Strategies for identifying outlier parcels in urban deliveries

An Explorative Analysis

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by

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Preface

Here marks the official conclusion of my academic journey at Delft University of Technology, signifying the end of my years as a student. Looking back, through the changing seasons, studying and living here has become almost a habit. Now that this chapter has truly come to an end, I find myself with a sense of surrealism. In the end, I completed this thesis and successfully reached this milestone. Along the way, I faced and overcame many challenges, and received much support and help, for which I am deeply grateful.

First and foremost, I want to express my heartfelt thanks to my thesis committee members. Thank you for your guidance, companionship, and support from the beginning to the end of this project. I would like to thank Prof. Lori, who pointed me in the right direction when I was confused about choosing my thesis topic, and who introduced me to this project. Throughout the project, you consistently provided constructive advice, helping me continuously refine my ideas. To Merve Cebeci, I feel incredibly fortunate to have you as my daily supervisor. Thank you for your dedicated guidance, for going through my thesis line by line, and for patiently answering all my questions, facilitating every step of the project. With your support, I was able to reflect, improve, and achieve today's results. To Frederik, thank you for providing valuable feedback on my report and for your insightful perspectives on the topic, which pushed me to continually improve throughout the writing process.

I would also like to express my deepest gratitude to my parents. From childhood until now, you have provided me with the best education possible within their means, supported my various interests and explorations, and never put any pressure on me. You have always encouraged me to try different things, and gave me the opportunity to study abroad, allowing me to see a much broader world.

At the same time, I want to thank my friends for their encouragement and companionship in daily life, and for listening to and comforting me when I was feeling stressed. A special thanks to my boyfriend for his unconditional trust, support, and companionship. Whenever I felt lost or overwhelmed, you always did everything you could to help me and firmly pulled me forward. Together, we will continue to walk through life, striving toward an even brighter future.

Lastly, I want to thank myselfthe one who has always worked hard and refused to give up in the face of challenges. It is this persistence and effort that have led me to todays achievements.This is not the end, but a new beginning. My 24-year-old self will remember the path Ive walked, and with that same purity, kindness, and sincerity, I will continue moving forward with more confidence and courage, living my life to the fullest.

Shenshen Sun
Delft, September 2024

Summary

Over the past decade, there has been a rapid surge in Business-to-Customer (B2C) e-commerce and this sustained growth has not tended to abate (Artemyeva et al., 2020). According to industry reports, international e-commerce has been predicted to grow by 26.6% from 2013 to 2020, while the global e-commerce growth rate for 2023 is estimated at 8.9%, bringing global e-commerce sales worldwide to $4.5 trillion (Oberlo, 2023, Vakulenko et al., 2018). The global B2C e-commerce market size is expected to reach USD 7.45 trillion by 2030, growing at a compound annual growth rate (CAGR) of 7.6% during this forecast period. In the Netherlands, PostNL, the largest parcel delivery service, noted a volume increase of 24.1% in performance annual report 2022 (PostNL, 2022), highlighting the growing demand in this area.

LMD service providers are under huge pressure to deal with a considerable number of parcels in a short period, and this aspect generates various issues, inefficiencies, and externalities affecting the industry. Many innovative solutions have emerged, and logistics service providers must continuously evolve and adapt to these emerging trends in order to remain competitiveness and meet their customer's expectations. There is a category of parcels that would bring a significant level of negative impact for LSPs and are also the potential candidates for innovative solutions called 'outlier parcels', which are urgent to be effectively handled. Therefore, developing methods to identifying outlier parcels is a potential and significant direction to conduct research, but studies in this area is still lacking.

Therefore, this research will develop different identification strategies for outlier parcels based on different perspectives within urban delivery plans, and on this basis, evaluate the proportion of outlier parcels in each strategy and finally conduct sensitivity analyses to explore the impact of specific parameter variations on the identification results. The main research question is: **How are outlier parcels identified in the context of urban deliveries?**.

The marginal cost method focuses on cost factors and identifies high-cost outlier parcels by calculating the marginal cost of each zone in the delivery network, i.e., the cost difference in total cost after skipping a zone in the delivery process, and then dividing the zonal marginal cost evenly among each parcel in the zone in order to identify high-cost outlier parcels.

The COFRET method, on the other hand, is based on sustainability and identifies outlier parcels by calculating the parcel CO_2 emissions during the delivery process. The method first calculates the total CO_2 emissions in the delivery tour, then allocates the CO_2 emissions for each zone based on the number of parcels in each zone and the Euclidean distance from the corresponding depots, and finally divides the zonal CO_2 emissions evenly among the parcels to identify those parcels with significantly high emissions above the average level.

MASS-GT is a key tool for utilizing these methods in the simulation, and it provides the parcel demand module and parcel scheduling modules. Parcel Demand module uses socio-economic data to estimate B2B and B2C parcel demand, while Parcel Scheduling module assigns parcels to delivery tours based on depot proximity and vehicle capacity. These modules ensure that the entire delivery process is fully simulated and provide data input for outlier parcel identification.

After clarifying the research methodology, the results of the implementation of the two methods will be demonstrated and the distribution of outlier parcels will be explained.

The study area for this research is five municipalities and cities in South Holland. Based on MASS-GT, in this study area, around 90,000 parcels are delivered one day in total and 484 delivery tours are made. These delivery tours are delivered by 6 CEPs.

Then, the results obtained from both outlier parcel identification methods are presented. The method utilizes the cumulative distribution function and the elbow point method to set the threshold value and parcels which exceed the threshold value are considered as outlier parcels.

Beyond that, the geographical distribution of outlier parcels and a hierarchical display of their numbers on the map of study area for each CEP have been demonstrated. The reasons for the generation of cost-based outlier parcels are further analyzed through these maps. The detours or tour formation implemented in scheduling or low parcel demand in some zones are all possible reasons that increase the marginal cost of parcels in a particular zone, leading to the generation of outlier parcels.

In addition, through the analysis of the combined distribution map of 6 CEPs for both methods, it is found that cost-based outlier parcels are more dispersed in central area, which suggests that despite the fact that the logistics networks in these areas are better developed, there are still efficiency issues that lead to higher costs for certain parcels. In contrast, the outlier parcels identified by the emission-based methods are mainly concentrated in edge areas away from logistics centers, where parcels are delivered over longer distances, resulting in higher CO2 emissions.

A sensitivity analysis is finally provided that explores how changes in carbon cost affect the identification of outlier parcels. The results show that the thresholds of identifying outlier parcels generally increase in each CEP as the carbon cost increases, with varying impacts on the proportion of outlier parcels in different CEPs. In addition, changes in carbon cost affected the geographic distribution of outlier parcels, with more outlier parcels occurring in high-emission zones away from depots, and a gradual decrease in zones closer to depots. This change suggests that the introduction of carbon cost in the logistics network may reshape the logistics cost structure.

In conclusion, this research explored the identification of outlier parcels in urban deliveries using cost-based and emission-based methods. The results show that different strategies can significantly impact which parcels are identified as outliers, emphasizing operational inefficiencies and environmental concerns.

Cost-based identification method reveals inefficient zones such as detours, tour formation implemented in scheduling, and low parcel demand that lead to higher delivery costs. In contrast, emission-based method identifies outlier parcels in edge areas where longer delivery distances lead to higher CO2 emissions, underscoring the environmental impact of logistics operations far from urban centers.

The sensitivity analysis shows how variations in carbon cost influence the identification thresholds and geographic distribution of outlier parcels, which shows expected results. These results suggest that incorporating carbon cost into logistics network could reshape the cost structure, leading to more environmentally focused delivery strategies.

For future research, some recommendations are presented. Expanding the study to different regions and countries could help refine the methods, considering variations in infrastructure, population, and regulations. The Introduction of more diverse identification methods that integrate multiple attributes such as equity and parcel size/weight might allow for more flexible decision-making. Additionally, future work should explore how innovative delivery methods, such as crowdshipping, can effectively handle outlier parcels, which can potentially improving overall logistics efficiency and sustainability.

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Abbreviations

Abbreviation	**Definition**
B2C	Business-to-Customer
LMD	Last-mile delivery
LSP	Logistics service provider
IQR	Interquartile range
ABC	Activity-based costing
EPM	Equal Profit Method
EPMU	Equal Proportion Mark-up Method
CEP	Courier, Express and Parcel Services
PA	Payload Weighted Allocation
GCD	Great circle distance
CDF	Cumulative distribution curve

1

Introduction

1.1. Background

Over the past decade, with rising disposable incomes, increased internet penetration, the popularity of smartphones, and the growth of global per capital incomes, there has been a rapid surge in Business-to-Customer (B2C) e-commerce (Artemyeva et al., 2020). According to industry reports, international e-commerce has been predicted to grow by 26.6% from 2013 to 2020, while the global e-commerce growth rate for 2023 is estimated at 8.9%, bringing global e-commerce sales worldwide to $4.5 trillion (Oberlo, 2023, Vakulenko et al., 2018). However, this sustained growth has not tended to abate. As can be seen in Figure 1.1, the global B2C e-commerce market size is expected to reach USD 7.45 trillion by 2030, growing at a compound annual growth rate (CAGR) of 7.6% during this forecast period. Rising global e-commerce sales have contributed to the growth of parcel shipments, a trend that is also evident in the Netherlands. PostNL, the largest Dutch parcel delivery service, noted a volume increase of 24.1% in performance annual report 2022 (PostNL, 2022). Zott et al. (2000) emphasize that B2C e-commerce is widely used globally because it offers many advantages to customers, especially in the critical area of last mile delivery (LMD). A common method in LMD is to deliver parcels directly to the recipient's residence or to a collection point, which provide great convenience for the consumers (Behnke, 2019).

Figure 1.1: B2C E-commerce market size, 2021 to 2030 (USD Trillion) (Research, 2023)

Many logistical challenges exist in the fulfillment of these orders, especially LMD is an important success factor in order fulfillment and a critical aspect in the customer purchase decision (Nguyen et al., 2019). However, with the continuous growth in the volume of parcels, the LMD service providers are under huge pressure in accommodating the customized consumer requests. In this sense, logistics service providers need to deal with a considerable number of parcels in a short period. This aspect generates various issues, inefficiencies, and externalities affecting the industry, particularly in this segment (Bertazzi et al., 2019, Perboli et al., 2016). As such, there is a greater awareness of the need to improve transportation activities in the last-mile while making them more sustainable, efficient and competitive, to reduce transportation costs and increase customer satisfaction (Giglio & Maio, 2022). Many innovative solutions have emerged, and logistics service providers must continuously evolve and adapt to these emerging trends in order to remain competitiveness and meet their customer's expectations.

1.2. Problem definition

In the last-mile delivery process, there is a category of parcels that would bring a significant level of negative impact for LSPs, and these parcels can be referred to as 'outlier parcels'. 'Outlier parcels' might potentially cause delivery delays, additional costs, and logistics management problems in traditional delivery systems that lead to inefficiencies. Due to the inefficiency of outlier parcels in the last-mile transportation process, effectively handling these parcels has become an urgent problem for the logistics industry. In the current landscape of the parcel delivery market, the competition among logistics service providers (LSPs) has intensified. Many small start-up companies entering LMD sector, which also lower the market share of LSPs (Du et al., 2018). As a result, many logistics service providers are strategically introducing innovative logistics solutions to take advantage of new technologies and enhance their competitiveness (Pourrahmani & Jaller, 2021). Some of these innovations are also seen as potential solutions for handling outlier parcels, with the promise of addressing these parcels in last-mile delivery.

A fast-developing innovation in LMD is crowdshipping, formally known as crowdsourced parcel delivery, which is defined as the outsourcing of parcel delivery service to occasional carriers that have unused space or capacity to deliver the parcels (Ghaderi et al., 2022). Parcels are delivered by the crowd, informed through online platforms and occasional carriers and get paid per delivery (Gatta et al., 2018). Crowdshippers can pick up parcels at a service point, locker, store or from the senders' address and deliver them to another service point, locker or customer's home (Berendschot, 2021). Several studies have shown that crowdshipping is scalable, cost-efficient, timely and sustainable. Joerss, Schroder, et al. (2016) indicate that crowdshipping opens up a labour group with fewer regulations and lower logistics service providers operational cost. In addition, crowdshipping reduces the distance of delivery by optimizing routes, intelligent scheduling, as well as integrating eco-friendly transportation such as electric vehicles, scooters, and bicycles to effectively reduce carbon emissions and congestions during the delivery process (Jain & Akbar, 2022, Macrina et al., 2020, Saryazdi et al., 2023). Autonomous Drone Delivery (ADD) model is also expected to become a significant pillar of the logistics industry in the future as a cost-effective and innovative solution to traditional LMD methods (Benarbia & Kyamakya, 2021). Currently, companies such as Amazon have successfully completed FAA-approved drone deliveries, demonstrating the viability and efficiency of this technology. Drones have the unique advantage of being independent of existing infrastructure, allowing them to traverse urban areas directly and thus optimise travel routes. By utilising drone deliveries, companies can streamline their operations while also reducing costs associated with labour and fuel (Jacobs et al., 2019). Additionally, the shift to drone delivery brings significant environmental benefits, especially in urban areas. Drones have the potential to substantially reduce carbon emissions and ease traffic congestion by providing more direct and efficient delivery routes (Baldisseri et al., 2022). Furthermore, many other innovative approaches have been proposed for solving the current problems of LMD. For instance, using self-driving vehicles for parcel delivery can reduce the reliance on human drivers and save labour costs. Round-the-clock operations can also significantly enhance delivery efficiency, while autonomous driving can reduce the risk of accidents and improve delivery safety (Feng, 2021).

The innovative methods mentioned above are all potential options for handling outlier parcels. These innovations are expected to complement but not entirely replace conventional deliveries using a commercial vehicle fleet (El-Adle et al., 2021). Due to the advantages of these innovations in terms of significantly improving the cost and efficiency of LMD delivery, using these methods to handle identified outlier parcels has great potential to effectively address the negative impacts brought by them. For example, crowdshipping allows these outlier parcels to be assigned to crowdshippers, enabling parcels to be delivered in a shorter time, thus reducing delays and additional costs. Drones and self-driving vehicles can be dedicated to delivering these outlier parcels, thereby avoiding disruption to regular delivery vehicles and wasted resources. In summary, by identifying and targeting outlier parcels, LSPs can more effectively apply a variety of innovations to optimize resource allocation, reduce delivery costs, and improve the efficiency and sustainability of the overall delivery system. Nevertheless, the identification of outlier parcels is a prerequisite for the application of these innovative methods. Therefore, exploring strategies to identify outlier parcels is a promising research direction.

1.3. Research objectives and questions

Previous research has rarely mentioned methods for identifying outlier parcels. Only (Zhang & Cheah, 2023) in a research related to crowdshipping using public transportation in urban logistics mentioned prioritizing outlier parcels as targets for crowdshipping. They applied a spatial outlier detection method, calculating the Local Outlier Factor (LOF) for each parcel based on the geographic coordinates of parcel demand points, so as to perform the identification of outlier parcels. As mentioned, developing methods to identifying outlier parcels is a potential and significant direction to conduct research, but studies in this area is still lacking. If strategies can be developed to help LSPs identify which parcels are performing anomalously according to the objectives that LSPs expect to achieve, this will help LSPs execute their delivery plans more efficiently, and also provide them with more flexible options for delivery management. Therefore, this research will develop different identification strategies for outlier parcels based on different perspectives within urban delivery plans, and on this basis, evaluate the proportion of outlier parcels in each strategy and finally conduct sensitivity analyses to explore the impact of specific parameter variations on the identification results.

Considering the research objectives, the main research question can be derived. The main research question of this research is:

How are outlier parcels identified in the context of urban deliveries?

To assist in answering the main research question, several sub-questions were presented:

SQ1: What is the definition of outlier parcels in the context of last-mile delivery?

Before the research is carried out, it is important to clarify the definition of 'outlier parcels' at first. The differences and connections between the definition of outliers in the context of LMD and statistics are elaborated through a literature review.

SQ2: Which cost and CO_2 allocation methods are used for outlier parcels compared to other strategies?
Attributes that can be used to determined outlier parcels are determined throughout a literature review first, which helps in developing effective identification methods. After determining cost and CO2 as the attributes for identifying outlier parcels, a various existing allocation strategies are compared and the appropriate cost and CO2 allocation strategy as research methods are selected in order to identify and handle outlier parcels more accurately.

SQ3:How do different strategies impact the volume of outlier parcels?
Taking 5 municipalities and cities in South Holland as study area, by comparing the identification results after applying the two methods, the specific effects of different strategies on the proportion of outlier parcels can be observed, which helps to assess the actual effects of these strategies. The generation of specific distribution tours and the distribution of outlier parcels will be analyzed in order to obtain the reasons for the formation of outlier parcels.

SQ4: What is the impact of different carbon cost settings on the identification of outlier parcels?
Carbon cost is an important factor in logistics operations, and investigating the impact of its changes on outlier parcel identification can help logistics service providers make a better trade-off between environmental protection and economic efficiency. The study finally combines the parcel cost calculated by the two strategies and perform a sensitivity analysis by changing the value of carbon cost to observe the changes in the zones that generate outlier parcels. The results of the sensitivity analysis can provide data support for policy makers to help them make more well-informed decisions when formulating carbon emission policies and logistics cost management strategies.

1.4. Thesis structure

The overall structure and workflow of the thesis and the chapters corresponding to the proposed research questions are shown in Figure 1.2. Chapter 2 aims to answer Subquestion 1 and 2, which presents the definition of outlier parcels in the context of LMD, clarifies the attributes that define outlier parcels, and selects a appropriate outlier parcel research methods through multiple comparisons, which provides a theoretical basis for the specific description of the research methods in Chapter 3. Chapter 3 describes the implementation process of the two research methods in detail and further refines the answer to Subquestion 2. Chapter 4 implements the proposed strategies and answers Subquestion 3 by presenting and analyzing the implementation results obtained. Then, on this basis, a sensitivity analysis is conducted by adjusting specific parameter to produce results on the volume as well as the changes in the delivery position of outlier parcels as affected by the parameter variations, which in turn answers Subquestion 4. Finally, Chapter 5 answers the main research question, discusses the results and the limitations of the study, and makes recommendations for further research.

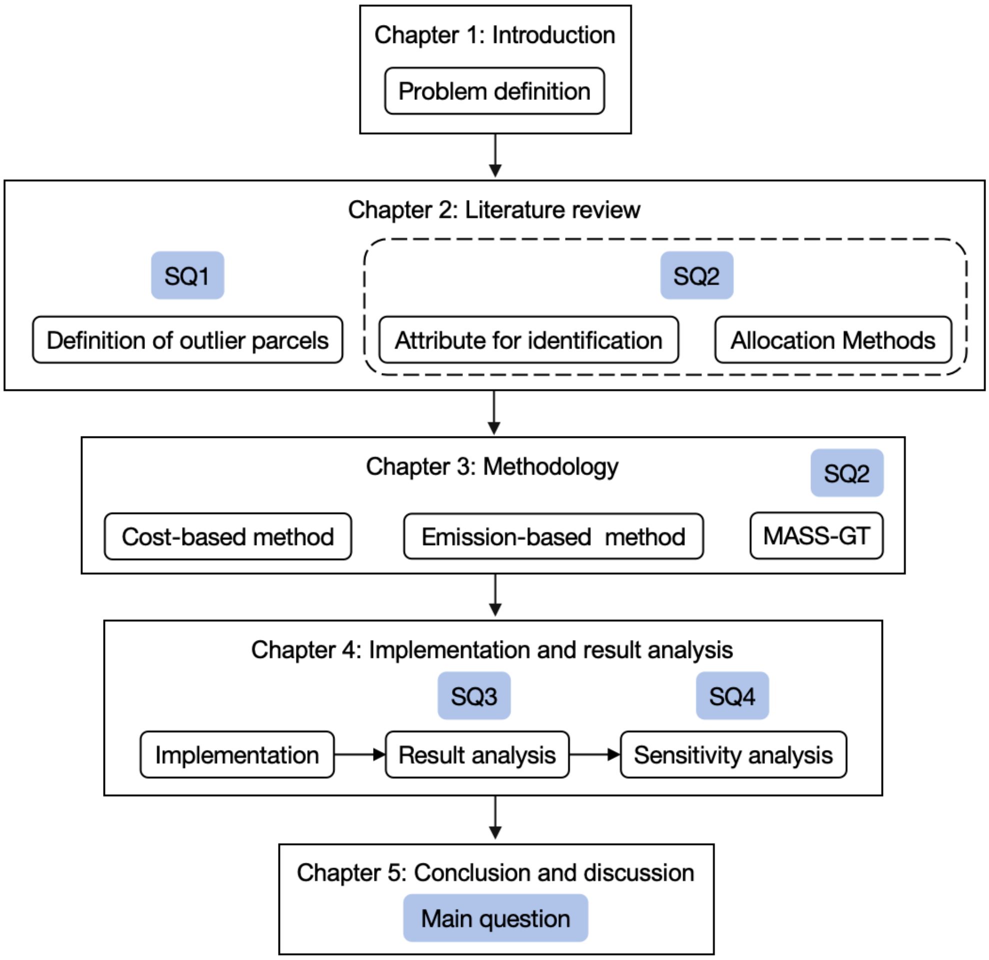


Figure 1.2: Research workflow

2 Literature review

In order to further answer the first three sub-questions, firstly, a clear definition of "outlier parcels" is needed, indicating the commonalities and differences between the "outlier" in "outlier parcels" and the outlier as defined in statistics. Secondly, the attributes of identifying outlier parcels are clearly enumerated and the attributes applied in this study are identified. Finally, after determining the identified attributes to be applied in the study, it is necessary to choose a suitable cost and CO2 allocation method in order to allocate the cost and CO2 emissions of the parcels in the delivery routes in a reasonable manner.

2.1. Definition of outlier parcels

In statistics, outliers are data points that deviate significantly from other observations in a data set. These outliers may occur for a variety of reasons, including data entry errors, measurement errors, or true anomalies (Kwak & Kim, 2017). There are several methods of identifying outliers in statistics, and common methods include Z-score method, Interquartile range method, Box plot method, Density-Based Spatial Clustering of Applications with Noise(DBSCAN), and Regression analysis methods etc. Z-score method identifies outliers by calculating the standard deviation distance from the mean for each data point, which is usually used for normally distributed data sets (Curtis et al., 2016). Interquartile range (IQR) and Box Plot methods do not depend on the type of distribution of the data set. Interquartile range method defines data points above Q3 + 1.5 * IQR or below Q1 - 1.5 * IQR as outliers by calculating the difference (IQR) between the first quartile (Q1) and the third quartile (Q3) (Frery, 2023). Box plot method is based on the graphical method of quintile generalization (minimum, first quartile, median, third quartile, and maximum values) to obtain outliers (Williamson et al., 1989). DBSCAN is a density-based clustering method that identifies outliers through density reachability and sets outliers as data points that are far from the clusters (Khan et al., 2014). Regression analysis method predicts data points and calculates residuals through regression models and sets data points with significant deviations from the residuals as outliers (Dan & Ijeoma, 2013).

In this study, outlier parcels need to be identified based on the context of LMD. However, using traditional statistical methods to identify outlier parcels is not exactly the right means to apply. Traditional statistical methods are usually designed to identify outlier parcels in the data, which may deviate from the majority data for a variety of reasons (e.g., data errors or natural variability) (Wada, 2020). But in the context of LMD, outlier parcels are defined as those parcels that negatively affect LSPs in actual operations. Therefore, in this study, the definition of "outlier" is target orientated, explicitly targeting parcels which negatively impact on CEPs and reduce their delivery efficiency, such as parcels with high costs, high emissions, operational complexity or increased risk. Furthermore, parcel attribute data in LMDs often do not conform to some conventional distribution pattern, and many traditional statistical methods are limited by the applicability of the data distribution (Walfish, 2006). Also, conventional methods such as standard deviation and interquartile range methods tend to be bilateral filters, with values above the upper limit or below the lower limit being set as outliers, but in LMD, it is mainly the high-value parcels that would significantly increase operational difficulty that need to be focused on.

In summary, outlier parcels are parcels that negatively affect CEPs during LMD, not just statistical outliers. Outlier parcels can be identified by setting a threshold, which is a more direct and effective approach. Parcels which are above the threshold are considered as outlier parcels.

2.2. Attributes for identifying outlier parcels

LMD is currently under huge pressure to deal with a large number of parcel deliveries in a short period, which creates challenges for logistics service providers in terms of cost, externalities, timeliness and reliability (Sorooshian et al., 2022). Among them, increasing cost is the most urgent problem to be solved in LMD. According to the delivery management platform FarEye, last-mile delivery accounts for 53% of overall shipping and delivery costs on average (Owens, 2023). Last-mile delivery involves shipping a small number of parcels to a large number of destinations, which limits economies of scale. Unlike bulk shipments to a central location, shipping individual parcels to dispersed residential addresses results in higher costs per delivery (Ha et al., 2023). In the urban areas, the density is higher and logistics carriers benefit from lower costs, but delivery costs in rural areas are approximately three times higher than in urban ones (Cárdenas et al., 2017). Meanwhile, Silva et al. (2023) indicates that deliveries in densely populated urban areas face challenges such as traffic congestion, limited parking and complex routes. These factors lead to longer delivery times and increased fuel consumption, which further drives up costs. Customer expectations are also a factor that LSPs focus on, while customers generally demand shorter delivery times, and meeting these expectations requires additional resources, such as more delivery vehicles and drivers, which can also increase costs (Joerss, Neuhaus, & Schröder, 2016). And as customer demand and the volume of parcels increase year on year, a substantial workforce is needed to handle the high volume of deliveries, which also requires higher labor rates being paid to couriers (Lim et al., 2018). Parcel costs are directly related to company profits and can directly reflect the efficiency and resource utilization in the delivery process, and therefore can be used as a key attribute to identify outlier parcels. Rising delivery costs usually mean inefficiency or waste of resources in some parts of the process. High-cost parcels can directly affect a company's profitability. Identifying and managing these high-cost parcels can effectively control overall operating costs and improve profit margins (Rounaghi et al., 2021).

LMD is not only costly but also contributes significantly to CO2 emissions. Due to the surge in online shopping has led to a huge increase in parcel deliveries, while more parcels means more delivery vehicles on the road, leading to an increase in CO2 emissions. Delivering parcels in densely populated urban areas often involves traversing congested traffic, frequent stopping and idling, which can also lead to increased fuel consumption and higher emissions (Zhao & Zhou, 2021). Some companies such as Amazon, DHL are beginning to invest in sustainable practices such as electric delivery trucks and optimized routing algorithms. However, these programs are still in the early stages and are not yet widespread enough to have a significant impact on overall emissions (Kreier, 2022). Figure 2.1 shows the predicted increment in LMD externality for global largest cities, where such a substantial increase doesn't align with the principles of sustainable urban development.

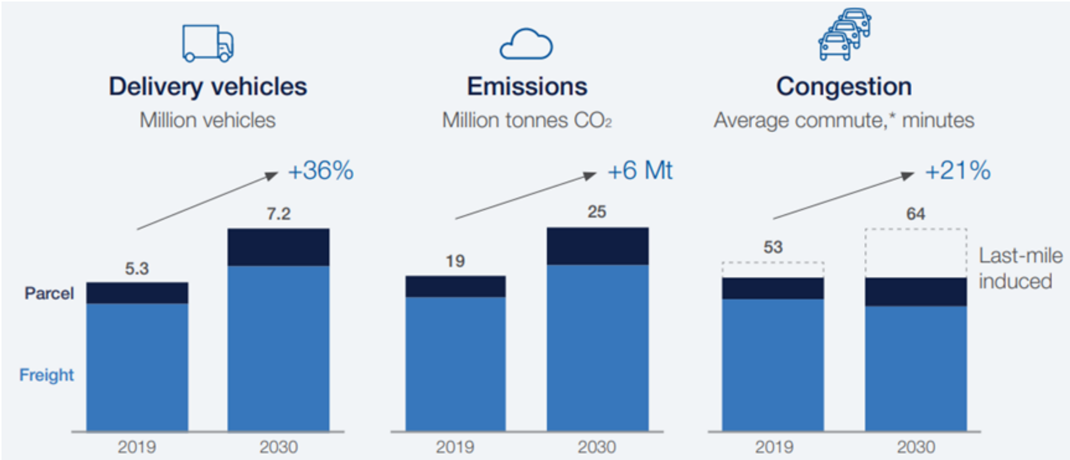


Figure 2.1: Impact of the growth of last-mile delivery in the top 100 global cities. *Average commute for representative city.(Deloison et al., 2020)

Modern businesses must fulfill their social responsibility by reducing their impact on the environment, and reducing CO2 emissions from transportation is an important aspect of this. Implementing environmental protection measures helps to enhance the company's public image and increase customer loyalty and market recognition (Ghosh et al., 2020). Qian et al. (2019) suggests that global controls on carbon emissions are tightening and LSPs need to prepare in advance for potentially stricter environmental regulations.

