Last-mile logistics optimization in the on-demand economy

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Last-mile logistics optimization in the on-demand economy

Qu Wei

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Supervisor(s):
Prof. G. Perboli, Supervisor
Prof. Z.X. Guo, Co-Supervisor

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Declaration

I hereby declare that, the contents and organization of this dissertation constitute my original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

Qu Wei
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Chapter 1

Introduction

City logistics aims to find appropriate strategies that can improve the overall efficiency of freight distribution in urban areas while mitigating congestion and environmental externalities. Many driving factors, including globalization, urbanization, e-commerce, and on-demand economy, have promoted significant paradigm shifts in city logistics over the past decades. On the one hand, the growth of e-commerce creates a new consumption pattern in Business-to-Consumer segments resulting in increasing demand for home deliveries and deliveries at alternative locations in the urban area. The e-commerce giant platforms are forced to provide fast and cheap deliveries, facing fierce competition.

On the other hand, urbanization and globalization increase freight flow dramatically, impacting and challenging the supply chain. Freight movements contribute significantly to congestion and environmental issues in the urban area. Moreover, recent phenomena as the on-demand economy, e-commerce, and advanced digital technologies, enlarge the framework of city logistics. Customers request more flexible and fast deliveries such as same day and even within 2 hours. It is thus crucial to develop innovative strategies to build a more efficient, cost-effective, and sustainable city logistics system.

City logistics is inherently interdisciplinary, challenging different stakeholders (i.e., City authorities, Freight carriers, Residents, and Retailers) to improve the overall performance of freight distribution while mitigating their externalities and inefficiencies. Many researchers and practitioners propose collaborative business models and initiatives to optimize city logistics' economic, operative, social, and environmental goals. However, not all initiatives and proposals are successfully implemented. One of the main reasons for failure is a lack of support and commitment from different stakeholders [1]. Besides, they fail to design suitable and sustainable policies for city logistics from a managerial perspective while mainly focusing on the technological issues as platforms or optimization tools, missing a global version and ignoring the interaction between business and operational model.

In the last decades, many research and state-of-the-art have developed different models, methods, and decision support tools for city logistics from technological perspectives [2-6]. However, there are still some critical issues in the application of city logistics. In the e-commerce era, the information related to orders appears online, mainly from private customers, generating a dynamic and uncertain setting. The number of orders is much larger than in the classical distribution services. Most orders have a significantly reduced weight and volume, challenging the decision-makers to cope with large-scale problems with uncertainty. Besides, online orders are increasingly associated with the explicit request, or at least the expectation, of faster delivery times, like same-day or even 2 hours deliveries. The decision-making process is thus contracted into very short-time horizons, highlighting the need for a flexible system that can represent different behaviors into an overall model. Some innovative strategies and new business models can be integrated into parcel delivery and freight transportation if a negotiation process is done between stakeholders. For example, the success factors of innovative proposals and initiatives should be considered in the actual application of parcel delivery. The adoption of new delivery options and crowdsourced delivery models should align with different actors' broad goals (e.g., economic, social, operational, and environmental goals). It is necessary to develop a holistic approach to investigate the managerial and operational application of city logistics, particularly the last-mile delivery, as it is the least efficient stage of the supply chain. However, such an approach is still missing in the literature.

This thesis aims to fill this gap in the literature in terms of multi-disciplinary approach and modeling framework for last-mile optimization. It starts with an extensive analysis of the recent relevant literature on smart city projects, highlighting these initiatives' critical success and failure factors. The review conducted on smart city projects confirms the interdisciplinary nature of applications in city logistics. The results highlight the need to merge technologies and strategies into sustainable solutions capable of facing the logistics challenges and, in the meantime, satisfying demanding customers. The challenge for sustainable solutions of city logistics is to integrate business models of the different actors, embedding prediction and optimization techniques considering the dynamism, pricing, and costing schemes, as well as operational issues of the new system.

In this direction, the thesis contributes to:

- demonstrate the potential value of integrating business and operational models in city logistics.
- investigate the benefits of the integration of business and operational models in the city context. In particular, the thesis focuses on the last-mile optimization of the supply chain, considering the integration of crowdsourced delivery and multiple delivery options in urban parcel delivery with large-scale and uncertain settings.
- investigate the possibility to reduce carbon emissions in parcel delivery applications, taking advantage of using real-world GPS trajectory data of floating vehicles in a megacity of China.

This thesis is organized as follows.

Chapter 2 provides an overview of city logistics, introducing the emerging trends and challenges and presenting the extensive analysis of smart city projects related to city logistics.

Chapter 3 presents the managerial and strategic analysis for urban parcel delivery, describing the stakeholders' profiles in terms of their needs, cost, and revenues structures. We propose a multi-disciplinary approach that integrates the traditional transportation modes (i.e., vans) and low-emission vehicles (i.e., cargo bikes). Besides, the integration of business and operational models is demonstrated by the performance analysis of two delivery options, based on the main variables such as travel distance and delivery time. This chapter is based on the paper [7] developed in collaboration with another PhD student.

In Chapter 4, we propose a multi-stage stochastic model to capture the dynamic and stochastic features of real-world parcel delivery application and solve a dynamic and stochastic vehicle routing problem with time windows by a simulation-optimization strategy. We extend the preliminary analysis of the integration of traditional transportation (i.e., vans) with new delivery options (i.e., cargo bikes). We also consider ordinary people as crowd drivers who offer their time and resources to provide transportation services, reflecting the emerging trend in practice. To demonstrate the potential benefits of this integration, we conduct a case study in the medium-sized city of Turin (Italy). This Chapter is based on the paper in [8].

Advanced improvements in technology enable researchers and practitioners to measure the real-time travel speed through the real-world GPS trajectory data of floating vehicles. In Chapter 5, we study a time-dependent green vehicle routing problem based on real-time travel speed in the road network of Chengdu, a megacity in western China, investigating the possibility of carbon emission reduction by calculating the lowest fuel consumption path in parcel delivery application. A branch and price algorithm is used to solve this problem. We also demonstrate that the time-dependent lowest consumption path is a promising choice for carrier companies in fuel consumption and travel-time saving.

Finally, Chapter 6 summarizes conclusions and future developments of the research activity

Chapter 2

Urban freight transportation and last-mile logistics

2.1 Urban freight transportation and logistics in the on-demand economy era

The growing urbanization and the development of megacities (having more than 10 million inhabitants) give rise to numerous city logistics challenges. City logistics, also known as urban freight transportation, is about finding efficient and effective ways to distribute goods in urban areas while avoiding undesirable consequences on congestion, human health, and the environment [9]. The definition of efficiency includes fewer vehicles, better vehicle capacity utilization, and reduction of CO2 emissions and other greenhouse gases. Efficiency is involved in the flexibility of operations, service quality, and synchronization of different services in cities. In addition, freight transportation is one of the significant causes of traffic congestion, air pollution, and noise, which significantly influence the quality of life in urban areas. Crainic et al. [3] highlighted that 30% of city street capacity is consumed by freight vehicles in major French cities. On average, freight transportation represents 10% of the total vehicle kilometers traveled in 13 American cities [10]. Figures are equally telling on energy consumption and CO2 emissions. Urban traffic accounts for 40% of CO2 emissions and 70% of emissions of other air pollutants within road transport-related CO2 emissions.

Consequently, traffic and congestion lead to almost 1% loss (i.e., about 100 billion Euros) of the European Gross Domestic Product (GDP) every year. Furthermore, in the US, transportation represented 27% of total U.S. greenhouse gas emissions in 2013 and increased more from 1990 to 2013 in absolute terms than any other sector [9]. It is thus crucial to design a more innovative and competitive freight transportation system while reducing the negative environmental impacts.

Moreover, it is well-recognized that city logistics is involved with several participants and key stakeholders which has different roles, problems, and concerns, including:

- City authorities. They implement policies to mitigate the negative impacts of city logistics and reconcile the often-conflicting interests of the different stakeholders.
- Freight carriers. They need to move freights around the urban areas to customer destinations. They require many urban infrastructures such as parking and loading area to complete the services. They are mainly concerned with the efficiency, capacity, and reliability of deliveries.
- Residents. They act as one of the primary recipients of urban parcels. Residents expect fast delivery services and not to be affected by traffic jams, noise, and pollution.
- Retailers. They are trying to maximize their profit while maintaining a stable, sustainable, and competitive business model. For example, they cooperate with third-party logistics providers to reduce the operational cost of last-mile delivery. In addition, they initiate some innovative strategies to increase customer orders, such as promotion and additional services.

It is challenging to suit all the user groups with such a range of disparate views and conflicting interests. For example, freight carriers are expected to provide a high level of service at a lower cost. Moreover, traffic congestion levels in urban areas have constantly risen because of the increasing traffic demand. Therefore, it is vital to view the individual stakeholders and decisions as components of an integrated city logistics system, which implies the cooperation of carriers, retailers, movements, and the consolidation of loads of different customers. Besides, city logistics encounters many changes in political, economic, and social conditions in the era of the on-demand economy. The main changes are following:

- Urbanization. Urban population growth is challenging the city logistics systems in both developed and developing countries. According to the

World Urbanization Prospects 2018 [11], the urban population reached approximately 78.7% and 50.6% in developed and developing countries by mid-2018.

- Globalization. Urban areas, as economic units, are supporting and are influenced by globalization. The scale and intensity of the mobility of capital, goods, residents, and techniques have been expanded by international transactions (e.g., trade liberalization). On the one hand, these phenomena are challenging the global design of city logistics systems such as facility location, infrastructure construction, and resource allocation. On the other hand, the urban region becomes a core organizational and competitive unit where logistics firms thrive on comparative costs and innovative capabilities.
- The blowout growth of e-Commerce reshapes the entire logistics chain. Daniela [12] reported that over two billion people purchased goods or services online, and e-retail sales surpassed 4.2 trillion U.S. dollars worldwide in 2020. Thanks to the ongoing digitalization of modern life, customers can request fast and even on-time delivery services for free or at a lower cost. With the extreme competitive conditions, the logistics firms are forced to reduce operational costs through innovative logistics solutions. Indeed, some leading e-Commerce platforms, such as Amazon and Alibaba, are facing increasing requests for fast, cheap, or even free deliveries with high-quality service. According to Marcucci et al. [13], 74% of consumers state that they will most likely buy a product that offers a same-day delivery service in the US. Only 32% of consumers are willing to wait 2 or 3 days for delivery in the UK. In this context, traditional delivery serves are transformed as the sale of immediately deliverable products. For example, *Amazon Prime* and *Amazon Now* enable online orders to be received within a day or even two hours. Therefore, the efficiency of logistics becomes vital for their competition.
- The intensive restrictions of greenhouse gas emissions from governments and city authorities force logistics firms to reduce fuel consumption and emissions. Indeed, as the world’s biggest greenhouse gas emitter, the Chinese government has announced to cut its carbon dioxide emissions per unit of gross domestic product, or carbon intensity, by more than 65% from 2005 levels by 2030 and achieve carbon neutrality by 2060. In addition, the EU has put in place legislation to reduce emissions by at least 40% by 2030 – as part of the EU's 2030 climate and energy framework and current contribution to the Paris Agreement. The

importance of environmental issues is continuously translated into regulations, with a tangible influence on logistics and supply chain management.

All these changes are reshaping the traditional city logistics. The increasing growth of e-commerce, for example, contributes to a significant increase in direct-to-customer services in urban areas, which leads to the so-called last-mile challenges. Besides, the ever-growing attention to sustainability continuously changes both solutions and decision support systems of urban freight transport. The basic idea is that the development of city logistics does not eventually lower the quality of life and attractiveness of city areas and does not impact the global climate and residents' health. It implies that multiple and competing objectives must be considered and handled suitably during city logistics system design, planning, and execution.

2.2 Trends and challenges

From a global perspective presented above, it is clear that city logistics is a complex system, challenging the city authorities and other stakeholders to find an appropriate solution to improve transportation efficiency while preserving the quality of life of residents. In particular, the most critical trend and related challenges for urban transportation and logistics are described as follows.

E-Commerce Growth. United Nations states that the urban population is set to increase by almost 700 million by the year 2030, reaching a total of 5.2 billion, which results in the increase of urban movement for goods in these areas. The considerable rise in urbanization rates results in a change in the people's demands for goods. With the deep integration of digital technology and the real economy, urban consumers can buy products and services electronically. E-commerce is developed as a new business model to fulfill the enormous market demand. It is experiencing growth of more than 10% per year worldwide and regionally. The first factor that explains this explosion is the increase of Internet users. Besides, the widespread use of the Internet is undergoing a further acceleration due to the pandemics caused by COVID-19. Online sellers gain massive success because of the safety and convenient services and lower prices. Amazon and Alibaba are reported to bill more than a trillion dollars a year. E-commerce changes the delivery pattern of city logistics, especially the last mile delivery. The number of freight movements increases significantly since the goods need to be delivered to consumers' homes rather than retail stores. In addition, the widespread diffusion of intelligent devices considerably increases the total number of mobile-based transactions. In this context, retailers and logistics firms need to provide on-demand logistic capabilities to keep up with consumer expectations that incorporate high logistics service quality and low costs.

On-demand Economy. The on-demand economy refers to a new business model based on online platforms that provide *immediate matching* between a user who needs a good or service and another who can share the assets of skill, time, or goods. It has led to the reorganization of the supply chain, which creates a new industrial philosophy, the so-called *just-in-time*. In the e-commerce sector, the delivery services are pushed to be completed within the same day or even two hours. Though the on-demand economy improves the experience perceived by customers, it undeniably increases the complexity of the logistic system, challenging the logistics service to develop more efficient and innovative solutions. Some leading retailers have started to share logistics infrastructure and services with competitors. It enables them to share existing assets and capacities through online sharing platforms, especially when the assets need a large amount of capital [14]. According to Savelsbergh and Woensel [9], sharing assets and capacities can increase consolidation and capacity utilization, reducing freight movements, fleet size, and empty travel for logistics firms. In addition, Amazon, DHL, and Wal-Mart have developed logistics service that takes advantage of professional crowdsourced delivery capabilities. For example, Wal-Mart, a major retailer in the US, has developed a collaborative service that encourages its employees to deliver online products to consumers' homes [15]. In 2015, Amazon implemented crowdsourced last-mile delivery by creating *Amazon Flex*, an on-demand package delivery service that employs freelance workers to deliver same-day delivery packages to final customers [16]. In addition to developments of this system by leading e-retailers, multiple start-ups have been launched in recent years that provide last-mile crowdsourced deliveries (e.g., Deliv, DoorDash, Hitch, Postmates) [17]. These collaborative business models can be both attractive and financially convenient for both operators and consumers as they can: (1) cut financial and environmental costs, taking advantage of using existing assets and resources; (2) increase the time and capacity flexibility for logistic operators and customers in performing their respective actions; (3) reduce the number of permanent drivers, driving kilometers, and double line parking thus implicitly decreasing operational cost. However, difficulties in these novel business models should not be underestimated regarding environmental sustainability, income distribution equality, and system resilience. For example, Alnaggar et al. [17] highlighted that there are many new challenges of making appropriate decisions for crowdsourced delivery system including matching decisions, routing decisions, scheduling decisions, and compensation decisions.

Improvements in Technology. The new and emerging technologies, such as digital connectivity, big data, and automation, can drive city logistics innovation and potentially reduce the negative impacts on congestion, safety, and the environment. Nowadays, data are everywhere. The availability of real-time data from different sources, including transportation infrastructure sensors, global positioning system (GPS) of vehicles, and various information systems from logistics firms and shippers, can improve reliability, efficiency, and visibility of freight transport operations. In addition, data is more and more openly available and shared with customers, enabling them to view the real-time status of deliveries via mobile devices and online platforms. However, there are still many challenges. For example, data needs to be extracted and analyzed in real-time, requiring advanced data analytics methods. Besides, the volume, velocity, and variety of data arriving in real-time continue to accelerate. Therefore, logistics firms need to transform these data into decisions quickly. However, embedding and effectively using high-value information in the decision support system is nontrivial, primarily when associated with uncertainty (i.e., demand, capacity, travel times, etc.)

Large-scale Problems and Uncertainty. The growing demand in e-commerce mentioned above has led to a rapid increase in freight movements in urban areas, calling for the appropriate solutions for solving large-scale problems. Indeed, the online shopping platforms allow consumers to order the fragmented demand more frequently than collecting in the retail stores, resulting in vast parcel flows. The high density of deliveries point-to-point leads to an increase in the delivery travel distance and service times because of traffic and congestion. Besides, the advances in technology enable consumers to buy a product or service through online platforms at any time, which contributes to multiple types of uncertainty for logistic systems. For example, the total demand, location, and travel time from the distribution center to the final customers' homes are unknown before planning execution.

2.3 Smart city and its link to city logistics

This section starts with a brief introduction of smart cities and their essential elements, followed by an extensive analysis of smart city projects (SCPs) in the literature. It then ends with some results that highlight the link between city logistics and smart cities.

2.3.1 Smart city and its key elements

Smart city, as technology and data-driven paradigm for sustainable city development, has received more and more attention in recent years. It is essential to understand the success and failure factors that influence smart city performance and its interactions with city logistics. There are some different definitions of the smart city in the literature. The European Commission [18] reported that a smart city has more efficient traditional networks and services that benefit its inhabitants and business, taking advantage of the information and communication technologies (ICT). It means a more interactive and responsive city administration, more innovative urban transport networks, and better facilities locations. This definition is aligned with the Smart City Foundations proposed by Harrison et al. [19]. They define a smart city as "connecting the physical infrastructure, the IT infrastructure, the social infrastructure, and the business infrastructure to leverage the collective intelligence of the city." Indeed, from a global view of a smart city, it should be considered a place where different types of resources and advanced technologies are well integrated. Smart cities actively involve various stakeholders, including the residents themselves, transforming them from mere observers to core contributors to innovation [20]. From the trend and challenges described in section 2.2, it is clear that the top-level design of smart cities plays a vital role in the reformation of city logistics. The smart city logistics solutions should be in line with the logic of smart city design. For example, the optimization of logistics activities is achieved based on the connectivity between various stakeholders. This optimization process aims to fulfill consumer expectation, minimizing operational cost, and related externalities including climate change, air pollution, noise, and congestion. The key elements of smart city logistics can be summarized as following:

- Digitalization and Big Data Analytics. Efficient data sharing is fundamental to extracting high-value information from the big data on city logistics, particularly the transportation sector. It contributes to data sharing across the different transport stakeholders and thus can improve the products and services. The Intelligent Transport System (ITS) effectively combines various technology, infrastructure, service, planning, and operation methods, supporting real-time data collection and decision-making processes. The smart devices are deployed in the network of ITS, such as sensors, controllers, GPS devices, mobile phones, cloud computing, and IoT [21], which enable ITS to provide secure and economic on-demand services.
- Collaboration among stakeholders. The cooperation of multiple and diverse stakeholders is more and more critical as it can benefit for increasing the transparency and communication between players. For example, different managers and workers may have different cultures and

backgrounds, resulting in a different understanding of operations or even conflicts in practice.

- Flexible deliveries by multimodal transport. Multimodal transport means the freights movements are involved with more than one mode of transportation. It offers more efficient and sustainable delivery and has thus developed as an essential component for city logistics worldwide. Besides, multimodal logistics increase the capability of ITS to address the uncertainty in dynamic decision-making problems in facing real-time changes (i.e., customer demand, locations, service time, and travel times). Perboli et al. [8] reported that the multiple delivery options benefit the management of last-mile delivery in terms of economic and environmental cost-saving, providing a flexible solution for on-demand delivery services.
- Urban Consolidation Center. Urban Consolidation Centers (UCCs) are logistic facilities located in urban areas that serve as terminals or satellites for multimodal logistics systems. They collect packages from different logistics firms, consolidate them, and then deliver them to final customers. It can reduce the total travel distance and pollution for last-mile freight transportation [22]. However, the efficient and sustainable operation of UCC requires many supports from stakeholders: (1) political support; (2) governance and financing viability; (3) strategic location design; (4) the organization of the last-mile logistics.

In summary, intelligent city logistics combines digital technologies that integrate stakeholders, systems, and transport means that interact with users to develop a sustainable and environmental-friendly logistics system that fulfills residents' expectations.

2.3.2 Analysis of SCPs

This section aims to fill the gap by applying the taxonomy proposed by [23] to a set of 199 outstanding SCPs globally to provide some relevant insights on the critical success and failure factors of projects in the transportation industry. Indeed, it emerged as the most predominant sector the city managers are looking for sustainable development, reflecting the close link between transportation, City Logistics, and Smart City.

Smart cities have received increasing attention in recent years. One part of the literature addresses the concept of smart cities by elaborating the definitions, applications, and main characteristics. For example, Albino et al. [24] provide an in-depth analysis of the literature and identify the primary descriptions of smart cities. Su et al. [25] identify the relevant content of the construction of smart city applications, including the wireless city, smart home, smart transportation, intelligent public service and social management, smart urban governance, and green city. Caragliu et al. [26] summarize smart cities' common characteristics from different perspectives concerning the smart economy, mobility, environment, living, and governance. Moreover, Zanella et al. [27] elaborate on the smart city concept and services, including buildings' structural health, waste management, noise monitoring, traffic congestion, city energy consumption, smart parking and lighting.

Although the concept of smart cities lacks universality due to the different vision and priorities, the improvement of people mobility and freight transportation in urban areas through the adoption of ICT solutions represents one of the main pillars to achieve a smart city, according to a consistent part of the literature. For example, Xiong et al. [28] review intelligent transportation systems for smart cities and illustrate the outlook of intelligent urban transportation in China. Intelligent transport planning is introduced in the 12th Five-Year Plan, the "Internet of Things" and "Smart City" major special projects.

Mohanty et al. [29] identify the different components of a smart city, such as smart infrastructure, smart transportation, smart energy, smart healthcare, and smart technology. The ICT, especially two emerging technology frameworks, Internet of Things (IoT) and Big Data (BD), enables keys for improving smart cities. Nowicka [30] presents smart city logistics on the cloud computing model for a sustainable city. The internet technologies promoting cloud-based services, IoT, use of smart phones and smart meters and RFIDs allow meeting the citizens' demand-driven requirements in City Logistics. Moreover, Awasthi et al. [31] apply a fuzzy TOPSIS method to evaluate sustainable transportation systems for smart cities. It provides a multi-criteria decision-making approach for decision-makers to assess the associated environmental costs, including air pollution, noise, etc., which is regarded as the quality of life in modern cities.

Malindretos et al. [32] introduce the link between City Logistics and Smart Cities reviewing the City Logistics models that have been implemented in Europe for the sustainability and the growth of smart cities. The models that the authors investigate concern the application of City Logistics measures as the Urban Freight Consolidation Centres.

Although we recognize the importance of City Logistics to foster the development of smart cities, we identify a lack of a global vision of the main trends and patterns and the critical success and failure factors of these initiatives. This study aims to fill the shortage in the literature concerning smart cities by proposing a cluster analysis of SCPs, based on a taxonomy with polythetic classes [33]. The taxonomy used is illustrated in Figure 2.1.

From a methodological point of view, we built it following a three-step method described by [33]. First, we began with an empirical analysis of the SCPs ended, ongoing, or at least already funded in 2018, retrieving information about projects from referred journals and conference proceedings as the source of Smart City literature, deliverables of the projects, governmental and consulting reports. This first phase yielded a selection of about 199 outstanding SCPs (25 in Europe, 55 in Canada, 25 in the USA, 20 in Brazil, 26 in Australia, and 48 in Asia), making our analysis, even if not exhaustive, the most extensive screening of SCPs in the selected areas.

According to the lean business methodology GUEST [34], we added to the taxonomy a further level of analysis based on a managerial perspective, which could help researchers and practitioners to define more appropriate business models in future projects. For this purpose, for each SCP, we analyzed the value proposition and the business model. The aim is to highlight the needs, gains, and pains of the main stakeholders involved and the components needed to make the project work, including the costs and revenues structures.

This further analysis represents a value-added for future real case studies and research projects. Considering these results, government and project initiators should be able to dene more appropriate business models and policies for Smart Cities applications, anticipating the stakeholders' requirements in the early stage of the project, with benefits regarding the success of the projects and financial sustainability in the long run.

Taxonomy

The taxonomy (Figure 2.1) is composed of three different axes, representing the three main criteria used to classify the various aspects of the SCPs. They are Description, Business Model, and Purpose. In the following subsection, we briefly describe the taxonomy, while the interested reader could refer for a detailed discussion of each axis and category to the original work of [23].

Description. It provides an overview of the project and its context, with particular regard to its categories, to the objectives faced and the industry (Objectives), the tools and the technologies adopted (Key Enabling Technologies), the nature of the project initiator (Project initiator), and the key actors involved in an SCP (Stakeholders).

Business model. The increasing Smart City interest leads to the need for redefining new business models and governance mechanisms. Thus, this axis addresses the aspects related to project management and the business and

governance models. It investigates the nature of the project manager (Management) and the providers of infrastructures, equipment, and financial resources (Infrastructure financing and Financial Resources). In particular, an essential building block of a Business Model is those concerning the key resources [35]. In SCPs, they are mainly represented by physical assets as infrastructures, equipment, vehicles, and devices or by financial resources essential for the project realization. Private entities, public or mixed, can provide these resources. According to the World Economic Forum [36], the private sector has a pivotal role, supporting the planning of the needed infrastructure and helping to address capacity issues across state governments and urban local bodies.
Purpose. This axis classifies the SCPs according to their final goal. It identifies the user that will adopt and benefit from the solution developed by the project (Client), the type of product (Product), and the geographical target (Geographical target).

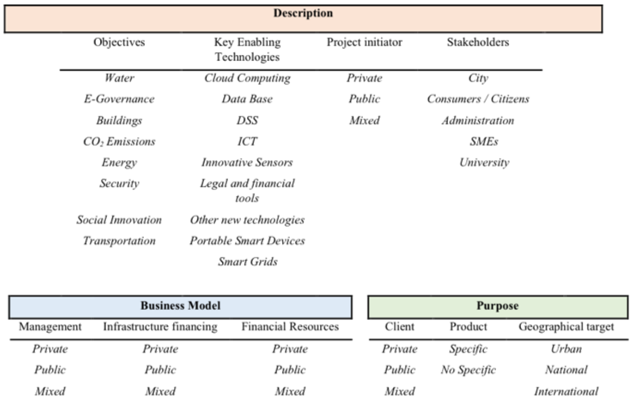


Figure 2.1 Taxonomy

2.3.3 Trends of the transportation industry in SCPs

This section presents the results obtained from applying the taxonomy to the sample of SCPs in different continents.

