highlight the importance of balancing cost efficiency with service quality in logistics operations.

5.5.3 Attended Pickup vs. Locker Analysis

The analysis of different delivery and pickup options for customers purchasing ambient-only and both products has revealed several important insights. The comparison focuses on two types of pickup points: attended pickup points (IDs 31-38) and lockers (IDs 39-43). These findings are based on several utility metrics, including total utility, distance utility, delivery time utility, and freshness utility.

For ambient-only customers (IDs 1-16), the total utility derived from selecting lockers (0.713) is notably higher than that of selecting attended pickup points (0.653). This suggests that customers who only purchase ambient products prioritize convenience and proximity, which lockers typically provide more effectively than attended pickup points. Lockers are often located in easily accessible locations and do not require customers to wait for assistance, thus improving their overall satisfaction.

When considering both products customers (IDs 17-30), lockers also show a higher total utility (0.725) than attended pickup points (0.656). Despite the added need for temperature control with frozen products, the analysis indicates that both product customers still prefer lockers over attended pickup points, likely due to the more favorable balance of convenience and cost. While attended pickup points offer temperature-controlled storage, which is essential for frozen products, lockers still contribute more due to their lower operational costs and greater accessibility, which makes the model assign some customers to locker consistently.

The distance utility, reflecting the satisfaction derived from the proximity of the pickup point to the customer's location, is another important factor. For ambient-only customers, the distance utility is significantly higher for lockers (0.4507) compared to attended pickup points (0.2313). This reinforces the idea that customers are generally inclined to select the more convenient option, which in this case is lockers located closer to their residences. The same pattern is observed for both products customers, with lockers showing a higher distance utility (0.5869) than attended pickup points (0.3458). Thus, even for customers with special requirements for frozen goods, convenience plays a dominant role in the choice of pickup point.

Regarding delivery time utility, the differences between lockers and attended pickup points are minimal. For both ambient-only and both products customers, the delivery time utility remains high, with values ranging from 0.8592 to 0.8824. This indicates that, regardless of whether customers choose lockers or attended pickup points, the time required to retrieve their items does not significantly impact their decision. One reason is company's current's delivery network is still in limited region with relatively low density. Both delivery methods offer comparable speeds, making other factors such as delivery fee and convenience more critical in the customer's selection process.

Lastly, the freshness utility, which is only relevant for both product customers, shows a clear preference for attended pickup points, with a freshness utility of 0.9007. This is in contrast to lockers, which provide a lower freshness utility (0.8643). The higher freshness utility of attended pickup points can be attributed to their temperature-controlled storage, which ensures that frozen products remain at the correct temperature during pickup. However, despite the advantages of attended pickup points in maintaining product freshness, lockers still present an attractive option for many customers due to their ease of access and lower delivery fee.

In summary, distance utilities play a substantial role in determining customer preferences. For both ambient-only customers and both product customers, lockers provide a more convenient and cost-effective solution, despite the added value of temperature control at attended pickup points. Even for customers purchasing frozen products, the convenience and proximity offered by lockers often outweigh the benefits provided by attended pickup points. Therefore, optimizing the location and availability of lockers could be an effective strategy for improving customer satisfaction while controlling delivery costs.

Table 14: Comparison of Utilities for Different Pickup Points and Customer Groups

Utility Type	Attended Ambient	Attended Both	Lockers Ambient	Lockers Both
Total Utility	0.6535	0.6563	0.7135	0.7254
Delivery fee Utility	0.4800	0.4375	0.4943	0.3508
Distance Utility	0.2313	0.3458	0.4507	0.5869
Delivery Time Utility	0.8824	0.8592	0.8810	0.8980
Freshness Utility	0.0000	0.9007	0.0000	0.8643

5.5.4 Customers' satisfaction rate

The relationship between the weight coefficients and customers' satisfaction rate is summarized in Table 15. The satisfaction rate is calculated by using the total utility divided by number of customers. The table demonstrates how satisfaction rate and utility values change as the weight placed on cost (W_{cost}) increases. There is a noticeable downward trend in satisfaction rate as W_{cost} increases, indicating that prioritizing cost negatively affects overall customer satisfaction.

