Author/s:
Kahalimoghadam, Masoud

Title:
Developing and Implementing Collaborative Urban Distribution Networks to Improve the Sustainability of Last-mile Logistics

Date:
2024-03

Developing and Implementing Collaborative Urban Distribution Networks to Improve the Sustainability of Last-mile Logistics

By

Masoud Kahalimoghadam

ORCID: 0000-0003-1983-5131

Doctor of Philosophy

March 2024

Department of Infrastructure Engineering,
Faculty of Engineering and Information Technology,
The University of Melbourne

Submitted in total fulfilment for the degree of Doctor of Philosophy

ABSTRACT:

Initiatives targeting global climate change, for example the 2015 Paris Agreement and the United Nations' Sustainable Development Goals (SDGs), have underscored the importance of environmentally friendly transportation. Despite efforts to fulfil these commitments, projections indicate a potential 16% increase in carbon dioxide (CO_2) emissions from transport vehicles of all kinds, by 2050, underscoring the urgent need for transformative action within the transport sector. Urban areas are particularly significant, contributing approximately 70% of global emissions, with one-third coming from transportation. Challenges within last-mile logistics (LML) are further compounded by factors like rapid urbanisation, ongoing stresses such as pandemics, and emerging trends influenced by the dynamic nature of the LML environment.

In recent years, electronic commerce (e-commerce) has experienced remarkable expansion, fundamentally transforming consumer shopping habits and business strategies. While offering numerous advantages, this surge has led to a significant increase in business-to-consumer (B2C) parcel deliveries, primarily through home delivery. This has resulted in a measurable rise in vehicle kilometres travelled (VKT) and CO_2 emissions in metropolitan areas, usually due to failed delivery and poorer vehicle consolidation efficiencies, posing a significant challenge to achieving sustainability. The recent COVID-19 pandemic has further boosted e-commerce growth, with consumers increasingly opting for online shopping to avoid physical stores and reduce their exposure to viruses or other air-borne diseases. This unexpected surge has strained e-commerce providers and logistics services, altering the geographical pattern of goods demands and delivery routes and relocating freight vehicles to local roads. In this complex environment, optimising LML relies on strategically locating innovative collaborative logistics hubs, as well as efficiently deploying urban delivery vehicles.

An integrated, Operations Research-based methodology is devised for tackling LML challenges, providing decision-makers with structured optimisation methods and mathematical problem-solving techniques or strategies. This research first conducts two thorough literature reviews on LML. The first review identifies four key unsustainable trends: urbanisation, e-commerce growth, rapid delivery demands, and disruptive events. Meanwhile the second review reveals key LML stakeholders, including residents, customers, carriers, shippers, governments, and proposes integrating Physical Internet managers (PI-Managers) to oversee shared and collaborative logistics hubs. Stakeholders' objectives are determined, and their interactions within the LML are mapped. Utilising data from Australia's largest B2C carrier, the impact of COVID-19 on business-to-business (B2B) and B2C parcel delivery in Sydney is explored. It reveals there has been a shift from CBD deliveries

to outer metropolitan areas and identifies employment, population, and internet access as key factors determining this demand pattern change.

At the strategic level, a spatial approach is developed to address the uncapacitated single allocation hub covering problem (USAHCP) by incorporating the spatial features and strategic legislation of Sydney. This location-based methodology minimises VKT by establishing a collaborative last-mile distribution network through the optimised placement of micro-consolidation centres (MCCs). Simultaneously, it maximises the coverage of parcel lockers serviced by MCCs, assuming parcels are collected from parcel lockers by end customers. A sensitivity analysis assesses how the distribution network design (number and location of MCCs) varies according to different driving time constraints and traffic patterns, exemplified by various times of day.

At the operational level, a new collaborative multi-depot green vehicle routing problem is introduced, utilising MCCs as shared hubs and linking emission rates to vehicle and route characteristics through a microscopic approach. An innovative self-adaptive metaheuristic algorithm is developed, combining intelligent water drops and simulated annealing with a feedback control system actively monitoring the algorithm's performance and convergence towards the global minimum solution. Through continuous adjustments to algorithm parameters via feedback, this methodology balances exploitation and exploration. The algorithm is tested first on the Cordeau benchmark, compared with previous state-of-the-art methods, and then in a case study comparing the collaborative network to an independent one.

By focusing on stakeholders' interactions, an intelligent multi-agent system (iMAS) is developed where carriers, shippers, and PI-Managers are deemed to be learning agents. Each agent's objectives, actions, and roles are meticulously defined for simulation. iMAS employs Q-learning, a machine learning method aiding optimal actions based on environmental rewards, within a distribution network and vehicle routing problem environment to evaluate interactions among agents. Seven simulations, varying agent combinations undergoing learning, demonstrate improved objective achievement when agents learn. iMAS acts as a decision support system, evaluating policies and actions for policymakers to enhance LML efficiency.

Declaration

This is to certify that:

- the thesis comprises only my original work towards the PhD except where indicated in the preface,
- due acknowledgement has been made in the text to all other materials used, and
- the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices,
- parts of this work were published as listed in the Preface section.

Masoud Kahalimoghadam
March 2024

Preface

This thesis draws upon material from several articles I have authored, currently in various stages of the publishing process. They include:

- ✓ Chapter 2: Kahalimoghadam, M., Thompson, R.G. and Rajabifard, A. (2024) Assessing unsustainable trends in city logistics. Transportation Research Procedia. Accepted
- ✓ Chapter 4: Kahalimoghadam, M., Stokoe, M., Thompson, R. G., and Rajabifard, A. (2021). The impact of COVID-19 pandemic on parcel delivery pattern in Sydney. 42nd Australasian Transport Research Forum (ATRF). https://australasiantransportresearchforum.org.au/papers/2021
- ✓ Chapter 5: Kahalimoghadam, M., Thompson, R.G. and Rajabifard, A. Determining the number and location of micro-consolidation centres as a solution to growing e-commerce demand. In *Journal of Transport Geography*. Under review [Second round of review].
- ✓ Chapter 6: Kahalimoghadam, M., Thompson, R.G. and Rajabifard, A. Self-Adaptive Metaheuristic-based Emissions Reduction in a Collaborative Routing Problem. In *Sustainable Cities and Society*. Under review [Minor revision].

The author spearheaded the development of these manuscripts, leading from conceptualisation through data analysis and initial drafts. The research findings and recommendations have additionally been presented at conferences, workshops, and roundtables to transportation experts from Australia, the United States, and Europe, who play a crucial role in translating this research into real-world applications.

Presentation at conferences, seminars, webinars, and workshops:

- ✓ Kahalimoghadam, M., Thompson, R. G., Rajabifard, A, and Stokoe, M. (2022) Evaluation of governments' role in coping with city logistics problems. 43rd Australasian Transport Research Forum (ATRF). https://australasiantransportresearchforum.org.au/papers/2022
- ✓ Kahalimoghadam, M., Thompson, R.G. and Rajabifard, A. (2023) Assessing unsustainable trends in city logistics. City Logistics conference.
- ✓ International Physical Internet Doctoral Seminar (IPIDS), hosted by Georgia Tech University and Paris Tech **02 November 2023**.
- ✓ Infrastructure Engineering Postgraduate Conference (IEPC), hosted by the Department of Infrastructure Engineering, The University of Melbourne **24 October 2023 || 2 November 2022 || 20 February 2022**.

- ✓ Physical Internet webinar, hosted by MINES Paris, **03 July 2023.**
- ✓ PI@ Melbourne Seminar, hosted by The University of Melbourne, **04 April 2023 || 28 November 2022 || 26 April 2022.**
- ✓ 3D Land Administration & Digital Twin Training workshop, hosted by CSDILA, **22 September 2021**.

Collaborative publications:

- ✓ Rajabifard, A., Kahalimoghadam, M., Lumantarna, E., Herath, N., Kin, F., Hui, P., and Assarkhaniki, Z. (2021). Applying SDGs as a systematic approach for incorporating sustainability in higher education. https://doi.org/10.1108/IJSHE-10-2020-0418
- ✓ Assarkhaniki, Z., Sabri, S., Rajabifard, A., and Kahalimoghadam, M. (2023). Advancing sustainable development goals: embedding resilience assessment. Sustainability Science, 18(5), 2405–2421. https://doi.org/10.1007/s11625-023-01372-7
- ✓ Mohri, S, Sina., Vijay, A, Kahalimoghadam, M., Stokoe, M., Nassir, N., and Thompson, G.R. (2022). Evaluating initiatives for improvement of urban freight deliveries: A case study of Sydney metropolitan area. 43rd Australasian Transport Research Forum (ATRF). https://australasiantransportresearchforum.org.au/papers/2022
- ✓ Thompson, G.R., Stokoe, M., Kahalimoghadam, M., Mohri, S, Sina., Vijay, A., and Nassir, N., Transforming distribution networks in metropolitan Sydney in response to COVID-19 (2024). Transportation Research Procedia. Accepted

Communicating the research and receiving recommendations from transportation experts:

- ✓ *Transport for New South Walse (TfNSW)*: Michael Stokoe, Director - urban freight at TfNSW, Paul Gaynor, Director - freight policy at TfNSW,
- ✓ *Pacific National:* Geoff Featherstone, Head of strategic planning and integration at Pacific National.

No work was carried out by the candidate prior to enrolment, and no work has been submitted for other qualifications. No third-party editorial assistance was used for the formatting of this thesis.

Acknowledgement

I extend my sincere appreciation to my primary supervisor and mentor, Professor Russell Thompson, for his unwavering support, guidance, and extensive expertise while undertaking this PhD thesis. Additionally, I would like to thank my second supervisor Prof. Abbas Rajabifard for his support during this journey. I am also grateful to Michael Stokoe, the Director of Urban Freight at Transport for New South Wales (TfNSW), for his valuable advice and encouragement.

I would also like to thank Asst. Prof. Zahra Assarkhaniki who has always encouraged me since my bachelor.

I wish to express my gratitude to all individuals who have been part of my life journey, including family members, friends, colleagues, and others. They have helped shape me into a stronger person and have assisted me in finding the best solutions in overcoming life's challenges.

Masoud Kahalimoghadam
March 2024

Table of Contents

List of Figures

List of Tables

Chapter 1: Research Description

1 Introduction

1.1 Motivation and Challenges

The International Transport Forum, in its 2021 transport outlook, states that current transportation trends are unsustainable (ITF, 2021). Since 2015, major global initiatives were implemented to improve the international response to climate change and move the world to a more sustainable pathway, including the Paris Agreement (United Nations, 2015a) and the United Nations' Sustainable Development Goals (SDGs) (United Nations, 2015b). In both initiatives, transportation plays a major role. Under the Paris Agreement, 55 countries have committed to reducing global greenhouse gas (GHG) emissions by at least 55% (United Nations, 2015a). The SDGs also provide a blueprint for assessing GHG emissions and sustainable transportation that aim to achieve sustainable development by 2030 (Kawakubo et al., 2018). Even if all the commitments are met, it is estimated that transportation-related CO_2 emissions will rise by 16% by 2050 (ITF, 2021), underlining the need for an urgent transformation of the transport industry.

Urban areas account for approximately 70% of global emissions, one-third of which is produced by transport (OECD, 2020). For instance, a total of 27% and 25% of all GHG emissions are produced by transportation in the United States and Europe, respectively (European Environment Agency, 2022). This issue in last-mile logistics (LML) is exacerbated due to various types of challenges, such as rapid urbanisation as persistent stresses, pandemics as extreme events and disruptions, and newly emerged trends as a consequence of the dynamic environment of the LML (Kahalimoghadam et al., 2024).

In recent years, e-commerce - the buying and selling of goods and services over the internet - has experienced explosive growth and transformed the way consumers shop and businesses operate. For instance, this sector experienced, respectively, 18.5%, and 23.3% annual growth in the United States and Australia from 2018 to 2020 (United Nations, 2021). E-commerce provides several benefits, including the ability to reach a worldwide market, opportunities for small enterprises, advances in marketing techniques, and the smooth integration of online and offline channels to enhance customers' experience. The growth of e-commerce, however, has been accompanied by a rise in business-to-consumer (B2C) deliveries of physical goods, such as books, clothes, and electronic devices, which necessitates additional attention being paid to issues in the last mile of the supply chain where customers are located.

The popularity of B2C e-commerce, for example, has altered the goods distribution structure by increasing the number of online orders and consequently the high number of home deliveries. This trend contributes to increased urban vehicle movements measured by vehicle kilometres travelled (VKT), mostly due to failed deliveries leading to redelivery by freight carriers (Kedia et al., 2017). Another change involves parcel features, wherein their quality and value have risen, accompanied by a reduction in both volume and weight (Schett et al., 2019). Additionally, due to e-commerce changes, consumers now have higher expectations in terms of quality of services and speed of delivery (same-day and even X-hour delivery). This triggers more VKT, more emissions, and additional transportation costs (L. K. de Oliveira et al., 2017).

Despite steady annual growth, the COVID-19 pandemic has accelerated the growth of e-commerce, as consumers have increasingly turned to e-shopping to avoid physical stores and reduce the risk of exposure to the virus. This has led to an unpredicted surge in demand for e-commerce providers and logistics services. Besides, governments restrictions, such as prohibiting long-distance travel (Borkowski et al., 2021), offices closure and working from home, and limiting shopping and entertainment to the local areas have altered the goods' distribution pattern (Kahalimoghadam et al., 2021). The significant change in the geographical pattern of goods delivery has resulted in the relocation of freight vehicles to local roads. These trends are in opposition to traditional urban freight generation analysis and modelling that relies on factors such as non-residential land use location and intensity (Pani et al., 2018). In such a complex environment, not only the location and number of logistics hubs are critical to improving the LML sustainability, but also the vital role of their type and functionality in timely delivery and optimised distribution is undeniable.

1.2 Opportunities

One of the relatively new urban logistics facilities that can handle the elevation in e-shopping and response time expectations is urban micro-consolidation centres (MCCs). An MCC is a logistics facility usually shared between various companies and used for consolidation purposes, including loading, unloading, sorting, storing, and delivering goods to customers. MCCs can promote the employment of environmentally friendly vehicles, such as cargo bikes and light electric vans (LEVs) to mitigate negative externalities in the last mile (Browne et al., 2011). It is because they are generally located in the inner urban areas close to the final delivery customers, and their implementation adds another layer to distribution networks that increase the opportunity of using various modes of transportation.

Although MCCs improve distribution system efficiency, the cost of launching such initiatives can be high due to their capital and operational requirements (Kovač et al., 2021). Reducing the overall cost of goods movement through the optimisation of vehicle allocation is one way to make this initiative financially viable. The nexus between urban logistics and the vehicle routing problem (VRP) resides in the intricate interplay of optimising transportation operations in densely populated urban environments. One concept that focuses on logistics activities optimisation in urban areas and reducing negative externalities is City Logistics. The City Logistics refers to the strategic management of freight movements, encompassing distribution, delivery and supply chain activities, and integrating all components of the logistics system, such as urban freight transport stakeholders, amidst the multifaceted challenges posed by urban congestion, environmental concerns, and spatial constraints (Arvianto et al., 2021; Taniguchi & Thompson, 2002; Widodo et al., 2018).

Multi-depot VRP (MDVRP), the closest variant of the VRP to the real world, involves DPs being fulfilled by several scattered MCCs. In the City Logistics context, the MDVRP, serving as an NP-hard (non-deterministic polynomial-time) problem, reflects the practical need to determine the most efficient allocation of vehicles to a set of geographically dispersed customers while minimising operational costs, travel distances, and time expenditures. The convergence of the City Logistics and VRP domains, especially at the operational level, exists in the adaptation and application of VRPs and entails optimisation methodologies that engender sustainable, economically viable, and operationally feasible solutions to the intricate logistics scenarios characteristic of urban settings (Lin et al., 2014). At the strategic level, the hub covering problem (HCP) involves determining the optimal locations of hubs to serve a set of demand points and is applied to minimise transportation costs (Calık et al., 2009). In the context of the City Logistics, it addresses the efficient establishment of MCCs to support urban freight delivery, optimising the flow of goods within a city while considering factors like traffic congestion, environmental concerns, and last-mile delivery efficiency.

The other solution to reduce the overall cost per hub is to design a network of collaborative MCCs, in which diverse stakeholders and companies employ shared and open MCCs. For the practical implementation of such a network, the concept of the Physical Internet (PI) comes into play. The PI revolves around using globally standardised, intelligent, environmentally friendly, and modular containers known as PI-containers. The goal is to speed up dispatching and minimise the distance these containers need to travel from their origin to their destination (Fazili et al., 2017; Venkatadri et al., 2016). The PI is a new, innovative, and open global distribution logistics system that offers a conceptual framework aiming to improve sustainability (in terms of economy, environment, and society) and efficiency of physical object transportation (Kim et al., 2021; Montreuil, 2011). Developing a collaborative network of MCCs enables last mile stakeholders, such as carriers and shippers, to reduce their delivery time and costs.

Agent collaboration in logistics is essential for creating a network of MCCs, as unified collaboration significantly enhances consolidation efficiency (Leitner et al., 2011). Depending on the stakeholders involved in the collaborative network, collaboration can be vertical, between stakeholders at different LML tiers, or horizontal, between stakeholders at the same LML tier. The level of collaboration can vary. For example, only MCC capacities can be shared, but companies use their own fleets independently. In a higher level of collaboration, central route planning can be implemented with shared facilities and fleets. In a fully cooperative scenario, decisions about routing and facility locations are made collectively by all entities involved in the LML (Frederik et al., 2022; Gansterer & Hartl, 2018). Overall, collaboration among stakeholders contributes to increased sustainability in goods movement by improving consolidation levels, thus reducing unnecessary trips.

Sustainable urban distribution (SUD) is introduced to balance the objectives of the various stakeholders involved in LML while enhancing sustainability. The SUD serves as a framework to achieve the following objectives: a) enabling easy access to the transportation system for all those involved in freight, b) minimising the harmful side effects of freight transport like air pollution and GHG emissions, c) making the best use of land without compromising residents' well-being, and d) enhancing economic efficiency by making goods distribution more cost-effective (He & Haasis, 2020).

The SDGs set forth by the United Nations offer a global framework for measuring, monitoring and tracking sustainable development achievements (United Nations, 2015b). This framework is linked to the SUD, serving as a means to assess the degree to which the objectives of SUD have been realised. A total of 17 goals, 169 targets, and 231 unique indicators are defined to support countries in achieving sustainability by 2030 (United Nations, 2015b). The SDGs, subsequently, cover several aspects of life, including logistics, in order to provide a comprehensive assessment of sustainability in all environmental, social, and economic dimensions (Woodbridge, 2015).

This research applies the City Logistics and PI concepts to enhance the flexibility, adaptability, and efficiency of the LML, as the most problematic partition of the urban goods distribution system, by employing different modelling techniques. In the modelling process, an intelligent multi-agent system (IMAS) is developed as a decision support system (DSS) to optimise the interactions of stakeholders. The other contribution made by this research is to design a collaborative distribution network that evaluates the performance of open and shared facilities. Figure 1.1 illustrates the connection between SUD's objectives, challenges to achieving them, and opportunities for their realisation.

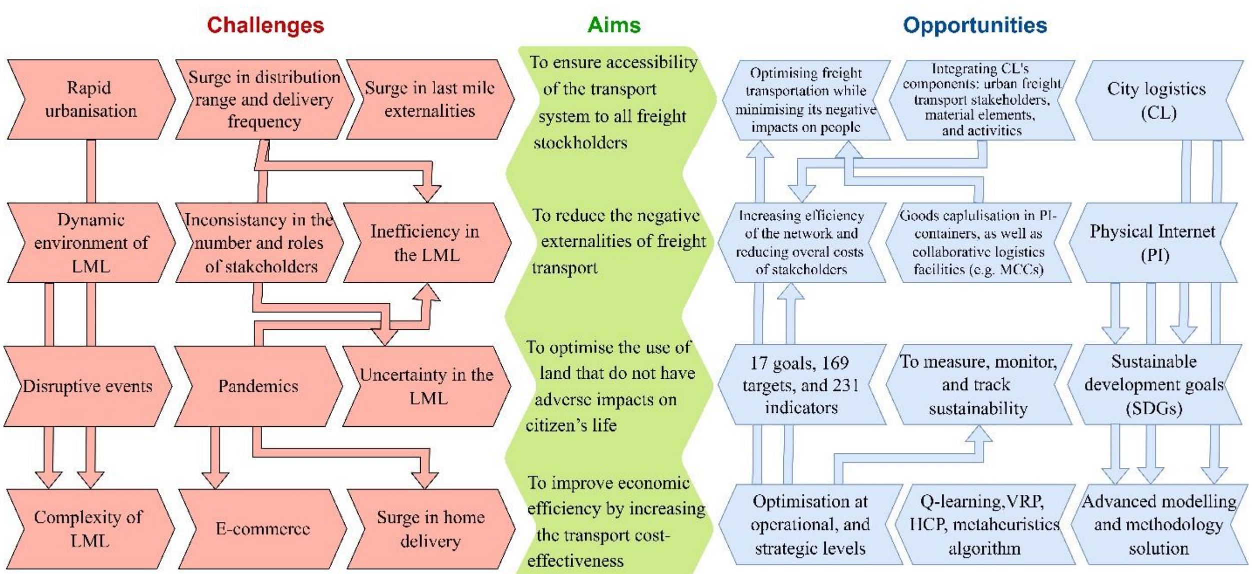


Figure 1.1. Aims, challenges, and opportunities for achieving SUD.

The primary focus of this research is to create a novel collaborative distribution network design that addresses the challenges arising from the popularity of e-commerce and the surge in business-to-customer (B2C) parcel delivery. In this designed distribution network, all stakeholders benefit from its implementation. The design process involves strategic and operational levels, achieved by developing and solving novel Hub Covering Problem (HCP) and Vehicle Routing Problem (VRP), respectively. To ensure the stakeholders derive benefits from this network, they and their objectives are identified. These stakeholders include governments such as city councils or state governments, shippers such as e-commerce platforms, carriers like freight transporter companies, customers such as online shoppers, and residents. To ensure effective collaboration, a new stakeholder called PI-Managers is introduced, responsible for managing MCCs. This addition enhances the coordination and management of the distribution network. Finally, the collaboration among stakeholders is extensively evaluated through realistic simulations and scenarios, ensuring the network's effectiveness and sustainability in real-world situations.

1.3 Problem Statement

The environment of last-mile logistics (LML) continually changes since it involves erratic e-commerce demand, disruptive events, and various existing and new stakeholders with evolving objectives and interactions. Such a dynamic environment leads to operational inefficiency in the network and a poorer level of environmental sustainability. Current modelling approaches are deemed to be inefficient in facilitating and incorporating City Logistics and Physical Internet into the collaborative last-mile distribution network design. A gap also exists in the current knowledge to assess the impacts of newly emerged stakeholder(s) due to the usage of collaborative logistics hubs on existing stakeholders and the network. Furthermore, decision-makers lack sufficient information to identify effective measures for mitigating the challenges.

1.4 Research Aim

This research aims to develop a strategic approach to designing a novel urban last-mile distribution network to optimise the allocation of urban delivery vehicles in metropolitan areas and the allocation of logistics hubs to ensure optimal coverage and improve sustainability. The network's flexibility and adaptability are improved by incorporating collaborative logistics hubs, and all relevant stakeholders' objectives. Hence, decision-makers are provided with sound optimum decisions aligned with sustainable urban distribution (SUD).

1.5 Research Objectives

1. To identify newly emerged trends in city logistics, especially in the last mile, that negatively impact sustainability in urban areas.
2. To investigate the recent COVID-19 pandemic's impact on e-commerce demand and last-mile delivery patterns in metropolitan areas.
3. To develop a novel metaheuristic algorithm for the multi-depot vehicle routing problem in the growing e-commerce sector, with a focus on curtailing vehicle

kilometres travelled and establishing the foundational environment for an intelligent multi-agent system.

4. To design a collaborative last-mile goods distribution network to optimise the allocation of logistics hubs, particularly micro-consolidation centres, for tighter and more flexible responsiveness to e-commerce demand.
5. To develop an intelligent multi-agent system in line with sustainable urban distribution that acts as a decision support system to optimise stakeholders' interactions and improve last mile performance.

1.6 Research Questions

1. What factors and trends cause unsustainability in city logistics, particularly in the last-mile logistics?
2. What are the existing and newly emerged stakeholders in the last-mile logistics? What are their interactions with themselves and the environment from the strategic, tactical, and operational decision perspectives?
3. What impact has the COVID-19 pandemic had on e-commerce delivery patterns in the Sydney metropolitan area?
4. What is the optimal configuration of micro-consolidation centres in a collaborative last mile distribution network?
5. What is the impact of optimising the allocation of urban delivery vehicles on the last-mile logistics? If a collaborative distribution network of micro-consolidation centres is used, how can this optimisation be achieved?
6. What is the impact of creating a DSS using an intelligent multi-agent system in line with sustainable urban distribution on stakeholders' interaction and last mile efficiency?

1.7 Research Methodology and Approach

According to the aim of this study, that is designing a DSS, Operations Research (OR) has been selected as the methodology for this research. OR refers to the application of mathematical problem-solving techniques and methods to the study and analysis of problems involving complex systems (Shukla et al., 2017; Sivazlian, 2008). This research methodology enables the optimisation of a complex system with given criteria to support decision-makers (Sivazlian, 2008). The detailed steps of the integrated methodology will be elucidated in Chapter 3.

1.8 Thesis Structure

This thesis is structured as follows in order to achieve the research objectives:

Chapter 2: Improving Efficiency of the Last-mile Logistics Network - Literature Review

This chapter provides all literature review of topics that are mainly employed in this research, including identifying unsustainable trends in lass-mile logistics, hub covering problem, vehicle routing problem, last-mile stakeholder analysis, and multi-agent systems Q-learning.

Chapter 3: The Integrated Methodology
Chapter 3 outlines an integrated methodology derived from Operations Research, comprising six sequential steps: problem identification, mathematical formulation, solution methodology, model evaluation, decision support system development, and implementation in a case study.

Chapter 4: The Impact of the COVID-19 Pandemic on Last-mile E-commerce
This chapter investigates the impact of the COVID-19 pandemic on both B2B and B2C parcel delivery in the Sydney metropolitan area. It begins by comparing the spatial patterns of parcel delivery in 2020 with those of 2019 (pre-pandemic) utilising ArcGIS software. The analysis results provide insights into changes in last-mile distribution efficiency caused by COVID-19. The knowledge gained from analysing this real-world problem serves as guidelines for formulating problems and methodology solution selection in subsequent chapters that eventually lead to a collaborative distribution network design.

Chapter 5: Uncapacitated Single Allocation Hub Covering Problem
A collaborative LML distribution network where MCCs, as logistics hubs, receive parcels from a central warehouse and then fulfil parcel lockers representing DPs is developed in this chapter. This problem is defined as an uncapacitated single allocation hub covering problem (USAHCP), in which the optimal location and number of MCCs are determined to maximise coverage areas. It integrates urban spatial characteristics and strategic regulations, including accessibility and the concept of the 15-minute city.

Chapter 6: Collaborative Multi-depot Green Vehicle Routing Problem (CMDGVRP)
This chapter presents a collaborative approach to solving the multi-depot green vehicle routing problem. The model integrates MCCs as shared hubs and incorporates a detailed analysis of emission rates linked to vehicle and route characteristics to evaluate the MCCs' impact on reducing CO_2 emissions. An innovative self-adaptive metaheuristic algorithm is introduced, which combines intelligent water drops and simulated annealing techniques, along with a feedback control system to monitor performance and convergence leading to the global minimum solution. The algorithm's effectiveness is tested through a context-specific approach.

Chapter 7: Intelligent Multi-agent System: A Last-mile Logistics Decision Support System
Chapter 7 presents the development of an intelligent multi-agent system (iMAS) that centres on stakeholders' interactions. In iMAS, carriers, shippers, and Physical Internet managers (PI-Managers) are regarded as learning agents. A distinct learning process is designed to capture the exchange of information and decision-making among agents, employing Q-learning to train agents to make the optimum decisions.

Chapter 7 integrates and builds upon the studies and models from the preceding chapters, offering a comprehensive synthesis. It builds upon the last-mile stakeholder analysis conducted in Chapter 2, which forms the foundational basis for the multi-agent model established in Chapter 7. The integration of the USAHCP and CMDGVRP discussed in Chapters 5 and 6 contributes to the simulation environment of the iMAS. Furthermore, this chapter evaluates the effectiveness of the PI-manager stakeholder, introduced in Chapter 2 in the LML domain, within the distribution network.

Chapter 8: Conclusion

The primary findings of this study are summarised in this chapter by discussing how each research question is answered. In addition, recommendations, research constraints, and directions for further investigation are included.

Chapter 2: Improving Efficiency of the Last-mile Logistics Network - Literature Review

A B S T R A C T:

In response to environmental challenges inherent in urban goods movements and the imperative to mitigate last-mile delivery vehicle movements, this chapter conducts an extensive examination of the relevant literature concerning last-mile logistics (LML). The first literature review highlights four significant unsustainable trends, namely urban population expansion, the increasing popularity of e-commerce, rapid delivery, and disruptive events. Subsequent investigation delves into the diverse stakeholders within LML, including residents, customers, carriers, shippers, and governments, and proposes the integration of Physical Internet managers to oversee shared logistics facilities. At a strategic level, the analysis focuses on minimising the number of hubs in the network while maximising coverage area via the uncapacitated single allocation hub covering problem. Operationally, attention shifts to the collaborative multi-depot green vehicle routing problem, aimed at optimising urban delivery vehicle allocation while reducing vehicle kilometres travelled and CO_2 emissions through carrier collaboration. Leveraging these insights, an innovative urban distribution network is envisaged, prioritising emission mitigation to harmonise with stakeholders' objectives and culminating in optimal decisions for sustainable urban distribution.

2.1 Introduction

Last-mile distribution networks play a crucial role in ensuring efficient and sustainable delivery of goods to metropolitan areas. Designing such networks to mitigate transportation-related CO_2 emissions and reduce vehicle movements due to last-mile deliveries (LMD) requires a deep understanding of various concepts in last-mile logistics (LML). This chapter presents a comprehensive literature review conducted for this dissertation to enhance LML efficiency and sustainability. We begin by defining sustainability in LML and identifying unsustainable trends in this field. Subsequently, we explore the development of innovative urban distribution networks to address these unsustainable trends. The key methodological solutions discussed include the hub covering problem, the vehicle routing problem, and the application of multi-agent systems in LML.

To begin with, unsustainable trends are identified as a priority, emphasising the need for sustainable solutions in urban distribution. Additionally, a systematic review identifies stakeholders in LML, analysing their objectives, interconnections, and links to sustainability. This structured approach aims to synthesise existing research on LML stakeholders, specifically to identify key stakeholders in the last mile and map their interconnections. The outcomes of these two literature reviews led to the choice of addressing the hub-covering problem and the vehicle routing problem in Chapters 5 and 6 to enhance the efficiency and sustainability of the distribution network at strategic and operational levels. Chapter 7, in particular, not only utilised the findings from the last-mile stakeholder literature review but also integrated the mathematical models developed in Chapters 5 and 6.

The uncapacitated single allocation hub covering problem, which is a variant of well-known hub location problems, is extensively investigated. Reviewing this problem provides valuable insights used in Chapter 5, in which a strategic approach is designed wherein the number and locations of micro-consolidation centres (MCCs) are optimised to maximise coverage while minimising total vehicle kilometres travelled (VKT). At the operational level, the vehicle routing problem is studied to efficiently allocate urban delivery vehicles, aiming to minimise VKT and CO_2 emissions. In this wide and rich research area, we particularly focus on green VRP and collaborative VRP, which leads to developing the novel collaborative multi-depot green VRP that is extensively described in Chapter 6. Furthermore, the application of multi-agent systems in LML is evaluated, taking into account the objectives and interactions of key stakeholders in city logistics. In addition to traditional stakeholders such as residents, customers, carriers, shippers, and government, the introduction of the Physical Internet manager as a new stakeholder in the network underscores the importance of collaborative logistics networks.

Through a comprehensive understanding of these concepts and stakeholders, an innovative urban distribution network is envisioned. Mitigation of VKT and emissions is prioritised to align with the objectives of all key stakeholders, ultimately leading to optimal decisions being made in line with sustainable urban distribution.

2.2 Sustainability in the Last-mile

Urban freight is essential for meeting residents' needs and drives economic growth by supporting businesses and enabling commerce in city environments. However, it can adversely impact the liveability of urban areas and environmental sustainability (Taniguchi & Thompson, 2014). This is primarily due to factors such as traffic congestion, greenhouse gas emissions, and safety issues associated with freight vehicle movements (Taniguchi et al., 2020). These problems are exacerbated by rapid urbanisation and the rise of e-commerce, leading to concerns about the possibility of achieving a balance between economic and environmental sustainability (Taniguchi & Thompson, 2014). For example, the rise of e-commerce, particularly business-to-customer home delivery, has increased social and environmental costs (Taniguchi et al., 2016). This highlights the urgent need for sustainable urban distribution solutions.

City logistics is defined as an approach to optimise logistics and transportation activities in urban areas to reduce the negative externalities of freight movements and traffic congestion while improving levels of service (Taniguchi & Thompson, 2002). Since City Logistics encompasses urban freight distribution, urban logistics, and LML, it poses a diverse range of challenges (Kahalimoghadam et al., 2024). Urban growth, traffic congestion, traffic density, increasing the volume of fleets, inadequate loading spaces, and unwillingness among different agents to accept new logistics regulations are some of the challenges in these domains (Arvianto et al., 2021; Widodo et al., 2018). Additionally, City Logistics involves various stakeholders with conflicting objectives whose aims are constantly changing (Kiba-Janiak, 2016). The former characteristic of City Logistics results in inefficiency in logistics networks, whereas the latter causes new trends to emerge. The consequences of these trends can adversely affect both logistics companies, such as shippers and carriers, and society, such as residents and customers, from an economic, social, and environmental standpoint (Kahalimoghadam et al., 2024; Nathanail et al., 2021). This highlights the importance of identifying unsustainable trends in City Logistics and evaluating the level of sustainability. These steps will assist authorities in taking the necessary measures to preserve natural resources for current and future generations.

This section aims to identify the major trends that lead to unsustainability in City logistics, particularly in the last mile, as well as to provide a method for assessing last-mile sustainability. In order to accomplish this goal, we discuss first the trends that lead to unsustainability, followed by an introduction to the Sustainable Development Goals (SDGs), which provide a framework for achieving a better world. The rest of this chapter is organised as follows. Section 2.2.1 introduces trends in City Logistics that reduce sustainability in urban areas. Section 2.2.2 describes sustainability and discusses the SDGs as a framework to measure sustainability. Then the SDGs are connected to logistics. After that, the sustainability plans of different companies and organisations in Australia are evaluated. Finally, a crucial step towards achieving sustainability in City Logistics is understanding the objectives and needs of key stakeholders, which will be discussed later in Section 2.5.

2.2.1 Unsustainable Trends in Last-mile Logistics

Urban population growth: An urbanisation process consists of increasing the number, area, and population of urban settlements, and therefore increasing the number of people living in urban areas (United Nations, 2018a). Currently, over 55% of people (4.3 billion) live in cities, and this percentage is predicted to reach 68% by 2050 (United Nations, 2018b). Dense populations in urban areas have the potential to increase the problems inherent in vehicle movement, including air pollution, noise pollution, and greenhouse gas (GHG) emissions.

As a major environmental health risk, outdoor air pollution is associated with 8.7 million premature deaths worldwide (Vohra et al., 2021) and is associated with major environmental health risks. In a study done on the global scale, a relationship between premature mortality and emissions sources was confirmed and concluded that vehicles' movement was the primary cause of air pollution deaths (Lelieveld et al., 2015). Further, it has been observed that LML activities, such as parcel delivery and goods collection, increase vehicle movements and traffic congestion, which has a negative effect on air quality.

Despite not causing as high a mortality rate as air pollution, noise pollution adversely affects urban quality of life, resulting in a range of physical and mental problems, including deafness, heart disease (attacks and strokes), high blood pressure, mental disorders, and nervous breakdowns. In general, prior research strongly suggests that vehicle movements are the primary source of noise pollution (Morillas et al., 2018; N. Singh & Davar, 2004). In cities, noise pollution may be worsened by the following factors: a) volume of traffic; b) vehicle distribution; c) traffic conditions; d) the speed of vehicles; and e) distance from the roads.

GHG emissions contribute to global warming, climate change, droughts, floods, and average temperature rise. Consequently, crop yields are declining, which threatens the food security of all countries (Environmental Protection Agency, 2017). Considering that Australia's total GHG emissions in 2021 were approximately 500 million tons, and 17.5% of them were attributed to the transportation sector (Department of Industry, Science, 2021), it is evident that City Logistics plays an active role in addressing this issue.

Increasing popularity of e-commerce: With its advantages over traditional channels, e-commerce has transformed business models. These advantages include: a) expanding marketing channels, b) lowering operational costs, c) fostering cooperation among companies, d) reducing initial investments, e) simplifying comparison of prices, f) gaining access to stores worldwide, g) increasing customer choice, and h) trading 24/7 (Q. Chen & Zhang, 2015; Najwa Ahmad et al., 2013).

Despite the fact that e-commerce is becoming increasingly popular due to its convenience and flexibility, it also carries a number of disadvantages, including: a) unknown quality of products, b) identity fraud, c) credit card fraud, and d) socio-environmental problems

(Morganti et al., 2014; Najwa Ahmad et al., 2013). The last problem relates to the delivery of products or goods, of which home delivery is the most popular and, at the same time, the most problematic method. Inefficient delivery methods cause: a) increase in service costs, b) failed deliveries, c) increase in vehicle movements, d) returns of products and reverse logistics, e) small-sized shipments, and f) highly competitive markets which lead to lower levels of consolidation (Edwards et al., 2009; Morganti et al., 2014).

Fast delivery: Technological advances and high-quality services have raised consumers' expectations, and online shoppers now expect their goods faster and at a lower price. As a result, the freight system becomes increasingly stressed, particularly LML, resulting in increased vehicle movements in urban areas as well as increased GHG emissions (L. K. de Oliveira et al., 2017). Furthermore, customers are demanding shorter delivery windows, which result in: a) less vehicle load factors, b) more frequent deliveries, c) higher transportation costs, and d) restrictions on retailers accepting future orders (Köhler et al., 2020; Muñoz-Villamizar et al., 2021). To effectively address the social and environmental impact of fast delivery, it is necessary to identify all major factors that affect last-mile distribution. These factors include products, customers, and delivery dimensions, which are discussed in the following paragraphs.

Products. In order to reduce risk and improve last-mile delivery efficiency and sustainability, it is essential to understand product characteristics. This can be explained by the fact that the total logistics cost and the volume of products demanded are dictated by the features of the products, especially in extreme cases. Products are mainly categorised based on demand uncertainty, value, and information complexity (Chopra, 2018). They can also be characterised by their physical aspects, such as their weight, volume, type, and variety (Lim & Srai, 2018).

Customers. E-commerce customers are divided into two types: price-conscious and service-conscious. Price-conscious customers refer to those who use price as the purchase decision standard when selecting an e-retailer, without considering the quality of their products or standard of service (Chopra, 2018). Service-conscious customers are willing to pay more if an e-retailer provides them with a higher standard of service (Chopra, 2018).

Delivery Dimensions. Additionally, other dimensions of delivery are cost, convenience, accuracy, timeliness, and environmental friendliness. There are different ways in which each dimension affects customers. An increase in delivery time, for example, may worsen ambiguity and riskiness, and consequently, lead to a decline in customer satisfaction and purchase intention.