Concerning the Description axis, the results represented in Table 2.1 highlight that transportation is one of the most frequent objectives in SCPs, particularly in the United States (60%), Europe (52%), Asia (75%), and Brazil (60%). Moreover, usually, transportation is combined with building, energy, and reduction of CO_2 emissions objectives due to the high correlation of these sectors and mutual benefits. These results are more significant in Europe and Asia. They relate to the encouragement of the European Commission to zero-emission transport with the Horizon 2020 program and the increasing attention of Asian countries on the City Logistics topic.

Table 2.1 Different objectives of smart city projects for each country*

Objectives	USA	Canada	Europe	Australia	Asia	Brazil
Transportation	60%	44%	52%	46%	175%	60%
City Logistics	8%	-	24%	8%	4%	-
Energy	44%	45%	68%	50%	65%	95%
Buildings	20%	24%	56%	27%	48%	25%
CO2 Emissions	52%	33%	68%	46%	44%	100%
Water	24%	22%	8%	23%	39%	5%
Security	40%	33%	12%	12%	63%	20%
E-Governance	24%	25%	24%	15%	48%	35%
Social Innovation	40%	47%	32%	58%	63%	25%
Multi-Objectives	72%	69%	92%	69%	92%	100%

*The sum of the percentages of the objectives category is more than 100% due to the great relevance of the multi-objective projects.

Due to the strict correlation between these industries, the SCPs that deal with the transportation objective commonly involve critical enabling technologies (Figure 2.2) as ICTs, new technologies (e.g., RFID and GIS), smart grids, and innovative sensors. The results highlight the higher propensity of European, Asian, and Canadian countries to adopt innovative technologies than the USA, where Cloud Computing and database tools are the most present in projects focused on logistics, transportation, and mobility of passengers and freight. This finding reflects the increasing diffusion of the IoT paradigm for Smart Mobility and City Logistics issues. In fact, according to Zanella et al. [27], urban IoTs are designed to support the smart city vision, which aims at exploiting the most advanced communication technologies to help added-value services for the administration of the city and the citizens. For example, the Smart Columbus initiative in districts in the Columbus Region adopts the ITS to deploy a Driver Assistive Truck Platooning System. It is based on wireless technology to ensure the efficient and safe movement of logistics-related vehicles.

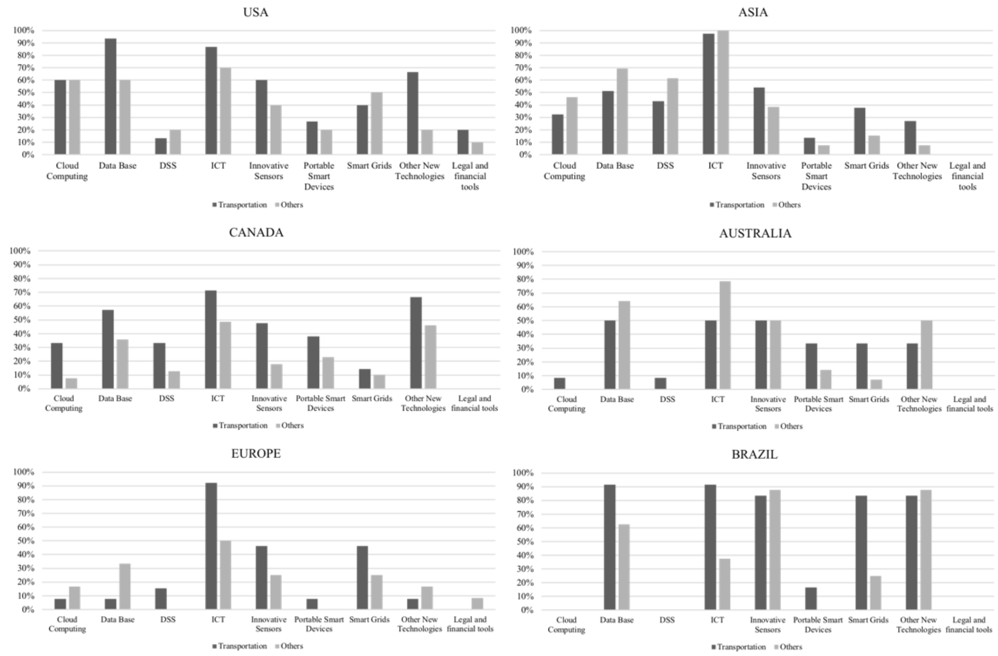


Figure 2.2 Key enabling technologies to deal with transportation in Smart Cities

The Grow Smarter initiative aims to guarantee a sustainable last-mile delivery of goods in dense urban areas in Barcelona. The proposed solution consists of installing an urban consolidation center for the micro delivery of goods, from which the last-mile operators perform deliveries using electric tricycles. These vehicles are equipped with IoT sensors to monitor environmental information (e.g., temperature, air pollutants, and humidity) and link them to their position through GPS technology.

Moreover, many city managers are adopting innovative transport solutions within the framework of the City Logistics to meet the biggest challenges that smart cities are facing today (e.g., traffic and congestion). An example is the URBeLOG project co-funded by the Italian Ministry of Education, Universities, and Research under “Smart Cities and Communities and Social Innovation” [37]. This initiative aims to develop an innovative open, dynamic and cooperative telematics platform combined with the adoption of infrastructure City Logistics measures as the mobile depot, providing services and applications for the last mile logistics in urban areas. Moreover, URBeLOG integrates main functions allowing the development of processes, services, and applications for City Logistics of the future (e.g., possibility to book loading/unloading zones, road pricing, and traffic restrictions).

On the other hand, the governments aware of the need for more efficiency and effective management of cities, due to the rapid urbanization, started to foster investment in ICT tools to improve the infrastructures and overcome socio-economic problems. In the majority of the projects, the ICT infrastructure is coupled with Operations Management and Operations Research tools to optimize the operations. Fewer projects are using such methods to incorporate user behaviors and integrate the business models. This trend confirms a more general trend in Operations Management, relegating the Operations Research methods to the operational and, sometimes, the tactical level and somehow losing the grip with the managerial and business model and development phases.

Moreover, smart cities initiatives lead promoters to adopt measures to improve transportation and mobility within urban and metropolitan areas attributed to social sustainability. These initiatives usually combine objectives as Transportation and Security, aiming to improve urban road safety.

Concerning the link between Smart City and City Logistics, Table 2.2 summarizes some SCPs with a strong emphasis on urban freight transport and logistics, highlighting the City Logistics measure adopted, according to the categories presented in the literature [37]. However, to our vision and as emerged in Table 2.1, SCPs are still too focused on people mobility, disregarding the potential for efficient and sustainable urban freight transportation in making cities smarter.

Table 2.2 Details of Smart City initiatives dealing with City Logistics

Project/Initiative	Location	City Logistics measure	Details
Gold Coast City Transport Strategy 2031	Australia	Infrastructure	Loading zones and off-street loading facilities for freight Multimodal urban arterial road
Adelaide Smart Move	Australia	Infrastructure Regulation, Technology	Consolidation center Management of smart parking and loading zones by "Park Adelaide"App
Ningbo	Asia	Technology	Cloud Logistics and IoT
Smart Columbus	USA	Technology, Infrastructure	Multimodal trip planning tool Connected vehicles Truck platooning through Intelligent Transport Systems Smart hub
Beyond Traffic: The Smart City Challenge Kansas City	USA	Technology	Connected vehicle freight applications Intermodal terminal reservation systems Sensors
Triangulum	Europe	Technology, New business models	Electric vehicles Last-mile cargo bikes Real time monitoring software and hardware systems
URBeLOG	Europe	Technology, Infrastructure	Hybrid and Electric vehicles equipped with on-board units Online platform for logistics management of last mile and booking loading/unloading zones IoT sensors
STRAIGHT SOL	Europe	Technology, Infrastructure, New business models	Mobile depot Electric vehicles Last-mile cargo bikes Hybrid Urban Consolidation Center
Sharing Cities London-Milan-Lisbon	Europe	Technology	GPS based monitoring system Implement Electric vehicles in City Logistics
REMOURBAN	Europe	Technology	Electric vehicles
Growth Smarter	Europe	Technology	Electric vehicles Smart traffic management and sustainable delivery systems Micro distribution of freight with the use of sensors

We looked at the managerial aspects representing our approach's novelty regarding the categories Project Initiator, Stakeholders, Management, Infrastructure Financing, Financial Resources, and Client. It emerges a massive public sector engagement in the SCPs focused on the transportation industry due to the enormous investment required by the infrastructures and the solutions for freight transport and intelligent mobility. For example, according to Li et al. [38], the rapid development of smart cities, particularly in China, is primarily attributed to the cooperation between IT companies and the government. This aspect highlights a general policy of the Chinese government to accelerate high-tech and strategic startups by putting them in SCPs with more significant funds. Besides, North America is more shaped by pro-business influences. The private sector assumes a valuable function as project initiator, provider of financial resources, and client, compared to the other countries as Europe that historically has been more welfare-oriented.

Some success factors, including the partnerships and business model, are also investigated. The current trends of partnership, infrastructure financing, and financial resources for SCPs are mixed, combining the advantages for both private companies and public institutions. Figure 2.3 shows the partnership in SCPs is hybrid for all the countries. The infrastructure financing and financial resources have the same results. According to Chen et al. [39], cities can benefit from intelligent mobility investments by involving all the public and private actors collaboratively and transparently.

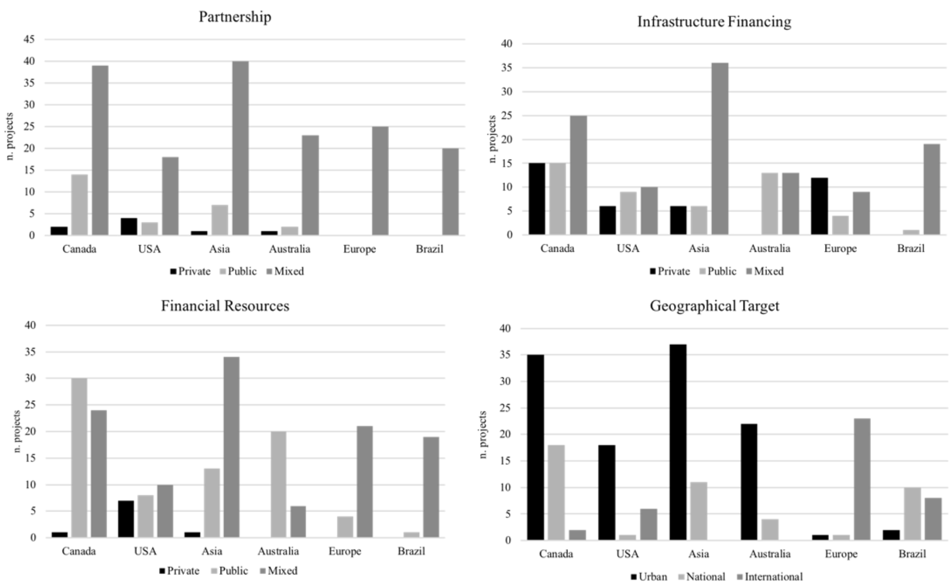


Figure 2.3 Business model and geographical target in SCPs

Another interesting outcome is that the geographical target of SCPs mainly focuses on the urban area, except for Europe and Brazil. It can be explained by the emerging need for demand-driven related ICT solutions, such as the car and bike-sharing system, on-demand delivery, and parking schedule. While considering Europe and Brazil, the more targets focus on the layer of international cooperation.

The efficiency of City Logistics is strongly affected by conflicting personal preferences and multi-attribute decision-makers. From the perspective of stakeholders, this paper analyses the perceptions of five different stakeholders, including City, Citizens, Administration, SMEs, and Universities, for all investigated countries. According to Table 2.3, the central stakeholders for all countries are City, Citizens, Administration, and SMEs. Almost all the perceptions are larger than 70%, with some 100% perceptions. On the contrary, University is less involved actors for four countries, with only 40% for the USA, 33% for Canada, and 27% for Australia and Asia. This result can be explained by the different intentions of local universities and the different levels of cooperation between government and universities. All stakeholders play the primary role of the SCPs for Europe and Brazi since all the perceptions are larger than 80%. Note that these two counties also pay more attention to international cooperation, according to Figure 2.3. In particular, Citizens is one of the most significant stakeholders since all the perceptions are larger than 87%. Considering that transportation is the most frequent objective in SCPs, efficient urban mobility requires improving citizens' participation.

Table 2.3 Different Stakeholders of smart city projects for different countries

Stakeholders	USA	Canada	Europe	Australia	Asia	Brazil
City	76%	95%	80%	100%	100%	100%
Citizens	100%	87%	96%	100%	100%	100%
Administration	80%	76%	80%	62%	98%	100%
SMEs	88%	80%	100%	73%	83%	100%
Universities	40%	33%	88%	27%	27%	85%

Chapter 3

A managerial analysis of urban parcel delivery

Urban freight transportation and parcel delivery have been subjected to significant paradigm shifts in recent years caused by the urbanization and development of megacities. Urbanization and globalization increase freight flow dramatically, with a considerable impact and challenge on the supply chain. Freight movements contribute significantly to congestion and environmental issues in the urban area. Recent phenomena as the on-demand economy, e-commerce, and advanced digital technologies, enlarge the framework of city logistics. Customers request more flexible and fast deliveries such as same day and even within 2 hours delivery. It is thus crucial to develop innovative strategies to build a more efficient, cost-effective, and sustainable city logistics system.

Besides, the increasing attention on the environmental impact of urban freight transportation (e.g., congestion, noise, climate change, and air pollution) stimulates the application of non-motorized transport tools to move people and goods (e.g., bikes and cargo bikes), new delivery options (e.g., lockers) and collaborative business models [40, 41]. However, integrating different delivery options is not straightforward, owing to the interactions and conflicts among actors, their business models, and the technologies themselves [42, 43].

To cope with the different issues of such a complex system, City Logistics develops many initiatives and proposals to optimize the traffic flow and jointly address the economic, operative, social, and environmental sustainability of transportation and logistics. Furthermore, it mitigates the inefficiencies and externalities, which are more evident in the last-mile segment of the supply chain [23]. However, despite the rich literature and state-of-the-art City Logistics, not all solutions and proposals are successfully implemented.

- They lack support and commitment from the different stakeholders (with diverse expertise) in the urban areas, missing a managerial perspective in designing sustainable policies appropriate for freight transportation and logistics.
- The implementation and proposal focus too much on the technical aspects as platforms, or optimization tools, missing a global vision and ignoring the coordination of different actors and their interactions.

To the best of our knowledge, a holistic vision of such a complex and hyper-connected system that integrates actors' behavior analysis, economic and managerial considerations into simulation and optimization tools has little attention in the literature. The study by [40, 44] are the first attempt to overcome this lack. The authors in [44] developed a last-mile typology and an instrument to simulate the total last-mile costs.

In this work, we integrate green transportation modes with traditional systems in business models, cost and revenue structures, and policies. First, we identify the different players in the transportation and parcel delivery system. Then, we consider several combinations of traditional vehicles (e.g., trucks and vans) and green carriers (e.g., electric or hybrid vehicles, bikes, and cargo bikes), investigating their business models and behaviors from a managerial perspective. Finally, a Lean Business methodology named GUEST is used to understand the context and gather information and data for solving the optimization problem.

This chapter is organized as follows. Section 3.1 introduces the multidisciplinary methodology in this study. Section 3.2 describes details of the managerial analysis of the urban parcel delivery and presents the business models of the actors. These actors' operational models are discussed in Section 3.3 regarding the times, distances, and costs (both operating and environmental) associated with different types of vehicles. Finally, in Section 3.4, we introduce our Monte Carlo-based simulation-optimization framework.

3.1 Methodology

The GUEST methodology is a Lean Business approach inspired by [45] and other lean startup applications, adapted for multi-actor complex systems (MACSs), such as city logistics [46, 47]. It is applied to analyze the actors' and stakeholders' needs from the early phases of the solution design to the different stages of the development and implementation. The development can thus be guided to meet stakeholders' needs from both the business model and operational aspects. The results provide a higher commitment from the different actors and market acceptance of the outputs, which can guide the creation of the new collaborative business models, mitigating the problems in current City Logistics measures. The fundamental five steps of the GUEST methodology are the following:

- Go. We first investigate the stakeholders in City Logistics, particularly the last mile segment application, analyzing their current behavior and internal and external forces that interact with them and affect their businesses. We mainly focus on an international courier delivery service operating in Italy, particularly in Europe, in general. The purpose is to gather information and obtain a complete description of the stakeholders' profiles, including their needs and cost structures.
- Uniform. The knowledge of the system must be assessed in a standard way to obtain a shared vision of the MACS. In this phase, we apply the Business Model Canvas to describe the governance and business models [45]. It is a graphical tool used to understand how the proposed solutions enable the creation of value for the involved stakeholders. It can simply and holistically present how integrating traditional transportation modes, and green delivery options can fulfill different operators' needs and benefit their gain. Besides, a SWOT analysis is used to identify the opportunities and threats of this integration.
- Evaluate. We propose a deep analysis and comparison to identify the key factors linking the business and operational models. Moreover, we explicitly describe the entire structure of the costs and revenues for each transportation option. Finally, the main variables that affect last-mile logistics in urban areas (e.g., travel distance and delivery time) are used to conduct a performance analysis of the traditional and green delivery options, supporting the integration of business and operational models.
- Solve. A simulation-optimization approach is conducted to obtain a comprehensive vision of the overall complex system based on the managerial analyses undertaken in the previous phases.
- Test. The results of the Monte Carlo simulation are analyzed and discussed to deduce mixed-fleet policies.

As highlighted by the authors in [40, 48], many benchmark instances for testing city logistics solitons do not come from actual or realistic settings. Still, they are generated based on the classical instances or artificial data, making difficulties and inaccuracy of assessing new models. In this work, we use three streams of realistic data concerning the business models, the cost structures, and the operations of all the stakeholders. These data are obtained from a major international parcel delivery company operating on all continents and involved in the URBan Electronic LOGistics (URBeLOG) project and the stakeholders involved in the Synchro-NET H2020 project [47, 49, 50]. In addition, the information and data concerning the business models and cost structures are collected from interviews with the Chief Executive Officer (CEO), Chief Operating Officer (COO), and the company's marketing directors.

3.2 Managerial analysis of the urban parcel delivery

Multiple actors with conflicting goals and objectives are involved in the city logistics and parcel delivery system. We list the five main actors as follow:

• International courier. The company operates the delivery services at international and national levels, particularly the long-haul shipments.

• Traditional subcontractor. Once the freights arrive at the urban distribution centers from the long-haul shipments, the traditional subcontractor operates their deliveries service in the last-mile segment. It is usually a small or medium-sized company, generally organized as a legal form of cooperatives with limited financial and fleet capacity.

• Green subcontractor. It is a small firm with a business model similar to the traditional subcontractor. However, a vital component of its value proposition relies on the low environmental impact of the delivery activity, taking advantage of adopting green vehicles.

• Customer. This category refers to the final receiver of parcel delivery services. There are different customer segments: business-to-business (B2B), business-to-consumer (B2C), consumer-to-business (C2B), consumer-to-consumer (C2C), and intra-business.

• Authority. It represents the local public administration designing policies for freight transportation in urban areas. It mitigates the negative externalities in transportation activities and the related social costs.

This section presents the analysis of the leading industry-driven operators, analyzing their business profiles and interactions. In particular, we use a business development approach based on the Business Model Canvas, which has not received relevant interest in the literature.

3.2.1 Business model of international couriers

Figure 3.1 depicts the Business Model Canvas of the international courier. Its main customers are listed in the following segments, each with different behaviors and goals. The B2B segment consists of firms that employ couriers to deliver products in their logistic chain towards other companies. It includes e-commerce, involving freights flows between e-retailers and producers. The B2C segment consists of companies that sell products directly to customers, bypassing supply chains, such as e-stores and online platforms.

On the contrary, the C2B segment represents returning goods in reverse logistics for different reasons, including waste collection, products recycling, customer rejections, or requests mismatches. The delivery services provided for personal needs between individuals who require to send goods or documents are parts of the C2C segment. Finally, intra-business companies employ couriers to move products among their different plants and warehouses. The international courier provides time-sensitive transportation services as one of its value propositions, pushed by the strict and short time windows. They also consider the flexibility and reliability of the delivery to deal with the increasing customer requests in the on-demand economy. Another value proposition component is a superior customer experience, taking advantage of shipment efficiency, speed, reliability, and security. Besides, consumers benefit from customized delivery services for different products (e.g., fragile or perishable products) in last-mile delivery. The international courier provides two types of value (i.e., cost optimization service and sales market extension) to small and medium-sized business customers.

On the one hand, express deliveries allow firms to reduce the inventory level in a Just-In-Time orientation and optimize production processes and costs. On the other hand, the sales market extension is strictly related to the customer strategy. Value propositions are delivered to customers through different channels (e.g., direct and indirect channels). Website and mobile applications are used as the first contact points with customers, raising the awareness of services and helping them understand the added values. Physical structures, such as retail stores and shopping malls, provide physical contact and interaction for customers. As one of the marketing strategies, brand identity is related to another type of channel. International carriers show their brand through personalized vehicles or digital advertising to increase public notice. The indirect channels are mainly available on partner-owned websites in e-commerce. The availability of websites, help desks, and call centers is used to foster customer relationships. These services provide customers with support and assistance in any phase of the delivery process, offering a high level of customer experience and increasing customer stickiness. As highlighted in the value chain analysis conducted by LUISS Business School and Associazione Italiana Corrieri Aerei Internazionali (AICAI) [51], the main activities that represent the core business of the international couriers are operations management and customer care. Operations management involves normal activities including route planning, intermodal transportation, pickups, and deliveries, checking the overall process) while customer care consists of customer relationship management related to every step in the delivery process: pre- and after-sales support, tracking and tracing of parcels, proof of delivery. To maintain its business model, the international courier creates partnerships and alliances with high strategic value. The key partners, such as suppliers, subcontractors for outsourcing activities in the last mile, cargo operators and handling agents, logistics, and commercial joint ventures, are all considered to make the business more efficient and develop new models. Finally, other partnerships are generated with local administrations to fulfill government regulations and ensure the sustainability of parcel delivery in urban areas (e.g., the URBeLOG project [50]). The international courier pays for critical resources to support the business model. These resources include materials (e.g., fuel costs, packages, consumables, etc.), staff costs, inventory costs, handling fees, acquisition and maintenance of vehicles, equipment, ICT systems and facilities, operation costs, and subcontractor fees in outsourcing parts. Other costs include marketing and advertising expenditure and those related to risk management.

<table>
<tr>
<td rowspan="2">Key Partners
• Suppliers
• Subcontractors
• Cargo operator and handling agent
• Joint Venture
• Local administration</td>
<td>Key Activities
• Process and operations management
• Customer care</td>
<td rowspan="2">Value Propositions
• Time-sensitive transportation services
Express deliveries
• Superior customer experience
• Costs optimization
• Sales market extension</td>
<td>Customer Relationships
• Retail stores
• Web site
• Help desk
• Call center
• Locker
• Community</td>
<td rowspan="2">Customer Segments
• Business-to-Business (B2B)
• Business-to-Consumer (B2C)
• Consumer-to-Business (C2B)
• Consumer-to Consumer (C2C)
• Intra-Business</td>
</tr>
<tr>
<td>Key Resources
• Physical assets
Vehicle fleets
Warehouses and retail stores
• Intangible assets
ICT
Licenses
Partnerships
• Human resources</td>
<td>Channels
• Direct channels
Web site and mobile apps
Retail stores
Brand identity
• Indirect channels
Partner web sites</td>
</tr>
<tr>
<td colspan="3">Cost Structure
• Costs of materials (e.g., fuel costs, packaging, consumables)
• Personnel costs
• Assets costs (e.g., vehicles, equipment, structure and warehouses, software)
• Handling fees
• Subcontractors fees
• Marketing & advertising
• Risk management
• Other operative costs (auditor and governmental)</td>
<td colspan="2">Revenue Streams
• Revenues from time-sensitive delivery services</td>
</tr>
</table>

Figure 3.1 Business Model Canvas of an international courier

3.2.2 Business model of traditional subcontractors

As described previously, international couriers outsource delivery services in the last-mile segment of the supply chain to subcontractor couriers (see Figure 3.2

for the BMC), increasing operational efficiency and customer stickiness. Outsourcing offers value for customers by several benefits in terms of cheap, fast, and flexible delivery. It takes advantage of good management of activities in urban areas concerning peak demand and temporal constraints forced by time-sensitive deliveries (e.g., prime customers, disaster relief [52]). The traditional subcontractor reaches their customers through commercial agreements and tenders. The relationship between subcontractors and customers is thus established and maintained by a constant negotiation and information exchange along with all delivery activities (e.g., tracking services and feedback), ensuring the co-creation of value for the final user. The coordination with international courier customers plays a key role, fundamental for the success of multimodality and the well-functioning of the on-demand logistics, with the consecutive satisfaction of final users. Other critical activities for the traditional subcontractors are the optimal management of delivery services and the scheduling of dispatchers to achieve high efficiency and reliability. It is coping with the challenges such as timeline constraints, the risk of delivery failure (approximately 12% of all deliveries) [53], and the last-mile split delivery problem [54].