Table 15: Customers' satisfaction rate

W_cost	W_utility	Value of utility	Satisfaction rate
0	1	26.67	88.90%
0.1	0.9	26.65	88.83%
0.2	0.8	25.98	86.60%
0.3	0.7	24.63	82.10%
0.4	0.6	22.65	75.50%
0.5	0.5	22.65	75.50%
0.6	0.4	21.463	71.54%
0.7	0.3	21.463	71.54 %
0.8	0.2	20.82	69.40%
0.9	0.1	20.82	69.40%
1	0	5.80	19.33%

5.5.5 Summary of Key Findings

The analysis demonstrates the significant impact of weight coefficients w_{cost} and $w_{utility}$ on delivery strategy, order fulfillment ways, and overall utility outcomes. A higher emphasis on w_{cost} leads to cost-efficient solutions, such as lockers and attended pickup points, while increased prioritization of $w_{utility}$ results in a preference for home delivery, which enhances service quality but incurs higher costs.

Correlation analysis reveals distinct trade-offs between cost minimization and service quality. As w_{cost} increases, cost utility improves; however, distance utility, delivery time utility, and freshness utility exhibit a decline, particularly affecting customers purchasing fresh and frozen goods. The selection of attended pickup points with temperature-controlled storage is notably reduced under cost-oriented strategies.

A comparison between attended pickup points and lockers highlights their differing functionalities. Lockers, optimized for cost efficiency and convenience, serve as a practical choice for non-perishable goods. In contrast, attended pickup points offer superior freshness utility, making them essential for perishable products. The selection between these options is contingent on the strategic balance between operational cost management and service quality enhancement.

The findings underscore the necessity of carefully calibrating w_{cost} and $w_{utility}$ to achieve a balanced approach that ensures both economic efficiency and customer satisfaction in last-mile delivery optimization.

5.6 Company's Cost Results

Table 16: Cost Analysis for Different Weight Coefficients

W_cost	W_utility	Value of cost	Delivery cost	PUP Cost	Delivery cost per address
0	1	817.98	777.98	40	25.93
0.1	0.9	668.95	668.95	0	22.30
0.2	0.8	477.77	427.77	50	14.26
0.3	0.7	288.45	238.45	50	7.95
0.4	0.6	142.33	92.33	50	3.08
0.5	0.5	142.3	92.3	50	3.08
0.6	0.4	97.76	67.76	30	2.26
0.7	0.3	97.76	67.76	30	2.26
0.8	0.2	89.94	69.94	20	2.33
0.9	0.1	89.94	69.94	20	2.33
1	0	88.5	68.5	20	2.28

Table 16 presents a comprehensive cost analysis under different allocations of w_{cost} and $w_{utility}$. The values reported in the table include the total cost incurred by the company, the breakdown into delivery and pickup point (PUP) costs, and the computed delivery cost per address. These figures provide critical insights into the financial implications of different weighting strategies. The results indicate a clear trend: as w_{cost} increases and $w_{utility}$ decreases, the overall cost is significantly reduced. When $w_{cost} = 1$, the total cost incurred is at its lowest value of 88.5, with a delivery cost per address of 2.28. Conversely, when $w_{cost} = 0$ and $w_{utility} = 1$, the total cost reaches its highest value of 817.98, with a corresponding delivery cost per address of 25.93.

The distribution between delivery and PUP costs also varies based on the weight coefficients. In high $w_{utility}$ scenarios, a significant portion of the cost is attributed to direct delivery expenses, whereas in cost-focused cases ($w_{cost} \geq 0.4$), the use of pickup points is maximized to reduce expenses. The transition point appears to be around $w_{cost} = 0.4$, beyond which the reduction in delivery cost per address stabilizes at approximately 2.3, implying an optimized balance of operational efficiency.

From a strategic perspective, the company should consider adopting a cost-weighting strategy in the range of $0.6 \leq w_{cost} \leq 0.8$. Within this range, the total cost remains low (approximately 90), and the delivery cost per address stabilizes at a minimal value without compromising pickup point utilization. This approach ensures a financially sustainable model while maintaining service efficiency.

