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Trade-offs in multi-channel delivery network design with perishable and non-perishable goods

Luyang Cao [1,2], Lóránt Tavasszy [1,2], Patrick Stokkink [1,*]

[1] Faculty of Technology, Policy and Management, Delft University of Technology, The Netherlands
[2] Faculty of Civil Engineering and Geosciences, Delft University of Technology, The Netherlands

*Corresponding author: p.s.a.stokkink@tudelft.nl

Abstract: This study focuses on optimizing last-mile delivery in e-commerce by balancing cost efficiency and customer preferences, particularly for mixed perishable and non-perishable goods distribution. As online grocery shopping grows, ensuring the timely and efficient delivery of perishable products while maintaining quality remains a critical challenge. The problem is modelled as a variant of the multi-objective Vehicle Routing Problem (VRP), where customer utility and operational costs are incorporated as two objectives. Customer utility is computed with parameters estimated using the Best-Worst Method (BWM). The multi-objective model is solved by linearizing the non-linear objectives and using a weighted sum method. The model evaluates home delivery, attended pickup points, and lockers, revealing that cost-driven strategies shift deliveries toward self-pickup, with perishable items primarily assigned to attended pickup points due to temperature control. The findings provide insights for improving delivery network design, enhancing service quality, and optimizing the distribution of both perishable and non-perishable products.

Keywords: Last mile delivery; Perishable goods logistics; Vehicle routing problem; Mixed integer linear programming; Best-Worst Method

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1 Introduction

The expansion of e-commerce and the increasing demand for online grocery shopping have significantly impacted last-mile logistics, particularly in the distribution of perishable goods. Efficient delivery strategies must not only minimize operational costs but also ensure high service quality, product integrity, and customer satisfaction. Traditional last-mile delivery models primarily rely on home delivery, which, while convenient for customers, is costly and inefficient at scale. To address these challenges, alternative delivery methods, such as attended pickup points and parcel lockers, have emerged as viable solutions. However, the integration of these alternatives into last-mile logistics remains complex, especially when considering the perishability of certain products.

This study develops a bi-objective optimization model that balances cost efficiency with customer preferences by evaluating the optimal allocation of home delivery, attended pickup points, and lockers. The model accounts for the perishability constraints of certain goods, ensuring that temperature-sensitive products are directed to suitable storage facilities. The results reveal that as cost minimization becomes a priority, deliveries transition from home to self-pickup locations, with attended pickup points being the preferred choice for perishable goods due to their temperature-controlled storage. Meanwhile, lockers, despite their cost-effectiveness, remain a less favored option for perishable items, highlighting the importance of considering storage conditions in last-mile delivery planning.

By optimizing the selection of delivery modes and routes, this research provides insights into how logistics providers can enhance operational efficiency while maintaining customer satisfaction. The findings suggest that integrating self-pickup options with home delivery can significantly reduce costs without compromising service quality, making last-mile logistics more adaptable to consumer needs. This study contributes to the growing field of e-commerce logistics by proposing a structured approach to balancing cost and service quality in last-mile delivery networks, particularly for perishable and non-perishable goods. To the best of the authors' knowledge, this paper is the first to address the problem of multi-objective multi-channel vehicle routing for perishable and non-perishable goods. Through this, we provide useful insights on how perishables and non-perishables are treated differently, even in an integrated system. Furthermore, the trade-offs between customer satisfaction and costs and between delivery channels are illustrated.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on last-mile delivery optimization, customer preferences, and perishable goods logistics. Section 3 presents the methodology, including the problem description, mathematical formulation, and optimization techniques. Section 4 discusses the computational results and key findings. Section 5 presents solution methods to solve the proposed model. Finally, Section 6 concludes the paper with a summary of key insights, practical implications, and future research directions.

2 Literature review

2.1 Last mile delivery considering customer preferences

Last-mile delivery is a critical component of urban logistics, focused on transporting goods efficiently to end consumers while minimizing costs, delivery failures, and inefficiencies (Boysen et al., 2021). Research highlights that last-mile delivery accounts for up to 53% of total shipping costs (Shashi, 2023), with failed deliveries adding an average cost of $17.78 per attempt and a failure rate exceeding 5% (Chu et al., 2021). These challenges have accelerated the adoption of alternative delivery solutions, such as pickup points and parcel lockers, particularly during crises like the COVID-19 pandemic.

Researchers have extensively analyzed the efficiency of different last-mile delivery methods. Wang et al. (2014) compare attended Home Delivery (AHD), Reception Boxes (RB), and Collection-and-Delivery Points (CDPs), finding that while AHD is viable for low-density areas, shared RBs and CDPs perform better in urban regions with high parcel volumes. Similarly, Song et al. (2009) demonstrate that self-pickup models significantly reduce transportation distances and delivery failures. Other studies have reinforced the benefits of pickup points, noting their potential to decrease vehicle kilometers traveled (VKT) and lower logistics costs (Cardenas et al., 2017; Song et al., 2019). Punakivi & Tanskanen (2002) research on Dutch food retailers further emphasizes that shared reception boxes reduce transportation costs by 55–66% compared to attended home delivery. Additionally, Song et al. (2019) indicate that when home delivery failure rates exceed 30%, switching to self-pickup solutions can lower customer collection costs by up to 84% and delivery company expenses by 67.1–71.3%.

While logistics efficiency remains a priority, customer preferences significantly influence the adoption and success of last-mile delivery models. Studies show that while home delivery remains the dominant choice due to its convenience, there is a growing willingness among consumers to use self-pickup solutions if they offer flexibility, lower costs, and improved accessibility (Hayel et al., 2016). Factors such as delivery time, parcel security, and ease of access play a crucial role in consumer decisions (Vakulenko et al., 2018). Molin et al. (2022) found that minor increases in home delivery fees, coupled with enhanced accessibility of parcel lockers, could drive a significant shift toward self-pickup. Similarly, Wang et al. (2023) identify that many consumers prefer unattended delivery options to minimize social interactions and reduce effort. Amorim et al. (2024) examine consumer behavior in the grocery sector, demonstrating that delivery attributes such as speed and precision significantly influence customer choices, and customizing delivery services for different consumer segments could increase shipping revenue by 9%. Guarino Neto & Geraldo Vidal Vieira (2023) study consumer willingness in developing countries. Their results reveal that customers from lower-income segments are more likely to use pickup points for cost savings and convenience, while those from wealthier regions prefer home delivery.