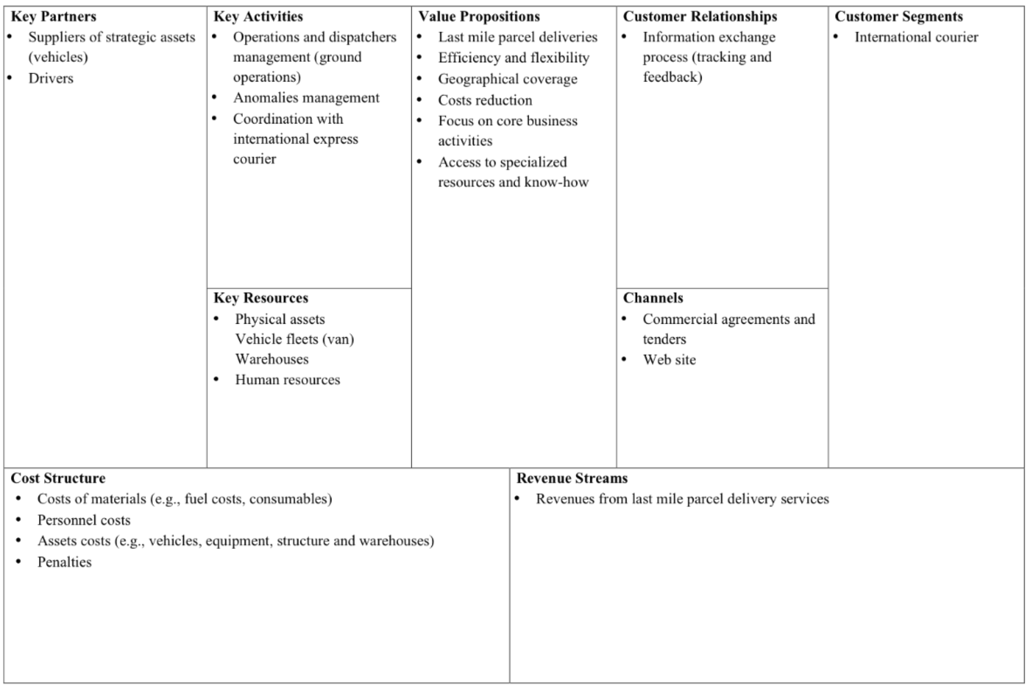


Figure 3.2 Business Model Canvas of a traditional subcontractor

3.2.3 Business model of green subcontractor

The increasing attention on environmental issues forces the logistics companies to develop innovative business models that guarantee the sustainability and efficiency of urban transportation, particularly the last-mile parcel deliveries. These companies apply business models similar to traditional subcontractors while considering their activities' environmental issues, often using bikes and cargo bikes as the green delivery options. Figure 3.3 depicts the BMC related to the green subcontractor. The international courier is the primary customer segment of the green subcontractor that outsources the last-mile operations and includes the B2B and B2C components for intercity and intracity postal services. The green subcontractors provide the value proposition by cycle-logistics services capable of overcoming the difficulties and complexities of parcel deliveries in urban areas. Indeed, there are different City Logistics regulation measures, including mobility restrictions (e.g., low traffic zones (LTZ) and low emission areas), inadequate or insufficient infrastructure (e.g., unavailability of loading/unloading zones). In addition, cycle logistics provide customers with different gain creators and pain relievers, such as speed, punctuality, and flexible service.

The better operation of bikes in city traffic and the integration between traditional vans and bikes decrease the operation cost reductions (e.g., fuel, insurance, parking fine, etc.) and maintain high service quality. The size of parcels delivered by green subcontractors is reduced dramatically into small-sized packages, between 0 to 3 kg, or up to 6 kg. Finally, the last value proposition for customer segments is offered by the green image and credentials needed to generate a sustainable supply chain. Green subcontractors use websites as the first channel to reach their customers. Information and advertising can be put on websites to increase awareness and knowledge of their services. Other channels (e.g., media and interviews in magazines) are used to specialize in transportation and environmental issues. Traditional and green subcontractors establish and maintain relationships with customer segments by constant information exchange among delivery activities such as tracking services, feedback, and information about CO2 savings. The main revenue stream for green subcontractors is the income they earn from customers for the last-mile parcel delivery services sale and cycle logistics, revenue from CO2 savings and the carbon credit trading, and fees and royalties from affiliates. Physical assets (i.e., bikes and cargo bikes, warehouses) and human resources (i.e., bikers) are the critical resources used to ensure the operation of the business model. In this model, the performance of bikers, external factors (e.g., weather condition, fatigue, and workload scheduling) can significantly influence the service quality and functioning. Other critical resources contain intangible assets, including partnerships that can reduce the repeatability of the model by competitors, the ICT tools and software applied to optimize operations management [55].

Key Partners
- Technological partners
- Investors
- Partner
- Bikers
- Local administration

Key Activities
- Operations and dispatchers management
- Anomalies management
- Fund raising

Key Resources
- Physical assets
  Vehicle fleets (bikes and cargo bikes)
  Warehouses
- Human resources (bikers)
- Intangibles assets
  Partnership
  ICT

Value Propositions
- Cycle-logistics services
- Costs optimization
- Small sized parcel delivery (0-3 kg and 3-6 kg)
- Green image and green credentials

Customer Relationships
- Information exchange process (tracking, feedback, CO_2 savings)

Channels
- Web site
- Media and interviews

Customer Segments
- International courier
- B2B and B2C for intercity and intracity postal services

Cost Structure
- Costs of materials (e.g., consumables, bags)
- Personnel costs
- Assets costs (e.g., vehicles, equipment, structure and warehouses, ICT tools)
- Marketing & advertising

Revenue Streams
- Revenues from last mile parcel delivery services
- Revenues from CO_2 savings and carbon credits trading

Figure 3.3 Business Model Canvas of a green subcontractor

From the analysis of BMCs, all operators provide their customer segments with a value proposition consisting of time-sensitive transportation services and express delivery. However, the inherent dynamic factors in transportation and parcel delivery services affect the performance of this complex system. Indeed, the major international couriers in the industry do not operate the entire process, while they outsource the deliveries in the last-mile segment to traditional and green subcontractors. This process enables better operational performance and economic efficiency, mitigating the issues caused by the diffusion of subcontracting and the partial autonomy of fleet managers, leading to customer proximity.

The SWOT analysis (Figure 3.4 and Figure 3.5) and the Business Model Canvas demonstrate that, for traditional subcontractors, the main weaknesses and threats are their influence on the environment and the critical issues affecting European regions, including traffic and congestion, LTZ, and the unavailability of loading and unloading zones. These factors compromise the management of deliveries, such as adverse conditions for couriers with traditional vehicles. On the contrary, green subcontractors have strengths on these same points, as they apply low-emission vehicles (e.g., bikes) with a low environmental impact in last-mile parcel deliveries. Green subcontractors are thus able to earn additional income from CO2 savings and carbon credit trading, as highlighted in the revenue streams block of the BMCs (Figure 3.3). However, the capacity limitation of bikes is one of the main drawbacks in the operational model of green subcontractors. This limitation is partially overcome using next-generation cargo bikes, which have a maximum payload of around 100–150 kg per bike, based on the estimation in Europe by [56]. The SWOT analysis highlights a threat related to the competition between traditional and green subcontractors. The strategy of the international courier can also affect the competition, as they can guide subcontractors using a financial lever. The pure cost competition between traditional and green subcontractors in the same geographical area originates a price war, which decreases their profitability or differentiation in terms of service quality for the final customer.

Moreover, as highlighted in [42], a similar situation might happen when a fleet is owned internally by an international courier. Besides, the partial organizational independence of local depot fleet managers and their strategic objectives in cost reductions might have similar effects to those of a price war between traditional and green subcontractors. From the analysis of the financial structure of each business model, the costs related to the vehicles and the social costs associated with the negative externalities have considerable relevance. To further analyze the relevance, we investigate these costs through quantitative research in Section 3.3.

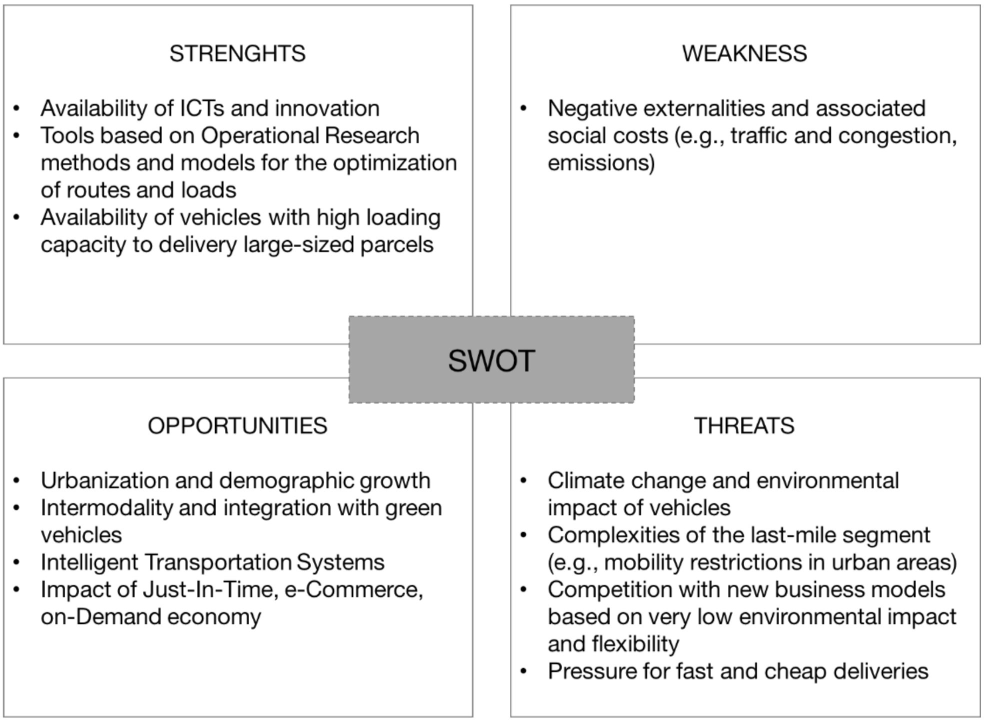


Figure 3.4 SWOT analysis for the traditional subcontractor

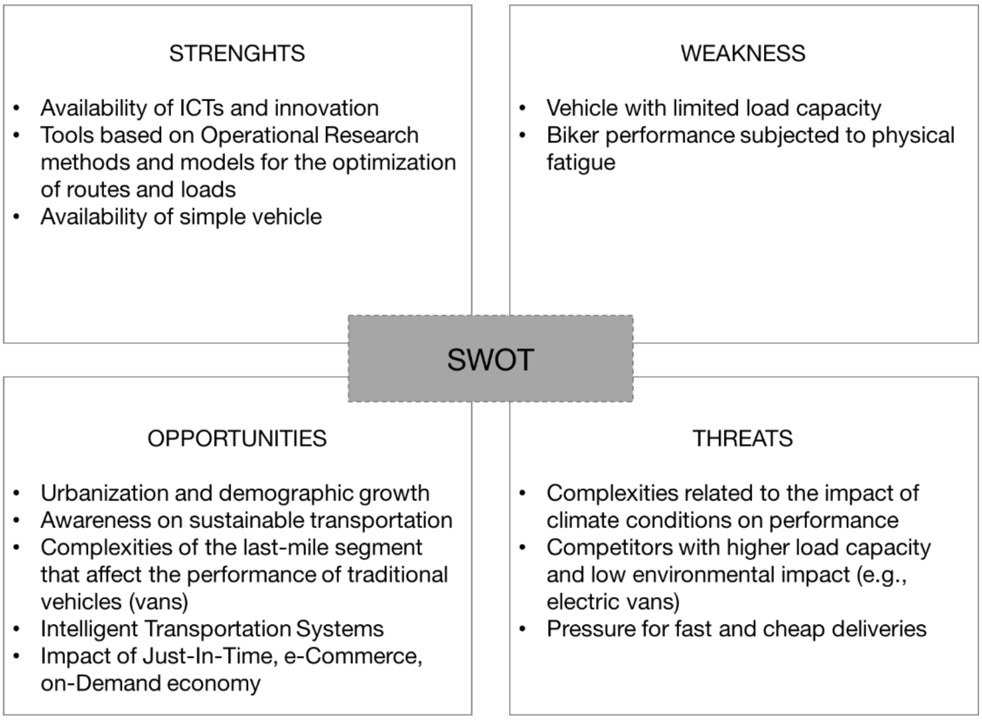


Figure 3.5 SWOT analysis for the green subcontractor

3.3 Operational model analysis in parcel delivery

As shown in the previous analysis of BMCs, combining traditional and green subcontractors might have benefits in terms of efficient last-mile delivery. In the meantime, it may cause a price war, decreasing the service quality. It is thus critical to further understand the cost and performance structure of the system. We mainly focus on operating cost and environmental costs as follow.

3.3.1 Operating costs analysis

We consider four types of vehicles: gasoline-fueled, diesel-fueled and electric vans, and cargo bikes reflecting the transition occurring in the industry and the standard vehicles composing the fleets of the large portion of delivery couriers. In addition, we consider the electric vehicle e-NV200 adopted in the partnership between Nissan Motor Co. Ltd. and DHL Express within the “GoGreen" program [57]. We estimate the operating and environmental costs for each class of vehicles as well as the different environmental and economic impacts, including investment, fleet management, and maintenance requirements, emissions. The Operating Costs per Kilometer (OCK) related to each type of vehicle are estimated and compared to identify the most cost-efficient, considering the operative performance. According to [58], the OCK includes both variable costs (e.g., gasoline) and the total cost of ownership, which are expressed in Euro per kilometers traveled in the last-mile segment [e/km]. This cost is composed of variable costs and fixed costs. The latter is not proportional to the distance, and the courier incurs regardless of the vehicle’s usage degree. The OCK function is:

$$OCK = \frac{FC + VC}{TK} = \frac{(v + tx + i + p) + (f + t + mr)}{TK}$$

Where, FC, VC, and TK represent the total annual fixed costs, variable costs, and traveled kilometers, respectively. The entity of each item has been estimated through primary data from market research on the commercial practices applied by the different stakeholders. Besides, it has been supported by formulating specific assumptions on the use conditions of the vehicles benchmark. These items and assumptions are listed in Table 3.1:

Table 3.1 Item description and estimated values

Item description	Estimated Values
Total annual traveled kilometers	25000 km\year
Total annual hours to reach customer destination and to do delivery operations	2000 hour\year
Commercial speed of vehicles in urban areas	35 km\h
Completed deliveries of each driver	80 deliveries per day
Average time of all operations including parking of the vehicle and collecting the proof of delivery	4.5 min\delivery
Each component of cost has charged in refers to the technical life cycle of the vehicle	5 years

The components of fixed and variable costs are briefly presented as follows.

• Purchase cost of the vehicle (v). It is estimated based on the realization by the fleet manager section of several car dealers. It is referred to as a leasing agreement of 5 years, considering both the interest and principal payments on the loans. The company operating for transportation and parcel delivery activities will manage the asset's depreciation and amortization schedule during this time horizon. A straight-line depreciation method is used to represent the simplest and most applied depreciation method in the market. We refer to the term as the so-called "useful life" based on the number of years the vehicle is expected to be a valuable asset for the logistics company. In our case, we adopt a life cycle of 5 years for both vehicles and batteries.

• Vehicle taxes (tx). It considers the vehicles' expenditures and taxes based on the current regulations (i.e., the ownership tax).

• Insurance (i). It is the total cost of the truck liability insurance accounting for the vehicle capacity and the third-party cargo insurance, excluding the theft and fire insurances. Several insurance companies offer the average value of the prices, according to secondary research.

• Personnel costs (p). It is the total salary payable to a driver, including taxes and employees' social security contributions, based on the National Collective Labour Agreement prescribed for the category to which they belong.

• Fuel (f). The total cost contains both fuel supply (fossil and diesel) and power supply. Their values are estimated by the consumption derived from the technical specifications offered by the manufacturer. The average monthly domestic prices are used to measure the cost of petrol and diesel fuel, according to the statistical data elaborated by the Italian Ministry of Economic Development for 2018. Besides, the electricity price is calculated as an average cost from the fees charged to the business customers by major energy industry suppliers.

• Tire costs (t). They are based on the list prices charged by the leading manufacturers, considering a 15% discount by a corrective factor to purchase high quantities for the whole fleet. In addition, the average usage is about 50000 km/year (data estimated and given by fleet managers).

• Maintenance and repair costs ($\boldsymbol{mr}$). They are estimated based on data from the Automobile Club Italia (ACI) [59] and related to the expenditures for the activities needed to keep the vehicle's performance during its life cycle. These activities are grouped in time or condition-based maintenance to prevent adverse events and maintain the standard use conditions. Otherwise, it is considered as breakdown maintenance or repair after a failure occurrence.

Tables 3.2-3.4 show the different cost items for the fossil-fueled, diesel-fueled, and electric vehicles.

Table 3.2 Operating Costs per Kilometre related to the fossil-fuelled vehicle

Cost item	Benchmark value [€]	Technical life cycle [years]	Annual cost [€]	Commercial Speed [km/h]	Total km [km]	OCK [€/km]
Purchasing cost of vehicle						
Advance payment	5000.00	5	1000.00	35	25000	0.0400
Lease fees and other insurance	11820.00	5	2364.00	35	25000	0.0946
Stamp duty	16.00	5	3.20	35	25000	0.0001
VAT 22%	3703.92	5	740.78	35	25000	0.0296
Total purchasing cost of vehicle	20539.92		4107.98			**0.1643**
Vehicle taxes						
IPT	319.00	5	63.80	35	25000	0.0026
DMV costs and PRA	100.00	5	20.00	35	25000	0.0008
Stamp duty	208.98		208.98	35	25000	0.0084
Total vehicle taxes	627.98		292.78			**0.0117**
Insurance						
Average truck liability insurance costs			2680.33	35	25000	0.1072
Total insurance cost						**0.1072**
Maintenance and repair costs						
Maintenance and repair costs						0.0573
Total maintenance and repair costs						**0.0573**
Tyres costs						
Average tyres costs			311.15	35	25000	0.0124
Average tyres costs						**0.0124**
Personnel costs						
Personnel costs			56000.00	35	25000	2.2400
Total personnel costs						**2.2400**
Vehicle fuelling						
		Price per litre [€/l]	**Consumption** [€/100km]	**Commercial Speed** [km/h]	**Total km** [km]	**Cost per Kilometre** [€/km]
Average manufacturing price	0.5375	0.072	35	25000	0.0387	
Average production tax		1.0069	0.072	35	25000	0.0725
Total vehicle fuelling costs						**0.0112**
				TOTAL OCK	**€/km**	**2.7042**

Table 3.3 Operating Costs per Kilometre related to the diesel-fuelled vehicle

Cost item	Benchmark value [€]	Technical life cycle [years]	Annual cost [€]	Commercial Speed [km/h]	Total km [km]	OCK [€/km]
Purchasing cost of vehicle						
Advance payment	5000.00	5	1000.00	35	25000	0.0400
Lease fees and other insurance	13740.00	5	2748.00	35	25000	0.1099
Stamp duty	16.00	5	3.20	35	25000	0.0001
VAT 22%	4126.32	5	825.26	35	25000	0.0330
Total purchasing cost of vehicle	22882.32		4575.46			**0.1831**
Vehicle taxes						
IPT	319.00	5	63.80	35	25000	0.0026
DMV costs and PRA	100.00	5	20.00	35	25000	0.0008
Stamp duty	170.28		170.28	35	25000	0.0017
Total vehicle taxes	627.98		292.78			**0.0102**
Insurance						
Average truck liability insurance costs			2680.33	35	25000	0.1072
Total insurance cost						**0.1072**
Maintenance and repair costs						
Maintenance and repair costs						0.0625
Total maintenance and repair costs						**0.0625**
Tyres costs						
Average tyres costs			311.15	35	25000	0.0124
Average tyres costs						**0.0124**
Personnel costs						
Personnel costs			56000.00	35	25000	2.2400
Total personnel costs						**2.2400**
Vehicle fuelling						
		Price per litre [€/l]	**Consumption** [€/100km]	**Commercial Speed** [km/h]	**Total km** [km]	**Cost per Kilometre** [€/km]
Average manufacturing price	0.5593	0.048	35	25000	0.0268	
Average production tax		0.8763	0.048	35	25000	0.0421
Total vehicle fuelling costs						**0.0689**
				TOTAL OCK	€/km	**2.6843**

Table 3.4 Operating Costs per Kilometer related to the electric vehicle

Cost item	Benchmark value [€]	Technical life cycle [years]	Annual cost [€]	Commercial Speed [km/h]	Total km [km]	OCK [€/km]
Purchasing cost of vehicle						
Advance payment	5000.00	5	1000.00	35	25000	0.0400
Lease fees and other insurance	21756.00	5	4351.20	35	25000	0.1740
Battery rental fee	4320.00	5	864.00	35	25000	0.0346
Stamp duty	16.00	5	3.20	35	25000	0.0001
VAT 22%	6840.24	5	1368.05	35	25000	0.0547
Total purchasing cost of vehicle	37932.24		7586.45			**0.3035**
Vehicle taxes						
IPT	319.00	5	63.80	35	25000	0.0026
DMV costs and PRA	100.00	5	20.00	35	25000	0.0008
Stamp duty	-		-			-
Total vehicle taxes	419.00		83.80			**0.0034**
Insurance						
Average truck liability insurance costs			932.50	35	25000	0.0373
Total insurance cost						**0.0373**
Maintenance and repair costs						
Maintenance and repair costs						0.0540
Total maintenance and repair costs						**0.0540**
Tyres costs						
Average tyres costs			230.92	35	25000	0.0092
Average tyres costs						**0.0092**
Personnel costs						
Personnel costs			56000.00	35	25000	2.2400
Total personnel costs						**2.2400**
Vehicle fuelling						
		Average price of electricity [€/kWh]	**Consumption** [kWh/km]	**Commercial Speed** [km/h]	**Total km** [km]	**Cost per Kilometre** [€/km]
Average price of electricity	0.0672	0.1650	35	25000	0.0111	
Total vehicle fuelling costs						**0.0111**
				TOTAL OCK	€/km	**2.6584**

3.3.2 Environmental costs analysis

The carbon footprint is defined as the total amount of greenhouses gas emitted directly or indirectly by an activity, a product, a company, or an individual, according to the technical specification ISO/TS 14067:2013 "Greenhouse gases – Carbon footprint of product - Requirements and guidelines for quantification and communication." We thus calculate the emissions for the last-mile delivery process that is in line with the technical specification. We consider the emissions derived directly from fuel combustion, the indirect emissions generated by the production process of fossil fuel, and the consumption of energy related to the charging of batteries. As our study focuses on the last-mile segment, we ignore the emissions generated from long-haul transportation and vehicles' production and disposal process. We also consider other pollutants originated by the transportation process, such as nitrogen oxides (NO_x) which are transferred into CO2, using a relevant factor of 4.7 kg per liter of fuel consumed [60]. To investigate how the cost efficiency of the courier is affected by environmental impacts, we denote the carbon footprint in economic terms by using the Pigouvian tax, known as the carbon tax, according to the price paid for CO2 emissions in the atmosphere (see Table 3.5). This price mechanism aims to reduce emissions by making it cost-effective to switch to innovative technologies, mitigating non-green behaviors and environmental impacts. We conduct a scenario analysis imposing different values of the carbon tax, according to the tariffs adopted in some countries (e.g., 17 $\frac{€}{t}$ in France[61] and 150 $\frac{€}{t}$ in Sweden[62]).

Table 3.5 Cost analysis results

Costs	Tariffs Carbon Tax [€/tons]	Fossil fuel vehicle	Diesel fuel vehicle	Electric vehicle	Bike
TCK [€/km]					
Annual kilometer cost		2.70	2.68	2.66	1.50
Environmental costs [€]					
Direct CO2 Emissions [tons]		4.15	3.38		
Indirect CO2 Emissions [tons]		4.15	3.38		
Equivalent CO2 Emissions [tons]		8.46	5.52		
Total Emissions [tons]		16.76	12.28		
Carbon Tax [€]	17.00	284.92	208.63		
	30.00	502.80	368.18		
	90.00	1508.40	1104.53		
	150.00	2514.00	1840.88		
Electric Battery Emissions [tons]				3.08	
Carbon Tax [€]	17.00			52.31	
	30.00			92.31	
	90.00			276.94	
	150.00			461.56	
Direct CO2 Emissions [tons]					0.00

As presented in BMCs, all operators have to pay for using vehicles, including the operational and social costs. The traditional subcontractors using fossil-fuel vehicles incur a higher price than the green subcontractors. Electric vehicles achieve better cost savings due to the lower insurance tariff and the exemption from the ownership tax payment. However, few electric vehicles are also applied in the market because of the high running costs concerning the total purchase cost. On the other hand, bike couriers permit an economic efficiency derived from lower vehicle management costs and lower personnel costs related to riders' skills. Besides, the green subcontract benefits from the additional revenue earned from CO2 savings and carbon credit trading. Compared with traditional vehicles (petrol and diesel), assuming that carbon credit prices are 30% lower than the carbon tax tariffs, applying bike subcontractors may earn average revenue of about 0.02€ per stop [42]. This estimate assumes greater relevance when we consider the high volumes of parcels delivered in urban areas.

3.4 Simulation

The findings obtained in the costs analysis are used as input in a decision-support system proposed for developing and managing mixed-fleet policies in a specified urban area. The overall system contains several modules, including the simulation-optimization approach integrating a Monte Carlo simulation, a last-mile optimization meta-heuristic, and data aggregation and analytic module. We use I1, I2, and I3 in the computational experiments, ranging from 1000 to 4000 parcels. These instances are originated from accurate analytics collected during three weeks at the end of 2014 by a medium-sized courier. As shown in Table 3.6, this data set contains three types of parcels in terms of their composition, based on the classification by the European Commission. We thus assort packages as "mailer" (0–3 kg), "small parcels" (3–6 kg), and "large deliveries" (larger than 6 kg). Mailers account for the most significant portion of the parcels, owing to the increasing impact of e-commerce. These parcels are easy to operate and move by the green subcontractors. Mailers are thus more profitable for both subcontractors, counting a significant part of their critical mass to make their business models sustainable. The large parcels account for almost 30% of all parcels, but their destinations are in semi-central or suburban areas, where the green courier cannot deliver. The courier operates from a central depot outside the city, while a secondary depot is located near the urban area for the cargo bikes.

Table 3.6 Classes of parcels and delivery locations

Parcel delivery features	n. delivery	%
In center	3395	22.51
Out of center	11688	77.49
0–3 kg	8577	56.87
3–6 kg	1915	12.7
> 6 kg	4590	30.43
Total deliveries	15083	100

To simulate the operational context, we define five operational scenarios combining the two geographical areas managed by the green subcontractors the three classes of parcels that each subcontractor can operate. The scenarios are listed as follows:

• **Scenario S_0**. Only the traditional subcontractor operates in this area.
• **Scenario S_3_C**. The green subcontractor manages the mailer parcels in the central area, while the traditional subcontractor delivers all remaining packages.
• **Scenario S_3_S**. The green subcontractor delivers mailer parcels in both the central and semi-central areas. The traditional subcontractor delivers all remaining packages.
• **Scenario S_5_C**. The green subcontractor delivers mailers and small parcels (up to 5 kg) in the central area. The traditional subcontractor delivers all remaining parcels.
• **Scenario S_5_S**. The green subcontractor delivers mailers and small parcels (up to 5 kg) in central and semi-central areas. The traditional subcontractor delivers all remaining parcels.

To evaluate the integration of traditional vehicles and green delivery options (i.e., cargo bikes) with low emission, we measured three key performance indicators (KPIs) as follows:

Equivalent vehicle (Veh Eq). We compute the number of equivalent vehicles used by the subcontractors. To compare traditional and green subcontractors, we implement a conversion from bikes to vans. The conversion considers a full-time work shift of a traditional subcontractor, which, based on European regulations, is six-and-a-half hours.