In addition to cost and CO2, there are several key attributes that negatively impact LMD that can be used as identification criteria for outlier parcels. Delivery time is one of the most important attributes affecting LMD. Consumers expect more and more shorter delivery times, which puts higher demands on LSPs, and slower delivery times not only affect customer satisfaction, but may also lead to a lack of competitiveness for LSPs (S. Liu et al., 2021). The size and weight of parcels will also directly affect delivery costs. Larger parcels take up more space and require more transport resources, while heavier parcels increase the load on delivery vehicles, leading to increased fuel consumption (Cortes & Suzuki, 2022). Yet in actual delivery, it is difficult to obtain data on the specific weight and size of parcels. Zonal population density can also be considered as one of the attributes. Rural areas have a low population density compared to urban areas, with more dispersed settlements, requiring a larger range for a single trip, taking more time to make a detour for delivery, which greatly reduces the efficiency of delivery (Seghezzi et al., 2022). Equity can be used as an attribute as well. There are differences in delivery services among zones, and sometimes it is not possible to ensure a fair and equitable distribution of resources and services, thus creating an element of inequality. For example, remote areas are inefficiently delivered due to sparse populations, and the high cost of services causes residents in remote areas to pay higher costs for equivalent services, creating equity issues(Schaefer & Figliozzi, 2021). However, assessing and quantifying equity is relatively complex. Equity relates not only geographic location, but also socio-economic factors, such as income levels, transportation infrastructure and Internet coverage, which can affect the assessment of equity. Furthermore, assessing equity requires a large amount of data support, which is difficult to realize(Keeling et al., 2021). In addition to

CO_2 emission, there are other externalities, such as traffic congestion, air pollution and noise pollution, that can also be regarded as attributes, as these factors also have a significant impact on society and the environment. Zones with high traffic congestion can lead to increased delivery times, significantly reducing the efficiency of delivery. In addition to CO_2, delivery vehicles emit other harmful gases such as nitrogen oxides (NO_x) and particulate matter (PM), which can pose a serious threat to human health. Noise from delivery vehicles has a negative impact on the quality of life of residents, interfering with their rest and daily life(Wygonik & Goodchild, 2017). However, CO_2 emissions are one of the main contributors to global climate change, and it is an important indicator for assessing environmental impacts. Data on CO_2 emissions are easier to obtain and quantify than other externalities, and the reduction of CO_2 emissions is a social consensus and a common goal.

Combining the multiple attributes mentioned above that have an impact on LMD and can be used in outlier parcels identification research, cost and CO_2 emission are selected as the key attributes for identifying outlier parcels in this study. Cost and CO_2 can inherently capture the inefficiencies associated with delivery in less dense areas, such as increased distance and delivery time. Moreover, the current research methods for cost and CO_2 are more complete and mature, and have been supported by a large amount of literature and data, which is helpful for data analysis and decision support in practical applications.

In conclusion, choosing cost as a key attribute for identifying outlier parcels can help companies focus on the factors that have the greatest impact on profitability and take measures to improve and develop targeted strategies to optimize operations and reduce expenses. Similarly, CO_2 emissions are also a critical factor, as CO_2 emissions of parcels directly impact environmental sustainability, regulatory compliance, and operational efficiency. By focusing on parcels with high CO_2 emissions, logistics companies can develop targeted strategies to reduce their carbon footprint, meet regulatory requirements and enhance their public image. Therefore, selecting cost and CO_2 emissions as key attributes for identifying outlier parcels is critical to optimizing last-mile delivery operations and achieving sustainability goals.

2.3. Cost allocation methods

After clarifying cost as one of the attributes for outlier parcel identification, it is necessary to choose a cost allocation method to reasonably allocate the total cost of parcel delivery to each parcel, in order to identify those outlier parcels which have significantly higher costs than the average. In the field of logistics and transportation, accurate cost allocation is not only the basis of enterprise financial management, but also an important means to optimise resource allocation and improve operational efficiency (Stemmler, 2002). With the rapid development of e-commerce, the demand for parcel delivery has increased dramatically, and how to scientifically apportion the total cost has become a key issue for logistics companies. Research on cost allocation methods aims to achieve fair, reasonable and efficient cost sharing, ensuring that each parcel is allocated according to its actual costs incurred, thus improving the transparency and fairness of the overall operation (ERGP, 2020).

Kaplan & Cooper (1998) proposed a method for determining the actual cost of a product or service by tracking and allocating activity costs, called activity-based costing (ABC), and described its principles and applications in detail. ABC was first applied in the manufacturing industry and allows for a more accurate apportionment of costs by identifying all of the major activities associated with a product or service within a company, identifying the cost drivers affecting each activity, and collecting cost data for each activity to allocate the activity costs to individual products or services. ABC can provide a more accurate representation of the actual cost of a product or service, especially in the case of diverse products or services. By identifying and managing cost drivers, companies can better control and reduce costs as well. However, Munich (2021) point out that the ABC method is limited in the allocation of common costs as it only allocates them proportionally and it is unable to accurately measure common costs. In addition, Udeh et al. (2024) note that ABC is complex and data-demanding to implement, especially in dynamic environments where cost drivers need to be updated frequently.

Frisk et al. (2010) proposed Equal Profit Method (EPM) in 2010, a cost allocation method based on equal distribution of profit, with the core idea of achieving fair cost allocation by minimizing the profit differences between companies. Relative savings are calculated through independent and cooperative allocation of costs, and then solved using linear programming to find a cost allocation solution that makes the relative savings of all companies to be as equal as possible. However, Guajardo & Rönnqvist (2016) discussed the computational complexity, data requirements, and other challenges faced in implementing EPM in their research, and illustrated that EPM is mainly suitable for scenarios where cost allocation is required in a collaborative environment, emphasising that it is not applicable when operating independently and not collaborating with other companies.

Cooperative game theory, as a widely used cost allocation method, is also only applicable to multi-party co-operative parcel delivery scenarios. The Shapley value and Nucleolus are two of the most commonly used cost allocation methods in Cooperative Game Theory, proposed by Shapley et al. (1953) and Schmeidler (1969) respectively. The Shapley value allocates costs by calculating the marginal contribution of each participant across all possible sequences of joining. Specifically, all possible participant joining sequences are first listed and the marginal contribution of each participants to the total cost in the different sequences is calculated. These marginal contributions are then averaged to obtain a Shapley value for each participant as its share of the costs. The Shapley value ensures fairness in cost allocation and reflects the actual contribution of each participants to the co-operation. The Nucleolus achieves a fair allocation of costs by minimizing the maximum inequity. First, the cost of each possible coalition and the unfairness of the coalition under the current allocation scheme are calculated. Then, the allocation scheme is iteratively adjusted to minimize the maximum inequity, resulting in an allocation scheme that minimizes dissatisfaction among coalitions. The Nucleolus is particularly suitable for scenarios that require ensuring the stability of long-term cooperation. N. Liu & Cheng (2019) studied the application of these two methods in parcel delivery cost allocation and found that they are theoretically unique and fair, but have high computational complexity and low practical feasibility.

Allocation of parcel cost can also be done through the Equal Proportion Mark-up Method (EPMU). EPMU is straightforward and suitable for situations where costs need to be allocated rapidly and transparently, and it works equally well with a single company or a single delivery task. It does not require complex analysis of cost drivers, but only the selection of an appropriate base, such as the weight, volume or transport distance of the parcel. Based on the chosen base, the proportion of each parcel that should be allocated is calculated and the cost is thus allocated. EPMU not only simplifies the allocation process, but also improves the transparency and accountability of cost allocation practices (Cremer et al., 2013). However, Baumol & Bradford (2005) have pointed out in their research that EPMU may lead to inaccurate allocation in cases where the common costs are significant and the differences between products are large. Cooper & Kaplan (1988) have also indicated that EPMU allocates the common costs proportionally without taking into account the specific characteristics of individual parcels and the differences in the actual costs, on which certain parcels may be unfairly cost-burdened.

Marginal cost method, first proposed by Dupuit (1844), allocates costs by calculating the additional cost incurred by each parcel added to the transportation system. The marginal cost of each parcel is first identified and calculated, i.e., the incremental cost incurred when the parcel is added to the current delivery system, including direct delivery costs, handling costs, and other related costs that would be added. Next, total costs are allocated based on the marginal cost of each parcel so that the price of delivering each parcel reflects its actual incremental cost. Marginal cost is a straightforward method, based on the actual incremental cost of pricing, ensuring the optimal allocation of resources and reducing waste and unnecessary costs (Panzar, 1989). It can also flexibly adapt to changes in the market and operating conditions, and in the case of fluctuations in parcel shipment volumes, it can dynamically adjust cost allocation so that it always reflects the actual operating costs (Nash, 2003).

In conclusion, Marginal cost method is the most suitable strategy for this research. EPM as well as Cooperative Game Theory have high computational complexity. They are usually applicable to parcel delivery scenarios where multiple logistics service providers collaborate, and are not applicable to the scenario where a single CEP carries a single delivery task in this research. Compared to the complexity and data requirements of ABC, Marginal cost method simplifies the cost allocation process by calculating the incremental cost of each parcel. While EPMU is easy to implement, it can lead to inaccurate allocation. By visually reflecting the actual incremental cost of each parcel, Marginal cost method can clearly show which parcels are significantly more expensive to deliver than others, thus helping operators to quickly identify and deal with potentially outlier parcels, so as to optimize the LMD delivery plan and improve the overall logistics efficiency.

2.4. CO2 emission allocation methods

The importance of CO2 as another key attribute in identifying outlier parcels cannot be ignored. In the context of environmental protection and sustainable development, LSPs need to strictly manage and control their carbon emissions (Kumar, 2015). Therefore, it is crucial to choose an appropriate CO2 allocation method to more accurately assess the carbon emissions of each parcel and identify those outliers whose carbon emissions are significantly higher than the average. This not only helps companies fulfill their environmental responsibilities, but also prompts them to optimize their logistics processes, reduce carbon emissions and improve their green operations. A scientific CO2 allocation method can ensure that the carbon emissions of each parcel are reasonably allocated according to the actual emissions it produces, thus enhancing the competitiveness of the companies in terms of environmental protection and realizing the goal of sustainable development (Leenders et al., 2017).

In order to fairly allocate the CO2 emissions generated during parcel delivery, researchers have proposed a variety of allocation methods. Each method has different advantages and disadvantages in terms of achieving fairness, calculation complexity, transparency and driving companies to reduce emissions. Some of the methods used for cost allocation are also applicable to CO2 allocation (Leenders et al., 2017). The Shapley value and Nucleolus are also applicable to CO2 allocation, with the Shapley value reflecting the customer's marginal contribution to the total emissions and providing a fairer allocation result, while the Nucleolus determines each customer's transportation demand and associated emissions, builds a mathematical model of the unfairly allocated quantity, and minimizes the maximum unfair allocation by solving a linear programming problem, providing a unique and fair allocation result. However, they are consistently computationally intensive, computationally complex, and difficult to apply. Naber et al. (2015) have shown in some sample computational experiments for emissions allocation that the Shapley value is not a core allocation, and Nucleolus cores do not necessarily exist and cannot be applied in some cases.

EPM can also be applied to CO2 emission allocation by minimizing the relative allocation differences to ensure that the allocation results are proportional to each customer's individual transport emissions (Dahlberg et al., 2017). EPM requires detailed individual customer transportation and emission data, requires subsequent optimization calculations, and focuses more on the fairness of the allocation ratio, which may not fully reflect the actual emission contribution during delivery, and does not reflect the true individual parcel emission level, makes it unsuitable for this study.

A few Distance-independent allocation methods have been proposed for CO2 allocation. The Payload Weighted Allocation (PA) method allocates CO2 emissions based on the weight of the parcel as a proportion of the total weight and PA method of has been applied in many logistics and transportation studies (Song et al., 2021). It is simple to calculate and easy to understand and implement. However, considering only the weight without considering the delivery distance may lead to unfair allocation. Leonardi & Browne (2010) proposed Allocation based on Tour Stops and Payload (SPA), an allocation method that allocates half of the total greenhouse gas (GHG) emissions equally according to the delivery stops, and the other half is allocated based on the mass (or number of EDUs) by the customer. This method requires high data accuracy, which is difficult to implement, and it also fails to account for delivery distance, which may lead to inaccurate allocation results. P. Liu et al. (2010) proposed the Weighted Relative Savings Allocation (WRSA) method, which calculates the cost or CO2 emissions saved by each participant in cooperation and weights the allocation based on the relative contribution of these savings. This method is more equitable and encourages participants to cooperate to reduce the total cost or CO2 emissions by calculating the amount of savings, but similarly does not consider the distance factor.

Distance-dependent allocation methods have also been proposed for CO2 allocation. Tons-km Weighted Allocation method combines the weight of the parcels with the distance traveled and allocates the total CO2 emissions based on the proportion of each parcel's ton-km to the total ton-km (Kellner & Otto, 2012). The Separate Deliveries Allocation (SDA) method is an allocation method based on emissions from independent deliveries. The actual total emissions are allocated by calculating the CO2 emissions of each parcel transported independently. However, this method fails to take into account the synergistic effect brought about by the combined delivery of multiple parcels, which may result in a less accurate allocation of total emissions (Fishburn & Pollak, 1983). The COFRET methodology (Logistiek, 2021) is a weighted allocation methodology based on the EN 16258 standard, proposed by the EU COFRET project and based on the distance traveled and the capacity occupied by the parcels, aiming at a fair allocation of carbon emissions in the logistics process. The method weights the total emissions of the means of transportation according to the calculated Great Circle Distance (GCD) from the depot to customer destination and the number of parcels at that destination. The method avoids the influence of the order of delivery on the allocation, preventing the last address from being allocated the most emissions. The COFRET method is compliant with the EN 16258 standard, which makes it easy to audit and validate, and incentivizes customers to optimize their delivery routes and choose more environmentally friendly modes of transport to reduce emissions.

In conclusion, compared to various CO2 allocation methods, the COFRET method ensures that CO2 emissions are accurately calculated for each parcel, which is essential for identifying those parcels whose CO2 emissions are significantly higher than the average. The COFRET method not only takes into account the weight of the parcels and the distance of the shipment, but also avoids the influence of the order of the deliveries on the allocation results, and this comprehensive consideration ensures the fairness and rationality of the allocation results. Although several factors need to be considered in the COFRET method, its computational complexity is lower than other methods (e.g., the Shapley value or Nucleolus), and it is easier to be implemented and applied in practical operation. Therefore, this research selects the COFRET method to allocate CO2 emissions, which can effectively assist companies in fulfilling their environmental responsibilities, optimizing logistics processes, reducing carbon emissions, and enhancing the level of green operations and competitiveness in environmental protection.

2.5. Chapter overview

In this chapter, the research question is first clarified and the first three sub-questions are answered. To better identify high cost and high CO2 emission outlier parcels, a detailed exploration of the definition and attributes of "outlier parcels" was conducted. Unlike the statistical definition of outliers, outliers in urban delivery context are defined as those parcels that negatively affect LSPs in actual operations. LMD faces significant cost and environmental challenges, and by selecting cost and CO2 emissions as key attributes, it can help logistics service providers optimize their operations, reduce costs and carbon emissions, and achieve sustainability goals.

Next, this chapter reviews different cost and CO2 emission allocation methods. In terms of cost allocation, the marginal cost method is considered the most suitable method for this study as it simplifies the allocation process and accurately reflects the actual incremental cost of each parcel. In terms of CO2 emission allocation, the COFRET method was selected as the best allocation method because it combines the parcel weights and delivery distances, takes into account the effect of delivery order, and ensures that CO2 emissions are realistically calculated.

In summary, this chapter defines outlier parcels and provides methodological options for identifying outlier parcels with high costs and high CO2 emissions, also, lays a solid foundation for subsequent simulation research. By adopting appropriate cost and CO2 allocation methods, LSPs can more effectively fulfill their environmental responsibilities, optimize logistics processes, and enhance green operations.

3 Method and Data

This chapter first illustrates the process of the specific implementation of the cost-based outlier parcel identification strategy and emission-based outlier parcel identification strategy in detail, which provides a comprehensive guide for the implementation of subsequent research. Both identification methods are implemented in an efficient tool MASS-GT, which simulates the freight transportation based on a large dataset, and provides research data for this study. Therefore, the working principle and modelling details of MASS-GT will also be described in detail in the second section.

3.1. Methods for identifying outlier parcels

3.1.1. Cost-based method

Based on the literature review, the marginal cost method, as a cost-based outlier parcel identification method, measures the last-mile marginal cost of each parcel as the key criterion, and defines outlier parcels as those parcels whose delivery marginal cost is significantly higher than the average. High-cost parcels usually mean that more resources are consumed during handling, transportation, or delivery, which can directly affect the profitability of LSPs. Handling high-cost parcels also requires more time and effort, which affects the delivery efficiency of other parcels and has a negative impact on the overall delivery efficiency. Therefore, it is meaningful and necessary to identify these high-cost parcels as outlier parcels and apply the correct method to deal with them.

Marginal costs method for parcels are carried out on a delivery tour basis. A van departs from a specific depot, visits several zones in turn, delivers a certain number of parcels at each zone, and then returns to the depot to form a complete delivery tour. Several tours form a whole delivery network. Through the calculation, the marginal cost of all parcels in the delivery network can be obtained. The research assumes that each parcel has a uniform size and weight, because these data are not available. Distribution of parcels in the zone is also unknown because parcels are not distributed according to a simple rule, but are influenced by multiple factors such as socio-economic (SE) characteristics, aggregated demand, and depot structure.

The visualization of the calculation method of parcel marginal cost is shown in Figure 3.1, and the unit of cost is €. Firstly, In one delivery tour, a method of calculating tour transportation cost is introduced for calculating the total tour parcel delivery cost. Then, in order to calculate the marginal cost incurred by a certain zone in the delivery tour, the process continues by sequentially skipping one zone at a time and calculating the total travel cost after skipping each zone. The difference in total travel cost before and after skipping each zone is calculated which represents the marginal cost for that specific zone. After marginal costs for each zone are measured, the zonal marginal cost is equally allocated to each parcel in each zone.

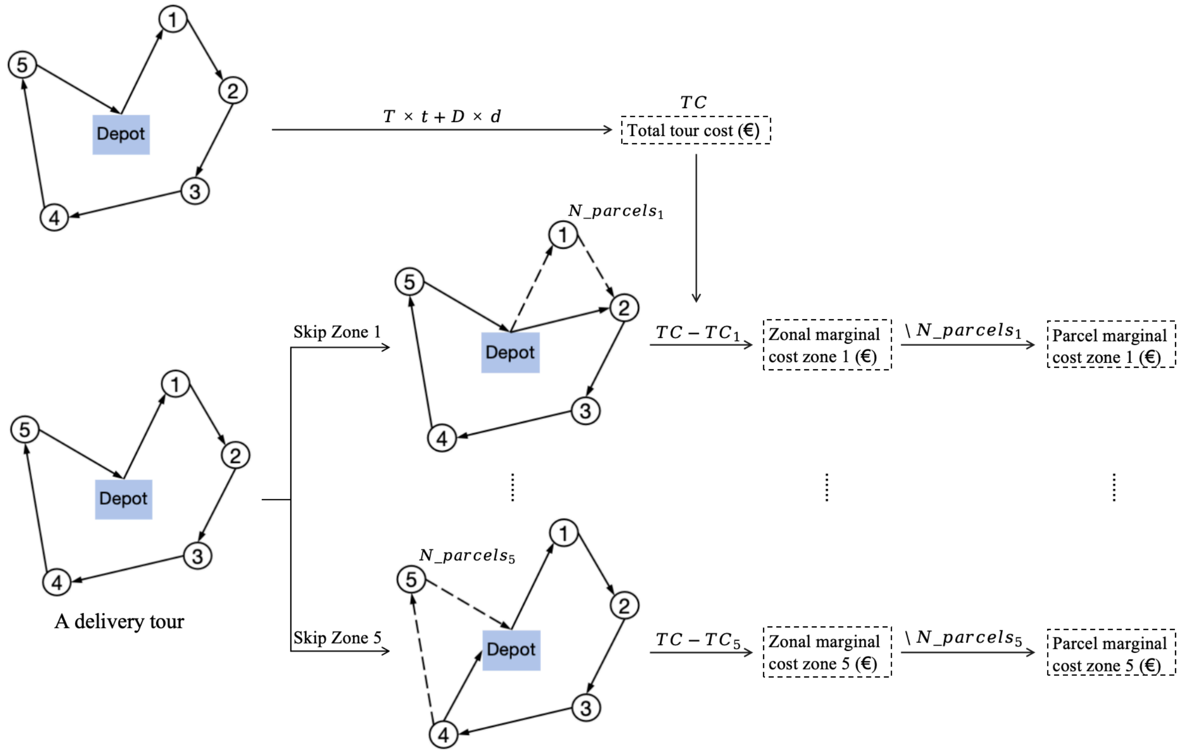


Figure 3.1: Marginal cost method

The marginal cost of a zone is calculated by the total tour cost of the original delivery tour minus the total tour cost of the new delivery tour which is generated by skipping that specific zone. Assume that the total delivery cost of the original travel tour is TC, the total delivery cost after skipping $zone_i$ is TC_i, then the marginal cost of $zone_i$ is shown in Equation 3.1.

$$Zonal\, marginal\, cost_i = TC - TC_i \tag{3.1}$$

In order to accurately and reasonably calculate this difference, this study cites a method proposed by Gevaers et al. (2014) for calculating total last-mile logistics cost per unit delivered using knowledge and data obtained from the literature and interviews, i.e., based on travel time and distance data to create a logistics last-mile cost function. The standard form of this function is denoted below in Equation 3.2.

$$TC = T \times t + D \times d \tag{3.2}$$

Where T stands for the duration/time of the delivery t stands for the time coefficient D stands for the distance driven/travel for the delivery d stands for the distance coefficient. The time coefficient (t) multiplied by the actual driving/working time (T) gives the total time-related cost of the total delivery cost. Similarly, the distance factor (d) multiplied by the total kilometers driven (D) gives the total distance-related cost of the total delivery cost. The total delivery cost

(TC) is the aggregate of these two costs. The value of time and distance coefficient varies based on the type of delivery vehicle and the vehicle payload.

It is worth noting that, in order to get the total cost (TC) of the tour, thus calculate the zonal marginal cost, it is necessary to determine the total delivery time and the total delivery distance. Since precise parcel delivery routes are difficult to estimate, distances between zones are represented as Euclidean distances between the centroids of the polygons in each zone, and the unit is km. The total delivery distance is then determined by summing the linear distances between each zone. Assume that $d(i, i+1)$ is the linear distance from zone i to zone $i+1$, 0 means the depot, n means the last customer, and $n+1$ means back to the depot. The total tour travel distance in Equation 3.3 is denoted as follows.

$$D = \sum_{i=0}^{n} d(i, i+1) \tag{3.3}$$

Similarly, total delivery time needs to be determined in order to obtain a value of TC. In contrast to just summing the inter-zonal delivery times, in Gevaers's study, the total delivery time is calculated as the actual working duration of the carriers, and therefore the parcel drop-off time is also taken into account, which is measured in $hour$. Assume that $h(i, i+1)$ is the linear travel time from zone i to zone $i+1$, 0 means the depot, p_i is the number of parcels delivered at the i^{th} demand point, t_d is the drop-off time of each parcel. The total tour delivery time is calculated as the sum of the linear time between zones plus the number of parcels shipped at each zone multiplied by the drop-off time for each parcel and shown in Equation 3.4.

$$T = \sum_{i=0}^{n} h(i, i+1) + \sum_{i=1}^{n} p_i * t_d \tag{3.4}$$

After completing the total tour delivery cost calculation, the zonal marginal cost for each zone can be obtained. This cost will be equally allocated to all the parcels that need to be delivered in the specific zone to get the marginal cost per parcel. Therefore, Equation 3.5 is to divide the obtained zonal costs equally to get zonal cost per parcel as the marginal cost of each parcel. $N\_parcels_i$ denotes the parcel demand in zone i.

$$Parcel\, marginal\, cost_i = \frac{Zonal\, marginal\, cost_i}{N\_parcels_i} \tag{3.5}$$

Overall, this method accurately reflects the price increments triggered by parcels in delivery and fairly allocates the total cost to individual parcels, thus making the cost of each parcel more transparent and calculable. This helps LSPs to optimize resource allocation and cost control in the delivery network. Through this approach, the marginal cost of each zone can be quantified, thus identifying which zones have a greater impact on the overall delivery cost, which thereby provides an important reference for improving logistics efficiency.

3.1.2. Emission-based method

The COFRET method, as a emission-based method for identifying outlier parcels, measures the CO2 emissions generated by LMD of parcels and aims to define outlier parcels as those with significantly higher than average delivery CO2 emissions. High CO2 emitting parcels mean that more energy is consumed during the delivery process, resulting in higher greenhouse gas emissions. This not only increases the environmental burden, but also has a negative impact on LSPs, including environmental regulatory compliance pressures, tarnished brand image and reduced customer satisfaction. Identifying and handling these parcels is therefore critical for LSPs to reduce their carbon footprint, improve green performance, increase operational efficiency and achieve sustainability goals.

Same as the marginal cost method, the COFRET method are carried out on a delivery tour basis, and several tours form a complete delivery network. A delivery tour visits several zones to deliver parcels. The COFRET method calculates the CO2 emissions of parcels in each tour separately, thus obtaining the CO2 emissions of all the parcels in the delivery network so as to filter the outlier parcels. Similarly, it is assumed that the parcels are uniformly distributed in the zones and the parcels have a uniform size and weight.

The procedure of calculating parcel emission by the COFRET method is shown in Figure 3.2, the unit of CO2 emission is kg. The method first measures the total CO2 emission produced in the tour using the travel distance of the delivery vehicles. Then, the total tour CO2 emission is assigned to each zone successively by utilizing the weight factor occupied by each zone. Due to the homogeneity of the parcels, zonal CO2 emission is eventually distributed evenly to each parcel.