Disruptive events: Supply chains are vulnerable to disruptive events (DEs) due to: a) the competitive business environment, b) ongoing and just-in-time demand for products, c) accurate transportation scheduling, and d) the pressure for cost reductions that have led to offshore manufacturing and, consequently, globalisation. DEs can wield a significant impact on City logistics, leading to critical shortages of supplies in urban areas as well as congestion due to rising demand for goods and services. This congestion can cause delays and increased logistics costs, which can further exacerbate the impact of the disruptive event on the logistics system. Additionally, DEs can lead to changes in delivery patterns due to an increased demand for home delivery, changes in consumer behaviour, and businesses being forced to switch to online delivery. Since DEs affect 56% of firms on a global scale (BCI-Business Continuity Institute, 2019) and usually cause various types of risks such as: a) supply risk, b) demand risk, c) transportation risk, d) infrastructure risk, and e) socio-political risk (Abdellaoui & Pache, 2019), identifying and categorising them is critical. DEs can be classified based on: a) in which supply chain's echelon disruptions occur, b) reasons for DEs, c) sources of DEs, d) typology of disruptions, and e) frequency of disruptions (Katsaliaki et al., 2021).

The summary of identified unsustainable trends is illustrated in Figure 2.1.

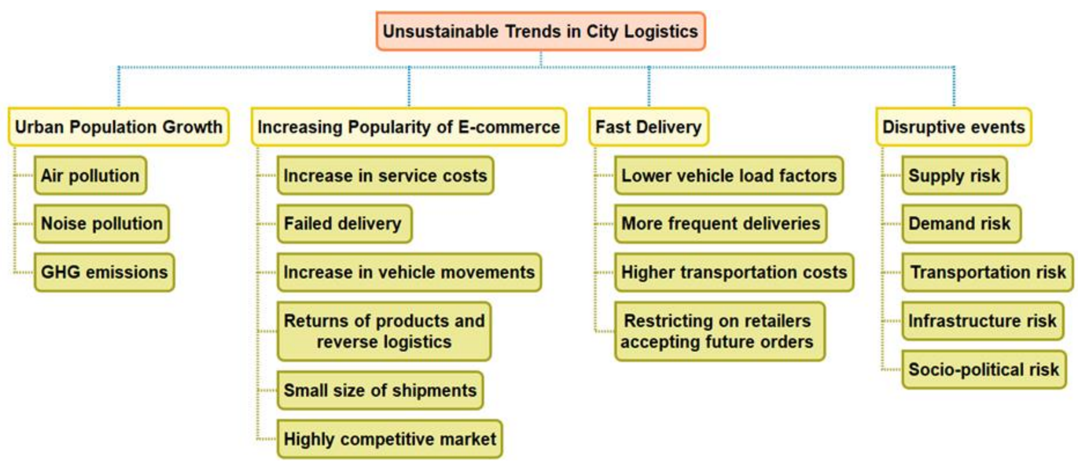


Figure 2.1. Unsustainable trends in City Logistics and their impacts on urban areas and logistics system.

2.2.2 Sustainability: SDGs and its Connection with LML

Sustainability has been defined as meeting the needs of the present without compromising the environmental, social, and economic interests of present and future generations (Adams, 2006; The World Commission on Environment and Development, 1987). Sustainability, therefore, can be considered as enduring functionality over time pertaining to a variety of aspects of life (The World Commission on Environment and Development, 1987). However, staying on track in all domains can be challenging, especially during DEs. To use a tangible example, logistics management has struggled with the unpredicted volume of goods delivery since the beginning of the global COVID-19 outbreak in early 2020 (Kahalimoghadam et al., 2021). A variety of sudden time travel restrictions and stoppages were introduced but these were gradually eased around the world. To guide stakeholders and businesses through these uncertain times, benchmarking is necessary. In order to achieve this, it is necessary to develop a framework to adapt to changes in delivery demand while remaining resilient and maintaining functionality across all domains, from environmental to economic and social.

For this purpose, several frameworks have been developed, including the SDGs, which evaluate and ensure sustainability in many areas, including logistics.

Sustainable Development Goals (SDGs): The United Nations promulgated the SDGs in 2015 as a standard framework to measure and monitor sustainable development. A total of 17 goals, 169 targets, and 231 unique indicators were defined to support countries in achieving sustainability by 2030 (United Nations, 2015b). The framework carries on the momentum initiated by the Millennium Development Goals (MDGs) adopted in 2000 as a guideline with eight targets for eradicating extreme poverty by 2015. In contrast, the SDGs cover several aspects of life, including logistics, in order to provide a more comprehensive assessment of sustainability in all environmental, social, and economic dimensions (Woodbridge, 2015).

The SDGs provide standardised metrics for quantifying and decomposing the abstract concepts of sustainability into measurable factors that can be used to evaluate sustainable development and sustainability. Data such as statistical and census information can be used to measure the SDGs' indicators. As an example, indicator 9.4.1 measures CO_2 emissions per unit of value-added, which can serve as a measurable indicator of the adoption of environmentally friendly technologies and sustainable infrastructure (United Nations Statistics Division, 2020). Due to what they seek to achieve, the SDGs have been universally accepted as a framework for assessing sustainability by governments, research organisations, and industry entities. Several cities have also incorporated this framework into their policymaking and daily practices. For instance, the Global Vision Urban Action programme was launched by the New York City Mayor's Office for International Affairs in July 2018 to communicate sustainability innovations and challenges worldwide (Woodbridge, 2015).

Connection between SDGs and logistics: Aside from evaluating sustainable development generally, the SDGs can also serve to assess and benchmark the level of sustainability in various subdomains, including sustainable logistics. Meanwhile, logistics impacts on sustainable development have been extensively evaluated in recent years. Sustainable logistics are now recognised as an influential factor in enhancing economic growth, social equity, as well as improving urban resilience and rural productivity. During the connecting process, the definition of sustainable logistics proposed by He and Haasis (2020) is used. Following their study, sustainable logistics aims to:

1) ensure all freight stakeholders have access to the transport system;
2) reduce the negative externalities of freight transport, such as air pollution and GHG emissions;
3) optimise the use of land so that it does not undermine citizens’ lives; and
4) improve economic efficiency by increasing the cost-effectiveness of goods distribution.

Figure 2.2. Connection between SDGs and logistics

Finally, the interdisciplinary approach developed by Rajabifard et al. (2021) is applied to identify the connection between the SDGs and logistics. Accordingly, each SDG's key phrases are identified and analysed through the lens of sustainable logistics. In target 9.1, for example, the focus is on providing affordable and equitable access to reliable and sustainable infrastructure. Therefore, this target is closely related to the first objective of sustainable logistics, which emphasises the accessibility of the logistics system for all stakeholders. Figure 2.2 shows how the SDGs can be used to assess logistics sustainability based on this analysis. This graph indicates that

13 out of 17 SDGs are directly linked to sustainable logistics. A lower level of analysis identifies 21 targets relevant to sustainable logistics. In addition, the thickness of lines in Figure 2.2 represents the connection strength between these two concepts, with thicker lines indicating higher relevance, which is determined by the number of relevant targets.

However, objective methods can be used to increase the accuracy of the connection between the SDGs and City Logistics as well as to expand the scope of the analysis. By using objective methods, such as machine learning and data mining, it is possible to identify patterns and correlations between the SDGs and City Logistics that may not be obvious. Additionally, these methods can be applied to extend the scope of the analysis.

Sustainability in different companies/organisations: The importance of maintaining a balance between different aspects of urban life has prompted companies and other types of organisations to prepare their own sustainability plans. This section provides a summary of the sustainability plans and measures set out by selected companies and organisations in our case study in Sydney, Australia. Particularly, the New South Wales (NSW) government and Transport for NSW (TfNSW) are selected as this research's case study is Sydney, NSW, incorporating their transportation policies and sustainability regulations into my modelling.

New South Wales government: In response to a number of challenges and opportunities, sustainability has been included in the New South Wales (NSW) government's Freight and Ports Plan 2018-2023 (Mavhura, 2019). As a means of achieving this objective, the NSW Government has set two primary objectives: to reduce freight emissions and to manage the noise impact of freight. The following three strategies have been developed to reduce freight emissions:

1) Develop electric vehicles: Developing a whole-of-government electric vehicles strategy to prepare for and support the transition to electric vehicles.
2) Advocate for stronger national vehicle emission standards: Supporting the strengthening of national vehicle emission standards for both heavy and light vehicles, and for a national approach to managing diesel emissions from non-road diesel equipment, under the National Clean Air Agreement.
3) Investigate emissions controls for diesel locomotives: Investigating the adoption of emissions limits for diesel locomotives in collaboration with industry.

In order to manage the effects of noise, four strategies have been developed:

1) Work with industry to reduce noise caused by rail freight: Continue to work with industry and regulators to deliver value-for-money rolling stock-based solutions to reduce noise from locomotives and wheel squeal.
2) Investigate environmental performance accountability improvements: Considering options to improve accountability for environmental performance in the freight industry, such as reforms to environmental protection authority licensing arrangements or industry standards.
3) Support electric vehicles in high density areas: Supporting their usage for deliveries in built-up areas to reduce the noise and emissions triggered by freight.
4) Further research into noise impacts: Conducting further research into the noise impacts of freight operations and the effectiveness of mitigation measures to inform future initiatives.

Transport for New South Wales

Transport for New South Wales (TfNSW) is a key government department that promotes sustainable design guidelines (Kahalimoghadam et al., 2022). In addition to minimising environmental impact, the guidelines aim to procure, deliver, and promote sustainable transport options with reduced lifecycle costs and value for money. They are also responsible for the development, expansion, and management of the transportation network. The guidelines cover seven themes: 1) energy and GHG emissions, 2) climate resilience, 3) materials and waste, 4) water, 5) pollution control, 6) biodiversity, and 7) community benefit.

There is a set of requirements for each theme. For example, one of the requirements for energy and greenhouses is stated as follows: “Projects are required to establish a baseline footprint using the Carbon Estimate and Reporting Tool and demonstrate a reduction of construction-related GHG emissions of at least 5% from the established project baseline”. The guidelines support achieving sustainability in designing and developing transportation infrastructure (Transport for NSW, 2017).

Figure 2.3. Australia Post’s aspirations to achieve the SDGs by 2030 (Australia Post, 2020)

Australia Post: Australia Post is another entity that has committed to improving sustainability through the adoption of the SDGs since 2016. A key component of Australia Post's mission is to meet the needs of its customers while also ensuring the welfare of its communities and maximising its profits. The sustainability plan of this government-owned company is based on three elements: prosperity (meeting everyone's needs with responsible and profitable delivery and providing outstanding customer service); people (inclusive action by fostering vibrant, inclusive communities; and ensuring that its extended workforce is provided with safe, fair, and fulfilling work); and the planet (acting in a way that ensures everyone thrives by reducing its environmental damage and facilitating a circular economy). This company has identified a number of SDGs, shown in Figure 2.3, relevant to different stages of its operations and value chain (Australia Post, 2020).

Woolworths: One of the largest privately owned food and grocery companies, Woolworths has implemented the SDGs. The company has divided its sustainability plan into three main areas: People, Planet, and Product. A connection has been made between each of the focus areas and the SDGs (Figure 2.4), and Woolworths has committed itself to achieve them by 2025 or 2050, depending on the goal. As an example, Woolworths is committed to achieving zero food waste ending up in landfills by 2025 to achieve SDG 2 (zero hunger). Similarly, to meet SDG 3 (good health and well-being), it plans to reach net positive carbon emissions by 2050 (Woolworths Group, 2020).

Although the purpose of this chapter is to provide an overview of solo concepts that are employed in the subsequent chapters, and they are not necessarily connected to each other, here it is discussed why each of them are incorporated in this research. These concepts and methods are employed to enhance the sustainability and efficiency of the LML. First, the hub covering problem, which optimises the distribution network at the strategic level, will be discussed in Section 2.3. This will be followed by an examination of the vehicle routing problem, which performs a similar function at the operational level in Section 2.4. Together, these two mathematical problems improve LML sustainability and efficiency. Aiming to build a decision support system, a last-mile stakeholder analysis is then conducted in Section 2.5 to identify the main LML stakeholders, who are subsequently considered as agents for the developed multi-agent system in Chapter 7. Lastly, to automate the decision-making process between agents and find the optimum policy that can satisfy agents' objectives, Q-learning, a type of reinforcement machine learning, is reviewed in Section 2.6.

2.3 Hub Covering Problem

This section investigates the principal studies on hub location problems (HLPs), particularly the uncapacitated single allocation hub covering problem (USAHCP). Later, MCCs and parcel lockers (PLs), two collaborative logistics facilities incorporated in this section to design a last-mile logistics (LML) distribution network, are reviewed.

Figure 2.4. Woolworths' sustainability plan based on SDGs.

2.3.1 Uncapacitated Single Allocation Hub Covering Problem

The HLP was first introduced in 1986 (O'Kelly, 1986), along with mathematical formulation and solution methods. Since then, the HLP has evolved over time, and a plethora of articles have been published, reflecting a notable upward trajectory. Initially, HLP research was mainly focused on modelling. For instance, Campbell (1994) presented a model that calculates the necessary number of hubs by taking into account the costs associated with hub establishment and transportation (Campbell, 1994b). HLP discussions gradually shifted to optimisation. As a counterpoint, Eiselt, et al. (2009) optimised hub locations using a heuristic concentration method in which first the Teitz and Bart algorithm was applied to limit the candidates' hubs, and then the problem was solved using either an exact method or an improvement heuristic (Eiselt & Marianov, 2009).

The current emphasis lies on utilising data to inform decisions, enabling enhanced accuracy and efficiency in decision-making processes. For example, Shahparvari et al. (2020) examined the geographical aspects of the HLP in decision-making by using multidimensional data at a country level (Shahparvari et al., 2020). They solved an HLP, which involved establishing a distribution centre for urban freight, by utilising a multi-method approach and developed a decision support tool that promoted transparency in freight decision-making. A hub-and-spoke framework was employed in another study to solve the location-allocation problem and optimise the number of bikes that need to be repositioned (Huang et al., 2020). The bike-sharing system's inefficiency was addressed through simulation and bootstrapping, as well as the use of real-world data. Hence, various types of HLP have been devised, one of which is the hub covering problem (HCP) (S. Alumur & Kara, 2008), which is the focus of this section.

The HCP refers to an optimisation problem that seeks to minimise the number of hubs selected while covering DPs within a specific distance from hubs (Kara & Tansel, 2003). In such a problem, each combination of origin and destination points is covered if the hubs are able to satisfy the constraints. The constraints may include covering all DPs while minimising costs or using a certain number of hubs to maximise flow coverage. A variety of HCPs are discussed in the literature, including ρ-hub covering location problem (Campbell, 1994a), ρ-hub maximal covering location problem (Silva & Cunha, 2017), and hub set covering location problem (Campbell, 1994a). These problems involve the allocation of DPs to single or multiple hubs, and the hubs' capacity can either be limited (capacitated) or unlimited (uncapacitated).

In this section, we focus on the uncapacitated single allocation hub covering problem (USAHCP). The USAHCP, itself, can be classified by several factors. Firstly, the number of hubs involved can be a fixed number (ρ-hub median), where the number of hubs is predetermined, or the number of hubs can be a decision variable. Secondly, the objective function may aim to minimise overall transportation costs or the maximum travel distance/time. Additionally, the problem structure can be deterministic with known parameters, or stochastic with uncertain variables (Nikokalam-Mozafar et al., 2014). Lastly, the network topology may be complete with direct links between all nodes, or incomplete with only certain direct links (Calık et al., 2009).

The USAHCP can be solved by heuristic (and meta-heuristic) or exact solutions. In practical applications, however, heuristics have demonstrated their effectiveness in achieving optimal or nearly optimal solutions faster than exact solutions (Zanjirani et al., 2013). As one of the earliest implementations of heuristic solutions in the real world, Ernst and Krishnamoorthy

(1998) developed a heuristic approach that employed the Floyd-Warshall algorithm to determine the shortest path. This approach was tested using postal delivery data from Australia Post and Civil Aeronautics Board datasets. Calık et al. (2009) developed a tabu-search-based heuristic approach for the USAHCP to determine optimal hub locations, establish hub links between selected hubs, and allocate non-hub nodes to hub nodes in Turkey. Another heuristic approach was developed by Markham and Doran (2015) by combining Teitz and Bart with Hillsman editing to minimise the total travel time between service hubs and DPs in Australia.

Another heuristic method known as genetic algorithms (GAs) are commonly utilised to address optimisation problems, especially HLPs. The GAs are intended to improve logistics and resource allocation by iteratively generating and evolving solutions. Ayough et al. (2022) solved the uncapacitated HCP by proposing novel mathematical formulations. They aimed to minimise total costs while covering all nodes within a certain radius. For solving the uncapacitated single allocation HLP, a robust GA was devised by Topcuoglu et al. (2005), wherein each chromosome was partitioned into two arrays, hubs and assignments. As another application of GA in USAHCP, queue estimation was taken into account while optimising hub locations and numbers (Hasanzadeh et al., 2018). Sadeghi et al. (2015) presented a spatial model for the HCP that aimed to minimise transportation costs while maximising flow. They assessed the quality of their results using the GA.

Some frequently used exact solutions include integer (linear) programming, mixed integer programming, and bender decomposition. However, since this section's focus is not on exact solutions, readers are directed to refer to Zanjirani et al. (2013) and S. A. Alumur et al. (2021) for further information.

2.3.2 Collaborative Logistics Hubs

Consolidation centres

Urban-consolidation centres (UCCs) are logistics facilities used for loading, unloading, sorting, storing, and delivering goods to customers. Several studies have evaluated the impact of UCCs on distribution networks. In one of the early studies on this type of hub, UCCs were used in London to transfer parcels from outer urban depots to these hubs and then deliver them to final customers in the inner urban areas via environmentally friendly vehicles (Browne et al., 2011). Recently, MCCs have been established with similar functions to UCCs but are smaller, not necessarily established for inner city distribution and tend to form a distribution network throughout metropolitan regions. The most significant advantage of a network of MCCs is improving distribution system efficiency. However, the cost of launching such a system can be high due to its capital and operational requirements (Kovač et al., 2021). To address this problem, one solution is to identify locations for MCCs that minimise the trip length between the MCCs and the DPs. This results in a reduction in travel time and improved distribution network efficiency. It is difficult, however, to find an appropriate location for consolidation centres due to the many factors that need to be taken into account, such as rising urban land costs, a lack of suitable facilities, varying demand, and city characteristics (Aljohani & Thompson, 2020; Rudolph et al., 2022). Minimising the travel distance between MCCs and DPs will reduce travel time and improve network efficiency.

MCCs contribute directly to the reduction of total costs, as well as external problems (noise and air pollution). That is because MCCs' location alters the types of vehicles used in the LML, reduces the VKT and consequently affects the level of GHG emissions. As well as dictating transport costs, they can affect both operational and rental costs, and this subsequently necessitates an evaluation of total costs for trade-offs between transport and facility costs. Nsamzinshuti et al. (2017) explored the implementation of MCCs in urban areas as a strategic solution to enhance distribution system efficiency, address the challenge of unsustainable distribution costs, enhance customer convenience, and mitigate issues related to traffic and environmental impact. By employing a fuzzy approach, Kovač et al. (2021) emphasised that an effective City Logistics concept for improving delivery efficiency and mitigating adverse environmental effects involved a two-tier distribution design utilising Mobile Charging Containers MCCs, which outperformed other initiatives. The socio-economic advantages of MCCs compared to direct delivery in Poznan were highlighted by Savchenko et al. (2022), while other research also highlighted MCCs' potential to enable smaller, cost-effective, and environmentally friendly vehicles for the LMD (Kaspi et al., 2022). Table 2.1 summarises the studies on MCCs, including their impact on environmental and financial costs.

An example of MCC implementation occurred in London by Transport for London, aimed at reducing the number of trips and efficiently managing multiple deliveries on-site (Transport for London, 2020). Through collective procurement, MCCs stored and consolidated goods before distributing them using low-impact vehicles. The Bentobox serves as another example of MCCs in Berlin and Lyon, introducing a flexible collection hub designed to handle packages and parcels (Quak et al., 2014). This initiative utilises cargo bikes for final delivery, showcasing an innovative approach to urban logistics. The conclusion drawn from this initiative is that MCCs represent a viable and transferable methodology for European cities, especially by focusing on light freights, such as parcels. Ecopostale in Brussels offers zero-emissions parcel deliveries using minivans, highlighting a sustainable approach to urban logistics (Ecopostale, 2024). In Germany, alternative delivery points utilise petrol stations as convenient delivery and pick-up locations (Janjevic et al., 2013). Furthermore, Chronocity in Strasbourg delivers parcels within inner urban areas by combining consolidation methods with the use of green vehicles. These examples showcase the diverse implementations of MCCs across different cities, emphasizing their versatility and potential for enhancing urban delivery systems (Janjevic et al., 2013).

Parcel lockers

E-commerce's rapid growth and the subsequent increase in parcel deliveries have posed significant challenges to traditional delivery methods. Parcel lockers (PLs) have emerged as a transformative solution in the LML, providing a secure and convenient method of parcel delivery and collection (Leung et al., 2023). PLs have the potential to improve customer convenience, increase delivery efficiency, and improve environmental sustainability. Therefore, PLs can benefit a wide range of stakeholders, including carriers, retailers, e-commerce enterprises, property management providers, and locker system companies (Rohmer & Gendron, 2020).

Table 2.1. Micro-consolidation centre literature

Year	Reference	Findings	Env. Cost*	Fin. Cost**
2017	(Nsamzinshuti et al., 2017)	In the Brussels-Capital Region, MCCs can significantly reduce wholesale distributor transportation costs and congestion.	✓	✓
2021	(Kovač et al., 2021)	The most effective concept for improving LML efficiency is a two-echelon system with MCCs.	✓	
2022	(Savchenko et al., 2022)	MCCs were more socioeconomically advantageous than direct delivery in Poznan.		✓
2022	(Rudolph et al., 2022)	In Stuttgart, MCCs have been used to facilitate the use of environmentally friendly vehicles.	✓	
2022	(Kaspi et al., 2022)	MCCs enabled smaller, cost-effective, and eco-friendly vehicles, but they led to complexities in planning and operations.	✓	✓
2022	(Arrieta-Prieto et al., 2022)	The implementation of MCCs in Manhattan resulted in reduced service time and pollution, as indicated by simulation results.	✓	
2022	(Tadić et al., 2022)	The reduction of adverse effects of goods movement was addressed by the combination of MCCs and autonomous vehicles in the LML.	✓	

* Environmental cost

** Financial cost

Entities such as property management providers and locker system companies offer PLs' services to many firms concurrently, thereby establishing a shared delivery network. Such a shared and collaborative network facilitates and promotes environmentally friendly transport (Enthoven et al., 2020). As an example, Pan et al. (2021) designed a PL network, as an uncapacitated HLP, to maximise overall profit, involving the optimal selection of facility numbers, locations, and sizes. They concluded that PLs reduced City Logistics flows, provided consolidation opportunities, minimised failed deliveries, decreased the number of vehicles, and achieved cost savings compared to regular home delivery. Leung et al. (2023) evaluated the effectiveness of PLs using real-world data in Australia. It was discovered that PLs were more popular in dense urban areas, during the weekdays, and among commuters.

PLs provide 24/7 service, which makes them a vital component of last-mile delivery (LMD) (Lachapelle et al., 2018; van Duin et al., 2020), which allows them to reduce inefficiencies and ultimately enhance customer satisfaction (Lim et al., 2018). While PLs' flexibility has resulted in various applications from collection and delivery points in B2C (Enthoven et al., 2020) to transfer points in business-to-business (Thompson et al., 2019), the current literature lacks studies that evaluate the combination of MCCs and PLs to address the LMD. In such a network, by establishing MCCs in strategic locations, online purchases can be consolidated and delivered to PLs within walking distance of customers in a streamlined way.

2.4 Vehicle Routing Problem (VRP)

This section provides an overview of the literature addressing green and collaborative vehicle routing problems. Finally, we review solution methodologies, particularly for multi-depot vehicle routing problems.

2.4.1 Green Vehicle Routing Problem (GVRP)

The GVRP is a pivotal focus within transportation and logistics management. Bektaş and Laporte (2011) were two of the first researchers to explore the pollution routing problem, examining vehicle efficiency factors such as VKT, GHG emissions or fuel usage, and travel time. Since then, GVRP has evolved, exploring features such as time window (Ganji et al., 2020), electric VRP (A. Kumar et al., 2023), pick-up and delivery (Olgun et al., 2021), and waste collection (Erdem, 2022). Numerous researchers have focused on devising more realistic emissions models, incorporating road and vehicle conditions into the model. For example, You (2022) reduced CO_2 emissions by incorporating road slope and real-time traffic into their VRP. In a recent study, a metaheuristic algorithm was developed to minimise energy consumption in rural last-mile delivery, involving trucks and drones collaboration (Xiao et al., 2024). However, these studies mainly assess costs related to emissions or fuel consumption, overlooking the quantity of CO_2 emissions. Moreover, they consider fuel consumption as a macroscopic model, that correlated the emissions to the travel distance and lacked accuracy.

Employing microscopic models is a viable approach to accurately calculate fuel consumption. The Comprehensive Modal Emission Model (CMEM) is a microscopic real-time CO_2 emissions estimating approach, demonstrating its effectiveness in estimating emissions for a range of vehicles (Demir et al., 2014). Although CMEM offers a precise approach for estimating emissions in GVRP, its adoption is constrained by computational costs, rendering its applications infrequent in GVRP. In Chapter 6, we will elaborate on CMEM.

While widespread adoption is still evolving, CMEM demonstrates potential in various GVRP applications, such as the study in which Kancharla and Ramadurai (2018) contemplated the load, speed, and acceleration of vehicles to optimise fuel efficiency by employing the CMEM in their model. Guo et al., (2022) devised a time-dependent GVRP for cold chain logistics, seeking to minimise total costs, covering transportation, refrigeration, and carbon emissions, with the emissions estimated via CMEM. In other research, to evaluate the effectiveness of open GVRP compared to a traditional DN in emission reduction, Niu et al., (2018) deployed CMEM in their model to estimate fuel consumption and based on that calculate the CO_2 emissions cost. Hong et al., (2023) included CMEM as part of their proposed waste collection logistics network, thereby minimising total travel costs and GHG emissions. In this way the environmental benefits of such systems are showcased.

The existing GVRP research predominantly centres on cost-related aspects of CO_2 emissions, employing macroscopic models. This study addresses this limitation by utilising the precise CMEM model to directly minimise the overall quantity of CO_2 emissions.

2.4.2 Collaborative Vehicle Routing Problem (CVRP)

Within the CVRP, multiple logistics providers collaborate horizontally to optimise the transportation of goods. The diverse particulars involved in the CVRP have led to various classifications, including centralised, decentralised, and auction-based decentralised models (Gansterer & Hartl, 2018). Zhang et al., (2022) addressed the collaborative heterogeneous MDVRP, emphasising product trans-shipment between vehicles from diverse depots. While they assessed the influence of the cost savings allocation mechanism on individual depots' collaboration incentives, they did not evaluate the impact of collaboration on emissions. In a more recent study, the last-mile express parcel distribution problem, including express packaging recycling, was modelled as a collaborative location and vehicle routing problem (VRP) with pick-up and delivery (Shi et al., 2023). However, their bi-objective solution method concentrated on optimising vehicle efficiency and cost savings rather than emissions-related aspects. Order sharing was identified as a fundamental approach to road transportation planning. Trucker collaboration addressed emissions caused by empty truck trips (Schulte et al., 2017). In their study, to minimise emissions and costs, a centralised collaborative model was introduced within a truck appointment system and solved as a traveling salesman problem.

Friedrich and Elbert (2022) explored VRP linked to City Logistics involving third-party trans-shipment facilities, e.g., UCCs. A heuristic method was employed to reduce the overall cost. However, they did not examine the impact of collaboration on the environmental aspects of the goods transportation. Although efforts have been made to explore emissions reduction in a collaborative network, the scope has been restricted to employing a simplified linear function for computing CO_2 emissions (Hacardiaux & Tancrez, 2020; Ouhader & EL kyal, 2023). For instance, Aloui et al., (2021) devised a collaborative two-echelon inventory, location, and routing problem to tackle sustainability issues in the network. However, they utilised a simplified linear approach that directly associates emissions with the VKT. Currently, there is a lack of studies evaluating the impact of a collaborative DN on CO_2 emissions using microscopic models.

2.4.3 MDVRP Solution Methodologies

Diverse single-based algorithms have been used to solve MDVRP, such as tabu search (TS), greedy randomised adaptive search, variable neighbourhood search, guided local search, and iterated local search (Blum & Roli, 2003). However, hybrid algorithms are currently widely used to solve the MDVRP. Firstly, this is due to their nature which involves the decomposition of the MDVRP to sub-problems, construction, and improvement (Ho et al., 2008). Additionally, this interest stems from the opportunity to harness the strengths of various algorithms.

As an example of hybrid solutions, Tu et al. (2014) developed a bi-level approach, consisting of the Voronoi diagram and SA, to restrict the scope of local search, by limiting customer reallocation between depots and reorganising customers within the routes of each depot. In their work, Chaabani et al. (2018) developed a new co-evolutionary decomposition algorithm, inspired by the chemical reaction optimisation algorithm, to address combinatorial bi-level optimisation problems, particularly bi-level MDVRP, achieving superior performance in terms of effectiveness and efficiency compared to previous methods. Escobar et al. (2014) used a two-level heuristic method in which the initial solution was found and then improved using TS. A multi-level composite heuristic was proposed by Hong et al. (2023). In their method’s first part, all feasible solutions were constructed using column generation, and in the following steps, they optimised routes employing adaptive large neighbourhood search. In another recent study, a self-adaptive tracing and tracking algorithm was developed in which first, a geographic information system module generated feasible routes and then the VRP was solved by ant colony optimisation (Nagarajan et al., 2022).

The IWD is a swarm intelligence-based algorithm used to solve combinatorial optimisation problems by mimicking water drops' behaviour (Shah-Hosseini, 2007). Several agents are simulated based on natural water drop movement and their interaction with riverbed soils to construct an ideal solution to achieve the shortest path between upriver and downriver. The IWD's velocity and the soil they carry are crucial agent characteristics. These values can change as agents interact with the environment to find the optimum solution. Due to IWD’s cooperative feature enabling agents to share their search knowledge with each other as well as its robustness to memorise the search history and consequently reduce iterations, it is widely applied to solve optimisation problems such as path planning in mobile robotics scenarios (Salmanpour et al., 2017), project scheduling (Alabajee et al., 2021), knapsack and the n-queen puzzle (Shah-Hosseini, 2008), and web service composition (Acharya & Singh, 2018).

Although more than 72% of VRP are solved utilising metaheuristic methods (Jaegere et al., 2014) and the IWD algorithm is powerful in dealing with optimisation problems, only a few studies have examined its application in the VRP (G. Chen et al., 2020). Among them, some can be categorised as VRP (Kamkar et al., 2010), GVRP with time windows (Tan et al., 2019), and the capacitated VRP (Contardo & Martinelli, 2014). Among the rare applications of IWD in the MDVRP, Samsuddin et al. (2020) applied IWD to Cordeau's benchmark and concluded that IWD was superior to ant colony optimisation (ACO). Despite the limited exploration of IWD in the context of MDVRP, it is a fitting choice for optimising MDVRP. This is due to: a) its swarm-based nature, mirroring the multiple-depot structure of MDVRP, b) the adaptive learning feature which allows water drops to adjust routes based on desirable solutions, facilitating convergence towards the optimal solution, and c) the stochasticity existing in IWD which helps overcome local optima, a prevalent challenge in MDVRP. This is achieved by injecting a random element that assists in exploring more possible solutions.

The SA algorithm, introduced by Kirkpatrick et al. (1983), is based on the annealing process utilised in the metalwork industry. The SA employs a stochastic approach to find new solutions. To accomplish this, neighbourhood solutions are defined, and the algorithm can be switched between them. Moving to a better neighbourhood with a higher fitness value is always accepted. However, a probability function is used to accept moving to a worse neighbourhood, thereby preventing the algorithm from sticking to a local minimum solution. Ting and Chen (2008) utilised a hybrid approach of combining SA with ACO to solve the MDVRP with time windows. Their study found that this approach led to improvements in solution accuracy and computational time. Furthermore, Peng et al. (2009) combined SA with genetic algorithm (GA) and TS to develop a hybrid solution for the MDVRP. Their algorithm functioned well for this problem, particularly when the scale of the network was large. In a more recent study, Yuan et al. (2022) hybridised SA with an artificial fish swarm algorithm. They used an adaptive visual strategy, dynamically adjusting the algorithm's visual range based on the current solution quality, ensuring effective and precise search.

In related work, two hybrid metaheuristics incorporated SA into the IWD algorithm were adopted for solving the MDVRP (Ezugwu et al., 2018). These algorithms improve the basic IWD's local search, preventing it from getting stuck in local minima. However, they lack the ability to adapt their search strategy to specific problem characteristics, reducing robustness and efficiency.

The primary gap identified, involving the lack of studies assessing the collaboration impact on VKT and CO_2 emissions, stands out as one of the challenges acknowledged by logistics carriers and government agencies (Department of Climate Change, Energy, the Environment and Water 2024; Hyperconnected Europe, 2022). Addressing the identified gaps in our knowledge can advance the understanding and application of optimisation algorithms in collaborative and green logistics. This is made possible by devising a model that incorporates a realistic collaboration procedure among stakeholders while accurately calculating CO_2 emissions. This combined model employs multi-objective optimisation to assess the holistic sustainability of collaborative logistics solutions, balancing environmental sustainability with other transportation objectives, such as the financial aspect, by finding trade-offs between them. Another solution involves integrating various levels of collaboration metrics into the optimisation framework, making it possible to measure efficiency gains and VKT reductions achieved through collaborative logistics networks. Finally, collecting real-time tracking of vehicle movements and emissions helps to create a more accurate emissions model.

2.5 Last-mile Stakeholders Analysis

A systematic literature review was conducted to identify the stakeholders engaged in the LML. This review involved meticulously examining the various stakeholders of the last mile, identifying their respective objectives, mapping out their interconnections, and establishing links to sustainability domains. This process involves a methodical and structured approach to gathering, evaluating, and synthesising existing research on LML's stakeholders and aims to provide a comprehensive and unbiased summary of the current state of knowledge in the last-mile.

In this investigation, to address research query 3, we first searched for pertinent papers using two extensive academic search platforms - Scopus and Web of Science. Next, we used EndNote software to remove any duplicate entries, and then we excluded irrelevant papers based on title screening. Finally, we screened the abstracts and full texts to identify papers that included at least one stakeholder in LML. Figure 2.5 illustrates the steps involved in conducting the literature review.

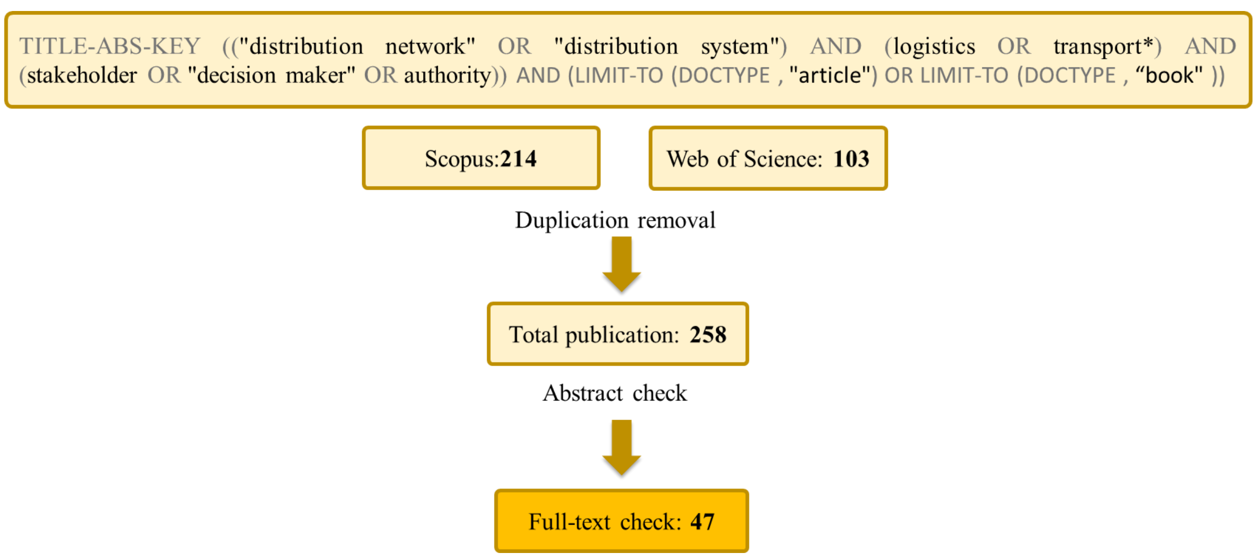


Figure 2.5. The process of collecting and extracting data

2.5.1 Stakeholders Identification

In pursuit of the primary objectives of this section, an examination of publications has been undertaken to identify the key stakeholders in the LML, their principal objectives, and their interconnectedness with sustainability across economic, social, and environmental dimensions. Within the LML context, five key stakeholders have been discerned: residents, customers, carriers, shippers, and government. It is important to note that various terminologies are employed in the literature; for instance, "carriers" and "freight forwarders" are used interchangeably, as are "residents" and "citizens". In such cases, preference is given to the terminology most suited to the LML and e-commerce market.

Throughout the literature review, a discernible trend towards the adoption of "collaborative", "corporative", or "open and shared" types of distribution networks and logistics facilities has been observed. In order to encapsulate this trend in our study, reference has been made to the Physical Internet (PI), as elucidated in Chapter 1, which is adept at facilitating such collaborative networks. Consequently, a new stakeholder has been introduced to the distribution network, referred to as PI-Managers. This stakeholder is primarily tasked with coordinating shared logistics resources. According to the literature, their objectives include optimising the utilisation of containers, vehicles, and hubs, whilst concurrently enhancing the security and traceability of goods movement. Table 2.2 summarises the stakeholders' objectives.

Table 2.2. Last-mile logistics key stakeholders and their objectives.

Stakeholders	Objectives
Residents	To have minimum noise pollution To have minimum air pollution and GHG emissions To have minimum traffic congestion To have maximum safety To have maximum employment rate
Customers	To receive deliveries in maximum quality/ convenient delivery (punctuality, security, time, location) To receive deliveries at the lowest price
Carriers	To increase shippers' satisfaction To increase profitability (minimising costs, maximising loading factors, optimum fleet size and frequency, minimising failed delivery) To maximise delivery quality (lead time and security)
Shippers	To increase customers' satisfaction (more delivery options) To maximise profit (minimise (transportation costs, minimise inventory costs, increase willingness to purchase) To improve customers' shopping behaviour (increase number of items per order, decrease number of returned parcels)
PI-Managers	To optimise the usage of transportation containers, vehicles, and facilities To maximise transportation security and trackability
Governments	To reduce traffic congestion To reduce noise pollution To reduce air pollution and GHG emissions To maximise employment rate To improve sustainability and efficiency

Furthermore, through the review process, the decisions within the purview of each stakeholder have been delineated and categorised into three levels: strategic (S), tactical (T), and operational (O). A total of 18 strategic decisions, 7 tactical decisions, and 3 operational decisions have been identified. The specifics of these decisions are detailed in Appendix A.

At each level, it is specified which stakeholders are responsible for making these decisions and which stakeholders are affected by them.

To enrich this analysis, decisions have been aligned with three key sustainability aspects: economic, social, and environmental. The diagram depicted in Figure 2.6 shows all identified and introduced stakeholders alongside the sustainability domains. The colour scheme of the decisions denotes which stakeholder holds authority over them. For instance, the colour of decision T4, allowed externalities, including emissions and noise, corresponds to governments, indicating their involvement in decision T4. Furthermore, in Figure 2.6, the placement of each decision indicates both the stakeholders influenced and the sustainability domains involved. For instance, based on the location of T4, residents are affected by both social and environmental perspectives, whereas carriers and PI-Managers are influenced from an economic standpoint.