• **CO2 savings**. We calculate the kilograms of CO2 not emitted in the scenarios with cargo bikes.
• **Number of parcels delivered (nD/h)**. To investigate to what extent the integration of cargo bikes influences the operative performance and the efficiency of the traditional courier, we calculate the number of parcels delivered per hour (nD/h), which is a common practice to define the efficiency of a courier.

Table 3.7 shows the results of the experiments. Applying cargo bikes to deliver the mailers and small parcels decreases the total emissions of around 14 tons per year, with an amount of CO2 savings larger than 40%. The value of CO2 savings in each scenario is emissions reduction compared with the scenario S_0. Another valuable outcome is that the service area of cargo bikes plays a massive role in that result. Indeed, the scenarios in which the green subcontractors access the central and the semi-central regions (i.e., S_3_S and S_5_S) have higher CO2 savings than scenarios S_3_C and S_5_C. The reason is that the traditional subcontractors no longer serve these areas, reducing 25% travel distance of vans, with substantial benefits in emissions and costs.

Moreover, outsourcing mailers and small parcels to one or more green subcontracts decrease the traditional subcontractor's operational efficiency and profitability. For instance, in scenarios S_5_C and S_5_S, the traditional subcontractor operates only large parcels, which generally require much time to handle and deliver. As a result, it reduces the needed vehicles (e.g., in Set I2, the value of VehEq decreases from 9.89 to less more than 3 or 4), increases the total service time, and reduces the number of deliveries fulfilled in a day. Furthermore, this number is diminished by the rapid saturation of van capacity (because of the large parcels) that imposes on the traditional subcontractors' frequent returns to the depots. Indeed, Table 3.7 highlights a decrease of up to 5 deliveries per hour transferring from scenario S_0 to the other scenarios applying bikes. This reduction is related to a loss of efficiency of about 15% when mailers are managed by cargo bikes. Besides, it is more than 30% when small parcels are outsourced.

Moreover, given that the existing contractual schemes imply revenues based on the operational performance and penalties on the failed deliveries, the new contract should consider increasing the number of deliveries required for the cargo bikes to balance the loss of efficiency for the traditional subcontractor without reducing the service quality. Indeed, if the traditional subcontractor manages its fleet, it should outsource only the mailers in central and semi-central areas and small parcels downtown, avoiding a significant reduction of efficiency while improving the service quality for customers. In the case of an internal fleet, the green subcontractor must deliver all the demand of dispatched mailers and small parcels in the traffic and congestion areas. In the case of the external fleet, the traditional subcontract should internalize the green fleet or outsource mailers in central and semi-central regions. At the same time, the outsourcing of small parcels (3-5 kg) requires changing the contractual scheme, decreasing the margins of the green subcontractor.

Table 3.7 Results of Monte Carlo simulation

KPI	Instances	Traditional subcontractor					Green subcontractor				
		S_0	S_3_C	S_3_S	S_5_C	S_5_S	S_0	S_3_C	S_3_S	S_5_C	S_5_S
nD/h	I1	15.65	12.82	12.98	10.44	10.38	NA	11.94	11.24	12.47	11.94
	I2	16.18	13.79	13.77	10.92	10.73	NA	12.03	11.36	12.51	12.06
	I3	15.47	13.29	13.01	10.50	10.21	NA	11.82	11.16	12.56	12.04
VehEq	I1	7.49	2.16	3.53	2.28	3.62	NA	3.70	6.55	3.88	6.88
	I2	9.89	3.03	4.86	3.07	4.98	NA	4.96	8.39	5.45	9.02
	I3	8.40	2.54	4.18	2.70	4.41	NA	3.85	6.89	4.12	7.14
CO2Sav	I1	NA	22%	34%	27%	45%					
	I2	NA	16%	34%	26%	44%					
	I3	NA	16%	41%	20%	48%					

Note that the green subcontractor has no value in S_0 since it is not included in this scenario.

Chapter 4

On-demand parcel delivery in sharing economy

4.1 Last mile logistics and crowdsourcing

Last-mile logistics is the least efficient stage of the supply chain and comprises up to 28% of the total delivery cost [63]. The efficiency of last-mile logistics is influenced by customer density and time windows, congestion, fragmentation of deliveries, and shipment size [64]. Besides, last-mile logistics generate different externalities, especially greenhouse gas emissions, air pollution, noise, and congestion. Therefore, it is crucial to find efficient and innovative solutions to improve the last-mile logistics. As a result, new last-mile delivery solutions have emerged in the last decade. For example, Melo and Baptista [65] reported that integrating cargo bikes with traditional vans improves traffic performance.

Moreover, the evolution of automation technology enables logistics firms to apply innovative business applications in last-mile logistics. In particular, automated goods delivery is forecasted to offer an appropriate solution for up to 80 percent of all Business-to-Customers (B2C) deliveries [66]. Many leading companies, including DHL, SF Express, Google, and Amazon, use unmanned aerial vehicles (UAVs) in real-world applications [67]. The trend of developing innovative technology in last-mile logistics is unstoppable as it can potentially reduce operational costs and pollutions in the long term. However, it doesn't indicate the innovative technologies will be applied as it has many difficulties for real-world application. For example, UAVs have some drawbacks in the application of last mile delivery such as high capital investments, low-carrying capability, and flying range limitation and legislation restrictions in urban areas. It cannot perform the delivery in certain conditions.

Consequently, some compromise solutions are currently widely considered and applied in the last mile delivery applications. One of these solutions is crowd shipping or known as crowdsourced delivery. The main idea behind crowdsourced delivery is to reorganize existing resources such as human resources, facilities, and other delivery capacities to complete the last leg of the distribution process. In particular, crowdsourcing or the so-called "Uberization of the last mile" is an emerging application for parcel delivery that outsources the parcels to crowd drivers [68, 69]. They are a group of local and non-professional drivers who are willing to temporarily work for delivery companies and provide their assets (e.g., the vehicle) to perform the parcel delivery [70]. A certain amount of money, named compensation, is rewarded after completing the pickup or delivery tasks [71].

Crowdsourced delivery has several definitions. One of them is:

A goods delivery service that is outsourced to occasional carriers drawn from the public of private travelers and is coordinated by a technical platform to obtain benefits for the involved stakeholders [72].

Kafle et al. [73] reported that they consider cyclists and pedestrians as crowdsources interested in transferring parcels with a truck carrier and undertaking jobs for the last-leg parcel delivery. Experiments show that replacing trucking with local crowdsources for the last leg reduces total operational cost compared to pure-truck delivery. In addition, Guo et al. [74] propose to build a hybrid city logistics system where crowdsourced delivery and the traditional delivery networks are closely integrated. Results show that applying crowdsourced delivery as a supplement to the conventional delivery network can reduce the last-mile logistic costs. Another idea is to use cargo bikes or electric bicycles to reduce distribution externalities and improve the performance of last-mile delivery. These bicycles are ideal for inner-city transportation since they are emission-free, quiet, and less disturbing for the residents [75]. Nocerino et al. [76] analyze the performance of electric bicycles and electric scooters for goods delivery in city areas and test the use of these vehicles in 7 European countries with 39 companies. They demonstrate that light electric cars can replace traditional combustion engines, mitigating logistic impacts in city areas.

The advantages of crowdsourcing are lower operation costs, higher flexibility, and lower emissions than traditional delivery options [72]. Indeed, it is a digital-driver business model with its asset (i.e., the crowd drivers bring their vehicles and provide for their maintenance). Paperless operations reduce overall costs and make the service attractive to online customers. Besides, in real-world parcel delivery applications, customer demand, locations, and other attributes are usually unknown beforehand or known only probabilistically. Therefore, the stochastic information on customers' attributes becomes increasingly important, given its impact on the activities at the operational level. Addressing the dynamic or stochastic contexts in parcel delivery has potential benefits in increasing solution quality and reducing operating cost and travel distance [77, 78]. In this direction, we thus investigate the dynamic and stochastic features of parcel delivery, considering multiple delivery options and crowd drivers as sources of delivery capacity.

The highlight of this work is following:

- We formulate a multi-stage stochastic model to capture the stochastic elements that arise in parcel delivery, namely the Dynamic and Stochastic Vehicle Routing Problem with Time Windows (DS-VRPTW). We thus address the uncertainty of some attributes and the possibility that some requests appear during the day, requiring adjustments in the delivery plan.
- We propose a simulation-optimization framework to solve the DS-VRPTW. The simulation can create realistic instances from real data, guiding to simulate various policies and scenarios. We solve the DS-VRPTW through a Large Neighborhood Search (LNS) metaheuristic integrating several solution improvement procedures because of its complexity and the large-size instances.
- As described before, we involve multiple and integrated transportation modes and delivery options, i.e., vans, cargo bikes, and crowd drivers. We also investigate the impact of varying customer demand. A case study in the medium-sized city of Turin (Italy) is conducted to analyze the potential influence of using multiple delivery options and crowd drivers in parcel delivery on operational cost, environmental cost, and delivery efficiency. The resulting managerial insights expressed in a set of policies are part of the outcomes of the Logistics and Mobility Plan 2019-2021 led by the Regional Council of Piedmont (ICELab@Polito, the general confederation of Italian industry Confindustria, Piedmont Region, and LINKS Foundation).

Our model attempts to reduce transportation by vans favoring cargo bikes and other delivery options and synchronizing the transport flow. It would aid planners in reacting to disruptions or new requests while improving the service's quality and sustainability through the efficient utilization of available resources [79].

4.2 Literature review

In this section, we review the literature on crowdsourcing and DS-VRPTW. Crowdsourcing is also known as crowd shipping [80] and crowdsourced delivery [81]. In addition, many researches in the literature have investigated the impact of using crowd-resources to operate deliveries.

Alnaggar et al. [82] present an extensive review of crowdsourced delivery from current industry and academic literature. They propose a taxonomy of available platforms according to their matching mechanisms, target markets, and compensation schemes. They classify four decisions that belongs to *operational* (e.g., matching and routing) and *tactical levels* (e.g., scheduling and compensation) to improve the crowdsourced delivery. Zhen et al. [83] propose six mathematical models to evaluate different operation modes of the crowdsourced delivery. The authors consider several realistic factors, including the latest service time for each task, task cancellation rate, and range distribution of tasks. Extensive experiments validate the effectiveness of the proposed models, and some managerial implications are outlined to help crowdsourced companies make scientific decisions. Yıldız [84] proposes a “courier friendly” crowd-shipping (CS) model to carry out express package deliveries in an urban area. This model uses transshipment points to enhance operational efficiency and a company-controlled backup delivery capacity to account for the uncertainty in the crowd-provided delivery capacity. The Monte-Carlo simulation approach is used to determine “shadow costs” of capacity utilization and make the assignment (matching) decisions. Le et al. [85] develop and evaluate four different pricing and compensation schemes for CS systems under additional demand and supply scenarios. The platform provider’s profits are more sensitive to the increase of willingness to pay than the rise of expected to be paid. The insights are helpful for CS firms to attract and retain customers and couriers in the system by setting up optimal prices and optimal compensations based on demand and supply levels as well as the firms’ expected profits and platform users’ presuming surplus. Devari et al. [71] investigate the potential of engaging friends or acquaintances in parcel delivery. They demonstrate that this strategy decreases total emissions and delivery costs. Dayarian and Savelsbergh [86] investigate a form of crowd shipping in which in-store customers supplement company drivers to serve online orders for a same-day delivery problem. They solve the static and dynamic variants of this problem by using myopic and sample-scenario planning approaches, respectively. Archetti et al. [87] consider occasional drivers as additional couriers to manage delivery. They develop a multi-start heuristic to generate the near-optimal solution. The extensive computational study demonstrates the potential advantages of employing occasional drivers for cost-saving. Dahle et al. [88] consider a pickup and delivery problem with time windows and occasional drivers that applys crowd drivers to take a detour to manage one or more customer requests. They model the problem through both load and flow formulation, and solve it to optimality for up to 70 requests. Their experiments demonstrate an average cost savings of 10-15% by engaging crowd drivers. Though good results have been proved in several papers, these research do not capture parcel delivery's stochastic and dynamic features. In the real-world operations, many online requests from customers are appeared dynamically. The requests information, including demand, location, and time windows are revealed over time when changing planned routes or rescheduling during the execution process.

As highlighted by Ritzinger et al. [89], exploring dynamic and stochastic information in VRPs achieves the benefits mainly up to 20% of cost-saving, carbon emissions reduction, and efficiency improvement. Various papers have been investigated on DS-VRPTW [90, 91]. For instance, bent and Van Hentenryck [92] consider a dynamic VRPTW with stochastic customers, where the objective function is to maximize the number of served customers. They develop a multiple scenario approach (MSA) to continuously obtain the routing plans for scenarios, considering known and future customer orders. The computational experiments demonstrate that MSA has significant improvements over approaches not exploiting stochastic information.

Florio et al. [93] propse a branch-price-and-cut algorithm for VRP with stochastic demands. Instances with up to 76 nodes are solved up to five hours. Furthermore, they prove that the solution to the stochastic problem is up to 10% less costly than the deterministic variant.

Subramanyam et al. [94] develop a robust optimization approach to address a wide class of heterogeneous VRPs under demand uncertainty. To evaluate and present this uncertain demand, they generate a robust solution that remains feasible for all expected demand realizations. Heuristic and exact methods are applied to enhance robust solutions. However, the trade-off between robustness and cost is highly dependent on the selection of the uncertainty set.

Hvattum et al. [95] apply a dynamic stochastic hedging heuristic (DSHH) to address a DS-VRP. Customer locations and demands are set to be unknown. Besides, the Poisson distribution is used to represent the number of customers revealed at each time period. A multi-stage stochastic model, extending the two-stage one, is applied to record the stochastic and dynamic elements of the real-world case. When the customers' information are revealed, two recourse actions are applied to rearrange the routing plans or start the new route. Compared to a myopic dynamic heuristic (MDH) that does not exploit future events, the DSHH can obtain more than 15% travel distances saving.

Sarasola et al. [96] propose an extended variable neighborhood search (VNS) algorithm to investigate a VRP with stochastic demand and dynamic requests. By using sampling-based VNS, they obtain improvements by 4.4% on average.

The previous research highlight how exploiting stochastic information generates many benefits for the routing plan in real-world applications. However, to the best of our knowledge, there is no research combining crowdsourcing with DS-VRPTW.

The main idea behind this combination is to investigate the potential benefits of considering crowd drivers in parcel delivery with stochastic and dynamic customer requests. In this paper, we model this problem as a multi-stage programming problem with recourse. The first recourse action allows crowd drivers to collect the demand of stochastic customers. Then, the second recourse action relocates the customers in planned routes. We develop a simulation-optimization-based multi-stage heuristic that gradually constructs routes by exploiting statistical information on future customer demand.

4.3 Problem description and mathematic model

In this section, we describe the problem setting and the mathematical model.

Different research and projects on urban logistics highlighted that freight networks should rely on the interoperability of several business models, stakeholders, and modes of transportation for managing the parcel delivery in the last mile [42, 97, 98]. This concept of urban synchromodality refers to the optimization and synchronization of both the transport modes and the parcel flows created from online shopping and reverse logistics. It would be beneficial for improving the economic and environmental sustainability and resilience of multimodal networks. In particular, we consider a decision-maker of a traditional courier company (i.e., using vans) that manages a set of customer deliveries with a limited and heterogeneous fleet of vehicles within one day. In doing so efficiently, it outsources the operation of some parcels to a green courier company (i.e., using cargo bikes) and crowd-sourced drivers.

Assuming that the traditional courier and the green courier start their operations from a satellite center (generally located in existing urban areas) and a mobile depot in the city center, respectively, where the parcels are consolidated. While the crowd drivers start the journey to pick up and deliver packages in urban areas from their original place (e.g., their home). The crowd operators earn compensation after completing the parcel delivery services. There are different ways to calculate payment depending on the exact commercial contract. Note that a crowd driver may not be available in certain timeslots or even only in a specific timeslot.

To reflect the real-world practices of the last-mile delivery, we assume that a significant part of customer orders arises the day before the decision-making process. Thus, they are known to the couriers at the beginning of the working day. In contrast, some other customer requests appear dynamically during the day. Furthermore, these requests are operated based on real-time routing decisions, making quantifying a priori of time and costs tricky. The investigated problem is an extended variant of vehicle routing problems (VRPs) [99] that aims to provide a fleet of vehicle routes to serve customers with minimum costs.

The DS-VRPTW problem contains features of both the Dynamic VRP and Stochastic VRP. The number of stochastic customers, their reveal time, and other attributes (e.g., time window, demand, and location) is only known by their probability distributions. The problem can be firstly solved as the deterministic VRPTW, generating an initial plan for these requests. When the stochastic customers reveal dynamically, some recourse actions must be taken. We permit that the dynamic customers can be inserted into the initial routes or reassigned to a crowd driver who manages the service. If none of the two actions are feasible, the customer requests are thus rejected. Note that if a vehicle has already moved to a new customer, then this customer must be served by that vehicle, i.e., the preemption of customers is not allowed.

4.3.1 Model formulation

We formulate the problem as a new variant of the DSVRPTW. In particular, a two-stage stochastic model with recourse that extends the deterministic VRPTW model is proposed. We list the symbols used in the model in Table 4.1.

We define some assumptions in this model. Firstly, the depot $\{0\}$ is operating during a given time horizon $[e_0, l_0]$, and there is a single known moment $t \in [e_0, l_0]$ at which all stochastic information are revealed. At this moment, several recourse actions can be applied so that new customers are served. Let the set of initial locations be denoted by $N = C \cup \{0\}$, where $C = \{1, 2, \dots, n\}$ denotes the initially known customers.

Table 4.1 Notation

Symbol	Definition
C, C^+	Initially known customers and stochastic customers
Q_k, Q_v	Maximum capacity of vehicles and crowd drivers
N, N'	Set of initial and total locations
K, V	Set of heterogeneous vehicles and crowd drivers
$\tilde{C}^+, \tilde{D}^+$	Random variable vector of customer location and demand
$\tilde{E}^+, \tilde{L}^+$	Random variable vector of earliest and latest arrival time
c_{ijk}, t_{ijk}	Travel cost and travel time from i to j by vehicle k
e_i, l_i	Earliest and latest arrival time of customer i or depot 0
x_{ijk}	Binary variable on whether vehicel k moves from i to j
x_{ijk}^+	Binary variable on whether vehicle k moves from i to j in second-stage recourse action but not in the first-stage solution
x_{ijk}^-	Binary variable on whether vehicle k moves from i to j in the first-stage solution but not after recourse action
y_{iv}	Binary variable on whether i is served by a crowd driver v
p_j	Binary variable on whether customer j is rejected
s_{ik}	The time at which the service of i is exactly completed by k
s_{ik}^+	The time at which the service of i has completed by k based on the second-stage recourse actions
h, a^h	Time interval and its corresponding operational decision
$\tilde{\xi}, E_{\tilde{\xi}}$	Random variable distribution and expected value of travel cost

Let the set of stochastic customers revealed at time t be denoted by $C^+ = \{n+1, n+2, \ldots, n+n^+\}$. We can then represent the set of all locations as $N' = C' \cup \{0\}$, where $C' = C \cup C^+$. Every pair of locations $i, j \in N'$ is associated with the travel time t_{ijk} and the travel cost c_{ijk} for the vehicle k, where the service time is included in t_{ijk}. Each customer $i \in C'$ has a demand d_i and a time window $[e_i, l_i]$. The service of a customer i must be started after e_i and before l_i. Waiting at a customer i is allowed while violating the latest time window l_i would incur a penalty. A set of heterogeneous vehicles $K = \{1, 2, \ldots, k\}$, each of maximum capacity Q_k, starts at and returns depot between time horizon $[e_0, l_0]$ after finishing all the services. Moreover, a set of crowd drivers $V = \{1, 2, \ldots, v\}$, each of handling capacity Q_v, starts at their original place O_v to serve the dispatched customers. Let $K' = K \cup V$ denotes all the available delivery options. The crowd drivers with a limited service radius are employed to collect the demand of stochastic customers and consolidate it at one of the customers' locations. Let $\tilde{\xi} = (\tilde{C}^+, \tilde{D}^+, \tilde{E}^+, \tilde{L}^+)$ be the random variable vector and $\xi = (C^+, D^+, E^+, L^+)$ is one of its particular realizations with probabilities p_ξ.

The two-stage stochastic programming problem can be defined as follows:

$$min \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} c_{ijk} x_{ijk} + \sum_{\xi \in \tilde{\xi}} p_\xi Q(x, p, s, \xi) \tag{4.1}$$

$$Q(x,p,s,\xi) = \sum_{i\in N'}\sum_{j\in N'}\sum_{k\in K'} c_{ijk}\left(x_{ijk} \pm x_{ijk}^{-}\right) + H_i \sum_{i\in C'}\sum_{v\in V} y_{iv} + P\sum_{j\in C'} p_j \tag{4.2}$$

s.t

$$\sum_{i\in N}\sum_{k\in K} x_{ijk} = 1 \quad \forall j \in C \tag{4.3}$$

$$\sum_{j\in N} x_{0jk} = 1 \quad \forall k \in K \tag{4.4}$$

$$\sum_{i\in N} x_{ihk} - \sum_{j\in N} x_{hjk} = 0 \quad \forall h \in C, \forall k \in K \tag{4.5}$$

$$\sum_{i\in N} x_{i0k} = 1 \quad \forall k \in K \tag{4.6}$$

$$\sum_{i\in N'}\sum_{k\in K'}\left(x_{ijk} + x_{ijk}^{\pm x_{ijk}^{-}}\right) = 1 \quad \forall j \in C' \tag{4.7}$$

$$\sum_{j\in N'}\left(x_{0jk} + x_{0jk}^{\pm x_{0jk}^{-}}\right) = 1 \quad \forall k \in K' \tag{4.8}$$

$$\sum_{i\in N'}\left(x_{ihk} + x_{ihk}^{\pm x_{ihk}^{-}}\right) - \sum_{j\in N'}\left(x_{hjk} + x_{hjk}^{\pm x_{hjk}^{-}}\right) = 0 \qquad \forall h \in C', \forall k \in K' \tag{4.9}$$

$$\sum_{i\in N'}\left(x_{i0k} + x_{i0k}^{\pm x_{i0k}^{-}}\right) = 1 \quad \forall k \in K' \tag{4.10}$$

$$\sum_{i\in C} d_i \sum_{j\in N} x_{ijk} \le Q_k \quad \forall k \in K \tag{4.11}$$

$$\sum_{i\in C} d_i \sum_{j\in N}\left(x_{ijk} + x_{ijk}^{\pm x_{ijk}^{-}}\right) \le Q_k \quad \forall k \in K' \tag{4.12}$$

$$x_{ijk}^{-} \le x_{ijk} \quad \forall i,j \in N, \forall k \in K \tag{4.13}$$

$$x_{ijk}^{-} = 0 \quad \forall i,j \in C^t, \forall k \in K \tag{4.14}$$

$$t x_{ijk}^{-} \le s_{ik} \quad \forall i,j \in N, \forall k \in K \tag{4.15}$$

$$s_{ik} + t_{ij} - M_{ij}\left(1 - x_{ijk}\right) \le s_{jk} \quad \forall j \in C, \forall i \in N, \forall k \in K \tag{4.16}$$

$$e_i \le s_{ik} \le l_i \quad \forall i \in N, \forall k \in K \tag{4.17}$$

$$s_{ik} + t_{i0} - M_{i0}(1 - x_{i0k}) \le l_0 \quad \forall i \in C, \forall k \in K \tag{4.18}$$

$$s_{ik}^{+} + t_{ij} - M_{ij}\left(1 - x_{ijk} - x_{ijk}^{+} + x_{ijk}^{-}\right) \le s_{jk}^{+} \quad \forall j \in C', \forall i \in N', \forall k \in K' \tag{4.19}$$

$$e_i \le s_{ik}^{+} \le l_i \quad \forall i \in N', \forall k \in K' \tag{4.20}$$

$$s_{ik}^{+} + t_{i0} - M_{i0}(1 - x_{i0k} - x_{i0k}^{+} + x_{i0k}^{-}) \le l_0 \quad \forall i \in C', \forall k \in K' \tag{4.21}$$

$$s_{0k} = e_0 \quad \forall k \in K \tag{4.22}$$

$$s_{0k}^{+} = e_0 + (t - e_0)x_{00k} \quad \forall k \in K' \tag{4.23}$$

$$x_{iik} = 0 \quad \forall i \in C, \forall k \in K \tag{4.24}$$

$$x_{iik}^{+} = 0 \quad \forall i \in C', \forall k \in K' \tag{4.25}$$

$$x_{ijk} \in \{0,1\} \quad \forall i,j \in N, \forall k \in K \tag{4.26}$$

$$x_{ijk}^{+}, x_{ijk}^{-} \in \{0,1\} \quad \forall i,j \in N', \forall k \in K' \tag{4.27}$$

$$y_{iv} \in \{0,1\} \quad \forall v \in V, \forall i \in C' \tag{4.28}$$

$$p_j \in \{0,1\} \quad \forall j \in J \tag{4.29}$$

$$s_{ik} \in [e_0, l_0] \quad \forall i \in C, \forall k \in K \tag{4.30}$$

$$s_{ik}^{+} \in [e_0, l_0] \quad \forall i \in C', \forall k \in K' \tag{4.31}$$

The objective function (4.1) minimizes the first stage routing cost as well as the cost of the recourse. Co. The random quantity $Q(x,p,s,\xi)$ is the expected cost at the second stage, which includes adjusting the routing, employing crowd drivers, and a penalty P paid for the customer rejection. We set a very high value of P so that the minimization of the objective function would result in minimizing the number of rejected customers as well. Note that a high value of P would make the rejection of a customer request unaffordable. Thus, in some cases, a suitable value of P should be considered.

Constraints (4.3) -(4.6) are similar to (4.7) -(4.10), ensuring that all customers are visited once, and any vehicle must start and end at one depot, respectively. Constraints (4.5) and (4.9) guarantee flow conservation. Constraints (4.11) and (4.12) ensure that the vehicle capacities are not violated in both first and second stage solutions. Constraints (4.13)-(4.15) ensure that a tour between the customer i and j in the first-stage solution cannot be skipped in second stage solution recourse if the service in departure location is finished before time t where C^t denotes the customers revealed at time t. Constraints (4.16)-(4.18) ensure that the time windows of both customers and depot are not violated, where M_{ij} is a sufficiently large constant, e.g., $M_{ij} = l_i + t_{ij} - e_j$. Constraints (4.19)-(4.21) are used to track when service is completed in the second-stage solution. Constraints (4.22) and (4.23) guarantee that vehicle k cannot leave the depot before time t in the second stage decision if it does not leave the depot in the first stage. Finally, constraints (4.26)-(4.31) express the domain of decision variables.