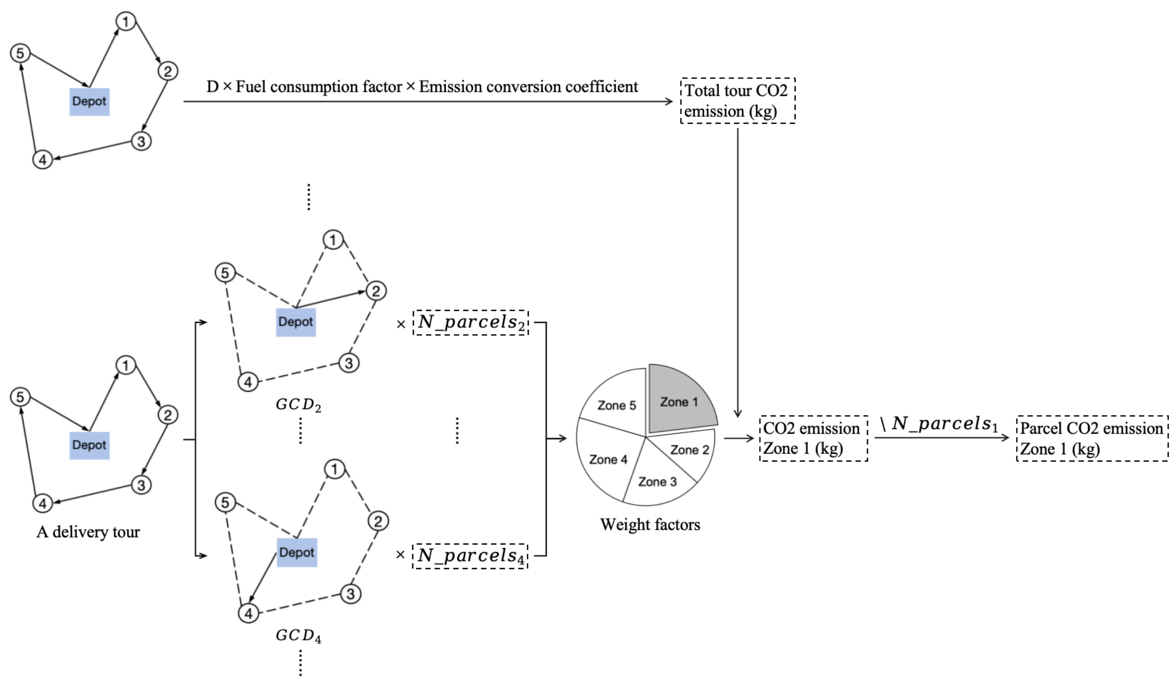


Figure 3.2: The COFRET method

In order to perform the allocation of CO2 emission, the first step is to calculate the total CO2 emission generated during the delivery by vehicle travel tour distance. There are two common approaches to measure vehicle CO2 emissions, one is called Activity-based approach, the other is called Energy-based approach. Activity-based approach is to take the travel distance (km) of the vehicle during delivery and multiply it directly by a CO2 conversion factor (kg/km) to obtain an estimate of emissions. Energy-based approach first converts the vehicle travel distance (km) during delivery to fuel consumption (kg) by multiplying a Fuel consumption factor (kg/km), and then multiplies the fuel consumption with an Emission conversion coefficient to finally obtain CO2 emissions (kg). Cefic (2011) pointed out in their research that Energy-based approach is the most accurate way for LSPs to calculate CO2 emissions, while Activity-based approach is usually an estimation method used in processes where fuel consumption is not directly accessible, and is mostly used in the chemical industry who outsources their cargoes, resulting in poor calculation accuracy. Therefore, in this study, Energy-based approach is selected to calculate the total tour CO2 emission. D also denotes the total tour travel distance, in the unit of km. The calculation formula of total tour CO2 emission is shown in Equation 3.6.

$$\begin{aligned} &Total\,tour\,CO2\,emission \\ &= D\,*\,Fuel\,consumption\,factor\,*\,Emission\,conversion\,coefficient \end{aligned} \tag{3.6}$$

After getting the total tour CO2 emission, the CO2 emission of each zone was then calculated. Based on the COPRET method, in order to allocate the emission to each zone, it is necessary to calculate the weight factor of each zone, i.e. the proportion of emission that each zone should be allocated. Weight factor is calculated based on the distance of the parcel transported to demand zone from the depot and the volume of parcels transported. The farther the parcels are transported and the more volume it take up, the greater the proportion of emissions allocated to each zone. The distance of parcels transported is measured by the GCD (Great circle distance), which is the straight line distance from the depot to the delivery zone in km. As mentioned in the literature review, this measurement avoids the influence of the delivery order on the allocation and ensures a fair allocation. The volume of parcels is measured by number of parcels delivered to the zone, since each parcel is assumed to be homogeneous.

Therefore, for a delivery tour that visits several zones sequentially, the zonal weight factor is calculated based on each zone in turn. For a given zone, the percentage obtained by multiplying the GCD from the depot with the number of parcels delivered to that zone and then dividing by the sum of the products is the zonal weight factor. Equation 3.7 shows the calculation of the weight factor for zone i in a total of n zones in one delivery tour. denotes great-circle distance between zone i and the depot, and $N\_parcels_i$ denotes the parcel demand in zone i.

$$WeightFactor_i = \frac{N\_parcels_i * GCD_i}{\sum_{i=1}^{n} N\_parcels_i * GCD_i} \tag{3.7}$$

Based on the zonal weight factor, the total tour CO2 emission is then allocated to each zone. Equation 3.8 denotes the zonal CO2 emission that allocate to in zone i in kg.

$$Zonal\,CO2\,emission_i = Total\,tour\,CO2\,emission * WeightFactor_i \tag{3.8}$$

In the last step of the method, the resulting zonal CO2 emission is allocated to each parcel within the zone to calculate the CO2 emission of individual parcels. Since the parcels are assumed to be uniformly distributed in the zone, the zonal CO2 emission is allocated to each parcel equally. To be specific, the CO2 emission allocation equation for zone i is shown as follows.

$$Parcel\,CO2\,emission_i = \frac{Zonal\,CO2\,emission_i}{N\_parcels_i} \tag{3.9}$$

Overall, through the calculation process described above, the COFRET method can accurately reflect the CO2 emissions generated by parcels during delivery and can equitably allocate the total emissions to each zone. These parcels usually result in higher emissions due to longer delivery distances or higher capacity. By calculating the carbon footprint of parcels, logistics service providers can identify outlier parcels with high emissions and take appropriate measures to optimize their delivery strategies and reduce their carbon impact, thereby improving green performance and ultimately achieving the goal of sustainable development.

3.2. MASS-GT - Data source

In order to implement the aforementioned methods for outlier parcel identification in LMD systems, MASS-GT can be used as an efficient tool. Assessing strategic decisions on freight policy is commonly conducted using simulation models. Yet, most operational models do lack the necessary behavioral complexity to effectively simulate representative and satisfactory impacts of developments in logistics services, policy measures, or planning scenarios (de Bok & Tavasszy, 2018). MASS-GT is an aggregated agent-based model developed by de Bok and Tavasszy that simulates the freight transportation in south Netherlands based on a large dataset. This model is built upon three main principles: commodity-based approach, representing agent-based decision making explicitly, and implementing empirically tested choice model(de Bok et al., 2022). In this research scenario, the agents could be LSPs, customers, etc., which could mimic real-world behaviors and decision-making processes in the simulation. Simulating the impact of different outlier parcel identification strategies on the logistics system can be achieved by adapting the behaviors and rules of these agents. Several modules are conducted in MASS-GT and two of them are related to last-mile parcel delivery, i.e., parcel demand module and parcel scheduling module, which will be applied in this research.

Parcel demand module is based on multiple datasets and is developed to accurately measure the demand for B2C and B2B parcels in each zone. B2B parcel demand is estimated based on the zonal socio-economic data collected by the National Bureau of Statistics (CBS), including employment and household data, together with market monitoring data from the Netherlands Authority for Consumers & Markets (ACM), which ensures that the model reflects the actual logistics demand. B2C parcel demand is estimated through an ordered logistic regression model that incorporates individual and household characteristics data from Mobility Panel Netherlands (MPN) to anticipate the frequency of online shopping for each individual, thus deriving the parcel demand in different zones. The demand is then calibrated to the base year market monitoring data in order to match the actual market size. This process preserves zonal demand differences and ensures the accuracy of the total demand volume. ACM's monitoring data also reflects the market share of the different CEP in the Netherlands. After determining the demand for parcels, it is then allocated according to the market share of each CEP. The parcels allocated to specific CEP are further allocated to their respective depots to make sure that each parcel has an origin (a depot) and a destination (a zone in which households are located). Parcel demand module provides the data base for the subsequent modules, while it does not contain a description of the weight and volume of the parcels. Table 3.1 shows the statistics of the market share for each CEP in the Netherlands applied in the parcel demand module. In this case, PostNL has a significantly higher market share than other CEP based on volume, followed by DHL. The remaining four CEP have close market shares.

Table 3.1: CEP market share

CEP	Share NL	Share Foreign	Share Total
PostNL	62.5%	24%	50.8%
DHL	27.5%	13%	23.1%
DPD	2.5%	28%	10.2%
GLS	2.5%	8%	4.2%
UPS	2.5%	24%	9.0%
FedEx	2.5%	3%	2.7%

Parcel scheduling module simulates the assignment of parcels and the formation of distribution routes in detail based on the data generated by parcel demand module. Parcel allocation is performed first, and the parcels to be delivered are assigned to the nearest depot of the corresponding CEP. Assume that each CEP has optimized its operations to deliver from the nearest depot. Next, based on the delivery zone, a list of parcels to be delivered is generated and assigned to specific depots. A list of parcels is created for each depot taking into account the maximum capacity of the vehicle. Parcel delivery with vans has been already modelled in parcel scheduling model, and the maximum capacity of van is set to 180 parcels with the travel time of van for a single trip is no more than 8 hours. Once the parcel list is generated, parcels will be assigned to available vehicles and the departure time will be determined based on the distribution of delivery times during the day. If the number of parcels exceeds the van capacity, the van will return to the depot, update the parcel list and reschedule the undelivered parcels. Finally, a matrix of tours and trips of 24 hours is created where each tour describes in detail its itinerary, start time, travel time and information about the parcels contained.

Table 3.2 shows an example of a delivery tour output by parcel scheduling module. The tour is handled by PostNL and each row represents a specific delivery task (trip). Each trip consists of several fields, for instance, CEP represents the delivery company, $Depot\_ID$ represents the depot number. $Tour\_ID$ is the unique identifier of the tour, while $Trip\_ID$ and $Unique\_ID$ are the unique identifiers of each delivery trip respectively. O_zone and D_zone represent the numbers of the origin and destination zones, and the precise delivery location of each parcel in the zone is unavailable. $N\_parcels$ field records the number of parcels in each trip, and $Traveltime$ is the travel time for each trip. $TourDepTime$ and $TripDepTime$ denote the tour departure time and the trip departure time. Type field identifies the type of the task, and only Delivery is considered in this study, though MASS-GT considers the case of pick up delivery in the simulation, it is not applicable to this research that studies the case of outlier parcels. $TourDist$ indicates the delivery distance of each trip, and $VehType$ is the vehicle type, which is only considered for van delivery in this study. $OrigType$ and $DestType$ indicate the type of origin and destination as Depot to HH (Household).

Table 3.2: Output of parcel scheduling module in MASS-GT

CEP	Depot_ID	Tour_ID	Trip_ID	O_zone	D_zone	N_parcels	Traveltime	TourDepTime	TripDepTime	Type	TourDist	VehType	OrigType	DestType
PostNL	1	1.0_83	1.0_83_0	2668	1	1	0.371	7.878	7.878	Delivery	19.128	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_1	1	52	11	0.116	7.878	8.283	Delivery	2.63	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_2	52	66	24	0.026	7.878	8.766	Delivery	1.61	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_3	66	68	26	0.048	7.878	9.592	Delivery	0.519	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_4	68	873	36	0.078	7.878	10.507	Delivery	2.197	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_5	873	872	55	0.058	7.878	11.784	Delivery	0.729	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_6	872	71	4	0.079	7.878	13.676	Delivery	1.852	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_7	71	51	12	0.091	7.878	13.888	Delivery	1.704	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_8	51	50	10	0.03	7.878	14.378	Delivery	0.772	Van	Depot	HH
PostNL	1	1.0_83	1.0_83_9	50	2668	0	0.366	7.878	14.742	Delivery	18.322	Van	Depot	HH

To conclude, parcel demand module and parcel scheduling module are closely related, with the former providing the base data for the latter. Parcel demand module first estimates the demand of parcels in different zones and generates a synthetic dataset containing the sources (depots) and receivers (zones) of parcels. Parcel scheduling module then utilizes these data to assign parcels to specific depots and form specific tours based on it. This undertaking relationship ensures the logic and continuity of the simulation of the entire parcel delivery process from demand estimation to actual scheduling, thus generating highly accurate simulation results. The simulation outcomes obtained from parcel scheduling module will be used as inputs to this study for identifying outlier parcels.

3.3. Chapter overview

This chapter describes in detail the outlier parcel identification strategies based on cost and CO2 emission, with specific implementations including the marginal cost method and the COFRET method. The marginal cost method accurately calculates the cost of parcels in LMD by calculating the marginal cost of each zone in delivery network, aiming at identifying those parcels that produce higher costs in the delivery process. The COFRET method measures the CO2 emissions of parcels in LMD, accurately reflecting the carbon footprint of each parcel to identify parcels with higher emissions in the delivery process.

These two approaches provide clear guidance for the subsequent simulation process. Outlier parcels will be identified based on setting thresholds, and parcels with high marginal costs as well as high CO2 emissions will be considered as outlier parcels. Cost-based and emission-based outlier parcel identification strategies can provide scientific and effective decision-making support for the logistics industry, thus enhancing customer satisfaction while reducing environmental burdens.

MASS-GT is an effective tool for implementing these two methodsproviding a comprehensive simulation platform for research. Parcel demand module and Parcel scheduling module in MASS-GT will be applied to ensure the logic and continuity of the whole parcel delivery process from demand estimation to actual scheduling. The output tours of the parcel scheduling module will be used as input for implementing cost-based and emission-based method for further outlier parcel identification and analysis.

4

Implementation and results

This chapter demonstrates the results of the implementation of the two methods described in Chapter 3 based on MASS-GT and provides a detailed analysis of the outlier parcel identification results. Firstly, the study area of this research and the delivery of parcels in this area are presented. Then, the results calculated by the two methods are shown separately and outlier parcels are identified for different CEPs, with a summary of the numbers and proportions. The geographical distribution of the existence of outlier parcels for each CEP and the combined geographical distribution will be presented and analyzed. After that, detailed explanation on tours of cost-based method will be provided to reasonably explain the reasons for the distribution of outlier parcels. Finally, a sensitivity analysis of carbon cost value is conducted to assess the impact of adding CO2 cost to marginal costs on the proportion and distribution of outlier parcels.

4.1. Use case

South Holland is one of the most economically developed regions of the Netherlands, with Europe's largest port, the Port of Rotterdam. It is highly urbanized and is the headquarters of many international organizations and companies. The province has one of the largest populations in the Netherlands, reaching up to 3.6 million and covering an area of 3,403 km^2. South Holland has a well-developed transportation network, including road, rail, water and public transport systems(Cavallo, 2007). Figure 4.1 illustrates the study area of this research located in South Holland as well as the locations where the depots of the CEPs are located as mentioned in the previous section. A total of 15 depots of these CEPs are located in the South Holland region, but only 8 of them are used to delivery parcels to the study area. The study area for this research consists of five municipalities and cities in South Holland, namely Delft, Midden-Delfland, Rijswijk, 's-Gravenhage (The Hague), and Leidschendam-Voorburg, which is divided into 2524 zones in MASS-GT with an area of 209.3 km^2. These areas are located in the western part of the Netherlands within the Randstad metropolitan area, which is one of the most important metropolitan areas in the country. In this study area, around 90,000 parcels are delivered one day in total. The delivery of these parcels are simulated in MASS-GT and the identification of outlier parcels will be based on these parcel delivery data output from MASS-GT.

In the study area, a total of 484 delivery tours are made within one day. These delivery tours are delivered by 6 CEPs as mentioned in the previous section. The number of tours delivered by each CEP is shown in Table 4.1, which matches well with their market share.

Table 4.1: Number of tours delivered by various CEPs

CEP Name	Number of tours
PostNL	239
DHL	116
DPD	50
GLS	21
UPS	44
FedEx	14
Total	484

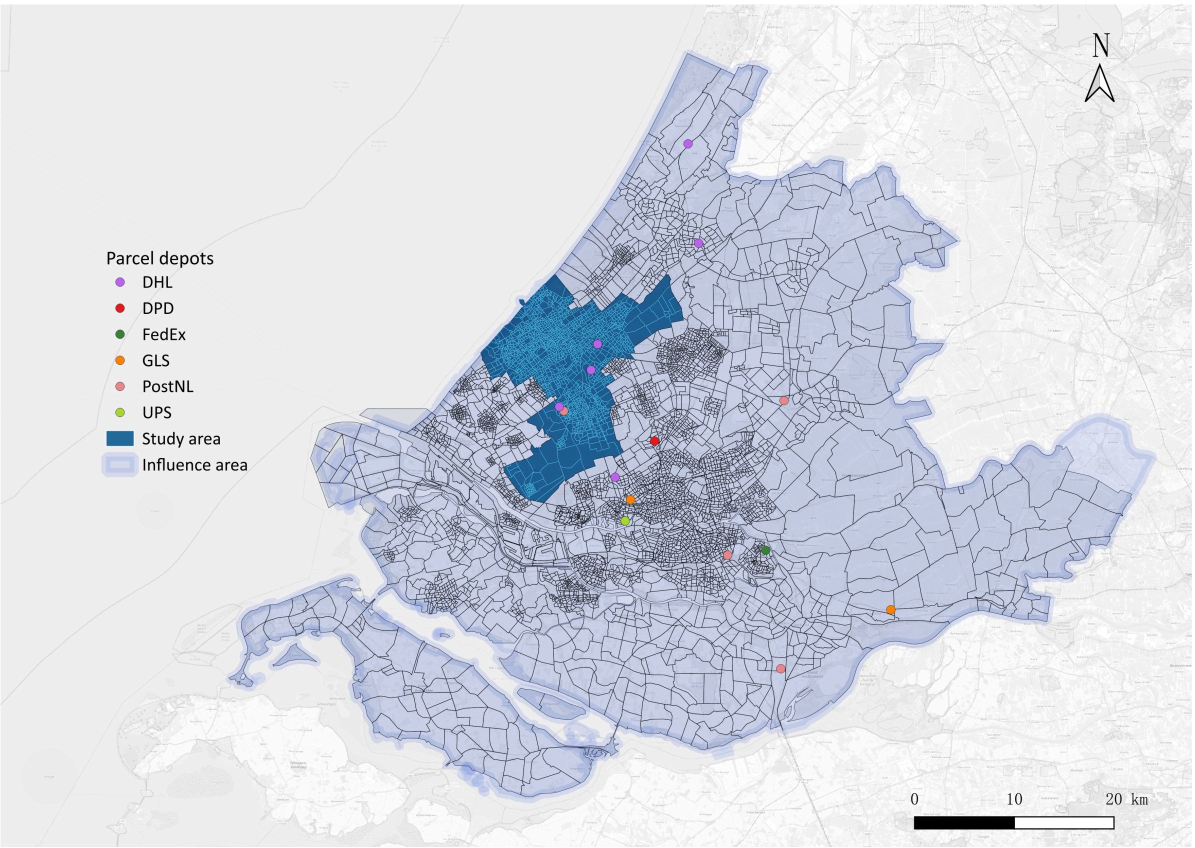


Figure 4.1: Study area and depot locations in MASS-GT

4.2. Cost-based identification

This section shows the results of implementing marginal cost method for cost allocation and the elbow point method for outlier parcel identification and then provides an intensive analysis of the results obtained. Due to the large differences between different CEPs such as depot location, market share, delivery routes, etc., a separate calculation and analysis will be performed for the tours for each CEP.

4.2.1. Identification result

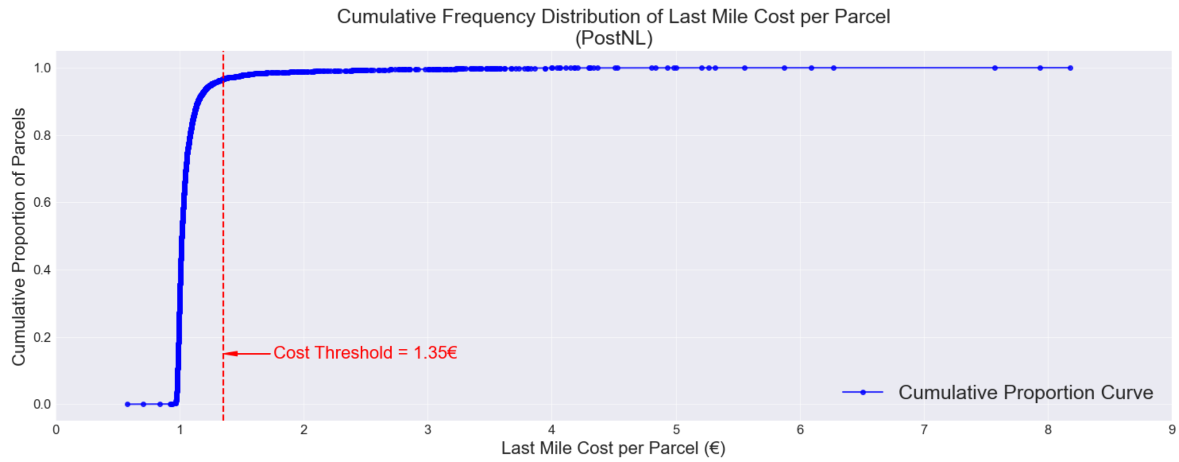
After implementing the cost-based allocation method mentioned in section 3.1 for all tours in the study area, the marginal costs of all parcels will be calculated. The drop-off time in MASS-GT is 120s per parcel and time coefficient and distance coefficient by van are 0.1644 euro/h and 29 euro/km respectively. By sorting the parcel data according to different CEPs, both the number of parcels delivered by each CEP and its corresponding marginal cost would be obtained. After getting all the relevant data, different cost thresholds will be selected for different CEPs in order to obtain the number and proportion of outlier parcels, as the network structure varies for each CEP.

In order to achieve the identification of outlier parcels, the study selects marginal cost of parcels as x-axis, creates the cumulative frequency curve for each CEP separately, and selects the elbow point on the curve, making the x value of elbow point as the cost threshold value. Cumulative distribution curve (CDF) is an effective way to show the data distribution, through which the distribution of parcel marginal cost could be clearly shown. CDF represents the x-axis as the marginal cost and the y-axis as the cumulative number of parcels that do not exceed that cost, so as to get a comprehensive understanding of the distribution of the cumulative number of parcels under different marginal cost levels.

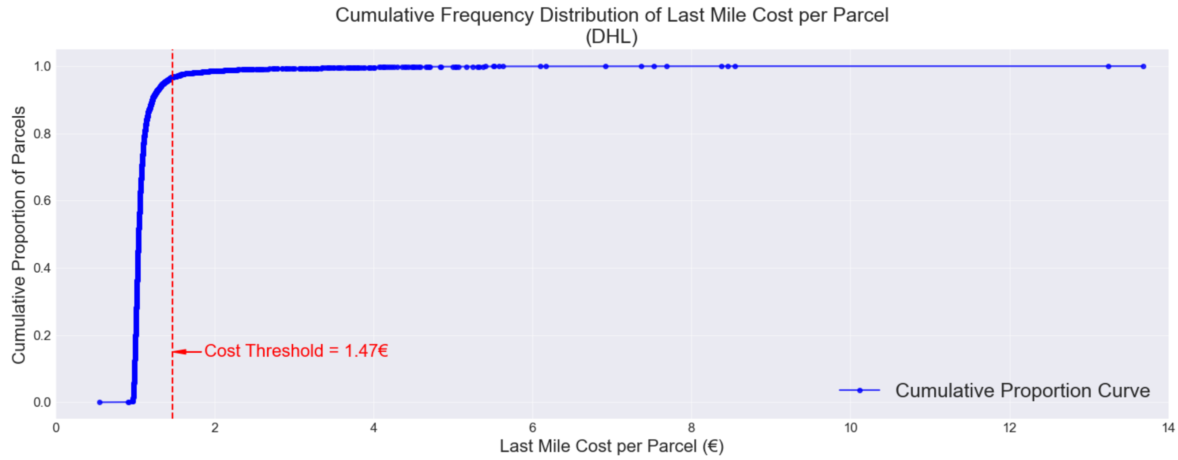
When determining the cost thresholds, the elbow point method is used, which is a threshold selection method based on the change in curvature of the data distribution. Specifically, it finds the point on CDF with the largest change in curvature, which usually represents the "inflection point" of the data distribution (Antunes et al., 2018). The core idea of the method is: before the inflection point, the curve is steep, indicating a slow increase in cost and a rapid increase in the number of parcels; after the inflection point, the curve is flat, indicating a faster increase in cost and a slower increase in the number of parcels. Therefore, the marginal cost at the inflection point can be used as a reasonable threshold for identifying high-cost outlier parcels. Elbow point method provides an objective and data-driven way of determining the threshold, avoiding the influence of subjective judgement. By selecting the point with the largest change in curvature, it is able to sensitively capture the key change points in the data distribution and ensure the reasonableness of the threshold.

At the level of company benefits, the elbow points represent the point where error minimization stagnates. Before the elbow point, cost reductions are significant, and the economic benefits from each unit of cost reduction are obvious. It means that a company's investment in this part of the process could lead to larger returns. But after the elbow point, the marginal benefit of cost reductions becomes pretty small that further optimization can only result in small cost reductions. This means that investing more resources to continue to reduce these costs will not result in significant economic benefits and may even lead to a waste of resources. Thus, using the elbow point as a threshold for outlier parcels can avoid the need to invest too much resources on these parcels and focusing on more cost-effective optimizations.

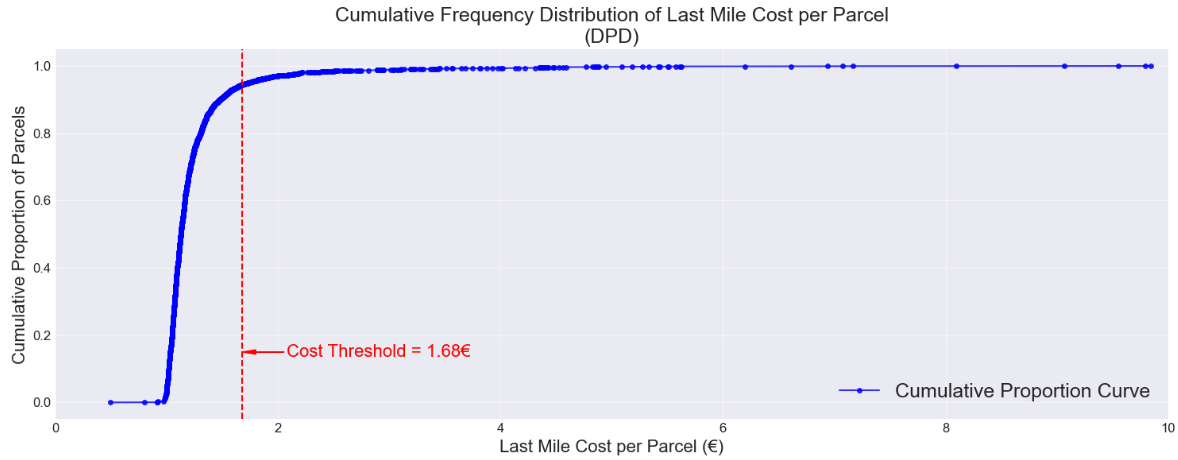
Figure 4.2 illustrates the CDF corresponding to each CEP as well as the results of the threshold selection. Each CEP has a different cost threshold, which are marked by the red dotted line on the figures. This threshold is the upper cost limit used to identify outliers.