However, if customer satisfaction remains a priority and service quality is non-negotiable, a moderate trade-off in cost efficiency may be required. For instance, setting $w_{cost} \approx 0.3$ provides a reasonable balance between cost minimization and service level maintenance, with a delivery cost per address of 7.95, which remains significantly lower than purely service-driven scenarios.

6 Conclusions and discussion

The research presented in this thesis has explored the optimization of last-mile delivery logistics by integrating cost considerations and customer preferences into a bi-objective decision framework. The study addressed the trade-offs between cost minimization and customer utility, incorporating different delivery methods, including home delivery, attended pickup points, and unattended lockers. Through mathematical modeling and computational optimization, the results provided key insights into how different weights assigned to cost and utility impact delivery strategies, customer choices, and operational efficiency.

The findings demonstrate several key trends:

- Different groups of customer have different view of order fulfillment criteria. For ambient-only customers, Delivery Time and Location & Distance are the most critical factors, indicating that these customers prioritize convenience and speed in receiving their orders. Customers purchasing both products place the highest importance on Freshness, highlighting their concern for maintaining the quality of frozen items. Delivery Time and Location & Distance remain important, but less critical compared to freshness. Cost is the least important factor for both the two groups of customer.

- There a clear trade-off between cost and customer satisfaction. In current distribution network, as the weight on cost increases, the value of cost decreases, but customer satisfaction also declines. Notably, when the company places moderate emphasis on cost, with weights between 0.2 and 0.4, there is a significant reduction in cost due to changes in the delivery method. Beyond this range, further increases in the cost weight do not lead to major changes in either cost or customer satisfaction.

- Locker is less attractive for fresh and frozen product buyers in terms of freshness, due to their lack of temperature control. However, a stable fraction of customers continue to use lockers regardless of freshness concern , indicating that locks outweigh normal attended pup from accessibility and flexibility.

Based on the analysis results, several meaningful findings could be raised to the company to improve their delivery service and customer experience:

1. Firstly, the company should prioritize Delivery Time and Location & Distance for ambient-only customers, as these are the most critical factors influencing their satisfaction. Focusing on improving delivery speed and accessibility will enhance the customer experience for this group. For customers purchasing both ambient and frozen products, the company should place a stronger emphasis on Freshness to maintain the quality of perishable goods.

2. In terms of balancing cost and customer satisfaction, the company should focus on a moderate weight on cost in its delivery strategies. Within this range, cost reductions can be achieved through optimized delivery methods without significantly compromising customer satisfaction.

3. Although lockers lack temperature control, they remain a popular choice due to their convenience and accessibility, leading to higher overall customer satisfaction. Company should prioritize the improvement of point density and service level of lockers. And to enhance their appeal for customers purchasing frozen products, the company should

consider introducing lockers with temperature control. This would combine the flexibility and accessibility of lockers with the necessary freshness preservation, offering a well-rounded solution for both ambient and frozen product buyers.

The implications of these findings extend to both theoretical and practical domains. Theoretically, the study contributes to the growing body of literature on last-mile logistics optimization by incorporating multiple objectives and real-world constraints, including perishability and delivery mode heterogeneity. Practically, the results provide actionable insights for logistics companies and policymakers. The transition from home delivery to self-pickup demonstrates the potential for cost savings, but the effectiveness of this approach depends on the strategic placement and management of attended pickup points. Businesses seeking to optimize their logistics networks must consider both operational costs and customer service quality, ensuring that the removal of home delivery does not lead to significant customer dissatisfaction.

Several areas for future research emerge from this study. Firstly, conducting a larger-scale survey involving a more diverse customer base would provide more comprehensive insights into customer preferences. A broader sample size would enable a more accurate understanding of the varying demands across different customer segments, improving the robustness of the findings. Secondly, applying heuristic methods to analyze larger datasets could provide additional insights, particularly in identifying complex patterns and optimizing delivery strategies at scale. These methods would be beneficial in handling the increased complexity of larger datasets, potentially leading to more nuanced recommendations and further enhancing the company's ability to tailor its delivery services to customer needs.