The crowd drivers are considered as sources of special delivery capacity that move within the city who are employed to pick up the demand from customers. They have to follow traditional drivers' constraints, including capacity, time windows, start and return at the original place. Note that the crowd drivers have a limited service distance. The stochastic requests are dispatched to crowd drivers by checking the service distance and feasibility of capacity and time windows constraints. We assume that crowd drivers should consolidate the parcels to a traditional van at the nearest customer location or a mobile depot. Both vans and crowd drivers have very tight schedules. Waiting for consolidation would incur the violation of time window constraints. It is thus crucial to synchronize the actions of crowd drivers and traditional vans, i.e., they should arrive at a selected customer location or mobile depot at the same time to operate the consolidation. We assume that the operational context of parcel delivery can be separated into a predefined number of time intervals h. The problem is modified with information revealed during each interval. A multi-stage model can thus be extended from a two-stage stochastic model into an h-stage model for any given h by adding additional variables and constraints for each stage [95].

4.4 Methodology description

The exact approach for multi-stage stochastic VRPs currently fails to solve the problems with a significant number of customers. The evaluation of recourse cost function (4.2) can become extremely difficult, depending on the distribution of random variables. Developing a practical heuristic is thus one of the promising approaches to solve this complex and large-size problem. Instead of assuming particular distributions of stochastic variables, we propose a simulation-optimization based multi-stage heuristic based on sample information. Sample scenarios are first obtained using a Monte Carlo simulation and then guide a heuristic approach that generates a routing plan for each time interval in turn. We assume that the time horizon can be divided into h intervals $H_1, \dots, H_h$ which is related to stages in the multi-stage model. At the beginning of each interval, the algorithm generates a routing plan that minimizes the expected travel cost of serving both known and stochastic customers. At each time interval $h \in [H_1, H_h]$, an action a^h must be decided. Each action a^h contains two parts: first, for each customer $i \in C'$ revealed at a time interval h, the action a^h must accept or reject the customer based on the given constraints. Second, the action a^h must provide the operational decisions for traditional vehicles or crowd drivers at time interval h (i.e., service a customer, travel to the next customer, or wait at the current position). Before the online execution, the first action a^1 at time interval H_1 is obtained based on a set of known offline customers. A solution is a sequence of actions $a^{1 \dots h}$ that covers the whole operational horizon. On the one hand, we apply the rescheduling and adoption of the crowd drivers as two recourse actions to cope with the dynamic feature of the problem. On the other hand, using stochastic information during the planning is to capture the stochastic elements. The key idea is to solve each sample scenario as a deterministic VRPTW and select the distinguished plan from the solutions [92]. A post-optimization procedure is finally applied to compute additional key performance indicators (KPIs).

Figure 4.1 illustrates the framework, and the remaining part of this section describes the details of this algorithm.

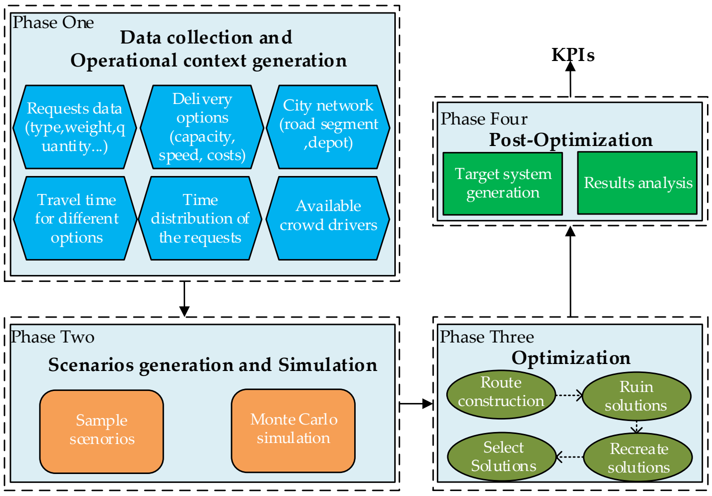


Figure 4.1 Simulation-Optimization Framework

4.4.1 Operational context generation

The operational context is obtained by collecting different sources of information, e.g., city network, vehicle fleet and travel time, customer attributes, and the company's objective and constraints. The city network is generated considering: i) the city map provided by the local government; ii) geographical coordinates and empirical distributions of customers and depots by courier companies.

Courier companies offer the specific attributes of a vehicle's fleet (i.e., capacity, speed, fuel consumption). Furthermore, we collect customer attributes, i.e., locations, demand, and time windows, and measure the travel times through the sensors spread in the city. Stochastic information is known as the probability distribution (e.g., demand and service time). Finally, the objectives and constraints are defined based on the specific optimization problem.

Some data may be stochastic since the uncertainty of some components in the operational context is involved. These data can be described by random variables, including service or travel time, customer demand, etc.

As some components of the operational context involve uncertainty, these data can be described by random variables and typically generated from the historical data of delivery companies. In other words, these data illustrate the structure of the problem, which would be solved in the subsequent few phases. The original data for generating the operational context is provided in the work [40].

4.4.2 Scenarios generation and simulation

We apply the Monte Carlo simulation or multi-scenario approach to calculate the expected (or recourse) costs. An approximation algorithm for deterministic VRPTW is thus used to evaluate a solution on a set of scenarios. Furthermore, metaheuristics such as LNS and tabu search can be efficiently engaged with sampling approaches to implement a simulation-based multi-stage stochastic optimization approach.

The scenarios are obtained according to the well-defined operational context and the knowledge about the probability distributions of the stochastic variables. Each scenario is related to a specific realization of all the random variables in an operational context. The distributions of demand, reveal time, time windows, and locations are applied to create possible future customer requests. Monte Carlo sampling is used to obtain a set of instances. Each instance includes both the known customers and the stochastic ones drawn from the given distributions. These sample instances show that likely events are associated with a high probability. For any given time interval h, solutions of these sample instances are generated by simple local search algorithms such as *insertion* heuristic and *regret* heuristic. The implementation starts with the routes which are already executed. Each start depot matches the vehicles' current position, while the capacity of each vehicle is calculated by reducing the weight of goods collected up to the current time. The end depot remains the same, and time windows are appropriately modified. We check the feasibility of dispatching the customers to crowd drivers based on service distance and other constraints. In addition, we identify the frequently visited customers among the sample instances and decide to serve these customers during h in the final plan. We generate more accurate travel time matrices by implementing the Google Earth application programming interfaces (APIs) through a georeference module.

4.4.3 Optimization

The optimization algorithm is an extended meta-heuristic that combines the ruin and recreate principle and a group of general heuristics proposed by [100] and [101]. It aims to obtain and enhance the routing plans for multiple scenarios. We first assume that an initial solution s has been generated by a simple insertion heuristic. Then, a quantity q of customers is removed from the solution. We conduct the ruin and recreate operations on the current solution s_{new}, to diversify the search space and enhance the solution. The algorithm ends when it reaches a certain number of iterations (i.e., 5000 iterations). Since the parameter q determines the neighborhood size, we select an appropriate value q that balances the computational efforts and solution quality. In our case, we set q equal to 10% of the maximum customers for each instance. The performance and robustness of LNS are dependent on the selected ruin and recreate operations. Note that in each ruin and recreate operation process, only one heuristic is chosen and applied based on the well-known roulette wheel selections. More details about the whole process are described as follow:

Construct an initial solution.

For the given scenario, the algorithm starts with an initial solution generated by the basic greedy heuristic. This heuristic aims to repeatedly insert a request at the best position (i.e., cheapest possible position), which means that the request is always inserted into a position with a minimum insertion cost in each iteration. In particular, let U be the set of unserved customers and Δf_{ik} be the change of objective value incurred by inserting request $i \in U$ at the *cheapest* position in the vehicle k, if request i fails to insert in the vehicle k, the value Δf_{ik} is set to infinite. We thus compute all the potential insertion and insert request i in vehicle k at its minimum cost position as follows:

$$(i, k) \coloneqq \arg min_{i \in U, k \in K} (\Delta f_{ik}) \tag{4.32}$$

In each iteration, we only change one route and terminate the process until all requests are inserted, or no feasible requests exist. As a simple construction heuristic, the basic greedy heuristic has the potential problem of postponing the placement of expensive customers (i.e., with larger Δf_{ik}) to the last iterations. The expensive customers are thus difficult to be served. Indeed, many routes might have no space at the last iterations, leading to creating new routes or rejecting customers. Therefore, repair operations are considered as an alternative approach to overcome this potential issue.

Ruin operations.

After generating the initial solution for each scenario, we use four ruin strategies (i.e., random removal, worst removal, related removal, and cluster removal) to ruin the initial solution. These heuristics take a given solution s as input and then output a partial solution with q removed requests.

Random removal is the most straightforward heuristic that selects q requests randomly and removes them from the current solution. It aims to diversify the search space.

Worst removal chooses some requests that have high costs in their current position. Given a solution s and a request i, we denote $f(s, i)$ as the objective value that request i has been removed from solution s. The change of objective value Δf_{-i} is defined as $\Delta f_{-i} = f(s) - f(s, i)$. The *worst removal* repeatedly selects a new request i with the highest cost of Δf_{-i} until q requests are removed. The function of the *worst removal* heuristic is to remove the requests at the worst positions and insert them at other positions to obtain better objective value in the recreate process. However, to avoid the same customers with expensive costs being removed repeatedly, it is crucial to keep the randomization of this heuristic.

It can be achieved by applying a parameter $p \geq 1$ that controls the selection process. A less expensive customer associated with a high value of p, may be selected. This probability decreases with the value Δf_{-i}. It means that if the value of p is small, then the most expensive customer is selected.

The *related removal* aims to remove the requests that are similar to each other in some sense. The motivation of this heuristic is that we may not gain any improvement when reinserting the removed requests in the case they are very similar to each other. The similarity of request i and request j is defined as *relatedness* $R(i,j)$. The main idea is to measure the similarity by computing the difference value in terms of capacity, service-starting time, and distance between requests i and j, as indicated in the equation (4.33).

$$R(i,j) = \varphi c_{ij} + \sigma(|s_i - s_j|) + \tau(|q_i - q_j|) \tag{4.33}$$

Note that all terms in this equation are normalized in the range $[0,1]$. The related removal procedure removes a random customer, and in the successive iterations, it chooses customers similar to the already removed customers. The parameter p is again used to control the selection process as we do in the *worst removal*. We refer to [102, 103] for further details of the heuristic.

The last heuristic, namely *cluster removal*, is a variant of the *related removal*. It is used to remove clusters of related requests from a few routes, which removes the groups of requests entirely from different routes if the single removed request is inserted back into the route.

Repair operations.

After applying the ruin operation, a group of repair operations is used to generate new solutions for each scenario. The operation is conducted in parallel since there are different scenarios. The *basic greedy* heuristic is used again to recreate the new solutions. However, this simple heuristic may insert some requests back in their previous position. The *regret* heuristics are then used to mitigate this problem by using a kind of look-ahead information. Let Δf_i^q be the change of objective value incurred by inserting customer i at its best position in the qth *cheapest* route for customer i. The value of Δf_i^2 is thus the change of objective value by inserting customer i into the route where the customer could be inserted *second-cheapest*. In each iteration, the customer i is chosen according to the equation $i \coloneqq \arg max_{i \in N} (\Delta f_i^2 - \Delta f_i^1)$ his operation aims to maximize the difference in the cost of inserting customer i at its best route and second-best route. This process is repeated until no customers can be inserted. Instead of using a simple acceptance criterion that only accepts the solution with a better objective value, the *simulated annealing* strategy is applied to choose the solutions based on a varying probability. The detail of this strategy can be found in the study by [100].

The abovementioned steps are repeated until the given termination criterion is met, i.e., reach the maximum running time or have no improvement for continuous iterations. As the optimization process continues, a set of routing plans is maintained at each interval. We use a natural operation to decide which customers should be fixed in the routes for the current interval. In particular, it is applied to exploit the common features among the maintained routing plans, i.e., select the customer that is most frequently visited in the current time interval in the multiple sample scenarios. Once identifying these customers, the action a^h is then fixed to visit these customers during the current time interval h in the final plan. At the end of the last time interval, we conduct a post-optimization and compute the related KPIs.

4.5 Case Study

We analyze the potential impact of crowdsourcing and multiple delivery options in terms of economic, environmental, and operational sustainability for on-demand parcel delivery. In doing so, a real case study is conducted related to urban logistics in Turin (Italy). We first present the description of the case study and the corresponding operational context. Then, we discuss the computational results to provide valuable insights for decision-makers.

4.5.1 Description of the operational context

Last-mile presents severe challenges to the operations of the supply chain network. Thus, alternative distribution systems architectures have been proposed to tackle these challenges and improve the efficiency of last-mile delivery. We consider a promising solution as the adoption of a two-tier system [104]. In the first level, vans perform deliveries from distribution centers located in a strategic node of the city to Urban Consolidation Centers named satellite. They are generally transshipment points near the city center. At the second level, orders are consolidated to city freighters, i.e., small vehicles that can move quickly and efficiently along any street in the city center area operated even partially with crowdsourcing contracts [105].

In this case study, we conduct four benchmarks integrating van, bike, and crowdsourcing:

- Benchmark 1 (B1): only traditional vans (fossil-fueled) are applied to operate the parcel delivery.
- Benchmark 2 (B2): green carriers, such as drivers using cargo bikes or bicycles with the messenger bag, are used as an environment-friendly

delivery option, providing economic and operational benefits for parcel delivery. In B2, we consider both van and bike as transportation modes.

- Benchmark 3 (B3): crowdsourcing is considered as a flexible delivery option. The crowd driver plays the role of additional capacity to fulfill the on-demand requests. In practice, the delivery tasks are dispatched according to the distance between crowd drivers and customers.
- Benchmark 4 (B4): all the above delivery options are applied.

The urban distribution setting and data used in this chapter are inspired from the analysis of a real case study of the city Turin conducted by the CARS@Polito [106] and the ICELab@Polito [107], with the collaboration of the Torino Living Lab project [108] and the Amazon Innovation Award. The managerial insights coming from this work will be part of the new Logistics and Mobility Plan to be activated in 2022 in the Piedmont region.

To generate specific operational contexts, we have fused the parameters and data coming from the following sources:

- URBeLOG project for the distribution of customers and real (and anonymized) information about their location [37];
- Municipality of Turin for what concerns the satellite location, city map, and data on the road network from sensors in the city;
- the study by [40] regarding vehicle characteristics, costs, and revenue structure of parcel delivery companies.

In particular, the city network presented in Figure 4.2 is generated using a 2.805×2.447 km^2 area in Turin that includes both the center of the city and a semi-central area. We consider that area because, according to [7], it is the area in which the different modes can coexist sustainably (from economic, environmental, social, and operational perspectives) and is also the most populated area of the city, covering more than the 80% of the total population. We consider a distribution center located on the city's outskirts to serve the traditional carriers, while a mobile depot in the city center is a satellite facility for the green carrier and crowd drivers. Two sequential connected points denote road segments of this network. The roads' information is extracted from the shapefiles provided by the local public authority in Turin. The average speed on each road segment is monitored by the speed sensors around the city area. Each point on this network is associated with a unique ID number and real GPS coordinates.

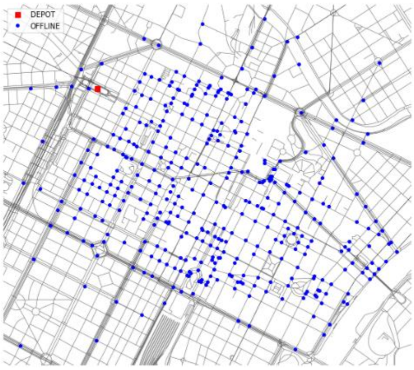


Figure 4.2 City network in the case study

Note that the red square represents the mobile, while the blue circles are the offline customers.

Table 4.2 shows the values of the capacity, speed, and service time for each delivery option. As an international parcel delivery company offers these parameters in Turin, their values are supposed to be fixed, and thus, we use them as input in our case study. As the crowd drivers move within the city, we thus randomly generate the location of crowd drivers on this graph. We conduct some preliminary experiments to obtain a suitable number of available crowd drivers. The aim is to analyze and test the impact of the different numbers of available crowd drivers for B4. The detailed results are shown in subsection 4.5.2. We classify the parcels according to their weights as mailers (0-3kg), small parcels (3-6kg), and large parcels (over 6kg). In particular, the percentage of total parcels for each type is defined as 57%, 13%, and 30%, respectively, according to section 3.4.

Table 4.2 Input parameters

Delivery Options	Maximum parcel size(kg)	Capacity	Coverage (km)	Speed (km/h)	Service time(min)		
					Mailers	small parcels	large parcels
Van	70	700kg	NA	40	4	4	5
Cargo Bike	15	70kg	NA	20	2	2	—
Crowd Driver	6	4 Parcels	2	15	2	—	—

In the operational context, we divide the eight working hours as four time buckets with the same length based on the current standard for timeslots in time-sensitive urban delivery (e.g., Amazon Prime Now, Uber Freight). Each bucket is split into 1 minute time unit. For each potential customer, the demand is generated based on its parcel type, while the time window is specified for the time bucket by the simulator. In our simulation, we consider instances with 550, 350, and 150 potential customers, respectively. For each context, 70% of offline requests are known before scheduling, while 30% of potential customers are assigned as prime members with a priority that restricts their time window to the first two buckets. The expected behavior of each potential customer for the investigated problem is described. For each potential customer location i and each time unit t of the time horizon, a probability is associated with an online request (i.e., picking up a parcel) that may reveal at a time t for location i.

Once all the locations are defined, the mutual distances between these customers and depots are generated. Instead of using Euclidean distance, the distance matrix among the points is computed by Dijkstra's shortest path method. Finally, the travel time matrixes are generated based on these distance matrixes and the original speed among the road segments in the input data.

We consider three different degrees of dynamism (DOD) to address dynamic online requests, i.e., 15%, 30%, and 45%. For example, DOD-15% means that there are 15% of dynamic requests in total customers. For each operational context, we thus generate three different sub-contexts, which are applied to measure the impact of DOD. We develop ten independent scenarios with ten sets of dynamic online requests for each sub-context, obtained by sampling their probability distributions. Each online request is associated with its location, demand, time windows, and when they appear in the time horizon. We generate a total of 360 instances. They are available on the Github repository at the following link: https://github.com/gcmswm/Benchmarks.

The objective function minimizes first the total travel cost (expected) of parcel delivery and second the number of rejected requests.

4.5.2 Numerical analysis

In this section, we measure the impact of adopting crow drivers and multimodality on the sustainability of parcel delivery.

Experiments are conducted based on some randomly generated test problems. For each benchmark and operational context, we conduct ten independent tests. Therefore, we solve the 360 instances independently by the optimization procedure. To analyze the experimental results, we compute different KPIs that reflect the mix of economic, environmental, and operational facets of the service:

- *Economic sustainability*. Based on the current real practices, the delivery cost is associated with the number of parcels served by different delivery options since different options have additional contract costs. We define the KPI as cost per delivery for each option:
  - cost per delivery (van), the unit cost of each parcel delivered by traditional van;
  - cost per delivery (bike), the unit cost of each parcel served by bike.

We consider the operating costs related to the vans and cargo bikes. These costs are computed per kilometer traveled in the last mile segment of the supply chain. They include variable costs (e.g., gasoline) and the total cost of vehicle ownership [7]. In particular, we consider both costs directly related to the vehicles (e.g., purchase cost, taxes, insurance, fuelling, and maintenance costs) and personnel costs (e.g., drivers/bikers salaries and related taxes). The typical contract scheme in the parcel delivery industry imposes the conversion from a cost per kilometer to a cost per stop.

In crowdsourcing, we consider the compensation per delivery that reflects the unit paid by the company to crowd driver for each delivered parcel. The exact compensation is dependent on many factors, including distance, weight, and the local market. However, we follow the investigation from [72] for the medium distance, inter-city market and adopt an average value (i.e., 1.8€ per delivery) as compensation for crowd drivers.

- *Environmental sustainability*. We consider the emissions and costs of the overall last-mile chain. In particular, we consider three types of emissions: direct emissions from the fuel combustion process, indirect emissions emitted by the fuel production process, and the long-haul shipment of the fuel, CO2 equivalent to including pollutants, such as nitrogen oxide. We thus compute the CO_2 emission saved in B2, B3, and B4, based on the lower travel distance by using green delivery options (i.e., bike and crowdsourcing).
- *Operational sustainability*. The operating efficiency of the delivery system is typically evaluated in terms of completed deliveries. We apply the total number of parcels served per hour $\left(\frac{nS}{h}\right)$ to measure operational sustainability.

Preliminary analysis for crowdsourcing

This section conducts a preliminary experiment to test the suitable number of crowd drivers in our case study. The average distance traveled by vans and the total average economic cost are computed for comparison. In this experiment, the number of crowd drivers is set equal to 5, 10, 15, 20, and 25, while their locations are randomly generated spreading within the urban area. The experiment is analyzed by using benchmark B4 with 350 potential customers.

In general, there are some limitations to the number of crowd drivers in real-world applications because of different reasons, including the customers' requests, the availability and motivation of crowd drivers, and suitable compensation strategies.

To find a decent number of crowd drivers in our case study, we analyze the results shown in Figure 4.3 and Figure 4.4. In particular, the values in Figure 4.3 highlight that when the number of available crowd drivers is low (i.e., five drivers), and the degree of dynamism is low (i.e., 15%), these drivers are used to manage the online requests given their flexibility. Besides, vans remain a good choice when the degree of dynamism increases while the number of available crowd drivers is still low and thus, insufficient to cope with the high online requests.

Increasing the number of crow drivers manages a more significant part of the requests than the previous scenario, although the degree of dynamism increases. It reduces the distances traveled by vans (e.g., when DOD is 45%, increasing the number of crowd drivers from 5 to 25, the average van distance decreases by 20%). Moreover, when the number of crowd workers is equal to 20, we reduce the average van distance for all the DODs. In particular, for DOD equals 15%, we reach the lowest value of the distance traveled using vans. It is reflected in the lowest value of the economic costs faced by the traditional courier company (Figure 4.4). While the economic cost for DOD-30% and DOD-45% has no significant variation for the different crowd drivers.

We thus decide to use 20 as the baseline number for crowd drivers for our case study. This choice is based on two reasons in the real-world application. First, when the number of crowd drivers is too large, some of the crowd drivers cannot receive enough delivery tasks during the execution, which will decrease their motivation for participating in the parcel delivery. Second, if the number of crowd drivers is too small, there can be a lack of available crowd drivers in some local areas, impacting the expected service quality.

However, the optimal capacity planning of crowd drivers is a complex problem due to many factors, including the compensation of delivery, the motivation of crowd drivers, and the available customer requests. The interested readers are referred for more details to [109].

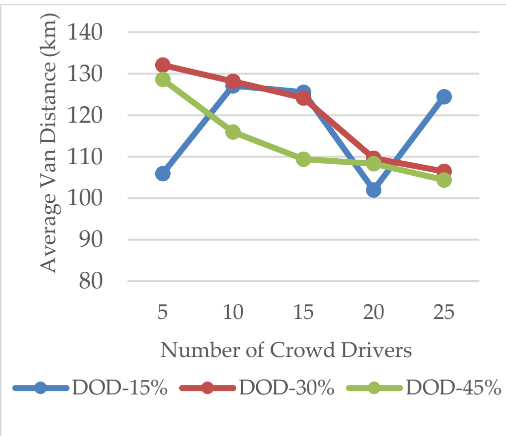


Figure 4.3 Comparison of van distance

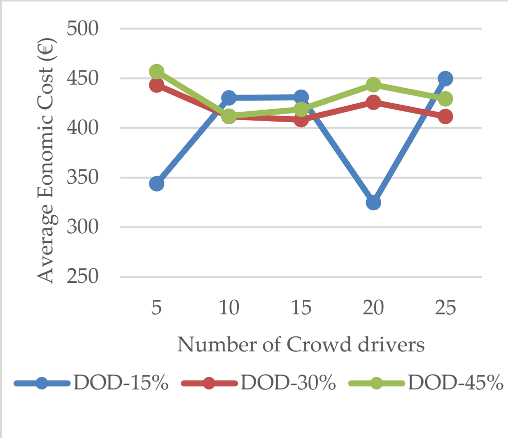


Figure 4.4 Comparison of economic cost

Performance comparison for benchmarks

We compute the percentage of each KPI compared with benchmark B1 to demonstrate the performance of using different options for parcel delivery. Figure 4.5 presents the performance of the traditional vans in B2, B3, and B4. The statistics are computed as a percentage variation of each KPI to the value of the same KPI in B1. The operating and environmental cost savings generated by using cargo bikes and crowdsourcing are denoted as ΔOC and ΔEC respectively. While $\Delta Efficiency$ denotes the reduction of efficiency incurred by the reduced number of services (We referred to [42] for a detailed description of the computation of the KPIs).

Figure 4.5 shows the improvement of economic and environmental sustainability when applying different delivery options (vans, cargo bikes, and crowdsourcing) for parcel delivery. As shown in Figure 4.5, the adoption of cargo bikes (B2), crowdsourcing (B3), and their combination (B4) lead to the reduction of economic and environmental costs. These reductions are obtained by reducing the number of vans and their total travel distance, which leads to a 25%, 21%, and 44% decrease in average economic cost for B2, B3, and B4, respectively. Besides, the average reductions of CO_2 emissions for B2, B3, and B4 are 116.68kg, 115.01kg, and 297.05kg, contributing to 17%, 16%, and 46% total average reductions of the environmental cost, respectively. In particular, when the degree of dynamism is equal to 45%, the ΔEC values are larger than the other two counterparts, i.e., DOD-15% and DOD-30%. According to the results, the potential benefits of using cargo bikes and crowdsourcing as green carriers are demonstrated for investigated three benchmarks. The most significant finding is that combining both cargo bikes and crowdsourcing into traditional van delivery reaches the highest reduction of economic and environmental costs. In addition, the loss of efficiency for B2, B3, and B4 is 25%,11%, and 33% on average, respectively. B3 reaches the minimum loss of efficiency for parcel delivery, while the economic and environmental cost saving is promising, i.e., 21% and 16% on average. Though the B4 reaches the maximum average loss of efficiency at 33%, the maximum economic and environmental cost savings (44% and 46%) are reached. In practice, when crowd drivers and cargo bikes are involved with traditional vans, there should be a balance between the increase in profits and service quality. The integration of different delivery options should be managed wisely to balance the workload, working conditions, efficiency, and service quality.