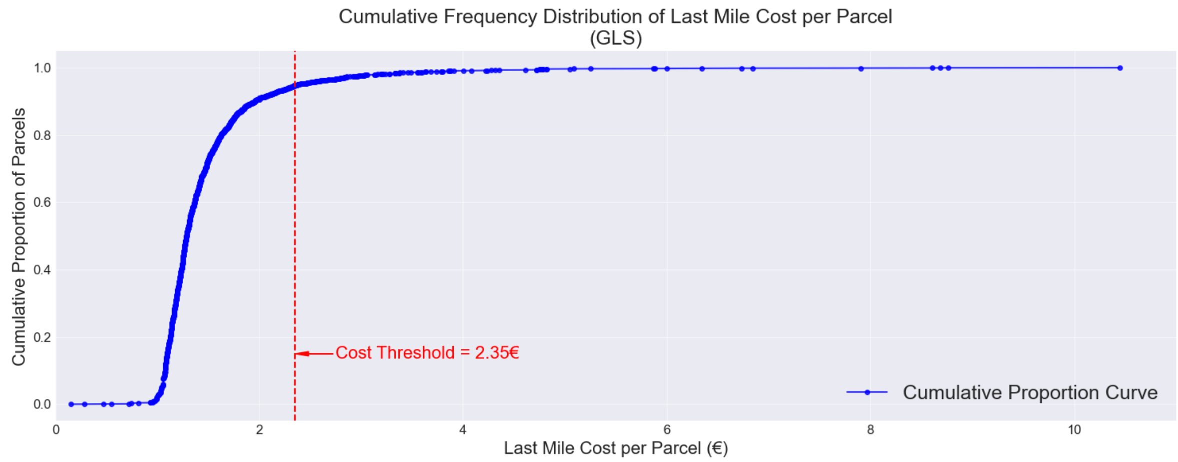
(a) PostNL



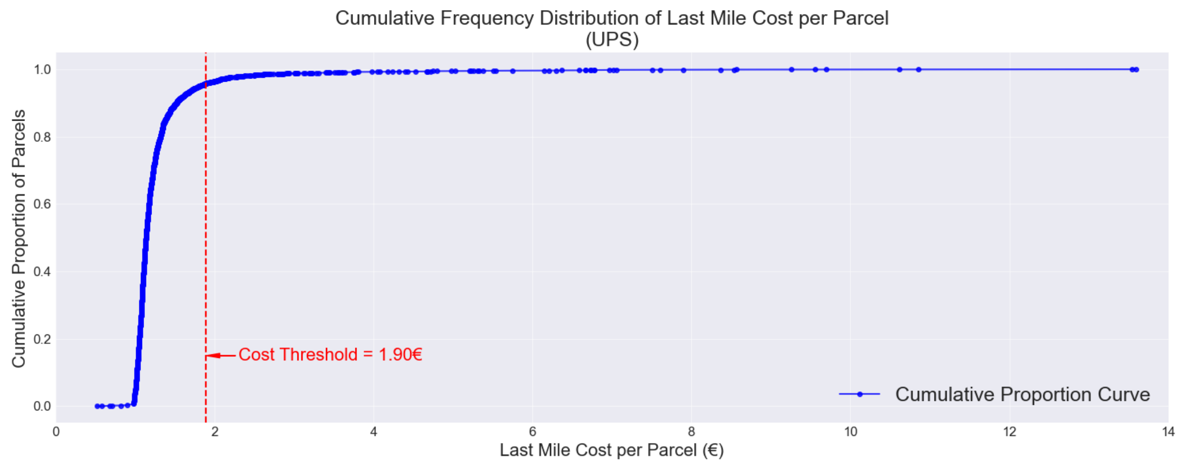
(b) DHL



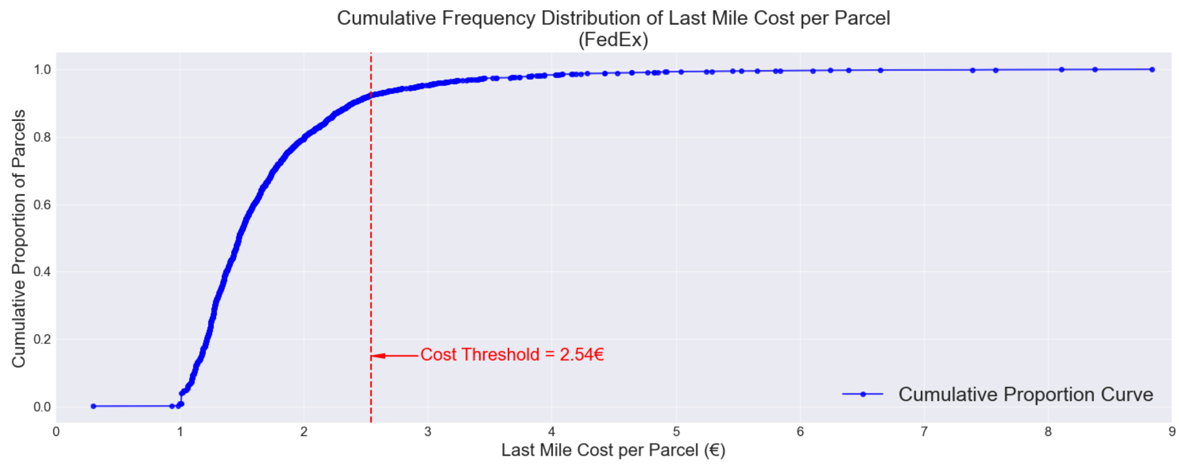
(c) DPD



(d) GLS



(e) UPS



(f) FedEX

Figure 4.2: Parcel cost distribution & Threshold for each CEP

According to the figures, all curves show a steep rise and then followed by a plateau period, which perfectly matches the typical characteristics of CDF. This indicates that most parcels have relative low last mile costs and only a few have significantly higher costs. It is worth noting that the ranking of the threshold for each CEP displays the same trend with the ranking of their market share. The curve for PostNL and DHL shows a relatively steep upward trend compared to others, suggesting that their last-mile marginal costs are more densely distributed. Meanwhile, they have relatively low cost thresholds compared to other CEPs, which are 1.35 euro and 1.47 euro, suggesting that they are more effective in controlling costs for last-mile delivery.

GLS and FedEx have flatter rising curves and larger thresholds than the other four CEPs, possibly due to the location of their depots being farther away from the main distribution areas, which raises the overall cost of parcel delivery. It may also be because of its low market share, which makes it difficult to realize economies of scale. A company with a low market share has fewer parcels in a certain area with insufficient coverage and density of its distribution network, resulting in the necessity to cover a larger geographic area for every single delivery, which also increases the delivery costs. At the same time, a low volume of parcels leads to a low loading rate of transport vehicles and inefficient transport, which also increases the unit cost of delivering parcels.

Table 4.2 counts the results of outlier parcel identification for each CEP. A total of 85,771 parcels are delivered in the study area, and a total of 3,229 parcels are identified as outlier parcels, which accounts for approximately 3.8% of the total number of parcels. The number of outliers is directly proportional to the number of parcels delivered. PostNL and DHL have the largest number of delivered parcels and the largest market share, but their proportion of outliers is relatively low, suggesting that they perform outstandingly in terms of cost control and operational efficiency. Fedex has a small number of outliers but the highest proportion (7.56%), which also confirms its several potential deficiencies. The number of outlier zones reflects the geographic distribution of outliers. PostNL has the highest number of outlier zones, and its broad service coverage results in outliers appearing in more zones. GLS and FedEx have a relatively low zonal average number of outlier parcels, suggesting that their outlier parcels are more dispersed within each zone.

Table 4.2: Cost-based outlier identification result for each CEP

CEP	#Parcel delivered	Threshold value (€)	#Outliers	Percentage (%)	#Outlier zones
PostNL	42792	1.35	1391	3.25	274
DHL	20313	1.47	656	3.23	244
DPD	8866	1.68	490	5.53	259
GLS	3684	2.35	192	5.21	161
UPS	7775	1.90	323	4.15	194
FedEx	2341	2.54	177	7.56	164

In order to validate the reasonableness of the elbow point method for identifying thresholds of outlier parcels from the companies' perspective, an interview was conducted with DHL. As DHL provided, the average cost per parcel delivered in last-mile delivery is 3.87€. In reality, however, this cost is a combination of several costs. Fleming (2023) concludes that the labour cost accounts for about 50-60% of the LMD parcel delivery cost, which is the most expensive part. Fuel costs, vehicle-related and equipment-related costs account for about 35%, while reverse logistics costs account for about 10% of the total cost. Since factors other than delivery distance and delivery time were not considered in the calculation of parcel costs in this study, the resulting parcel costs should be the aforementioned fuel and vehicle-related costs. In this case, the average parcel cost should be 35% of 3.87€, i.e., 1.35€. And for this study, the average parcel cost for DHL is calculated to be 1.4€, which is quite similar to the value obtained in the interviews, indicating that the dataset used in the study is representative and generally consistent with reality. DHL cost threshold identified by the Elbow Point method is 1.47 , which is slightly higher than the average value. By using a threshold slightly above the average, it ensures that high-cost parcels are identified. The average value, as a representation of the trend in the dataset, proves that the threshold is in line with the statistical rule.

Figure 4.3 shows the geographical distribution of outlier parcels and a hierarchical display of their numbers on the map of study area for each CEP. Different classes of the outlier parcel numbers are indicated by shades of color. The map also shows the location of the depot for each CEP, and some CEP depot locations are not shown due to being far away from the study area such as UPS and FedEX whose depot are located in the south-east part of the study area.

(a) PostNL

(b) DHL

(c) DPD

(d) GLS

(e) UPS

(f) FedEX

Figure 4.3: Cost-based geographic distribution of outlier parcels for each CEP

From the figures, it is worth noting that some outlier parcels are distributed very close to the depot, representing that the marginal costs of these parcels are relatively high, and this situation is reflected in the distribution maps of PostNL and DHL. As these parcels are not delivered over long distances or in long delivery times, the clustering of these parcels around the depot seems to be unreasonable. Also, some zones have a higher probability of having outlier parcels, for example, several CEPs have outlier parcels in the most southern and eastern zones of the study area. It is observed that the distribution of outlier parcels of PostNL, DHL, DPD and UPS are more aggregated at the edges of the study area, which may be due to the higher operation cost and delivery difficulty in the edge zones. The distribution is more dispersed in the city centers, and the formation of these outlier zones is strongly correlated with the formation of the tours that pass through them. Detailed explanation of the reasons for the distribution of these outlier parcels will be given in the next sub-section.

4.2.2. Analysis for the distribution of outlier parcels

Based on the above mentioned characteristics of the distribution of outlier parcels in the study area, detailed explanations are provided to explain the reasons for these distributions respectively regarding the outlier parcels around the depot, in the edge area, and in the center of the region. The first aspect of the analysis focuses on the distribution of outlier parcels in the adjacent zones around the depots. Figure 4.4 shows two delivery tours by PostNL and DHL from their depots respectively, both of which pass through one of the surrounding zone of their depots and generate outlier parcels. In this case, the outlier zones of the parcels are highlighted in red and the trips entering and leaving the zones are also marked in red in order to show the detours generated by delivering parcels to those zones. The parcel depot for each CEP is also shown in the figure, with the depot for PostNL marked with a pink dot and the depot for DHL marked with a purple dot. It is clear that the vehicles make a certain detour to deliver the parcels, which results in a higher incremental cost in these two outlier zone.

However, it is not just detour that causes the generation of outlier parcels in these near-depot zones, but also because the number of parcels delivered to these zones by trips in each tour is low. It is important to note that both of the two outlier zones in the figures have more than one tour passing through and delivering parcels, and several parcels delivered by

(a) PostNL delivery tour (b) DHL delivery tour

Figure 4.4: Tours of outlier parcels around depots

trips in those tours to these zones are defined as outlier parcels. Setting DHL as an example, the outlier zone number of DHL shown in Figure 4.9b is 1409, and there are totally 11 outlier parcels exist in that zone and these outlier parcels are generated from 11 different trips in 11 different tours that pass through this zone.

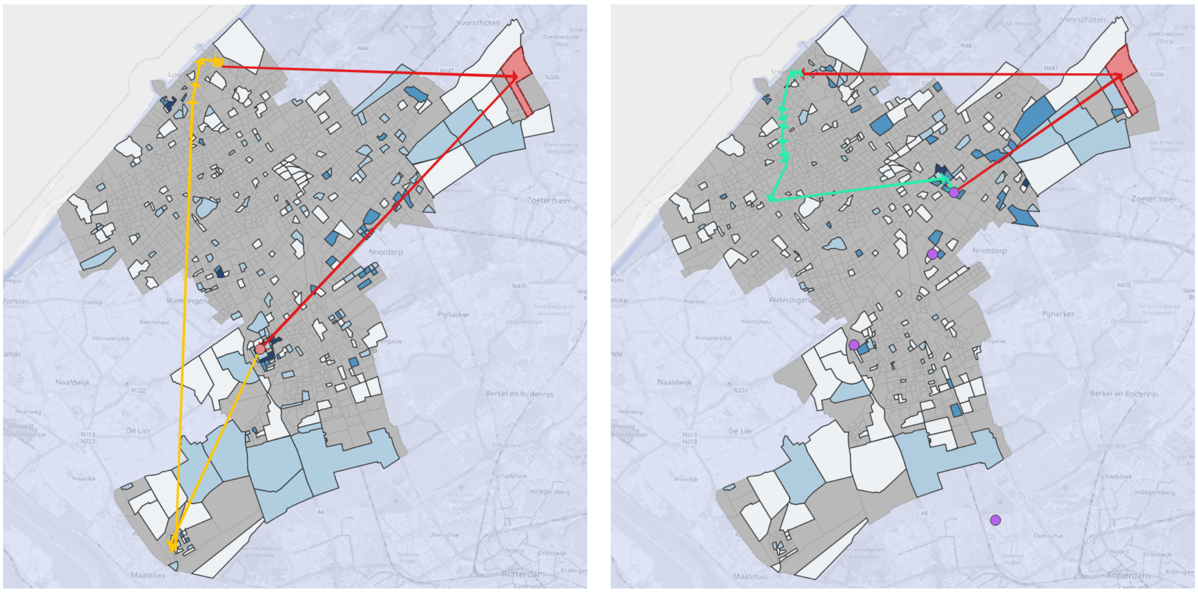
Table 4.3 shows the aforementioned 11 Tour_IDs and Trip_IDs of all the outlier parcels exist in this zone as well as the number of parcels delivered to this zone in each trip. As can be seen from the table, each trip that generates outlier parcels in this zone has only assigned one parcel to be delivered to the zone. Since in the calculation of parcel marginal cost for each tour, the zonal marginal cost is divided by the total parcel demand in each zone in order to evenly allocate the cost to all parcels within the zone, thus low number of parcels delivered by each trip in zone 1409 is also the main reason for generating high cost parcels. Similarly, by analyzing the other few zones surrounding the depot that generate outlier parcels, almost all trips in different tours deliver only one parcel when passing through these near-depot zones, and only a few trips deliver 2-3 parcels, which is also a low volume. Therefore, although delivering parcels from depot to these neighboring zones does not require a long detour, the average parcel marginal cost in these zones are still large that lead to the generation of outlier parcels.

Table 4.3: DHL outlier trips & tours and delivery parcel numbers in Zone 1409

CEP	Tour_ID	Trip_ID	D_zone	N_parcels
DHL	9.0_376	9.0_376_0	1409	1
DHL	9.0_369	9.0_369_0	1409	1
DHL	9.0_374	9.0_374_11	1409	1
DHL	9.0_375	9.0_375_2	1409	1
DHL	9.0_370	9.0_370_0	1409	1
DHL	9.0_371	9.0_371_0	1409	1
DHL	9.0_378	9.0_378_0	1409	1
DHL	9.0_373	9.0_373_0	1409	1
DHL	9.0_377	9.0_377_0	1409	1
DHL	9.0_372	9.0_372_13	1409	1
DHL	9.0_433	9.0_433_1	1409	1

The second aspect is concerning the zones where most of the courier companies have outlier parcels. These outlier zones are located in the eastern and southern fringe of the study area. These areas are far from centers with sparse populations and low parcel demand, while delivery is more difficult, as vehicles often need to take long detours to deliver the small volume of parcels in these areas, resulting in higher delivery costs.

Taking the tours delivered by PostNL and DHL in the most eastern part of the study area as an example, as shown in Figure 4.5, both of the two CEPs generate outlier parcels in the same zone that coloured in red, and the trips in and out that zone and the depots location are also shown in both of the figures. The number of parcels delivered by PostNL and DHL in that zone is 3 and 2, respectively, which are quite low, proving the low demand for parcels in the remote area. In the process of delivering parcels to this zone, very long detours are made, which further increases the delivery cost, resulting in high marginal cost for parcels in those zones.



(a) PostNL delivery tour

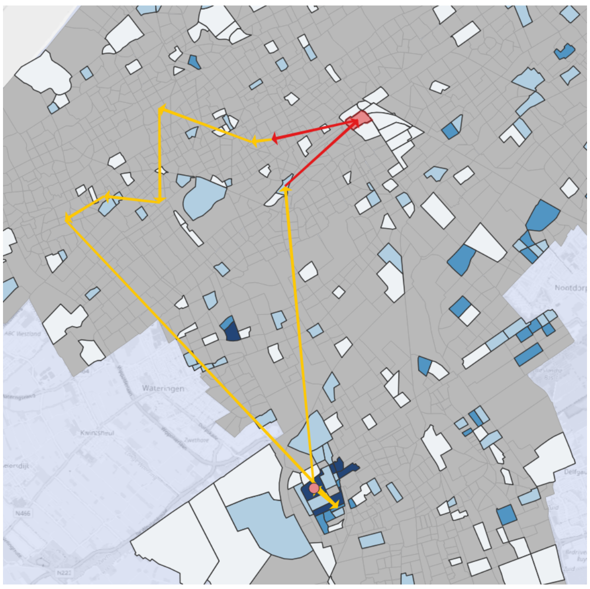
(b) DHL delivery tour

Figure 4.5: Tours of outlier parcels in edge area

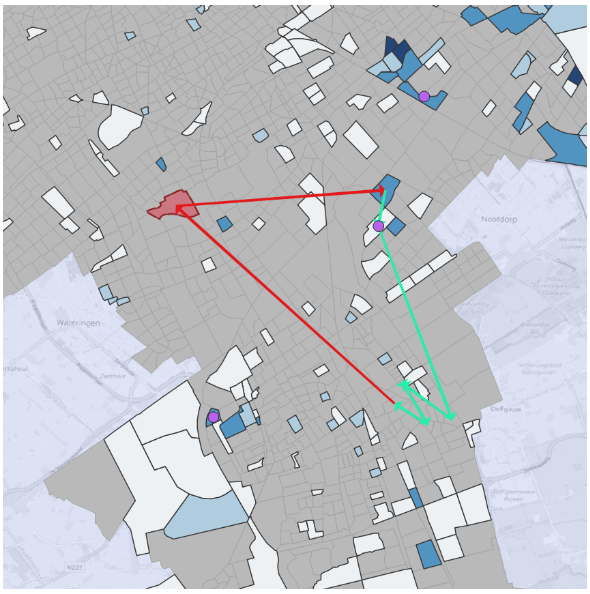
Similarly, by analyzing different delivery tours in all other edge zones, it is found that this phenomenon is generalized across different CEPs. After delivering the parcels in the central region, vehicles generally have to take long detours to deliver these parcels in the edge zones, which also leads to a significant increase in the delivery time, resulting in the generation of outlier parcels in most of the edge zones and forming a cluster of outlier zones.

However, in the geographical distribution of GLS and FedEx, no such clusters of outlier zones are shown in eastern and southern edge areas as can be seen in the other four CEPs. This is due to the fact that when parcel scheduling is performed, the network structure of their deliveries results in their parcels being delivered to limited zones in that area, and thus no significant clusters of outlier zones are formed. In contrast, the other four CEPs have more delivery coverage in eastern and southern edge areas, thus all of them form clusters of outlier zones in the context of high delivery effort in these areas.

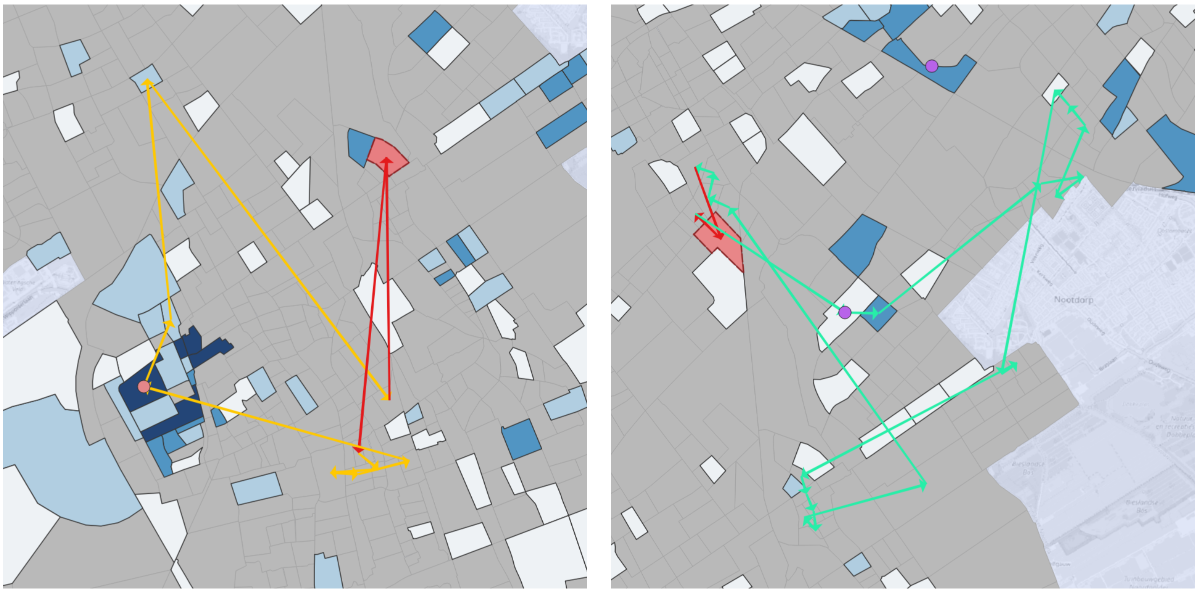
The third aspect analyzes the outlier zones that are in the center of the study area. For each CEP, some zones in the center of the study area are also distributed with different numbers of outlier parcels, which do not present a specific pattern but are caused by vehicle detour or the formation of tours. Taking PostNL and DHL as examples, Figure 4.6a & 4.6b show their delivery tours starting from depot and generating outlier parcels in a certain zone in the center of the study area respectively. The generation of these outlier parcels is also due to the fact that vehicles need to make detours when delivering parcels in these zones, which takes more delivery time and resources. Figure 4.6c & 4.6d also show delivery tours that generate outlier parcels in city center area. Different from Figure 4.6a & 4.6b, these outlier zones are caused by tour formation. In the parcel delivery process, the vehicle did not choose the optimal delivery route for nearby deliveries, but made a return trip. This irrational routing choice led to a reduction in overall delivery efficiency, increased delivery time and path redundancy, which resulted in the formation of outlier parcels.



(a) PostNL delivery tour



(b) DHL delivery tour



(c) PostNL delivery tour (d) DHL delivery tour

Figure 4.6: Tours of outlier parcels in the center of study area

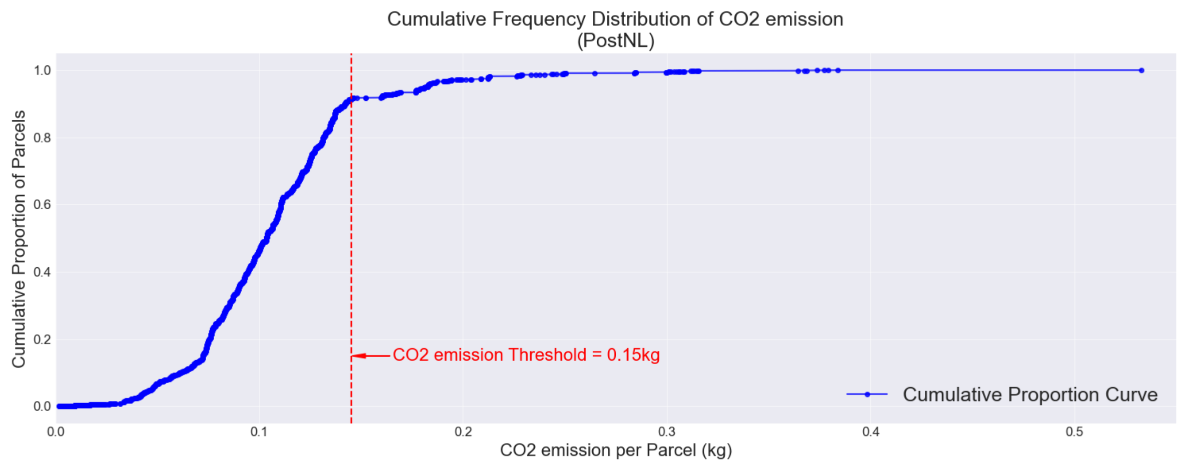
Through these analyses, the main reasons for the emergence of outlier parcels in different zones are revealed, providing an important basis for understanding and optimizing the delivery network.

4.3. Emission-based identification

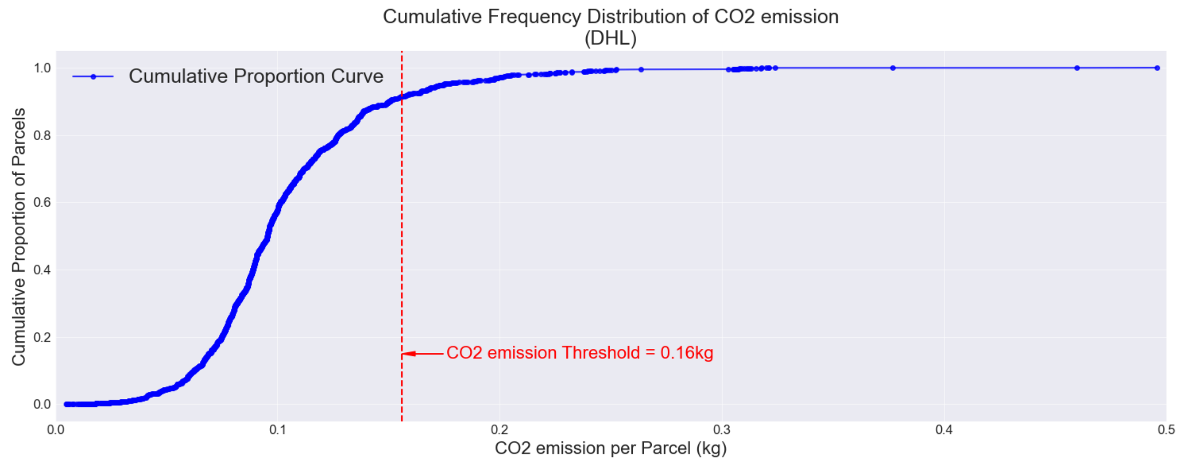
After applying the emission-based allocation method mentioned in section 3.2 to all tours in the study area, the last-mile CO2 emission values of all parcels in unit kg will be obtained. Similarly, the obtained parcel data are categorized according to the CEPs and the CDFs are plotted separately to show the distribution of parcel CO2 emission for each CEP. Also the elbow point method is carried out to select CO2 emission thresholds for each CEP in order to obtain the number and proportion of outlier parcels for sustainability considerations.

According to the COFRET method, the Fuel consumption factor and Emission conversion factor must first be obtained to convert the total tour travel distance into fuel consumption, and then convert the fuel consumption into CO2 emissions. Light Commercial Vehicles (LCVs) are used for parcel deliveries. According to a statistic from the European Automobile Manufacturers' Association (ACEA), 93.3% of LCVs in the Netherlands use diesel as fuel Association (2023). ARTEMIS project simulates the actual driving cycles of vehicles in the European urban environment and evaluates vehicle emissions and fuel consumption under different driving conditions. Based on the data provided by ARTEMIS, the diesel consumption for LCVs per kilometer in urban driving ranges from $0.1362 - 0.1343L/km$ Mellios et al. (2011). Therefore, 0.135 as an intermediate value L/km is selected as the fuel consumption factor in this study. Emission conversion factor is obtained from CO2 Emissiefactoren (2024), which records official statistics on CO2 emission factors in the Netherlands.The Well-to-Wheel (WTW) emission conversion factor for diesel is 3.468 kg CO2 per liter for LCV.