Despite these insights, most studies primarily assess customer preferences in isolation without integrating them into delivery route optimization or pickup point selection. Smeets (2017) highlights significant variations in preferences between urban and rural consumers, suggesting that tailored logistics solutions could enhance customer satisfaction. However, there remains a gap in the literature regarding the simultaneous optimization of delivery routes and self-pickup locations while accounting for both cost and customer expectations. Future research should focus on developing comprehensive models that systematically incorporate consumer preferences into last-mile delivery planning, ensuring that logistics networks remain both operationally efficient and customer-centric.

2.2 Multi-channel delivery network design

Customer preferences in last-mile delivery focus on convenience, speed, flexibility, and reliability. Consumers increasingly favor options that offer precise delivery windows, real-time tracking, and flexible delivery locations, including home delivery, pickup points, and parcel lockers. The decision often involves balancing cost with delivery time and location convenience, reflecting a shift toward personalized services tailored to individual needs.

Zhang & Li (2011) propose a heuristic algorithm for the Vehicle Routing Problem (VRP), integrating customer service preferences into routing decisions. The study introduces a multi-objective model with a hybrid genetic algorithm, improving efficiency through a modified push-bump-throw approach. Tilk et al. (2021) examine the Vehicle Routing Problem with Delivery Options (VRPDO), allowing shipments to alternative locations with different time windows. Genius Coca (2020) optimize parcel locker networks by solving a routing problem that maximizes receiver utility, obtaining a Pareto frontier for cost and service trade-offs. Guerrero-Lorente et al. (2020) design a Mixed Integer Program (MIP) for optimizing parcel carrier networks in omnichannel retail, incorporating consumer preferences and logistics facility types. Abdulkader et al. (2018) extend VRP models for omnichannel retail, integrating retail store assignments and direct consumer deliveries, proposing heuristic and Multi-Ant Colony (MAC) algorithms. Liu et al. (2022) evaluate delivery mode capacities and consumer rationality in omnichannel logistics, highlighting the need for integrating multiple delivery methods to optimize both efficiency and customer satisfaction.

Kurowski et al. (2022) apply a geometric approach to parcel locker network design, demonstrating that a triangular network enhances efficiency by covering a wider area with fewer lockers compared to a square model. The study emphasizes balancing user convenience with environmental and operational efficiency.

The literature underscores a shift in VRP research toward customer-centric models, where integrating consumer preferences enhances last-mile logistics efficiency. However, a significant research gap remains: existing studies do not comprehensively analyze a delivery network that simultaneously integrates home delivery, attended pickup points, and unattended parcel lockers. Addressing this gap could offer a more flexible and customer-oriented logistics framework. The role of customer preferences is even more crucial for perishable products, as unattended lockers lack refrigeration, making appropriate delivery mode selection essential to maintaining product freshness and improving overall consumer satisfaction.

2.3 Perishable product delivery

Integrating perishable product delivery into last-mile logistics alongside non-perishable goods presents unique challenges and opportunities. Ensuring perishables are delivered within strict time constraints while maintaining product integrity requires advanced planning and route optimization. The combination of perishable and nonperishable deliveries necessitates innovative logistics strategies, such as multi-temperature vehicles and dynamic routing, to maximize efficiency while meeting diverse customer expectations. While the inclusion of perishables increases logistical complexity, effective management can significantly enhance service quality and operational sustainability in the evolving e-commerce landscape.

Several studies have explored optimization strategies for perishable goods delivery. Liang et al. (2023) model perishable delivery as a bi-objective vehicle routing problem, minimizing transportation costs while maximizing customer satisfaction through freshness preservation. Wang et al. (2017) propose a multi-objective scheduling model incorporating customer- preferred delivery times and freshness constraints, solved using a priority-based genetic algorithm, demonstrating significant efficiency gains. Song & Ko (2015) introduce a vehicle routing approach using both refrigerated and general vehicles, optimizing routes to maintain freshness while balancing operational costs. Wang et al. (2018) develop a heuristic-based multi-objective optimization model focusing on spatiotemporal characteristics to enhance freshness and cost-efficiency. These studies highlight advanced methodologies that blend cost efficiency with service quality, showcasing their potential to improve last-mile perishable distribution.

Despite these advancements, existing research primarily focuses on direct home delivery, overlooking alternative distribution models such as parcel lockers and attended pickup points. This gap represents an opportunity to explore self-pickup options, which could reduce missed deliveries and increase consumer flexibility. Self-pickup solutions also offer extended pickup hours, aligning better with varied consumer schedules.

Furthermore, limited research has examined the simultaneous distribution of perishable and non-perishable items within the same logistics network. Integrating these product categories could optimize delivery routes, lower transportation costs, and reduce carbon footprints while improving customer convenience. Consolidating multiple order types into single delivery events would streamline operations and enhance the consumer experience. Future research should focus on developing models that incorporate diverse delivery methods to improve efficiency and service in perishable goods logistics.

2.4 Research gap and contribution

While existing studies have made significant contributions to optimizing last-mile delivery, several critical research gaps remain. First, studies focus on either home delivery or self-pickup solutions, but overlook the integration of home delivery, attended pickup points, and unattended parcel lockers, particularly for perishable goods. Second, although customer preferences play a vital role in last-mile logistics, comprehensive studies assessing consumer behavior across multiple delivery modes remain scarce and do not capture how customers make trade-offs between alternative delivery methods. Third, current research rarely considers the simultaneous distribution of perishable and non-perishable items in delivery route and pickup point optimization.

In this paper, we fill these gaps by formulating a multi-objective multi-channel vehicle routing problem for perishable and non-perishable goods. In this model, we can consider the costs from an operator perspective, as well as customer utility. We consider optimal routing decisions, together with decisions of which delivery channel to use. We estimate the preferences of customers for a variety of delivery features by using the Best-Worst-Method (BWM). The estimated coefficients are then used to solve the multi-objective optimization problem using the weighted-sum method. Despite the seemingly natural integration of these methods, applications remain scarce. Lo et al. (2018) combined fuzzy BWM with fuzzy multi-objective linear programming to solve the supplier selection and order allocation problem. Tu et al. (2022) combined BWM with a genetic algorithm for a travel route planning problem. Rabet et al. (2024) combined BWM with a hybrid metaheuristic in a project scheduling context. The limited integration of BWM with other methods has also been marked by Mi et al. (2019). This paper contributes to this growing body of literature.

3 Problem definition and model formulations

3.1 Problem definition

In modern e-commerce and logistics, last-mile delivery plays a crucial role in operational efficiency and customer satisfaction. This challenge is particularly significant in urban areas, where congestion and high demand require optimized delivery strategies. This study aims to address last-mile delivery optimization by simultaneously tackling route planning, delivery mode selection, and facility location decisions while incorporating customer preferences and the distribution of both perishable and non-perishable goods.