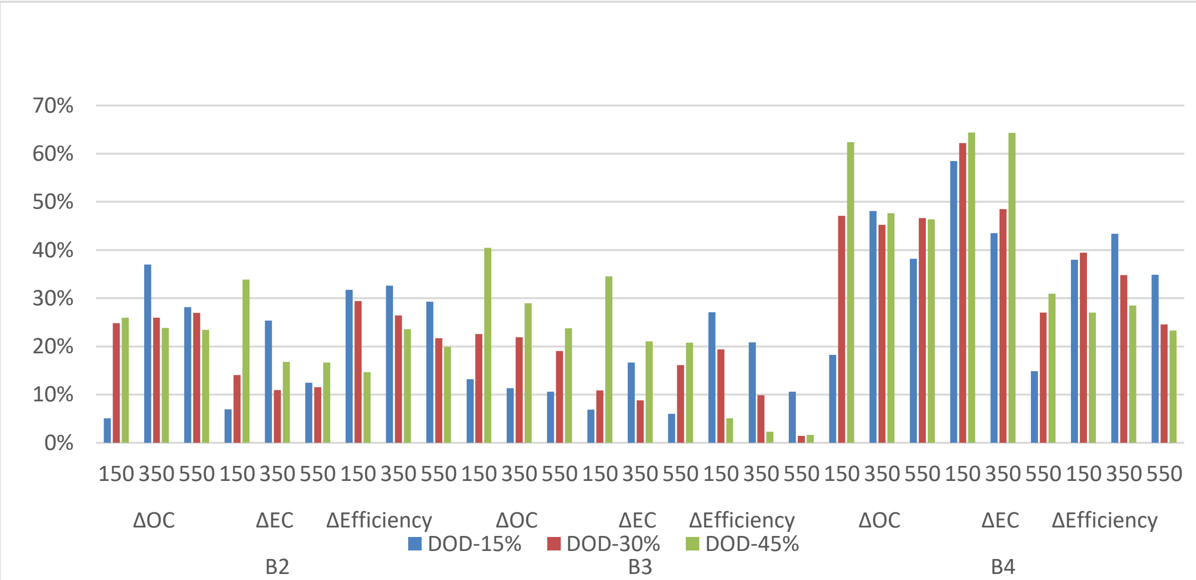


Figure 4.5 Performance comparison of different benchmarks

In this work, we consider two strategies to deal with the high demand for dynamic requests. The first one is to dispatch the online requests to the spreading crowd drivers based on the available recourse actions proposed by the optimization solver. The second is to accommodate the online requests to the existing vehicles with spare capacity.

To demonstrate the impact of crowd drivers for on-demand parcel delivery, we compare the rejected customer requests for each benchmark. Figure 4.6 presents a boxplot of the results for the four benchmarks. This figure represents the case with 550 potential customers, as there are no rejected requests in instances with 150 and 350 customers. Three different DODs are considered since the different number of dynamic requests may have different influences on the number of rejected requests. As shown in Figure 4.6, the number of rejected requests in B1 is the largest independently by the DOD. When the DOD increases, the number of rejected requests increases significantly. This result shows that only using traditional vans as the delivery option would cause more rejected requests when the dynamic requests are higher. When the cargo bikes are integrated, as shown in B2, the number of rejected requests decreases while the result has the same trend with B1 since the number of rejected requests is also increased with DOD. However, the trend in B3 and B4 is different. The number of rejected requests in both B3 and B4 remains stable for different DODs. Note that the results of B4 are better than B3 for each DOD since they have a lower minimum, average and maximum number of rejected requests according to the boxplot. Besides, there are only a few numbers of rejected requests in both B3 and B4. This result indicates that introducing crowd drivers as a delivery option can significantly reduce the number of rejected requests for our investigated instances. Therefore, considering these results, we conclude that green carriers and crowd drivers are promising delivery options to deal with online customer requests in the context of stochastic and dynamic parcel delivery.

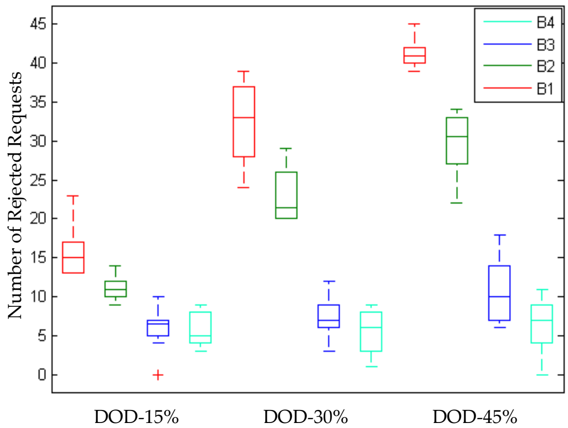


Figure 4.6 Comparison of rejected requests for different benchmarks

Influence of different customer demand

To analyze the influence of varying customer demand on sustainability performance (i.e., operational cost, environmental cost, and efficiency), we conduct a group of experiments on B4 by changing customer demand. Furthermore, we decide to conduct a sensitivity analysis on this parameter as the uncertainty on the composition of the demand will affect the congestion and the development of urban areas [42, 110].

In doing so, we generate three new groups of customer demand varying the composition of the demand as follows:

- reduction of 20% resulting in a market downturn;
- increase of 20% and 40% to suppose a market expansion.

The results are represented in Table 4.3 concerning the current situation of demand.

Table 4.3 Impact of different customer demand

Demand	instance size	△OC	△EC	△Efficiency
	150	13.9%	9.4%	10.0%
80%	350	5.3%	13.8%	29.1%
	550	3.9%	12.5%	36.7%
	150	-7.8%	-9.7%	-6.3%
120%	350	-14.1%	-17.3%	-0.2%
	550	-8.2%	-14.8%	-2.6%
	150	-17.1%	-35.6%	-18.7%
140%	350	-18.2%	-34.7%	-11.7%
	550	-14.6%	-28.2%	-8.1%

The values of ΔOC , ΔEC and $\Delta Efficiency$ represent the percentage variations of operational cost, environmental cost, and efficiency, respectively, between the normal customer demand and three other different groups of demand. Table 4.3 shows that when the customer demand decreases to 80%, the operational cost, environmental cost, and delivery efficiency of the delivery system decrease for all investigated instances. When the customer demand increases to 120%, the operational cost increases from 7.8%-14.1% for the investigated cases. The environmental cost increases by 9.7%, 17.3%, and 14.8% for three different instance sizes. The efficiency of parcel delivery is witnessed to a few increases ranging from 0.2%-6.3%. Moreover, the demand expansion of 40% has the most significant change among other instances. For example, the operational cost increases by 17.1%, 18.2%, and 14.6%, respectively, while the environmental cost increases by 35.6%, 34.7%, and 28.2%, respectively.

The delivery efficiency has a significant increase in all instances. The results show that customer demand has a significant impact on operational cost as well as environmental cost. When the customer demand decreases/increases, operational and environmental cost decreases/increases. The potential reason for this phenomenon is the total required delivery capacity is changed. However, it is not a linear function between customer demand and costs since many other factors must be considered. Thus, it is difficult for companies to decide how many vehicles should be prepared for varying customer demand. To solve this issue, one of the potential solutions, we believe, is to introduce more flexible delivery options like cargo bikes from a third-party or crowd drivers from the social community. Both options are suitable for the on-demand market and would not cause much more fixed costs for delivery companies.

Chapter 5

Time-dependent green vehicle routing problem with time windows

5.1 Introduction

The ever-growing concern over environmental issues has led many countries to reduce emissions and fuel consumption. As the world's biggest greenhouse gas emitter, China has announced to cut its CO_2 emissions per unit of gross domestic product, or carbon intensity, by more than 65% from 2005 levels by 2030 and achieve carbon neutrality by 2060. In addition, the European Union (EU) has put in place legislation to reduce emissions by at least 40% by 2030 – as part of the EU's 2030 climate and energy framework and current contribution to the Paris Agreement. The importance of environmental protection is continuously translated into regulations that have a tangible influence on logistics and supply chain management. The contribution of logistics activities in terms of emissions cannot be ignored. According to the annual report for Inventory of U.S. Greenhouse Gas Emissions and Sinks, the transportation sector generates the largest share of greenhouse gas emissions, i.e., 28.2% in total.

Given that road freight transportation accounts for a large portion of CO_2 emissions, reducing emission and fuel consumption is inevitable in transportation management. There is an increasing number of studies on the interface between logistics and environmental issues in this direction. Sbihi and Eglese [111] investigate some combinatorial optimization problems existing in reverse logistics, waste management, and vehicle routing and scheduling in the context of green logistics. Lin et al. [112] reviewed many environmental management applications in sustainable supply chain management. Demir et al. [113] discuss the fuel estimation models to reduce CO_2 emissions in green road freight transportation. Ericsson et al. [114] mention that CO_2, directly related to carbon-based fuel consumption, is regarded as one of the most severe environmental threats through the greenhouse effect.

This chapter incorporates CO_2-related considerations in city logistics, specifically in the Vehicle Routing Problem (VRP) framework. The CO_2 emission and fuel consumption are influenced by vehicle speed, vehicle load, and travel time [115]. Assuming constant vehicle speed is unrealistic for most logistics applications due to traffic congestion or cannot calculate precise fuel consumption and CO_2 emissions. Thus, the time-dependent travel times are considered in the calculation of fuel consumption. Time dependency is usually modeled by partitioning the planning horizon into a series of short time intervals, in which the constant speed is assumed. The investigated problem is relevant to Time-Dependent Green Vehicle Routing Problem with Time Windows (TDGVRPTW), accounting for time-dependent travel times, fuel consumption, and CO_2 emissions costs. There have been many studies for solving TDGVRP based on different solution methods. Xiao and Konak [116] applied a hybrid algorithm of MIP and iterated neighborhood search to solve a GVRP under traffic congestion. Soysal and Çimen [117] propose a simulation based on a restricted dynamic programming approach for the TDGVRP. Kazemian et al. [118] investigate a GTDVRPTW by presenting a graph transformation approach to reduce the problem complexity.

However, many previous studies conducted their experiments based on the simple customer graph instead of the real road network (geographical graph). In the customer graph, travel distances or expected travel time are typically calculated based on the Euclidean distance. It is an approximate approach to measure fuel consumption and time dependency. Another main drawback of testing on a customer graph is that it ignores path selection decisions since there are typically multiple road segments connecting two customers. According to [119], considering path selection decisions in a real road network results in significant savings in cost and fuel consumption compared to traditional TDVRP. Besides, in the previous studies, the time-dependent travel speed is assumed by the different proportions of a constant speed, resulting in the so-called fast, normal, and slow speed profiles. This assumption cannot truly reflect the real-time travel times and traffic congestion in a real road network. In this paper, the time-dependent travel time is measured using real-time GPS trajectory data of floating vehicles in Chengdu, a megacity in western China. In addition, all experiments are conducted on Chengdu's real road network to consider path selection decisions in TDVRP explicitly. We propose three different path selection decisions with the objective function accounts for total travel distance, travel duration, and fuel consumption, respectively. For any given two customers in a real road network, we can then generate three different paths, namely shortest distance path (SDP), time-dependent quickest time path (TDQTP), and time-dependent lowest consumption path (TDLCP), respectively. Incorporating routing and path selection decisions has potential benefits for cost and fuel consumption savings since it considers the temporal and spatial differences of congestion in a real road network.

This work has three main contributions to the literature.

- We propose an efficient branch and price algorithm for solving the time-dependent green vehicle routing problem based on real-time travel speed in the road network of Chengdu, a megacity in western China. This algorithm is proved to be efficient for solving the investigated TDGVRPTW up to 40 customers in the large road network with 1502 nodes and 4641 road segments.
- We demonstrate the benefits of incorporating time-dependent lowest consumption path into vehicle routing compared to the traditional shortest distance and quickest time path selection decisions. The saving of CO_2 emission and travel time is up to 4.79% and 6.91% for investigated instances. It is also demonstrated that the benefits would be more significant in the larger size of the real road network.
- The proposed TDLCP algorithm can be used as a fundamental technique for fuel-optimized navigation systems in real road networks. In addition, the branch and price algorithm for solving TDGVRPTW can also be applied in the operation of logistics companies to minimize fuel consumption and CO_2 emission.

This Chapter is organized as follows. Section 5.2 reviews the relevant literature. Section 5.3 describes the TDGVRPTW model. The exact solution method is discussed in Section 5.4. The experimental settings and results are presented in Section 5.5.

5.2 Literature review

This chapter considers the time-dependent travel time, time windows, carbon emission, and fuel consumption in vehicle routing. To provide a clear review of previous research, we briefly summarize the literature related to TDVRPs, GVRPs, and TDGVRPs.

Time-dependent vehicle routing. The TDVRP is first formulated as a mixed-integer linear programming formulation by [120] to measure the traffic congestion effects on vehicle routing. A greedy nearest-neighbor heuristic and a branch and cut algorithm are proposed to solve the TDVRP. Ichoua et al. [121] introduce a travel speed model with a First In–First Out (FIFO) property for TDVRP. The FIFO property guarantees that if a vehicle travels from a customer i to a customer j at time t, any identical vehicle leaving customer i to customer j at time $t + s$, where $s > 0$, would always arrive later. They propose a tabu search method to solve TDVRP and test it using modified Solomon instances with three time periods and three types of time-dependent arcs. The experiment results show that the time-dependent speed model significantly improves over the traditional vehicle routing model with fixed travel times. Donati et al. [122] introduce a multi ant colony optimization algorithm (MACO) to solve TDVRP. The results show that the proposed MACO can solve TDVRP by using Solomon instances and real-network data. Kok et al. [123] employ a modified Dijkstra algorithm and a restricted dynamic programming heuristic to solve TDVRP. Several strategies to avoid traffic congestion are investigated, including selecting alternative routes, changing the customer visit sequences, and changing the vehicle-customer assignments. Gendreau et al. [124] present a comprehensive review of the travel speed model, application, and solution method for TDVRP. Gmira et al. [125] propose a tabu search heuristic for TDVRPTW on a road network. They emphasize the importance of considering the travel speed variations on road segments for realistic delivery routing. Computational tests show that the tabu search heuristic can obtain high-quality solutions in very reasonable computation times on recent benchmark instances in the literature.

Green vehicle routing. There have been increasing and various studies focusing on the GVRP in recent years. Bektas and Laporte [115] present a variant of GVRP, named Pollution-Routing Problem (PRP), with a comprehensive objective function that accounts for the total travel distance and the fuel consumption, travel times, and their costs. The computational results show that, contrary to the VRP, the PRP is significantly more difficult to solve to optimality but has the potential of total cost savings. Erdoğan and Miller-Hooks [126] formulate a GVRP that minimizes total distance while incorporating stops at alternative fueling stations in routing plans. Demir et al. [127] present an adaptive large neighborhood search algorithm (ALNS) and a speed optimization procedure to solve a bi-objective PRP that accounts for CO_2 emissions and driving time. However, their model cannot consider traffic congestion since the complete traffic data are not available at the planning stage. Dabia et al. [128] propose a branch and price algorithm for a variant of PRP. The master problem is a set partitioning problem and is solved using column generation. The pricing problem is a speed- and start-time elementary shortest path problem with resource constraints and solved by a tailored labeling algorithm. Extensive computational experiments show the good performance of the proposed algorithm. Moghdani et al. [129] propose an extensive structure compromising various aspects, including variants of GVRPs, objective functions, uncertainty, and solutions approach for GVRPs.

Time-dependent green vehicle routing. In recent years, TDGVRP has received increasing attention in both the academic and industry community since traffic congestion can significantly affect fuel consumption and CO_2 emission. Jabali et al. [130] propose an Emissions-based Time-Dependent Vehicle Routing Problem (E-TDVRP) for calculating CO_2 emissions in a TDVRP context. Based on the optimal VRP solutions in the literature, they construct an upper and lower bound for CO_2 emissions. Experiments show the results of the E-TDVRP were relatively close to the lower bound, with a CO_2 emissions reduction of 4.3% on average. Ehmke et al. [131] present a tabu search algorithm to solve TDVRP to minimize CO_2 emissions. The test is conducted on instances from a real road network dataset and 230 million speed observations. Experiments show that significant savings in emissions can occur mainly in the suburbs, with heavier vehicles, and with heterogeneous pickup quantities compared with routes created with more traditional objectives. Huang et al. [119] investigate a time-dependent vehicle routing problem with path flexibility (TDVRP–PF) and formulate it under deterministic and stochastic travel speed. Compared to VRP, the TDVRP–PF generates significant savings in terms of cost and fuel consumption. Franceschetti et al. [132] propose a metaheuristic for the TDPRP consisting of routing several vehicles to serve a set of customers and determining their speed on each route segment with minimizing the cost of driver's wage and carbon emissions. An ALNS heuristic and several new removal and insertion operators significantly improve the solution quality. Soysal and Cimen [117] address a TDGVRP that accounts for transportation emissions. The problem is formulated and solved by simulation-based restricted dynamic programming. The results reveal that 2.3% benefit on total emissions and 0.9% benefit on total routing cost could be obtained if vehicles start delivery after the heavily congested period is passed. Xu et al. [133] investigate a GVRPTW with time-varying vehicle speed. An improved non-dominated sorting genetic algorithm (NSGA-II) with adaptive and greedy strategies is developed to solve the GVRP. Sung and Nielsen [134] address a speed optimization problem under time-dependent travel conditions to minimize fuel consumption. An exact approach with approximation schemes is proposed to solve this problem. Experiments verify the performance of the proposed method in terms of finding near-optimal solutions within a short computation time. Fan et al. [135] investigate a multi-depot TDGVRP with minimizing the fixed costs of vehicles, penalty costs, and fuel costs. A hybrid genetic algorithm with variable neighborhood search is proposed to solve this problem. Cai et al. [136] investigate a GVRP with carbon emissions minimization. The differentiation in speed limits in each time period and each type of road is considered. A hybrid particle swarm optimization is proposed to solve this problem.

5.3 Problem description

We first summarize the symbols and their definitions in Table 5.1 and then describe the mathematical model of the investigated TDGVRPTW.

Table 5.1 Notation

Symbol	Definition
N, N_c	Set of intersections; Subset of N consisting of a set of customer nodes C and a depot $\{o\}$
a, A, A_c	Index of road segment; Set of road segments; Arc set of customers
K, Q, μ	A fleet of identical vehicles; Capacity of vehicles; Curb-weight of vehicles
s_i, w_i	Service time and demand of node i
e_i, l_i	Earliest and latest time at which collection can start at the customer
w, v, Γ	Carrying weight, travel speed and travel time of vehicle on any given road segment respectively
$\theta_1, \theta_2, \theta_3$	Parameters of the engine, speed, and weight modules used in FCEM to estimate the fuel consumption
T, H, h	Time horizon; Time intervals; Index of time interval
$P_{ij}^p = \{a_1^p, a_2^p, \dots\}$	A path that contains a sequence of road segments traveling from node i to node j
$P_{ij} = \{P_{ij}^1, P_{ij}^2, \dots\}$	Set of possible paths traveling from node i to node j
d_{ij}	Total distance from node i to node j
$\tau_{ij}^p(t)$	Travel time through path P_{ij}^p when departing from node i at time t
$f_{ij}^p(t)$	Fuel consumption of a vehicle traveling on a path P_{ij}^p at time t
r, Ω, Ω'	Index of feasible route; Set of all feasible routes; A relatively small subset of route in the LP relaxation
f_r, π_i	Fuel consumption of route r; Dual variables
Υ_i^r	Binary variable that specifies whether customer i is visited on a route r
y_r	Binary variable that specifies whether a route r is included in the solution
x_{ij}	Binary variable that is associated with two branching decisions

Let $G(N, A)$ be a road network, where N denotes the set of interactions and A denotes the set of road segments. Figure 5.1 shows an example of a real road network. Let N_c be a subset of N, which consists of a set of customer nodes C and the depot o (i.e., $N_c = C \cup \{o\}$ c). Let A_c be the arc set of customers. There is a fleet of identical vehicles K, each with capacity Q, starting at depot o to collect freight from customers C scattered in $G(N, A)$. Let a node $i \in C$ be associated with its service time s_i, demand w_i and time window $[e_i, l_i]$, with $e_i(l_i)$ the earliest (latest) time at which collection can start at the customer. We set the depot demand to zero, and the time window of the depot is set to be $[e_o, l_o] = [0, T]$ by given a finite time horizon T. The objective is to minimize the overall operational cost, including vehicle drivers' cost and fuel consumption cost. The vehicle drivers' cost is paid by the fixed monthly salary and is thus considered as a constant. The objective is thus to minimize the total fuel consumption cost. We adapt a widely used Fuel Consumption Estimation Model (FCEM) to calculate the fuel consumption. This model can be simplified as a function of carrying weight w, travel speed v and travel duration Γ of vehicle on any given road segment as follow:

$$F(w, v, t) = \theta_1 t + \theta_2 v^3 t + \theta_3 (\mu + w) vt) \tag{5.1}$$

where μ is the curb-weight of vehicles, and θ_1, θ_2 and θ_3 are parameters of the engine, speed, and weight modules, respectively. The detailed description of FCEM can be found in Appendix A.

Figure 5.1 An example of real road network

5.3.1 Time-dependent travel time

Similar to [121, 137], we associate each road segment $a \in A$ with a speed profile that divides the time horizon $[0, T]$ into H time intervals. In this profile, the travel speeds are assumed to be constant in any time interval $h \in H$ but may vary from one interval to the next. With this setting, the corresponding travel time function is a continuous piecewise linear function that satisfies the FIFO property, meaning that the travel time functions are all strictly increasing. We define a path $P_{ij}^p = \{a_1^p, a_2^p, \dots\}$ as a sequence of road segments traveling from node i to node j.

There are normally multiple paths connecting node i and node j in the real road network. We thus define $P_{ij} = \{P_{ij}^1, P_{ij}^2, \dots\}$ as the set of possible paths traveling from node i to node j. Let $\tau_{ij}^p(t)$ be the travel time through path P_{ij}^p when departing from node i at time $t \in h = [\underline{t}_h, \overline{t}_h]$ where $\underline{t}_h$ and $\overline{t}_h$ are the lower and upper boundary of time interval h.

Algorithm 1 describes the procedure for calculating the total travel time $\tau_{ij}^p(t)$ from node i to node j for any departing time t according to [121]. Suppose that the vehicle leaves node i at time $t \in h$ to travel an arc(i,j) with total distance d_{ij}, the travel time it travels at speed v_h is denoted by $\tau_{ij}^{ph}(t)$. We have:

$$\tau_{ij}^p(t) = \sum_{h \in H} \tau_{ij}^{ph}(t) \tag{5.2}$$

which is the sum of travel time spent at speed v_h for related time interval h. This function has a finite set of break points that denote the change of speed (hence the travel time). Figure 5.2 presents an example of the travel time and travel speed function for an arc of distance 1. Besides, let t_c and t' denote the current time and arrival time respectively. According to equation (5.1), the fuel consumption of a vehicle traveling on a path P_{ij}^p at time t can be calculated as

$$f_{ij}^p(t) = \theta_1 \sum_{h \in H} \tau_{ij}^{ph}(t) + \theta_2 \sum_{h \in H} (v_h)^3 \tau_{ij}^{ph}(t) + \theta_3 \sum_{h \in H} (\mu + w) v_h \tau_{ij}^{ph}(t) \tag{5.3}$$

Algorithm1 Travel time calculation

Step 1. Initialization
- 1.1 $t_c := t$
- 1.2 $d := d_{ij}$
- 1.3 $t' := t_c + (d/v_h)$

Step 2. While $(t' > \overline{t}_h)$ do
- 2.1 $d := d - v_h(\overline{t}_h - t_c)$
- 2.2 $t_c := \overline{t}_h$
- 2.3 $t' := t_c + (d/v_h)$
- 2.4 $h := h + 1$

Step 3. Return $(t' - t)$

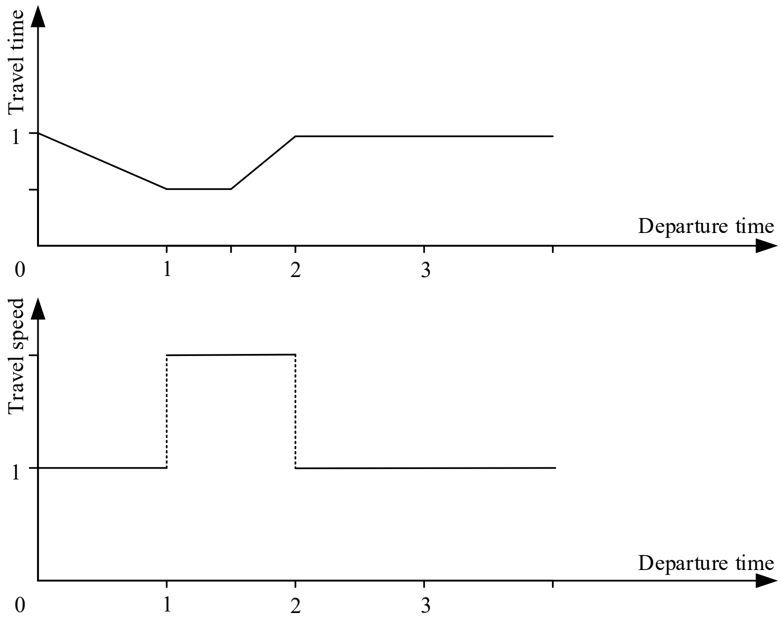


Figure 5.2 An example of travel time and travel speed function

The investigated TDGVRPTW is clearly a complex problem, as in addition to the complexity of TDVRP, it also considers the real time travel speed. The complexity of the problem is $O(|N|^2 \cdot |A| \cdot |H|)$, where $|N|$ is the number of served customers, $|A|$ is the number of network road-links and $|H|$ is the number of time intervals. The carrier company needs to allocate customers to vehicles, determine the exact order in which are visited, and make the path selection decisions based on time-dependent travel speed. The time-dependent travel speed influences not only the resulting travel time function of each road segment, and in return, affects the departure time vehicles leave at the depot, but also path selection between customers due to the temporal and spatial differences of congestion.