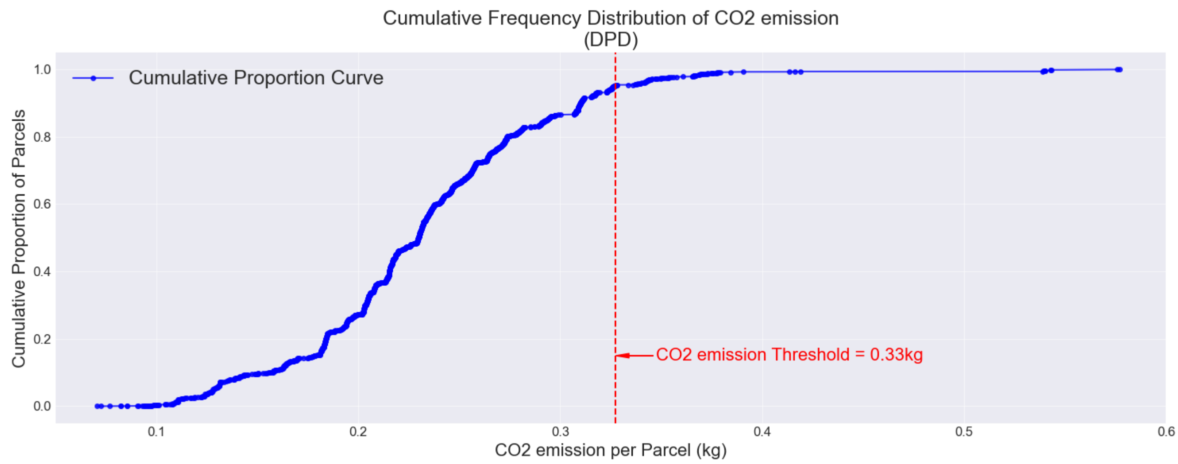
Figure 4.7 demonstrates the results of the COFRET method for identifying outlier parcels for each CEP. Similarly, there are significant differences in the CO2 emission thresholds for each CEP, reflecting the differences in the environmental impacts of each CEP during the LMD process. The red dashed lines mark the threshold positions.



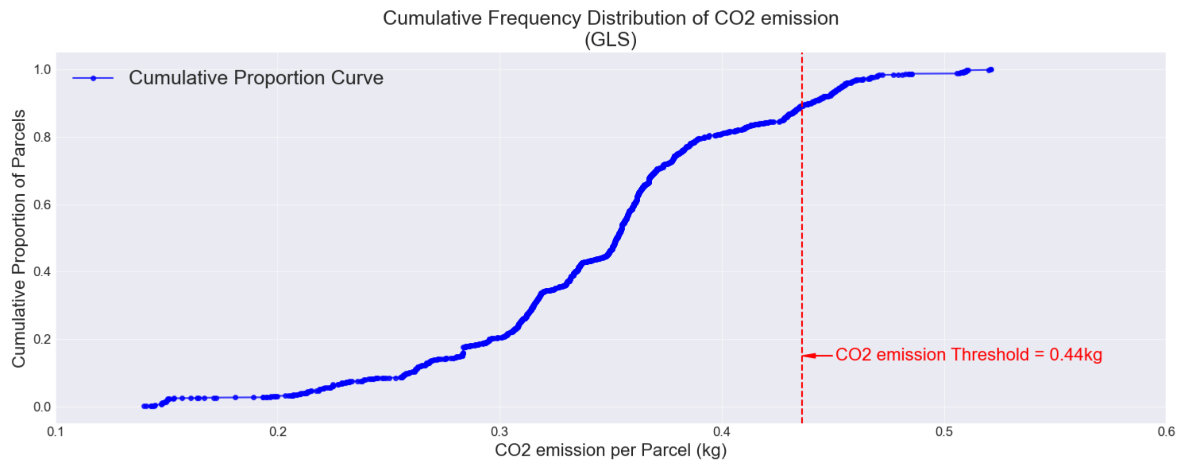
(a) PostNL



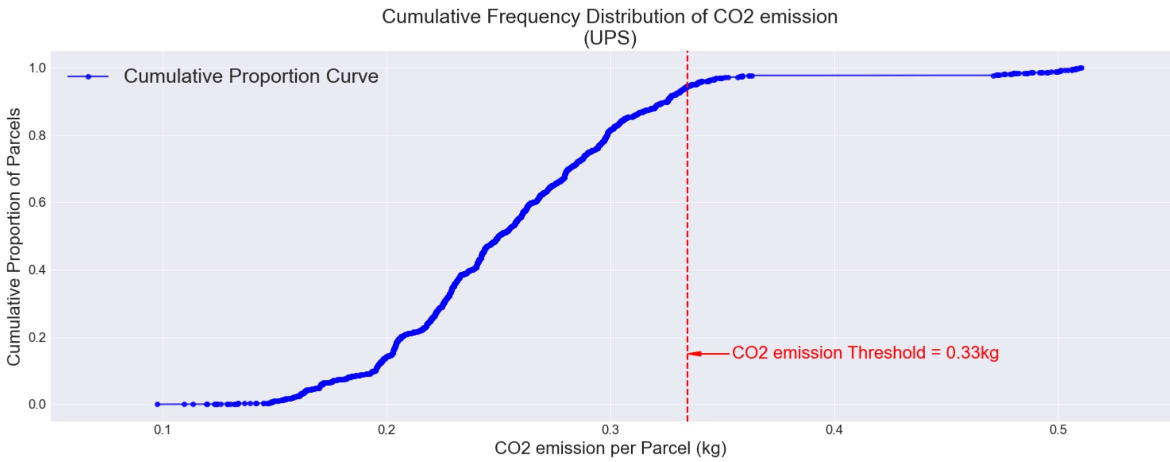
(b) DHL



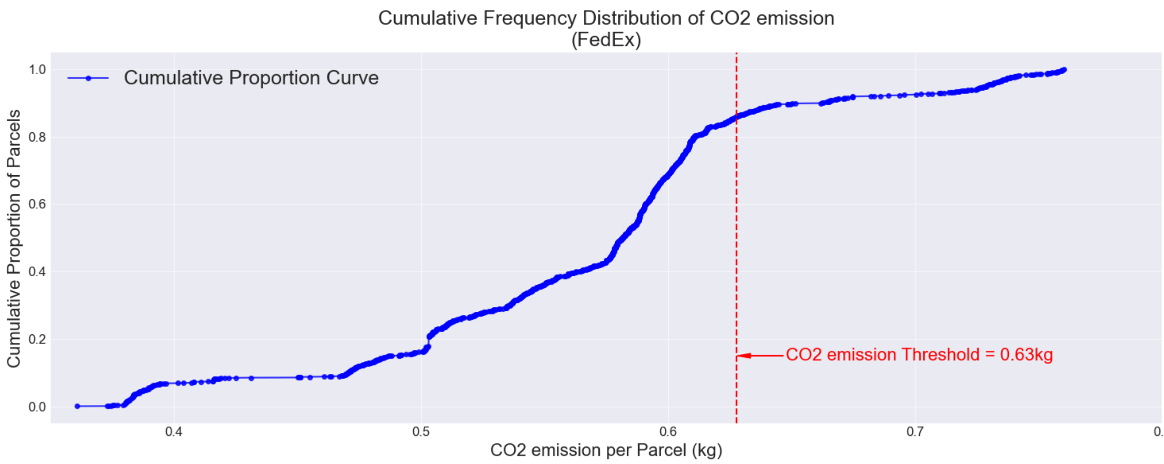
(c) DPD



(d) GLS



(e) UPS



(f) FedEX

Figure 4.7: Parcel CO2 emission distribution & Threshold for each CEP

Slightly different from the CDF distribution shown by the cost-based method, all of the curves of six CEPs rise more gradually, possibly due to the more evenly distribution of the parcel CO2 emission values accross the emission intervals. PostNL and DHL show the same trend of CO2 emission thresholds as cost thresholds, which are the lowest among the 6 CEPs, which may be due to their high market shares and high vehicle loading rate, thus allowing them to better optimize their delivery networks and reduce emissions. And the transportation distance is the main factor contributing to CO2 emissions. There are three DHL depots and one PostNL depot in the study area and all of them are centrally located, which also reduces the parcel delivery distance.

In contrast, FedEx has the highest CO2 emission threshold and the curve is flatter around this value, indicating that its parcel CO2 emissions are generally higher. The increased delivery distance due to the distance of its depot from the main delivery area is also the primary reason for its high parcel emissions.

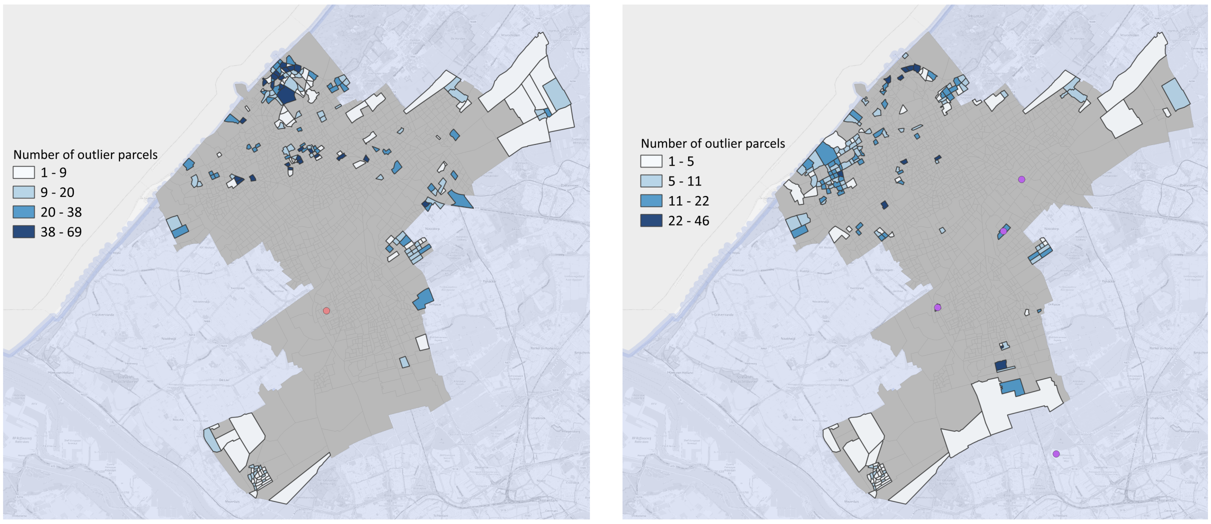
Table 4.4 counts the results of outlier parcel identification for each CEP. The total of 85771 parcels are delivered in the study area, and 7220 parcels are identified as outlier parcels, accounting for about 8.4% of the total parcels, which is much more than cost-based method.

DPD has the lowest proportion of outlier parcels and outlier zones, indicating its environmental protection control in LMD is more effective. FedEx has the highest proportion of outlier parcels and the highest number of outlier zones, which may be caused by the complex geographical conditions and the unevenness of the demand area.

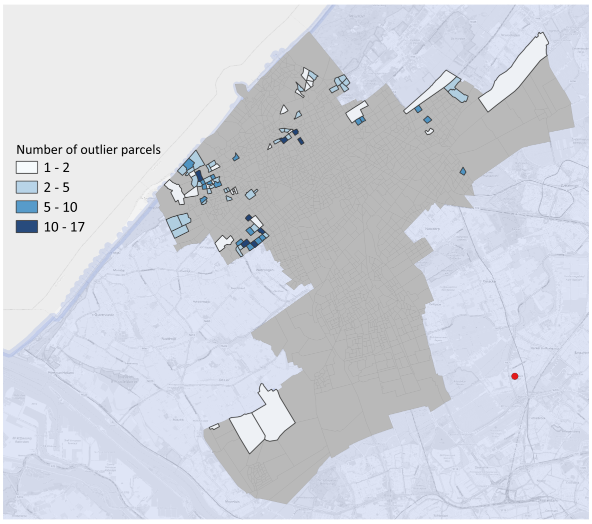
Table 4.4: Emission-based outlier identification result for each CEP

CEP	#Parcel delivered	Threshold value (kg)	#Outliers	Percentage (%)	#Outlier zones
PostNL	42794	0.15	3579	8.36	201
DHL	20316	0.16	1722	8.48	191
DPD	8867	0.33	422	4.76	89
GLS	3684	0.44	398	10.80	147
UPS	7776	0.33	424	5.45	111
FedEx	2341	0.63	325	13.88	192

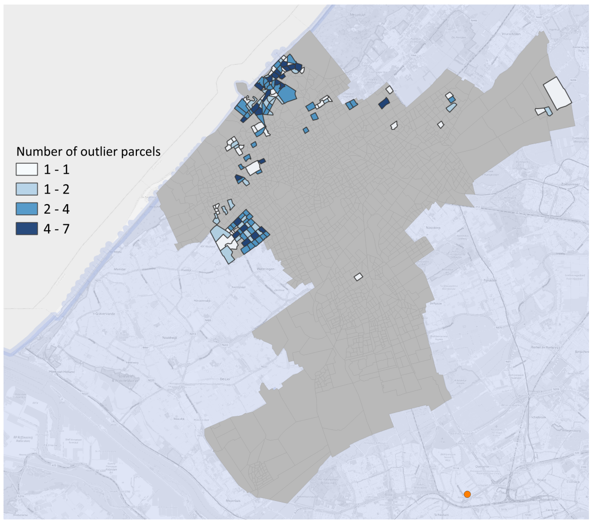
Figure 4.8 shows the geographic distribution of outlier parcels as well as a hierarchical display of their quantities. The shades indicate the cumulative number of outlier parcels in specific zones. Some depots are also failed to be shown in the map. The geographic distribution of outlier parcels reinforces the plausibility that parcel delivery distance is directly proportional to CO2 emissions, as the vast majority of outlier parcels are located in areas farther away from the depot. Parcels at the edges require more delivery effort and are therefore more likely to contain outlier parcels. It's important to note that outlier parcels are mostly clustered, as seen in several CEPs. Aggregation of outlier parcels also exists in the middle of the study area. And there is a situation in DHL where outlier parcels exist in the zone where one of the DHL depots is located, which does not seem to be reasonable. But in reality, the outlier parcels that exist in the zones where these depots are located are not issued by this depot, but are handled by other depots, thus generating higher CO2 emissions.



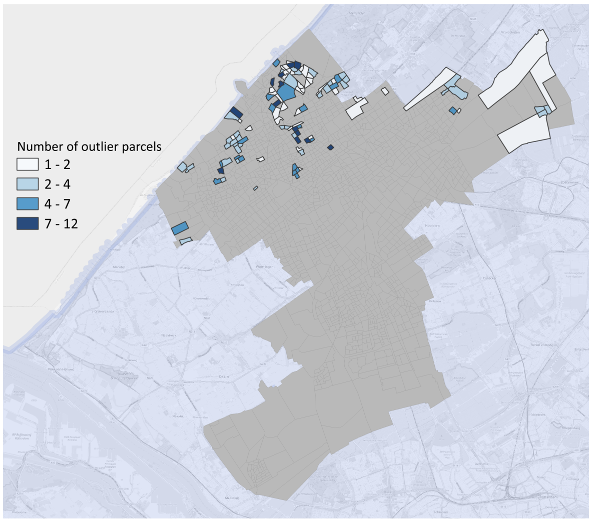
(a) PostNL (b) DHL



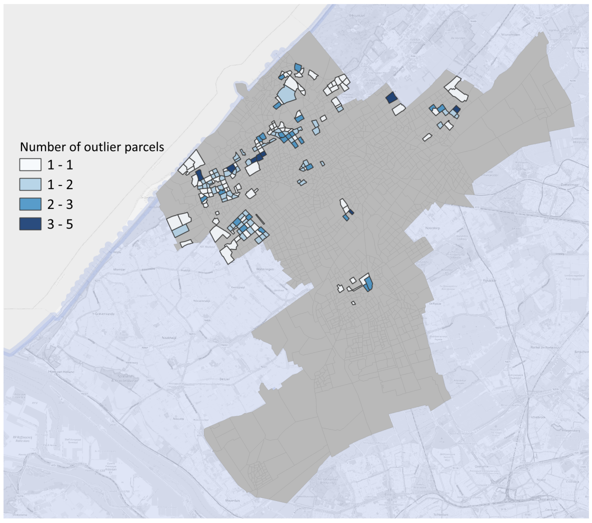
(c) DPD



(d) GLS



(e) UPS



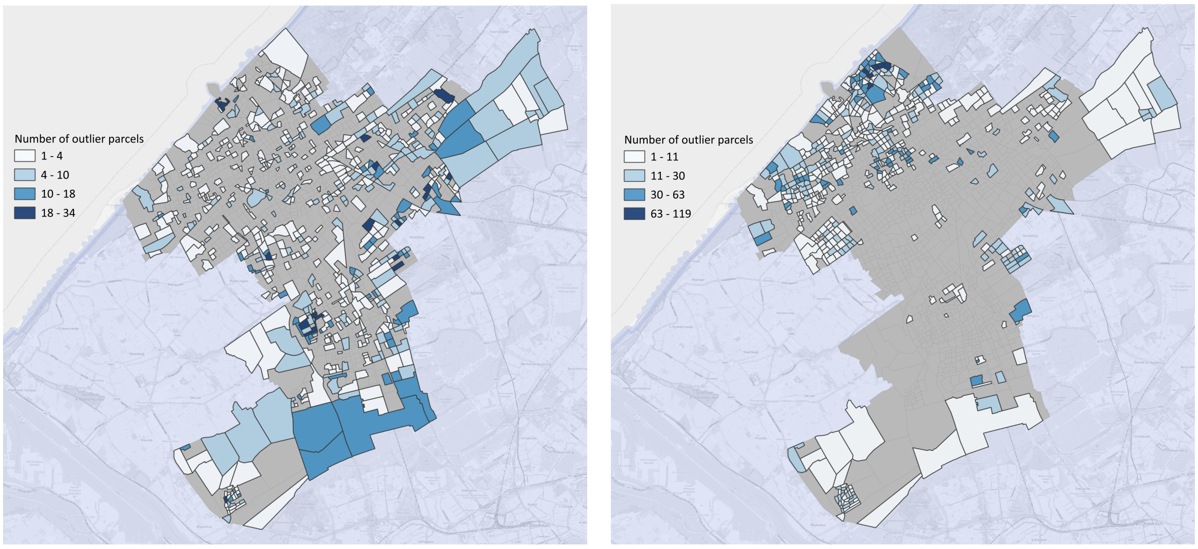
(f) FedEX

Figure 4.8: Emission-based geographic distribution of outlier parcels for each CEP

4.4. Combined identification result

After completing the identification of outlier parcels for different CEPs for two methods, the amount of outlier parcels identified by different CEPs based on the cost-based and emission-based method and their distribution zones are combined and displayed in two maps below respectively, as shown in Figure 4.9a and Figure 4.9. Shades of colour in the zones indicate the superposed number of outlier parcels. It can be seen that for cost-based method, 619 out of 2524 zones contain outlier parcels, which accounts for 24.5%. The number of outlier parcels in zones ranges from 1 to 34, which are decentralized in the center of the study area and have relatively small numbers, implying that the logistics services in the center area are comparatively more complete. Concentrated distribution is shown in the edge of the study area, and the number is relatively larger. One of the reasons is that the need for large detour to deliver parcels to edge areas and the low delivery volume of these parcels in each CEP, obtained from the previous detailed tours analysis, leading to the accumulation of high-cost parcels at the edge of the study area. It may also be due to the lack of logistics services and poor transportation conditions in edge areas, resulting in higher delivery costs.

For emission-based method, a total of 536 zones have outlier parcels, accounting for 21.2% of all 2,524 zones. The highest cumulative number of outlier parcels in a zone reaches 119. Most of the outlier zones are concentrated in the edge of the study area. It is worth noting that the northwestern part of the study area, i.e., s-Gravenhage region, contains 942 zones but 392 outlier zones, accounting for 41.6% of total outlier parcel zones, which is pretty high, being the main distribution area of the outlier zones. This is due to the fact that the value of CO2 emission is largely determined by the distance of the distribution zones from their corresponding depots. While among the depots of 6 CEPs, except for PostNL and DHL, which have 1 and 3 depots respectively that are located within the study area, thus might reduce the CO2 emission of their corresponding parcels to a certain extent, the rest of the depots are distributed in the southeast side out of the study area, which is far away from the s-Gravenhage region, thereby resulting in higher CO2 emissions generated during the delivery process. The detailed locations of the depots for different CEPs can be referred to Figure 4.1.



(a) Cost-based distribution

(b) Emission-based distribution

Figure 4.9: Combined distribution of outlier parcels

By comparing the cost-based and emission-based methods, it becomes evident that while both methods highlight outlier parcel zones concentrated on the edge of the study area, the emission-based method identifies a larger cluster in the northwestern region, driven by depot distance. These suggest that not only does logistics inefficiency in remote zones lead to higher costs, but also significant CO2 emissions. Therefore, optimizing both logistics operations and depot locations could reduce both the financial and environmental impact of deliveries. This combined identification result offers a crucial insight for designing sustainable and cost-effective logistics strategies.

4.5. Sensitivity analysis

In this section, in order to explore the impact of taking both cost and environmental factors into account on the identification of outlier parcels, firstly, the CO2 emissions (kg) of each parcel calculated by the COFRET method would be converted to the corresponding CO2 cost (€). This conversion process based on a predefined value of carbon cost, which reflects the economic impact of the carbon emissions on the environment. The conversion equation is performed as follows.

$$CO_2\ cost\ per\ parcel = Carbon\ cost \times CO_2\ emission\ per\ parcel \tag{4.1}$$

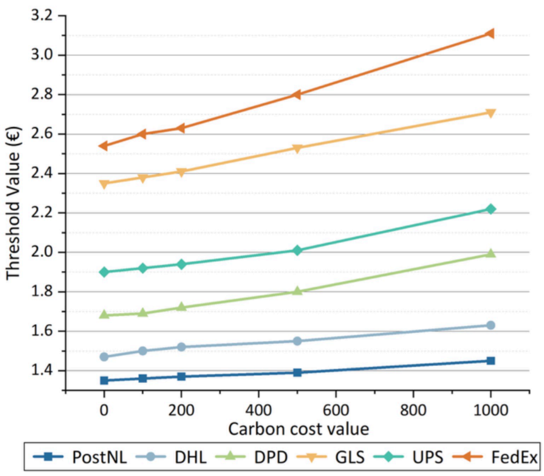
Then, it would be added to the corresponding parcel marginal cost to obtain a new integrated cost indicator that includes not only the economic cost of all parcels, but also the environmental cost. Based on the new integrated cost index, the identification of outlier parcels can be re-conducted. Meanwhile, by changing the value of carbon cost to make sensitivity analysis, the impact of different carbon cost on the outlier parcel identification results can be evaluated. Specifically, by observing the changes in the identification of outlier parcel thresholds, the proportion of outlier parcels, and the number of outlier parcel zones for different values of carbon cost, the impact of the introduction of carbon cost on the economic cost and the sensitivity of different parcels and zones to the carbon cost can be revealed.

Four carbon cost scenarios were tested, with carbon price of 100, 200, 500 and 1000, covering a range of carbon costs from low to high. Napp et al. (2019) pointed out in their study that although the carbon price is currently stabilized at 70 $€/ton$, the price of carbon is expected to rise gradually over time and is expected to reach 1,000 $€/ton$ in 2050, or even 3,000 $€/ton$ by the end of the century, which is an inevitable result of combating the policy of climate change. Therefore setting a range of carbon prices from 100 to 1,000 euros can cover from the current low level to the high price levels that may be reached in the future, so as to simulate parcel delivery operations under different time points and policy scenarios. In practice, the proportion of environmental costs is relatively small compared to the economic costs of parcels, and even if a high carbon price value is set, the impact on integrated costs is limited. Nevertheless, with the gradual increase of the carbon price, the impact of this cost may gradually emerge, especially in scenarios where parcels are delivered over long distances. In current situation, even if the carbon cost reaches 1000 $€/ton$, the average parcel CO2 cost will only reach about 10% of the average marginal cost. Only when the carbon cost reaches 10,000 $€/ton$ will they reach the same weight, which is not possible to achieve. The outlier parcels identification results obtained after the integrated cost calculation for each of the 6 CEPs at different carbon cost values are shown in Table 4.5.

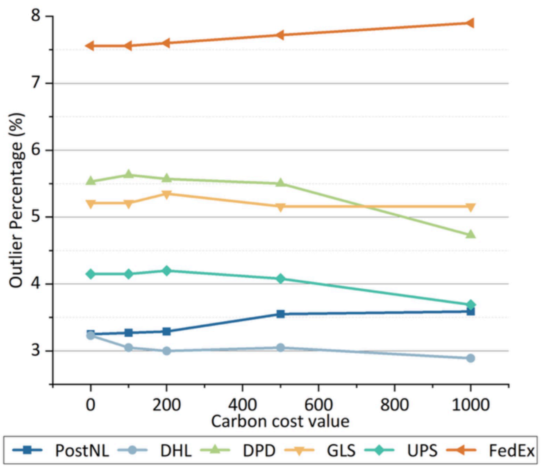
Table 4.5: Sensitivity analysis of carbon cost

CEP	Indicators	Carbon cost value (€/ton)				
		0	100	200	500	1000
PostNL	Threshold Value (€)	1.35	1.36	1.37	1.39	1.45
	Outlier Proportion (%)	3.25	3.27	3.29	3.55	3.59
	# Outlier Zones	274	275	274	284	286
DHL	Threshold Value (€)	1.47	1.50	1.52	1.55	1.63
	Outlier Proportion (%)	3.23	3.05	3.00	3.05	2.89
	# Outlier Zones	244	235	231	231	228
DPD	Threshold Value (€)	1.68	1.69	1.72	1.80	1.99
	Outlier Proportion (%)	5.53	5.63	5.57	5.50	4.73
	# Outlier Zones	259	261	259	257	229
GLS	Threshold Value (€)	2.35	2.38	2.41	2.53	2.71
	Outlier Proportion (%)	5.21	5.21	5.35	5.16	5.16
	# Outlier Zones	161	161	165	161	161
UPS	Threshold Value (€)	1.90	1.92	1.94	2.01	2.22
	Outlier Proportion (%)	4.15	4.15	4.20	4.08	3.69
	# Outlier Zones	194	194	192	190	179
FedEx	Threshold Value (€)	2.54	2.60	2.63	2.80	3.11
	Outlier Proportion (%)	7.56	7.56	7.60	7.72	7.90
	# Outlier Zones	164	164	165	167	172

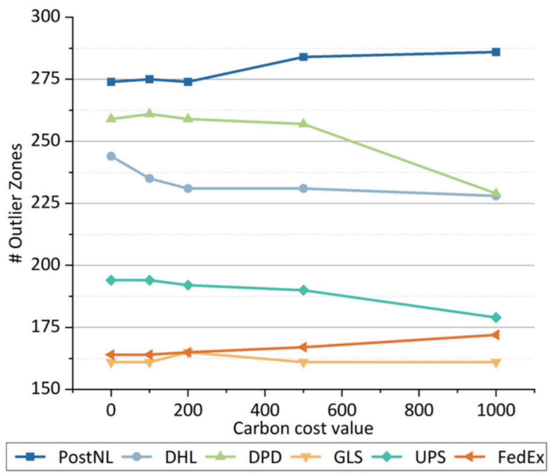
Based on Table 4.5, line charts of each indicator for 6 CEPs with different carbon cost values are plotted in Figure 4.10 to show the trend of the variation of the different indicators.