The problem is formulated as a variant of the Capacitated Vehicle Routing Problem (CVRP). It is defined on a directed graph $G = (N, A)$, where the node set N includes customers I, attended pickup points J_A , unattended pickup points J_U , and the depot 0. The arc set A consists of all possible connections between these nodes. Customers can order ambient, fresh, or frozen items, with the total customer set represented as $I = I_1 \cup I_2$, where I_1 consists of customers ordering only ambient products, and I_2 includes those ordering both ambient and fresh or frozen products. Customers can choose between home delivery and pickup points, which are further categorized into attended (J_A) and unattended (J_U) locations.

For fresh and frozen goods, proper storage conditions must be maintained to preserve quality. Attended pickup points are equipped with refrigeration and freezing facilities to ensure product integrity, while unattended pickup points, such as parcel lockers, lack such equipment, making them unsuitable for perishable goods.

The travel time between two nodes (i, j) is defined as t_{ij}. A customer has a demand of d_i parcels and a service time s_i. A vehicle can carry a total of Q parcels. Three cost components are considered: a variable cost per unit of time travelled by a delivery van, $c^{variable}$, a fixed daily cost per used truck, c^{fixed}, and a cost for opening a pickup point, c_j^{point}.

The decision variables are defined as follows. Binary decision variables x_{ijk} indicate whether arc (i, j) is traversed by vehicle k. Binary decision variables y_{ij} indicate whether customer i chooses self-pickup at point j. In case of home delivery, we denote this as $j = i$. Binary decision variables z_j indicate whether pickup point j is open and v_k indicate whether vehicle k is used. Integer decision variables u_{ik} denote the cumulative demand carried by vehicle k up to node i. Continuous decision variables τ_{ik} denote the time vehicle k arrives at node i.

On top of this, two decision variables are introduced to implicitly compute the utility of customers within the formulation. Continuous decision variables U_i^{home} denote the home delivery utility for customer i and U_{ij}^{pick} denote the self-pickup utility for customer i at pickup point j.

The problem is formulated as a bi-objective optimization model, aiming to minimize delivery costs while maximizing customer utility. The utility function accounts for delivery costs, travel time, and freshness preservation, particularly for perishable items. A set of constraints ensures the feasibility of the delivery routes, incorporating vehicle capacity limits, flow conservation, mandatory customer visits, and the prevention of subtours. By integrating these factors, the model seeks to optimize last-mile logistics while enhancing service quality and operational efficiency. To simplify last-mile delivery optimization while maintaining practical relevance, the following assumptions are made:

1. **Customer Utility Maximization:** Customers select their delivery method based on maximizing perceived utility, influenced by the following factors: cost, delivery time, pickup point proximity, and freshness of perishable goods. This assumption ensures consumer preferences are reflected in optimizing the delivery network.
2. **Static Travel Metrics:** Travel distances and times between all locations are assumed to be constant, unaffected by real-world factors such as traffic or weather. This allows the model to focus on optimizing facility selection and delivery modes.
3. **Facility Capabilities:** Attended pickup points are equipped with refrigeration for perishable goods, while unattended parcel lockers lack such facilities. This distinction determines the feasible delivery options for different product types.
4. **Initial Freshness:** Perishable products start at full freshness when leaving the depot and degrade over time based on travel duration. This assumption establishes a baseline for optimizing routes to minimize quality loss.

These assumptions help ensure the model remains computationally tractable while accurately capturing key aspects of last-mile delivery.

3.2 Problem formulation

The model bi-objective optimization model is formulated as follows:

$$\min Z_1 = \sum_{k\in K}\sum_{(i,j)\in A} c^{variable}\, t_{ij} x_{ijk} + \sum_{k\in K} c^{fixed}\, v_k + \sum_{j\in J} c_j^{point} z_j \tag{1}$$

$$\max Z_2 = \sum_{i\in I}\sum_{j\in J} U_{ij}^{pick}\, y_{ij} + \sum_{i\in I} U_i^{home}\, y_{ii} \tag{2}$$

Subject to:

$$\textstyle\sum_{j\in J} y_{ij} + y_{ii} = 1 \qquad \forall_i \in I \tag{3}$$

$$y_{ij} \le z_j \qquad \forall_i \in I, j \in J \tag{4}$$

$$y_{ii} = \sum_{j \in N, i \neq j} \sum_{k \in K} x_{ijk} \qquad \forall_i \in I \tag{5}$$

$$y_{ij} \leq \sum_{m \in N, m \neq j} \sum_{k \in K} x_{mjk} \qquad \forall_i \in I, j \in J \tag{6}$$

$$\sum_{j \in N, j \neq i} x_{jik} = \sum_{j \in N, j \neq i} x_{ijk} \qquad \forall_i \in I \,/\, \{0\}, k \in K \tag{7}$$

$$\sum_{i \in N \,/\, \{0\}} x_{0ik} = \sum_{j \in N \,/\, \{0\}} x_{j0k} \qquad \forall_k \in K \tag{8}$$

$$\sum_{j \in J} \sum_{k \in K} x_{ijk} \leq 1 \qquad \forall_i \in N \,/\, \{0\} \tag{9}$$

$$\tau_{ik} + t_{ij} + s_i \leq \tau_{jk} + M\left(1 - x_{ijk}\right) \qquad \forall_i \in N,\ j \in N/\{0\}, k \in K \tag{10}$$

$$u_{ik} + d_j \leq u_{jk} + M\left(1 - x_{ijk}\right) \qquad \forall_i \in N,\ j \in N/\{0\}, k \in K \tag{11}$$

$$u_{ik} \leq Q \qquad \forall_i \in N, k \in K \tag{12}$$

$$\sum_{i \in N} \sum_{j \in N} x_{ijk} \leq M_{v_k} \qquad \forall_k \in K \tag{13}$$

$$U_{ii}^{home} = f(\tau_{ik}, \forall_k \in K) \qquad \forall_i \in I \tag{14}$$

$$U_{ij}^{pick} = f\left(\tau_{jk}, \forall_k \in K\right) \qquad \forall_i \in I, j \in J \tag{15}$$