Ultimately, by delineating stakeholders' objectives and their interplay with others through identified decisions, a cohesive connection between them is established. This outcome is depicted in Figure 2.7. Furthermore, this figure illustrates the primary sustainability domain(s) associated with each stakeholder based on their decision categories. This connection between stakeholders, is later used in Chapter 7 to design an intelligent multi-agent decision support system.

2.6 Machine learning

Reinforcement Learning (RL) is a computational method for addressing sequential decision-making challenges. In each decision step, the RL controller determines an appropriate action using a policy function based on the current state estimated by a value function, aiming to maximise the obtained rewards (Islam, 2017). To structure such decision-making problems, RL frameworks are often built upon Markov Decision Processes (MDPs). In an MDP, a policy function determines the allowable actions at each decision point, depending on the current state. MDP is to find an optimal policy function that maximises the total expected rewards accumulated over time. A key characteristic of an MDP is that, given the current state, the system's future state is independent of past states. Another fundamental aspect integrated into MDP is the discount factor, which determines the value of rewards for the future state.

Achieving an exact solution for the MDP is frequently unfeasible and computationally challenging (Bertsekas, 2019), prompting the exploration of various approaches to solving MDP through approximation techniques. Two primary types of approximations are prevalent: value-based and policy-based. In value-based approximation, such as Q-learning or deep Q-networks (Tampuu et al., 2017), the current state's value function is estimated using an alternative function. Conversely, policy-based approximation, such as proximal policy optimisation and advantage actor-critic (H. Zhang et al., 2020), presents an alternative method for tackling MDPs, where an approximation is applied to the policy function rather than the value function.

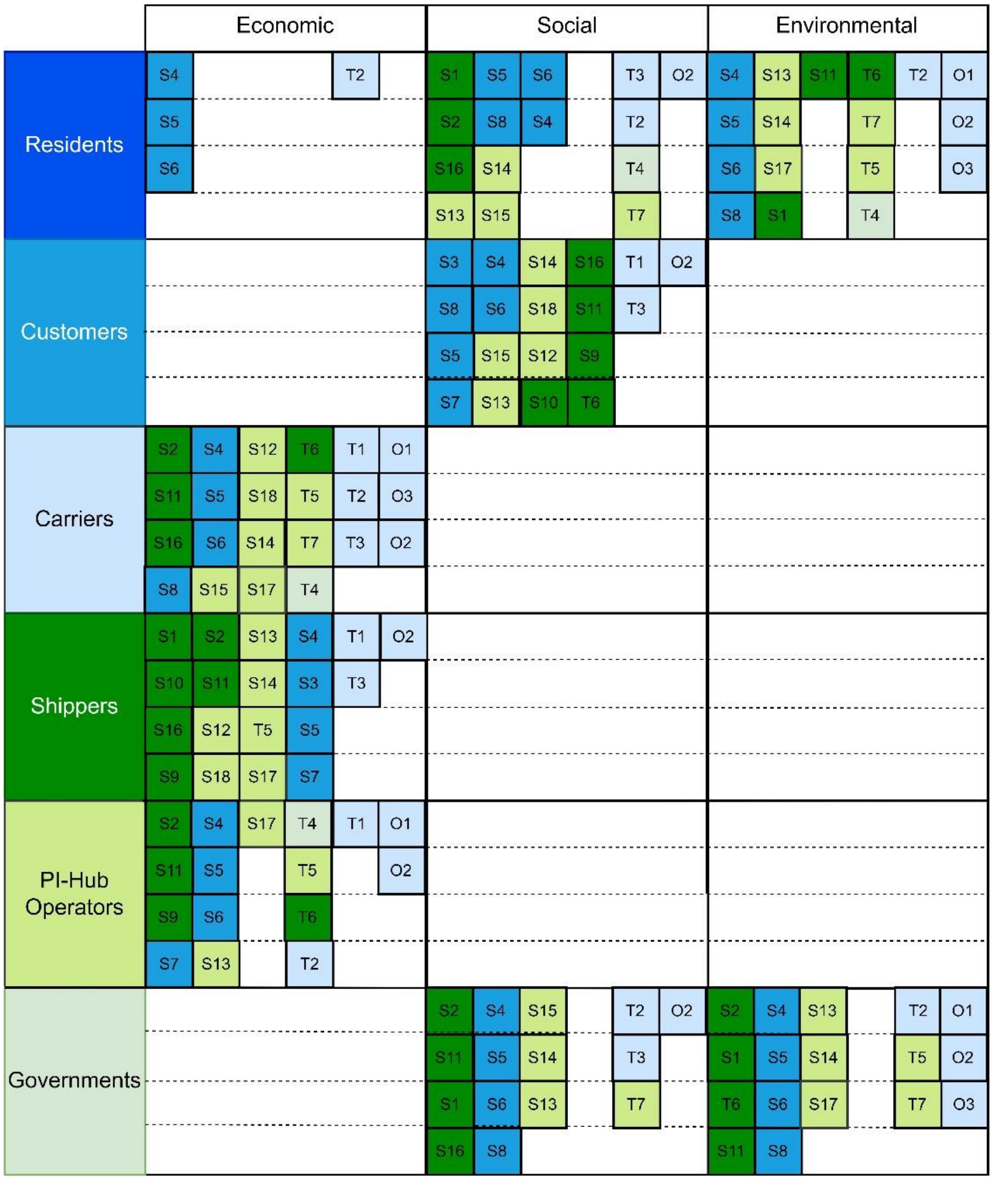


Figure 2.6. Last-mile logistics stakeholders and their decisions alongside other stakeholders and sustainability domains, categorised as S (strategic), T (tactical), and O (operational).

Whether employing a value-based or policy-based approximation, an RL framework can be realised through either a model-based or model-free approach (Kober et al., 2013). In a model-based implementation, it is presumed that the inherent state transition and its probability distribution can be described using explicit functions or models. Conversely, in a model-free implementation, state transition and expected reward values are determined through Monte Carlo simulations, devoid of an explicit mathematical model. Typically, model-based algorithms entail higher computational costs but exhibit superior performance in exploration. Readers are encouraged to refer to Yan et al.'s (2022) study for a deeper exploration of RL categorisations.

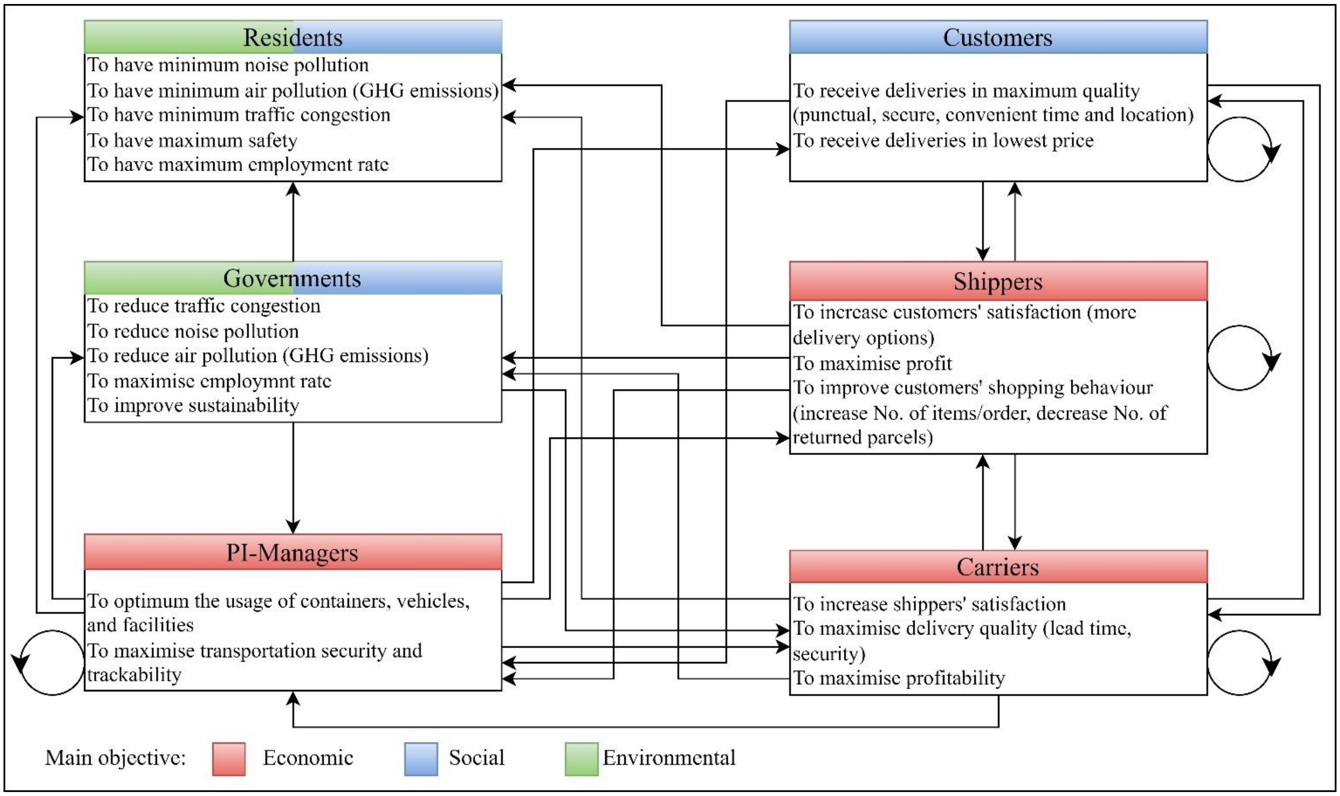


Figure 2.7. Last-mile logistics key stakeholders, their main objectives, and the interconnections.

In the domain of transportation and logistics, system states typically encompass vehicle statuses, customer demands and locations, time constraints, and inventory levels. Meanwhile, actions may involve determining vehicle routes, order quantities, or delivery service pricing. Rewards are associated with generated profits, distance travelled, energy consumption, or other performance metrics. The advancement and utilisation of RL holds significant potential in shaping the future of intelligent logistics and supply chain systems.

As identified in Section 2.5, there are multiple stakeholders, agents, in the LML. Hence, in this section we focus on multi-agent systems (MASs). MASs, a subfield of artificial intelligence (AI), aim to offer principles for constructing complex systems involving multiple agents. These systems have garnered significant attention due to their capacity to model and address intricate real-world challenges. MAS Q-learning, which merges Q-learning with multiple agents operating within a shared environment (Xu et al., 2020), is employed in this thesis. In MAS Q-learning, agents not only learn their own Q-values, representing expected future rewards for their actions but also need to account for the actions and rewards of other agents to make optimal decisions. This raises complexities such as agent cooperation, competition, and coordination.

In a recent study, a multi-agent Q-learning-based algorithm with curriculum learning and transfer learning to perform path planning in a warehouse logistics scenario is proposed, demonstrating high success rates of up to 94% after training, with applications in disaster management, surveillance, object transportation, and search-and-rescue (I. R. L. de Oliveira et al., 2023). In another study, MAS Q-learning is employed in the logistics sector, specifically focusing on optimising recharging schedules for automated guided vehicles in container terminals (Stephen et al., 2020). Within port logistics, an MAs Q-learning is introduced to optimise inter-terminal transportation planning, emphasising the reduction of empty-truck trips and enhancing computational efficiency compared to a previous single-agent model (Adi et al., 2020).

2.7 Chapter Summary

To improve efficiency in distribution networks at the strategic level, we examined the uncapacitated single allocation hub covering problem (USAHCP) within the context of last-mile logistics (LML). The USAHCP, a specific type of HLP, is evaluated in this chapter, taking into account various factors such as the number of hubs, objective functions, network topology, and solution methods. Recent studies have prioritised leveraging data for decision-making processes, leading to heightened accuracy and efficiency. Various solution methodologies for addressing HCP were explored, encompassing heuristic methods such as genetic algorithms alongside exact solutions like integer programming and bender decomposition. Furthermore, the incorporation of micro-consolidation centres (MCCs) and parcel lockers (PLs) as collaborative logistics facilities in designing LML distribution networks is explored.

We conducted a thorough review of the literature on the green vehicle routing problem (GVRP) and collaborative vehicle routing problem (CVRP). The evolution of the green vehicle routing problem (GVRP) was reviewed, with emphasis placed on the importance of employing microscopic models like the Comprehensive Modal Emission Model (CMEM) for more accurate emissions estimation, since emissions-related costs are primarily assessed using macroscopic models in existing studies. The potential of CMEM in various GVRP applications was demonstrated, showcasing its effectiveness in optimising fuel efficiency and minimising GHG emissions.

Similarly, within the CVRP domain, various collaborative models and solution methodologies were discussed, underscoring the need for a more comprehensive evaluation of the environmental impact of collaboration on emissions reduction. Furthermore, we explored solution methodologies for the Multi-Depot Vehicle Routing Problem (MDVRP), highlighting the advantages of hybrid algorithms such as the Improved Water Drops (IWD) algorithm and Simulated Annealing (SA) algorithm in addressing complex optimisation challenges. Despite the progress that has been made, the primary gap identified in the literature remains the lack of studies evaluating the collaborative impact on vehicle kilometres travelled (VKT) and CO_2 emissions, indicating a critical area for future research.

Addressing this gap could significantly advance the understanding and application of optimisation algorithms in collaborative and green logistics, ultimately contributing to more sustainable transportation practices.

The systematic literature review then conducted aimed to comprehensively identify and analyse the stakeholders involved in the LML. Through meticulous examination, the key stakeholders—residents, customers, carriers, shippers, and government—were identified, along with their respective objectives and interconnections within sustainability domains. Additionally, the emerging trend towards collaborative distribution networks and logistics facilities was highlighted, leading to the introduction of a new stakeholder: PI-Managers, coordinating shared logistics resources. Through categorising decisions into strategic, tactical, and operational levels and aligning them with economic, social, and environmental sustainability aspects, a comprehensive understanding of stakeholder interactions and their implications on sustainability was achieved. This holistic analysis lays the groundwork for developing an intelligent multi-agent decision support system in Chapter 7, facilitating informed decision-making in the LML context.

Chapter 3: The Integrated Methodology

A B S T R A C T:

This chapter provides an integrated methodology adapted from Operations Research (OR). OR is selected due to its systematic approach to addressing operational challenges within complex systems, offering decision-makers structured optimisation methods and mathematical problem-solving techniques that effectively optimise resource allocation, enhance efficiency, and minimise costs, ultimately leading to improved overall performance. The integrated methodology includes six steps: problem identification, mathematical formulation, solution methodology, model evaluation, decision support system, and implementation in a case study.

3.1 Introduction to Operations Research

According to the aim of this study, which focuses on developing a decision support system (DSS) to design a novel urban last-mile distribution network and optimise the network at strategic and operational levels, a methodology is adopted based on Operations Research (OR). OR aims to offer decision-makers a systematic approach to addressing operational challenges within a system, ultimately providing solutions that serve the organisation's best interests (Gupta, 1992). OR involves applying mathematical problem-solving techniques and methods to analyse complex systems. It offers a structured approach to optimising complex systems based on predetermined criteria, providing valuable support to decision-makers. As outlined by Shukla et al., (2017) and Sivazlian, (2008), OR serves as a powerful tool for tackling intricate problems in various domains.

The OR methodology typically consists of five to seven steps (Gupta, 1992; Morse et al., 2003), but for this study, we have crafted a six-step process, which will be elaborated on in Section 3.2.

3.2 The Integrated Methodology

This section explains the integrated methodology designed for this thesis including the following steps: problem identification, mathematical formulation, solution methodology, model evaluation, decision support system, and implementation of the models in a case study. These steps are illustrated in Figure 3.1.

3.2.1 Problem Identification

In problem identification, a pivotal first step entails delving into scholarly resources to lay the groundwork for the study. Once this foundation is laid, homing in on a specific area of interest refines the scope, fostering clarity and accuracy in the investigation. This focused approach naturally prompts the formulation of research questions, guiding the inquiry process with precision. Key to this progression is crafting a well-defined problem statement, succinctly capturing the essence of the issue or obstacle in question. With an articulated problem, the research's objective becomes apparent, outlining the overarching goal.

Essential data and resources for the next phases of the project are identified. Then unsustainable trends in the LML are identified, ensuring the long-term viability of the designed network. A systemic literature review of last-mile stakeholders is conducted to enhance comprehension of the network and provide insights into the system interactions.

3.2.2 Mathematical Formulation

Developing mathematical formulations begins with an exploration of the nature of the required modelling, which involves understanding the intricacies and dynamics of the LML to devise appropriate mathematical representations. Defining performance measures establishes criteria for evaluating the effectiveness and efficiency of the models, with a primary focus on VKT and CO_2 emissions. Identifying quantifiable decisions involves pinpointing specific actions or choices that can be expressed numerically in the models. This process also entails identifying variables and parameters, which are essential elements in formulating objective functions and constraint equations.

The first principal developed model addresses strategic issues. For this purpose, the uncapacitated single allocation hub covering problem (USAHCP) is developed to minimise the number of hubs in the system while maximising the coverage area. At the operational level, a collaborative multi-depot green vehicle routing problem (CMDGVRP) is formulated, focusing on sustainable routing solutions across multiple depots. Finally, the third modelling procedure explores an intelligent multi-agent system, leveraging agent interactions for complex decision-making scenarios and integrating elements from the USAHCP and CMDGVRP. Each model presents unique challenges and opportunities, reflecting diverse aspects of real-world optimisation problems.

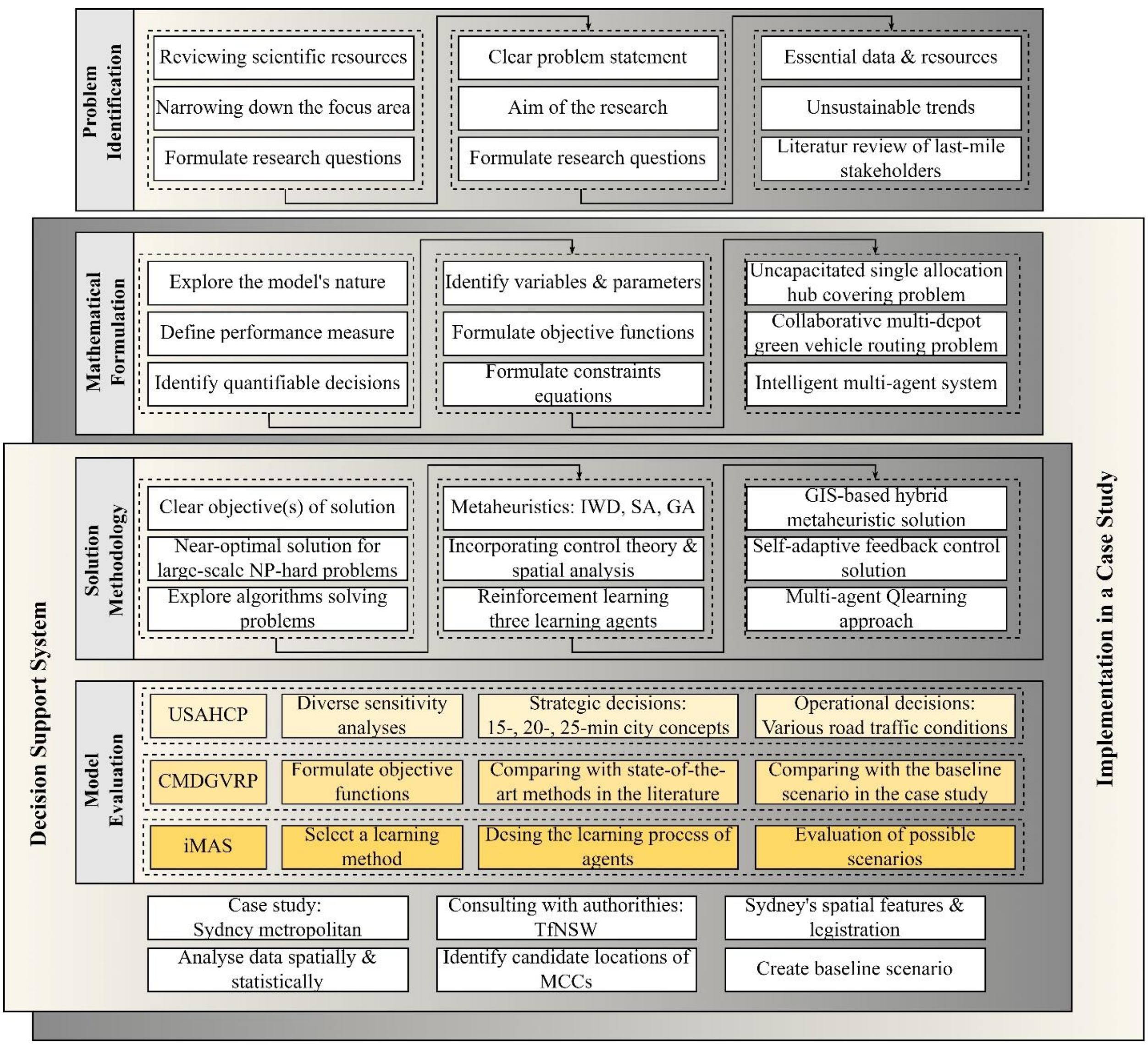


Figure 3.1. The integrated methodology

3.2.3 Solution Methodology

The solution methodology step is one of the pivotal parts of the OR, ensuring novelty and quality results. The solution's objectives are clearly defined: to achieve near-optimal solutions for large-scale NP-hard problems. For this purpose, various metaheuristics algorithms are explored, such as the intelligent water drop (IWD), simulated annealing (SA), and genetic algorithm (GA), each tailored to address specific challenges within the problem domain. The incorporation of control theory and spatial analysis enhances the solution methodology, offering insights into system dynamics and spatial interactions. Additionally, reinforcement learning is utilised, employing three learning agents to enhance adaptability and decision-making capabilities. The integration of GIS-based hybrid metaheuristics provides a comprehensive approach, merging geographical information systems with metaheuristic techniques for enhanced optimisation. Lastly, a multi-agent Q-learning approach further enhances the solution's effectiveness by promoting collaborative learning and decision-making among multiple agents. Collectively, these components establish a vigorous framework for efficiently and effectively addressing complex optimisation problems.

3.2.4 Model Evaluation

In this step, the three primary models are developed and evaluated based on the nature of the study. Each problem domain presents unique challenges and opportunities, with specific objectives tailored to address them effectively. For the uncapacitated single allocation hub covering problem, the focus lies on conducting diverse sensitivity analyses to understand the system's robustness. Strategic decisions involve evaluating the accessibility of the 15-minute, 20-minute, and 25-minute city concepts. Operational decisions are influenced by various road traffic conditions at different times of the day, shaping the practical implementation of solutions.

In the collaborative multi-depot green vehicle routing problem, the aim includes formulating objective functions to minimise VKT and CO_2 emissions. Furthermore, the results are compared with state-of-the-art methods from the literature and baseline scenarios in the case study, providing a benchmark for performance evaluation. Regarding the realm of the intelligent multi-agent system, key tasks involve selecting an appropriate learning method and designing the learning process for agents. Additionally, evaluating possible scenarios helps to assess the system's adaptability and effectiveness in a wide range of environments.

3.2.5 Decision Support System

In developing the decision support system the entire component of steps 3 and 4 are utilised. Then, selecting the case study area involves choosing the Sydney metropolitan area due to its complexity and significance. Secondly, analysing data spatially and statistically is crucial for understanding the spatial features and legislative aspects of Sydney. Next, consulting with government authorities, such as Transport for New South Wales (TFNSW), provides important insights into regulations and stakeholder requirements. Subsequently, identifying candidate locations for micro-consolidation centres (MCCs) involves strategic spatial analysis. Lastly, creating a baseline scenario establishes a reference point for evaluating the effectiveness of proposed solutions.

3.2.6 Implementation in a Case study

The final step involves applying the developed models and solution methodologies in a case study to evaluate their performance in the real world. Consequently, this step encompasses mathematical formulation, solution methodology, model evaluation, and development of the decision support system (steps 2 to 5).

Chapter 4: The Impact of the COVID-19 Pandemic on Last-mile E-commerce

A B S T R A C T:

The COVID-19 pandemic has altered the distribution patterns of goods for both Business-to-Business (B2B) and Business-to-Customer (B2C) segments. This chapter examines how the COVID-19 pandemic affected B2B and B2C parcel delivery in the Sydney metropolitan area. Initially, the spatial pattern of parcel delivery in 2020 was compared with that of 2019 (before the pandemic) using ArcGIS software. Based on this analysis, a significant reduction in parcel and freight deliveries to the central business district (CBD) occurred during the lockdown, while the inner and outer metropolitan areas experienced higher demand for parcel deliveries. After identifying metropolitan areas with significant shifts in demand, we identified the key factors that influence parcel delivery patterns. These changes are correlated with employment, internet access, and population factors. The results suggest a more decentralised demand for e-commerce and parcel delivery across the Sydney metropolitan area, posing challenges for traditional last-mile logistics models. This analysis will support logistics stakeholders in their future work involving mitigation and disaster preparedness actions designed to overcome the effects of pandemics.

4.1 Introduction

The ongoing outbreak of the new coronavirus disease (COVID-19), which commenced in December 2019, has vastly affected not only human health but also wide-ranging social and economic activities. The adverse impact of the pandemic on the world economy is comparable to the global financial crisis of 2008–09 or could be even worse (Loayza & Pennings, 2020). The pandemic has been affecting many sectors such as manufacturing operations, global supply chains and logistics, as well as the automotive sector and tourism industry (S. Singh et al., 2021).

In Australia, the COVID-19 pandemic has infected more than 30,000 people and killed 910 persons as of July 2nd, 2021 (Australian Government, 2021). The situation has led to implementing new rules, such as social distancing, lockdowns, self-isolation, closure of many stores, and an exponential increase in the number of people working from home (WFH). The new practice has caused a surge in the number of home deliveries and significantly changed the spatial pattern of freight distribution in the metropolitan area.

Kiba-Janiak et al. (2021) investigated the impact of the pandemic on e-commerce and e-customers' behaviour in Brazil and Poland. They reported that both countries experienced a drastic increase in the number of home deliveries after the pandemic occurred. By applying a multidimensional statistical analysis, they concluded that the increase in parcel demand could enhance sustainability while at the same time cause some minor environmental problems (Kiba-Janiak et al., 2021). As another example, it has been observed that North America and Europe have experienced a 100% and 50% increase in online orders during the last year, respectively (Gulc, 2021). Although the pandemic has affected the volume of deliveries, its impact has been different for Business to Business (B2B) and Business to Customer (B2C) couriers.

4.1.1 Characteristics of B2B and B2C Sectors

Major differences exist between the structure of B2B and B2C sectors. Buyers and sellers in the B2B environment are both companies and act as partners with a regular plan for shopping (Du et al., 2005; V. Kumar & Reinartz, 2018). Therefore, their demand is more consistent (Du et al., 2005). On the other hand, the demand in the B2C market is instantaneous, and the number of its transactions is more than B2B's (Du et al., 2005; Glynn & Woodside, 2012). Hence, the B2C sector possesses the potential to be more affected by different events and is less predictable than B2B in the normal situation. For instance, during Christmas or Mothers' Day, the demand for B2C can fluctuate dramatically (Becerril-arreola 2013).

The differences in the structure of B2B and B2C sectors trigger the diverse responses to the pandemic. For instance, while B2C increased more than 400% in Sweden and reached 50% of total deliveries, at the same time, B2B has declined by about 25% (AIT, 2020). Similarly, in Poland B2B shipments were 18.7% of total deliveries in 2020, while B2C e-commerce reached 76% (Gulc, 2021). As the impacts of COVID-19 differ from one location to another, this chapter aims to investigate how the pandemic affects the pattern of parcel deliveries in B2B and B2C sectors in Sydney, Australia, and what factors contribute to the change.

To answer the first question, the changes in delivery demand patterns during COVID-19 have been analysed in Sydney's metropolitan area by using the GIS software. Later, applying the Chi-square test, the second question has been answered and influencing factors have been defined. The results will provide a local understanding of changes in freight demand drivers during the COVID-19 pandemic. The insights will support urban logistics stakeholders to improve the performance of deliveries through data-driven decision-making.

4.2 Method and Material

In this section, first, the method used to evaluate the changes in parcel demand is explained. Then, the case study is introduced, and e-commerce data are elaborated upon.

4.2.1 Methods

To spatially analyse the parcel demand changes in the Sydney metropolitan area that have occurred during the pandemic, three steps have been followed:

1) Data preparation: Parcel delivery changes for each postcode were calculated by subtracting the number of parcel deliveries in each month of 2020 from the data for the same month of 2019 (before the COVID-19 pandemic).
2) Visualisation and analysis of parcel demand patterns.: The calculated changes were visualised and spatially analysed to identify patterns and trends in parcel demand across different postcodes in Sydney.
3) Identifying pivotal factors driving changes: Factors contributing to the observed changes in parcel demand were identified and analysed to comprehend the underlying drivers of these changes.

4.2.2 Case Study and Data Acquisition

Sydney, Australia's most populous city and one of the fastest-growing metropolitan areas in the country, has been selected as the case study for this research. The specific area under investigation is depicted in Figure 4.1. The boundaries delineated in this figure correspond to postcodes, and parcel demand changes were analysed at this level.

To explore how the COVID-19 pandemic has affected parcel deliveries in Sydney, changes in demand have been analysed based on data provided by a major Business-to-Business & Business-to-Consumer (B2B & B2C) courier as well as a major Business to Consumer (B2C) courier. The dataset for the former spans from January 2019 to December 2020, while for the latter, it ranges from March 2019 to February 2020. Both datasets are resolved at least at the postcode level and include the exact amount of parcel delivery. The similarity in the range and resolution of the datasets offers a unique opportunity to compare the pattern of delivery changes in the two segments during the pandemic.

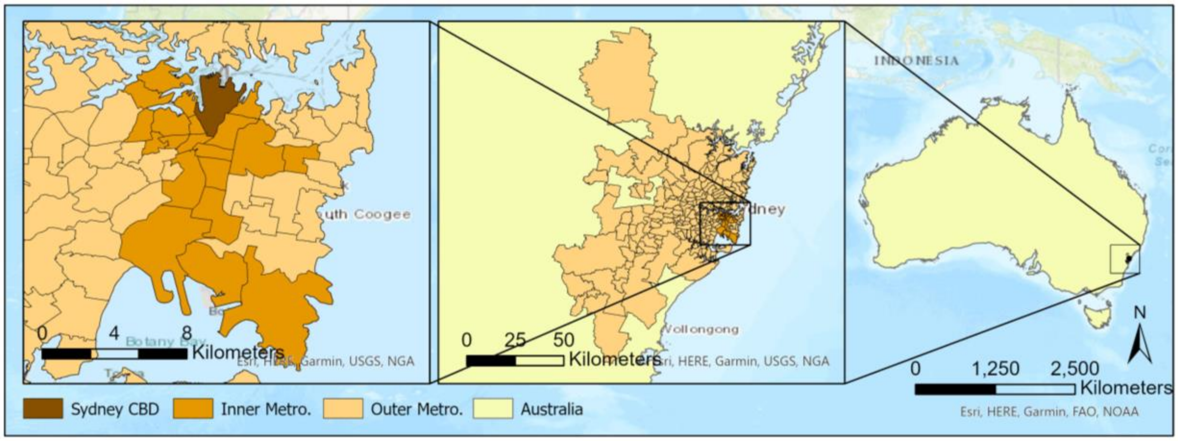


Figure 4.1. The study area, located in Sydney metropolitan area, in New South Wales, Australia.

4.2.3 Analysing the Delivery Patterns

The delivery pattern changes, first, are spatially analysed. For this purpose, the prepared data was imported into the ArcGIS Pro software to convert the statistical data to the spatial data as maps. After preparing the maps for comparative month-versus-month demand changes, postcodes were categorised to display the pattern for the demand changes. Here postcodes were categorised based on the Manual method into nine groups. The Manual interval method allows manually add class breaks and to set class ranges that are appropriate for the data rather than setting the classes based on the equal breaks or standard deviation. This method enables us to set a similar class range for categorising the areas based on demand for each month, where data ranges differ from month to month. Therefore, the demand changes in each postcode are more trackable and comparable for different months.

The last stage entailed determining the causes behind fluctuations in parcel demand across the broader Sydney area amid the pandemic. Based on expert suggestions (from Transport for NSW) and existing literature, we identified potential variables related to demand changes. These factors include average income, internet accessibility, population and population density, average age, and employment features (including the total number of employed, professionally employed, and labor-employed individuals). The Chi-square test was applied to evaluate the dependency relationship between the identified factors and demand changes. This test served to examine whether there is a statistically significant relationship between two categorical variables (Mchugh, 2013). The higher the Chi-square value, the more certainty a statistically significant relationship exists between factors (Fisher, 1950; Schervish, 1996).

To apply the Chi-square test to the potential factors, they were categorised using both median and standard deviation-based methods. Each factor's data was divided into three groups: low, medium, and high. For example, to categorise average income, a median-based method was applied. The median of average income was calculated for all postcodes. Postcodes with an average income lower than 80% of the median were considered to be the low-income group, while postcodes with an average income between 80% and 120% of the median were classified as moderate income. Postcodes with an average income greater than 120% of the median were considered high income.

To comprehensively investigate all aspects of parcel demand patterns in Sydney, demand changes in April, October, November, and total demand changes were individually analysed against selected variables. April was chosen for investigation as it marks the onset of government restrictions. October and November were selected as they represent periods with more typical parcel demand, unlike December, which is heavily influenced by social events such as Christmas and associated retail promotions. By scrutinising demand changes across these specific months, a more thorough understanding of the dynamics of parcel demand patterns throughout the year in Sydney can be achieved.

4.3 Results

4.3.1 B2C Demand for Parcel Deliveries

Figure 4.2 illustrates the B2C demand changes before the pandemic, based on data for March 2019 and March 2020, across different postcodes within the Sydney metropolitan area.

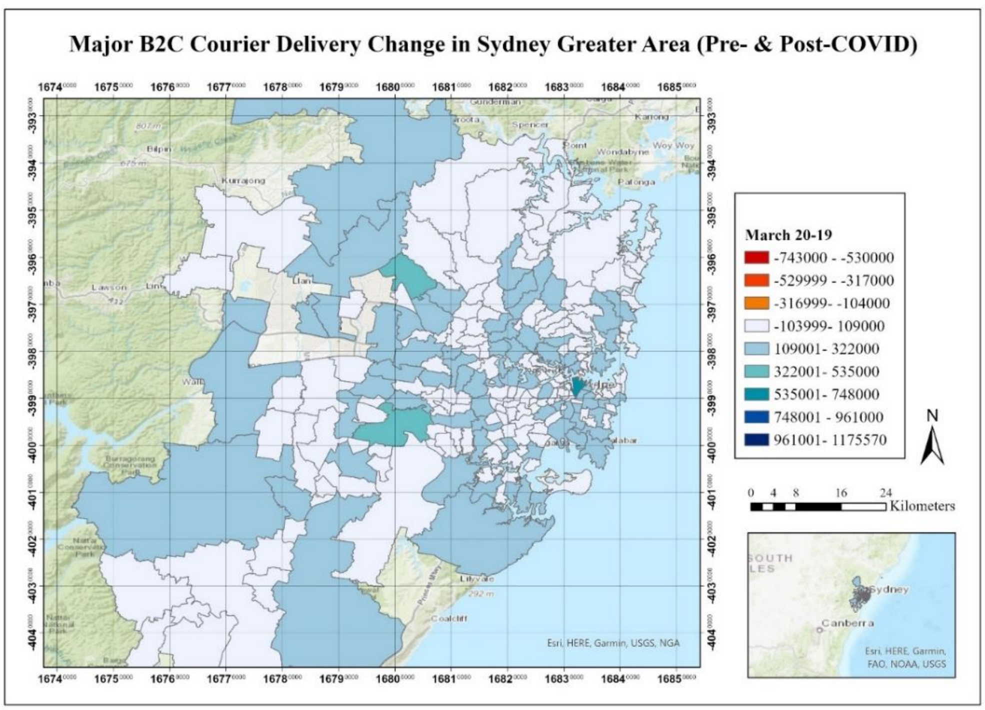


Figure 4.2. B2C demand change before COVID-19 (March 2020 compared to March 2019)

In Figure 4.2, demand changes are categorised into nine groups. Darker shades of blue indicate greater parcel demand growth, while red categories represent decreases in parcel demand changes. The numbers next to each category represent the range of demand changes within that category. For example, postcodes in the dark blue category experienced growth ranging from 961,001 to 1,175,570 in March 2020 compared to March 2019. Conversely, dark red areas indicate a reduction in demand ranging from -743,000 to -530,000.

By applying the same methodology, parcel demand in April 2020 is compared with the demand in April 2019, as shown in Figure 4.3. This map highlights postcodes and hotspots that experienced a significant rise or fall in parcel demand changes. Additional information, such as the population and income of highlighted areas is provided. For example, the red postcode in Figure 4.3 corresponds to Sydney CBD with the postcode 2000, a population of 52,601, and an average income of A$1,173 per week. It is noted that the population and income of Sydney CBD are high and moderate, respectively, compared to all other postcodes. The twelve comparisons of B2C demand changes during the periods of March 2019 to February 2020 and March 2020 to February 2021 are presented in Appendix B.

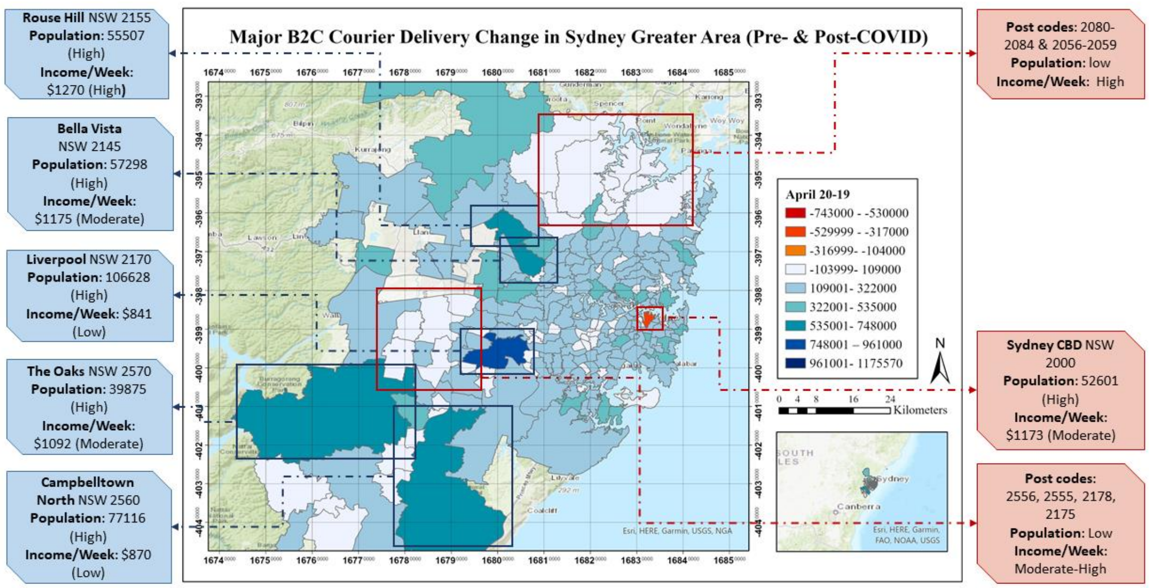


Figure 4.3. B2C demand changes after COVID-19 (April 2020 compared to April 2019)

4.3.2 B2B & B2C Demand for Parcel Deliveries

A major courier delivering both B2B & B2C consignments provided monthly demand data from January 2019 to December 2020 at the postcode level in the Sydney metropolitan area. This data made it possible for us to analyse demand changes before and during the COVID-19 pandemic. The changes in B2B & B2C delivery demand before COVID-19, similar to B2C's, exhibit a uniform pattern, as shown in Figure 4.4, with no significant changes in deliveries based on the data for March 2019 and March 2020 (before COVID-19).