(a) Threshold value



(b) Percentage of outlier parcels



(c) Number of outlier zones

Figure 4.10: Line charts of different indicators for 6 CEPs

For threshold values, the variations are in line with the expected trend, since with the introduction of carbon cost and its incremental increase, the parcel integrated costs increase accordingly, and thus for each CEP, the threshold value requires to be higher in order to identify the outlier parcels. While the extent of threshold changes varies between CEPs, among them, PostNL has the lowest change, which changes from 1.35 to 1.45, but FedEx has the largest threshold change, which changes from 2.54 to 3.11. This is due to the fact that CO2 cost is directly related to the delivery distance, and the depot of FedEx is the farthest away from the study area compared to others, with parcels generating the highest CO2 emission. Therefore, when the carbon cost increases, their integrated cost of the parcels increases significantly, which leads to a remarkable impact on the threshold of outlier parcels.

The change of the proportion of outlier parcels shows different trends among CEPs as carbon cost increases. For PostNL and FedEx, the percentage of outlier parcels rises as carbon cost increases. PostNL handles a large number of parcels, including many deliveries to remote areas. Long transport distances in remote areas and increased carbon costs further push up the integrated cost of these parcels, making the cost of these parcels more likely to exceed the outlier identification threshold and leading to a higher proportion of outlier parcels. The change in GLS is relatively flat, while the other three CEPs show a decreasing trend. DPD has the most significant downward trend, which changes from 5.53% to 4.73%, probably due to its greater market share in areas with some short-distance, low-emission deliveries, where the increase in the carbon cost has less impact on the integrated parcel cost, and therefore makes the proportion of outlier parcels decrease.

The change in the number of outlier zones has the same trend as the change in the proportion of outlier parcels, which indicates that the change in the proportion of outlier parcels directly affects the number of their distribution zones. For CEPs with a reduced number of outlier zones, with the increase of carbon cost, the proportion of parcel CO2 cost in the integrated cost increases, which makes some outlier zones originally located around the depot gradually disappear from the outlier zones due to the marginal cost advantage is no longer significant. The integrated cost of parcels in these areas becomes closer to the overall average, thus they are no longer identified as outlier parcels. At the same time, the integrated costs of parcels in high CO2 emitting areas that are farther away from depots increase significantly, allowing outlier zones to gradually shift to these areas. This shift centrally reflects the reshaping of the logistics cost structure in different zones by carbon costs, resulting in a remarkable geographic shift in the distribution of outlier parcels. The change in the geographic distribution of outlier zones from carbon cost 0 €/ton to 1000 €/ton for DHL is shown in Appendix B.

In conclusion, through sensitivity analysis, the multilevel impact of changes in carbon costs on logistics operations can be clearly revealed. Specifically, the increase in carbon cost not only directly affects the integrated cost of parcels, which in turn leads to changes in the threshold for identifying outlier parcels, but also has a significant impact on the proportion and geographical distribution of outlier parcels. These changes reflect the differences between different CEPs when facing an increase in carbon cost. By analyzing the changes in the integrated cost of parcels under different carbon cost scenarios, it is possible to assess the direct economic impact of carbon costs on logistics operations. This is crucial for logistics companies to optimize their operations and adjust their market strategies.

4.6. Chapter overview

This chapter shows the results of the implementation of the cost-based and emission-based methods based on MASS-GT in detail and provides an in-depth analysis of the results of the identification of outlier parcels.

Firstly, the study area is introduced, i.e. five cities and municipalities in the province of South Holland. Through the simulation results of MASS-GT, about 90,000 parcels are delivered in this area in one day, involving six major CEPs, and the market shares of these CEPs are roughly matched to the number of tours they deliver in this area.

Subsequently, the results of the identification of outlier parcels and the differences that occur in each CEP are analysed in detail. In the cost-based method, by analyzing the parcel delivery cost of each CEP in the study area, the marginal cost accumulation curve is plotted and the threshold for each CEP is determined by elbow point method. The results show that PostNL and DHL are better in cost control and have lower cost thresholds, while GLS and FedEx have higher delivery costs due to their depot locations being farther away from the center.

The reasons for the generation of outlier parcels are further analyzed through the geographic distribution map of outlier parcels. Among them, the detours or unreasonable tour formation of delivery vehicles in some cases increase the marginal cost of parcels in a particular zone, leading to the generation of outlier parcels. Low demand of parcels in remote zones as well as zones around the depots is also one of the reasons for outlier generation. In addition, through the analysis of the superposed distribution map, it is found that outlier parcels are more dispersed in central area, while the distribution is more concentrated in edge area, which indicates that the logistics network needs to be optimized.

For emission-based method, the cumulative distribution curve and elbow point method are also used to identify outlier parcels with high environmental impacts. Compared to cost-based method, emission-based method identifies a higher percentage of outlier parcels, and the distribution of outlier parcels is more concentrated in the area farther from the depots. This suggests that parcel delivery distance is a major factor affecting CO_2 emissions, especially if the depots are far from the distribution area.

Finally, a sensitivity analysis is conducted to evaluate the impact of economic and environmental costs in the identification of outlier parcels, in order to assess the challenges and changes that logistics operations may face in the future as carbon emission policies are strengthened. Four different carbon cost scenarios are set up in the analysis, covering carbon prices from current low levels to high levels that may be reached in a few decades. The results show that the thresholds of identifying outlier parcels generally increase in each CEP as the carbon cost increases, with varying impacts on the proportion of outlier parcels in different CEPs. In addition, changes in carbon cost affected the geographic distribution of outlier parcels, with more outlier parcels occurring in high-emission zones away from depots, and a gradual decrease in zones closer to depots. This change suggests that the introduction of carbon cost in the logistics network may reshape the logistics cost structure in different regions and affect the geographical distribution of parcel delivery.

5 Conclusion and discussion

5.1. Conclusion

This chapter summarizes the research process as well as the conclusions of the study. The main objective of this study is to explore strategies for identifying outlier parcels in urban delivery environments. The identified outlier parcels are potential candidates for some innovative solutions in LMD which can help LSPs to adapt to the trend of LMD, remain competitive, and enhance the operational efficiency and environmental sustainability. Four sub-questions presented in Chapter 1 are first answered sequentially and the main question is then answered.

SQ1: What is the definition of outlier parcels in the context of last-mile delivery?

In the context of last-mile delivery, outlier parcels are defined as parcels that have a significant negative impact on LSPs during the operations. These parcels may be considered outliers due to their increased operational complexity, or additional logistics management challenges. Unlike traditional statistical outliers, outlier parcels in this study are not defined solely on the basis of the degree of deviation from a numerical value, but rather on the basis of their actual contribution to the efficiency, cost control and environmental impact of the logistics system. Attributes such as cost, CO2 emission, equity, parcel size and weight etc. can all be used for identifying outlier parcels, which affect the operation of LMD.

SQ2: Which cost and CO_2 allocation methods are used for outlier parcels compared to other strategies?

Cost and CO2 emissions are chosen as two key attributes for the identification of outlier parcels. In order to effectively identify these outlier parcels, this study explored a variety of cost and CO2 emission allocation methods in detail and ultimately chose the marginal cost method and the COFRET method as the core methods.The marginal cost method was chosen as it can accurately identify those parcels that significantly increase operational costs by calculating the incremental cost of each parcel over the entire delivery network. By modeling multiple delivery tours and calculating the cost difference when a particular zone is skipped, it was able to accurately assess the impact of parcels from different zones on overall costs. For example, in a given delivery tour, if skipping a parcel in a zone can significantly reduce the overall delivery cost, then parcels in that zone would be defined as outlier parcels.

The COFRET method is used for the allocation and assessment of CO2 emission. The method takes into account the weight of the parcel and the delivery distance to, which ensures that the CO_2 emission of each parcel reflects its true impact on the environment. Through this method, the parcels whose CO_2 emissions are significantly higher than the average are able to identify. The identification of these parcels is critical to achieving the goal of environmental sustainability for LSPs.

SQ3:How do different strategies impact the proportion of outlier parcels?

In this study, the effects of different strategies on the proportion of outlier parcels show significant differences. The study area was selected as five municipalities in the province of South Holland, which are representative of the population density and traffic conditions. MASS-GT was used as the main research tool to simulate parcel delivery in LMD. With information collected from multiple data sources, MASS-GT is able to estimate the demand for parcels in the study area, followed by a detailed simulation of parcel dispatch and delivery tours formation with the parcel scheduling module. The parcel scheduling simulated data was used as the source of parcel data for this study, providing detailed base data for the strategy of outlier parcel identification.

Under cost-based strategy, the study identifies outlier parcels by calculating the marginal cost of each parcel. Using elbow point method, the marginal cost thresholds of outlier parcels are defined and the results of parcel identification including the number of outlier parcels, the proportion of outlier parcels, and the number of outlier zones are counted for six CEPs. The proportion of outlier parcels identified under this strategy is relatively low. PostNL and DHL as the top two CEPs with the highest market share identify the lowest proportion of outlier parcels with 3.25% and 3.23% respectively, while the proportion of outlier parcels for FedEx is the highest with 7.56%. At the same time, the obtained results were validated by interviews with DHL, proving the accuracy and representativeness of the research data.

In terms of geographic distribution, cost-based outlier parcels are mainly caused by large detour, low demand for zonal parcels, or irrational tour formation. Overall, the outlier parcels are mainly gathered in the edge area, and the outlier parcels in the center area are more dispersed and do not show a certain pattern.

Under the emission-based strategy, the study identifies outlier parcels by calculating the CO_2 emissions of each parcel. Under the emission-based strategy, the cumulative distribution functions of the six CEPs are flatter than those of the cost-based method, indicating that the CO_2 values of parcels are more dispersed, and the proportions of identified outlier parcels are significantly higher. The proportion of outlier parcels for FedEx reaches 13.88%, while the proportions of outlier parcels for PostNL and DHL reach 8.36% and 8.48%, respectively. These outlier parcels are usually due to long delivery distances or complex transportation conditions, resulting in a significant increase in CO_2 emissions. In terms of geographic distribution, the formation of outlier parcels is mainly due to the fact that the parcel demand zones are far away from the corresponding depots. For example, in the northwestern part of the study area, outlier parcels are concentrated in zones that are farther away from depots, and the CO_2 emissions of these zones are significantly higher than the average.

Cost-based strategies focus on identifying parcels that increase the operating costs of LSPs, while emission-based strategies focus on identifying parcels that have a high environmental impact. Both identify parcels with different locations and different proportions. This difference indicates that different identification strategies have their own advantages under different operational goals. In actual logistics operations, choosing the appropriate strategy for outlier parcel identification can help logistics service providers optimize resource allocation, reduce operational costs, while reducing environmental impacts and achieving more efficient and sustainable urban delivery.

SQ4: What is the impact of different carbon cost settings on the identification of outlier parcels?

In order to further explore the effect of carbon cost setting on outlier parcel identification, this study explored in detail the effect of carbon cost change on the threshold, proportion and distribution area of outlier parcel identification through sensitivity analysis. The analysis found that the increase in carbon cost had a significant effect on outlier parcel identification. The introduction of carbon cost directly affects the integrated cost of each parcel. As the carbon cost increases, the integrated cost of each parcel increases, and thus the identification threshold of outlier parcels increases. PostNL threshold rises the least, with an identification threshold of 1.35€ when the carbon cost is 0, and it rises to 1.45 when the carbon cost is elevated to 1,000€/ton. the FedEx threshold rises the most, from 2.54€ to 3.11€.

As the carbon cost increases, the proportion of outlier parcels also changes, with different LSPs behaving variously. The proportion of outlier parcels for PostNL is 3.25% when the carbon cost is 0, and rises to 3.59% when the carbon cost is raised to 1,000€/ton. This is because many parcels in PostNL need to be delivered to edge areas, and the increased CO2 cost increases the integrated cost of these parcels significantly, making them more likely to exceed the identification threshold. In contrast, the proportion of outlier parcels for DPD decreased from 5.53% to 4.73%, probably because DPD has a larger market share in short-distance, low-emission zones, and the increase in carbon costs has less impact on its integrated costs, resulting in a reduction in the proportion of outlier parcels.

Changes in carbon costs also affect the geographic distribution of outlier parcels. When the carbon cost increases, the integrated cost of parcels located in high-emission zones far away from depots increases significantly, and the concentration of outlier parcels increases, while it decreases in zones close to depots. Different CEPs show different sensitivities in response to carbon cost increases, suggesting that the specific operating environments and market strategies of each LSP need to be taken into account when formulating and implementing carbon emission policies.

MRQ: How are outlier parcels identified in the context of urban deliveries?

In this study, identifying outlier parcels in urban distribution relies on two key attributes: cost and CO2 emission. Outlier parcels increase the challenge of LMD as they cause negative impacts on LSPs during the delivery process. For this reason, the study applied cost-based and emission-based strategies to identify outlier parcels, respectively.

In cost-based strategy, the incremental cost of each parcel to the whole delivery network is calculated by marginal cost method to identify those parcels that significantly increase the operation cost. These parcels are usually located in zones that require significant detours, have low demand, or have implausible delivery tours. LSPs can specially handle these identified high-cost parcels to optimize resource allocation, reduce operational costs, and improve delivery efficiency.

In the emission-based strategy, the CO2 emissions of each parcel are calculated by the COFRET method to identify those parcels with a significantly high CO2 emission. These parcels usually result in high carbon emissions due to delivery zones that are far from depots. This strategy helps LSPs to develop more environmentally friendly delivery solutions while reducing environmental impacts and promoting sustainable urban delivery.

In conclusion, the identification of outlier parcels in urban delivery needs to be combined with specific operational objectives and adopt different strategies. In addition to the above-mentioned two identification strategies, LSPs can choose appropriate identification strategies based on different parcel attributes according to their own operational needs, so as to realize the optimal allocation of resources, improve the overall operational efficiency, and promote the development of green logistics.

5.2. Discussion

This section first discusses the contribution and reflection of the study. After that, the limitations as well as the potential improvements of the study are analyzed, and then the recommendations for future research directions are provided.

5.2.1. Contribution

A major contribution of this study is the development of two new methods for identifying outlier parcels based on cost and emission. These methods provide a quantitative approach that enables LSPs to identify parcels with significant deviations in terms of cost or environmental impact. There is no previous study that systematically combines these two perspectives in outlier identification, making this study unique and original.

Moreover, the use of the elbow point method to set thresholds for identifying outlier parcels is a significant advancement. In contrast to arbitrary or heuristic methods used in earlier studies, the elbow point algorithm provides an objective, data-driven approach to determine at which point parcels become inefficient in terms of cost or emissions. This method ensures that LSPs can easily identify outliers without manually adjusting parameters, thereby enhancing the practicality and applicability of this research in real-world logistics operations.

While Zhang & Cheah (2023) on crowdshipping also explored methods to identify outlier parcels, the approach and focus of this research are fundamentally different. They prioritizes outlier parcels based on their suitability for public transport-based crowdshipping, aiming to reduce vehicle kilometers traveled and carbon emissions. In contrast, this research focuses on identifying outliers from a cost and emission efficiency standpoint within a traditional delivery framework. The elbow point method used in this research is particularly effective in identifying parcels that incur higher costs or emissions than average, providing LSPs with actionable insights into operational inefficiencies.

There are several reflections could be obtained from this study. One significant finding is the different trends observed when plotting the CDF figures for marginal costs and CO2 emission across different CEPs. The CDF for marginal costs appears more concentrated, showing a better fit, while the distribution of carbon dioxide emissions is more scattered and flat, with a less perfect fit. This discrepancy may be attributed to cost factors being influenced by various operational factors, which are more predictable and easier to standardize across different zones. In contrast, carbon dioxide emissions are largely influenced by delivery distances, and the varying parcel demand locations across different CEPs lead to a more dispersed distribution.

Additionally, the study found that the reasons of cost-based outlier parcels are varied, including detours, zonal parcel demand, and tour formation. These factors significantly increase marginal costs in certain areas, resulting in the creation of outlier parcels. In contrast, emission-based outlier parcels are primarily determined by delivery distance, even though the COFRET method considers zonal parcel numbers during the calculation. This explains why different methods for identifying outlier parcels result in varying impacts that cost-based outliers are more evenly distributed, while emission-based outliers are concentrated in edge areas farther away from depots.

The study also shows that, compared to marginal cost, the proportion of carbon cost is extremely low. This is because current carbon price remains at a low level, and thus incorporating carbon costs into integrated costs does not have a significant impact on current outlier parcel identification. Even in the future, with an increase in the share of carbon costs, it would be difficult to reach parity with marginal costs. As a result, many companies continue to prioritize traditional costs over environmental costs in their operations, unless significant increases in carbon costs are driven by policy or market pressures.

Lastly, the current delivery network has six different CEPs, each with its own depots, market share, and delivery routes, providing a certain degree of robustness to the network. However, after network integration or optimization among CEPs, the status of some outlier parcels may change. Outlier parcels identified currently could no longer be classified as such due to route optimization or resource reallocation, while parcels that are currently not outliers may become new outliers due to changes in the network structure, resulting in higher delivery costs or emission. Therefore, while integration helps improve overall network efficiency, it may also create new outlier parcel issues. Companies need to carefully assess the potential impacts of network optimization on different zones and parcels to ensure that the final operational goals are achieved.

5.2.2. Limitations

When evaluating the cost of parcel delivery, it relies heavily on delivery distance and time to calculate the total cost. While this method reflects delivery costs to some extent, it ignores other cost factors in logistics operations such as vehicle maintenance costs, fuel consumption variance, and labor costs. This simplification fails to realistically portray the delivery cost of parcels and may lead to bias in the identification of outlier parcels.

The study fails to adequately consider the impact of delivery success on delivery costs. In reality, first delivery failures are common, and second deliveries increase labor and costs. Especially in certain urban areas with high density or complex transportation, the incidence of second deliveries is higher, and its cost impact cannot be ignored. Neglect of this important factor in the study may lead to underestimation of the true cost for particular parcels, affecting the results of the identification of outlier parcels.

The CO2 emission calculation method used in this study is relatively simplified and is mainly based on the distance traveled and the fuel consumed by the vehicle. However, there are many factors that affect the emissions in real life such as road inclination, traffic congestion, and pull over time that can lead to a significant increase in emissions. In addition to CO2, vehicle exhaust contains other pollutants that are harmful to the environment and health, and focusing only on CO2 emission in this study may not allow for a comprehensive assessment of the environmental impacts, while using a more complex emission estimation model will help to assess the emissions in a comprehensive manner.

The study mainly considered the use of vans for parcel delivery. However, in real-life logistics operations, a variety of delivery vehicle types are used, including electric trucks, bicycles. Different types of vehicles have significant differences in terms of delivery costs, fuel consumption, and CO2 emissions. Considering the differences in delivery vehicles can enhance the applicability of the study results in diverse logistics environments.

The elbow point method was used to determine the cost and CO2 emission thresholds to identify outlier parcels. However, this method is mainly based on statistical analysis, which fails to take into account the specific needs and strategic goals of logistics companies in actual operations, and the results are not fully verified from the actual operation perspective of the companies. If the actual data from companies can be added to validate and support the results, the results of would be more persuasive.

MASS-GT, as the main research tool, has some limitations in its tour formation as well. Due to the vehicle capacity set to 180 parcels in MASS-GT, and the simulator's rule that each vehicle must be assigned enough parcels, many parcels located at relatively distant areas are assigned to vehicles, which leads to unreasonable tour formation and causes more detours. In addition, the simulator assumes that all parcels have a uniform weight and volume, and such simplification ignores the impact of parcel characteristics in real logistics operations.

5.2.3. Recommendation for future research

In this sub-section, some suggestions for future research are made to further improve the understanding of methods for identifying and processing outlier parcels as well as to improve the value of practical applications of the research results.

Future research could consider expanding the geographic scope and applying the study to more regions and countries with different logistics characteristics. Existing studies have focused on South Netherlands, while different regions may have significant differences in terms of transportation infrastructure, population density, consumer behavior, and government legislation. By conducting studies in different geographical regions, the applicability of the existing methods can be verified and adapted and optimized for different regional characteristics, thus providing a more extensive and applicable strategy for outlier parcel identification.

Future research could introduce and compare a wider variety of outlier parcel identification methods to improve the accuracy and diversity of identification. In real logistics operations, the decisions faced by LSPs are often diverse. Future research could explore an identification method that integrates multiple attributes. Instead of relying on a single attribute, the method integrates multiple key attributes so that LSPs can make more balanced decisions between different operational goals and flexibly choose the most appropriate identification strategy to support diverse operational decisions. This approach not only helps LSPs optimize in a single dimension, but also improves the overall logistics efficiency by taking multiple dimensions into account.

Future research should not only focus on identifying outlier parcels, but should also delve into how to effectively handle these outlier parcels, especially with the advancement of new innovative LMD methods. While outlier parcels often bring additional burden and negative impacts to logistics operations, the application of innovative LMD methods offers new possibilities for handling these outlier parcels and has the potential to mitigate these negative impacts and significantly improve the KPIs of logistics operations. By applying outlier parcels to innovative technologies such as crowdshipping, LSPs can manage and handle these complex delivery tasks more efficiently and realize higher operational effectiveness. Future research should focus on exploring the effectiveness and potential of these new technologies to reduce the negative impact of outlier parcels in order to comprehensively improve the overall performance of the logistics industry.

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A

Python code

Three parts of codes by Python are shown below. The first part is about the calculation of parcel marginal cost.

```python
# Cost-bsed identification
time_coefficient = 29  # Time coefficient
distance_coefficient = 0.1644  # Distance coefficient

# Function to calculate cost per shipped unit
def calculate_cost_per_shipped(df):
    df_filtered = df[~df['CEP'].str.contains("Cycloon", case=False, na=True)]
    df_filtered = df_filtered[~df_filtered['Type'].str.contains("Pickup", case=False, na=True)]

    # Calculate 'T' as the total travel time per tour
    departure_time_first = df_filtered.groupby('Tour_ID')['TripDepTime'].transform('first')
    departure_time_last = df_filtered.groupby('Tour_ID')['TripDepTime'].transform('last')
    travel_time_last = df_filtered.groupby('Tour_ID')['Traveltime'].transform('last')
    df_filtered['T'] = ((departure_time_last - departure_time_first) + travel_time_last).round(3)

    # Calculate the total distance 'D' per tour
    df_filtered['D'] = df_filtered.groupby('Tour_ID')['TourDist'].transform('sum').round(3)

    # Calculate last mile cost per unit shipped
    df_filtered['Last_mile_cost_per_shipped'] = (
        (df_filtered['T'] * time_coefficient +
            df_filtered['D'] * distance_coefficient)
    ).astype(float)

    # Remove cost for the last row in each tour
    last_indices = df_filtered.groupby('Tour_ID').tail(1).index
    df_filtered.loc[last_indices, 'Last_mile_cost_per_shipped'] = None

    return df_filtered

# Function to extract zones per tour
def extract_tour_zones(df_filtered):
    tours_shipzones = {}
    for tour_id, group in df_filtered.groupby('Tour_ID', sort=False):
```

```
        zones = [group.iloc[0]['O_zone']]  # Start with the origin zone
        for _, trip in group.iterrows():
            zones.append(trip['D_zone'])  # Include all destination zones
        tours_shipzones[tour_id] = zones
    return tours_shipzones

# Function to calculate total distance after deleting each intermediate point
def calculate_total_distances_deleted(tours_zones, invZoneDict, get_distance, skimDist_flat, nSkimZones):
    results_totaldistance = {}
    for tour_id, zones in tours_zones.items():
        distances = {}
        if len(zones) > 3:
            for i in range(1, len(zones) - 1):
                modified_zones = zones[:i] + zones[i+1:]
                total_distance = round(sum(
                    get_distance(invZoneDict[modified_zones[j]], invZoneDict[modified_zones[j+1]], skimDist_flat, nSkimZones)
                    for j in range(len(modified_zones) - 1)), 3)
                distances[zones[i]] = total_distance
        else:
            distance_1 = get_distance(invZoneDict[zones[0]], invZoneDict[zones[1]], skimDist_flat, nSkimZones)
            distance_2 = get_distance(invZoneDict[zones[1]], invZoneDict[zones[2]], skimDist_flat, nSkimZones)
            total_distance = round(distance_1 + distance_2, 3)
            distances[zones[1]] = total_distance
        results_totaldistance[tour_id] = distances
    return results_totaldistance

# Function to calculate total travel time after deleting each intermediate point
def calculate_total_travel_times_deleted(tours_zones, parcel_dict, invZoneDict, skimTravTime, dropOffTime=120):
    results_totaltraveltime = {}
    for tour_id, zones in tours_zones.items():
        travel_times = {}
        if len(zones) > 3:
            for i in range(1, len(zones) - 1):
                modified_zones = zones[:i] + zones[i+1:]
                total_travel_time = sum(
                    skimTravTime[invZoneDict[modified_zones[j]], invZoneDict[modified_zones[j+1]]]
                    for j in range(len(modified_zones) - 1))
                parcels_time = sum(parcel_dict.get(tour_id, {}).get(zone, 0) * dropOffTime for zone in modified_zones[1:-1])
                total_travel_time += parcels_time
                travel_times[zones[i]] = round(total_travel_time / 3600, 3)  # Convert to hours
        else:
            travel_time_1 = skimTravTime[invZoneDict[zones[0]], invZoneDict[zones[1]]]
            travel_time_2 = skimTravTime[invZoneDict[zones[1]], invZoneDict[zones[2]]]
            total_travel_time = travel_time_1 + travel_time_2
            parcels_time = parcel_dict.get(tour_id, {}).get(zones[1], 0) * dropOffTime
            total_travel_time += parcels_time
            travel_times[zones[1]] = round(total_travel_time / 3600, 3)
        results_totaltraveltime[tour_id] = travel_times
    return results_totaltraveltime
```

```
# Function to calculate cost after deleting each intermediate point
def calculate_costs_per_parcel(results_totaldistance, results_totaltraveltime):
    total_cost_deleted = {}
    for tour_id in results_totaldistance:
        costs = {}
        if tour_id in results_totaltraveltime:
            for index in results_totaldistance[tour_id]:
                if index in results_totaltraveltime[tour_id]:
                    D = results_totaldistance[tour_id][index]
                    T = results_totaltraveltime[tour_id][index]
                    cost = (
                            T  * time_coefficient + D  * distance_coefficient
                    )
                    costs[index] = cost
            total_cost_deleted[tour_id] = costs
    return total_cost_deleted

# Update DataFrame with total cost after deletion for each intermediate point
def update_dataframe_with_costs(df_filtered, total_cost_deleted):
    df_filtered['total_cost_deleted'] = None
    for index, row in df_filtered.iterrows():
        tour_id = row['Tour_ID']
        d_zone = row['D_zone']
        if tour_id in total_cost_deleted and d_zone in total_cost_deleted[tour_id]:
            df_filtered.at[index, 'total_cost_deleted'] = total_cost_deleted[tour_id][d_zone]
    last_indices = df_filtered.groupby('Tour_ID').tail(1).index
    df_filtered.loc[last_indices, 'total_cost_deleted'] = None
    trip_counts = df_filtered['Tour_ID'].value_counts()
    tours_to_remove = trip_counts[trip_counts == 2].index
    df_filtered = df_filtered[~df_filtered['Tour_ID'].isin(tours_to_remove)]
    return df_filtered
```

The second part is about the allocation of parcel CO2 emission.

```
#Sustainability-based method
# Calculate distances for each tour and store in a dictionary
tour_distances = {}
tour_groups = df.groupby('Tour_ID', sort=False)

for tour_id, group in tour_groups:
    depot = group.iloc[0]['O_zone']
    distances = {row['D_zone']: get_distance(invZoneDict[depot], invZoneDict[row['D_zone']], skimDist_flat, nSkimZones)
                 for _, row in group.iloc[:-1].iterrows()}
    tour_distances[tour_id] = distances

# Add calculated distances (GCD) to the DataFrame
df['GCD'] = df.apply(lambda row: tour_distances.get(row['Tour_ID'], {}).get(row['D_zone'], None), axis=1)

# Calculate cluster weight and related metrics
df['cluster_weight'] = df['GCD'] * df['N_parcels']
total_cluster_weight = df.groupby('Tour_ID')['cluster_weight'].transform('sum')
df['cluster_weight_factor'] = df['cluster_weight'] / total_cluster_weight
df['Cluster_Carbon_Footprint(kg)'] = df['cluster_weight_factor'] * df['TourCarbonFootprint(kg)']
df['Cluster_Carbon_Footprint_per_parcel(kg)'] = df['Cluster_Carbon_Footprint(kg)'] / df['N_parcels']

# Calculate sustainable zonal carbon cost
```

```
carbon_coefficient = 0.1
df['sustainable_zonal_carbon_cost'] = df['Cluster_Carbon_Footprint_per_parcel(kg)'] * carbon_coefficient
```