$$x_{ijk} \in \{0,1\} \qquad \forall (i,j) \in A, k \in K \tag{16}$$

$$y_{ij} \in \{0,1\} \qquad \forall_i \in N, j \in N \tag{17}$$

$$z_j \in \{0,1\} \qquad \forall_j \in J \tag{18}$$

$$v_k \in \{0,1\} \qquad \forall_k \in K \tag{19}$$

$$u_{ik} \in \{0, Q\} \qquad \forall_i \in N, k \in K \tag{20}$$

$$\tau_{ik} \in [0, M] \qquad \forall_i \in N, k \in K \tag{21}$$

Objective (1) minimizes the total variable and fixed travel cost and the cost of opening pick-up points. Objective (2) maximizes the utility of users. Constraints (3) require the customer to choose either home delivery or self-pickup. Constraints (4) indicate that pickup point j needs to open if there is one customer who chooses this pickup point to pick up their parcels. Constraints (5) define that if the customer i chooses home delivery, there must be a truck passing that customer. Constraints (6) apply the same logic to pickup points. Constraints (7) are flow conservation constraints. Constraints (8) require all vehicles to return to the depot if they leave the depot. Constraints (9) limit that a node can be visited only once. Constraints (10) calculate the arrival time of each node, and with that also eliminate subtours. Constraints (11) compute the cumulative demand that a vehicle carries, and together with Constraints (12), this enforces the capacity of each vehicle. Constraints (13) determine the usage of each truck. Constraints (14) and (15) define the utility values for home delivery and pickup point delivery, respectively. The utility values are dependent on the delivery times. Constraints (16) - (21) define the range of the decision variables.

4 Solution method

To solve the problem in Section 3, a combination of two solution methods is used. First, BWM is applied to estimate the coefficients of the utility function for two classes of customers. This is described in Section 4.1. Then, the non-linearity in the second objective is linearized, and the bi-objective MILP is solved using the weighted sum method. This is described in Sections 4.2 and 4.3.

4.1 Coefficients calculation of customer's choice

BWM is applied to determine the relative importance of criteria for evaluating customer utility in selecting order-fulfillment methods (Rezaei, 2015, 2016). BWM is chosen to estimate the coefficients over other methods like Analytic Hierarchy Process (AHP) (Saaty, 2013) or pairwise comparisons for consistency reasons among respondents. BWM requires fewer pairwise comparisons and thus reduces cognitive load on respondents, leading to more consistent data. The process of collecting data from respondents is simple and intuitive, which makes it especially suitable for the respondents in this study, who are likely inexperienced in making these comparisons. Some example steps for how to model the coefficients 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:

$$C = \{Freshness, Delivery\ time, Location\ \&\ Distance, Delivery\ fee\}$$

These criteria have been established together with the LMD company, which also provided the case study data, and 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).
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:

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

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:

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

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:

$$Minimize\ \xi$$

Subject to:

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

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

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

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:
   $$\boldsymbol{w} = \{Freshness: w_1, Delivery\ time: w_2, Location\ \&\ Distance: w_3, Delivery\ fee: w_4\}$$

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 obtained utility function can then be expressed as a linear function of the estimated coefficients multiplied by the respective factors. Given that these factors are measured in different units, they are all normalized on the [0,1] interval.

4.1.1 Consistency checking of Best-Worst Method

The acceptability of the computed CRI values is evaluated using the threshold table proposed by Liang et al. (2020), which specifies upper bounds depending on the number of criteria and the preference scale used (typically 1–9 in our case). This metric evaluates the logical coherence between the Best-to-Others and Others-to-Worst comparisons by measuring their deviation from the implied Best-to-Worst value. A lower CR indicates higher internal consistency. Importantly, threshold values for CR vary depending on the number of criteria and the preference scale, as summarized in Table 1. Integrating this check strengthens the robustness of the derived weights and provides a basis for assessing the credibility of respondents' judgments. For instance, when 4 criteria are compared using a 1–9 scale, the acceptable CRI threshold is 0.2683. The threshold when criteria is 3 is 0.1667 correspondingly. If the computed CRI for a given respondent or customer segment is below this threshold, the input is deemed sufficiently consistent.

4.2 Linearization

One of the advantages of using the best-worst method for coefficient estimation is that it leads to a linear utility function. This means Constraints (14) and (15) are now linear equalities depending on the delivery time. Nevertheless, the second objective function 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 is introduced to linearize the product, in line with the approach defined by Belotti et al. (2013). 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.

Table 1: CRI thresholds for different numbers of criteria and preference scales (Liang et al., 2020)

Scales	Criteria						
	3	**4**	**5**	**6**	**7**	**8**	**9**
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1898	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1330	0.1990	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

4.3 Weighted sum method and normalization

To solve the bi-objective problem, the 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. In this case, the weighted-sum method is preferred over other methods like ϵ-constraint method or goal programming due to its alignment with the decision-making context of our problem. Specifically, the weighted sum method allows for integration of stakeholder preferences through explicitly defined weights, which were derived using the BWM, as explained in Section 4.1. In addition to this, it allows for performing a clear sensitivity analysis with respect to the weights, offering practical insights for decision-makers.

The two objectives are measured in different units (cost versus utility). To properly compare the two, they are first normalized and then combined using the weighted sum method. The full objective Z can then be expressed as:

$$Z = min[\omega_1 Z_1 - \omega_2 Z_2],$$

where ω_1 and ω_2 are non-negative weights ($\omega_1 , \omega_2 \geq 0$) that represent the relative importance of the objectives and satisfy the condition ($\omega_c + \omega_u = 1$). A negative sign for Z_2 is used, given that it is a maximization instead of a minimization.

5 Experimental results

5.1 Case study

A case study is performed to evaluate the performance of the developed model and methodology. The data used in this case study consists of two parts. Firstly, survey data is used from 100 potential customers to evaluate the utility function of customers using the BWM. 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 the customer base of the associated LMD company.

Secondly, a sample of customer demand data is used in the Rotterdam-Delft (the Netherlands) area. The dataset includes 44 customer demand requests, 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. This dataset is displayed in Figure 1. Coordinates of actual customers are hidden to protect their privacy. The point marked in pink is the depot from which all trucks start. Customers who order only ambient products and order both ambient and F&F are labeled as green and orange, respectively. Attended pickup points and lockers are colored in red and purple, respectively.

The parameters are set as follows. Based on historic data, a truck can make at most 20 stops. For this, we set $d_i = 1$ and $Q = 20$. We consider a set of 30 customers, out of which approximately half also order fresh and frozen products. The cost of opening an attended pickup point is set to 20, and the cost of opening a locker is set to 10. The hourly cost of a vehicle is set to 45.5. These values are set based on discussions with the LMD partner to display a realistic tradeoff that they make.