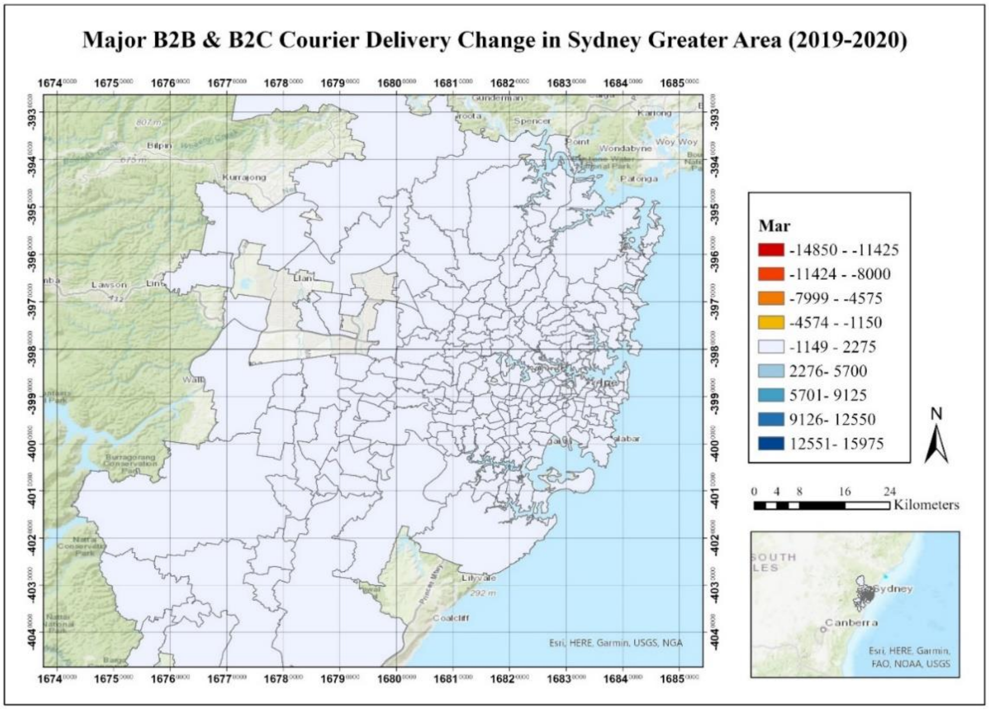


Figure 4.4. B2B & B2C courier demand changes before COVID-19 (March 2020 compared to March 2019)

By comparison, the demand changes between April 2020 and the same month in 2019 are illustrated in Figure 4.5. Highlighted areas are those that are mostly affected by the pandemic.

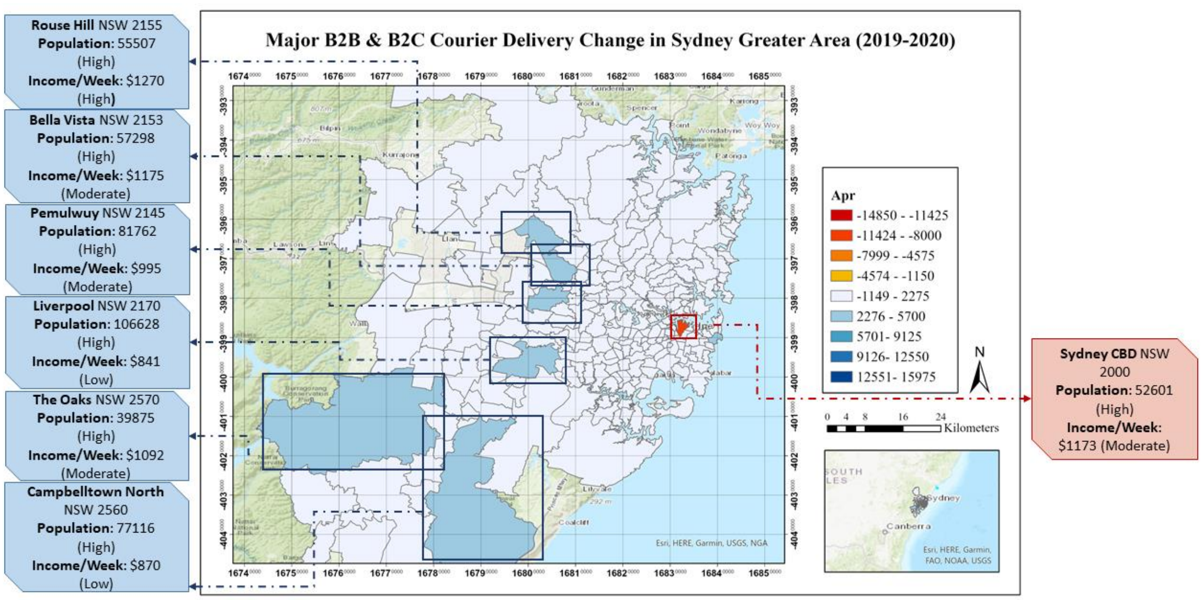


Figure 4.5. Changes in B2B & B2C demand pattern caused by COVID-19 pandemic (April 2020 compared to April 2019)

To accurately ascertain the parcel delivery pattern in Sydney, the case study is segmented into three zones. Postcode 2000, representing Sydney's CBD, is considered the first zone.

The second zone comprises the inner metro, including all postcodes surrounding the CBD, while the remaining postcodes are categorised as outer metropolitan areas. The amount of parcel delivery in each zone, for both B2C and B2B & B2C couriers, is normalised based on delivery volumes in March 2019. This normalisation makes it possible to compare delivery changes across different zones. These changes for both couriers are illustrated in Figure 4.6.

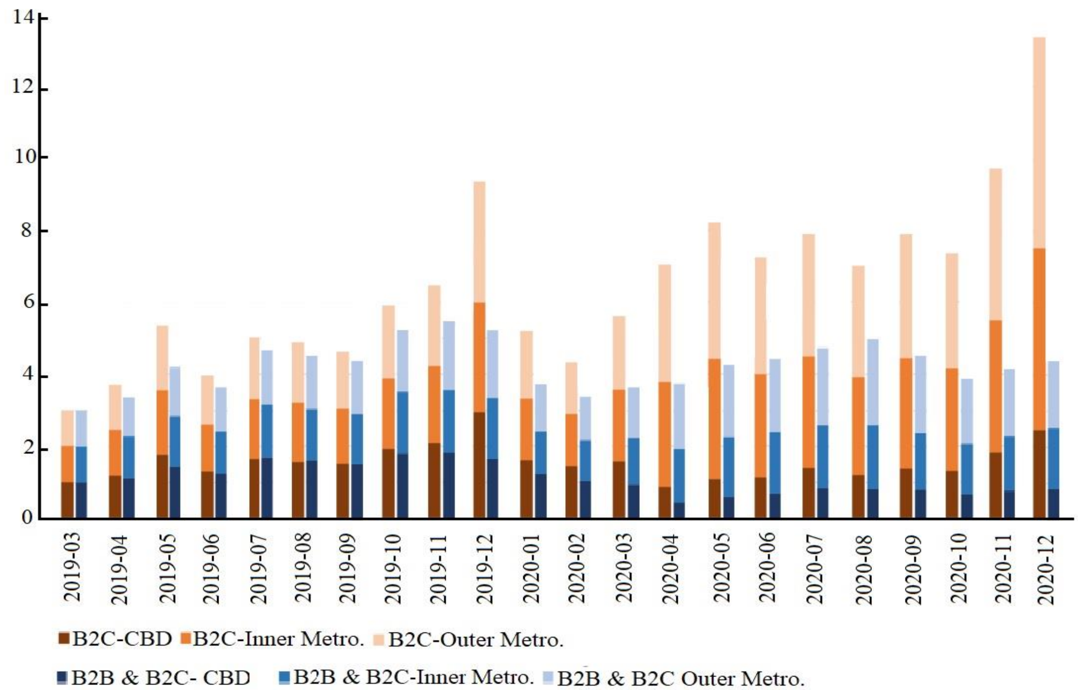


Figure 4.6. Trends in parcel demand in Sydney before and during the COVID-19 pandemic.

Later, as discussed in Section 4.3.2, the Chi-square test is applied as the final step. Table 4.1 presents the relationship between demand changes in various periods and the selected variables. Variables with a Chi-square value higher than the significance level (0.05) are considered dependent variables in the table, such as total employment with April delivery changes, while the remaining variables are considered independent.

4.4 Evaluating the Pandemic's Effect on Parcel Delivery

Based on the analysis of parcel delivery volume for B2C and B2B & B2C couriers prior to the COVID-19 pandemic, the parcel demand pattern in Sydney in March 2020 resembled that of March 2019. Observed here is that the majority of areas experienced minimal or no growth in demand, while a few postcodes, including the CBD, experienced moderate growth. Figure 4.2 and Figure 4.4 which were generated by GIS, illustrate this trend.

Spatial analysis of demand changes in the Sydney metropolitan area for B2C and B2B & B2C couriers during the COVID-19 pandemic reveals a significant decrease in parcel delivery in the CBD. Conversely, outer metropolitan areas, particularly western postcodes, experienced substantial growth for both segments immediately following the lockdown in

April 2020. This trend is depicted in Figures 4.3 and 4.5, representing the parcel delivery pattern changes in B2C and B2B & B2C segments, respectively.

Table 4.1: Relationship between parcel demand changes and selected variables.

Time Period	Total Employed	Professional Employed	Labour Employed	Average Income	Internet Accessed	Average Age	Population	Density
April Delivery Changes	Dependent	Dependent	Dependent	Independent	Dependent	Independent	Dependent	Independent
October Delivery Changes	Dependent	Dependent	Dependent	Independent	Dependent	Independent	Dependent	Dependent
November Delivery Changes	Dependent	Dependent	Dependent	Independent	Dependent	Independent	Dependent	Dependent
Total Delivery Changes	Dependent	Dependent	Dependent	Independent	Dependent	Independent	Dependent	Dependent

Unlike the usual trends in B2C and B2B & B2C demand, significant changes have been observed in both courier sectors during the COVID-19 pandemic. This signifies an imbalanced pattern, characterised by a notable increase in delivery demand for inner and outer metropolitan postcodes, alongside a reduction in demand in the CBD. The parcel delivery pattern in Sydney before and during the pandemic is depicted in Figure 4.6. According to this graph, Sydney's CBD experienced a substantial decrease in parcel delivery in April 2020 in both the B2C and B2B sectors. Subsequently, delivery volumes in both sectors gradually increased, indicating CBD’s recovery and return to the new normal situation.

In contrast to the parcel delivery trend in the CBD, the inner and outer metro postcodes experienced a significant increase in delivery volume immediately after the onset of the pandemic. In 2019, the rate of delivery changes in the CBD and the inner and outer metro postcodes was more or less equal. However, the pandemic disrupted this balance, and from April 2020, parcel delivery in the inner and outer metro areas increased more rapidly than in the CBD. This trend is more pronounced in B2C rather than B2B & B2C. The notable shifts in B2C deliveries during the pandemic can be attributed to various restrictions imposed by the NSW government, such as lockdowns, social distancing measures, and reduced capacity for public transport and offices. These measures led to a significant number of office workers and customers transitioning to remote work, thereby amplifying the demand for home deliveries.

Overall, throughout the Sydney CBD, the decline in parcel demand began in March 2020, reaching its lowest point in April 2020. ABS statistics indicated an increase in the unemployment rate to 6.2% in 2020. Subsequently, the Australian government implemented business survival initiatives, such as increasing the JobKeeper allowance and providing loans for small and medium-sized businesses (O'Sullivan et al., 2020). Additionally, from 27 April 2020, the JobSeeker allowance was doubled for six months (ending in September), contributing to maintaining balance in B2C deliveries (*The Guardian*, 2020). Consequently, a gradual increase in parcel delivery volumes has been observed since April 2020. This can be attributed to a gradual rise in office occupancy, the easing of COVID-19 restrictions, and supportive government initiatives aimed at economic recovery and facilitating the return to work in the CBD.

Based on the Chi-square test, the observed parcel demand changes are dependent on levels of employment, internet access, population, and population density. These factors served as drivers for the demand changes during the pandemic. Identifying the key influential factors is a fundamental and crucial step in modelling and predicting the impact of pandemics on parcel demand changes, thus ensuring that future disasters are prepared for. However, based on our current knowledge, it remains unknown whether these factors have a positive or negative impact on delivery changes, which is the future direction for the present study.

4.5 Chapter Summary

The COVID-19 pandemic and responsive measures, such as lockdowns, social distancing, and limited office capacities, have disrupted the goods distribution pattern in numerous metropolitan areas worldwide. While some countries experienced a significant increase in delivery demand for both business-to-business (B2B) and business-to-customer (B2C) carriers, others saw growth only in B2C demand, with B2B demand declining. These variations can be attributed to the characteristics of B2C and B2B environments in different countries, including the structure of buyers and sellers and the frequency of shopping, as discussed in Section 4.1.1.

This chapter focuses on the Sydney metropolitan area as the case study, with parcel delivery data collected from two major couriers. One courier primarily serves B2C customers, while the other covers both B2C and B2B clients. Both datasets span two years and are analysed at the postcode level. To illustrate the impact of COVID-19 on Sydney's goods distribution, we first spatially analysed demand changes before and during the pandemic. Our analysis reveals a decline in demand across Sydney's inner areas during the pandemic, while certain outer postcodes, particularly in the western areas, experienced an increase in parcel demands.

Based on observations, both B2C and B2B & B2C couriers experienced an uptick in parcel delivery to the CBD from March 2020 onward. This trend is attributed to government initiated support measures and the return of people to CBD offices. Conversely, a different trend was observed in the inner and outer metropolitan areas, where an increase in parcel delivery for both couriers has been noted since the beginning of the pandemic. This increase is primarily due to a significant proportion of office workers adopting work-from-home practices and the closure of several stores and shopping centres.

The key factors relevant to demand changes have been examined through the Chi-square test to determine their correlation with the changes. According to the results, demand for parcel delivery in Sydney was found to be dependent on various levels of employment, internet access, population, and population density. The statistical and spatial assessment of parcel delivery demand quantity and location before and after the pandemic revealed a shift towards decentralised e-commerce demand. This insight is utilised in Chapter 5, which emphasises the adoption of smaller consolidation centres spread across the metropolitan area rather than relying on a large centralised warehouse. As detailed in Chapter 5, these compact freight hubs are more adept at meeting e-commerce demands.

While the insights presented here contribute to future disruptions preparedness and mitigation plans, further studies are necessary to understand how correlated factors influence delivery changes, including: firstly, the extent to which each factor affects these changes; and secondly, whether the impact is negative or positive. Additionally, while this chapter mainly focused on demographic factors, future research should explore other relevant factors, such as the status of logistic systems or provided civic services. Another avenue for research could investigate the role of policy in addressing the needs of different freight stakeholders in both B2B and B2C sectors amidst parcel demand changes.

Chapter 5: Uncapacitated Single Allocation Hub Covering Problem

A B S T R A C T:

E-commerce growth has led to an increase in vehicle kilometres travelled (VKT) by delivery vehicles and this has seriously affected the environment. This chapter proposes a spatial approach to address the uncapacitated single allocation hub covering problem (USAHCP) to reduce the VKT by optimising the number and location of logistics hub locations. In this approach, the spatial features and strategic legislation of urban areas, such as accessibility and the 15-minute city paradigm, are analysed. Integrating existing models, this location-based approach aims to design a collaborative last mile distribution network by locating micro-consolidation centres (MCCs) in urban areas to service parcel lockers (PLs) where end customers pick up their parcels. The combination of MCCs and PLs leads to the design of more sustainable urban distribution systems by reducing failed deliveries and fostering accessibility. The method is applied to Sydney, New South Wales (NSW), Australia, using data provided by one of the largest courier companies in the country. For the evaluation of diverse scenarios, two key variables have been taken into account: 1) the maximum driving time constraint; and 2) specific times of day, serving as proxies for variations in road traffic patterns. Not only do the results offer potential benefits for logistics stakeholders, especially Transport for NSW in terms of reducing the impact on the environment; they can also enhance the overall efficiency of other logistics stakeholders such as carriers and shippers in other cities by applying the method developed.

5.1. Introduction

As discussed in Chapter 4, the COVID-19 pandemic has further propelled the expansion of e-commerce, with consumers increasingly embracing online shopping to avoid physical stores and minimise any potential exposure to the virus. This has led to an unpredicted surge in demand for e-commerce providers and logistics services. Besides, government restrictions, such as prohibiting long-distance travel (Borkowski et al., 2021), closure of offices and working from home, and limiting shopping and entertainment to the local areas have altered the goods distribution patterns (Kahalimoghadam et al., 2021). The significant change in the geographical pattern of goods delivery has resulted in a rise in freight vehicles' movements on local roads. These trends conflict with traditional urban freight generation analysis and modelling that rely on factors such as non-residential land use location and population density (Pani et al., 2018).

Modelling and optimising the new trends in goods delivery is a complex process where different factors and phases have to be factored in. Referring to the different phases of goods delivery, significant attention should be paid to the final leg, commonly referred to as last-mile logistics (LML). This is because business-to-consumer (B2C) orders should be delivered to dispersed destinations. Thus, assembling and gathering shipments is often inefficient and costly in the last-mile. It is estimated that LML comprises between 28% and 50% of the total delivery cost (Ranieri et al., 2018; Vanelslander et al., 2013).

Home delivery by urban freight vehicles, such as vans, can be even more costly. This is at the core, because in low-density suburbs, customers are usually spread out, and home delivery services often involve delivering only one parcel per stop, which is inefficient and costly (Waßmuth et al., 2023). In highly populated areas such as inner cities, although the customer density is high, higher delivery cost often comes from traffic jams and a lack of sufficient parking locations (Boysen et al., 2020). Cost efficiency, however, poses more challenges. The literature addresses four main LML challenges to enhance the cost efficiency of home delivery.

The first challenge is LML management and optimisation. The well-known issue in this stream is the vehicle routing problem (VRP) that was first introduced by Dantzig and Ramser (1959). The VRP and its variants optimise the routing of vehicles delivering goods from one or more depots to several geographically scattered customers (Bräysy et al., 2009). Fast delivery (Rodrigue, 2020), just-in-time services (Halldórsson & Wehner, 2020), coordination between the actors involved in the LML (Calle, 2017), and home delivery and small parcels (Lachapelle et al., 2018) are among the other issues categorised in this challenge.

The second challenge is technology. Although the invention of new technologies such as information communication tools (ICT) has led to e-commerce expansion, they have also led to problems for LML. ICT has resulted in more customers expecting faster and cheaper delivery options (Rodrigue, 2020), which can be difficult for companies to meet. It can also lead to increased operational costs due to the need for more sophisticated tracking and monitoring systems. Drone delivery is another example of technology that can facilitate faster delivery (Feng et al., 2021) and enhance customers' experience. However, this type of delivery is associated with various challenges, including legal restrictions, limited service regions, less productivity than van delivery, and crashes (Sah et al., 2021).

The third challenge in LML is environmental and financial costs. In terms of environmental costs, transportation accounts for 30% of greenhouse gas (GHG) emissions in urban areas (OECD, 2020). Air and noise pollution are other adverse outcomes of last-mile activities and they greatly affect residents' health (Abbaspour et al., 2015; Lelieveld et al., 2015). One of the primary drivers of the health cost is vehicle kilometres travelled (VKT) to deliver parcels to end customers. In home delivery, for example, VKT includes the distance from the warehouse(s) to the customers. Other factors that increase financial costs include labour costs, the products being returned, and failed deliveries (Mommens et al., 2021).

The final challenge pertains to infrastructure, which occurs at the strategic level and involves establishing, maintaining, and upgrading vehicles and facilities (Clausen et al., 2016), as well as dealing with limitations related to facilities and geographical space (Ewedairo et al., 2018). Hubs are among the most critical facilities that function as specialised centres within many-to-many distribution systems, facilitating switching, transhipment, and sorting activities. These hubs strategically consolidate flows rather than managing individual origin-destination connections independently (S. Alumur & Kara, 2008). The hub location problem (HLP) aims to determine the optimal location for facilities in a transportation or logistics network, and allocating demand points (DPs) to them is also in this category. Designing and implementing a collaborative distribution network is categorised in this stream. The Physical Internet (PI) concept introduced by Montreuil et al., (2010) is the primary innovative concept for enabling collaborative logistics facilities. The PI is based on the idea of standardisation and collaboration, where logistics assets, particularly containers, vehicles, and warehouses, are shared and utilised more efficiently.

Parcel lockers (PLs), which are secure and automated storage units designed to facilitate self-service last-mile deliveries, are an example of PI hubs. Customer convenience is not the only benefit of PLs, as they reduce the burden on traditional delivery services by optimising the delivery process, as well. PLs allow delivery providers to consolidate packages in one location, reducing the number of individual stops and improving efficiency and cost-effectiveness. However, it is crucial to locate PLs strategically in areas easily accessible to customers, such as densely populated urban areas, to maximise their effectiveness. Typically, PLs are located in convenient and accessible locations, such as public places, shopping centres, and transportation hubs to reduce delivery times and VKT (Lagorio & Pinto, 2020).

City logistics, which aims to optimise logistics and urban goods transportation and reduce or remove negative externalities caused by freight distribution (Taniguchi & Thompson, 2002), is another logistics concept focused on logistics infrastructure. Micro-consolidation centres (MCCs) are vital infrastructure alternatives in City logistics, to deal with the LML challenges.

MCCs are collaborative hubs that consolidate freight shipments from multiple suppliers and transport them to end customers using more efficient and environmentally friendly vehicles. In contrast to traditional urban consolidation centres in terms of size and spatial placement, MCCs are strategically positioned in urban areas. Although they may only handle a limited number of items, automated picking and packing systems and real-time tracking systems improve their efficiency, making them suitable for next-day or same-day delivery.

The concept of the 15-minute city has garnered significant attention in contemporary urban planning discussions, especially given the impact of the COVID-19 pandemic and how it transformed the way business is done. It emphasises diverse activities integration within neighbourhoods to bolster urban vibrancy and alleviate daily commuting burdens. In tandem with the burgeoning prominence of e-commerce and expedited delivery standards, incorporating a combination of PLs and MCCs in the distribution network fosters a more sustainable LML.

In this chapter, we design a collaborative LML distribution network where MCCs, as logistics hubs, receive goods from a central warehouse and then fulfil the PLs representing DPs. This approach contrasts with the traditional method of shipping products directly from the distributors to the customer, which can be expensive and often results in underutilised truck capacity. This problem is defined as an uncapacitated single allocation hub covering problem (USAHCP), in which the optimal location and number of MCCs are determined to maximise coverage areas. For locating MCCs in urban areas, an innovative methodology has been developed by integrating existing models, including utilising geographic information systems (GIS) and heuristics and dynamic programming algorithms. Using real-world B2C data from Australia Post, we evaluated the efficiency of the designed collaborative LML distribution network in reducing delivery times in Sydney, which experienced changes in e-commerce demand.

Various scenarios with different constraints are solved using the spatial method developed. This approach enables decision-makers, including Transport for NSW in this chapter, to optimise the number and location of facilities based on their needs to reduce transportation costs and adverse impacts through improved operational efficiency. In addition, it provides visual insights into collaborative distribution networks. Since the case study contains openly available geographical data, the method can be applied to any location with access to e-commerce data.

The rest of the chapter is organised as follows. In Section 5.2, first, the USAHCP is formulated and then a methodology compromised of a GIS database and solution algorithm is developed to optimise the location and number of MCCs. Section 5.3 describes the data related to the case study and the scenario-based driving time analysis. The results of applying the method developed for the case study are also presented in this section. In section 5.4, each scenario is discussed from the standpoint of the LML stakeholder's objectives. Additionally, traffic congestion impacts on optimal solutions are assessed through sensitivity analysis. Lastly, Section 5.5 summarises this chapter's findings and suggests future directions of research on this topic.

5.2 Methodological Approach

In this section, the methodology to determine the suitable locations and numbers of micro-consolidation centres (MCCs) fulfilling parcel lockers in LML will be explained. First, this optimisation problem will be formulated as an uncapacitated single allocation hub covering problem (USAHCP). Then, the method devised to solve this problem will be introduced, including creating a geographic information system as well as the utilisation of heuristic and dynamic programming algorithms.

5.2.1 Uncapacitated Single Allocation Hub Covering Problem

To determine the most suitable number and location of MCCs fulfilling PLs, the USAHCP is utilised. The aim is to minimise both total VKT and driving time, since these factors influence transportation costs and GHG emissions.

The USAHCP is formulated here based on the model introduced by Campbell (1994b). The network contains n nodes, $N = 1,2,\dots,n$, compromising n_{MCCs} MCCs and n_{PLs} PLs. The n_{PLs} are always fixed, but the n_{MCCs} may be a decision variable. Interconnectivity exists among all MCCs, while PLs' nodes lack direct connections, necessitating flow routing through MCCs (S. Alumur & Kara, 2008). Moreover, within this allocation problem, each PL node is constrained to a solitary assignment to a singular MCC, thereby facilitating an efficient and exclusive allocation of nodes to hubs. Hence, the problem is formulated as follows.

$$\text{Minimise} \quad \sum_i \sum_j \sum_k \sum_m W_{ij} X_{ijk} C_{ijkm} \tag{1}$$

$$\text{subject to} \quad \sum_k Y_k \leq p, \tag{2}$$

$$Y_k \in \{0,1\} \ \forall\, k \in N, \tag{3}$$

$$0 \leq X_{ijkm} \leq 1 \ \forall\, i,j,k,m \in N, \tag{4}$$

$$\sum_k \sum_m X_{ijkm} = 1 \ \forall\, i,j \in N, \tag{5}$$

$$X_{ijkm} \leq Y_k \ \forall\, i,j,k,m \in N, \tag{6}$$

$$X_{ijkm} \leq Y_m \ \forall\, i,j,k,m \in N, \tag{7}$$

Where X_{ijkm} is the fraction of flow from $node_i$ to $node_j$ that is routed via hub at location k. If Y_k is 1, $node_k$ is an MCC and 0 otherwise. The flow from $node_i$ to $node_j$ is represented by W_{ij}. C_{ijkm} represents the cost per unit from origin include to destination j via hubs k and m, ranging from 1 to n_{MCCs}, in that order. $C_{ijkm} = c_{ik} + \alpha c_{km} + c_{mj}$ in which c_{ij} representing the cost related to the shortest path between nodes i and j and c_{ik}, c_{km}, and c_{mj} represents the collection, transfer, and delivery costs, respectively. α is the coefficient of transfer cost valued between 0 and 1. Since there are not any intermediate hubs in our problem, k always equals m. Moreover, F_k represents the fixed costs associated with establishing an MCC at node k.

In this model, equation (1) represents the objective function that needs to be minimised. Constraint (2) limits the number of hubs that can be selected. Compared to the original formulation, this equation has been adjusted based on García and Marín's (2015) suggestions to achieve maximum coverage while reducing the number of hubs. Constraints (3) and (4) restrict the value of Y_k and X_{ijkm}. Equation (5) guarantees that every MCC-PL pair's parcel transportation is systematically directed through a designated hub pair. Parcels are routed via MCCs according to constraints (6) and (7).

5.2.2 Method

Figure 5.1 illustrates a multi-objective methodology aimed at optimising allocation to minimise total driving time (TDT) while simultaneously maximising LMD coverage. As outlined below, this method consists of six distinct phases.

Geographic information system

A geographic information system (GIS) was developed for integrating and organising spatial data sources. The first component is to obtain road network data from OpenStreetMap (OSM), a crowdsourced mapping platform. The OSM provides a comprehensive and up-to-date representation of road infrastructure. This data includes road types, connectivity, and attribute information such as road names and speed limits. Road network data is imported into ArcGIS Pro 3.1.2 software and organised into a suitable format for further analysis and visualisation.

Based on the available traffic data on the TomTom website (TomTom, 2023), the road traffic pattern is identified. Five timeframes throughout the day are considered, including midnight (4:00 AM), morning peak (8:00 AM), off peak (12:00 PM), afternoon peak (5:00 PM), and night (10:00 PM) periods. Based on the historical traffic model provided within ArcGIS Pro, traffic data was applied to the route network at specific time intervals throughout the day. This historical traffic model provides travel speeds and congestion on road segments at a certain time on a day of the week.

The third component of the GIS database is PLs' information, including their number and precise location. The data are acquired by geocoding the geographical centre of postcodes in the case study (see Section 5.4). The third component involves identifying candidate locations for MCCs. Based on the same rationale, candidate locations of the MCCs are determined based on the geographical centre of Statistical Area Level 3 (SA3) in the case study. Section 5.4 provides more information about this process and the relevant legislation that enabled us to take this into account.

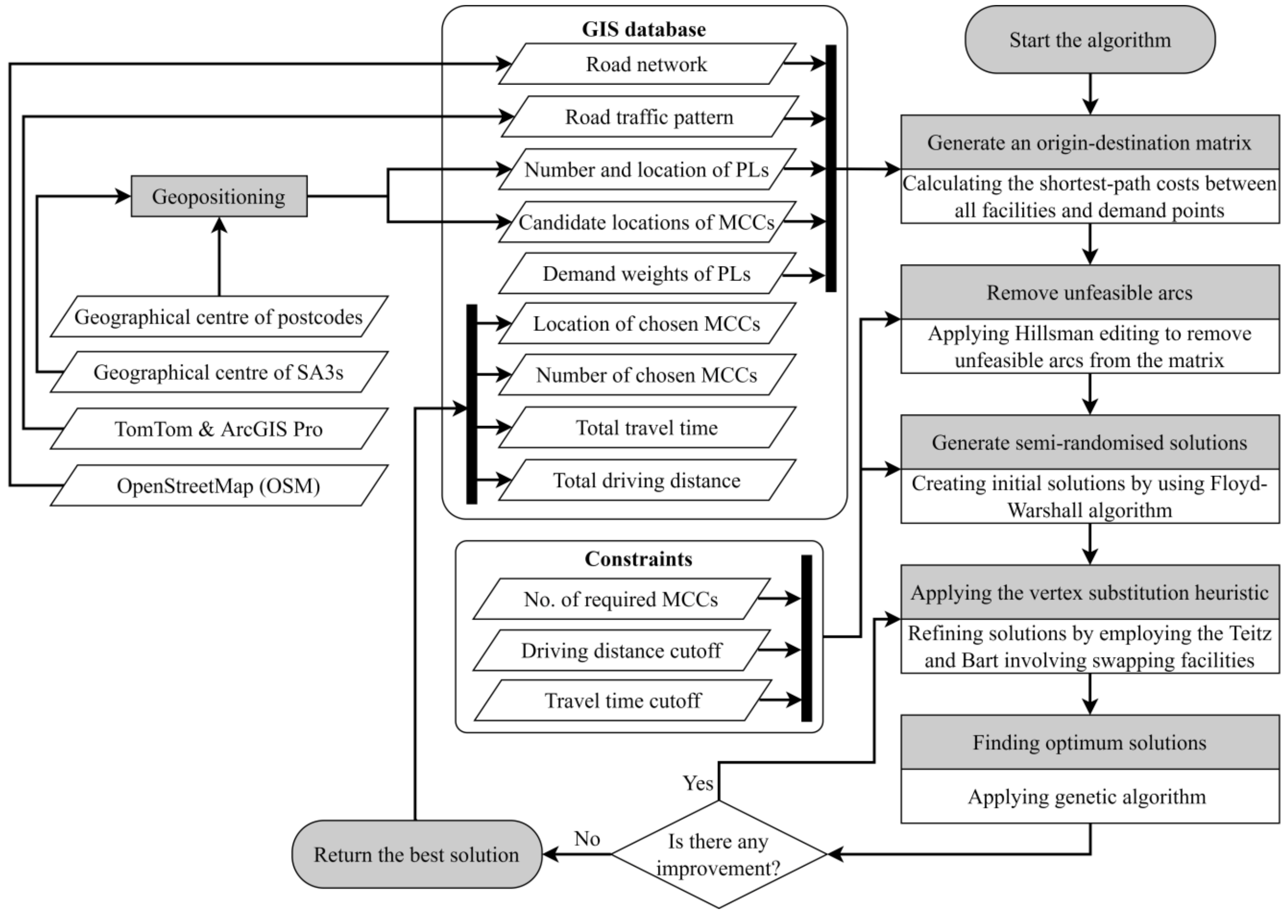


Figure 5.1. Methodology to find the optimum location for MCCs in urban areas.

Before incorporating the PLs and MCCs data into the GIS, a geoprocessing step is employed. The geoprocessing involves spatially analysing and manipulating data to derive meaningful insights. In this case, the initial location of PLs and MCCs' candidates undergo the process to ensure all MCCs and PLs are located in accessible locations. For instance, the centre of some postcodes or SA3s was located in wetlands or green land areas. In such cases, their location is adjusted to the closest available alternative location. Additionally, MCC candidate sites are not considered in SA3s with a low level of e-commerce parcel demand. These SA3s are usually located near the case study border.

The remainder of the components in the GIS are related to the output of the model. They include the number and location of the chosen MCCs, VKT, and TDT.

Generating an origin-destination matrix

The first step of the methodology involves generating an origin-destination matrix by calculating the shortest-path costs between all MCCs and PLs. This step utilises the inputs obtained from the GIS database, which include road network data and the precise locations of the MCCs and PLs, to compute travel distances between different locations. The MCCs act as origins, representing potential hubs for consolidating and redistributing parcels, while the PLs serve as destinations. Driving time is also calculated based on road traffic. The most efficient routes are determined by considering distances, driving times, and road attributes. Subsequently, an origin-destination matrix that serves as a fundamental input to the other steps is generated.

Removing infeasible arcs

This step involves constructing an edited version of the origin-destination cost matrix by Hillsman editing (Hillsman, 1979). Hillsman's editing process is as follows:

- Set a threshold distance. Let d_0 be the threshold distance. If the problem is driving time scenario-base, the d_0 is calculated based on the maximum allowed travel time. Otherwise, the d_0 is calculated based on Hillsman's editing method.
- For each PL, if the distance to the nearest MCC is longer than the d_0, remove it from the problem.
- Solve the USAHCP using the modified origin-destination matrix.

Hillsman's editing suggests that arcs can be truncated to a certain extent due to the unlikely occurrence of assignments beyond a specific distance, ensuring that only valid and rational arcs between MCCs and PLs are considered. Thus, PLs not within a certain travel distance or travel time of existing MCCs are removed. By implementing this approach, USAHCP feasibility is enhanced, leading to overall solution quality improvement.

Generating semi-randomised solutions

The next step in the methodology involves generating semi-randomised solutions by creating initial solutions through the random assignment of MCCs to PLs. This step aims to establish a starting point for further optimisation and evaluation processes in the USAHCP while adhering to specific constraints. Floyd–Warshall algorithm, which is a dynamic programming approach to finding the shortest paths between pairs of nodes in a graph (Floyd, 1962), is employed. For this purpose, the shortest path connecting an origin and destination node (i, j) within the network N is determined by taking into account the direct connection between nodes i and j. This process ensures the PL i accesses the distribution network through the nearest candidate MCC. The generated solutions are then evaluated according to other constraints, such as the VKT or TDT. The most efficient solutions are then selected and further optimised to reach the best solution.

Applying the vertex substitution heuristic

The next step involves applying the vertex substitution heuristic to improve the semi-randomised solutions. The enhancement process involves employing the Teitz and Bart algorithm, known for optimising the USAHCP by exchanging MCCs (Teitz, 1968). This algorithm, tailored for the HLPs, substitutes facilities between neighbouring DPs. During the swapping process, the algorithm assesses the impact of facility substitution on the total cost. If the swap reduces costs and maximises service coverage, the substitution is accepted and incorporated into the refined solution. Otherwise, the original assignment is retained. This iterative process continues until no further improvements are possible.

Finding optimum solutions

In this step, a GA is applied as a global search to combine the low-cost solutions obtained from the previous steps to create better solutions. The GA, introduced by Holland (1992), is a metaheuristic optimisation technique inspired by natural selection and evolution. The GA starts by considering a population of candidate solutions generated by combining and modifying the low-cost solutions obtained earlier. Each candidate solution is represented as a chromosome in the GA, typically encoded as a string of genes or variables that define the hub-location configuration. Then, genetic operators of the GA, including selection, crossover, and mutation, are iteratively applied to evolve the population of candidate solutions.

During the selection process, individuals with better fitness, determined by their cost, are more likely to be chosen as parents for the next generation. This selection mechanism allows the algorithm to favour promising solutions and encourage convergence towards optimum solutions.

Solution representation of HLP: Before applying the above-mentioned operators, it is essential to represent the problem based on the GA approach. Here, the USAHCP consisting of N nodes, m MCCs and n PLs, is represented as a 2N-dimensional array, including MCC_Array and Assign_Array, similar to the approach introduced by Topcuoglu et al., (2005). Each bit position in the MCC_Array corresponds to a node. If its value is true then the node is an MCC, while a false value indicates it is a PL. The Assign_Array represents the assignment of PLs nodes to MCCs. Whenever PL i is assigned to MCC k, its corresponding entry in the Assign_Array is set to k. In addition, every MCC is assigned to itself within the Assign_Array.

Population initialisation: In this step, each PL node in the Assign_Array is randomly assigned to one of the selected MCCs. This encoding scheme guarantees the feasibility of initially generated chromosomes that satisfy the problem's predetermined constraints. This process is repeated as many times as the population size to generate a set of feasible chromosomes. This procedure allows random chromosome initialisation while maintaining feasibility. Furthermore, this ensures that the initial population represents valid solutions within the given problem domain.

Selection procedure: Chromosomes are selected using the roulette wheel selection method, where probability is proportional to each chromosome's fitness. By using this approach, better chromosomes with smaller objective values are more likely to be selected for reproduction. However, a limitation of the roulette wheel selection method is that the most desirable individual might not always produce offspring (Yang et al., 2013).

Elite strategies have been incorporated to address this issue. As part of the elite strategy, the most fit individuals from the previous generation are preserved and passed directly on to the next generation. Thus, the population is assured of maintaining the highest-performing chromosomes, providing stability, and preventing the loss of highly advantageous solutions. By combining roulette wheel selection with an elitist strategy, we balance exploration and exploitation, ensuring the propagation of high-quality individuals while maintaining diversity and promoting the search for improved solutions in subsequent generations.

Crossover process: The crossover process is a fundamental operator in the GA used to create new offspring solutions by combining genetic information from two parent solutions. In this process, genetic material is exchanged between individuals to produce genetically diverse offspring. Following the selection process, a crossover point representing the position along the chromosome of MCC_Array and Assign_Array, where the genetic material exchange takes place, is randomly selected. If the hubs in the offspring do not satisfy predetermined constraints, an adjustment phase is required on the MCC_Arrays. Hence, the crossover operator is repeated by generating another random crossover point. Upon crossover on the MCC_Arrays, a node that is no longer an MCC is reassigned to the closest MCC according to the Assign_Arrays of the offspring.

Figure 5.2 illustrates an example in which MCC_Array1 consists of nodes 1 and 6, and MCC_Array2 includes nodes 2 and 5 as MCCs. After selecting a crossover point randomly, the crossover process is started. The initial offspring for Assign_Array1, including nodes 1, 2, 5, and 6, are generated. However, based on the modified MCC_array1, only nodes 2 and 6 can be assigned to MCCs. Consequently, in the arrangement process, nodes 1 and 5 are reassigned to their closest MCCs, node 2 and node 6, respectively, to generate the ultimate offspring. Assign_Array2 follows a similar process.