The third part is about the implementation of the elbow point method that decides the threshold values of cost/CO2 for 6 CEPs

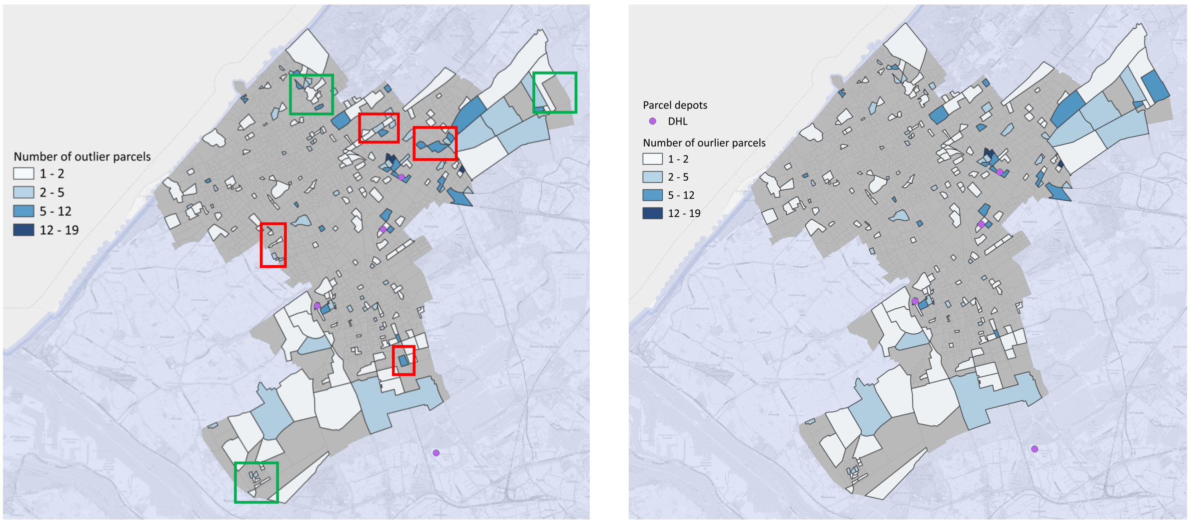
```
# Outlier identification
# Function to find the farthest point from the line
def find_elbow_point(x, y, start_index, end_index):
    p1, p2 = np.array([x.iloc[start_index], y.iloc[start_index]]), np.array([x.iloc[end_index], y.iloc[end_index]])
    distances = abs(y - ((p2[1] - p1[1]) / (p2[0] - p1[0]) * (x - p1[0]) + p1[1]))
    return distances

# Function to find the first valid start point based on slope
def find_valid_start_point(x, y):
    end_index = len(x) - 1
    for i in range(len(x) - 1):
        if (y.iloc[i + 1] - y.iloc[i]) / (x.iloc[i + 1] - x.iloc[i]) >= (y.iloc[end_index] - y.iloc[i]) / (x.iloc[end_index] - x.iloc[i]):
            return i + 1
    return 0

# Process each dataset
def process_data(data, xlim):
    # Data cleaning and preprocessing
    data = data.dropna(subset=['Last_mile_cost_per_parcel', 'N_parcels'])
    data['Last_mile_cost_per_parcel'] = data['Last_mile_cost_per_parcel'].astype(float)
    data['N_parcels'] = data['N_parcels'].astype(int)

    # Group by cost and calculate cumulative parcel count
    grouped_data = data.groupby('Last_mile_cost_per_parcel').sum(numeric_only=True).reset_index()
    grouped_data['cumulative_proportion'] = grouped_data['N_parcels'].cumsum() / grouped_data['N_parcels'].sum()

    # Find the valid start point and the elbow point
    start_index = find_valid_start_point(grouped_data['Last_mile_cost_per_parcel'], grouped_data['cumulative_proportion'])
    end_index = len(grouped_data) - 1
    distances = find_elbow_point(grouped_data['Last_mile_cost_per_parcel'], grouped_data['cumulative_proportion'], start_index, end_index)

    # Calculate the threshold as the x-coordinate of the farthest point
    threshold_index = np.nanargmax(distances[start_index:])
    threshold_x = grouped_data['Last_mile_cost_per_parcel'].iloc[start_index + threshold_index]

    # Plotting
    plt.figure(figsize=(15, 6))
    plt.plot(grouped_data['Last_mile_cost_per_parcel'], grouped_data['cumulative_proportion'], marker='o', color='blue', label='Cumulative Proportion')
    plt.axvline(x=threshold_x, color='red', linestyle='--')
    plt.annotate(f'Cost Threshold = {threshold_x:.2f€}', xy=(threshold_x, 0.15), xytext=(threshold_x + 0.4, 0.15),
                 arrowprops=dict(facecolor='red', shrink=0.01, width=0.2, headwidth=4), fontsize=16, color='red')

    # Plot line from start to end point
```

```
    plt.plot([grouped_data['Last_mile_cost_per_parcel'].iloc[start_index], grouped_data['Last_mile_cost_per_parcel'].iloc[end_index]],
             [grouped_data['cumulative_proportion'].iloc[start_index], grouped_data['cumulative_proportion'].iloc[end_index]], color='green', linestyle='--')

    plt.xlim(xlim)
    plt.xlabel('Last Mile Cost per Parcel €()')
    plt.ylabel('Cumulative Proportion of Parcels')
    plt.title('Cumulative Distribution of Last Mile Cost per Parcel')
    plt.legend()
    plt.tight_layout()
    plt.show()

    # Output results
    parcels_beyond = grouped_data[grouped_data['Last_mile_cost_per_parcel'] > threshold_x]['N_parcels'].sum()
    proportion_beyond = parcels_beyond / grouped_data['N_parcels'].sum()
    print(f"Threshold: {threshold_x€}")
    print(f"Parcels beyond {threshold_x€}: {parcels_beyond} ({proportion_beyond:.8%})\n")
```

B

Geographic distribution change

Figure B.1 shows the comparison of geographic distribution of DHL with carbon cost=0€/ton and carbon cost=1000€/ton. The red boxes mark zones that were originally outliers but were no longer considered outliers after the carbon cost was increased to 1,000€/ton, which is usually found in zones closer to depots, while the green boxes mark zones that were added after the carbon cost was increased to 1,000€/ton, which are generally located at the edges of the zones, farther away from the depots. In addition, the geographic maps show changes in the depth of the outlier zones as the carbon cost increases.



(a) DHL, carbon cost=0

(b) DHL, carbon cost=1000€/ton

Figure B.1: Comparison of cost-based outlier parcel distribution with different carbon cost

C

Cost reduction analysis

Table C.1 shows how the outlier parcel identification results and indicators change for each CEP when the cost is reduced by 10% while the carbon cost remains the same. The results show that despite the 10% reduction in cost, which reduces its share of the integrated cost, there is no impact on the proportion and distribution of outlier parcels except that the thresholds are reduced as expected. This is because even with a 10% reduction in cost, the proportion of CO2 cost in the integrated cost is still low. If future technological advances can further significantly reduce the parcel delivery cost, it will probably change the outlier parcel identification results and distribution patterns significantly.The relative weight of CO2 cost in the integrated cost may increase, thus affecting the identification of outlier parcels.

Table C.1: Impact of 10% reduction in cost on outlier parcel identification

CEP	Indicators	Carbon cost value=100; Cost 100%	Carbon cost value=100; Cost 90%
PostNL	Threshold Value (€)	1.36	1.2
	Outlier Proportion (%)	3.27	3.27
	# Outlier Zones	275	275
DHL	Threshold Value (€)	1.5	1.35
	Outlier Proportion (%)	3.05	3.05
	# Outlier Zones	235	235
DPD	Threshold Value (€)	1.69	1.52
	Outlier Proportion (%)	5.63	5.63
	# Outlier Zones	261	261
GLS	Threshold Value (€)	2.38	2.15
	Outlier Proportion (%)	5.21	5.21
	# Outlier Zones	161	161
UPS	Threshold Value (€)	1.92	1.73
	Outlier Proportion (%)	4.15	4.15
	# Outlier Zones	194	194
FedEx	Threshold Value (€)	2.6	2.35
	Outlier Proportion (%)	7.56	7.56
	# Outlier Zones	164	164

D
Scientific paper

The scientific paper can be found on the following pages.

Strategies for Identifying Outlier Parcels in Urban Deliveries

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***Abstract*—This paper presents two novel strategies for identifying outlier parcels in urban deliveries, focusing on cost and environmental impact. With the growth of Business-to-Customer (B2C) e-commerce, the logistics industry faces increased pressure to improve last-mile delivery (LMD) efficiency. Outlier parcels, characterized by higher costs and emissions, pose significant challenges to logistics service providers (LSPs). Using the Marginal Cost Method and the COFRET method, this study develops cost-based and emission-based identification strategies to help LSPs address inefficiencies. The elbow point method is introduced to set objective thresholds for identifying outliers. Results from simulations in the South Holland region reveal significant differences in outlier parcel distributions across various carriers. Additionally, a sensitivity analysis assesses the impact of carbon pricing on parcel identification. The findings provide actionable insights for LSPs to optimize delivery operations and achieve sustainability goals. Future work will explore the application of these methods in different regions and consider alternative delivery methods for handling outlier parcels.**

***Index Terms*—Outlier parcels, last-mile delivery, cost allocation, CO2 emissions, urban freight, elbow point**

I. Introduction

Over the past decade, with rising disposable incomes, increased internet penetration, the popularity of smartphones, and the growth of global per capital incomes, there has been a rapid surge in Business-to-Customer (B2C) e-commerce [1]. According to industry reports, international e-commerce has been predicted to grow by 26.6% from 2013 to 2020, while the global e-commerce growth rate for 2023 is estimated at 8.9%, bringing global e-commerce sales worldwide to \$4.5 trillion [2], [3]. However, this sustained growth has not tended to abate. As can be seen in 1, the global B2C e-commerce market size is expected to reach USD 7.45 trillion by 2030, growing at a compound annual growth rate (CAGR) of 7.6% during this forecast period. Rising global e-commerce sales have contributed to the growth of parcel shipments, a trend that is also evident in the Netherlands. PostNL, the largest Dutch parcel delivery service, noted a volume increase of 24.1% in performance annual report 2022 [4]. Zott et al. [5] emphasize that B2C e-commerce is widely used globally because it offers many advantages to customers, especially in the critical area of last mile delivery (LMD). A common method in LMD is to deliver parcels directly to the recipient's residence or to a collection point, which provide great convenience for the consumers [6].

LMD service providers are under huge pressure to deal with a considerable number of parcels in a short period, and this aspect generates various issues, inefficiencies, and externalities affecting the industry [8]. Many innovative solutions have emerged, and logistics service providers must continuously evolve and adapt to these emerging trends in order to remain competitiveness and meet their customer's expectations [9]. There is a category of parcels that would bring a significant level of negative impact for LSPs and are also the potential candidates for innovative solutions called 'outlier parcels', which are urgent to be effectively handled. Therefore, developing methods to identifying outlier parcels is a potential and significant direction to conduct research, but studies in this area is still lacking.

Fig. 1: B2C E-commerce market size, 2021 to 2030 (USD Trillion) [7]

Previous research has rarely mentioned methods for identifying outlier parcels. Only Zhang et al. [10] in a research related to crowdshipping using public transportation in urban logistics mentioned prioritizing outlier parcels as targets for crowdshipping. They applied a spatial outlier detection method, calculating the Local Outlier Factor (LOF) for each parcel based on the geographic coordinates of parcel demand points, so as to perform the identification of outlier parcels. As mentioned, developing methods to identifying outlier parcels is a potential and significant direction to conduct research, but studies in this area is still lacking. If strategies can be developed to help LSPs identify which parcels are performing anomalously according to the objectives that LSPs expect to achieve, this will help LSPs execute their delivery plans more efficiently, and also provide them with more flexible options for delivery management. Therefore, this research will develop different identification strategies for outlier parcels based on different perspectives within urban delivery plans, and on this basis, evaluate the proportion of outlier parcels in each strategy and finally conduct sensitivity analyses to explore the impact of specific parameter variations on the identification results.

II. Literature review

A. Definition of outlier parcels

In statistics, outliers are data points that deviate significantly from other observations in a data set. These outliers may occur for a variety of reasons, including data entry errors, measurement errors, or true anomalies [11]. In this study, outlier parcels need to be identified based on the context of LMD. However, using traditional statistical methods to identify outlier parcels is not exactly the right means to apply. Traditional statistical methods are usually designed to identify outlier parcels in the data, which may deviate from the majority data for a variety of reasons (e.g., data errors or natural variability) [12]. But in the context of LMD, outlier parcels are defined as those parcels that negatively affect LSPs in actual operations. Therefore, in this study, the definition of "outlier" is target orientated, explicitly targeting parcels which negatively impact on CEPs and reduce their delivery efficiency, such as parcels with high costs, high emissions, operational complexity or increased risk. Furthermore, parcel attribute data in LMDs often do not conform to some conventional distribution pattern, and many traditional statistical methods are limited by the applicability of the data distribution [13]. Also, conventional methods such as standard deviation and interquartile range methods tend to be bilateral filters, with values above the upper limit or below the lower limit being set as outliers, but in LMD, it is mainly the high-value parcels that would significantly increase operational difficulty that need to be focused on.

B. Attributes for identifying outlier parcels

LMD faces significant challenges due to increasing costs, externalities, and customer demands for timeliness and reliability [14]. Of these, rising costs are the most pressing concern. FarEye reports that last-mile delivery accounts for 53% of shipping costs, largely due to the inefficiencies of delivering small parcels to dispersed locations [15]. While urban deliveries benefit from economies of scale, rural deliveries can cost three times more [16]. Labor costs also rise as the volume of deliveries grows [17]. Identifying high-cost parcels can help address inefficiencies and improve profit margins [18].

Additionally, LMD significantly contributes to CO2 emissions. The rise in online shopping has led to more delivery vehicles, exacerbating emissions, especially in congested urban areas [19]. Some companies, such as Amazon and DHL, are investing in sustainable solutions, including electric trucks and optimized routing, but these efforts remain in early stages [20]. Businesses must reduce transportation-related CO2 emissions to meet environmental goals and enhance public perception [21]. Global regulations on carbon emissions are tightening, and LSPs must prepare for stricter requirements [22].

Delivery time, parcel size and weight, and population density also impact LMD costs and efficiency. Larger parcels and dispersed rural deliveries reduce efficiency, while high costs and slow deliveries affect competitiveness [23]. Externalities such as traffic congestion, air pollution, and noise pollution also create challenges, with CO2 emissions being a particularly significant factor [24]. Given the complexity of assessing externalities, cost and CO2 emissions are selected as the primary attributes for identifying outlier parcels in this study. These attributes capture the inefficiencies in delivery operations, especially in less dense areas, and are supported by established research methodologies and data [18].

In conclusion, focusing on cost and CO2 emissions enables companies to address the most significant factors impacting profitability and sustainability. By targeting high-cost, high-emission parcels, logistics providers can improve operational efficiency, meet regulatory requirements, and reduce their environmental impact.

C. Cost Allocation Methods

To identify outlier parcels with significantly higher costs, it is crucial to select a suitable cost allocation method. Accurate cost allocation is essential for financial management and optimizing resource allocation in logistics, particularly as e-commerce drives up demand for parcel deliveries [25].

Activity-based costing (ABC), introduced by Kaplan et al. [26], provides precise cost allocation by tracking activity costs and identifying cost drivers. However, ABC is complex, data-intensive, and struggles with allocating common costs [27]. The Equal Profit Method (EPM) allocates costs by minimizing profit differences, but it is computationally complex and mainly suitable for collaborative environments [28]. Cooperative Game Theory methods, such as the Shapley value and Nucleolus, offer fair allocation but are computationally intensive and impractical for single-company scenarios [29]. The Equal Proportion Mark-up Method (EPMU) offers simplicity but may lead to inaccurate allocations when common costs are significant [30].

The Marginal Cost Method, first proposed by Dupuit and Jules [31], allocates costs based on the incremental cost of each parcel, making it well-suited for reflecting actual delivery costs. This method ensures optimal resource allocation and is more adaptable to market fluctuations [32].

Thus, the Marginal Cost Method is selected for this study, as it simplifies cost allocation, accurately reflects incremental costs, and helps identify outlier parcels for optimizing last-mile delivery (LMD) operations.

D. CO2 Emission Allocation Methods

CO2 emissions are another critical attribute for identifying outlier parcels. Proper allocation of emissions is essential for companies to meet environmental goals and enhance their competitive edge in sustainability [33].

The Shapley value and Nucleolus from Cooperative Game Theory can allocate CO2 emissions fairly but are computationally demanding [29]. Equal Profit Method (EPM) ensures proportional CO2 allocation but may not fully reflect actual emissions contributions [34]. Payload Weighted Allocation (PA) and Tour Stops and Payload Allocation (SPA) methods allocate emissions based on parcel weight and stops but often overlook delivery distance, leading to potential inaccuracies [35].

Distance-dependent methods like the Tons-km Weighted Allocation and Separate Deliveries Allocation calculate emissions based on parcel weight and delivery distance but may fail to account for synergistic effects from combined deliveries [36]. The COFRET methodology, developed under the EU COFRET project, allocates emissions based on parcel weight, distance, and delivery stops, ensuring fairness and compliance with EN 16258 standards [37]. It provides a balance between accuracy, computational feasibility, and transparency.

Given its lower complexity and practical applicability, the COFRET method is selected for this study to allocate CO2 emissions. This method ensures accurate and fair allocation, enabling companies to optimize logistics processes and reduce emissions, ultimately enhancing their green operations and competitiveness.

III. Method and Data

This chapter details the process for implementing the cost-based and emission-based outlier parcel identification strategies, providing a guide for subsequent research. Both identification methods are implemented using the MASS-GT tool, which simulates freight transportation and provides data for this study. The second section explains the working principles and modeling details of MASS-GT.

A. Methods for identifying outlier parcels

1) Cost-based method: The marginal cost method is used to identify cost-based outlier parcels. Outliers are defined as parcels whose delivery marginal cost is significantly higher than average. High-cost parcels consume more resources and handling time, which impacts both profitability and delivery efficiency. Therefore, identifying these outliers is essential to optimize logistics operations.

The method calculates marginal costs on a delivery tour basis, where a vehicle departs from a depot, visits zones to deliver parcels, and returns. To calculate marginal cost, zones are sequentially skipped to measure the cost difference. The visualization of the process is shown in Figure 2, with the unit cost in €.

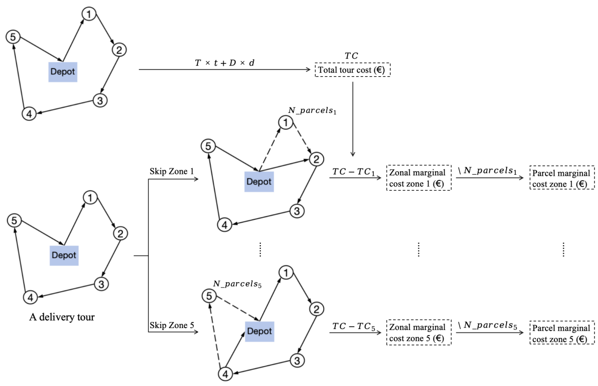


Fig. 2: Marginal cost method

The zonal marginal cost is calculated by subtracting the total cost of a tour with a skipped zone from the original tour cost. The formula is as follows:

$$Zonal\, marginal\, cost_i = TC - TC_i \tag{1}$$

To calculate the total last-mile cost, the study uses the model from [38], based on travel time and distance:

$$TC = T \times t + D \times d \tag{2}$$

Where T is the delivery time, t is the time coefficient, D is the distance traveled, and d is the distance coefficient. The total distance traveled is the sum of linear distances between zones:

$$D = \sum_{i=0}^{n} d(i, i+1) \tag{3}$$

The total delivery time includes both travel time and parcel drop-off time:

$$T = \sum_{i=0}^{n} h(i, i+1) + \sum_{i=1}^{n} p_i * t_d \tag{4}$$

Finally, the zonal marginal cost is divided equally among the parcels in that zone:

$$Parcel\, marginal\, cost_i = \frac{Zonal\, marginal\, cost_i}{N\_parcels_i} \tag{5}$$

This method helps LSPs identify high-cost zones and optimize resource allocation to improve efficiency.

2) Emission-based method: The COFRET method is used to identify emission-based outliers, where outliers are defined as parcels with significantly higher CO2 emissions than average. These high-emission parcels consume more energy and increase the environmental burden, affecting both operational efficiency and sustainability goals. The visualization of the process is shown in Figure 3.

The COFRET method calculates emissions on a delivery tour basis. The total CO2 emission is determined using an energy-based approach, which is more accurate than activity-based approaches [39]. The formula for total CO2 emissions is:

$$\begin{aligned} &Total\,tour\,CO2\,emission \\ &= D * Fuel\,consumption\,factor * \\ &Emission\,conversion\,coefficient \end{aligned} \tag{6}$$

The emissions for each zone are allocated based on the distance from the depot (using Great Circle Distance, GCD) and the number of parcels delivered. The zonal weight factor is calculated as follows:

$$WeightFactor_i = \frac{N\_parcels_i * GCD_i}{\sum_{i=1}^{n} N\_parcels_i * GCD_i} \tag{7}$$

The total CO2 emission for a zone is then calculated:

$$\begin{aligned} Zonal\,CO2\,emission_i = &\,Total\,tour\,CO2\,emission \\ &* WeightFactor_i \end{aligned} \tag{8}$$

Finally, the zonal emissions are divided equally among parcels:

$$Parcel\,CO2\,emission_i = \frac{Zonal\,CO2\,emission_i}{N\_parcels_i} \tag{9}$$

This method helps identify parcels with disproportionately high emissions, allowing LSPs to reduce their carbon footprint and achieve sustainability targets.

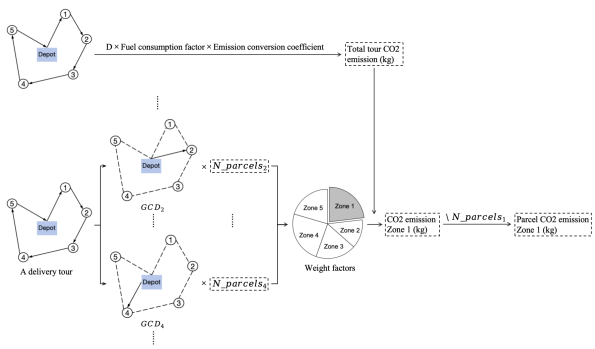


Fig. 3: The COFRET method

B. MASS-GT - Data source

MASS-GT serves as an efficient tool for implementing outlier parcel identification strategies in LMD systems. Simulation models are commonly used for assessing freight policies, but most lack the behavioral complexity needed to simulate the impacts of logistics developments [40]. MASS-GT, developed by de Bok and Tavasszy, is an agent-based model that simulates freight transportation in South Netherlands based on a large dataset. It operates on three key principles: a commodity-based approach, explicit agent-based decision-making, and an empirically tested choice model [41]. In this study, the agents (e.g., LSPs, customers) mimic real-world behaviors and decision-making. The impact of outlier parcel identification strategies can be simulated by adjusting agent behaviors.

Two relevant modules in MASS-GT for this study are the parcel demand and parcel scheduling modules.

The parcel demand module uses datasets to estimate B2C and B2B parcel demand in each zone. B2B demand is based on socio-economic data from the National Bureau of Statistics (CBS) and market monitoring data from the Netherlands Authority for Consumers & Markets (ACM). B2C demand is estimated through an ordered logistic regression model that incorporates individual and household characteristics from the Mobility Panel Netherlands (MPN). The model is calibrated to match actual market size and takes into account the market share of each CEP, where PostNL has the largest share, followed by DHL. Once parcel demand is determined, it is allocated to the respective CEPs and depots, ensuring each parcel has a defined origin and destination.

The parcel scheduling module assigns parcels and generates delivery routes based on parcel demand data. Each parcel is assigned to the nearest depot of its corresponding CEP, with optimized operations assumed for each company. Vans are modeled with a maximum capacity of 180 parcels and a maximum travel time of 8 hours per trip. If the number of parcels exceeds van capacity, the van returns to the depot, reschedules, and completes further deliveries. The module generates a matrix of tours and trips over a 24-hour period, including itinerary details, start times, travel times, and parcel data.

In summary, the parcel demand and scheduling modules work closely together. The demand module estimates parcel demand and allocates parcels to specific depots, while the scheduling module uses this data to form delivery routes. These outputs will serve as inputs for identifying outlier parcels using cost-based and emission-based methods.

IV. Implementation and Results

This chapter demonstrates the results of the implementation of the cost-based and emission-based outlier parcel identification methods using MASS-GT, along with a detailed analysis of the results. The study area and parcel delivery process are introduced first, followed by a presentation of the results from each method. Outlier parcels are identified for different CEPs, and their geographical distribution is analyzed. Lastly, a sensitivity analysis is conducted to assess the impact of adding CO2 cost to marginal costs.

A. Use Case

South Holland is one of the most economically developed regions in the Netherlands, home to the Port of Rotterdam and many international companies. It has a population of 3.6 million and covers an area of 3,403 km^2. The study area consists of five municipalities in South Holland: Delft, Midden-Delfland, Rijswijk, 's-Gravenhage (The Hague), and Leidschendam-Voorburg based on Figure 4. This area is divided into 2524 zones in MASS-GT, covering 209.3 km^2. Around 90,000 parcels are delivered in this region daily,

TABLE I: Cost-based outlier identification result for each CEP

CEP	#Parcel delivered	Threshold value ($Euro$)	#Outliers	Percentage (%)	#Outlier zones
PostNL	42792	1.35	1391	3.25	274
DHL	20313	1.47	656	3.23	244
DPD	8866	1.68	490	5.53	259
GLS	3684	2.35	192	5.21	161
UPS	7775	1.90	323	4.15	194
FedEx	2341	2.54	177	7.56	164

simulated by MASS-GT. Outlier parcel identification is based on this delivery data. In total, 484 delivery tours are made in one day by six different CEPs. The number of tours delivered by each CEP corresponds to their market share.

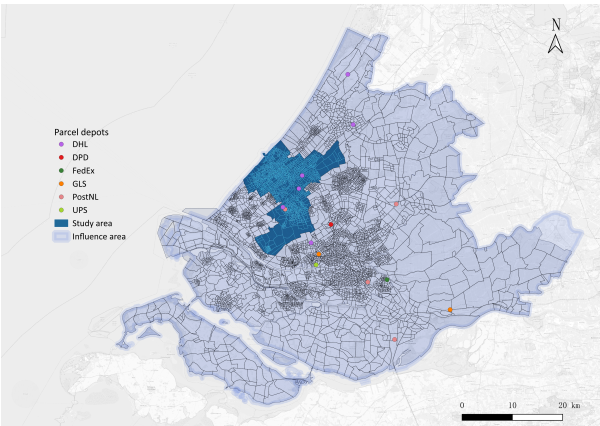


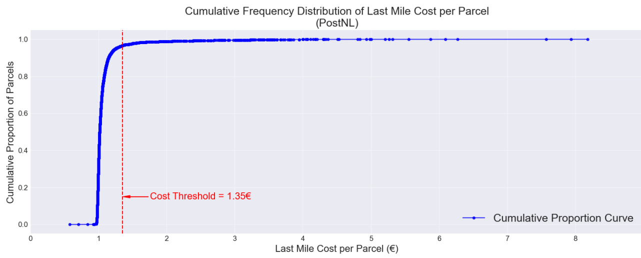
Fig. 4: Study area and depot locations in MASS-GT

B. Cost-Based Identification

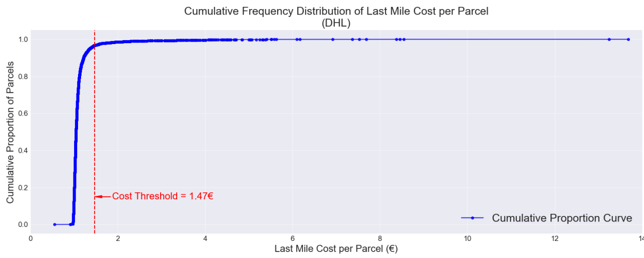
This section presents the results of the marginal cost method for cost-based outlier parcel identification. Due to the differences between CEPs (e.g., depot location, market share, delivery routes), the analysis is performed separately for each CEP.