Figure 1: Case study network

5.2 Coefficient estimation

The BWM is applied to evaluate the coefficients of the utility function for two classes of customers. We consider customers who order only ambient products and customers who order fresh and frozen products next to their ambient order. The coefficients that were obtained as a result of the BWM are displayed in Table 2. These coefficients show that, for customers who order fresh and frozen products, the freshness of these products is the most influential component for their utility. For customers who only order ambient products, delivery time is the most important factor. We highlight the correlation between these two factors. When delivery times are higher, freshness typically decreases. Nevertheless, given the presence of cooling facilities at pickup points, this also influences the freshness factor. Interestingly, the delivery fee is the least influential factor for both classes of customers.

Table 2: BWM coefficients

Customers order ...	ambient	ambient, fresh and frozen
Delivery time	0.61	0.13
Location and distance	0.27	0.08
Delivery fee	0.11	0.07
Freshness		0.71

5.2.1 Assessment of the reliability of the BWM results

To evaluate the internal reliability of the pairwise comparisons collected through the Best-Worst Method, input-based Consistency Ratio (CR) values were calculated for all respondents following the method proposed by Liang et al. (2020). For the group with four criteria and a 1–9 preference scale, the recommended threshold is 0.2683. Among 50 respondents, 14 (28%) produced CR values below this threshold, indicating acceptable levels of consistency. The remaining 72% exceeded the threshold, suggesting potential inconsistencies in their judgments. The average CR across all participants was 0.360, with a minimum of 0.125 and a maximum of 0.690.

These findings underline the variability in the cognitive consistency of respondents and highlight the importance of integrating consistency checks in multi-criteria decision-making. Although some inconsistencies were observed, the CR values provide a quantitative basis to assess the reliability of the derived preference weights. Sensitivity analysis can further be used to evaluate the impact of these inconsistencies on the final decision outcomes.

For the comparison group with three criteria (Delivery Time, Cost, and Location & Distance), the input-based Consistency Ratio (CR) was calculated, with a recommended threshold of 0.1667. Among the 50 participants, exactly 25 respondents (50%) achieved CR values below this threshold, indicating acceptable consistency. The remaining 25 participants exhibited higher CRs, suggesting potential inconsistencies in their judgments. The average CR was 0.298, with values ranging from 0.024 to 1.833, and a standard deviation of 0.352, indicating substantial variability across participants. These results highlight a more balanced distribution of consistency levels compared to the 4-criteria group. While half of the participants demonstrated reliable pairwise comparisons, the other half may require further review, adjustment, or sensitivity testing to assess the robustness of the resulting preference weights.

5.3 Trade-off between the objectives

The model is run with different combinations of ω_1 and ω_2. As the weights of cost and utility change, the objective values change, but also the distribution across home delivery (HD) and self-pickup (SP) changes. The results are displayed in Table 3. The model finds near-optimal solutions in a reasonable time, with the computation times ranging between 10 and 1500 seconds. The optimality gap always stays below 5%.

The optimization results reveal a trade-off between minimizing total delivery cost and maximizing customer utility. As the weight assigned to cost minimization (ω_1) increases, the model shifts deliveries from home to pick up points, reducing costs but lowering customer utility. This is also displayed in Figure 4. When customer utility is prioritized ($\omega_1 = 0$), 26 home deliveries are assigned, leading to the highest total cost of €817.98 and maximum customer utility of 26.67. As ω_1 increases, home deliveries decrease while pickup point usage rises, notably between $\omega_1 = 0.2$ and $\omega_1 = 0.4$, where costs drop from €477.77 to €142.33, and utility declines from 25.98 to 22.65. Beyond $\omega_1 = 0.4$, all deliveries shift to pick up points, minimizing costs but reducing utility further. At $\omega_1 = 1$, total cost reaches its lowest at €88.5, but utility drops sharply to 5.8.

These results emphasize the need for balance. Businesses focusing solely on cost reduction risk lower customer satisfaction, while prioritizing service quality incurs higher costs. An optimal balance appears around $\omega_1 = 0.3$ to $\omega_1 = 0.5$, where costs are reduced significantly while customer utility remains acceptable.

Table 3: Results for varying weights

(ω_1, ω_2)	# HD	# SP	Z_1	Z_2	CPU time (s)	Optimality gap (%)
(0.0,1.0)	26	4	817.98	26.67	607	3.15
(0.1,0.9)	30	0	668.95	26.65	181	4.80
(0.2,0.8)	12	18	477.77	25.98	86	4.93
(0.3,0.7)	7	23	288.45	24.63	115	3.32
(0.4,0.6)	1	29	142.33	22.65	190	2.00
(0.5,0.5)	0	30	142.30	22.65	1506	1.50
(0.6,0.4)	0	30	97.76	21.463	190	1.00
(0.7,0.3)	0	30	97.76	21.463	211	0.90
(0.8,0.2)	0	30	89.94	20.82	215	0.90
(0.9,0.1)	0	30	89.94	20.82	172	0.50
(1.0,0.0)	0	30	88.50	5.80	10	0.00

The trade-off, according to different parameter weights, can be translated into a Pareto frontier. Figure 3 illustrates the approximated Pareto front representing the trade-off between the two objectives: cost and utility. The plot shows how varying the weight coefficients for cost (ω_1) and utility (ω_2) 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. As the two objectives are a combination of a maximization and a minimization problem, the Pareto curve looks slightly different from its conventional shape. Here, the approximated ideal point can be found in the top-left corner, and the approximated nadir point can be found in the bottom-right corner.

Each point on the Pareto front represents a solution where no other solution can simultaneously improve both objectives (Stiglitz, 1981). 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.

We emphasize that this is an approximation of the Pareto front. Given that the problem is formulated as an MILP, the feasible region is non-convex, which suggests that the weighted-sum method cannot guarantee that all solutions lie on the true Pareto front. On top of that, an optimality gap of 5% is used, suggesting the reported solutions may deviate slightly from the actual optimal solutions. Nevertheless, the obtained approximation is highly suitable to fulfill the goal of this analysis, which is not to exhaustively map the Pareto front but to identify representative trade-off solutions aligned with stakeholder-defined priorities.