5.3.2 Time-dependent lowest fuel consumption path (TDLFCP)

A modified Dijkstra's algorithm is proposed to find the time-dependent lowest fuel consumption path from node i to node j efficiently for any given departure time t, carrying load w and speed profile. The pseudo-code of this algorithm is present in Algorithm 2. In step 1, all the parameters are first initialized. In particular, each node is labeled by the departure time, predecessor node, fuel consumption and current load. The label is then updated from the original node i based on the dynamic programming principle in step 2. The step 3 aims to find the unvisited node with lowest fuel consumption and mark it as 'visited'. The algorithm is terminated if node j is visited, otherwise it goes to step 2.

Algorithm 2 Modified Dijkstra's algorithm for time dependent lowest fuel consumption path from node i to j

Step 1. Initialize graph *G(N,A)*, departure time t, load w, and speed profile.
  1.1. Label the original node i as $[0, -, 0, w]$, where $[t_i, n_i^{pre}, FC_i, w_i]$ represents the departure time, the predecessor node n_i^{pre}, fuel consumption and current load of node i
  1.2. Label all other nodes as $[\infty, -, \infty, w_n]$
  1.3. Set node i as "visited"
Step 2. Label update.
  2.1. Denote the last visited node as n^l
  2.2. For any not visited node $n \in N$ and arc$(n^l, n) \in A$ do
    a)Calculate $F_n = F_{n^l} + f_{n^l n}(t_{n^l})$, where $f_{n^l n}(t_{n^l})$ represents the fuel consumption on arc $(n^l, n) \in A$ when the truck travels from node n^l to node n at time t_{n^l} with load w_{n^l}
    b)If $F_n < FC_n$, update the label of node n with $[t_{n^l} + \tau_{n^l n}(t_{n^l}), n^l, F_n, w_{n^l} + w_n]$ where $\tau_{n^l n}(t_{n^l})$ is the travel time on arc $(n^l, n) \in A$
Step 3. Scan a node.
  Find the unvisited node with the lowest fuel consumption F_n and mark it as "visited"
Step 4. Termination.
  If node j is visited, stop.
  Else, go to step 2.

5.4 Set partitioning formulation and column generation

Let Ω be the set of all feasible routes that satisfy vehicle capacity and time windows. A binary variable Υ_i^r specifies whether customer $i \in C$ is visited on a route $r \in \Omega$. For each route $r \in \Omega$, define a binary parameter y_r, which equals to 1 if route r is included in the solution and 0 otherwise. The TDGVRPTW can be formulated as the following set partitioning model:

$$\text{Min} \sum_{r \in \Omega} f_r y_r \tag{5.4}$$

subject to

$$\sum_{r \in \Omega} \Upsilon_i^r \, y_r = 1, \qquad \forall i \in C \tag{5.5}$$

$$y_r \in \{0,1\}, \qquad \forall i \in C \tag{5.6}$$

The objective function (5.4) aims to minimize the total fuel consumption where f_r is the fuel consumption of route r. Constraint (5.5) guarantees that each customer is visited exactly once, while constraint (5.6) defines the range of the variables. A column generation (CG) method is used to solve a restricted master problem (RMP) by replacing Ω with a relatively small subset $\Omega' \subseteq \Omega$ in the linear programming (LP) relaxation of (5.4)-(5.6). At each iteration of CG process, an optimal primal solution for this RMP is obtained by solving a pricing subproblem that searches for variables with negative reduced cost. The reduced cost of a variable (route) can be calculated as

$$\overline{f_r} = f_r - \sum_{r \in \Omega} \Upsilon_i^r \, \pi_i, \qquad \forall i \in C \tag{5.7}$$

where $\pi_i, i \in C$ are the dual variables associated with constraint (5.5). When negative reduced cost routes are found, they are added to subset Ω' before starting next iteration. Otherwise, the CG process is terminated with an optimal solution to the MP.

5.4.1 Branching

To derive integer solutions, branching is the ultimate operation to conduct in a branch and price algorithm. We adapt a robust branching scheme based on flow variables $x_{ij} = \sum_{r\in\Omega'} y_r^*, (i,j) \in A_c$, where y_r^* is the (fractional) optimal solution of the LP relaxation of RMP. It is one of the most common branching rules introduced by Desrosiers et al. [138] for VRPTW. x_{ij} is a binary and is associated with two branching decisions (i.e., $x_{ij} = 0$ and $x_{ij} = 1$). The former decision indicates that the arc (i,j) will be removed from the arc set when solving the pricing problem. On the contrary, the arc (i,j) must be included in a solution if $x_{ij} = 1$. To enforce this, we first identify two type of arcs (i.e., arc$(i,k), k \neq j, i \in C$ and arc$(k,j), k \neq i, j \in C$) in all route variables in current RMP. All these arcs are then removed from arc set A_c to enforce that node j will always be visited immediately after node i in any route generated by the pricing problem. We select branching variables by using *Strong branching* [139]. Strong branching aims to quickly evaluate the impact of branching on several candidates. For each branch candidate, the lower bound of two children nodes is estimated by solving the associated LP relaxation. In particular, for any given arc branching node, a subset of arcs $A_c' \subset A_c$ that are candidates for branching is selected. The lower bounds lb_a^- and lb_a^+ of both children nodes can then be calculated if arc $a \subset A_c'$ was chosen for branching. After calculating all these lower bounds, one can select the branch that maximizes the lower bound in the weakest of the two children nodes. The number of nodes to explore in the search tree can be reduced significantly by using Strong branching, while it would increase the time to select the branching candidate at each node. Consequently, the common practice is to limit the size of candidates to evaluate and to calculate approximate lower bounds in the strong branching selection process.

5.4.2 Pricing problem

We solve the pricing problem by using *bidirectional labeling* that consists of extending labels in both directions (from node 0 to its successors and from node $n+1$ to its predecessors). The forward labels and backward labels are merged to obtain the complete feasible routes.

The forward labeling algorithm

In this algorithm, labels are extended from the start depot to its successors. We assume the vehicle leaves depot at time 0. We record the following information to a label L_f:

$v(L_f)$ Last node visited on the partial path $p(L_f)$.

$F(L_f)$ Total fuel consumption used on the partial path $p(L_f)$.

$w(L_f)$ Total load delivered along the partial path $p(L_f)$.

$\delta_{L_f}(t)$ The ready time function at $v(L_f)$.

$S(L_f)$ Set of nodes visited along the partial path $p(L_f)$.

The partial path $p(L_f)$ can be deduced from iteratively

Given a label L'_f, its extension label L_f along arc$(v(L)'_f, j)$ to a node j can then be created based on following equations:

$$\delta_{L_f}(t) = \max\left\{e_j + s_j, \delta_{L'_f}(t) + \tau_{v(L'_f)j}\left(\delta_{L'_f}(t)\right) + s_j\right\}, \tag{5.8}$$

$$S(L_f) = S(L'_f) \cup \{j\}, \tag{5.9}$$

$$F(L_f) = F(L'_f) + \pi_j, \tag{5.10}$$

$$w(L_f) = w(L'_f) + w_j, \tag{5.11}$$

The new label L_f is feasible if it simultaneously satisfies the following three conditions:

$$\delta_{L_f'}(0) + \tau_{v(L_f')j}(\delta_{L_f'}(0)) + s_j \leq \min\{t_m, l_j + s_j\} \quad \wedge \quad j \in N\backslash\{0\} \tag{5.12}$$

$$w(L_f') + w_j < Q \quad \wedge \quad j \in N\backslash\{0\} \tag{5.13}$$

$$S(L_f') \cap \{j\} = \emptyset \quad \wedge \quad j \in N\backslash\{0\} \tag{5.14}$$

Condition (5.12) ensures that the node j can be arrived within its time window and do not exceed the fixed time t_m. Condition (5.13) ensures that the total load $w(L_f)$ of label L_f do not exceed the vehicle's capacity. Condition (5.14) avoids the repetitive label extension.

In the labeling algorithm, there are typically very large number of labels needed to be derived and stored. To reduce the number of labels and accelerate the label extension process, several dominance rules proposed by Dabia et al. [137] are used to eliminate the unpromising labels. Let $E(L_f)$ be the set of feasible extensions of the label L_f to node $n+1$. More formally, the set $E(L_f)$ contains all partial paths that can leave node $v(L_f)$ at time $\delta_{L_f}(0)$ or later and arrive node $n+1$ within time windows, which has total load less than $Q - w(L_f)$ and that do not visit nodes from $S(L_f)$. For any label $L \in E(L_f)$, we define $L_{f\oplus L}$ as the label generated from extending L_f by L. In forward labeling algorithm, dominance is defined as following:

DEFINITION 1. *Label L_f^2 is dominated by label L_f^1 if*

1. $v(L_f^1) = v(L_f^2)$,
2. $E(L_f^2) \subseteq E(L_f^1)$
3. $F(L_f^{1\oplus L}) \leq F(L_f^{2\oplus L}),\ \forall L \in E(L_f^2)$.

Condition 2 indicates that any feasible extension of label L_f^2 must be feasible for label L_f^1. In addition, condition 3 ensures that extending label L_f^1 should always generate a better route with lower fuel consumption. However, it is difficult to verify all the conditions of definition 1 without evaluating all feasible extensions of both label L_f^1 and L_f^2. Instead, more sufficient dominance rules are introduced in proposition 1 to further reduce the computational efforts.

PROPOSITION 1. *Label L_f^2 is dominated by label L_f^1 if*

a. $v(L_f^1) = v(L_f^2)$,

b. $F(L_f^1) \leq F(L_f^2)$,

c. $S(L_f^1) \subseteq S(L_f^2)$,

d. $dom(L_f^2) \subseteq dom(L_f^1)$,

e. $\delta_{L_f^1}(t) \leq \delta_{L_f^2}(t), \forall t \in dom(L_f^2)$,

f. $w(L_f^1) < w(L_f^2)$.

Conditions *c*, *e*, and *f* enforce that any feasible extension of label L_f^2 is feasible for label L_f^1. Conditions *b*, *d*, and *f* ensure that for any feasible extension L of label L_f^2, the fuel consumption of the path $p(L_f^{1\oplus L})$ is less than or equal to the fuel consumption of the path $p(L_f^{2\oplus L})$.

The backward labeling algorithm.

In the backward labeling algorithm, labels are extended from the depot (i.e., node $n+1$) to its predecessors. For a label L_b, we record the following information:

$v(L_b)$ First node visited on the partial path $p(L_b)$.

$F(L_b)$ Total fuel consumption used on the partial path $p(L_b)$.

$w(L_b)$ Total load delivered along the partial path $p(L_b)$.

$\delta_{L_b}(t)$ Ready time at node $n+1$ along the partial path $p(L_b)$ when leaving node $v(L_b)$ at time t.

$S(L_b)$ Set of nodes visited along the partial path $p(L_b)$.

Let $t_l(L_b)$ denote the latest possible ready time at node $v(L_b)$. The set of feasible extensions $E(L_b)$ of L_b is the set of partial paths such that when leaving at the depot and reaching node $v(L_b)$ at some time $t \leq t_l(L_b)$ within time windows. The basic operation in the backward labelling algorithm is quite similar to the forward labelling algorithm which aims to extend a label L'_b along an arc$(j, v(L'_b)\ )$ to a node j to generate a new label L_b. The ready time function of a new label L_b can be calculated as follows:

$$\delta_{L_b}(t) = \delta_{L'_b}\left(\max\left\{e_{v(L'_b)} + s_{v(L'_b)}, t + \tau_{jv(L'_b)}(t) + s_{v(L'_b)}\right\}\right), \tag{5.15}$$

In addition, we can update other information of label by

$$S(L_b) = S(L'_b) \cup \{j\}, \tag{5.16}$$

$$F(L_b) = F(L'_b) + \pi_j, \tag{5.17}$$

$$w(L_b) = w(L'_b) + w_j, \tag{5.18}$$

The extension of L'_b of L_b is feasible respect to the following three conditions

$$w(L\_b^{\wedge\prime}\ ) + w\_j < Q \quad \wedge \quad j \in N \backslash \{n+1\}, \tag{5.19}$$

$$t\_l\ (L\_b\ ) \geq \max\ (t\_m, e\_j + s\_j\ ) \quad \wedge \quad j \in N \backslash \{n+1\}, \tag{5.20}$$

$$S(L\_b^{\wedge\prime}\ ) \cap \{j\} = \emptyset \quad \wedge \quad j \in N \backslash \{n+1\}, \tag{5.21}$$

Condition (5.19) ensures the capacity feasibility while the condition (5.20) ensures that node j can be arrived within its time windows and the extension will be terminated before t_m. To avoid redundancy, we omit the dominance rules as they can be applied in the same way as in forward labelling algorithm.

Merging forward and backward labels.

After all the forward and backward labels are generated, they are merged to obtain the complete feasible routes with negative reduced cost. The resulting label $L = L_{b \oplus L_f}$ is feasible if it satisfies the condition (5.22).

$$v(L_b) = v(L_f) \quad \wedge \quad S(L_b) \cap S(L_f) = \{v(L_f)\} \quad \wedge \quad w(L_b) + w(L_f) - w_{v(L_f)} \leq Q, \tag{5.22}$$

Furthermore, it has the following attributes:

- $v(L) = n + 1,$
- $F(L) = F(L_b) + F(L_b) - \pi_{v(L_f)},$
- $w(L) = w(L_b) + w(L_f) - w_{v(L_f)},$
- $S(l) = S(L_b) \cup S(L_f)$

The new labels L with negative reduced cost are then added to the RMP as new columns. Otherwise, the CG process is terminated for current iteration.

5.5 Computational results

This section presents the results of computational experiments using the mixed-integer formulation of TDGVRPTW described in section 5.3 and the branch and price algorithm presented in section 5.4. All tests are conducted using a different set of instances with respectively 10, 20, 30, and 40 customers. These instances are that are stored in a Github repository (https://github.com/gcmswm/InstancesForTDGVRP). All experiments are tested by using CPLEX 12.10 on an Intel(R) Core(TM) i9-10850K computer with 3.60 GHz and 16 Gb RAM.

To compare the potential difference in the size of a real-road network, we generate three different sizes of real road networks based on the map of Chengdu. Table 5.2 lists the number of nodes and road segments for small, medium, and large road network cases, respectively, while Figure 5.3 shows the image of each road network.

Table 5.2 Information of three different road network

Road network	# Road segments	# Nodes
Small	1250	408
Medium	2233	835
Large	4641	1502

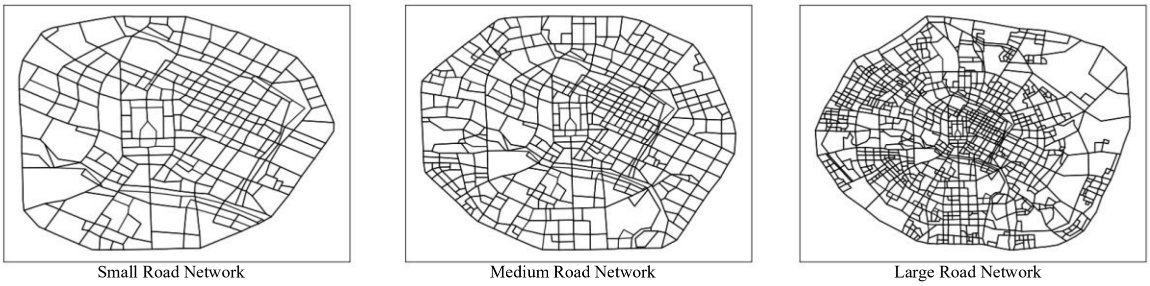


Figure 5.3 Three road network cases with different network sizes

Instead of assuming the equal demand and service time of each customer, we generate the customer demand based on the random samples from normal (Gaussian) distribution. After generating the customer demand, the service time is generated based on an adequate proportion of customer demand. The main point is that more customer demand needs more time to load or unload. The customer locations are generated by randomly selecting from the nodes of each road network, and time windows of each customer are also randomly generated based on some reasonable rules. For each road network, we generate 80 instances with four different numbers of total customers. For example, the instance name 'S1-10' means the first instance of the small road network with ten customers, while the instance name 'L5-30' means the fifth instance of the large road network with 30 customers. Customers are served by a fleet of homogeneous light-duty vehicles, each with a capacity of 4995 kg. Other parameters of the vehicles are presented in Table A.1 in Appendix A. According to [140], the burning of a liter of diesel produces around 2.65 kg of CO_2 (based on the calorific value of diesel with a density of 0.835 $kg\ dm^{-3}$). We apply the 2.65 kg as a diesel emission factor of CO_2-emissions per liter. The CO_2 emission can thus be calculated by the product of fuel consumption and emission factor.

We generate the speed profile by using real time travel speed obtained by GPS data of taxis in the city of Chengdu, China. The details of generation of speed profile are present in Appendix B.

Figure 5.4 presents two examples of speed profiles for 40 randomly chosen road segments in the large road network. The time horizon starts at 8:00 am and ends at 18:00 pm. We divide the total 10 hours into 30 time intervals. Each interval has 20 minutes with a constant speed.

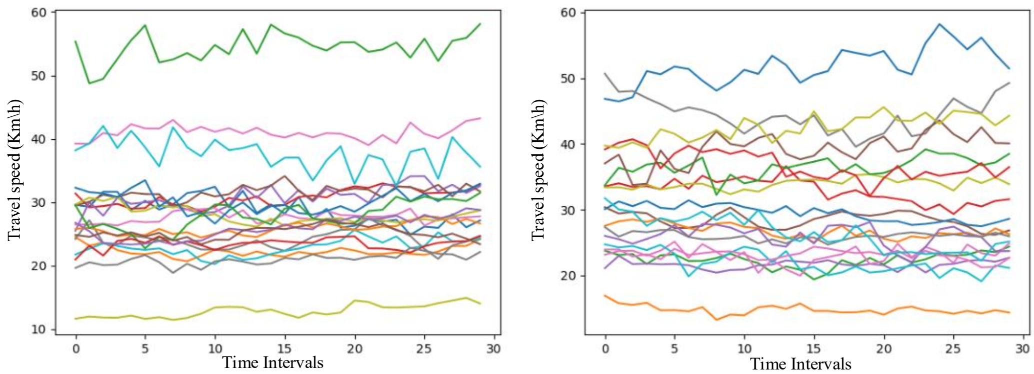
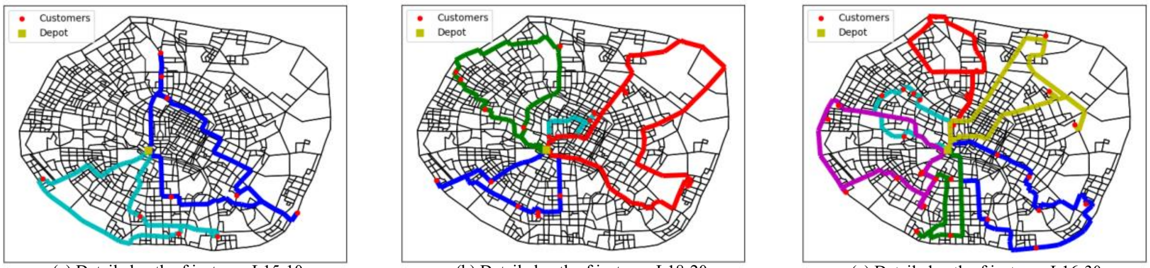


Figure 5.4 Two examples of speed profiles for 40 randomly chosen road segments

5.5.1 Performance of branch and price algorithm

To provide a clear graph view of the solution for TDGVRPTW, we first generate detailed paths of solving three instances in Figure 5.5. In Figure 5.5, different colored lines indicate different vehicle routes. For example, in Figure 5.5 (b), 20 customers are served by four vehicles in different routes. Next, Table 5.3 presents the detailed solution of instance L18-20, including vehicle routes, travel distance, fuel consumption, CO_2 emission, and travel times.



(a) Detailed path of instance L15-10 (b) Detailed path of instance L18-20 (c) Detailed path of instance L16-30

Figure 5.5 Detailed paths of three instances in a large road network

Table 5.3 Detailed solution of instance L18-20

Vehicle Routes	Distance (km)	Fuel (Liter)	CO_2 Emissions (kg)	Travel Times (min)
0-13-17-3-18-0	9.48	0.56	1.47	21.5
0-5-10-16-1-9-20-0	21.43	1.16	3.08	43.8
0-2-14-6-19-12-0	25.66	1.51	4.00	57.9
0-8-15-11-4-7-0	40.09	2.14	5.67	79.1
Total	96.65	5.37	14.23	202.3

To review the performance efficiency of the proposed branch and price algorithm, we summarize the minimum, average and maximum CPU time and the gap of solving these instances in Table 5.4. It is clear that the branch and price algorithm is fully efficient for the instances with 10 and 20 customers as all of these instances can be solved optimally within a few seconds or minutes. On the other hand, the computational efforts for solving the instances with 30 customers increase to about 50 minutes on average while optimality is still guaranteed. In addition, the CPU time increases significantly for almost all the cases with 40 customers, i.e., 4.3 hours on average. This is because our procedure is only terminated when the gap is reached to 0.0% or the CPU time is reached to 18000s. The gap between lower bound and upper bound is about 2.5% on average, which is typically acceptable for many real-world industrial problems.

Table 5.4 Time consumption and gap of solving different instances

Problem Size	Road Network	CPU Time(s)			Gap(%)		
		Minimum	Maximum	Average	Minimum	Maximum	Average
10 customers	Small	0.3	1.2	0.6	0.0	0.0	0.0
	Medium	0.5	7.5	2.2	0.0	0.0	0.0
	Large	1.5	20.5	5.5	0.0	0.0	0.0
20 customers	Small	12.7	375.8	96.9	0.0	0.0	0.0
	Medium	31.6	382.4	110.6	0.0	0.0	0.0
	Large	44.2	677.8	196.4	0.0	0.0	0.0
30 customers	Small	55.3	3198.3	991.2	0.0	0.0	0.0
	Medium	85.5	5845.1	1613.7	0.0	0.0	0.0
	Large	179.0	18000.0	5158.1	0.0	0.0	0.0
40 customers	Small	772.6	18000.0	14051.3	0.0	6.9	1.6
	Medium	5098.8	18000.0	16483.2	0.0	6.6	2.5
	Large	7582.8	18000.0	16398.2	0.0	7.7	2.5

5.5.2 Comparison of three different path selection decisions

To demonstrate the potential difference of the proposed different path selection decisions in the real road network, i.e., TDLEP, SDP, and TDQTP, we generate the shortest distance path, quickest time path, and lowest consumption path for six given origin-destination (OD) pairs, respectively. Figure 5.6 presents the detailed paths for a vehicle traveling from the origin to its destination at departure time 10:00 am with a load of 4000 kg. To make a clear comparison, we also list all the information including travel distance, travel time, and fuel consumption for the three paths in Table 5.5. In Figure 5.6, there are distinctive paths for traveling each OD pair. Most notable is shown in Figure 5.6(f), where the three paths are almost totally different. In Figure 5.6(b), (c), (e), and (f), the SDP starts from the origin and then across the city center to its destination, while the TDQTP detours through the outmost ring road. From our common sense, this is usually a good decision when the road segments of the city center have heavy traffic. However, it is worth stating that the TDLCP should be considered a practical choice since it has the lowest consumption while the values of travel distance and travel time are all between the counterpart values in SDP and TDQTP in the given six cases. Take the OD pair '641—771' in Figure 5.6(c) as an example. Its travel distance through SDP, TDQTP and TDLCP is 16.332 km, 20.913 km, and 16.779 km, respectively. The travel distance with TDQTP increases 28.05% compared to the counterpart in SDP, while the distance through TDLCP only increases 2.66%. The situation is similar for travel time, while the TDLCP decreases the consumption by 11.63% and 6.57% compared to SDP and TDQTP, respectively. Note that this is not a coincidence since our experiments on all investigated 240 instances further prove this interesting finding.

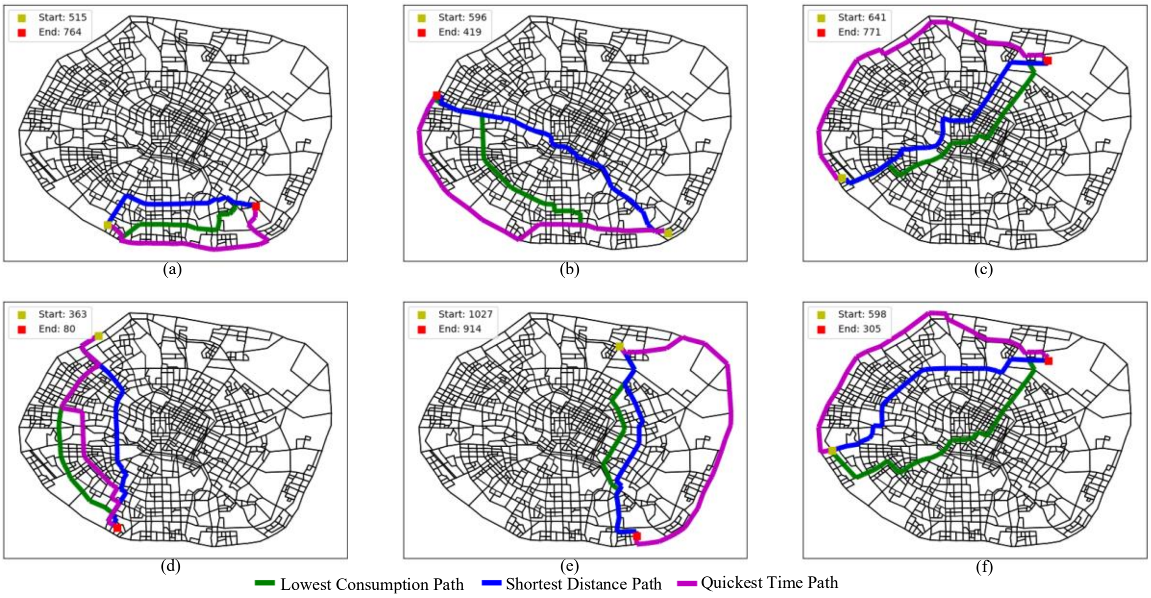


Figure 5.6 Detailed paths for three different path selections in a large road network

Table 5.5 Detailed information of different path selections for six OD pairs

OD Pairs	Order in Figure 7	Model	Distance (km)	Consumption (Liter)	Travel Time (min)
515—764	(a)	SDP	**9.717**	0.581	22.25
		TDQTP	12.492	0.595	**18.67**
		TDLCP	10.319	**0.558**	20.77
596—419	(b)	SDP	**16.848**	0.996	37.58
		TDQTP	20.287	0.959	**30.17**
		TDLCP	18.485	**0.904**	31.84
641—771	(c)	SDP	**16.332**	1.036	40.15
		TDQTP	20.913	0.989	**34.41**
		TDLCP	16.779	**0.928**	34.73
363—80	(d)	SDP	**14.415**	0.951	37.25
		TDQTP	16.805	0.841	**30.62**
		TDLCP	14.919	**0.824**	31.33
1027—914	(e)	SDP	**14.182**	0.925	36.23
		TDQTP	21.110	0.988	**31.85**
		TDLCP	14.353	**0.876**	33.75
598—305	(f)	SDP	**15.371**	0.946	36.25
		TDQTP	19.778	0.940	**32.65**
		TDLCP	15.919	**0.936**	35.67

To further verify the potential benefits of incorporating TDLCP into time-dependent vehicle routing in real road networks, we conducted the experiments based on all investigated 240 instances. Table 5.6 lists the results of average travel distance, consumption, emissions, and travel times. The column 'Problem Size' indicates the number of customers in the group of instances. The column 'Road Network' and 'Model' identify the road network size and path selection decision, respectively. The column 'Average Distance' lists the average travel distance based on 20 instances for each road network and problem size. The gap is calculated by comparing the value of TDQTP and TDLCP with the value of SDP, respectively. As the CO_2 emission is calculated by multiplying a factor with fuel consumption, the gap of CO_2 emission is thus the same as the gap of fuel consumption. Besides, the average travel times and their gap are listed in the last two columns. Let us start looking at the average travel distance. The average travel distance of TDLCP is always less than the counterpart of TDQTP for all instances. This result indicates that TDLCP is a better choice than TDQTP in the case of saving travel distance. Besides, the savings of average consumption and emissions for TDLCP and TDQTP range from 2.75% to 4.79% and from 2.72% to 4.33%, respectively. The value of TDLCP is for sure less than the value of TDQTP for all instances, but there is no significant difference between them. This is because the TDLCP and TDQTP have the same paths for some OD pairs. Take the extreme case as an example. For any two connected nodes, the TDQTP, SDP, and TDLCP are for sure the same no matter how heavy traffic on the road segment since there is only one way to travel from the origin to its destination. In addition, the saving of average travel time for TDLCP and TDQTP is up to 6.91% and 7.40%, respectively.