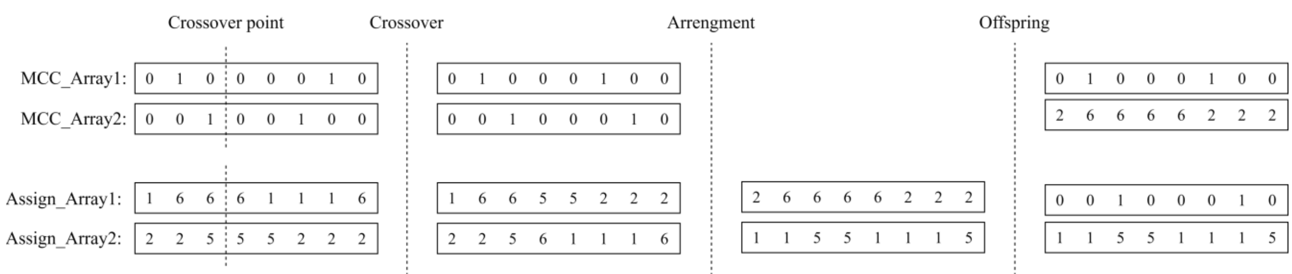


Figure 5.2. Crossover operator example

Mutation process: Due to the distinct nature of MCC_Array and Assign_Array, we define two parameters, α_1 and α_2, which represent mutation probabilities for each array. For the MCC_Array mutation, first, an MCC node position, denoted as $node_1$, is randomly selected from the set of selected MCCs, n_{MCC}. Next, a PL node position, denoted as $node_2$, is randomly chosen from the remainder of nodes, n - n_{MCC}. The leading positions, which consist of the mutated 1s and 0s, are exchanged. This mutation operator maintains the number of open MCCs and ensures that the mutated chromosomes remain feasible. Assign_Array's mutation process is designed according to the specific requirements of the problem, taking into account the significance of each gene's mutation and ensuring that the resulting chromosomes are feasible.

In addition to the MCC_Array mutation, we apply a mutation operator to the Assign_Array to modify node assignments. This mutation operator selects a PL node and reassigns it to another MCC chosen randomly. By incorporating this mutation operation into the Assign_Arrays, we introduce variation in node assignments, allowing different solutions to be explored. The mutation process ensures that the newly generated offspring remains feasible by maintaining chromosome integrity.

5.3 Applying the Developed Methodology in the Case Study

With over five million people, Sydney is a prominent hub for e-commerce in the Asia-Pacific region. However, the city faces challenges such as traffic congestion and limited warehouse space, which can hinder logistics efficiency. Overcoming these obstacles, which can be achieved through strategic interventions, is necessary to improve the city's logistics infrastructure and ensure continued economic growth.

In Sydney, the 15-minute postcode framework is centred on the establishment of localised communities that prioritise the provision of essential amenities and services within a short distance. This concept of achieving accessibility within a 15-minute timeframe aims to enhance sustainability, foster autonomous mobility for residents, and revitalise local centres, as stipulated by Transport for NSW (Transport for NSW, 2023). To address this pertinent real-world challenge, we propose the implementation of a PL at the geographical centroid of every 198 postcodes located in the case study.

Within the case study, there are 34 SA3 entities, which are delineated as functional regions within metropolitan zones accommodating a total population of more than 20,000 individuals. These regions exhibit a clustering of interconnected suburbs surrounding commercial and transportation hubs, as defined by the Australian Bureau of Statistics (Australian Bureau of Statistics, 2023). In contrast to a conventional HLP, wherein potential warehouse sites are selected based on specific criteria or constraints that limit the pool of viable areas, the regulatory framework established by the New South Wales (NSW) Government for Local Distribution Premises (NSW Government, 2022) permits the establishment of MCCs across a diverse range of land uses, albeit contingent upon the preferences of local government councils in Sydney. Consequently, our approach involves considering the geographical centroid of each SA3 as a viable candidate location for establishing MCCs.

5.3.1 Real-world B2C Data

Australia Post provides high-quality B2C e-commerce data. The data resolution is at the postcode level, and the duration is from March 2019 to February 2022. Even though the data includes monthly e-commerce deliveries, we normalise it and use it as delivery weights for postcodes. This is because our problem is an uncapacitated HLP. This approach helps the algorithm differentiate PLs with higher demand volume from those with lower volume and prioritises them.

5.3.2 Results: Driving Time Scenario-based Analysis

Three delivery scenarios were assessed in Sydney, encompassing delivery configurations of 15-minutes, 20-minutes, and 25-minutes. The scenarios were evaluated at midnight (4:00 AM) to examine free-flow conditions.

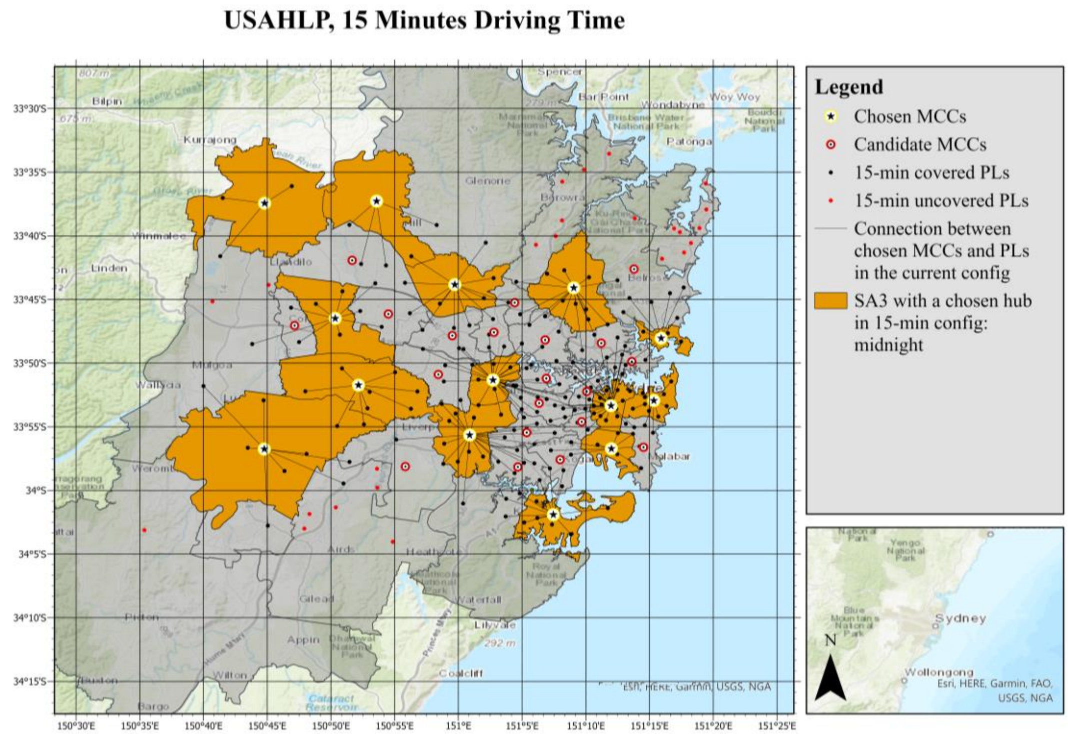


Figure 5.3. 15-minute delivery configuration.

PLs need to be within 15 minutes driving time of MCCs in the first scenario. Figure 5.3 illustrates this analysis. The legend of this figure shows uncovered postcodes in the 15-minute configuration, chosen MCCs, candidate MCCs, covered postcodes in the 15-minute configuration, allocation between chosen MCCs and PLs, and SA3s with a chosen MCC. According to the analysis, 14 MCCs are necessary when developing a 15-minute delivery network.

In the second scenario, all parameters remain consistent with the previous scenario, except for the maximum allowable driving time, which is limited to 20 minutes. Figure 5.4 shows the optimum number and location of MCCs in this configuration. In this scenario, 8 MCCs are selected. This figure also compares 20-minute and 15-minute scenarios. The light orange areas show SA3s with a chosen MCC only in the 15-minute scenario, while dark orange areas illustrate SA3s with a chosen MCC in both 15-minute and 20-minute scenarios. The brown areas only depict SA3s with a chosen MCC in the 20-minute scenario.

In the last scenario, the maximum allowed driving time is set to 25 minutes, enabling the examination of Sydney's 25-minute delivery configuration. Figure 5.5 shows this scenario and indicates that 6 MCCs are needed. In this figure, the light orange, dark orange, and brown areas show SA3s with a chosen MCC only in 15-minute configuration, SA3s with a chosen MCC in both 15-minute and 25-minute configurations, and SA3s with a chosen MCC only in 25-minute configuration, respectively.

USAHLP, 20 Minutes Driving Time

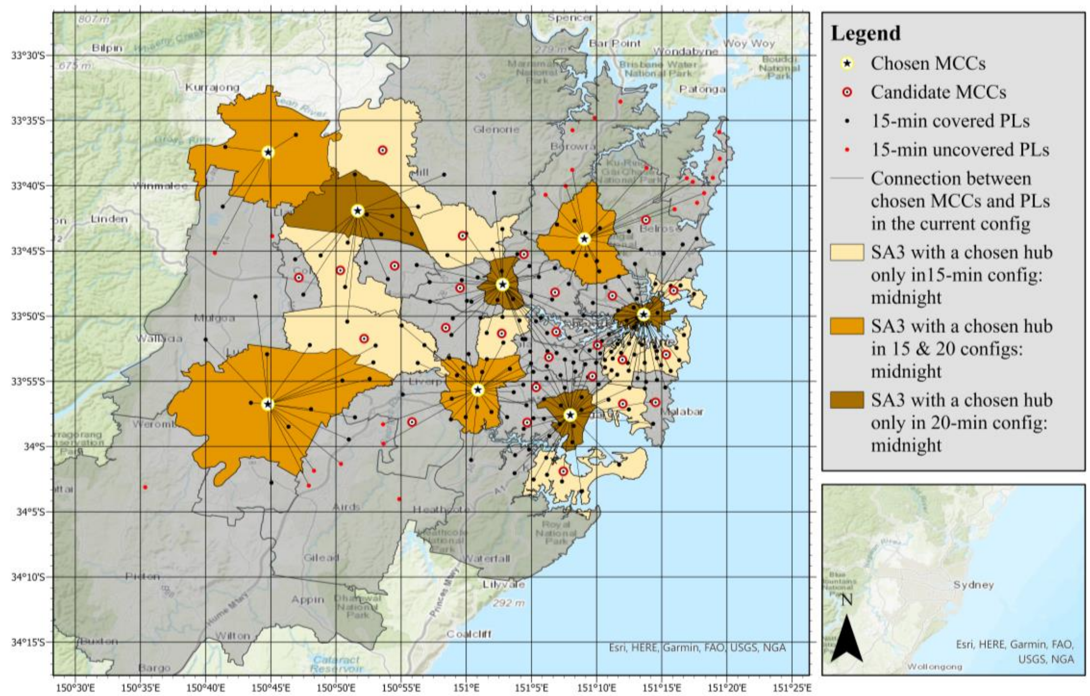


Figure 5.4. 20-minute delivery configuration.

USAHLP, 25 Minutes Driving Time

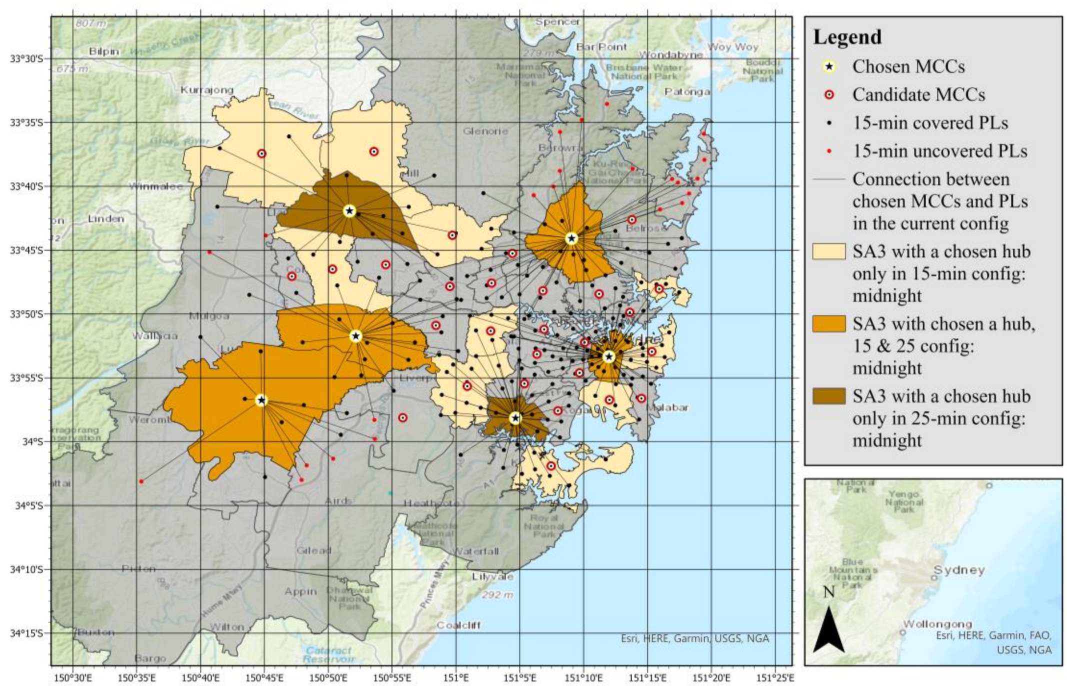


Figure 5.5. 25-minute delivery configuration

The detailed results of the USAHCP for the scenarios, including the optimum location of MCCs, TDT, total weighted driving time (TWDT), and total VKT are represented in Appendix C, Table C.1. In this table, Auburn (SA3 code: 12501), for example, was selected as one of the SA3s for a 15-minute delivery configuration. In this area, the MCC fulfils a high number of PLs, resulting in high TDT, TWDT, and VKT values.

5.4 Assessing Strategic and Operational Decisions within the Network

In this chapter the USAHCP is solved to determine how the interaction between MCCs and PLs can minimise the movement of urban freight vehicles. We investigated and developed a methodology for facilitating the combination of MCCs and PLs operations in the LML distribution network, by incorporating geographical characteristics of urban areas as well as the e-commerce demands' aspects. To determine the optimal location of MCCs to meet the demand of given PLs, the method developed was applied to Sydney as a case study. By considering the regulations in Sydney that promote fast goods transportation (Transport for NSW, 2023) and allowing to establish small logistics facilities in different land uses (NSW Government, 2022), we integrated e-commerce demands in the geographical centre of postcodes, and also considered candidate MCCs in the centre of SA3s. Then, the spatial configurations of parcel distribution in three distinct delivery configurations were evaluated, including 15-minute, 20-minute, and 25-minute delivery scenarios. Since the developed method can be applied to other locations, however, it is critical to determine how each scenario can benefit logistics stakeholders.

Figure 5.6 compares the above-mentioned scenarios in terms of the number of MCCs required, the percentage of covered PLs (postcodes), and the covered population. 14 MCCs were selected to develop a 15-minute delivery configuration. By establishing these numbers of MCCs in the locations presented in Table C.1, 89% of PLs and 92% of Sydney's population can be covered. Considering that setting up 14 MCCs would increase carriers' expenses and not be financially feasible, this scenario may not be their first choice. Conversely, it may be in the interests of local and state governments since it can increase the quality of services provided to residents and reduce the VKT compared to 20- and 25-minute scenarios.

The 20-minute scenario showed that by establishing 8 MCCs, 96% of PLs and 98% of the population could be covered. From a management standpoint, by targeting longer delivery times, the required MCCs were reduced by 42%, resulting in a reduction in total costs, especially facility costs. This scenario is advantageous for both governmental bodies and carriers, given that the majority of PLs are adequately covered.

With the 25-minute delivery scenario, more than 99% of PLs could be fulfilled by setting up 6 MCCs. Carriers are the primary stakeholders interested in using this scenario since fewer MCCs will reduce costs. On the other hand, customer satisfaction, which is one of the objectives of governments and customers themselves, can still be achieved since online orders are received relatively rapidly.

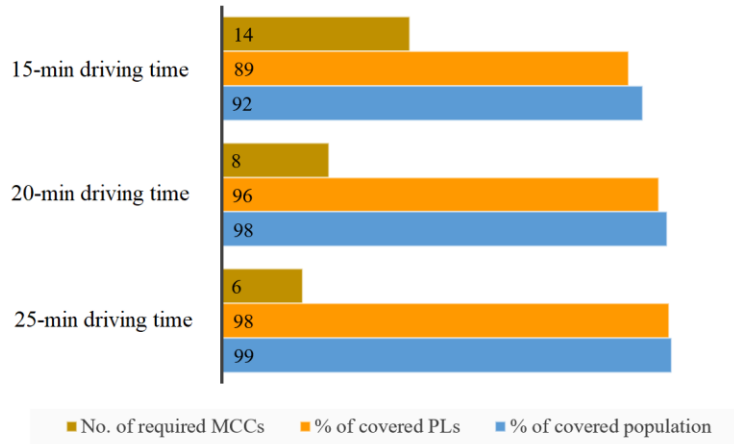


Figure 5.6. Coverage of the Sydney in different driving time scenarios.

5.4.1 Sensitivity Analysis

In the real world, traffic congestion directly impacts driving speed, reducing accessibility within a fixed time frame. As a result, traffic congestion levels influence the number of MCCs required to service PLs. Logistics carriers may need to strategically adjust their hub locations to ensure timely and efficient delivery services based on how quickly they are willing to meet their customers' needs and at what time of day.

This section evaluates the USAHCP's robustness and performance under road traffic conditions by solving it at different times of the day. Based on TomTom data, Sydney's traffic patterns can be categorised into five groups: midnight, morning peak, off peak, afternoon peak, and night. In Section 5.3.2, the USAHCP was solved for the midnight category. Here, the USAHCP is assessed in other periods. Figure 5.7 illustrates how traffic during various time periods affects the number and location of the chosen MCCs in different scenarios. Additionally, Table C.1 in Appendix C presents the location of the chosen MCCs, TDT, and TWDT.

Based on TomTom historical data, Sydney's lowest traffic congestion level occurs during midnight (4:00 AM). Hence, the optimal number of MCCs for 15-, 20-, and 25-minute scenarios, $(n_{mccs}^{15min}, n_{mccs}^{20min}, n_{mccs}^{25min})$, was (14, 8, 6), which is the lowest number of hubs compared with other time periods. Traffic congestion in the night period (10:00 PM) is very similar to that at midnight. The obtained results of solving the USAHCP also mimicked this fact as the number of required MCCs was (15, 8, 6). Although the number of required MCCs in the 20- and 25-minute scenarios for midnight and night was the same, their optimum location differed slightly. For the 20-minute scenario, for example, the location of MCCs was slightly shifted to the central north area.

As parcels are delivered to PLs instead of home deliveries, delivery at night and midnight presents unique opportunities for logistics providers to establish fewer logistics facilities. This reduces infrastructure and maintenance costs. On the other hand, lower traffic congestion results in faster and more reliable delivery operations. This allows carriers to serve more customers. However, conducting parcel deliveries at night also entails challenges, such as potential safety concerns and noise level restrictions.

During the off-peak period, the optimum number of MCCs was (19, 14, 8). As compared to midnight, the highest increase in the number of chosen MCCs occurred in the 20-minute scenario, which increased by 75%. The number of required MCCs in the 15- and 25-minute scenarios increased by 35% and 33%, respectively.

Sydney's morning and afternoon traffic is very congested. In the morning peak, the optimum number of MCCs to fulfil PLs was (25,14, 9) indicating 78.5%, 75%, and 50% increase compared to 15-, 20-, and 25-minute scenarios at the midnight period. During the afternoon peak, the optimum number of MCCs required to serve PLs was (22, 16, 10). This demonstrated a respective increase of 57%, 100%, and 66.7% compared to the 15-, 20-, and 25-minute scenarios observed at midnight. Thus, the delivery of goods during these periods is not economically feasible.

Figure 5.8 shows the TDT in hours for all the evaluated scenarios. It was observed that by increasing the driving time constraint from 15 minutes to 25 minutes, the TDT was increased regardless of the period of the day. This is because when the driving time constraint is higher, the number of chosen MCCs increases, which imposes longer trips from the MCCs to PLs.

The relationship between the number of chosen MCCs and TDT is also repeated in the 20- and 25-minute scenarios. In these scenarios, when the number of selected MCCs was maximum, the TDT was minimal. For the 20- and 25-minute scenarios the minimum TDT occurred in the morning peak and afternoon peak, respectively. In contrast, although in the 15-minute scenario, the maximum number of MCCs was in the afternoon peak period, the minimum TDT occurred in the off-peak period.

The other factor contributing to logistics stakeholders' strategic planning is the amount of demand handled by each MCC. To discuss this issue, we provide the TWDT, even though, in this chapter, we assess the uncapacitated HCP. In Table C.1, this factor, which emphasises to what extent the role of MCCs is crucial, is calculated by multiplying the normalised demand associated with each MCC by the TDT. In the 15-minute scenario in the off-peak period, for example, although the MCC located at SA3 12003 has the maximum TDT, the maximum TWDT occurs at the MCC located at SA3 11703. This indicates that the MCC at SA3 11703 is responsible for the largest number of e-commerce parcels and requires additional capacity.

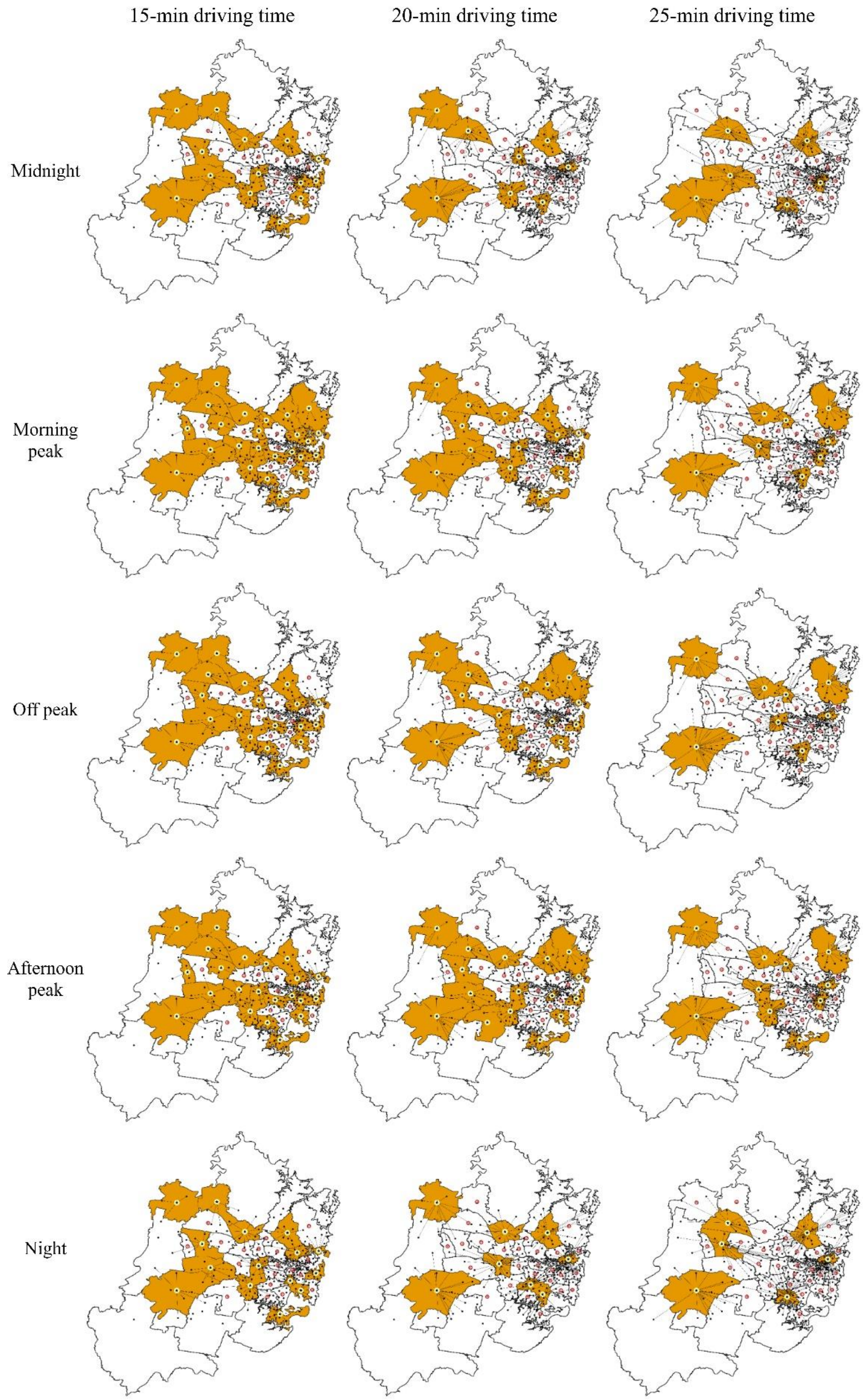


Figure 5.7. The optimum configuration of MCCs in different scenarios and time periods.

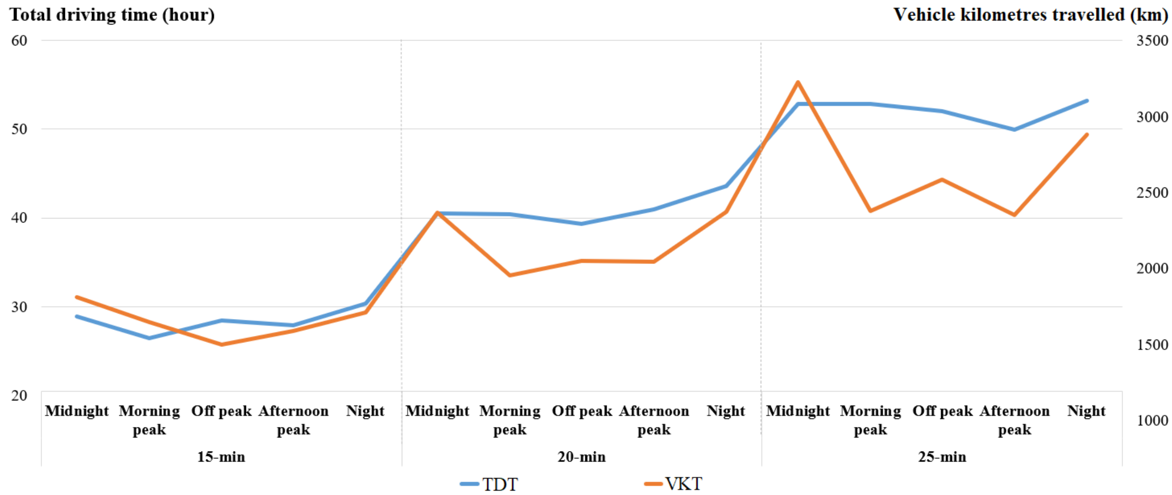


Figure 5.8. Total driving time for different scenarios and time periods.

5.4.2 Comparative Analysis of Current and Collaborative Distribution Networks

To assess the described collaborative distribution network's effectiveness in reducing the TDT and VKT, we solve the HCP for an independent distribution system used by carriers. Most carriers have only one warehouse in Sydney, usually located in Mount Druitt SA3, as shown in Figure 5.9. Based on this assumption, the HCP is solved, and the TDT and VKT for fulfilling PLs are calculated. In such a network, the TDT is more than 122 hours, which is more than twice the maximum TDT of all scenarios evaluated in Section 5.4.1. The total VKT is 8216 kilometres, which is 154% more than the maximum VKT obtained in the previous section. Hence, regardless of the desired delivery time, the establishment of MCCs to fulfil the PLs can reduce the TDT and VKT in the network.

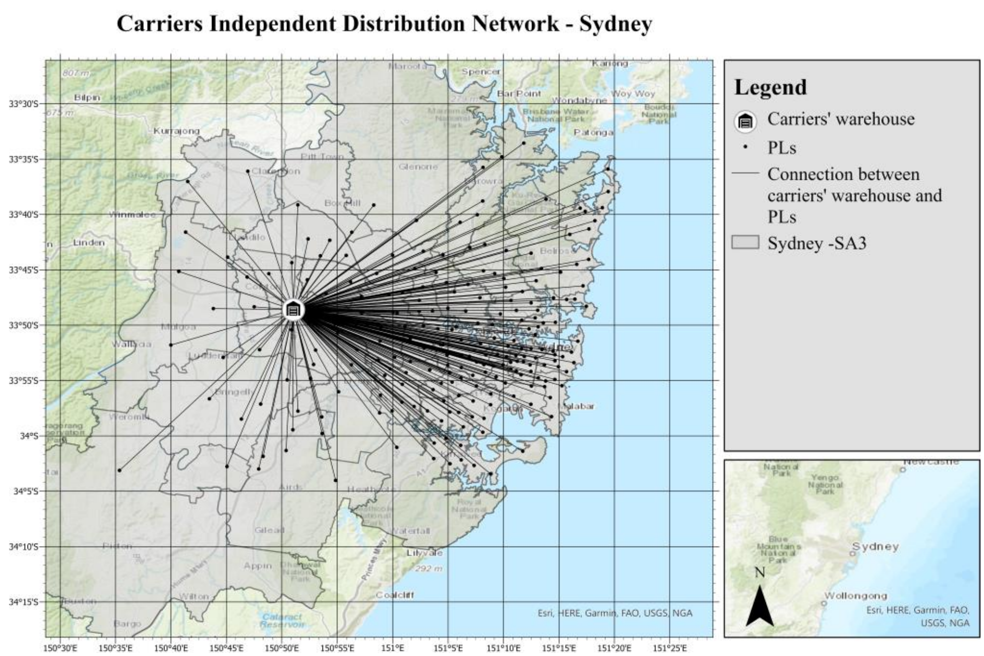


Figure 5.9. Connections between carriers' warehouse and PLs considering the carriers freight system.

5.5 Discussion

In this chapter, the USAHCP is solved by considering possible strategic and operational decisions. This approach benefits a wide range of stakeholders in LML. At the strategic level, by comparing the distribution network configuration with 15-, 20-, and 25-minute delivery constraints, the optimum number and location of MCCs are identified. These comparative results can provide governments, such as city councils and state governments, with a perspective on how their future plans for city accessibility can affect the shape of the distribution system in urban areas. Consequently, they can adjust their policies to encourage other freight stakeholders, primarily shippers, to move in this direction. Shippers, including any retailers involved in e-commerce, are another crucial stakeholder in LML who can directly benefit from the strategic sensitivity analysis conducted in this chapter. By utilizing their demand data, they can apply the introduced methodology to determine the optimum number and location of their hubs.

At the operational level, five different delivery time periods are examined in this chapter. While carriers—logistics companies that transport goods between origins and destinations—are the immediate stakeholders who can use the insights from this sensitivity analysis, governments and shippers can also benefit from these results. The lowest number of required MCCs is observed when deliveries are scheduled at night or midnight. While deliveries during these periods may reduce costs for some stakeholders, they might not be suitable for others due to noise concerns and regulations typically imposed by governments.

Although delivery timing appears to be an operational decision, it significantly impacts the number and location of MCCs, which is a strategic decision. Overall, the 15 scenarios evaluated in this chapter provide detailed insights for LML stakeholders to inform their policy choices and decision-making processes.

5.6 Chapter Summary

E-commerce has rapidly grown, leading to substantial shifts in consumer purchasing patterns and business practices. This expansion has been accompanied by a notable increase in business-to-consumer (B2C) shipments, primarily involving small physical products. Consequently, this upsurge has led to a rise in urban freight vehicle movement, which has been further amplified by the online demand surge triggered by the COVID-19 pandemic, leading to geographically dispersed goods and more vehicle kilometres travelled (VKT). Hence, the optimisation of last-mile logistics (LML) is critical to reducing the VKT and negative externalities.

In this chapter, a spatial methodology incorporating five steps was designed to solve uncapacitated single allocation hub covering problem (USAHCP) aiming to minimise the VKT in urban areas while maximising coverage areas. In this optimisation, suitable locations and numbers for micro-consolidation centres (MCCs) were determined based on varied scenarios to fulfil parcel lockers (PLs). Firstly, an origin-destination matrix was generated by calculating the shortest-path costs between MCCs and PLs. Unfeasible arcs were then removed from the matrix using Hillsman editing. Semi-randomised solutions were generated by assigning MCCs to PLs, and these solutions were improved using the vertex substitution heuristic. The next step involved applying a GA to combine low-cost solutions and created better solutions. The problem was represented using a 2N-dimensional array, and the initial population was generated randomly while ensuring feasibility. Selection, crossover, and mutation processes were iteratively applied to evolve the population and identified optimal solutions.

The USAHCP inputs and constraints were structured according to the strategic plan and geographical features of our case study, Sydney. The 15-minute postcode framework in Sydney aims to create self-contained communities by providing essential amenities and services within a short distance. This concept, promoted by Transport for New South Wales, aims to enhance sustainability, autonomous mobility, and revitalise local centres. To address this challenge, we proposed implementing a PL at the geographical centre of every 225 postcodes in the case study. The case study also includes 42 Statistical Area Level 3 (SA3) regions, which are functional regions with interconnected suburbs surrounding commercial and transportation hubs. Unlike traditional hub location problems (HLPs), the NSW Government permits the establishment of MCCs across various land uses based on the preferences of local governing bodies. Therefore, the proposed approach considers the geographical centroid of each SA3 as a potential location for MCCs.

Three delivery configurations, aligned with accessibility concept, were considered in the scenario-based analysis: 15-, 20-, and 25-minute scenarios. Considering the free-flow conditions, occurring at midnight, as the baseline traffic pattern, the results of solving the USAHCP for the 15-minute scenario pinpointed that 14 MCCs were required. By having these MCCs at the locations presented in Table C.1 92% of PLs and 89% of the population were served. The optimal number of MCCs in the 20-minute scenario was 8, and 96% of the PLS and 98% of the population were covered. In the 25-minute scenario, 6 MCCs were needed to cover 98% of PLs and 99% of the population.

The sensitivity analysis of the developed methodology under various time periods and traffic conditions was done. This analysis revealed that traffic congestion significantly impacts the number and location of MCCs. The least required MCCs were observed during the midnight and night periods. Hence, delivering parcels during these periods offers opportunities to reduce costs and improve delivery efficiency. In contrast, morning and afternoon peak hours exhibited high traffic congestion, leading to a substantial increase in MCCs required, making deliveries during these periods economically unfeasible. The 25-minute scenario demonstrated greater robustness in handling traffic level shifts from free-flow to congested conditions, with the number of MCCs increasing from six to ten. These results highlight the importance of strategic hub planning to satisfy customers' needs in a cost-effective manner.

As demonstrated in this chapter, incorporating geographical characteristics and demands into the design of the LML distribution network can reduce the VKT. The comparative analysis in Section 5.4.2 revealed that TDT and VKT were reduced using collaborative distribution networks of MCCs. Additionally, the comparison of various scenarios based on the percentage of covered PLs, and the population provided insight into their application for decision makers. While establishing more MCCs can increase PLs coverage, it may not be financially feasible. It was emphasised that local and state governments may benefit from scenarios that improve service quality for residents and minimise the VKT. On the other hand, carriers may prioritise scenarios with fewer logistics hubs to reduce costs.

In future studies, it is essential to quantitatively evaluate the trade-off between coverage and cost. Finding the right balance between the number of MCCs and the percentage of covered PLs will optimise operational costs effectively. Additionally, it is essential to assess the impact of different scenarios on CO_2 and GHG emissions. Another future direction is to incorporate uncertainty into modelling to develop a more reliable and realistic approach. By acknowledging the uncertainties associated with input data, assumptions, and model parameters, decision-makers can better evaluate the potential variations and limitations of the model and results.

Chapter 6: Collaborative Multi-depot Green Vehicle Routing Problem

A B S T R A C T:

Global climate change-related initiatives such as the 2015 Paris Agreement have highlighted the necessity of sustainable transportation. Nevertheless, the rapid growth of e-commerce has notably escalated vehicle kilometres travelled (VKT) and CO_2 emissions within cities, posing a direct challenge to sustainability initiatives. To address these challenges, this chapter formulates a collaborative multi-depot green vehicle routing problem. This model utilises micro-consolidation centres (MCCs) as shared hubs alongside a microscopic approach linking emission rates to vehicle and route characteristics, in order to assess MCCs' effectiveness in reducing CO_2 emissions. Introduced here is an innovative self-adaptive metaheuristic algorithm hybridising intelligent water drops and simulated annealing. This methodology differs from established approaches by incorporating a feedback control system that actively monitors the algorithm's performance and convergence towards the global minimum solution. Through continuous adjustments to algorithm parameters via a feedback loop, this methodology strikes a balance between exploitation and exploration. The algorithm is tested in a context-specific approach, first applying it to the Cordeau benchmark and comparing it with previous state-of-the-arts, followed by a case study comparing the collaborative network to an independent one. This approach achieves 43% and 25% reductions in VKT and emissions, respectively, enhancing urban logistics networks' efficiency and sustainability.

6.1 Introduction

The International Transport Forum in its 2021 transport outlook stated that current transportation trends are unsustainable (ITF, 2021). Since 2015, major global initiatives have been adopted to improve the international response to climate change and make the world more sustainable, including the Paris Agreement (United Nations, 2015a) and the United Nations' Sustainable Development Goals (SDGs) (United Nations, 2015b). In both initiatives, transportation plays a major role. Under the Paris Agreement, 55 countries have committed to reducing global greenhouse gas (GHG) emissions by at least 55% (United Nations, 2015a). The SDGs also provide a blueprint for assessing GHG emissions and sustainable transportation that aims to achieve sustainable development by 2030 (Kawakubo et al., 2018). Even if all the commitments are met, it is estimated that transportation-related carbon dioxide (CO_2) emissions will rise by 16% by 2050 (ITF, 2021), underlining the need for an urgent transformation within the transport industry.

Urban areas account for approximately 70% of global emissions, one-third of which are produced by transport (OECD, 2020). Among the trends exacerbating this issue is the rise of e-commerce, which has contributed to increased vehicle kilometres travelled (VKT) in urban areas (Kahalimoghadam et al., 2024). The popularity of e-commerce popularity has compelled retailers to offer shorter delivery lead-times and prioritise fast delivery. In an increasingly competitive environment, vehicle load factors have decreased, simultaneously increasing service costs and CO_2 emissions (Muñoz-Villamizar et al., 2021). This underscores the pressing demand for green vehicle routing problem (GVRP) where the aim is to reduce the environmental impact of goods transport.

To overcome the issues associated with e-commerce, concepts such as the Physical Internet (PI) and Hyperconnected City Logistics (HCL) present promising solutions. The PI revolves around standardising containers and procedures, facilitating smoother and more efficient transportation. This concept advocates for an interconnected and open global logistics system (Crainic & Montreuil, 2016). On the other hand, HCL concentrates on enhancing goods movement in urban settings, addressing issues related to last-mile delivery, traffic congestion, and environmental impact (Crainic & Montreuil, 2016). For this purpose, HCL promotes the integration of smart technologies, shared data, and cultivating more collaboration among key stakeholders.

A network of micro-consolidation centres (MCCs) can be established in metropolitan areas to facilitate the implementation of PI and HCL. MCCs can sort, consolidate, and distribute goods in a more efficient way, thus reducing the number of vehicles on the roads while increasing vehicle load factors (Nsamzinshuti et al. 2017). Furthermore, MCCs are closer to the final customers resulting in a decrease in VKT and thereby reducing costs. These actions enhance the prospects of employing sustainable and lighter vehicles for last-mile delivery, thereby mitigating CO_2 emissions. This chapter complements the strategic MCC network design from Chapter 5 by focusing on the operational level. Here, we optimise vehicle allocation to customers within a collaborative distribution network, utilising the MCC locations identified in Chapter 5.