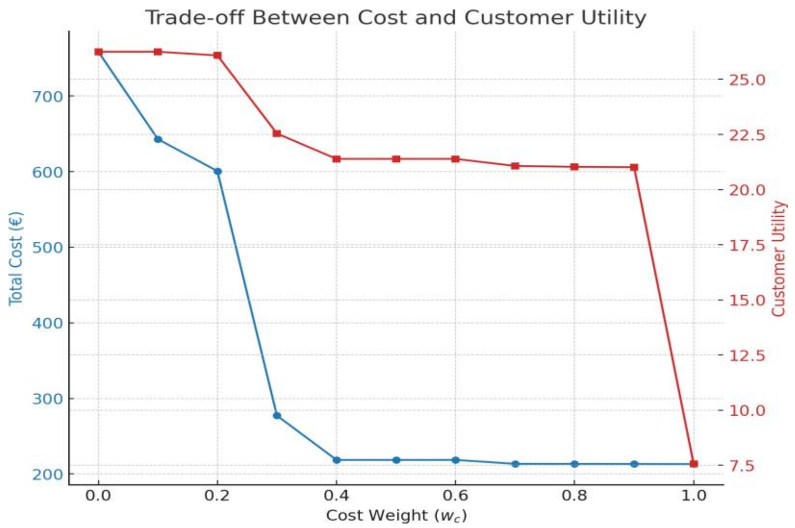


Figure 2: Trade-off between cost and customer utility

5.4 Tradeoff between delivery modes

The weights of the objectives play a crucial role in determining the balance between home deliveries and pickup points. This is displayed in Figure 4. At lower values of ω_1, home delivery is prioritized to maximize customer satisfaction, but as it increases, the model shifts toward pickup points to reduce costs. At $\omega_1 = 0$, home deliveries dominate, with 26 home deliveries and only 4 self-pickups. However, even a slight increase to $\omega_1 = 0.1$ results in a complete shift to home deliveries for all 30 customers, showing the model's sensitivity to cost considerations. Between $\omega_1 = 0.2$ and $\omega_1 = 0.3$, a transitional phase occurs where both delivery modes are used, balancing cost and customer convenience. By $\omega_1 = 0.4$, all deliveries are assigned to pick-up points, minimizing costs but reducing customer satisfaction. We can further detail these results for the two classes of customers we consider, and considering the differences between attended pickup points and lockers. These results are displayed in Figure 5. At low cost weights ($\omega_1 = 0$), most customers are assigned to home delivery, especially ambient-only buyers. As ω_1 increases, home deliveries decrease and are shifted to self-pickup. Ambient-only customers are overwhelmingly assigned to attended pickup points (PUPs), with minimal locker usage. Customers ordering both fresh/frozen and ambient products exhibit more varied results. At ω_1= 0,12 of these customers use home delivery, but by ω_1 = 0.4, all have switched to self-pickup. Unlike ambient-only buyers, fresh/frozen customers are divided between attended PUPs and lockers, with 5-6 consistently assigned to lockers despite the lack of temperature control. The continued assignment of lockers suggests that convenience or proximity may outweigh freshness concerns for some fresh/frozen buyers from the perspective of overall company performance. Some customers may have short pickup-to-consumption times or alternative means of preserving product quality, making lockers a viable option under cost-minimization strategies for the company. Another reason is network limitations. The algorithm assigns most of the customers to their nearest pickup point in use, showing that proximity outweighs other factors, as the delivery times of different customers do not show a significant difference.

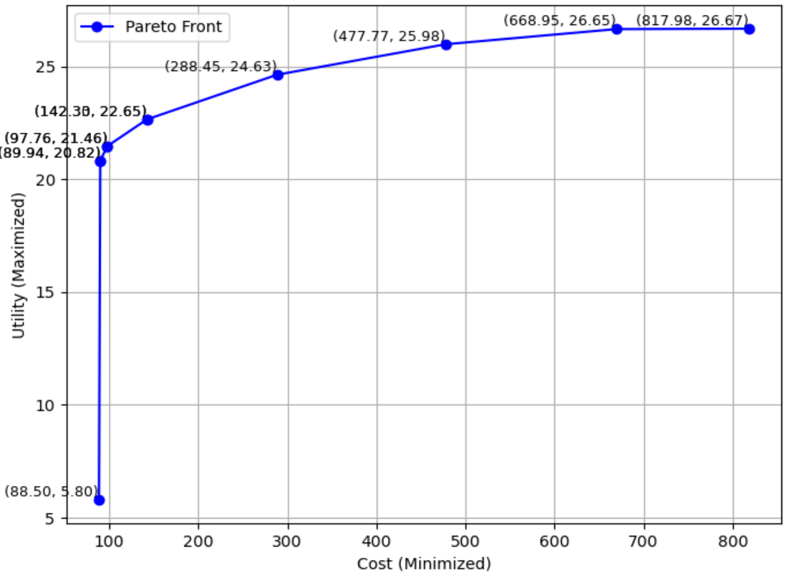


Figure 3: Pareto curve between cost and utility

The results show a clear trend: as ω_1 increases, all customers transition to self-pickup. However, ambient-only buyers are overwhelmingly assigned to attended PUPs, while fresh/frozen customers are split between attended PUPs and lockers. Businesses optimizing cost and service should prioritize attended PUPs, especially for ambient-only customers. The steady locker usage among fresh/frozen buyers suggests that placement strategies should consider factors beyond temperature control, such as accessibility and convenience. It has to be noted that the results are prone to the network features, with distributions of lockers and attended pickup points being significantly different. For different network configurations, different effects may be observed when freshness concerns outweigh distance factors.

5.5 Network analysis

Figure 6 displays the vehicle routes and delivery mode choices for two weight configurations. At $\omega_1 = 0.2$, customer utility remains a key priority, resulting in 12 out of 30 customers having home delivery. This highlights the strong preference from the company side for direct-to-home service when cost is not the dominant concern. However, 18 customers are assigned for self-pickup, demonstrating that even with an emphasis on utility, cost considerations influence decision-making. Among self-pickup users, 4 are assigned to attended PUPs, while 14 are assigned to lockers. Lockers attract a larger share due to their affordability and convenience, whereas attended PUPs, despite offering higher service quality, remain underutilized due to their higher operational cost.