1) Identification Result: The marginal costs for all parcels were calculated based on the cost allocation method. For each CEP, cumulative frequency curves (CDF) were created to display the marginal cost distribution. The elbow point method was used to determine the cost threshold for identifying outliers. The elbow point represents the point where the increase in parcel marginal cost is significant, and further optimization yields diminishing returns. This method provides an objective, data-driven approach to threshold selection. The method that implemented on PostNL and DHL are shown in Figure 5.

The results show that all curves follow a typical CDF pattern, with a steep rise followed by a plateau. PostNL and DHL have relatively low cost thresholds (1.35 € and 1.47 €, respectively), indicating more efficient cost control compared to other CEPs. GLS and FedEx have higher thresholds, likely due to depots being farther from main distribution areas or a smaller market share leading to inefficiencies.



(a) PostNL



(b) DHL

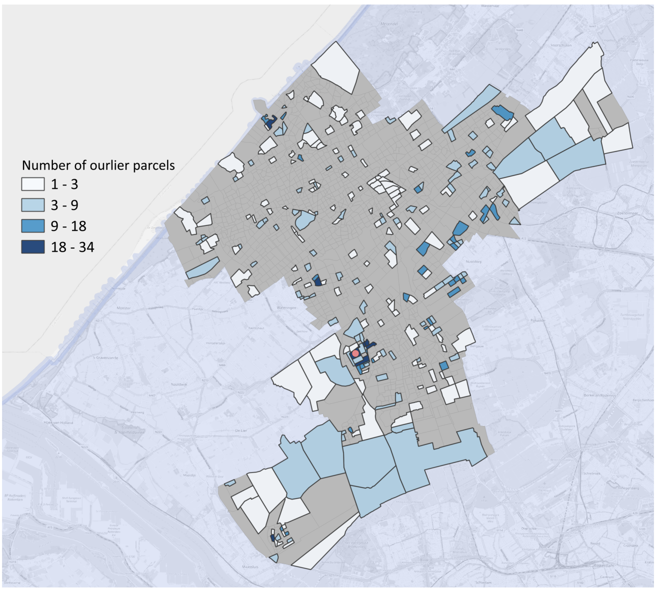
Fig. 5: Parcel cost distribution & Threshold for PostNL and DHL

A total of 85,771 parcels were delivered in the study area, and 3,229 parcels (approximately 3.8%) were identified as outliers. PostNL and DHL, despite delivering the most parcels, had a lower proportion of outliers, indicating strong cost control and operational efficiency. In contrast, FedEx had the highest proportion of outliers (7.56%), reflecting potential inefficiencies in their delivery process.

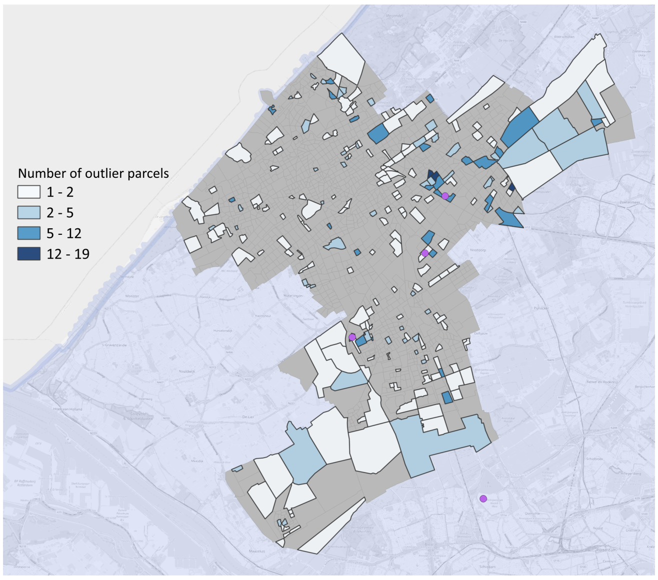
Figure 6 shows the geographical distribution of outlier parcels and a hierarchical display of their numbers on the map of study area for PostNL and DHL. Different classes of the outlier parcel numbers are indicated by shades of color.

2) Analysis for the distribution of outlier parcels: Based on the identified characteristics of the distribution of outlier parcels in the study area, this section provides detailed explanations regarding the reasons for their presence around depots, in the edge areas, and in the central part of the region.

The first aspect focuses on the distribution of outlier parcels in zones adjacent to the depots. Figure **??** shows two delivery tours by PostNL and DHL from their respective depots, both generating outlier parcels in zones near the depot. In these



(a) PostNL



(b) DHL

Fig. 6: Cost-based geographic distribution of outlier parcels for each CEP

figures, the zones with outlier parcels are highlighted in red, and the trips entering and leaving these zones are marked in red to show the detours made during delivery. The locations of the depots are also indicated by pink and purple dots for PostNL and DHL, respectively.

From the figure, it is clear that the vehicles made a detour to deliver parcels to these nearby zones, which increases the delivery cost, resulting in higher marginal costs for parcels in these zones. However, detours are not the only reason for these high costs. A low number of parcels delivered to these zones by each tour also contributes to the higher marginal cost. When the zonal marginal cost is divided by a small number of parcels, each parcel ends up bearing a higher proportion of the cost, leading to the identification of outliers.

For example, in the case of DHL, several different tours deliver only one parcel each to the same zone, and this low volume of parcels increases the average marginal cost, thus contributing to the creation of outlier parcels in that zone. This phenomenon of low delivery volumes near the depot zones is a key reason for generating high-cost parcels.

The second aspect concerns the presence of outlier parcels in the eastern and southern fringe areas of the study area. These remote areas are sparsely populated, and parcel demand is low. Consequently, delivery to these areas often requires longer detours, increasing the delivery cost significantly. In the figures, PostNL and DHL deliver a small number of parcels to the same zone in the most eastern part of the study area, but the detours made by both companies result in high marginal costs for these deliveries. This pattern is observed across multiple edge zones, where low demand and longer delivery routes combine to produce higher delivery costs.

The third aspect considers the generation of outlier parcels in the center of the study area. In certain central zones, outliers are caused by detours or inefficient tour formation. In some cases, vehicles do not follow the most optimal route for nearby deliveries, resulting in unnecessary returns or backtracking. This inefficient routing increases delivery times and costs, leading to the creation of outlier parcels in the central zones. The formation of these outliers is less systematic than in the depot-adjacent or edge zones but is driven by specific inefficiencies in the routing process.

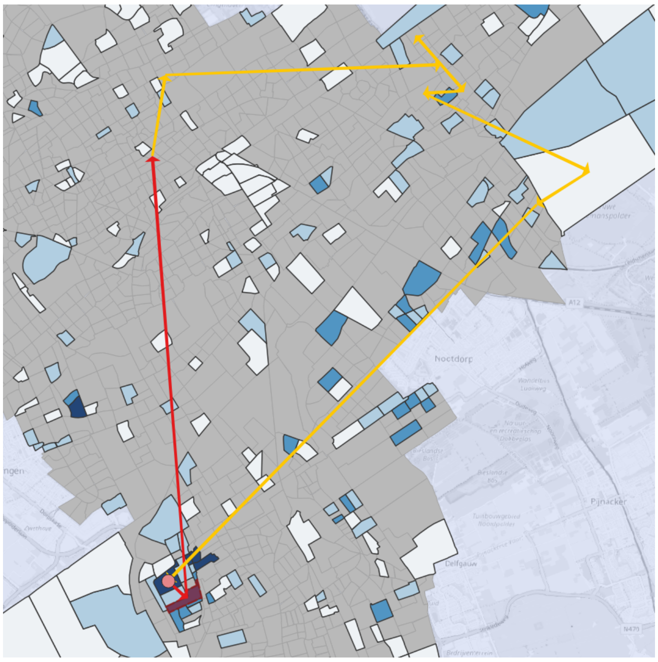
Through these analyses, the primary causes of outlier parcels in different zones—whether due to detours, low delivery volumes, or inefficient routing—are identified, providing insights into optimizing delivery networks.

C. Emission-based identification

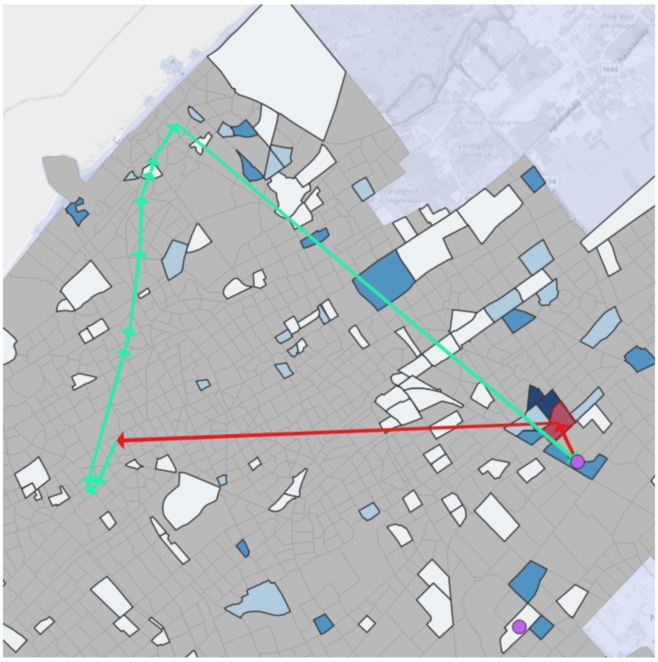
After applying the emission-based allocation method described in section 3.2 to all tours in the study area, the last-mile CO2 emission values of all parcels (in units of kg) are obtained. The parcel data are categorized according to the CEPs, and cumulative distribution functions (CDFs) are plotted for each CEP to show the distribution of CO2 emissions. The elbow point method is then used to select CO2 emission thresholds for each CEP to identify the number and proportion of outlier parcels.

For CO2 emission calculation, the fuel consumption factor and emission conversion factor are used to convert the total tour distance into fuel consumption, and then into CO2 emissions. Light Commercial Vehicles (LCVs) are used for parcel deliveries. According to the European Automobile Manufacturers' Association (ACEA), 93.3% of LCVs in the Netherlands use diesel as fuel [42]. The ARTEMIS project evaluates fuel consumption for LCVs, and based on its data, $0.135L/km$ is selected as the fuel consumption factor [43]. The emission conversion factor is $3.468kg$ CO2 per liter for diesel LCVs [44].

Figure 8 shows the CO2 emission CDFs for each CEP, with red dashed lines marking the threshold values. The thresholds reflect the different environmental impacts of each CEP during the last-mile delivery process.

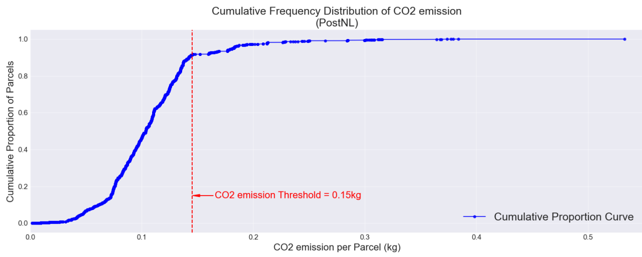


(a) PostNL delivery tour

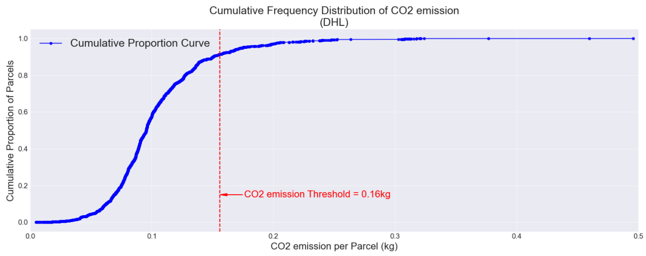


(b) DHL delivery tour

Fig. 7: Tours of outlier parcels around depots



(a) PostNL



(b) DHL

Fig. 8: Parcel CO2 emission distribution & Threshold for PostNL and DHL

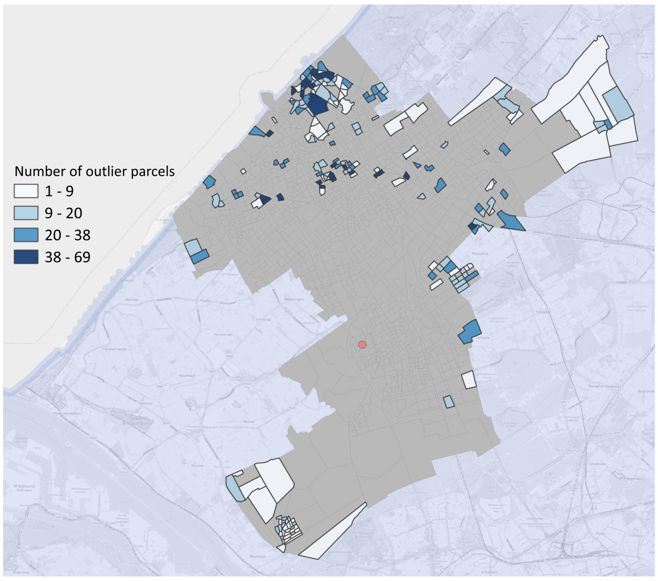
The CDFs for the six CEPs rise more gradually compared to the cost-based method, indicating a more even distribution of CO2 emissions across parcels. PostNL and DHL show the lowest CO2 emission thresholds, possibly due to their larger market share and higher vehicle loading rates, allowing them to optimize delivery networks and reduce emissions. In contrast, FedEx has the highest CO2 emission threshold, which may be attributed to its depot being located farther from the main delivery areas, resulting in longer travel distances.

Table II summarizes the results of outlier parcel identification for each CEP. A total of 85,771 parcels were delivered, and 7,220 parcels were identified as outliers, representing about 8.4% of all parcels—significantly higher than the proportion identified using the cost-based method. DPD has the lowest proportion of outliers, while FedEx has the highest, likely due to geographical and demand distribution factors.

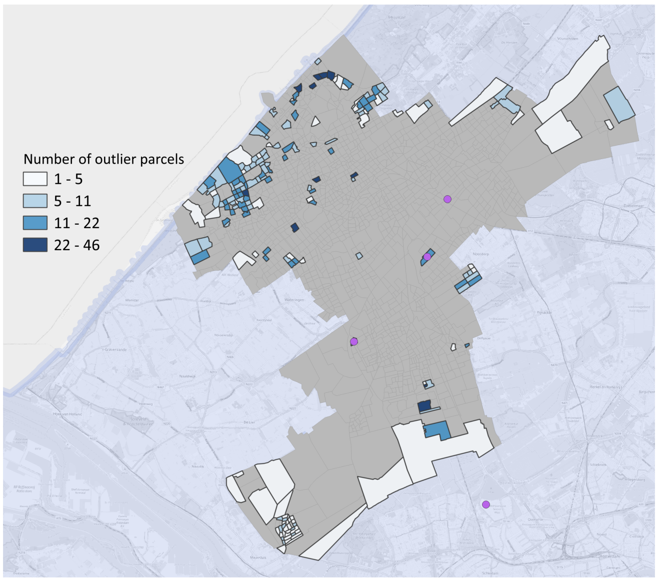
Figure 9 shows the geographic distribution of outlier parcels and a hierarchical display of their quantities for PostNL and DHL. The shades indicate the cumulative number of outlier parcels in specific zones. The distribution reinforces the relationship between delivery distance and CO2 emissions, with the majority of outlier parcels located farther from depots. Some zones near depots, especially for DHL, also contain outlier parcels, but these were handled by other depots, leading to higher emissions.

TABLE II: Emission-based outlier identification result for each CEP

CEP	#Parcel delivered	Threshold value (kg)	#Outliers	Percentage (%)	#Outlier zones
PostNL	42794	0.15	3579	8.36	201
DHL	20316	0.16	1722	8.48	191
DPD	8867	0.33	422	4.76	89
GLS	3684	0.44	398	10.80	147
UPS	7776	0.33	424	5.45	111
FedEx	2341	0.63	325	13.88	192



(a) PostNL



(b) DHL

Fig. 9: Emission-based geographic distribution of outlier parcels for PostNL and DHL

D. Combined identification results

After identifying outlier parcels using both the cost-based and emission-based methods, the results are shown in Figure 10a and Figure 10b. The color shading indicates the combined number of outlier parcels in each zone.

For the cost-based method, 619 zones (24.5% of the total) contain outlier parcels, with parcel counts ranging from 1 to 34. The central zones have fewer outlier parcels, indicating more efficient logistics, while the edge zones show higher concentrations, likely due to longer delivery detours and lower parcel volumes, which increase delivery costs.

For the emission-based method, 536 zones (21.2% of the total) contain outliers, with the maximum number of parcels reaching 119 in some zones. Outliers are mostly concentrated at the edges of the study area, with a particularly large cluster in the s-Gravenhage region (41.6% of outlier zones). This is mainly due to the longer distances from most depots, except for those of PostNL and DHL, which are located within the study area.

Both methods show outlier parcels concentrated in the edge zones. The emission-based method highlights a larger cluster in the northwestern part of the study area, driven by the greater distance from depots. This suggests that optimizing depot locations and logistics routes could reduce both costs and CO2 emissions, leading to more sustainable and efficient logistics operations.

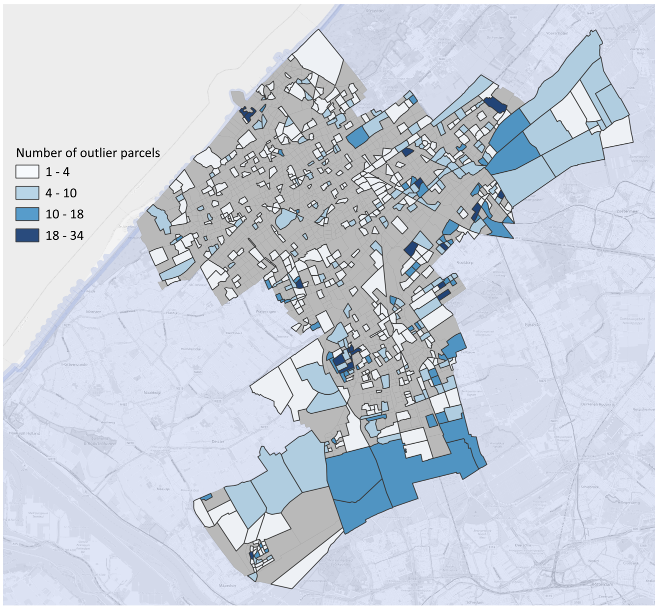
E. Sensitivity analysis

This section explores the impact of including both cost and environmental factors on the identification of outlier parcels. The CO2 emissions of each parcel, calculated by the COFRET method, are converted to a corresponding CO2 cost () using the following equation:

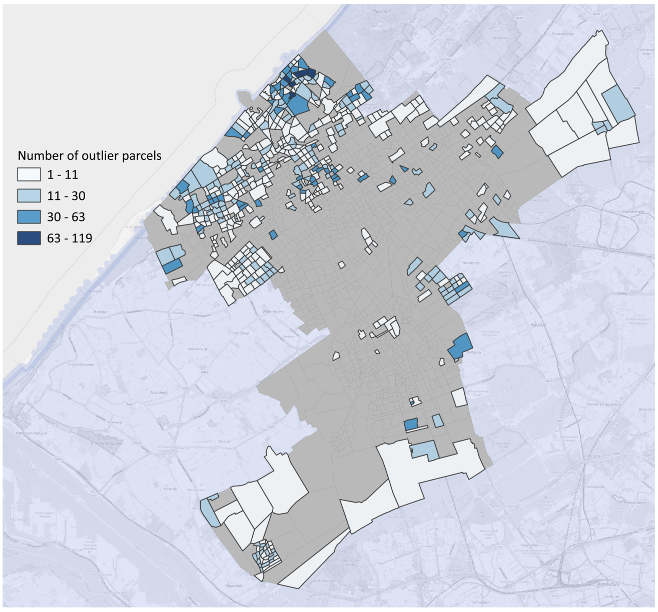
$$CO_2\ cost\ per\ parcel = Carbon\ cost\ * \\ CO_2\ emission\ per\ parcel \tag{10}$$

The CO2 cost is then added to the parcel's marginal cost to create a new integrated cost indicator. This integrated cost accounts for both economic and environmental factors, and outlier parcels are re-identified using this adjusted value.

Four carbon cost scenarios were tested: 100, 200, 500, and 1000 $/ton$. These values reflect current and future carbon pricing projections, as outlined by [45]. The aim is to assess how different carbon cost levels affect the identification of outlier



(a) Cost-based distribution



(b) Combined distribution of outlier parcels

Fig. 10: Combined distribution of outlier parcels

parcels by observing changes in thresholds, the proportion of outlier parcels, and the number of outlier zones.

Figure 11 shows the results for the six CEPs, displaying the trends in threshold values, outlier parcel percentages, and the number of outlier zones across different carbon cost levels.

The results show that as the carbon cost increases, the threshold values for identifying outliers rise for all CEPs, reflecting the higher integrated costs. Among the CEPs, PostNL shows the smallest change, while FedEx exhibits the largest, due to the long distances between its depot and the delivery zones, which lead to higher CO2 emissions.

The proportion of outlier parcels and the number of outlier zones vary differently for each CEP. For PostNL and FedEx, the proportion of outliers increases as carbon costs rise, driven by long-distance deliveries to remote areas. DPD and UPS, however, show a decrease in outlier parcels, as their more localized operations result in lower CO2 costs.

The geographical distribution of outlier parcels also shifts as carbon costs rise. Parcels in areas closer to depots tend to disappear from the outlier list, while parcels delivered to farther, high-emission areas become outliers. This shift highlights how carbon costs can reshape the logistics cost structure and influence the distribution of high-cost parcels.

V. Discussion

This section discusses the study's contributions, limitations, and potential improvements, as well as recommendations for future research.

A. Contribution

A key contribution of this study is the development of two methods for identifying outlier parcels based on cost and emissions. These methods offer a quantitative approach for logistics service providers (LSPs) to pinpoint parcels with unusually high costs or environmental impact. This is the first study to systematically combine cost and emissions in outlier identification, making it a novel contribution.

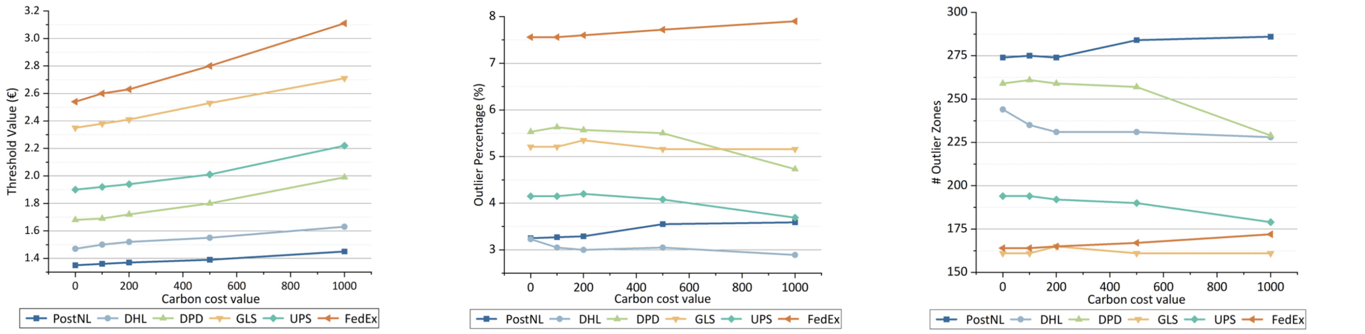
Additionally, the use of the elbow point method to set thresholds for outlier identification is a significant improvement. Unlike previous studies that used arbitrary methods, the elbow point provides a data-driven way to objectively identify inefficient parcels, making it easier for LSPs to apply in real-world settings.

While Zhang et al. [10] explored outlier parcels in crowdshipping, this study focuses on outlier identification in traditional delivery networks. The elbow point method effectively identifies parcels with higher costs or emissions, providing actionable insights into operational inefficiencies.

The study also reveals interesting trends. For example, marginal costs are more concentrated than CO2 emissions across different CEPs, likely because cost factors are more predictable. Emission outliers tend to cluster in edge areas due to longer delivery distances, whereas cost-based outliers are more evenly distributed.

The analysis shows that carbon costs currently have a limited impact on integrated costs because of the low carbon price. As carbon prices rise, the impact on outlier identification will become more significant, but traditional costs still dominate most companies' operational decisions.

Lastly, the study highlights the potential changes in outlier parcels if CEP networks are integrated. Some parcels currently classified as outliers may no longer be so after optimization, and new outliers may emerge. This suggests that while integration improves network efficiency, companies should carefully assess its impact on specific zones.



(a) Threshold value (b) Percentage of outlier parcels (c) Number of outlier zones

Fig. 11: Line charts of different indicators for 6 CEPs

B. Limitations

The study's reliance on delivery distance and time to calculate costs is a limitation, as it overlooks factors like vehicle maintenance, fuel consumption variance, and labor costs. This simplification may lead to biased outlier identification.

Another limitation is the exclusion of delivery success rates. Failed first deliveries, which are common in urban areas, increase costs, and ignoring this factor may underestimate the true costs of certain parcels.

The CO2 emission calculation is simplified, based on distance and fuel consumption, but doesn't account for real-world factors like road conditions or traffic congestion. It also focuses solely on CO2, ignoring other pollutants.

The study assumes that only vans are used for delivery, but in reality, a range of vehicles, including electric trucks and bicycles, are involved. Considering different vehicle types would improve the study's applicability.

The elbow point method, while useful, is purely statistical and does not account for the specific needs of logistics companies. Incorporating actual operational data from companies would strengthen the study's validity.

Finally, the MASS-GT simulator has limitations in tour formation. It assumes all parcels are of uniform size and weight, and its vehicle capacity assumptions may lead to unrealistic detours, affecting the accuracy of outlier identification.

VI. Conclusion

This research explored the identification of outlier parcels in urban deliveries using cost-based and emission-based methods. The results show that different strategies can significantly impact which parcels are identified as outliers, emphasizing operational inefficiencies and environmental concerns.

Cost-based identification method reveals inefficient zones such as detours, unreasonable tour formations, and low parcel demand that lead to higher delivery costs. In contrast, emission-based method identifies outlier parcels in edge areas where longer delivery distances lead to higher CO2 emissions, underscoring the environmental impact of logistics operations far from urban centers.

The sensitivity analysis shows how variations in carbon cost influence the identification thresholds and geographic distribution of outlier parcels. These results suggest that incorporating carbon cost into logistics network could reshape the cost structure, leading to more environmentally focused delivery strategies.

For future research, some recommendations are presented. Expanding the study to different regions and countries could help refine the methods, considering variations in infrastructure, population, and regulations. The Introduction of more diverse identification methods that integrate multiple attributes might allow for more flexible decision-making. Additionally, future work should explore how innovative delivery methods, such as drones and crowdshipping, can effectively handle outlier parcels, which can potentially improving overall logistics efficiency and sustainability.

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