Collaboration among logistics providers is vital for establishing a network of MCCs since more unified collaboration amplifies the potential for efficient consolidation (Leitner et al., 2011). It has been demonstrated that collaboration effectively enhances the efficiency of goods movement and successfully reduces CO_2 emissions (Gansterer & Hartl, 2018; Pan, 2019). This collaboration leads to devising a collaborative multi-depot distribution network (CMDDN). In addition to improving distribution network (DN) operation efficiency by optimising logistics resource allocation, the CMDDN can reduce transportation costs by minimising the VKT. However, the level of collaboration may vary when attempting to achieve economies of scale. In the low-collaborative scenario, depot capacities are shared among multiple entities; however, each company independently serves its customers through dedicated vehicle fleets. The semi-collaborative case involves centralised route planning decisions, wherein participating enterprises jointly utilise shared facilities and fleets to optimise their operations. In the fully cooperative scenario, consensus-driven decision-making extends to both routing plans and facility-location choices, involving active participation and agreement among all involved entities (Leitner et al., 2011).

Collaboration in logistics can be horizontal or vertical. In contrast to typical vertical collaboration, horizontal collaboration entails companies forging alliances with other companies operating at the same supply chain level. Based on the level of information shared between coalition partners, horizontal collaboration can be categorised into centralised, decentralised, and auction-based (for more details about types of collaboration, readers can refer to (Frederik et al., 2022) and (Gansterer & Hartl, 2018)). This chapter concentrates on centralised collaborative vehicle routing problem (CVRP) in which logistics providers have greater flexibility and independence. Throughout the remainder of this chapter, we will employ the term "collaboration" or "collaborative" in this context, unless explicitly specified otherwise.

In an independent distribution system, logistics providers fulfil customers' needs using their own depot(s), resulting in limited or inefficient distribution. Moreover, this consequence leads to a lack of equilibrium between the capacity of delivery vehicles and the demand for goods distribution in both temporal and spatial dimensions, resulting in challenges such as the underutilisation of distribution vehicles, insufficient distribution capacity, or an increase in VKT (Wang et al., 2021; Xu et al., 2017). In contrast, the CMDDN enhances logistics stakeholders' economic and social benefits through optimal resource utilisation, including delivery vehicles and depots, and cost reduction (Q. Zhang et al., 2022).

Previous studies have addressed many aspects of CMDDN but suffer from the following issues. Firstly, to the best of our knowledge, no attention has been paid to the application of MCCs, as most studies focus on larger logistics facilities, such as urban consolidation centres (UCCs) or distribution centres. Secondly, minimal attention has been paid to the environmental impacts of the CMDDN, with most studies primarily focusing on the fair profit allocation of different parties. Thirdly, given the intricate structure and vast scale of a large-scale CMDNN, directly implementing conventional (meta)heuristic algorithms is challenging. Hence, in this chapter we focus on the application of MCCs in the CMDNN aiming to minimise both CO_2 emissions and VKT. This is done by applying a novel feedback control-based metaheuristic algorithm. Considering both collaboration and environmentally friendly transportation, this chapter introduces the collaborative multi-depot green vehicle routing problem (CMDGVRP). The CMDGVRP compromises a multi-objective programming model that optimises the total VKT and CO_2 emissions. The collaboration between depots is facilitated by medium commercial vehicles (MCVs), e.g., small trucks, while the distribution of goods from depots to customers is carried out by urban goods delivery vehicles (UGDVs), for instance., vans. By incorporating the microscopic emission model into the CMDGVRP, several factors, such as vehicle type, speed, and acceleration are deemed as able to ensure the accuracy and reliability of the emissions analysis.

In this chapter, we formulate the CMDGVRP to facilitate the establishment of a network of MCCs. To achieve this goal, we have developed a self-adaptive intelligent water drops simulated annealing (SAIWDSA) algorithm. The SAIWDSA incorporates two knowledge-based systems (KBSs) created based on the performance and convergence of the algorithm. In particular, a feedback control approach is included in the SAIWDSA to modify its parameters based on the objective functions' values. The developed algorithm is applied to the Cordeau multi-depot vehicle routing problem (MDVRP) benchmark and a case study where an instance is created based on real-world e-commerce data. Results indicate the reduction of VKT and CO_2 in urban goods transportation.

The contributions made by this modelling are as follows:

- We define the CMDGVRP and mathematically formulate it as a multi-objective optimisation problem to minimise VKT and reduce CO_2 emissions. Within CMDGVRP, goods are transferred between MCCs via MCVs and subsequently distributed to end customers using UGDVs. The inherent flexibility of CMDGVRP's core structure renders it suitable for modelling a wide range of specialised applications characterised by diverse objectives and constraints.
- We develop a SAIWDSA algorithm to solve the CMDGVRP and optimise vehicle movements in a network of MCCs. This algorithm not only incorporates intelligent water drops (IWD) and simulated annealing (SA) but also uses a feedback control technique to dynamically adjust algorithm parameters. It is based on the convergence of the outputs (objective functions) towards the global minimum. In the solution methodology, two KBSs are generated by mathematically analysing the parameter sensitivity of the IWD algorithm. Creating an KBS using the parameter sensitivity analysis method can be extended to any other metaheuristic algorithm, providing a versatile approach.

- Compared to previous state-of-the-art methods, our numerical experiments demonstrate that we attain the best results across the majority of instances. Through a case study where we compared the CMDDN with a traditional independent DN to solve a real-world e-commerce problem, we offer valuable insights into collaborative green logistics decision-making.

This chapter is structured as follows. Section 6.2 explains the CMDGVRP, its assumptions and model formulation. Section 6.3 outlines the solution methodology, including how IWD and SA are incorporated into the hybrid SAIWDSA algorithm. Furthermore, it describes performance-based and convergence-based KBSs. The developed algorithm is applied to the standard 33 Cordeau instances in Section 6.4 and the results are compared with what previous research published. In this section, a new instance is also generated for a case study using real-world e-commerce data and the application of the CMDDN in CO_2 reduction is evaluated. Section 6.5 presents the chapter's conclusion and suggestions for future work.

6.2 Narrative of CMDGVRP

6.2.1 Problem Description of CMDGVRP

We consider the complete graph $G = (N, A)$, in which $N = N_{DP} \cup N_{MCC}$ is the nodes' set including the demand points (DPs) set, N_{DP}, and depots set, N_{MCC}. The total number of DPs is n, $N_{DP} = \{dp_1, dp_2, \dots, dp_n\}$, and there are m MCCs in the network, $N_{MCC} = \{m_1, m_2, \dots, m_m\}$. As discussed before, the geographical location of DPs and depots are assumed to be known. $A = \{(a_i, a_j): a_i, a_j \in V,\ i \neq j\}$ is a representation of all possible routes between MCCs and DPs. A_{ij}, as a subset of A ($A_{ij} \subset A$), is the tour of vehicle k that starts and ends in MCC j and fulfil some DPs: $A_{ij} = \{mcc_j,\ dp_{first}, \dots, dp_{last}, mcc_j\}$, where $mcc_j \in N_{MCC}$, and dp_{first} and dp_{last} are the first and last visited DPs in the tour, respectively. It is also assumed that K homogeneous UGDVs of capacity C_k are available. Furthermore, all possible distances between DPs and depots are calculated and stored in a distance matrix which is used to generate solutions. Table 6.1 categorises the sets, parameters, decision variables, and other variable classifications utilised in the model. The values for UGDVs and MCVs are derived from (Wang et al., 2019) and (Nie & Li, 2013), respectively.

Figure 6.1 presents a comparative analysis between an independent network and a collaborative one, both consisting of 3 MCCs and 23 DPs. Figure 6.1 (a) depicts a typical DN where individual carriers independently serve their respective customers utilising UGDVs. Despite the optimisation of the VRP for each carrier (MCC), the overall VRP within the network remains suboptimal, resulting in notably poor efficiency levels. Conversely, in the collaborative setting depicted in Figure 6.1 (b), carriers share their customer base, leading to the optimisation of the VRP across the entire network. However, this collaborative framework requires goods exchange between carriers, necessitating the usage of MCVs in addition to UGDVs.

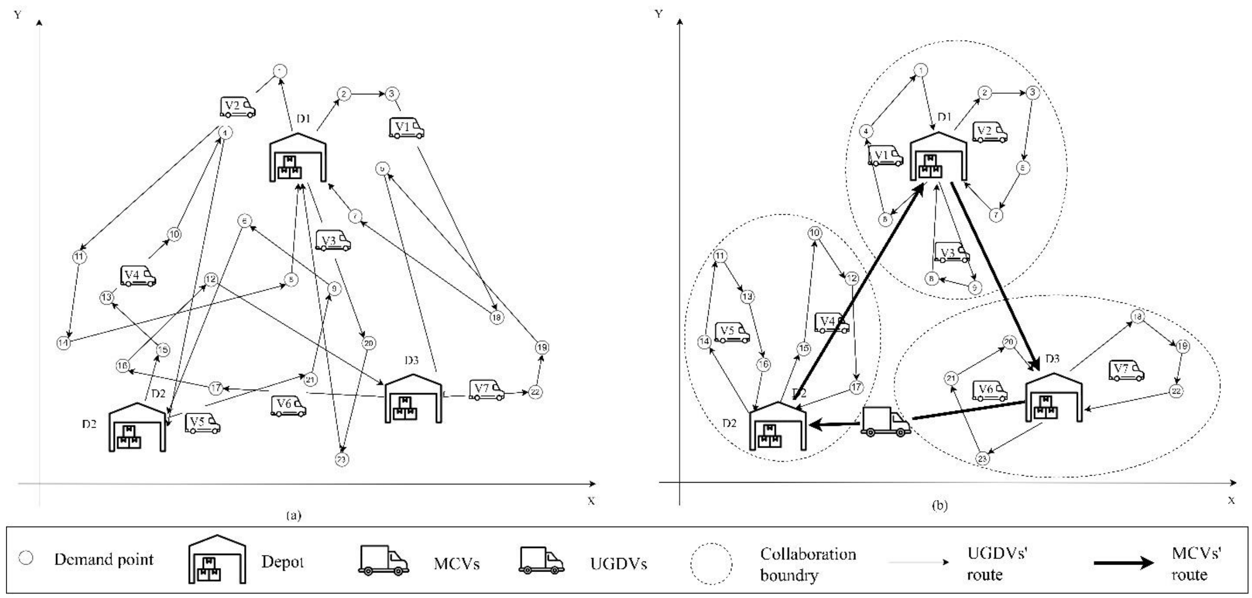


Figure 6.1. CMDGVRP clustering and routing processes.

Moreover, the illustrated DN in Figure 6.1 differs from a two-echelon network. In a standard two-echelon DN, goods move from suppliers to distribution centres in the first echelon and, in the second tier, from distribution centres to the DPs. In the proposed DN, goods transportation occurs in one echelon, even though distinct vehicles handle different responsibilities. Such a DN balances the demand between MCCs, which can enhance cost efficiency and expedite deliveries.

6.2.2 Mathematic Formulation of CMDGVRP

CO_2 emissions are usually determined by fuel consumption, which incorporates an emission coefficient. In the existing literature, diverse models for estimating fuel consumption have been examined, encompassing both macroscopic and microscopic approaches. Nevertheless, microscopic models are favoured for their ability to provide real-time emission predictions and heightened precision. This chapter employs the CMEM, designed to calculate UGDVs' second-by-second fuel consumption using emissions data from diverse light-duty vehicles and laboratory driving cycles (Demir et al., 2014). The model requires detailed vehicle-specific parameters, including the engine friction coefficient, vehicle engine speed, engine power, and fuel rate, for precision. Aimed at emissions reduction, the CMEM incorporates intricate calculations. Recognised for its applicability, it serves as a state-of-the-art microscopic emission model for evaluating emissions in diverse VRPs. Following CMEM, the equation for computing CO_2 emissions between n_i and n_j is expressed as follows:

$$E_{ij}(t) = r \times FC_{ij}(t) \tag{1}$$

$FC_{ij}(t)$ represents the instantaneous fuel consumption. The subsequent procedure is employed to calculate the $FC_{ij}(t)$ based on the UGDVs' engine power and speed.

$$FC_{ij}(t) = TT_{ij}\left(\alpha_1 + \alpha_2 \times \left(W + f_{ij}\right)\right) \tag{2}$$

$$\alpha_1 = \frac{\xi}{\kappa}\left(E_k E_N E_V + \frac{P_{acc}}{1000\varepsilon\varpi} \right) \quad (3)$$

$$\alpha_2 = \frac{\xi}{\kappa} \times \frac{P_{tract}}{1000\varepsilon\varpi} \quad (4)$$

In equation (2), $TT_{ij} = D_{ij}/v$ is travel time between n_i and n_j and calculated by dividing the distance between the nodes and speed on the vehicle, v. In equation (3), α_1 is the emissions related to air resistance in which $P_{acc} = 0.5C_m A\rho v^3$ is accessories power. Finally, in equation (4), $P_{tract} = v(g\, sin\, \varphi + gC_r\, cos\, \varphi + a_t)$ is the tractive power per mass unit.

By taking into account the parameters relevant to MCVs, a similar process is applied to compute their CO_2 emissions, which are represented as $E'_{ij}(t)$.

$$Z_1 = \sum_i \sum_j \sum_k D_{ij} \times x_{ijk} \quad (5)$$

$$Z_2 = \sum_m \sum_n \sum_{k'} D_{mn} \times y_{mnk'} \quad (6)$$

$$Z_3 = \sum_i \sum_j \sum_k (E_{ij} \times x_{ijk}) + \sum_m \sum_n \sum_{k'} (E'_{mn} \times y_{mnk'}) \quad (7)$$

The CMDGVRP optimisation model is formulated as follows:

$$\min(Z_1 + Z_2) \quad (8)$$

$$\min(Z_3) \quad (9)$$

$$s.t. \quad \sum_{i \in N} \sum_{j \in N_{DP}} x_{ijk} = 1, \qquad \forall j \in N_{DP}, i \neq j \quad (10)$$

$$\sum_{i \in N} \sum_{j \in N_{DP}} x_{ijk} \leq 1, \qquad \forall k \in K \quad (11)$$

$$\sum_{j \in N_{DP}} x_{ijk} = \sum_{j \in N_{DP}} x_{jik}, \qquad \forall i \in N, \forall k \in K \quad (12)$$

$$\sum_{j \in N_{DP}} \left(pv_j \times \sum_{i \in N} x_{ijk} \right) \leq C_k \qquad \forall k \in K \quad (13)$$

$$\sum_{n \in N_{MCC}} \sum_{m \in N_{MCC}} pv_{mn} \times y_{mnk'} \leq C_{k'} \qquad \forall k' \in K' \quad (14)$$

$$\sum_{i,j \in N} \sum_{m \in N_{MCC}} pv_j \times \chi_{ijkm} \leq C_m \qquad \forall m \in N_{MCC} \quad (15)$$

$$pv_{mn} = \sum_{j \in N_{DP}} \psi_{mnj} \times pv_j \qquad \forall\, m, n \in N_{MCC} \quad (16)$$

$$\beta_i - \beta_j + C_k \times x_{ijk} \leq C_k - pv_j \qquad \forall\, i, j \in N_{DP}, \forall k \in K, i \neq j \quad (17)$$

$$pv_j \leq \beta_j \leq C_k \qquad \forall\, j \in N_{DP}, \forall k \in K \quad (18)$$

$$x_{ijk} = \{0,1\} \qquad \forall\, i \in N, \forall\, j \in N_{DP}, \forall k \in K \quad (19)$$

$$\chi_{ijkm} = \{0,1\} \qquad \forall\, i \in N, \forall\, j \in N_{DP}, \forall k \in K, \forall m \in N_{MCC} \quad (20)$$

$y_{mnk'} = \{0,1\}$ $\quad \forall\, m,n \in N_{MCC}, \forall k' \in K'$ $\quad (21)$

$\psi_{mnj} = \{0,1\}$ $\quad \forall\, m,n \in N_{MCC}, \forall\, j \in N_{DP}$ $\quad (22)$

Table 6.1. Notation used in the CMDGVRP model.

Notation	Symbol	Description	Value	Unit
Set	N	Nodes in the network		
	A	All possible routes		
	N_{MCC}	MCCs in the network		
	N_{DP}	DPs in the network		
	K	UGDVs serving PLs		
	K'	MCVs exchanging goods between MCCs		
	G^{C}_{IWD}	Nodes to be avoided by IWDs to satisfy constraints		
Parameter	D_{ij}	Distance between a pair of nodes $(i,j), i,j \in N$		
	C_k	Capacity of UGDVs $k, k \in K$		
	$C_{k'}$	Capacity of MCVs $k', k' \in K'$		
	C_{mcc}	Capacity of MCC $m, m \in N_{MCC}$		
	φ_{ij}	Average road angle on route a_{ij}, $a_{ij} \in A$		
	pv_j	Parcel volume of the customer j		
	pv_{mn}	Delivery volume from MCC m to n calculating by comparing customers of independent network with collaborative network		
	β_i, β_j	Coefficient employed to restrict the elimination of sub-tours		
	ρ_l	Local soil updating parameter in IWD		
	ρ_g	Global soil updating parameter		
	ε_v	A small positive auxiliary parameter		
	ε_s	Auxiliary parameter		
	r/r'	CO_2 emission factor of UGDVs/ MCVs		
	ω/ω'	Unload vehicle weight of UGDVs/ MCVs		kg
	f_{ij}/f'_{ij}	Payload of transporting from n_i/n_m to n_j/n_n of UGDVs/ MCVs		kg
	W/W'	Mass of UGDVs/ MCVs	1500/5500	kg
	C_m/C'_m	Coefficient of aerodynamic drag of UGDVs/ MCVs	0.3/0.7	—
	A/A'	Frontal surface area of UGDVs/ MCVs	2.0/8.0	m^2
	ρ	Coefficient of air friction	1.204	—
	ε/ε'	Efficiency of the vehicle drivetrain of UGDVs/ MCVs	0.85/0.45	—
	ϖ/ϖ'	Efficiency of vehicle engine of UGDVs/ MCVs	0.4/0.45	—
	E_k/E'_k	Engine's friction factor of UGDVs/ MCVs	0.2	—
	E_N/E'_N	Engine's speed of UGDVs/ MCVs	16.67/36.67	rpm
	E_N/E'_N	Engine's displacement of UGDVs/ MCVs	2/6.9	L
	ξ/ξ'	Fuel-to-air ratio of UGDVs/ MCVs	1/1:14.7	—
	κ/κ'	Heating value of a diesel fuel of UGDVs/ MCVs	44/4.4	MJ/kg
	g	Gravitational constant	9.81	m/s^2
	C_r/C'_r	Coefficient rolling resistance of UGDVs/ MCVs	0.01*/0.01	—
	a_t/a'_t	Vehicle instantaneous acceleration of UGDVs/ MCVs	0/0	m/s^2
Variable	$E_{ij}(t)$	CO_2 emissions between n_i and n_j, i and $j \in N$		kg
	D_{ij}	Distance between n_i and n_j, i and $j \in N$		km
	D_{mn}	Distance between MCC m and n, $m,n \in N_{MCC}$		km
	a_v, b_v, c_v	IWD's velocity updating variables		—
	a_s, b_s, c_s	IWD's soil updating variables		—
	$Soil(i,j)$	Path soil between n_i and n_j, i and $j \in N$		—
	Vel_{IWD}(t)	Current velocity in IWD		—
	Vel_{IWD}(t+1)	Velocity of the next step in IWD		—
	Time (n_i, n_j; Vel_{IWD})	Time takes IWDs traverse the path between n_i and n_j		—

Table 6.1. Notation used in the CMDGVRP model.

Notation	Symbol	Description	Value	Unit
	T_t	Temperature at the tth iteration in SA		—
Decision variable	x_{ijk}	Equal to 1 when UGDV k serves the arc (i, j) and 0 otherwise, $i \in N, j \in N_{DP}, k \in K$		
	$y_{mnk'}$	Equal to 1 when MCV k' transports from MCC m to n, and 0 otherwise, m,$n \in N_{MCC}, k' \in K'$		
	χ_{ijkm}	Equal to 1 when vehicle k departs from MCC m and serves the arc (i, j), and 0 otherwise $i \in N, j \in N_{DP}, k \in K, m \in N_{MCC}$		
	ψ_{mnj}	Equal to 1 if the fulfilling centre of customer j is changed from MCC m to MCC n and 0 otherwise, $m, n \in N_{MCC}, j \in N_{DP}$		

Equations (5), (6), and (7) represent the VKT by UGDV, VKT by MCVs, and total CO_2 emissions, respectively. The goal is to minimise VKT and CO_2 emissions, as calculated by equations (8) and (9). Constraint (10) guarantees that a single distribution route serves each customer exclusively. Constraint (11) ensures that each UGDV serves, at most, a distribution route and an MCC. Constraint (12) guarantees flow conservation. When considered collectively, Constraints (10) through (12) ensure that each UGDV must commence its journey from a MCC and return to the same MCC after completing the delivery task. Constraint (13) specifies the capacity of each UGDV to fulfil the total demand from the customers it serves. Constraint (14) demonstrates that the volume of goods transported between MCCs does not surpass each MCV's capacity. Constraint (15) ensures that each MCC's inventory satisfies its customer demand. Constraint (16) defines the volume of goods transported from MCC m to n, which equals the total volume distributed from MCC n, but originally from MCC m. Constraints (17) and (18) embody the constraints for eliminating sub-tours. Constraints (19) through (22) confine the decision variables to binary values and ensure their alignment with their respective definitions.

6.3 Self-Adaptive Metaheuristic Algorithm

To tackle the CMDGVRP as discussed in Section 6.2, we propose two self-adaptive intelligent water drop simulated annealing (SAIWDSA) algorithms. Unless the basic IWD that its velocity and soils parameters are static (see Section 6.3.1), the SAIWDSA algorithms modify their parameters dynamically based on the algorithms' performance and convergence towards the global optimum solution (see Sections 6.3.4 and 6.3.5). For each SAIWDSA two unique KBSs are developed (see Appendix E) which reflects the results of parameter sensitivity analysis applied to IWD (see Appendix D). The main pseudocode is presented in Section 6.3.4.

To escape from local minima, the SA algorithm is combined with IWD allowing water drop movements that could potentially result in inferior solutions (see Section 6.3.2). Algorithm 2 in Section 6.3.2 represents the incorporation of SA into IWD. The main values of SAIWDSA include hyperparameters tuning, solving the CMDGVRP, and finding the optimum solution is presented in Section 6.3.3 in detail. The following sections elaborate on the procedures involved in this approach.

6.3.1 IWD Algorithm

The IWD algorithm contains two principal features, the quantity of soil transported by a single drop, $Soil_{IWD}$, and the velocity at which it moves, Vel_{IWD} that are initially set to $Init_{soil}$ and $Init_{vel}$, respectively. During each iteration, IWDs interact with the environment, in our case the CMDGVRP, and the value of both features may change. Assuming a water drop moves from node n_i to n_j, the IWD algorithm can be formulated as follows.

$$\Delta Vel_{IWD} = \frac{a_v}{b_v + c_v\left(Soil(n_i, n_j)\right)^2} \tag{23}$$

$$Vel_{IWD}(t+1) = Vel_{IWD}(t) + \Delta Vel_{IWD} \tag{24}$$

$$\Delta Soil(i,j) = \frac{a_s}{b_s + c_s\left(Time(n_i, n_j; Vel_{IWD})\right)^2} \tag{25}$$

$$Time\left(n_i, n_j; Vel_{IWD}\right) = \frac{D(n_i, n_j)}{\max(\varepsilon_v, Vel_{IWD}(\mathrm{t}))} \tag{26}$$

$$D_{ij} = \sqrt{}(\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2) \tag{27}$$

$$Soil\left(n_i, n_j; t+1\right) = (1 - \rho_l)\left(Soil\left(n_i, n_j; t\right) - \rho_l \Delta Soil\left(n_i, n_j\right)\right) \tag{28}$$

$$Soil_{IWD}(t+1) = Soil_{IWD}(t) + \Delta Soil\left(n_i, n_j\right) \tag{29}$$

$$P_{IWD}\left(n_i, n_j\right) = \frac{f\left(Soil(n_i, n_j)\right)}{\sum_{k \notin G_{IWD}^C} f\left(Soil(n_i, n_k)\right)} \tag{30}$$

$$f\left(Soil\left(n_i, n_j\right)\right) = \frac{DM_{ij}}{\varepsilon_s + g\left(Soil(n_i, n_j)\right)} \tag{31}$$

$$DM_{ij} = D_{mi} + D_{mj} - D_{ij} \tag{32}$$

$$g\left(Soil\left(n_i, n_j\right)\right) = \begin{cases} Soil\left(n_i, n_j\right) & If \quad \min\limits_{l \notin G_{IWD}^C} \left(Soil(n_i, n_l)\right) \geq 0 \\ Soil\left(n_i, n_j\right) - \min\limits_{l \notin G_{IWD}^C} \left(Soil(n_i, n_l)\right) & Otherwise \end{cases} \tag{33}$$

$$LocalS_{IWD} = \sum_{i=1}^{n-1}\left(D_{ij} + \left(E_{ij} + E'_{ij}\right)\right) + (D_{n1} + E_{n1} + E'_{n1}) \tag{34}$$

$$LocalS_{IWD}^{best} = \min(LocalS_{IWD}) \tag{35}$$

$$Soil\left(n_i, n_j; t+1\right) = \left(1 - \rho_g\right) Soil\left(n_i, n_j; t\right) + \rho_g \frac{2}{n(n-1)} Soil_{IWD}^{best}(t) \quad \forall \left(n_i, n_j\right) \in LocalS_{IWD}^{best} \tag{36}$$

$$GlobalS_{IWD}^{best}(t+1) = \begin{cases} GlobalS_{IWD}^{best}(t) & If \quad GlobalS_{IWD}^{best}(t+1) \geq LocalS_{IWD}^{best}(t) \\ LocalS_{IWD}^{best}(t+1) & Otherwise \end{cases} \tag{37}$$

In equation (23), the change in velocity, ΔVel_{IWD}, is calculated. Equation (24) calculates velocity of the next step in IWD. The movement of IWDs between n_i and n_j results in a reduction of soil along this path. This reduction is a function of $Time\left(n_i, n_j; Vel_{IWD}\right)$ and is calculated by equation (25). Equation (26) represents how $Time\left(n_i, n_j; Vel_{IWD}\right)$ is calculated based on the distance between n_i and n_j as well as velocity of IWD in this path. In this equation, the max(.) function compares the velocity with a small positive number, ε_v to ensure $Time\left(n_i, n_j; Vel_{IWD}\right)$ is a positive number. Equation (27) computes the Euclidean distance which is the foundation of clustering process. The clustering process commences with a distance matrix construction, capturing distances between each DP and MCC. This matrix forms the basis for DP clustering based on proximity to MCCs. DPs are grouped by assigning each to the MCC with the shortest distance in the matrix, ensuring optimal allocation. In cases where distances to two MCCs are equal, a DP can be assigned to either. This clustering simplifies route planning and enables the implementation of a local search algorithm like SA within each cluster determining the optimum route for each vehicle assigned to DPs within that group.

The updating procedures, which govern the soil conditions along the path from n_i to n_j and the quantity of soil carried by IWDs, are delineated in equations (28) and (29), with ρ_l denoting the local soil updating parameter. According to the probability $P_{IWD}(.)$, IWD selects an optimal path to a node. A unique P_{IWD} is allocated to each potential path from the subsequent n_i to the next n_j.

The mechanism for selecting the connection between nodes is as follows: Suppose there is an IWD at n_i, equation (32) calculates the probability of selecting the next destination of the IWD. In (31), $f\big(Soil(.)\big)$ is the fitness function and ε_s is a small positive number preventing singularity issue. The distance between every pair of nodes is calculated using equation (32). Then, equation (33) calculates $g\big(Soil(i,j)\big)$ which is an auxiliary function preventing $Soil(i,j)$ from having negative values.

Algorithm 1: IWD pseudocode

Input: $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{A}), N_{DP}, N_{Depot}, K$	*Applied Equations*
Output: $GlobalS_{IWD}^{best}(t)$	
Initialise static parameters	
$\boldsymbol{for}\ k = 1\ to\ MaxIter$	
Initialise dynamic parameters	
Calculate the IWD variables	*Equations (23)-(26)*
Cluster DPs for each depot	*Equation (27)*
Spread the IWDs randomly	
Update dynamic parameters	*Equations (28)-(29)*
Identify the next destination of each IWD	*Equations (30)-(33)*
Calculate $LocalS_{IWD}$	*Equation (34)*
Find the best local solution ($LocalS_{IWD}^{best}$*)*	*Equation (35)*
Update the soil of paths globally	*Equation (36)*
Find the global solution $GlobalS_{IWD}^{best}$	*Equation (37)*
$\boldsymbol{end\ for}$	

Figure 6.2. Pseudocode of intelligent water drop (IWD).

Additionally, a set of IWDs is utilised to find the optimal solution. Each IWD is associated with a local solution, $LocalS_{IWD}$ which is calculated by the sum of total Euclidean distances and emissions represented in equation (34). On the right side of this equation, the first term calculates the distance and CO_2 emissions between each node and its subsequent node, for example, D_{12} and D_{23}. Furthermore, the second term computes the distance and emissions from the last node back to the first node, guaranteeing a closed loop for every tour. During each iteration, equation (35) determines the local best solution, $LocalS_{IWD}^{best}$, by assessing the degree to which the fitness function is met. For our specific problem, the shortest distance solution minimises this function.

Equation (28) determines the amount of soil that is updated at every edge of the path that the IWD follows, considering both the quantity of soil on the edges and the velocity of IWD. This updating process, however, is executed with local information, which could end up in finding a local optimum. To prevent this, the edges' soil in $LocalS_{IWD}^{best}$ is adjusted by comparing the best solution of the current iteration and the previous one. Consequently, equation (36) globally updates the $Soil(n_i, n_j)$ belonging to $LocalS_{IWD}^{best}$ based on the soil of the previous iteration remains and the best current solution. In this equation, n represents nodes' number, and $Soil_{IWD}^{best}(t)$ denotes the amount of soil carried by the best IWD in the current iteration. Finally, equation (37) compares the local solution found, $LocalS_{IWD}^{best}(t)$, with the previous global optimum, $GlobalS_{IWD}^{best}(t-1)$, to identify the global optimum solution, $GlobalS_{IWD}^{best}(t)$. As a result, the IWD algorithm can guarantee that $GlobalS_{IWD}^{best}$ holds the best solution. In Figure 6.2, Algorithm 1 represents the main steps of the IWD.

6.3.2 Incorporating SA into the IWD Algorithm

Since its introduction, SA has been employed in a variety of optimisation problems, either as a standalone approach or as a component of hybrid algorithms. The SA algorithm accepts moves that may lead to solutions of inferior quality to the current solution, in order to avoid getting trapped in local minima. The probability of accepting such a move decrease through parameter temperature during the search. The SA algorithm begins with a solution i and then generates the next candidate solution j from its neighbourhood. Based on the acceptance probability in equation (38), candidate solution j is accepted as the current solution.

$$p(\Delta E) = \exp\left(\frac{-\Delta E}{k_b T_t}\right) \tag{38}$$

In the original concept of annealing, ΔE represents the change in the level of energy of the system and T_t the temperature at the tth iteration. Inspired from this concept, here, $\Delta Q = LocalS_{IWD}^{best}(t)^* - LocalS_{IWD}^{best}(t)$ is defined as the representation of change in solution quality. Here, $LocalS_{IWD}^{best}(t)^*$ is the generated solution. The other change in the original algorithm is to consider $k_b = 1$ to improve the performance of the algorithm (Van Breedam, 1995). Hence, equation (38) can be rewritten as equation (39) in which when the temperature is reduced, it is less likely that low-quality solutions will be selected.

$$p(\Delta Q) = \exp\left(-\frac{LocalS_{IWD}^{best}(t+1) - LocalS_{IWD}^{best}(t)}{T_t}\right) \tag{39}$$

There are three parameters in SA to be specified, initial temperature T_{init}, final temperature T_{finl}, and a constant linear slope, α, which is called the cooling parameter and used here to lower the temperature. Equation (40) shows the relationship between the current temperature and the subsequent temperature.

$$T_{t+1} = \alpha T_t \tag{40}$$

The key stages of intelligent water drop simulated annealing (IWDSA) are outlined in Algorithm 2 (Figure 6.3). In IWDSA, if $LocalS_{IWD}^{best}(t)^*$ is less than $LocalS_{IWD}^{best}(t)$, the solution found by Algorithm 1 is replaced by the generated solution. Otherwise, the generated solution may still be accepted based on the comparison result of equation (40) and the Mersenne Twister (MT) function, which is a widely used approach to produce a long-period sequence of high-quality random numbers (Matsumoto & Nishimura, 1998).

Algorithm 2: Pseudocode the IWDSA algorithm

Input: *current solution*
Output: $LocalS_{IWD}^{best}$
Initialise temperature
Initialise linear slope (cooling rate).
$\boldsymbol{while}$ $T > T_{finl}$
    Generate a new solution
    Generate a new candidate solution.
    Check the quality of the new solution
    $\boldsymbol{if}$ $LocalS_{IWD}^{best}(t)^* < LocalS_{IWD}^{best}(t)$
        $LocalS_{IWD}^{best}(t) \leftarrow LocalS_{IWD}^{best}(t)^*$
    else
        Calculating $p(\Delta Q)$
        rand= MT(.)
            $\boldsymbol{if}$ $p(\Delta Q) > rand$
                $LocalS_{IWD}^{best}(t) \leftarrow LocalS_{IWD}^{best}(t)^*$
            $\boldsymbol{end\ if}$
    $\boldsymbol{end\ if}$
    Decrease the temperature $T_t \leftarrow \alpha T_t$
$\boldsymbol{end\ while}$

Figure 6.3. Incorporating SA in IWD.

6.3.3 Tuning Hyperparameters

The initialisation of static parameters, including the number of IWDs (vehicles), their velocities, and the soil properties of the edges, is required to ensure SAIWDSA's robust performance. Hyperparameters can be tuned using various algorithms, such as Grid search (Miranker & Karplus, 1991), and Random search (Bergstra & Bengio, 2012). In this chapter, however, the Bayesian optimisation algorithm (BOA) is applied due to its ability to solve expensive-to-evaluate problems. The aim is to identify the best combination of parameters to maximise the SAIWDSA-1 and SAIWDSA-2 algorithms' performance. Subsequently, there is a greater likelihood of reaching the $GlobalS_{IWD}^{best}$.

The BOA iteratively samples variables across a possible range, utilising a Gaussian process as its probabilistic model. The process is initiated by assigning initial values to each parameter. Then, the parameters are evaluated in a specific order, beginning with those pertaining to the acceptance and stopping criteria, followed by the basic IWDSA algorithm. Since this chapter focuses on the dynamically changing $a_v(t), b_v(t), c_v(t), a_s(t), b_s(t), and\ c_s(t)$ variables, we divided their range into 10 intervals to facilitate a more accurate selection. We conducted tests on all 33 instances and recorded the best solutions from 5 separate runs.

Based on the relevant literature, the upper and lower bounds for a_v and a_s are determined as [1, 1000], while the search space for b_v and b_s cannot exceed [0.01, 0.1] (Acharya & Singh, 2018; Shah-Hosseini, 2008). We also assume that the search space of c_v and c_s is $[0.5 - 2]$. Additionally, parameters that have consistently been set to the same value in previous research are excluded from hyperparameter tuning. Algorithm 3, illustrated in Figure 6.4, outlines the hyperparameter tuning procedure employed in this chapter. However, since hyperparameter tuning is not the central focus of this chapter, readers seeking a more detailed understanding of BOA can refer Brochu et al., (2010) and we only report the results of employing this algorithm. Table 6.2 presents the feasible range and selected values of SAIWDSA's parameters.

6.3.4 Feedback Control to Create Self-Adaptive Mechanism

Although the IWDSA algorithm provides a useful solution to the CMDGVRP, exploration of the algorithm diminishes as the number of iterations increases. That is because based on equation (25), the more time spent, the more $\Delta Soil(n_i, n_j)$ is decreased. As a result, both the velocity and amount of soil that IWDs carry are less likely to increase. On the other hand, the amount of soil in the paths also is less likely to change. Consequently, as time passes, there will be fewer changes in velocity and soil. This will reduce the likelihood of finding new routes or better solutions, leading to a degradation in IWDSA performance. To improve the algorithm's performance, we propose incorporating a feedback control mechanism that dynamically adjusts both velocity and soil. This mechanism automatically adapts the increase percentages based on how well the algorithm improves the global solution during the past iterations. Consequently, this adaptive mechanism facilitates the exploration of new paths that have the potential to improve the solution's quality and refine vehicle routes by preventing entrapment at a local minimum.

Feedback control is a control system mechanism in which the output of a system is monitored, and this information is used to make real-time adjustments to the input, ensuring that the system operates as desired (Dorf & Bishop, 2017). Feedback control has been successfully used in VRPs to automatically adjust solving algorithms and achieve suitable solutions (Jiang et al., 2021; Lee & Prabhu, 2016; Muñoz-Morera et al., 2018). The feedback control integration steers the algorithm to dynamically adjust velocity and soil parameters. This innovative algorithm, named the self-adaptive intelligent water drop simulated annealing algorithm (SAIWDSA), continuously adapts its parameters based on the latest solution, enabling effective navigation of the solution space for optimal outcomes. This feedback mechanism is illustrated in Figure 6.5.

Algorithm 3: Pseudocode of BOA

Input: *hyperparameters search space*
Output: *optimum values of hyperparameters*
Define $GlobalS_{IWD}^{best}$ *as a function of* a_v, a_s, b_v, b_s, c_v and c_s
Run IWDSA algorithm.
Create a Gaussian process model as the surrogate model.
Create an expected improvement as an acquisition function.
$\boldsymbol{for}$ $iteration < Max\ iteration$
    Find the next set of hyperparameters to maximise acquisition function.
    Evaluate the objective function with the updated hyperparameters.
    Update the surrogate model.
$\boldsymbol{end\ for}$
Evaluate the IWDSA performance using the optimal hyperparameters.

Figure 6.4. Pseudocode of Bayesian optimisation algorithm (BOA).

Table 6.2. SAIWDSA parameters and their values.

Algorithm	Parameters	Description	Range	Tuned value
IWD	$MaxIter$	Maximum number of iterations	100-110	110
	$Init_{vel}$	Initial velocity of IWDs	4	4
	$Initial\ a_v$	Initial amount of velocity updating parameter	[1, 1000]	112.1
	$Initial\ b_v$	Initial amount of velocity updating parameter	[0.01, 0.1]	0.06
	$Initial\ c_v$	Initial amount of velocity updating parameter	$[0.5-2]$	0.88
	ε_v	A small positive auxiliary parameter	0.001	0.001
	$Init_{soil}$	Initial soil of IWDs	1000	1000
	$Initial\ a_s$	Initial amount of soil updating parameter	[1, 1000]	1
	$Initial\ b_s$	Initial amount of soil updating parameter	[0.01, 0.1]	0.1
	$Initial\ c_s$	Initial amount of soil updating parameter	$[0.5-2]$	0.69
	ρ_l	Local soil updating parameter	0.9	0.9
	ε_s	Auxiliary parameter	0.01	0.01
	ρ_g	Global soil updating parameter	0.9	0.9
SA	T_{init}	Initial temperature	100	100
	T_{finl}	Final allowed temperature	10	10
	α	Cooling parameter	0.98	0.98

To incorporate parameter alteration during the algorithm's iterations, equations (23) and (25) are modified using equations (41) and (42).

$$\Delta Vel_{IWD} = \frac{a_v(t)}{b_v(t)+c_v(t)\left(Soil(n_i,n_j)\right)^2} \tag{41}$$

$$\Delta Soil(i,j) = \frac{a_s(t)}{b_s(t)+c_s(t)\left(Time(n_i,n_j;Vel_{IWD})\right)^2} \tag{42}$$

Henceforth, variables $a_v(t), b_v(t), c_v(t), a_s(t), b_s(t), and\ c_s(t)$ will be denoted as updating variables. The objective here is to modify these variables to encourage exploration within the algorithm that leads to: firstly, finding new routes; and secondly, ultimately increases the likelihood of obtaining the global minimum solution. For this purpose, it is necessary to select an assessment criterion that evaluates how effective the algorithm is at finding the optimal solution. Here, we employ the improvement of $GlobalS_{IWD}^{best}(t)$ as the primary stimulus for the adaptive mechanism, as our objective is to reduce VKT.