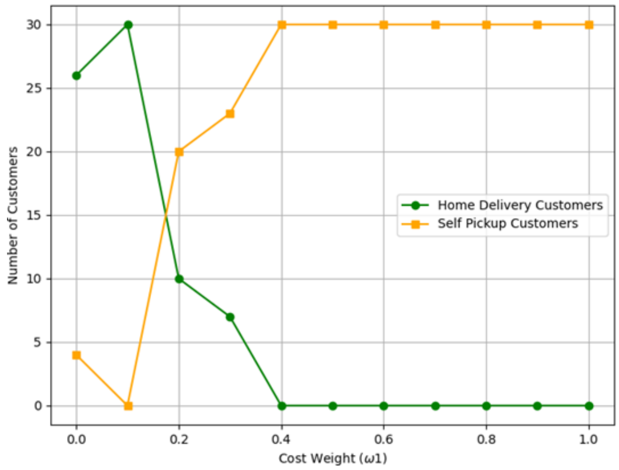


Figure 4: Impact of weights on delivery modes

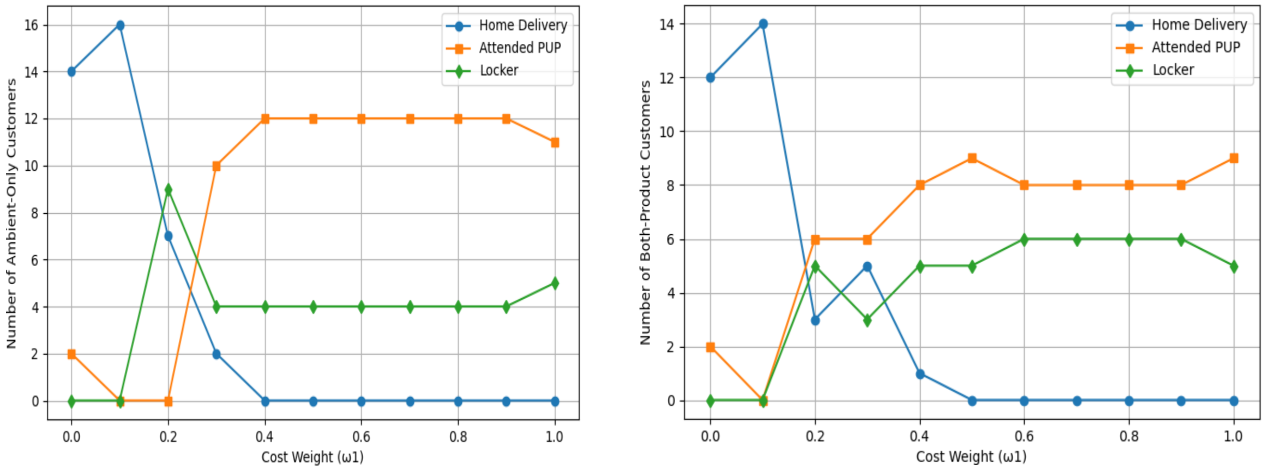
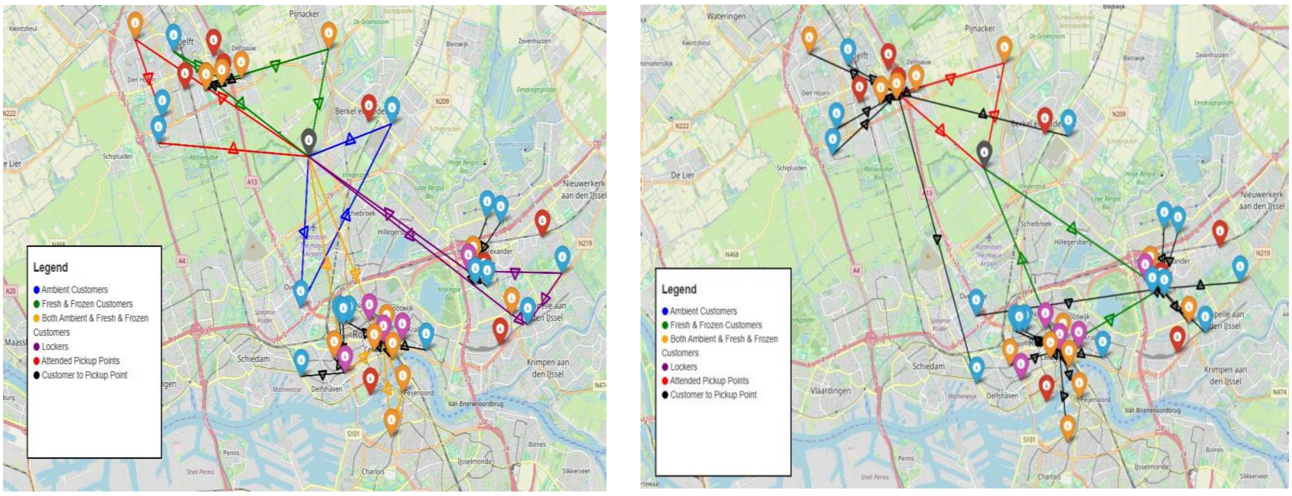


Figure 5: Delivery mode for two classes of customers

At $\omega_1 = 0.4$, the model significantly reduces home deliveries, with only one customer assigned with this option. The majority, 29 customers, shift to self-pickup, reflecting the model's emphasis on cost efficiency. Notably, attended PUPs become the dominant choice, serving 20 customers at full capacity. This contrasts with the lower utilization at $\omega_1 = 0.2$, suggesting that when cost concerns intensify, attended PUPs provide an optimal balance between affordability and service quality. Lockers, while still relevant, are assigned to only 9 customers, indicating that attended pickup points can still provide some additional benefits.

For fresh/frozen buyers, fulfillment ways shift more dynamically. At $\omega_1 = 0.2$, they show a balanced preference between attended PUPs and lockers. By $\omega_1 = 0.4$, lockers remain relevant but with reduced adoption, as the company favors more attended pickup points due to their larger capacity and structured service. The continued assignment of lockers by some fresh/frozen buyers suggests that convenience and accessibility sometimes outweigh temperature control concerns.

These findings highlight the importance of balancing cost and customer preferences. Home delivery remains valuable for maximizing customer satisfaction, but becomes unsustainable as cost minimization takes priority. Attended PUPs gain traction at higher ω_1, demonstrating their role as a scalable, cost-effective alternative. Lockers continue to serve a segment of the customer base, though their underutilization suggests potential for optimization through better placement or incentive strategies.



(a) $\omega_1 = 0.2$ (b) $\omega_1 = 0.4$

Figure 6: Delivery routes and modes for varying weight configurations

5.6 Customer's satisfaction

This study examines how varying weight coefficients, ω_1 and ω_2, influence delivery mode selection and overall customer utility. A higher ω_1 shifts priorities toward cost minimization, encouraging the use of low-cost fulfillment strategies such as lockers and shared attended pickup points. In contrast, a higher ω_2 prioritizes service quality, increasing home deliveries and attended pickup locations with enhanced facilities like temperature-controlled storage.

The analysis reveals a strong correlation between ω_2 and total utility, showing that prioritizing customer satisfaction enhances service experience. However, excessive emphasis on cost minimization ($\omega_2 \rightarrow 1$) significantly reduces total utility due to increased travel distances, longer delivery times, and lower freshness for perishable goods. The trade-offs are further explored in Figure 7, illustrating the relationship between weight coefficients and customer utility outcomes.