In conclusion, this research highlights the inherent trade-offs in last-mile logistics optimization and provides a structured approach to balancing cost efficiency with customer utility. The findings underscore the importance of strategic decision-making in logistics planning, where businesses must carefully evaluate the impact of cost-driven policies on customer satisfaction and operational feasibility. By leveraging the insights from this study, logistics companies can develop adaptive, customer-centric delivery solutions that optimize both economic performance and service quality in an increasingly complex urban logistics landscape.

A Questionnaire

This questionnaire is designed to gather preferences for selecting criteria in order-fulfillment methods. Please compare the following criteria pairwise based on your preferences and rate them using a scale from 1 to 9. The scale is defined as follows:

- 1: Both criteria are equally important.
- 3: One criterion is moderately more important than the other.
- 5: One criterion is significantly more important than the other.
- 7: One criterion is strongly more important than the other.
- 9: One criterion is extremely more important than the other.
- 2, 4, 6, 8: Intermediate values for finer granularity.

Pairwise Comparisons

1. Compare the importance of Delivery Time vs. Location & Distance.
2. Compare the importance of Delivery Time vs. Cost.
3. Compare the importance of Location & Distance vs. Cost.

Instructions for Completion

1. For each pair, circle the number that reflects how much more important one criterion is compared to the other. For example:
   - If Delivery Time is moderately more important than Location & Distance, circle 3 under Delivery Time.
   - If both criteria are equally important, circle 1 under Equal.
2. Ensure that all pairs are rated.
3. Submit the completed questionnaire.

Example Table for Comparison

Criterion 1	Scale									Criterion 2
Delivery Time	9	8	7	6	5	4	3	2	1	Location & Distance
Delivery Time	9	8	7	6	5	4	3	2	1	Cost
Location & Distance	9	8	7	6	5	4	3	2	1	Cost

Table 17: Example Pairwise Comparison Table

B BWM Questionnaire result for customers who order both ambient and F&F

	Freshness vs. Location & Distance	Freshness vs. Delivery Time	Freshness vs. Cost	Location & Distance vs. Cost	Delivery Time vs. Cost
Participant 1	8	7	9	3	4
Participant 2	9	7	8	4	5
Participant 3	7	8	9	2	3
Participant 4	6	7	8	5	4
Participant 5	9	7	9	3	5
Participant 6	8	6	9	4	3
Participant 7	7	8	9	2	4
Participant 8	9	9	8	3	4
Participant 9	8	6	7	4	5
Participant 10	9	8	9	3	2
Participant 11	7	7	9	4	5
Participant 12	6	9	9	3	3
Participant 13	8	8	8	2	4
Participant 14	9	6	7	4	5
Participant 15	8	7	9	3	4
Participant 16	7	9	9	4	2
Participant 17	8	8	9	2	3
Participant 18	6	6	9	5	4
Participant 19	9	7	8	4	3
Participant 20	8	9	9	3	5
Participant 21	7	6	8	4	4
Participant 22	9	9	9	2	3
Participant 23	6	7	9	3	5
Participant 24	8	6	8	4	3
Participant 25	9	8	9	3	4
Participant 26	7	9	9	4	2
Participant 27	8	8	9	3	5
Participant 28	9	7	8	4	4
Participant 29	6	6	9	5	3
Participant 30	9	9	9	2	4
Participant 31	8	7	9	3	3
Participant 32	7	8	9	4	5
Participant 33	9	9	8	3	4
Participant 34	9	6	8	4	5
Participant 35	8	7	9	2	3
Participant 36	6	8	9	5	4
Participant 37	7	9	9	3	2
Participant 38	8	6	9	4	3
Participant 39	9	9	9	3	5
Participant 40	7	8	8	4	4
Participant 41	9	7	9	2	3
Participant 42	8	9	9	4	5
Participant 43	6	8	9	5	4
Participant 44	9	7	8	3	4
Participant 45	9	8	9	4	5
Participant 46	7	6	9	2	3
Participant 47	8	9	8	4	4
Participant 48	9	7	9	3	5
Participant 49	6	8	9	5	3
Participant 50	9	9	9	3	4