Here, we introduce two SAIWDSA algorithms that monitor its own performance and improve the solution accordingly. For this purpose, the knowledge-based system (KBS), which is a type of artificial intelligence (AI) that uses pre-defined rules to make decisions or solve problems is employed. The KBS consists of domain-specific information, typically referred to as rules, each of which is associated with one or more inputs and outputs. KBS is employed here to achieve an input-output mapping specified linguistically. The implementation of KBS in this context aims to streamline the analysis of the intricate CMDGVRP and elevate the solution's overall quality by decomposing the problem into more manageable components. The maximum number of rules is determined by all possible combinations of inputs.

Designing these rules requires expert knowledge and experience. To address this issue, we not only reviewed the previous implementations of the IWD in CMDGVRP but also conducted a parameter sensitive analysis. This was done to assess how different parameters influenced the algorithm's behaviour. Two different KBSs are described in Sections 6.3.5 and 6.3.6.

The proposed framework and methodology, grounded in well-established graph theory and the widely utilised CMEM fuel emission model (Sections 6.2.1 and 6.2.2), can be adapted to various VRP types. Additionally, the SAIWDSA algorithm exhibits flexibility in accommodating different constraints associated with various VRP variants. To showcase this adaptability, let us consider the VRP with time windows. This variant introduces time window constraints and penalty costs for early or late arrivals, potentially altering the desired solutions. From the perspective of solution methodology, the distinctions involve service time calculations, increased computational complexity, and a more constrained solution space.

6.3.5 Performance-based KBS

Performance-based adaptation is incorporated into the IWDSA to monitor $GlobalS_{IWD}^{best}$ improvement and adjust parameters accordingly. This algorithm is called SAIWDSA-1 and guarantees that the algorithm learns and adapts constantly, ensuring its solution improves over time. For SAIWDSA-1, the input to KBS is defined as the average improvement of $GlobalS_{IWD}^{best}$ which is calculated as follows:

$$\overline{\Delta GlobalS} = 100 \times \sum_{n} \frac{\left(GlobalS_{IWD}^{best}(t+1) - GlobalS_{IWD}^{best}(t)\right)}{n \times GlobalS_{IWD}^{best}(t)} \tag{43}$$

Where, $\overline{\Delta GlobalS}$ is the average improvement of optimum solution in n interval iterations.

For a successful implementation, frequent monitoring of the algorithm's performance (Sang-To et al., 2023) and continuous adjustment of its parameters is essential. This chapter investigates the SAIWDSA-1 algorithm's performance using thirty distinct iteration intervals. This interval is selected based on the average iterations IWD required to reach the optimum output (Nagalakshmi et al., 2011). Additionally, $\overline{\Delta GlobalS}$ is classified in five levels. If $\overline{\Delta GlobalS}$ is more than –0.25%, -0.5%, -1%, -2%, and -4% the improvement of $\overline{\Delta GlobalS}$ is determined as "very low", "low", "moderate", "high" and "very high", respectively. The numerical thresholds are based on the change in the $GlobalS_{IWD}^{best}$ score compared to the baseline. This categorisation facilitates the development of a more effective KBS, making the SAIWDSA-1 more adaptive and refined in achieving the global minimum solutions.

To obtain a comprehensive understanding of SAIWDSA-1's behaviour, parameter sensitivity analyses on equation (41) were conducted to determine how velocity and soil parameters influence the algorithm. This analysis not only aids in optimising SAIWDSA-1 performance but also aligns the KBS with the average improvement of the optimum solution.

Meanwhile the parameter sensitivity analysis is presented in Appendix D and shows ΔVel_{IWD} is more sensitive to a_v, followed by c_v while it has least sensitivity to b_v. Therefore, changes in a_v should be responsible for "very low" and "low" improvements in $\overline{\Delta GlobalS}$, while c_v and b_v are responsible for "moderate", high", and "very high" improvements. The same approach is applied to equation (42) and the results demonstrate that a_s has the strongest influence on $\Delta Soil(i,j)$, followed by c_s, and b_s. Detailed information about the parameter sensitivity analysis of $\Delta Soil(i,j)$ can be found in Appendix D.

The sensitivity analysis results, along with the implementation of the basic IWDSA, establish the foundational understanding of the necessary parameter modifications within each rule. Table E.1 in Appendix E describes the KBS for the SAIWDSA-1. For instant, when the improvement of $\overline{\Delta GlobalS}$ is very low, *Rule #1* is triggered leading to a 2.5% increase in both a_v and a_s. By making this adjustment, ΔVel_{IWD} and $\Delta Soil(i,j)$ are rapidly elevated, leading to enhanced exploration. Although reducing b_v, b_s, c_v and c_s can also increase velocity and soil, such modifications are not suitable when there has been a consistently minimal improvement over a prolonged number of iterations. The rationale for this is the low sensitivity of ΔVel_{IWD} and $\Delta Soil(i,j)$ to these parameters.

Figure 6.5 depicts the interaction between CMDGVRP and SAIWDSA. Furthermore, this diagram illustrates the workflow between various components of the SAIWDSA. The CMDGVRP establishes the initial requirements for the SAIWDSA, including $G = (N, A), N_{DP}, N_{Depot}$, and K. BOA also provides the SAIWDSA with tuned parameters. In the SAIWDSA, IWD first solves the problem and then passes $LocalS_{IWD}$ to SA. Afterwards, the SA calculates the local best solution and sends it to the IWD as $LocalS_{IWD}^{best}$. The aim of the IWDSA is to find $GlobalS_{IWD}$ and deliver $\overline{\Delta GlobalS}$ to KBS. Then, based on the quality of the $\overline{\Delta GlobalS}$ and the value of other variables in the IWDSA, $a_v(t), b_v(t), c_v(t), a_s(t), b_s(t), and\ c_s(t)$ may be modified and passed to the IWDSA. The updated vehicle location is also sent from the SAIWDSA to the CMDGVRP. Additionally, the SAIWDSA identifies $GlobalS_{IWD}^{best}$.

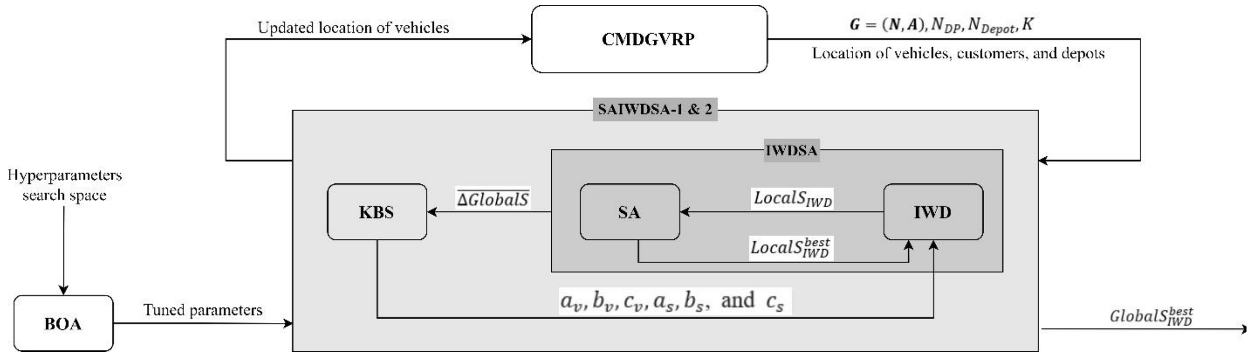


Figure 6.5. Implementing feedback control to ensure self-adaptation.

Figure 6.6 illustrates the principal aspects of the SAIWDSA algorithm. The pseudocode displays three significant components of the algorithm: tuning hyperparameters, solving the CMDGVRP, and finding the optimum solution. Additionally, all other algorithms discussed in previous sections are included.

6.3.6 Convergence-based KBS

The convergence of the IWDSA to the global optimum depends on how well the water drops explore the search space towards the optimal solution. Through controlling the magnitude and rate of change in water drop velocity and soil, $a_v, b_v, c_v, a_s, b_s,$ and c_s parameters influence the behaviour of water drops. Hence, to improve the algorithm's convergence to the global optimum, it is necessary to dynamically adjust these parameters in the algorithm.

Considering how complex the problem is, we propose SAIWDSA-2 in which a dynamic parameter tuning strategy is adopted based on the algorithm's performance in improving the global minimum solution as well as changes in ΔVel_{IWD} and $\Delta soil$. This results in the generation of more rules and a greater ability to control the overall performance in comparison to the SAIWDSA-1. Same as before, five levels of improvement are considered for $\Delta GlobalS$. Additionally, changes in ΔVel_{IWD} and $\Delta soil$ is classified into three groups, i.e. "low", "relatively low", and "moderate" which are defined respectively as 0.5%, 1.25%, and 2.5% changes in these two features.

Based on the results of parameter sensitivity analysis, generally, a higher of a_v and a_s and a lower of $b_v, c_v, b_s,$ and c_s increase the exploration of the search space and improve convergence to the global optimum. That is rooted in how each water drop traverses toward the next solution. In equation (39), the variable $a_v(t)$ controls the initial velocity of the water drop, while $b_v(t)$ *and* $c_v(t)$ control the influence of soil on the velocity change. A higher value of $b_v(t)$ and $c_v(t)$ means that the soil exerts a stronger impact on the velocity change, slowing down the movement of the water drops.

Similarly, the soil update rule, equation (42), controls the soil level of each solution, which represents the quality of the solution. The variable $a_s(t)$ controls the initial soil level, while

$b_s(t)$ *and* $c_s(t)$ control the impact of time and velocity on soil change. A higher value of $b_s(t)$ *and* $c_s(t)$ means that time and velocity have a stronger effect on soil change. This makes the solution more sensitive to water drop movement. Table E.2 in Appendix E provides the KBS related to SAIWDSA-2 which includes 25 rules. This KBS is developed based on the effects of the various variables on the algorithm discussed here.

6.4 Computational Study

This section evaluates how the SAIWDSA-1 and SAIWDSA-2 algorithms perform in terms of reducing the VKT and CO_2 emissions. To assess the effectiveness of a newly developed methodology, a two-tier evaluation process is typically employed. Firstly, the proposed method's performance is compared to well-established solvers such as CPLEX, using small-scale instances. Following this, the approach is benchmarked against prominent metaheuristic algorithms on larger-scale instances.

Given the context of the last-mile logistics (LML) environment, our developed methodology is primarily tailored to tackle medium- and large-scale problems. Consequently, our evaluation procedure diverges from conventional practices. In our evaluation, we initially applied our methodology to the MDVRP Cordeau benchmark. This choice is due to our proposed DN that includes multiple MCCs (depots), making it a variant of the CMDGVRP. Furthermore, the presence of numerous state-of-the-art methodologies in the CMDGVRP makes it a suitable benchmark for rigorous assessment. Subsequently, we devised a custom-made case study instance and conducted a comparative analysis between the collaborative network and a traditional network in which carriers independently deliver parcels. This process validates our algorithms' effectiveness and assesses their potential to improve cost-efficiency and environmental sustainability in urban goods movement.

For each instance of Cordeau benchmark as well as the case study, the algorithm was run 10 times with a maximum of 110 iterations. Simulations and evaluations were conducted using MATLAB R2022a software on a Windows 10 OS with an Intel Core i7 CPU running at 1.80 GHz and 16 GB of RAM.

6.4.1 Solution Quality

Cordeau benchmark problems were solved by employing the developed algorithms, SAIWDSA-1, and SAIWDSA-2. These algorithms were run 10 times for each instance and the average VKT (Ave), best VKT (Best), standard deviation (SD), and average computational time (Ave t) are calculated for each instance. Table 6.3 presents details for each instance, including the number of DPs, depots, and vehicles, alongside our results, and the best-known results (BKRs) from prior studies (Cordeau et al., 1997; Cordeau & Maischberger, 2012; Escobar et al., 2014; Pisinger & Ropke, 2007; Sadati et al., 2021; Vidal et al., 2012).

The SAIWDSA algorithm

Input graph $G = (N, A)$.	**Tuning hyperparameters**
Initialise IWD parameters:	
General parameters: MaxIter and number of IWDs.	
Tuning IWD's hyperparameters	*Applying Algorithm 3*
Velocity: $Init_{vel}$, a_v, b_v, *and* c_v.	
Soil: $Init_{soil}$, a_s, b_s, *and* c_s.	
Initialise SA parameters:	
General parameters: T_0, T_F, *and* α.	
$\boldsymbol{for}\ k = 1\ to\ MaxIter$	**Solving the CMDGVRP**
Initialise $LocalS_{IWD}$ *as empty.*	*Applying Algorithm 1*
Initialise $Soil_{IWD}$ *as* $Init_{soil}$.	
Initialise Vel_{IWD} *as* $Init_{vel}$.	
Create a cluster of DPs for each depot based on distance matrix.	
Randomly spread IWDs in the graph.	
Choose a path for each IWD based on probability function.	
Calculate $\Delta Soil(n_i, n_j)$.	
Calculate ΔVel_{IWD}.	
Update soil of IWDs ($Soil_{IWD}$*) and paths (*$Soil(n_i, n_j)$*).*	
Update Vel_{IWD}.	
Calculate all local solutions ($LocalS_{IWD}$*).*	**Finding the optimum solution**
Find the best local solution ($LocalS_{IWD}^{best}$*):*	
$\boldsymbol{if}\ LocalS_{IWD}^{best}(t)^* < LocalS_{IWD}^{best}(t)$	
$LocalS_{IWD}^{best}(t)^* \leftarrow LocalS_{IWD}^{best}(t)$	
$\boldsymbol{else}$	
$Calculating\ p(\Delta Q)$	*Applying Algorithm 2*
rand= MT(.)	
$\boldsymbol{if}\ \ p(\Delta Q) > rand(0{,}1)$	
$LocalS_{IWD}^{best}(t)^* \leftarrow LocalS_{IWD}^{best}(t)$	
$\boldsymbol{end\ if}$	
$\boldsymbol{end\ if}$	
Update the soil of paths globally.	
$Soil(n_i, n_j; t+1) \leftarrow (1-\rho_g) Soil(n_i, n_j; t) + 2\rho_g/(N(N-1))\ Soil_{IWD}^{best}(t)$	
Update the temperature:	
$T_{t+1} \leftarrow \alpha T_t$	
Find the global solution:	
$\boldsymbol{if}\ \ GlobalS_{IWD}^{best}(t+1) \geq LocalS_{IWD}^{best}(t)$	
$GlobalS_{IWD}^{best}\ (t+1) \leftarrow GlobalS_{IWD}^{best}\ (t)$	
$\boldsymbol{else}\ GlobalS_{IWD}^{best}\ (t+1) \leftarrow LocalS_{IWD}^{best}(t+1)$	
$Applying\ SAIWDSA-1\ \ OR\ \ SAIWDSA-2$	*Applying one of the self-adaptive algorithms*
$\boldsymbol{end\ if}$	
$\boldsymbol{end\ for}$	

Figure 6.6. Pseudocode of proposed SAIWDSA algorithm.

In the BKRs column, values marked with an asterisk, *, are those whose optimality is proven (Contardo & Martinelli, 2014). Equation (44) is utilised to determine the VKT enhancement in comparison to the BKRs, and the resulting values are presented in Gap (%) column.

$$Gap = \frac{GlobalS_{IWD}^{best} - BKR}{GlobalS_{IWD}^{best}} \times 100 \tag{44}$$

The SAIWDSA-1 achieved optimality for 22 out of 33 instances with an average SD of 0.60, an average Gap of 0.13, and Ave t of 1157.3 seconds. The SDIWDSA-2, on the other hand, exhibited slightly superior performance to SDIWDSA-1, solving 24 out of the 33 instances to optimality with an average SD, Gap, and Ave t of 0.42, 0.07, 1168.1, respectively.

6.4.2 Implementation of the Model in the Case Study

A new instance is created for Sydney, Australia in which a LML distribution network consisting of micro-consolidation centres (MCCs) and parcel lockers (PLs) is designed. Here, e-commerce parcels are delivered from MCCs to local PLs. All parcels are assumed to be collected by end customers from PLs.

Creating a New Instance Using ArcGIS Pro

To identify the optimal number and location of MCCs, we tackle a location-allocation problem. Based on the Australian legislation, our case study is divided into 34 regions each with at least 20,000 people. Unlike traditional location-allocation problems with strict criteria and limitations on potential hub selection, New South Wales (NSW) regulations for Local Distribution Premises (NSW Government, 2022) allow MCCs to be established in various land use categories. Consequently, we consider the geographical centre of each region as a candidate MCC location.

In Sydney, the concept of 15-minute postcodes focuses on creating local communities that prioritise accessibility to essential amenities and services within a short walking or cycling distance. This 15-minute accessibility concept aims to enhance sustainability, promote independent mobility for residents, and revitalise local centres (Transport for NSW, 2023). To address this real-world problem, we consider a PL at the centre of every 198 postcodes located in the case study. Therefore, the 15-minute driving constraint from MCCs to PLs is employed in the location-allocation problem implemented. Other problem settings include the problem type "Maximize Coverage and Minimize Facilities" and the cost function "power", with $\beta = 2$. We calculate the demand for each PL using real-world data from one of Australia's largest B2C couriers. The data is monthly, from March 2019 to February 2022, and resolved at the postcode level.

MCCs were strategically positioned within the Sydney metropolitan area using ArcGIS Pro 3.1.0. Our objective was to maximise DP coverage, adhering to the 15-minute city accessibility legislation. This involved formulating a location-allocation problem as "Maximize Coverage and Minimize Facilities" to address the accessibility constraints in our analysis. For in-depth details, interested readers are referred to the Esri documentation (Esri, 2022). The result shows that the optimum number of MCCs is 7 and by having them all postcodes (198 PLs) will be fulfilled. The data for this instance including the locations of MCCs and PLs can be accessed at https://github.com/Masdlab/new-MDVRP-instance.

Table 6.3. Results of applying SAIWDSA-1 and SAIWDSA-2 to the Cordeau CMDGVRP benchmark

Instance						SAIWDSA-1					SAIWDSA-2				
ID	DPs	Veh	Depot	BKRs	Ref	Ave	Best	SD	Ave t	Gap (%)	Ave	Best	SD	Ave t	Gap (%)
P01	50	4	4	576.87*	a	576.87	576.87	0.00	9.67	**0.00**	576.87	576.87	0.00	13.10	**0.00**
P02	50	2	4	473.53*	b	473.53	473.53	0.00	8.92	**0.00**	473.53	473.53	0.00	10.82	**0.00**
P03	75	3	5	641.19*	b	643.07	641.19	0.02	30.46	**0.00**	641.19	641.19	0.00	25.80	**0.00**
P04	100	8	2	1001.04*	b	1011.23	1001.04	0.03	75.86	**0.00**	1003.5	1001.04	0.02	80.10	**0.00**
P05	100	5	2	750.03*	c	750.03	750.03	0.00	41.81	**0.00**	752.13	750.03	0.01	52.45	**0.00**
P06	100	6	3	876.5*	c	876.5	876.5	0.01	71.05	**0.00**	876.5	876.5	0.01	67.28	**0.00**
P07	100	4	4	881.97*	b	884.43	881.97	0.02	68.83	**0.00**	883.27	881.97	0.02	62.26	**0.00**
P08	249	14	2	4369.95	d	4532.58	4396.64	1.18	430.41	0.61	4395.71	4369.95	0.11	642.23	**0.00**
P09	249	12	3	3858.66	e	3954.73	3883.06	0.10	571.60	0.63	3882.91	3859.83	0.07	639.04	0.03
P10	249	8	4	3629.6	f	3711.49	3643.05	0.89	640.69	0.37	3644.94	3632.61	0.04	657.20	0.08
P11	249	6	5	3545.18	f	3557.18	3550.52	0.02	398.21	0.15	3560.46	3545.18	0.03	490.91	**0.00**
P12	80	5	2	1318.95*	a	1318.95	1318.95	0.00	19.94	**0.00**	1321.41	1318.95	0.01	23.69	**0.00**
P13	80	5	2	1318.95*	a	1318.95	1318.95	0.00	25.45	**0.00**	1318.99	1318.95	0.01	23.69	**0.00**
P14	80	5	2	1360.12*	a	1388.12	1360.12	0.15	21.95	**0.00**	1360.12	1360.12	0.00	30.16	**0.00**
P15	160	5	4	2505.42*	b	2617.42	2505.42	0.61	89.87	**0.00**	2586.92	2505.42	0.34	112.44	**0.00**
P16	160	5	4	2572.23*	a	2681.64	2572.23	1.34	135.91	**0.00**	2583.48	2572.23	0.06	156.58	**0.00**
P17	160	5	4	2709.09*	b	2715.9	2709.09	0.04	372.13	**0.00**	2717.84	2709.09	0.01	491.37	**0.00**
P18	240	5	6	3702.85*	b	3778.85	3702.85	0.13	489.05	**0.00**	3784.92	3702.85	0.26	492.03	**0.00**
P19	240	5	6	3827.06*	a	3922.58	3827.06	2.17	454.98	**0.00**	3944.21	3827.06	2.71	482.50	**0.00**
P20	240	5	6	4058.07*	a	4234.89	4058.07	1.87	278.24	**0.00**	4168.08	4058.07	1.18	287.17	**0.00**
P21	360	5	9	5474.84	b	5660.66	5474.84	2.68	694.13	**0.00**	5510.87	5474.84	0.08	1020.72	**0.00**
P22	360	5	9	5702.16	b	5702.16	5702.16	0.00	457.33	**0.00**	5702.16	5702.16	0.00	450.82	**0.00**
P23	360	5	9	6078.75	b	6245.48	6083.29	1.34	487.00	0.07	6147.13	6083.07	0.51	555.65	0.07
Pr01	48	1	4	861.32	a	861.32	861.32	0.01	8.71	**0.00**	861.32	861.32	0.01	9.78	**0.00**
Pr02	96	2	4	1296.25	d	1314.25	1304.25	0.06	33.93	0.61	1314.25	1304.25	0.06	35.73	0.61
Pr03	144	3	4	1803.8	e	1832.80	1806.6	0.10	117.09	0.15	1830.33	1806.6	0.08	118.60	0.15
Pr04	192	4	4	2058.31	e	2086.87	2062.13	0.10	300.51	0.19	2087.72	2059.43	0.12	331.51	0.05
Pr05	240	5	4	2331.2	e	2473.2	2363.72	0.75	589.06	1.38	2438.12	2354.99	0.41	648.34	1.01
Pr06	288	6	4	2674.07	e	2758.45	2679.39	0.67	726.59	0.20	2786.79	2676.67	2.03	913.64	0.10
Pr07	72	7	6	1089.56	d	1105.56	1089.56	0.09	16.79	**0.00**	1105.56	1089.56	0.09	18.69	**0.00**
Pr08	144	2	6	1664.85	d	1783.27	1664.85	1.27	133.31	**0.00**	1735.05	1664.85	0.42	164.72	**0.00**
Pr09	216	3	6	2133.2	e	2361.89	2133.99	3.52	338.88	0.04	2361.89	2133.99	4.32	434.52	0.04
Pr010	288	4	6	2820.88	d	2827.53	2820.88	0.48	779.51	**0.00**	2876.98	2820.88	0.78	1089.57	**0.00**
Average								0.60	270.24	0.13			0.42	322.21	0.07

* Optimality proven by Contardo & Martinelli (2014)

[a] Results of Cordeau et al., (1997)

[b] Results of Pisinger & Ropke (2007)

[c] Results of Cordeau & Maischberger (2012)

[d] Results of Sadati et al., (2021)

[e] Results of Vidal et al., (2012)

[f] Results of Escobar et al., (2014)

Table 6.4. Collaborative network compared with an independent one.

Vehicles	Independent scenario				Collaborative scenario			
	SAIWDSA-1		SAIWDSA-2		SAIWDSA-1		SAIWDSA-2	
	VKT	CO_2	VKT	CO_2	VKT	CO_2	VKT	CO_2
UGDVs	2490.44	448.28	2435.63	415.76	849.63	144.26	826.97	134.19
MCVs	-	-	-	-	569.01	187.77	569.01	187.77
Total	2490.44	448.28	2435.63	415.76	1418.64	332.03	1395.98	321.96
Change (%)					-43.03	-25.93	-42.68	-22.56

Comparative Analysis Between Collaborative and Independent Networks

Both collaborative and carrier-centred independent networks operate with 12 UGDVs. The collaborative network involves 3 MCVs exchanging parcels between MCCs daily, whereas the independent network does not involve any MCVs. Moreover, the PLs are randomly assigned to the MCCs. The results of total VKT and CO_2 emissions are presented in Table 6.4. In the collaborative scenario, both SAIWDSA-1 and SAIWDSA-2 showcased diminished values for VKT in *km* and CO_2 *kg* in contrast to the independent scenario. Notably, there exists a more pronounced reduction in VKT compared to CO_2. This disparity can be attributed to the utilisation of MCVs within the collaborative network, which, as indicated in Table 6.1, typically generate higher emission levels per kilometre.

Decreasing the VKT lowers the total logistics costs. This improvement, in addition to direct financial benefits for relevant stakeholders, enables the application of newly emerging and demand orientated initiatives, such as MCCs and PI-hubs (Crainic & Montreuil, 2016; Taniguchi, 2014). These alternatives are rarely implemented due to high initial and operating costs, which can enhance sustainability if successfully implemented.

As SAIWDSA-2 outperformed SAIWDSA-1, we only showcase CMDGVRP results solved by this algorithm in Figure 6.7. This figure shows the location MCCs and PLs, and how the SAIWDSA-2 algorithm allocated PLs to MCCs. PLs that were served in a same route illustrated by the same symbol. The sequence of DPs visits in the optimal solution is presented in Table 6.5 and furthermore, the vehicle paths in routes 1 and 2 are illustrated in Figure 6.7.

The 43% VKT reduction in urban logistics can boost efficiency, providing economic and environmental advantages. Lower VKT leads to less congestion, lower fuel consumption, faster deliveries, and reduced operational costs. Integrating the CMEM into the model allows for quantifiable measurement of CO_2 emissions, showing a 25% reduction in the proposed approach, affirming the success of the novel DN design in improving urban logistics sustainability.

Table 6.5. SAIWDSA-2 optimal solution for the case study.

MCCs	Routes' detail	VKT (km)
1: route 1	197 → 192 → 195 → 115 → 194 → 188 → 189 → 198 → 190 → 121 → 122 → 196 → 191	90.17
1: route 2	187 → 193 → 186	40.84
2: route 3	134 → 163 → 149 → 148 → 126 → 127 → 130 → 129 → 128 → 112 → 124 → 125 → 111 → 108 → 110 → 150 → 151	70.37
2: route 4	147 → 146 → 141 → 142 → 143 → 145 → 157 → 158 → 159 → 171 → 170 → 168 → 173 → 174 → 180 → 181 → 160 → 162 → 161	83.66
3: route 5	165 → 167 → 179 → 178 → 177 → 175 → 176 → 172 → 169 → 166 → 164 → 154 → 152 → 97 → 144 → 155 → 156	72.49
3: route 6	37 → 153 → 42 → 41 → 43 → 31 → 35 → 8 → 36 → 2 → 4 → 10 → 11 → 26 → 44 → 25 → 28 → 29 → 12 → 13	64.04
4: route 7	68 → 47 → 48 → 53 → 52 → 49 → 50 → 51 → 78 → 40 → 39 → 38 → 33 → 34 → 32 → 30 → 5 → 46 → 45 → 67	56.32
4: route 8	1 → 3 → 9 → 6 → 14 → 18 → 15 → 24 → 27 → 17 → 19 → 22 → 23 → 16 → 21 → 20 → 7 → 66	57.12
5: route 9	64 → 69 → 70 → 71 → 72 → 73 → 74 → 75 → 76 → 65 → 54 → 55 → 56 → 57 → 58 → 61 → 59 → 60 → 62 → 63	100.08
6: route 10	95 → 94 → 96 → 107 → 102 → 103 → 100 → 98 → 99 → 101 → 104 → 105 → 106 → 80 → 79 → 81 → 77 → 90 → 82 → 83	61.89
6: route 11	140 → 184 → 185 → 135 → 133 → 131 → 132 → 138 → 137 → 136 → 139 → 182 → 183	106.67
7: route 12	85 → 84 → 109 → 116 → 91 → 117 → 118 → 113 → 114 → 119 → 120 → 123 → 93 → 92 → 88 → 87 → 89 → 86	81.19

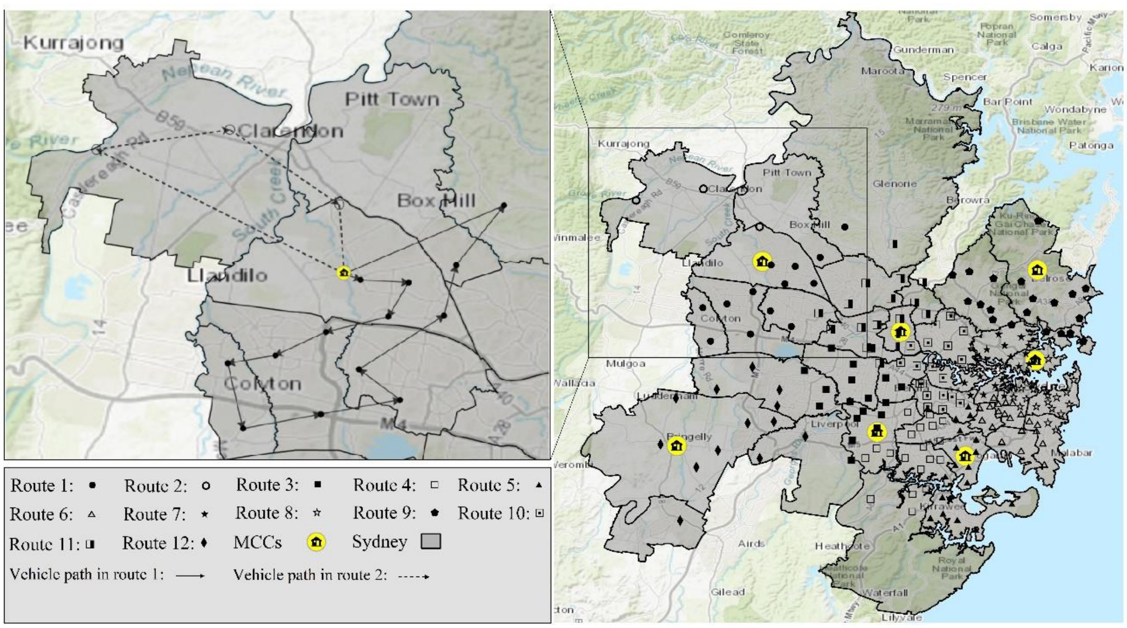


Figure 6.7. Illustration of CMDGVRP solution and sequence of DPs fulfilment in routes 1 and 2 in the case study.

The case study's key contributions are as follows. Firstly, a comparative analysis of the current and the proposed DN in Sydney metropolitan area revealed significant reductions in VKT and CO_2 emissions, encouraging authorities to support CMDDN. The VKT reduction can also benefit carriers by reducing their operational costs. Secondly, the instance aligns with the 15-minute accessibility concept, promoting enhanced customer and resident satisfaction for improved social sustainability. Thirdly and lastly, the created instance can be used by multiple variations of MPVRP, for example, those with time windows or pick-up and delivery, in future studies. This can offer decision-makers additional insights to address issues related to goods transportation in metropolitan areas.

6.5 Chapter Summary

The popularity of e-commerce has led to an increased demand for fast parcel delivery, resulting in a rise in vehicle kilometres travelled (VKT) and, consequently, carbon dioxide (CO_2) emissions (Muñoz-Villamizar et al., 2021). This issue can be mitigated by using a collaborative multi-depot distribution network (CMDDN), align with Physical Internet (PI) and Hyperconnected City Logistics (HCL). In such a network, micro-consolidation centres (MCCs) act as open and shared transhipment hubs facilitating collaboration among carriers.

To address the challenges, we defined a collaborative multi-depot green vehicle routing problem (CMDGVRP) minimising both VKT and CO_2 emissions. In CMDGVRP, goods are transported between MCCs using medium-commercial vehicles (MCVs) and then delivered to end customers via urban goods delivery vehicles (UGDVs). To evaluate the efficacy of MCCs in reducing CO_2 emissions, we integrated a microscopic model connecting emission rates to vehicle and route characteristics, encompassing factors such as mass, speed, and route slope.

With the increasing customer expectations regarding the quality of e-commerce delivery, particularly the speed of delivery, having multiple small hubs, or MCCs, across the urban area can be a viable solution. To reduce the costs associated with these hubs and make them economically viable, collaboration between stakeholders is essential. Shared hubs can be used by different stakeholders to achieve this. This underscores the need for a collaborative multi-depot distribution network where various shippers and carriers can collectively meet customer parcel demands. In this chapter, we formulate this collaboration concept and integrate it into the vehicle routing problem. Additionally, the reduction of CO2 emissions is a widely recognised and urgent objective for many organisations globally. Therefore, this objective is also incorporated into the model to address a more realistic and holistic problem.

Two self-adaptive intelligent water drop simulated annealing (SAIWDSA) algorithms were developed to solve the CMDGVRP. Hybridising the IWD as a swarm-population search approach with SA as a local search method can itself diversify the solution space. However, we have proposed two knowledge-based systems (KBSs) as a self-adaptive mechanism to increase the convergence, reach the optimum exploration-exploitation balance, and avoid local minimum trapping. This adaptive feature makes it possible to update the velocity and soil parameters if the performance and convergence of the algorithm towards global minimum has not improved properly over the past iterations. By incorporating this functionality, the algorithm ensures perpetual learning and adaptation, guaranteeing a continuous enhancement of its solution.

The KBSs are constructed based on parameter sensitivity analyses applied to the IWD algorithm to determine the extent to which the algorithm responds to changes in its parameters. In the SAIWDSA-1 algorithm, the KBS is created to improve the algorithm's performance by classifying $GlobalS_{IWD}^{best}$ improvement ($\overline{\Delta GlobalS}$), modifying velocity and soil parameters accordingly. The SAIWDSA-2 algorithm, on the other hand, aims to improve convergence towards the global minimum solution. To achieve this objective, the algorithm integrates ΔVel_{IWD} and $\Delta Soil(i,j)$ changes into its KBS alongside the $\overline{\Delta GlobalS}$.

SAIWDSA-1 and SAIWDSA-2 performance was evaluated by solving the CMDGVRP for Cordeau benchmark problems (Cordeau et al., 1997) and compared with previous best-known results (BKRs). Computational results demonstrate that the SAIWDSA-1 was able to solve 22 out of 33 instances to optimality. Based on the observed results, the SAIWDSA-2 produces superior outcomes that are both more reliable and consistent than SAIWDSA-1 since its average gap was 0.07%. The SAIWDSA-2 was also able to solve 24 instances equal to the BKRs.

The SAIWDSA-2 algorithm's superior performance can be attributed to the broader range of inputs in its KBS. This algorithm's inputs are $\overline{(\Delta GlobalS)}, \Delta Vel, \Delta Soil$, and $Interval$, while SAIWDSA-1's inputs are limited to $\overline{(\Delta GlobalS)}$ and $Interval$. Including more inputs allows the algorithm to better comprehend the complex nature of the CMDGVRP leading it to respond more accurately to $GlobalS_{IWD}^{best}$ changes and consequently less VKT and CO_2 emissions. With more inputs, the algorithm can also draw on a broader context and more extensive information to adjust the velocity and soil parameters.

Leveraging a location-allocation model and real high-quality e-commerce data, a novel scenario was generated for Sydney, Australia. This newly created scenario facilitated a comparative analysis of VKT and CO_2 emissions in the CMDDN and the independent network. The findings illustrated a substantial reduction in VKT and CO_2 emissions within the collaborative network, reaching up to -43.03% and -25.93%, respectively. The relatively smaller reduction in CO_2 emissions was attributed to the fact that, in the independent network, only UGDVs were utilised, while the collaborative network MCVs were operated as well, contributing to more CO_2 emissions.

The potential research directions are categorised into three parts. Firstly, the inherent adaptability of CMDGVRP's core framework makes it well-suited for simulating various specialised applications, such as VRP with time windows or incorporating uncertainty into the model. The integration of electric vehicles into the CMDGVRP is another potential application, providing a significant reduction in emissions in urban areas and advancing sustainable goods transportation. These applications broaden the evaluation of the developed algorithms to a wider range of VRP benchmarks, providing a more comprehensive understanding of their performance and applicability in diverse contexts. Secondly, specific parts of the algorithm could be refined to enhance overall performance. For instance, investigation could focus on improving the KBSs by applying artificial intelligence or learning systems. Another potential direction for exploration is addressing sustainability challenges in economic, social, and environmental contexts simultaneously.

Chapter 7: Intelligent Multi-agent System: A Last-mile Logistics Decision Support System

A B S T R A C T:

The dynamic nature of last-mile logistics (LML), characterised by fluctuating e-commerce demands, unforeseen disruptions, and several stakeholders with evolving objectives, often leads to operational inefficiencies within the distribution network (DN). By focusing on stakeholders' interactions, this chapter endeavours to devise an intelligent multi-agent system (iMAS). In the iMAS, carriers, shippers, and Physical Internet managers (PI-Managers) are considered as learning agents (stakeholders). Each agent's objectives, actions, and roles are meticulously defined and subsequently formulated for simulation purposes. In this complex problem, the structure of DN is dynamic. When carriers and shippers choose to use PI-hubs, DN transforms from a single-tier system to a two-tier network. Moreover, the inclusion of two vehicle types, vans and medium commercial vehicles, in the DN enhances the realism of the simulations. Q-learning, an advanced machine-learning technique that facilitates the selection of optimal actions by considering rewards from the simulation environment, has been tailored for iMAS. It leverages agents' attributes to facilitate information exchange and enable diverse decision-making. The environment is intricately designed, drawing upon the distribution network and vehicle routing problems addressed in previous chapters. Seven simulations are conducted, each varying in terms of which combination of agents is undergoing the learning process. The results reveal that when agents are trained, they exhibit a greater tendency to achieve their desired objectives. The increased utilisation of higher PI-hubs in the network results in a substantial decrease in total VKT, underscoring their effectiveness in alleviating the adverse impacts of freight vehicle mobility within metropolitan areas. The impact of the initial PI-hub fee policy on DN efficiency, including PI-hub usage, VKT, carriers' and shippers' costs, and PI-Manager profit, is assessed through a sensitivity analysis. The developed iMAS acts as a decision support system, enabling policymakers to evaluate various policies and actions, aiding in identifying optimal decisions within the LML framework.

7.1 Introduction

The ever-changing landscape of last-mile logistics (LML) is characterised by fluctuating e-commerce demands, unforeseen disruptions, and the involvement of diverse stakeholders with evolving goals and interactions. This dynamic setting often results in operational inefficiencies within the network and compromises its environmental sustainability. To achieve equilibrium among different, and sometimes conflicting, interests across stakeholders, various City Logistics solutions have been suggested. Among these solutions are micro-consolidation centres (MCCs), usually located in inner urban areas, which involve the movement of goods to these hubs and then delivery to the final customers.