To further examine the impact of cost prioritization, the correlation heatmap in Figure 8 highlights key trade-offs. A strong positive correlation between ω_1 and cost-utility confirms that cost-driven strategies enhance savings. However, this comes at the expense of service quality, as distance and delivery time utilities show moderate negative correlations, indicating longer travel distances and increased delivery times. Freshness utility is particularly affected for perishable goods, declining as cost minimization reduces the likelihood of delivery to attended pickup points with temperature-controlled storage. The strong negative correlation between total utility and ω1 underscores the challenge of maintaining customer satisfaction while reducing costs.

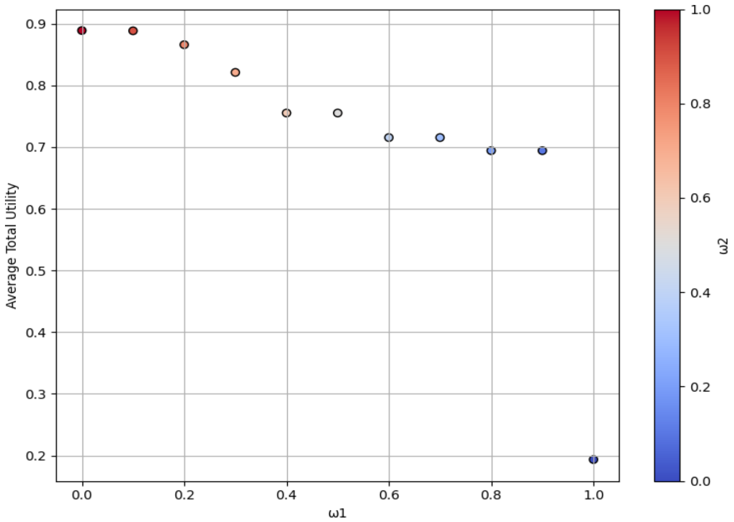


Figure 7: Impact of ω_1 and ω_2 on customer's utility

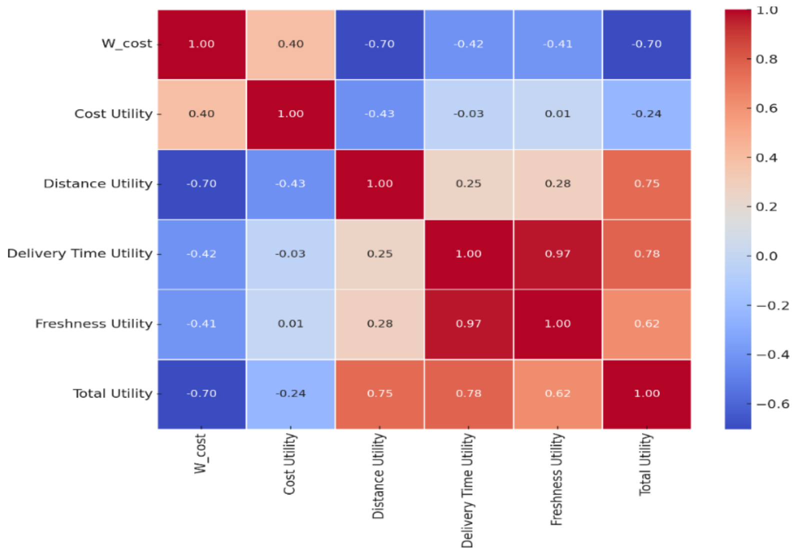


Figure 8: Correlation heatmap

5.7 Attended pickup versus lockers

The analysis of delivery and pickup options for ambient-only and both product customers reveals key insights into customer preferences. The comparison focuses on two types of pickup points: attended pickup points and lockers, with metrics such as total utility, distance utility, delivery time utility, and freshness utility. The results are displayed in Table 4.

For ambient-only customers, lockers offer higher total utility (0.713) than attended pickup points (0.653), suggesting that these customers prioritize convenience and proximity, which lockers provide more effectively. Lockers are located in easily accessible spots and do not require waiting, enhancing customer satisfaction.

For both product customers, lockers again outperform attended pickup points (0.725 vs. 0.656). While temperature control is important for frozen goods, the analysis shows that lockers' lower operational costs and greater accessibility outweigh the benefits of temperature-controlled attended pickup points.

Distance utility further reinforces the preference for lockers. Ambient-only customers show significantly higher distance utility for lockers (0.4507) than for attended pickup points (0.2313). Similarly, both product customers also prefer lockers (0.5869) to attended pickup points (0.3458), highlighting the importance of convenience.

Regarding delivery time utility, the differences between lockers and attended pickup points are minimal, with values ranging from 0.8592 to 0.8824, suggesting that delivery speed does not heavily influence customer decisions. This may be due to the limited region and low density of the current delivery network, where both options provide comparable delivery times.

Finally, freshness utility, relevant only for both product customers, shows a clear preference for attended pickup points (0.9007 vs. 0.8643). However, despite the temperature control advantage, lockers remain appealing due to their convenience and lower delivery fees.

Table 4: 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

6 Conclusion

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 customers have different views 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 groups of customers.

- There is a clear trade-off between cost and customer satisfaction. In the 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 concerns, indicating that locks outweigh normal attended PUP from accessibility and flexibility.

Based on the analysis results, several meaningful findings could be raised for the company to improve its 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. Companies should prioritize the improvement of point density and service level of lockers and pickup points. To enhance the appeal of customers purchasing frozen products, companies 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. Future research should focus on comprehensive multi-modal delivery models that integrate home delivery, attended pickup points, and lockers while considering consumer behavior, product perishability, and logistics efficiency in a unified optimization framework.

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.

Contributor Statement

Luyang Cao contributed through conceptualization, data curation, formal analysis, investigation, methodology, software, resources, validation, visualization, and writing. Lóri (Lóránt) Tavasszy contributed through conceptualization, methodology, and supervision. Patrick Stokkink contributed through conceptualization, investigation, methodology, validation, writing, and supervision. All authors approved the final version of the manuscript and take responsibility for their respective contributions.

Use of AI

During the preparation of this work, the author(s) used Grammarly and ChatGPT for language editing and grammar checks to enhance the clarity and readability of the manuscript. After using this tool/service, the author(s) reviewed, edited, made the content their own and validated the outcome as needed, and take(s) full responsibility for the content of the publication.

Conflict Of Interest (COI)

There is no conflict of interest.

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