In summary, compared to SDP, incorporating TDLCP into time-dependent vehicle routing would result in up to 4.79% consumption and emission savings and 6.91% travel time savings, while the travel distance increases up to 2.90%. On the contrary, the TDQTP witnesses emission savings and travel time savings up to 4.33% and 7.40% respectively while the travel distance increases up to 4.94%. Another interesting finding is that when the size of the real road network increases, the value of the gap also increases relatively. The potential reason is that the larger the road network is involved, the more different paths could travel between OD pairs. This finding indicates that the benefits of considering TDLCP in time-dependent vehicle routing would be more significant in the larger and more complex road network.

Table 5.6 Comparison of three different path selection models.

Problem Size	Road Network	Model	Average Distance		Average Consumption and Emissions			Average Travel Time	
			(km)	Gap(%)	(Liter)	(Kg)	Gap(%)	(min)	Gap(%)
10 Customers	Small	SDP	28.585	-	1.825	4.84	-	71.26	-
		TDQTP	29.549	3.37	1.758	4.66	-3.70	67.74	-4.93
		TDLCP	29.380	2.78	1.757	4.65	-3.77	67.77	-4.89
	Medium	SDP	35.212	-	2.154	5.71	-	83.20	-
		TDQTP	36.291	3.06	2.078	5.51	-3.52	79.17	-4.84
		TDLCP	35.955	2.11	2.076	5.50	-3.63	79.25	-4.75
	Large	SDP	55.477	-	3.307	8.76	-	126.21	-
		TDQTP	58.214	4.94	3.164	8.38	-4.33	116.86	-7.40
		TDLCP	57.088	2.90	3.148	8.34	-4.79	117.48	-6.91
20 Customers	Small	SDP	39.904	-	2.536	6.72	-	98.91	-
		TDQTP	40.923	2.56	2.448	6.49	-3.48	94.40	-4.56
		TDLCP	40.711	2.02	2.447	6.48	-3.52	94.47	-4.48
	Medium	SDP	57.099	-	3.451	9.15	-	133.12	-
		TDQTP	58.666	2.74	3.334	8.83	-3.42	126.80	-4.75
		TDLCP	58.216	1.96	3.331	8.83	-3.50	126.94	-4.64
	Large	SDP	87.522	-	5.189	13.75	-	197.99	-
		TDQTP	91.177	4.18	4.994	13.23	-3.76	186.10	-6.01
		TDLCP	89.782	2.58	4.982	13.20	-3.98	186.70	-5.70
30 Customers	Small	SDP	65.172	-	4.121	10.92	-	160.71	-
		TDQTP	66.550	2.12	4.009	10.63	-2.72	155.04	-3.53
		TDLCP	66.192	1.57	4.008	10.62	-2.75	155.15	-3.45
	Medium	SDP	87.681	-	5.355	14.19	-	207.14	-
		TDQTP	89.954	2.59	5.165	13.69	-3.54	197.29	-4.75
		TDLCP	89.350	1.90	5.162	13.68	-3.60	197.45	-4.68
	Large	SDP	125.460	-	7.534	19.97	-	289.13	-
		TDQTP	130.745	4.21	7.208	19.10	-4.32	269.66	-6.73
		TDLCP	129.020	2.84	7.188	19.05	-4.60	270.51	-6.44
40 Customers	Small	SDP	84.284	-	5.317	14.09	-	207.23	-
		TDQTP	86.164	2.23	5.171	13.70	-2.76	199.75	-3.61
		TDLCP	85.859	1.87	5.168	13.70	-2.80	199.79	-3.59
	Medium	SDP	112.179	-	6.857	18.17	-	265.34	-
		TDQTP	115.264	2.75	6.617	17.53	-3.51	252.68	-4.77
		TDLCP	114.435	2.01	6.611	17.52	-3.58	252.90	-4.69
	Large	SDP	172.011	-	10.285	27.26	-	394.67	-
		TDQTP	178.156	3.57	9.867	26.15	-4.07	370.60	-6.10
		TDLCP	176.433	2.57	9.849	26.10	-4.24	371.29	-5.92

Chapter 6

Conclusions

This thesis investigates urban freight transportation and logistics problems arising in the City Logistics from both managerial and application points of view.

Nowadays, the urban freight transportation and logistics system must be more competitive and well-functioning, pushed by many factors such as the undergoing fierce competition, increasing demand from e-commerce, and high expectations of customers. It requires the commitment and cooperation of multiple stakeholders and actors and the integration of different business and operational models. In doing so, a holistic representation of this complex and hyper-connected system is needed. It means that the system should be managed in a modular manner that integrates, on the one hand of existing logistics subsystems such as single and multi-echelon structures, multimodal and intermodal delivery options (i.e., cargo bikes and crowd drivers). On the other hand, a macro-level of interconnections among actors, stakeholders, and subsystems should be considered in the top-level design of the system.

This integration considers the behavioral, technological, and optimization components of urban freight transportation, enabling decision-makers to cope with the various issues arising in urban areas and decisional levels. In particular, it requires a multi-disciplinary approach from different research communities (e.g., Operational Research, Computer Science, Data Science, Transportation Science) to model the overall system.

The previous study has demonstrated the effectiveness of using a multi-disciplinary approach to cope with emerging critical problems in City Logistics. These problems include the integration of traditional transportation modes (i.e., vans) and, low-emission vehicle (i.e., cargo bikes) and new delivery options (i.e., crowd drivers), the dynamic and stochastic vehicle routing problem in the form of stochastic demand and location, and time-dependent vehicle routing problem in the real road network.

We have investigated these new applications to overcome a noteworthy portion of a gap in the literature considering the integration of different logistics and transportation business and operational models and the mixing of managerial and operational perspectives to provide public and private policies and jointly optimize the parcel delivery process. Furthermore, after analyzing the state-of-the-art research on smart city projects, we found that the current trend of partnership, infrastructure financing, and financial resources for SCPs is mixed, which can benefit and encourage all public and private actors to collaborative business models. Besides, there is a need for innovative business models, methods, and software to represent the entire transportation system, including public governance, individuals, and freight movement.

To develop and demonstrate the effectiveness of an innovative business model, we applied the multi-disciplinary approach to deal with the current practice in last-mile delivery. We consider substituting traditional single-echelon routing structures with two-echelon ones involving satellites centers and low emission delivery options. Indeed, outsourcing the last-mile delivery tasks to third-party companies with lower operational cost or flexible delivery options (e.g., crowd drivers) is current practice.

First, we identified the main actors involved in the City Logistics system from both business and operational perspectives and explicitly investigated these actors' behaviors, costs, and revenues structures. The operational and economic performance of the traditional and green delivery options are also analyzed based on the main variables in last-mile delivery (e.g., distance, delivery time, personnel cost, etc.). This managerial analysis supports the operational actions and their implementation in practice.

Second, we addressed a DSVRPTW problem with crowdsourcing for on-demand parcel delivery. Multiple delivery options are considered into this problem together with crowd drivers. A new simulation-optimization framework is proposed and applied for the last-mile delivery system, enabling decision-makers to combine different sources of data, conduct simulation and optimization on various realistic instance sets, and analyze the KPIs.

We conducted a case study in the medium-sized city of Turin (Italy) to measure the potential impact of using cargo bikes, crowdsourcing in parcel delivery. Our results show that combining crowd drivers and green carriers into traditional van delivery is beneficial to economic and environmental cost-saving, while the delivery efficiency decreases. In particular, the total travel distance and CO_2 emissions are reduced in our investigated instances. In addition, green carriers and crowdsourcing are promising and flexible solutions when dealing with many online requests. We varied the customer demand investigating its potential impacts on the system. The results show that operational and environmental costs are sensitive to customer demand variations.

Finally, we investigated a time-dependent green vehicle routing problem based on real-time travel speeds in the road network of Chengdu, a megacity in western China. A branch and price algorithm is proposed to solve this problem. Three different path selection decisions are considered to incorporate into vehicle routing. Extensive experiments show that the proposed branch and price algorithm efficiently solves the problem of up to 40 customers in the large road network with 1502 nodes and 4641 road segments. In addition, the comparison of three different path selection decisions demonstrates that the time-dependent lowest consumption path is a promising choice for carrier companies in terms of fuel consumption and travel-time saving.

Future directions will consider the optimal workforce capacity planning in crowdsourcing applications and their compensation strategies, i.e., hourly compensation, per-delivery compensation, and driver-determined compensation [82]. Besides, it is also a promising research direction to use the emerging techniques (e.g., deep reinforcement learning) from deep learning areas to solve combinatorial optimization problems in urban freight transportation and logistics systems.

Appendix

A. Fuel Consumption Estimation Model

A widely used comprehensive model by [141] and [142] is adopted to estimate fuel consumption. For a vehicle carrying weight $w(kg)$ and traveling distance $d(m)$ with a constant speed $v\left(\frac{m}{s}\right)$ in travel duration Γ, the fuel consumption $F(w, v, \Gamma)$ can be estimated as

$$F(w, v, \Gamma) = \lambda(kN_eV\Gamma + \gamma\beta v^3\Gamma + \gamma\alpha(\mu + w)d) \quad \text{(A.1)}$$

where contains three different modules, namely *engine*, *speed,* and *weight* module, respectively. The *engine module* $kN_eV\Gamma$ is linear in travel duration Γ, while the *speed module* $\gamma\beta v^3\Gamma$ is cubic in speed. The last term $\gamma\alpha(\mu + w)d$ is called *weight module* that is linear in the total weight $(\mu + w)$. Note that μ is the vehicle curb-weight, $\lambda = \frac{\xi}{\psi\kappa}$, $\gamma = \frac{1}{1000\epsilon\varpi}$, $\alpha = g\sin(\phi) + gC_r\cos(\phi)$, and $\beta = 0.5C_dA_f\rho$. For simplicity, we denote the constant parameter θ_1, θ_2 and θ_3 as the parameter of *engine*, *speed,* and *weight* module respectively. It thus simplifies the original equation A.1 to a simple version in equation 5.1. Table A.1 presents all the parameters based on a light vehicle (type: BJ1089VEJDA-A2) and other constants adapted from [142].

Table A.1 Parameters in the FCEM model

Type	Notation	Desciption	Value
Truck-dependent	k	Engine friction factor (kJ/rev/liter)	0.2
	N_e	Engine speed (rev/s)	33
	V	Engine displacement (liter)	5
	μ	Curb-weight (kg)	2850
	Q	Truck Capacity(kg)	4995
	A_f	Front surface area(m^2)	3.912
	ε	Truck drive train efficiency	0.4
	ϖ	Efficiency parameters for diesel engines	0.9
Road-dependent	ϕ	Road angle	0
	C_r	Coefficient of rolling resistance	0.01
Emission parameters	κ	Heating value of a typical diesel fuel (kJ/g)	44
	ψ	Conversion factor (g/liter)	737
	ξ	Fuel-to-air mass ratio	1
	ρ	Air density (kg/m^3)	1.2041
	g	Gravitational constant (m/s^2)	9.81
	C_d	Coefficient of aerodynamic drag	0.7

B. Road segment speed

We generate the speed profiles by using a link travel speed dataset. This dataset is obtained by first collecting real-time GPS trajectory data of floating vehicles in Chengdu, a megacity in western China, from March 1st to June 30th, 2017. Then, a map matching technique is used to output the projected paths of the trajectories on the map and estimate the travel speeds on each link in different time periods. The detailed steps to obtain the dataset are referred to [143].

C. Complete results of branch and price algorithm

In Tables A.2-A.5, we present the results of investigated 240 instances for solving the TDGVRPTW. The column ‘Instance’ contains the information about the size of the road network and the number of customers for each instance. The columns denoted as ‘LB’ and ‘UB’ show the best lower and upper bounds found all over a branching tree. In the column “Gap”, we calculate the difference between lower bound and upper bound. The computational time (in seconds) spent to solve an instance is listed in the column ‘Time’. Table A.2 Instances with 10 customers shows that the proposed algorithm is fully efficient for small instances with ten customers. Almost all small instances can be solved to optimality within a few seconds. Table A.3 shows that when the number of customers increases to 20, the instances can also be solved to optimality with a relatively longer CPU time. Besides, the size of road network does not have a significant impact on solving instances with ten customers and 20 customers. When the customer number increases to 30, even though all the instances can be solved to optimality, it takes much more computation effort, as shown in Table A.4. However, when the customer number increases to 40, only a few instances can be solved to optimality within a reasonable computation time (a predefined time limit:18000s). According to Table A.5, there are six instances, three instances, and four instances solved to optimality for small, medium, and large road networks, respectively, within 18000 seconds. Besides, the gap between lower bound and upper bound for instances in the small road network ranges from 0.0% to 6.9%, while the counterpart values in the medium and large road networks range from 0.0% to 6.6% and from 0.0% to 7.7% respectively.

Table A.2 Instances with 10 customers

Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)
S1-10	1.87	1.87	0	1.1	M1-10	2.06	2.06	0	1.6	L1-10	2.72	2.72	0	5.5
S2-10	1.85	1.85	0	1.2	M2-10	2.17	2.17	0	0.5	L2-10	3.42	3.42	0	5.9
S3-10	1.58	1.58	0	0.6	M3-10	1.99	1.99	0	1.3	L3-10	3.56	3.56	0	6.5
S4-10	2.08	2.08	0	0.7	M4-10	2.09	2.09	0	0.6	L4-10	2.47	2.47	0	2.5
S5-10	1.67	1.67	0	0.6	M5-10	2.23	2.23	0	0.5	L5-10	3.19	3.19	0	20.5
S6-10	1.81	1.81	0	0.8	M6-10	1.94	1.94	0	0.8	L6-10	2.58	2.58	0	7.2
S7-10	1.80	1.80	0	0.6	M7-10	1.67	1.67	0	0.7	L7-10	3.35	3.35	0	3.4
S8-10	1.70	1.70	0	0.4	M8-10	2.03	2.03	0	0.8	L8-10	2.72	2.72	0	3.8
S9-10	1.72	1.72	0	0.6	M9-10	1.81	1.81	0	0.9	L9-10	3.39	3.39	0	6.1
S10-10	1.75	1.75	0	0.4	M10-10	1.82	1.82	0	4.8	L10-10	2.51	2.51	0	2.5
S11-10	1.72	1.72	0	0.3	M11-10	2.34	2.34	0	3.8	L11-10	3.50	3.50	0	1.5
S12-10	1.62	1.62	0	0.6	M12-10	1.92	1.92	0	0.8	L12-10	3.22	3.22	0	5.3
S13-10	1.66	1.66	0	0.8	M13-10	1.99	1.99	0	1.6	L13-10	3.45	3.45	0	6.5
S14-10	1.56	1.56	0	0.5	M14-10	2.45	2.45	0	0.8	L14-10	3.72	3.72	0	6.1
S15-10	1.88	1.88	0	0.4	M15-10	2.53	2.53	0	7.5	L15-10	3.65	3.65	0	6.9
S16-10	1.63	1.63	0	0.7	M16-10	1.95	1.95	0	0.6	L16-10	2.93	2.93	0	3.6
S17-10	1.92	1.92	0	0.9	M17-10	1.92	1.92	0	5.7	L17-10	3.19	3.19	0	2.3
S18-10	1.80	1.80	0	0.4	M18-10	2.61	2.61	0	2.8	L18-10	3.23	3.23	0	9.7
S19-10	1.59	1.59	0	0.3	M19-10	2.10	2.10	0	1.3	L19-10	3.25	3.25	0	2.2
S20-10	1.92	1.92	0	1.1	M20-10	1.89	1.89	0	7.1	L20-10	2.91	2.91	0	1.9

Table A.3 Instances with 20 customers

Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)
S1-20	2.33	2.33	0	26.4	M1-20	3.11	3.11	0	117.9	L1-20	5.18	5.18	0	206.8
S2-20	2.56	2.56	0	19.8	M2-20	3.28	3.28	0	33.1	L2-20	5.61	5.61	0	86.5
S3-20	2.66	2.66	0	72.1	M3-20	3.22	3.22	0	48.7	L3-20	4.79	4.79	0	44.2
S4-20	2.44	2.44	0	44.4	M4-20	3.43	3.43	0	160.5	L4-20	5.50	5.50	0	92.8
S5-20	2.37	2.37	0	146.1	M5-20	3.69	3.69	0	66.5	L5-20	4.86	4.86	0	677.8
S6-20	2.38	2.38	0	169.2	M6-20	3.10	3.10	0	382.4	L6-20	4.55	4.55	0	539.8
S7-20	2.44	2.44	0	55.2	M7-20	3.18	3.18	0	59.1	L7-20	4.71	4.71	0	105.5
S8-20	2.36	2.36	0	23.2	M8-20	3.21	3.21	0	192.8	L8-20	3.86	3.86	0	284.6
S9-20	2.44	2.44	0	159.0	M9-20	3.20	3.20	0	31.6	L9-20	5.70	5.70	0	154.8
S10-20	2.70	2.70	0	296.4	M10-20	3.29	3.29	0	125.4	L10-20	5.07	5.07	0	193.2
S11-20	2.67	2.67	0	16.7	M11-20	2.95	2.95	0	305.9	L11-20	5.12	5.12	0	63.5
S12-20	2.52	2.52	0	63.3	M12-20	3.34	3.34	0	34.1	L12-20	4.86	4.86	0	106.1
S13-20	2.73	2.73	0	46.9	M13-20	3.04	3.04	0	32.5	L13-20	5.11	5.11	0	298.2
S14-20	2.13	2.13	0	12.7	M14-20	3.93	3.93	0	56.6	L14-20	5.66	5.66	0	190.1
S15-20	2.24	2.24	0	45.2	M15-20	3.22	3.22	0	151.7	L15-20	4.62	4.62	0	123.1
S16-20	2.22	2.22	0	15.6	M16-20	3.41	3.41	0	33.0	L16-20	4.89	4.89	0	44.2
S17-20	2.09	2.09	0	375.8	M17-20	3.80	3.80	0	139.0	L17-20	4.24	4.24	0	62.0
S18-20	2.61	2.61	0	70.0	M18-20	2.88	2.88	0	88.5	L18-20	5.37	5.37	0	91.7
S19-20	2.68	2.68	0	140.4	M19-20	3.39	3.39	0	100.0	L19-20	5.05	5.05	0	306.8
S20-20	2.68	2.68	0	138.7	M20-20	3.09	3.09	0	51.9	L20-20	4.90	4.90	0	256.2

Table A.4 Instances with 30 customers

Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)
S1-30	4.20	4.20	0	546.4	M1-30	5.30	5.30	0	417.4	L1-30	6.90	6.90	0	7258.8
S2-30	4.01	4.01	0	428.5	M2-30	4.60	4.60	0	929.5	L2-30	7.65	7.65	0	3462.9
S3-30	3.91	3.91	0	1019.0	M3-30	5.00	5.00	0	2514.2	L3-30	6.87	6.87	0	301.6
S4-30	3.88	3.88	0	663.6	M4-30	5.25	5.25	0	398.0	L4-30	7.10	7.10	0	18000.0
S5-30	4.03	4.03	0	114.3	M5-30	4.87	4.87	0	5845.1	L5-30	7.04	7.04	0	819.6
S6-30	4.31	4.31	0	205.2	M6-30	5.01	5.01	0	1767.2	L6-30	7.42	7.42	0	2295.4
S7-30	4.17	4.17	0	154.6	M7-30	5.68	5.68	0	651.8	L7-30	7.43	7.43	0	4290.9
S8-30	3.99	3.99	0	1781.7	M8-30	5.04	5.04	0	1853.7	L8-30	7.12	7.12	0	13139.3
S9-30	3.93	3.93	0	588.4	M9-30	5.48	5.48	0	482.1	L9-30	6.85	6.85	0	3732.2
S10-30	3.65	3.65	0	506.0	M10-30	4.83	4.83	0	3977.6	L10-30	7.28	7.28	0	12841.2
S11-30	3.56	3.56	0	155.9	M11-30	4.87	4.87	0	340.5	L11-30	7.39	7.39	0	249.9
S12-30	4.18	4.18	0	3198.3	M12-30	5.47	5.47	0	2813.7	L12-30	7.22	7.22	0	13046.2
S13-30	3.83	3.83	0	1475.5	M13-30	5.04	5.04	0	988.7	L13-30	7.01	7.01	0	2395.7
S14-30	4.14	4.14	0	2480.1	M14-30	5.07	5.07	0	255.4	L14-30	7.52	7.52	0	1404.0
S15-30	4.47	4.47	0	2533.3	M15-30	5.08	5.08	0	490.5	L15-30	6.85	6.85	0	2381.2
S16-30	4.02	4.02	0	73.8	M16-30	5.10	5.10	0	85.5	L16-30	7.92	7.92	0	404.5
S17-30	4.23	4.23	0	55.3	M17-30	5.78	5.78	0	3156.3	L17-30	6.73	6.73	0	179.0
S18-30	3.97	3.97	0	780.1	M18-30	5.21	5.21	0	4962.6	L18-30	6.97	6.97	0	3103.5
S19-30	3.55	3.55	0	1526.2	M19-30	5.22	5.22	0	234.2	L19-30	6.91	6.91	0	13375.5
S20-30	4.11	4.11	0	1537.1	M20-30	5.32	5.32	0	110.6	L20-30	7.57	7.57	0	481.1

Table A.5 Instances with 40 customers

Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)	Instance	LB	UB	Gap(%)	Time(s)
S1-40	5.41	5.48	1.3	18000.0	M1-40	6.93	7.22	4.0	18000.0	L1-40	9.38	9.67	3.0	18000.0
S2-40	5.30	5.30	0.0	8559.2	M2-40	6.97	6.97	0.0	5098.8	L2-40	9.11	9.87	7.7	18000.0
S3-40	5.44	5.50	1.2	18000.0	M3-40	6.71	7.18	6.6	18000.0	L3-40	10.36	10.52	1.6	18000.0
S4-40	4.99	5.14	3.0	18000.0	M4-40	6.77	6.83	0.8	18000.0	L4-40	11.17	11.70	4.6	18000.0
S5-40	5.51	5.58	1.3	18000.0	M5-40	6.69	6.94	3.6	18000.0	L5-40	10.88	11.36	4.2	18000.0
S6-40	5.09	5.30	4.0	18000.0	M6-40	6.72	6.86	1.9	18000.0	L6-40	10.18	10.79	5.6	18000.0
S7-40	5.25	5.34	1.6	18000.0	M7-40	6.68	6.75	1.0	18000.0	L7-40	9.55	9.63	0.9	18000.0
S8-40	5.54	5.95	6.9	18000.0	M8-40	6.89	7.18	4.1	18000.0	L8-40	9.44	9.61	1.8	18000.0
S9-40	5.24	5.24	0.0	3352.3	M9-40	6.63	6.63	0.0	11175.4	L9-40	10.68	10.68	0.0	12243.2
S10-40	5.26	5.26	0.0	11095.6	M10-40	6.92	7.04	1.7	18000.0	L10-40	9.27	9.67	4.1	18000.0
S11-40	4.88	4.93	0.9	18000.0	M11-40	6.22	6.48	4.0	18000.0	L11-40	9.91	9.91	0.0	9310.4
S12-40	5.12	5.12	0.0	3112.0	M12-40	6.86	6.86	0.0	7361.6	L12-40	10.46	10.64	1.8	18000.0
S13-40	5.27	5.42	2.8	18000.0	M13-40	6.97	7.21	3.4	18000.0	L13-40	10.90	11.04	1.3	18000.0
S14-40	5.39	5.52	2.5	18000.0	M14-40	7.07	7.13	0.9	18000.0	L14-40	9.96	9.96	0.0	10828.1
S15-40	4.96	5.00	0.8	18000.0	M15-40	7.03	7.42	5.3	18000.0	L15-40	10.00	10.00	0.0	7582.8
S16-40	5.44	5.54	1.8	18000.0	M16-40	6.60	6.80	3.0	18029.0	L16-40	9.09	9.29	2.1	18000.0
S17-40	5.19	5.28	1.7	18000.0	M17-40	6.64	6.87	3.4	18000.0	L17-40	10.10	10.62	5.0	18000.0
S18-40	5.55	5.71	2.9	18000.0	M18-40	6.54	6.70	2.4	18000.0	L18-40	10.43	10.72	2.7	18000.0
S19-40	5.35	5.35	0.0	2183.6	M19-40	6.37	6.62	3.7	18000.0	L19-40	10.70	10.90	1.8	18000.0
S20-40	5.57	5.57	0.0	722.6	M20-40	6.44	6.48	0.6	18000.0	L20-40	9.05	9.14	1.0	18000.0

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