Figure 12: BWM Questionnaire result for customers who order both ambient and F&F

C BWM Questionnaire result for customers who order only ambient

	Delivery Time vs. Location & Distance:	Delivery Time	Cost
Participant 1	5	6	2
Participant 2	3	5	1
Participant 3	7	8	3
Participant 4	6	7	4
Participant 5	5	6	2
Participant 6	4	6	2
Participant 7	5	4	1
Participant 8	3	5	3
Participant 9	7	6	2
Participant 10	5	6	3
Participant 11	4	4	2
Participant 12	6	7	4
Participant 13	8	6	3
Participant 14	4	3	1
Participant 15	5	7	2
Participant 16	3	6	3
Participant 17	6	8	2
Participant 18	7	6	1
Participant 19	4	5	4
Participant 20	5	7	3
Participant 21	6	4	1
Participant 22	5	8	3
Participant 23	3	5	2
Participant 24	4	7	3
Participant 25	6	6	2
Participant 26	5	5	3
Participant 27	3	8	1
Participant 28	6	5	2
Participant 29	8	7	1
Participant 30	5	5	3
Participant 31	4	3	2
Participant 32	7	6	1
Participant 33	5	4	2
Participant 34	6	8	3
Participant 35	3	6	1
Participant 36	5	5	4
Participant 37	7	3	2
Participant 38	4	8	1
Participant 39	3	7	3
Participant 40	5	5	2
Participant 41	7	6	4
Participant 42	4	5	1
Participant 43	6	8	2
Participant 44	3	4	3
Participant 45	8	6	2
Participant 46	5	7	1
Participant 47	4	3	3
Participant 48	7	5	2
Participant 49	5	4	1
Participant 50	3	8	2

Figure 13: BWM Questionnaire result for customers who order both ambient and F&F

References

I. D. Cardenas, W. Dewulf, J. Beckers, C. Smet, and T. Vanelslander, "The e-commerce parcel delivery market and the implications of home b2c deliveries vs pick-up points," *The e-commerce parcel delivery market and the implications of home B2C deliveries vs pick-up points*, pp. 235–256, 2017.

X. Mi, M. Tang, H. Liao, W. Shen, and B. Lev, "The state-of-the-art survey on integrations and applications of the best worst method in decision making: Why, what, what for and what's next?" *Omega*, vol. 87, pp. 205–225, 2019.

T. Pinto-Varela, A. P. F. Barbosa-Póvoa, and A. Q. Novais, "Bi-objective optimization approach to the design and planning of supply chains: Economic versus environmental performances," *Computers & Chemical Engineering*, vol. 35, no. 8, pp. 1454–1468, 2011.

N. Boysen, S. Fedtke, and S. Schwerdfeger, "Last-mile delivery concepts: a survey from an operational research perspective," *Or Spectrum*, vol. 43, pp. 1–58, 2021.

M. Shashi, "Leveraging digitalization in last-mile logistics."

H. Chu, W. Zhang, P. Bai, and Y. Chen, "Data-driven optimization for last-mile delivery," *Complex & Intelligent Systems*, pp. 1–14, 2021.

X. Wang, L. Zhan, J. Ruan, J. Zhang *et al.*, "How to choose "last mile" delivery modes for e-fulfillment," *Mathematical Problems in Engineering*, vol. 2014, 2014.

L. Song, T. Cherrett, F. McLeod, and W. Guan, "Addressing the last mile problem–the transport impacts of collection/delivery points, paper given to the 88th annual meeting of the transportation research board," 2009.

L. Song, B. Mao, Z. Wu, and J. Wang, "Investigation of home delivery models and logistics services in china," *Transportation Research Record*, vol. 2673, no. 9, pp. 11–22, 2019.

M. Punakivi and K. Tanskanen, "Increasing the cost efficiency of e-fulfilment using shared reception boxes," *International Journal of Retail & Distribution Management*, vol. 30, no. 10, pp. 498–507, 2002.

Y. Hayel, D. Quadri, T. Jiménez, and L. Brotcorne, "Decentralized optimization of last-mile delivery services with non-cooperative bounded rational customers," *Annals of Operations Research*, vol. 239, pp. 451–469, 2016.

L. G. Neto and J. G. V. Vieira, "An investigation of consumer intention to use pick-up point services for last-mile distribution in a developing country," *Journal of Retailing and Consumer Services*, vol. 74, p. 103425, 2023.

Y. Vakulenko, D. Hellström, and K. Hjort, "What's in the parcel locker? exploring customer value in e-commerce last mile delivery," *journal of Business Research*, vol. 88, pp. 421–427, 2018.

X. Wang, Y. D. Wong, W. Shi, and K. F. J. T. I. J. o. L. M. Yuen, "An investigation on consumers' preferences for parcel deliveries: applying consumer logistics in omni-channel shopping," 2023.

E. Molin, M. Kosicki, and R. van Duin, "Consumer preferences for parcel delivery methods: the potential of parcel locker use in the netherlands," *European Journal of Transport and Infrastructure Research*, vol. 22, no. 2, pp. 183–200, 2022.

P. Amorim, N. DeHoratius, F. Eng-Larsson, and S. J. M. s. Martins, "Customer preferences for delivery service attributes in attended home delivery," 2024.

B. Smeets, "Customer choice behavior in the delivery phase of online grocery shopping: A stated choice experiment on customer'preferences for home delivery and pick-up points," *Retreived from TU/e research portal*, 2017.

J.-y. Zhang and J. Li, "A heuristic algorithm to vehicle routing problem with the consideration of customers' service preference," in *ICSSSM11*. IEEE, 2011, pp. 1–6.

C. Tilk, K. Olkis, and S. Irnich, "The last-mile vehicle routing problem with delivery options," *Or Spectrum*, vol. 43, no. 4, pp. 877–904, 2021.

A. Genius Coca, "Implementation of receiver preferences in a parcel locker network for last mile deliveries," 2020.

J. Guerrero-Lorente, A. F. Gabor, E. J. C. Ponce-Cueto, and I. Engineering, "Omnichannel logistics network design with integrated customer preference for deliveries and returns," vol. 144, p. 106433, 2020.

M. M. S. Abdulkader, Y. Gajpal, and T. Y. ElMekkawy, "Vehicle routing problem in omni-channel retailing distribution systems," *International Journal of Production Economics*, vol. 196, pp. 43–55, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925527317303584

P. Liu, A. Hendalianpour, M. Feylizadeh, and W. Pedrycz, "Mathematical modeling of vehicle routing problem in omni-channel retailing," *Applied Soft Computing*, vol. 131, p. 109791, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1568494622008407

M. Kurowski, M. Sobolewski, and M. Koszorek, "Geometrical parcel locker network design with consideration of users' preferences as a solution for sustainable last mile delivery," *Sustainability*, vol. 15, no. 20, p. 15114, 2023.

X. Liang, N. Wang, M. Zhang, and B. J. E. S. w. A. Jiang, "Bi-objective multi-period vehicle routing for perishable goods delivery considering customer satisfaction," vol. 220, p. 119712, 2023.

X. Wang, X. Sun, J. Dong, M. Wang, and J. J. M. P. i. E. Ruan, "Optimizing terminal delivery of perishable products considering customer satisfaction," vol. 2017, 2017.

B. D. Song and Y. D. Ko, "A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery," *Journal of food engineering*, vol. 169, pp. 61–71, 2016.

X. Wang, M. Wang, J. Ruan, and Y. Li, "Multi-objective optimization for delivering perishable products with mixed time windows," *Advances in Production Engineering & Management*, vol. 13, no. 3, pp. 321–332, 2018.

J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega*, vol. 53, pp. 49–57, 2015.

K. Deb, "Multi-objective optimisation using evolutionary algorithms: an introduction," in *Multi-objective evolutionary optimisation for product design and manufacturing*. Springer, 2011, pp. 3–34.

K. Miettinen, *Nonlinear multiobjective optimization.* Springer Science & Business Media, 1999, vol. 12.

R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and multidisciplinary optimization*, vol. 26, pp. 369–395, 2004.

N. Vafaei, R. A. Ribeiro, L. M. Camarinha-Matos, and L. R. Valera, "Normalization techniques for collaborative networks," *Kybernetes*, vol. 49, no. 4, pp. 1285–1304, 2020.

J. E. Stiglitz, "Pareto optimality and competition," *The Journal of Finance*, vol. 36, no. 2, pp. 235–251, 1981.