MCCs could be a promising solution for reducing vehicle kilometres travelled (VKT) and empty trips as outlined and calculated in Chapter 6. To incorporate MCCs, which are shared logistics facilities, into the distribution network (DN), adopting the concept of the Physical Internet (PI) is necessary. The PI concept emphasises deploying collaborative facilities to streamline logistics processes (Montreuil et al., 2010), emphasises standardisation and collaboration to enhance the efficiency of logistics assets like containers, vehicles, and hubs. Moreover, PI advocates for an interconnected and open global logistics system, aiming to streamline transportation processes.

Implementing a network of MCCs not only requires linking these hubs but also necessitates collaboration and communication among stakeholders (Ballot et al., 2012). This challenge is addressed by integrating the Physical Internet (PI) concept, such as minimising empty freight vehicle travel, reducing truck movements, optimising storage facility efficiency, and ensuring swift and dependable delivery (Montreuil, 2011), into the modelling in this chapter. Hereby, MCCs are referred to as Physical Internet hubs (PI-hubs) to underscore the incorporation of PI principles in the DN design. PI-hubs are compact consolidation logistics facilities in inner urban areas where stakeholders collaborate to fulfil delivery demand. This collaboration leads to a reduction in VKT and enhances DN efficiency due to increased consolidation levels. Additionally, being located near end customers, PI-hubs enable rapid delivery, making them well-suited for the e-commerce sector.

PI-Managers, introduced in Section 2.5, underpin the optimisation of transportation resource allocation and enhance security and traceability throughout the DN. They oversee the efficient deployment of transportation containers, vehicles, and facilities, ensuring maximum usage and minimising wastage. Additionally, PI-Managers implement measures to enhance transportation security, utilising advanced tracking technologies and monitoring systems to safeguard shipments during transit. By maintaining visibility and traceability throughout the transportation process, they mitigate the risk of loss or theft and ensure timely delivery of goods. In such networks, the interactions of freight carriers, PI-Managers operating PI-hubs, and shippers as the primary stakeholders are pivotal. These stakeholders exhibit varied responses to the DN, reflecting their distinct objectives within the shared and open City Logistics framework.

City Logistics is inherently unpredictable, making it challenging to evaluate and select policies. However, due to the significant impact on various stakeholders, it is crucial to conduct a thorough assessment of potential policy measures before implementation (Perera & Thompson, 2021). To achieve this, decision-makers rely on decision support systems (DSS), which utilise modelling, optimisation, simulation, and evaluation techniques to generate solutions that consider the needs of all involved parties.

Multi-agent systems (MASs) are commonly used to address the decentralised decision-making of various stakeholders in City Logistics by representing each stakeholder as an independent agent (Benenson, 2014). MASs, a subfield of artificial intelligence (AI), offer principles for constructing intricate systems involving multiple agents, making them suitable for modeling and addressing real-world challenges. It proves valuable in comprehending the behaviour and interactions of stakeholders engaged in City logistics, as well as in assessing the impacts of urban logistics measures (Anand et al., 2010; L. K. de Oliveira et al., 2017). An MAS represents a group of independent decision-making entities within a defined environment and timeframe. Throughout the simulation, each agent makes decisions autonomously according to predefined rules. MASs illustrate phenomena arising from interactions among diverse stakeholders, showcasing how individual actions contribute to collective behaviours (Li et al., 2021).

This chapter endeavours to assess the impact of PI-hubs on VKT and examine the financial dynamics among key LML stakeholders. It further delves into employing an intelligent MAS (iMAS) to manage the intricate interactions among PI-Managers, carriers, and shippers in the LML environment. Specifically, MAS Q-learning, a technique merging Q-learning with multiple agents operating within a shared environment, is utilised. This enables agents not only to learn their own Q-values, representing expected future rewards for their actions, but also to consider the actions and rewards of other agents in decision-making processes. By leveraging MAS Q-learning, this chapter evaluates the effectiveness of PI-hubs in the LML in mitigating VKT.

The remaining part of this chapter is as follows. In Section 7.2, the concept of iMAS is introduced by discussing the necessary steps to develop the model and assuming rational goods movement within the network. Section 7.3 defines learning agents, including their goals and actions, the learning process, and the sequence of agents' decisions. Section 7.4 introduces a MAS Q-learning algorithm specifically designed to accommodate the unique characteristics of the agents involved. Section 7.5 introduces multiple simulations designed to thoroughly evaluate the effectiveness of PI-hubs in reducing VKT and assessing the performance of the agents involved. In Section 7.6, a sensitivity analysis is conducted by varying the initial PI-hub fee to analyse the impact of PI-managers' decisions on VKT and other agents. Finally, Section 7.7 provides insights obtained from this chapter.

7.2 Conceptualisation of iMAS

The development of an iMAS establishes a decision support system, making it possible to evaluate policies' impacts on stakeholders and the LML. This system is formulated through three key steps. The first step is identification of the main stakeholders (agents) involved in LML, along with their objectives, roles, and interactions, as discussed in Section 2.5. Further elaboration on these findings is provided in Section 7.3. Secondly, an environment is established to enable stakeholders to interact with both the environment and other agents. This environment is constructed based on the state-of-the-art collaborative multi-depot green vehicle routing problem (CMPGVRP) and the uncapacitated single allocation hub covering problem (USAHCP) introduced in Chapters 5 and 6.

This chapter exclusively focuses on the third step which includes defining the learning procedure between learning agents and applying a reinforcement method to discover the stakeholders' optimum interactions. Another objective of this analysis is to assess the efficacy of the PI-hub in reducing VKT, as it stands as one of the principal goals of this chapter. Hereafter, 'agent' and 'stakeholder' are used interchangeably. Figure 7.1 illustrates the three steps undertaken in developing the iMAS.

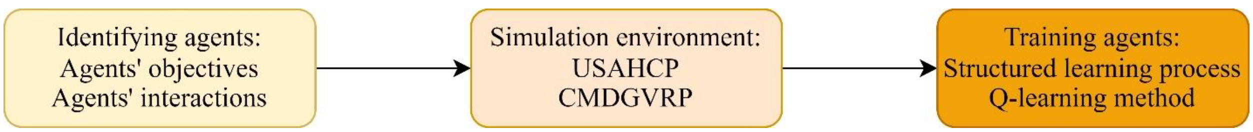


Figure 7.1. Three steps in iMAS development.

7.3 Development of Learning Procedure Between Agents

Based on the literature review conducted in Section 2.5, six stakeholders are identified in the LML, including residents, customers, carriers, shippers, government, and PI-Managers. While the objectives of residents, customers, and governments influence the overall last-mile ecosystem, their direct impact on optimising goods movement is limited. Therefore, this chapter focuses on carriers, shippers, and PI-Managers as the primary learning agents (stakeholders) involved in last-mile optimisation. To the best of the author's knowledge, this is the first time that a multi-agent reinforcement learning approach has been applied to model the interactions between three stakeholders in the context of CL.

The establishment of a novel learning process among carriers, shippers, and PI-Managers is grounded in their respective roles within the LML. Carriers aim to enhance shippers' satisfaction while simultaneously reducing transportation costs. Cost minimisation entails maximising load factors, optimising fleet size and frequency, and reducing failed deliveries. Additionally, carriers strive to maximise delivery quality by improving lead times and ensuring security throughout the transportation process. Shippers seek to bolster customer satisfaction by providing more delivery options, thereby enhancing the overall experience. Moreover, their focus is on minimising transportation and inventory costs, as well as fostering a greater willingness for customers to purchase products. PI-Managers are tasked with optimising the utilisation of transportation containers, vehicles, and facilities to ensure efficiency and cost-effectiveness. Additionally, they aim to maximise transportation security and trackability to safeguard shipments and provide accurate monitoring throughout the logistics process. With a focus on profit maximisation, PI-Managers strive to identify the most suitable PI-hub fee structure for the services provided to carriers and shippers. For more details about the stakeholders' interactions, please refer to Table 2.2, Figure 2.6 and Figure 2.7.

Evaluating rational goods movement pathways is essential for designing the learning process between agents. Three delivery scenarios are considered, as follows:

- Shippers' direct delivery: In this scenario, the delivery network operates on a single tier, where the shipper directly delivers goods to customers using their own fleet, involving medium commercial vehicles (MCVs). The delivery cost remains unknown to the shipper due to uncertainties in vehicle routing and the delivery process.
- Delivery via carriers: In this approach, carriers deliver goods from shippers' warehouses to the end customers using either MCVs or vans. In this single-tiered DN the delivery cost is known to the shipper due to pre-offered rates by carriers. The operational cost for carriers, however, remains undisclosed, with only estimations being available.
- Delivery through PI-hubs: This method involves a two-tiered delivery network. Given the role of the PI-Manager agent outlined previously, it is assumed they do not possess their own fleet but rather coordinate the flow of goods in the DN. Therefore, in this scenario, goods are transferred to PI-hubs by MCVs, and after consolidation, they are delivered to customers using vans. Both shippers and carriers have the independent ability to decide whether to use PI-Manager services or not. Here, shippers and carriers know the delivery cost in advance, as offered by the PI-Manager. Additionally, the PI-Manager is aware of the delivery costs for both tiers, as these are provided by third-party logistics firms with whom the PI-Manager has long-term contracts. However, PI-Manager's profit is uncertain during the learning period since PI-hub fee is based on expected demand, with the actual demand only becoming known after other agents accept the PI-hub fee and put orders.

The DN structure simulated in this chapter is noteworthy for its dynamism. Both the number of tiers in the DN and the types of vehicles incorporated into the DN are variable. Figure 7.2 provides comprehensive details regarding this network. Goods can be delivered directly from the shippers' warehouses to customers. In this scenario, the DN operates as a single-tier system, and delivery can be carried out by the shippers' MCVs or carriers' fleets, including MCVs and vans. However, if any of the shippers or carriers opt to utilise PI-managers' services, the DN transforms into a two-tier system. In the first tier, goods are initially transferred to PI-hubs and consolidated. Then, in the second tier, they are delivered from PI-hubs to the final customers.

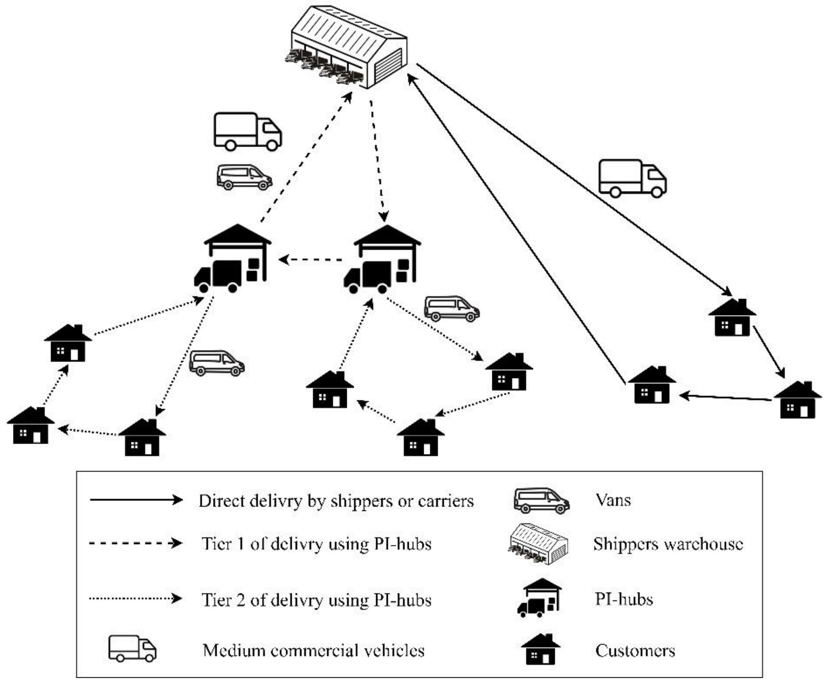


Figure 7.2. Goods movement in iMAS within the LML.

While Figure 7.2 depicts goods movement within the DN, it lacks comprehensive information regarding decision-making, policies, and requests exchanged among agents. To bridge this gap, findings from Section 2.5 have been incorporated to design an interaction diagram between agents, as illustrated in Figure 7.3. Within this diagram, learning agents are denoted in green, while non-learning agents are depicted in grey. Actions pertaining to the learning process are represented by bold arrows, indicating the direction of decision-making authority and the consequential impact on other agents. For example, decision (1) involves the PI-Manager setting the fee per parcel for PI-hub utilisation, directly affecting carrier operations. Dotted lines signify non-learning policies and requests, with their directional interpreted the same way as bold arrows; however, these interactions remain static throughout the learning process.

The exchange of information and decisions among learning agents is vital for creating the MAS Q-learning system. The learning process between the PI-Manager, carriers, and shippers is illustrated in Figure 7.4. Here is an example illustrating how agents exchange information, excluding carriers' influence on the decision-making process for simplicity. Initially, the PI-Manager assesses their profit based on expected demand at the start of the learning period and calculates the PI-hub fee accordingly. They then offer this fee to the shipper. Shippers analyse customer data, including location and demand volume, to calculate expected direct delivery costs. Additionally, they request delivery pricing from PI-Managers. Subsequently, the shipper conducts a comparative analysis between these fees and the estimated direct delivery cost to determine whether to use their own fleet or outsource orders. If the shippers choose to use their fleet, they proceed with delivering goods to customers. At the end of the learning period, they compare the expected delivery cost with the actual cost to update their delivery cost estimation, concluding the process. Alternatively, if the shippers opt for PI-hub services, their order is transferred to the PI-hubs. Finally, adjustments to the PI-hub fee for the upcoming learning period are made based on actual profits and adherence to the profit margin policy. Additional details regarding the specific criteria influencing each agent's decisions will be presented in Section 7.4.

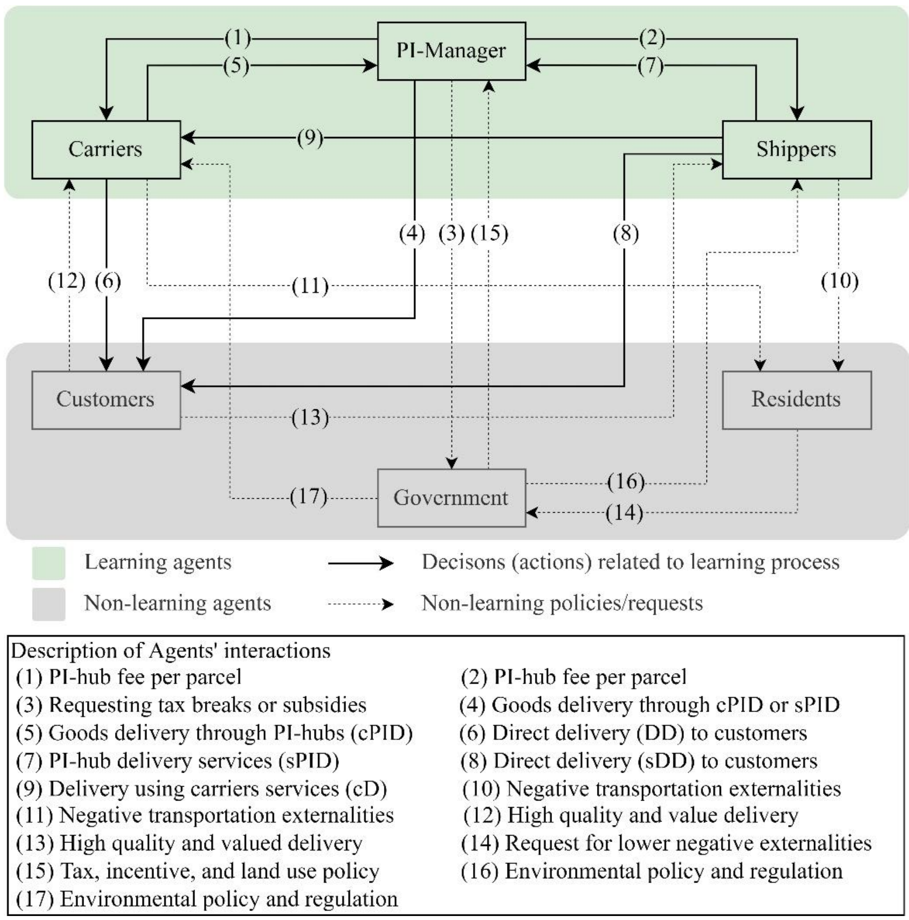


Figure 7.3. Agents' interactions diagram, depicting their decisions, policies, and requests.

Due to the sensitivity of the learning process to the sequence of decisions, establishing a well-defined decision-making order is crucial. Let us consider the simulation at state s_t. Leveraging prior information, which encompasses the calculation of the expected total demand for s_t, their reward function, and their profit margin, the PI-Manager establishes the PI-hub fee. Once this decision is made, it remains fixed until the commencement of s_{t+1}. Subsequently, shippers calculate the estimated delivery costs using their fleets and solicit quotations from carriers and PI-Manager. Carriers evaluate the delivery costs and provide pricing proposals to the shippers. Shippers then deliberate on their actions and arrive at a decision with the minimum cost. Lastly, carriers assess delivery costs assigned to them. They initially estimate the delivery costs and subsequently seek a quotation from the PI-Manager. Carriers evaluate the cost of their actions and choose the one with the lowest cost. Upon the conclusion of the learning period at s_t, agents' knowledge is updated, facilitating more effective strategies towards their objectives. This update encompasses revisions to their reward functions and demand estimation processes. As s_{t+1} unfolds, the aforementioned processes are reiterated based on the updated parameters of the learning algorithm. The learning decision sequences are shown in Figure 7.5.

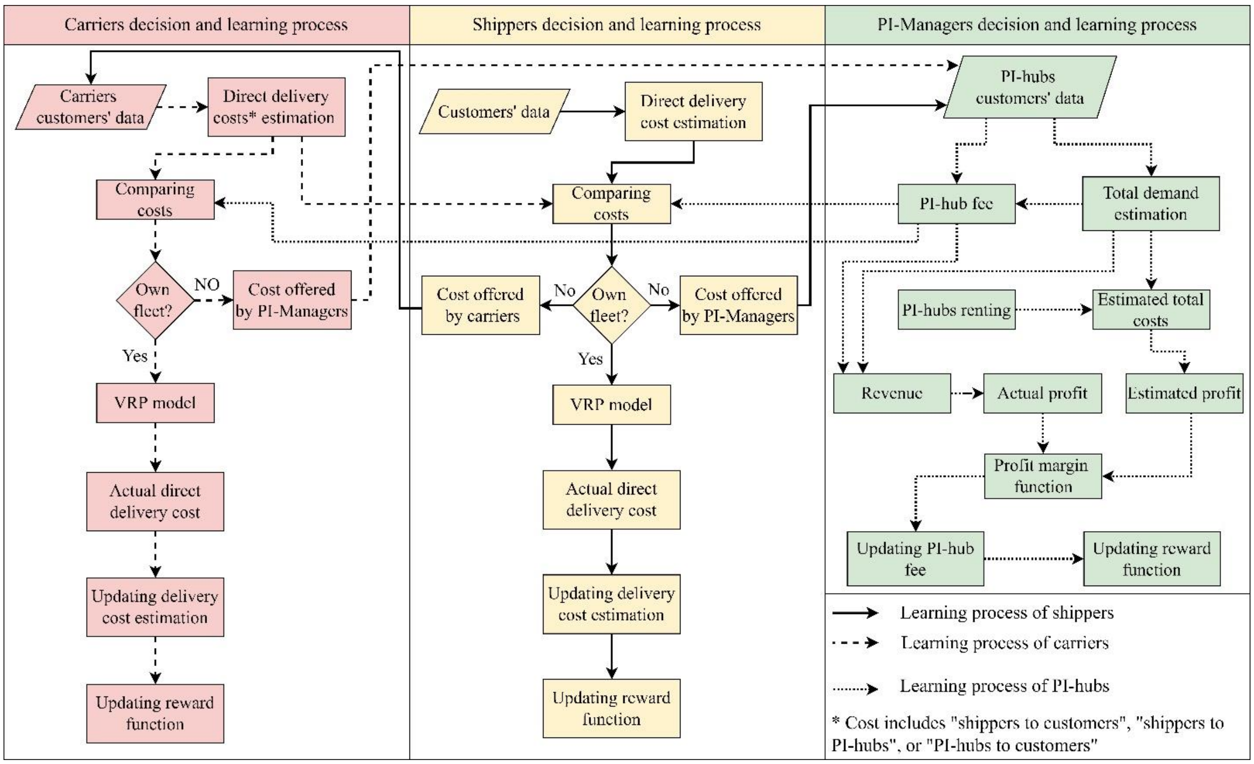


Figure 7.4. Agents' learning process and information flow.

7.4 Formulating the Model Framework

To formulate the learning process explained in Section 7.3, first the required features, including roles, actions, goals, and rewards are defined for learning agents. The agents' roles are defined by their general functionality within the DN, as explained previously. Their actions consist of a range of options that they can select based on their objectives. For shippers, their set of actions includes determining how to deliver goods to the final customers, which involves shippers' direct delivery (sDD) where they use their own fleet, shippers decide delivery through PI-hubs ($sPID$), or shippers use carriers for delivery ($scDD$). Once shippers strategise to outsource goods deliveries to carriers, carriers can navigate between delivery through PI-hubs ($cPID$) or direct delivery to customers (cDD). The actions of PI-hubs differ significantly from those of shippers and carriers. They provide PI-hub services to the other agents and charge them based on the number of parcels they handle. Consequently, their action set comprises increasing PI-hub fees, decreasing PI-hub fees, or maintaining current fee levels to achieve the maximum profits. Detailed explanations about agents' actions will be provided in Section 7.4.2.

Each agent's decision-making process is driven by their respective goals. Shippers aim to minimise transportation costs from their warehouse to the final customers, selecting the action with the lowest cost. Carriers also strive to minimise their transportation costs. Finally, the PI-Manager aims to maximise their profit by making appropriate decisions regarding the PI-hub fee.

Decision process

PI-Manager:
- *Requirements:*
  - PI-manager's reward function at s_t
  - Profit margin function
- *Calculation:*
  - Expected demand at s_t
  - PI-hub fee per parcel

Shippers:
- *Requirements:*
  - Customers' data
  - Shippers' reward function at s_t
- *Calculation:*
  - Estimate direct delivery using their fleet
  - Choose an action to minimise delivery cost

Carriers:
- *Requirements:*
  - Shippers' orders
  - Carriers' reward function at s_t
- *Calculation:*
  - Estimate direct delivery using their fleet
  - Choose an action to minimise delivery cost

Update all reward functions for s_{t+1}

Figure 7.5. Decision sequence among learning agents.

Agents' rewards are tailored to their specific goals, ensuring alignment with the overarching system objective. For shippers and carriers, the rewards are determined by their costs across their actions. The VRP developed in Chapter 6 is used to calculate the delivery cost for various actions. Alongside routing costs, it also computes the VKT in each action. This information is later utilised in Sections 7.5 and 7.6 for comparative analysis. The reward function of the PI-Manager is defined to maximise their profit. For this purpose, the operating profit margin (OPM) is defined and calculated by dividing the difference between revenue and operational costs by the operational costs. Section 7.4.2 will specify these functions. Finally, agents' characteristics are summarised in Table 7.1.

7.4.1 Reinforcement Learning

Reinforcement learning (RL) is a method through which an agent learns to choose actions within various states of environment, aiming to maximise its long-term rewards (Sutton & Barto, 1998). Typically, the environment is conceptualised as a Markov Decision Process

(MDP). At each learning period, the agent perceives a state from the state space. It then selects an action from the action space, receives a real-valued reward, and transitions to the next state. The agent's behaviour is governed by a policy, dictating the probabilities of action selection for each state. The reward and the subsequent state are determined by functions that are defined in advance. The primary objective of the RL agent is to determine a policy that maximises the expected return, defined as the discounted sum of rewards. Table 7.2 defines the key concepts utilised in Q-learning.

Table 7.1. Required agents' characteristics for the learning methodology.

Agent	Role	Action	Goal	Reward
Shipper	Engaged in e-commerce, selling goods in relatively small parcels.	Direct delivery (sDD), PI-hub delivery services ($sPID$), or delivery using carriers ($scDD$)	To minimise their transportation costs without losing generality.	Transportation cost associated with the selected action.
Carrier	Responsible for transporting goods from shippers to customers.	Delivering goods through PI-hubs ($cPID$) or opting for self/direct delivery (cDD) to customers.	To minimise delivery costs, successfully deliver goods on time, and optimise transportation efficiency.	Transportation cost associated with the selected action.
PI-Manager	PI-Managers are entities that operate intermediate.	Increase PI-hub fee, decrease PI-hub fee, or no changes in PI-hub fee	To maximise their profits and optimise hub operations.	Operating profit margin associated with the selected action.

Table 7.2. Key RL' concepts and their definitions.

RL key concepts	Definition
State	The state refers to a collection S of observable conditions experienced by an agent. State here denotes the observation of the agent's current situation.
Action	Within a given state, S, an agent is presented with a set of potential actions, denoted by A. Set A typically remains constant across all states, signifying a uniform range of choices available to the agent regardless of the specific context.
State transition probability	In RL, state transition probability quantifies the likelihood of an agent transitioning from its current state (s_t) to a new state (s_{t+1}) upon taking a specific action (a). This probability essentially captures the dynamics of the environment, indicating how the agent's actions influence the progression of states and the potential rewards it might encounter.
Reward	Within the learning environment, rewards act as a crucial feedback mechanism for the agent. These rewards can be understood as expected future value, as the agent might encounter different rewards for the same action in the same state due to environmental variability. This stochastic nature of rewards necessitates the agent's ability to learn from average outcomes rather than focusing solely on individual reward values.
Discount	In RL, the discount factor tackles reward accumulation issues. Rewards weaken over time, so discounting prioritises immediate rewards while still considering the long-term through the non-zero factor.
Policy	A policy defines the strategy or decision-making process an agent employs to select actions in different states, aiming to maximise cumulative rewards. It serves as a mapping from states to actions, guiding the agent's behaviour within an environment.

The action-value function, commonly referred to as the Q-function, for a specific policy. Q-learning focuses on learning the value of actions (Q) rather than the value of states (V) and introduced by Watkins and Dayan (1992). The basic one-step Q-learning formulation is illustrated in equation (1).

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \ \ell \left[r_{t+1} + d \max_a Q(s_{t+1}, a) - \ Q(s_t, a_t)\right] \tag{1}$$

In equation (1), $Q(s_t, a)$ is Q-value in state s_t due to the action a_t, r_{t+1} is the immediate reward, d is agent's discount rate, is categorised into three distinct criteria, ℓ is agent's learning rate, which is divided into three criteria, and $\max_a Q(s_{t+1}, a)$ is the maximum Q-value of the next state s_{t+1} for all possible actions a. Equations (2) and (3) represent d and ℓ, respectively.

$$\begin{cases} Agent\ consider\ long - term\ reward & d = 1 \\ Agent\ considers\ medium - term\ reward & 0 < d < 1 \\ Agent\ considers\ current\ reward & d = 0 \end{cases} \tag{2}$$

$$\begin{cases} Agent\ learns\ from\ the\ most\ current\ information & \ell = 1 \\ Agent\ learns\ from\ the\ previous\ information & 0 < \ell < 1 \\ Agent\ does\ not\ learn\ from\ the\ previous\ information & \ell = 0 \end{cases} \tag{3}$$

7.4.2 Formulating Agents' Interactions

The model for learning should depict the dynamics and conduct of stakeholders involved in the LML. A carrier, denoted as c, typically specialises in the last-mile delivery of goods to customers. In this MAS implementation, carriers must decide between two actions: delivering goods through PI-hubs, *cPID*, or opting for self/direct delivery, *cDD*, to customers. The action set available to carriers includes $A_c = \{cPID, \mathrm{c}DD\}$. The goal of the carrier is defined as minimising the overall operational cost incurred in delivering goods, whether through cDD or via the $cPID$. Hence, carriers select the delivery option with the minimum cost. Equation (4) guides carriers in selecting among their actions.

$$Obj_c = \min[cost_{cDD}, cost_{cPID}] \tag{4}$$

Where, $Cost_{cDD}$ is overall cost of goods delivery with cDD, and $Cost_{cPID}$ is the total cost of delivery using $cPID$. Carriers know $Cost_{cPID}$ as offered by PI-Manager, whereas $Cost_{cDD}$ signifies an anticipated cost. The former cost, offered by the PI-Manager, remains fixed for carriers during a learning period, while the latter varies depending on unpredictable operational conditions encountered during delivery. Factors like traffic congestion, which can lengthen operational hours, contribute to variations in $Cost_{cDD}$.

The PI-Manager is depicted as either a private or public entity responsible for sorting, consolidating, and distributing goods received from carriers to customers within the PI-hubs. The primary objective of the PI-Manager is to maximise the expected profit by proposing various policies regarding a PI-hub fee, as outlined in equation (5).

$$\max E\left[P_{f_i^{PI-hub}}\right] = \sum_{i}^{N} E\left[\mathrm{D}\left(f_i^{PI-hub}\right)\right] \times f_i^{PI-hub} - \left(TC_i^{PI-hub} + C_i^{PI-hub}\right) \tag{5}$$

Where,

f_i^{PI-hub} = fee per parcel in ith PI-hub;
$P_{f_i^{\mathrm{PI-hub}}}$ = profit at $f_i^{\mathrm{PI-hub}}$ in ith PI-hub;
$D\left(f_i^{\mathrm{PI-hub}}\right)$ = demand received by ith PI-Manager from carriers or shippers at $f_i^{\mathrm{PI-hub}}$;
$TC_i^{\mathrm{PI-hub}}$ = transportation costs to deliver through ith PI-hub to customers;
$C_i^{\mathrm{PI-hub}}$ = facility cost for renting a warehouse for ith PI-hub.

The PI-Manager's revenue is calculated by multiplying the expected demand from carriers or shippers by the current PI-hub fee. The PI-Manager's operational costs encompass transportation expenses (through long-term logistics contracts) and warehouse rental fees. Profit is the difference between total revenue and total cost.

The PI-hub fee per parcel varies daily based on the targeted profit margin (denoted by g) and the expected profit associated with it. If the expected profit falls within the range of g, the fee remains unchanged from the previous period. If the expected profit exceeds g, the fee increases; if it falls below g, the fee decreases. This strategy aims to balance profit around g and attract more demand. The target profit margin is defined as $g = [g_{min}, g_{max}]$. Hence, the possible actions for PI-Manager are defined in equation (6).

$$A_{PI-hubs} = \begin{cases} Increase & if \quad E\left[P_{f_i^{PI-hub}}\right] > g_{max} \\ No\ changes & if \quad E\left[P_{f_i^{PI-hub}}\right] \in g \\ Decrease & if \quad E\left[P_{f_i^{PI-hub}}\right] < g_{min} \end{cases} \tag{6}$$

$P_{f_i^{PI-hub}}$ stands as an expected profit, given the uncertainty regarding the actual demand for PI-hubs at the outset of decision-making. This depends on whether carriers (and shippers as we will explain later) opt to use PI-hubs or pursue alternative delivery methods, a decision which remains entirely unknown to the PI-Manager.

Shippers, denoted by s, are agents whose set of actions includes sending goods to customers using their own fleet, sDD, or outsourcing it. When they opt to outsource orders, they must choose between utilising PI-hub delivery services, $sPID$, or delivery using carriers, $scDD$. In the final stage of the decision-making process, it is assumed that shippers make decisions solely based on the prices offered by carriers and PI-Managers. Hence, the shipper set of actions involves $A_s = \{sDD, scDD, sPID\}$. Same as carriers, shippers are to minimise delivery cost, hence their objective function is defined by equation (7):

$$Obj_s = \min[cost_{sDD}, cost_{scDD}, cost_{sPID}] \tag{7}$$

In the learning framework, the utility value representing carriers' delivery costs and the profit for the PI-Manager can be depicted through a set of action value functions $Q(s_t, a_t)$ associated with a policy π. Let S represents the set of all possible states, and A denotes the set of all possible actions. The optimal state-action value functions, $Q^*(s_t, a_t)$, for learning agents is delineated in equations (8).

$$Q^*(s_t, a_t) = \max[Q^{\pi}(s_t, a_t)] \qquad \forall\, s_t \in S, \quad \forall\, a_t \in A \tag{8}$$

The decision period for all agents occurs daily, and they independently decide what actions they should take. Once a decision is made at learning period t, the simulation proceeds without permitting agents to alter their decisions. However, learning agents receive rewards that shape their subsequent decisions during learning period $t+1$. Nonetheless, each learning agent exhibits distinct behavioural responses to information received from other agents via the system environment, contingent upon their respective objectives. This information impacts the decisions they make in the subsequent learning period. For example, if at learning period t, shippers find that the cost of outsourcing to carriers and PI-Managers is excessively high and would escalate their delivery costs, they decide to use their own fleets.

7.4.3 Employing MAS Q-learning on Agents

In the MAS Q-learning framework, agents acquire knowledge through an action-value function. To fulfill this objective, equation (1) is employed in the agents' learning process. The utility Q for carriers and shippers is construed as a negative cost, indicating that the highest action-value corresponds to the lowest delivery expense for carriers. Conversely, the utility Q for PI-Manager represents maximum profit. Equation (9) delineates the immediate reward for carriers based on their actions ($cPID$ or cDD) at learning period t. Meanwhile, equation (10) illustrates the immediate reward the PI-Manager receives for the potential actions regarding the PI-hub fee (increase, decrease, or no change) during learning period t. Lastly, equation (11) represents the immediate reward for shippers based on their actions (sDD, $scDD$, or $sPID$) at tth period.

$$r^{\pi}_{C,\,a_t}(S_t) = \begin{cases} TC_{cDD}(S_t) & if\ a_t = cDD \\ TC_{cPID}(S_t) + P_{f_i^{PI-hub}}, & if\ a_t = cPID \end{cases} \tag{9}$$

$$r^{\pi}_{PI,\,a_t}(S_t) = \begin{cases} OPT_{increase}(S_t) & if\ a_t = increase \\ OPT_{no\ change}(S_t) & if\ a_t = no\ change \\ OPT_{decrease}(S_t) & if\ a_t = decrease \end{cases} \tag{10}$$

$$r^{\pi}_{S,\,a_t}(S_t) = \begin{cases} TC_{sDD}(S_t) & if\ a_t = sDD \\ TC_{scDD}(S_t) & if\ a_t = scDD \\ TC_{sPID}(S_t) + P_{f_i^{PI-hub}}, & if\ a_t = sPID \end{cases} \tag{11}$$

Where,

$TC_{cDD}(s_t)$ represents carriers' transportation cost in direct delivery at state s_t.

$TC_{cPID}(s_t)$ represents carriers' transportation cost using PI-hub's services at state s_t.

$TC_{sDD}(s_t)$ represents shippers' transportation cost using their own fleet at state s_t.

$TC_{scDD}(s_t)$ represents shippers' transportation cost using carriers' services at state s_t.
$TC_{cDD}(s_t)$ represents shippers' transportation cost using PI-hub services at state s_t.

In equation (10), OPT is operating profit margin. For each action, including increase, no change, or decrease, the corresponding PI-hub fee is utilised.

Upon receiving an immediate reward in a specific state, s_t, equation (12) is used to update the reward function.

$$R^{\pi}(s_t) \leftarrow R^{\pi}(s_t) + \ell\big(r_a^{\pi}(s_t) - R^{\pi}(s_t)\big), \qquad \forall a \in A \tag{12}$$

Where, $r_a^{\pi}(s_t)$ represents the immediate reward acquired by the learning agents when adhering to a policy π that employs a specific action a within a given state s.

A state is presumed to possess the Markov property, implying that the decisions made by the learning agents hinge on the disparity between immediate rewards and the expected future rewards. In MAS Q-learning, a policy guides the progression from the current state to the subsequent state. This alteration of the system's states is termed a transition, with transition probabilities denoting the likelihoods linked to different state transitions. Upon observing a transition, the expected transition probabilities for learning agents are adjusted by equation (13).

$$T^{\pi}(s_t) \leftarrow T^{\pi}(s_t) + \ell\big(\tau_a^{\pi}(s_t) - T^{\pi}(s_t)\big) \qquad \forall a \in A \tag{13}$$

Where, $\tau_a^{\pi}(s_t)$ denotes the observed transition transpiring when executing a policy with a particular action at a specific state s_t, and $T^{\pi}(s_t)$ signifies the expected transition probabilities utilising the current policy.

7.5 MAS Q-learning Simulation

This simulation analysis incorporates the demand data analysed in Chapter 4, the developed vehicle routing problem in Chapter 6, and the DN discussed in Chapter 5. The DN includes 4 carriers, 2 shippers, 34 customers, and 1 PI-Manager who coordinates 7 PI-hubs. The location of PI-hubs is illustrated in Figure 6.7. As elucidated in Chapter 4, population significantly influences e-commerce demand generation. Hence, we considered customers at the geometrical centre of the 34 most populated postcodes in Sydney. Detailed customer data is available in Appendix F. The location of Shipper 1 is determined by the chosen warehouse location detailed in Section 5.4.2 and shown in Figure 5.9. Additionally, we assume Shipper 2 is situated in the northeast region of Sydney, with coordinates latitude: -33.76603 and longitude: 151.266361.

Table 7.3 shows seven simulations that were evaluated in this chapter. In each simulation at least one stakeholder is a learning agent. The following are assumptions considered for all simulations. PI-Manager specialises in consolidating goods for final delivery to customers. Despite not owning their own fleet, they maintain long-term contracts with third-party freight companies. These agreements provide them with discounted rates for goods delivery. Both carriers and shippers operate fleets; however, there are notable differences. Carriers, specialising in goods movement, maintain two types of vehicles: MCV with a capacity of 450 parcels and vans with a capacity of 100 parcels. They utilise trucks for the primary tier of delivery, particularly to destinations with high parcel volumes, such as PI-hubs. In the secondary delivery tier, vans are employed. This choice is based on their suitability for urban environments and their ability to enhance vehicle load factors. In contrast, shippers exclusively operate only MCVs.

Table 7.3. List of simulations based on agents' ability to learn.

Simulation ID	**Agent**		
	Carrier	Shipper	PI-Manager
S1	Learning	Non-learning	Non-learning
S2	Non-learning	Learning	Non-learning
S3	Non-learning	Non-learning	Learning
S4	Learning	Learning	Non-learning
S5	Learning	Non-learning	Learning
S6	Non-learning	Learning	Learning
S7	Learning	Learning	Learning

The simulation period spans one year, encompassing 300 working days, during which learning agents make decisions daily. We employ real-world parcel demand data initially recorded on a monthly basis, from which we derived the daily averages for analysis. Furthermore, simulations and evaluations are carried out utilising MATLAB R2022a software on a Windows 10 operating system equipped with an Intel Core i7 CPU running at 1.80 GHz and 16 GB of RAM. Leasing, insurance, and operational costs for vans and MCVs are extracted from one of the state government in Australia (Industrial Relations Victoria Department of Premier and Cabinet, 2023b, 2023a). The remaining parameters utilised in the simulation are delineated in Table 7.4. Additionally PI-Manager charges their customers $1 per parcel (Ciardiello et al., 2023).

7.5.1 Assumptions for Non-learning Agents

When agents are not involved in the learning process, they follow predefined rules, resulting in a fixed operational pattern for them. Specifically, the PI-Manager is expected to adhere to a fixed PI-hub fee when they are not learning. Within such simulation contexts, carriers and shippers can assess their expected delivery costs against the offerings provided by the PI-Manager, thereby making their own decisions.

Conversely, in simulations where carriers are non-learning, they are limited to utilising only their own fleet and cannot access PI-Manager services. Moreover, a uniform delivery cost is presented to shippers throughout all learning periods, who can choose from three available actions.

However, addressing shippers as non-learning agents poses distinct challenges. Unlike carriers, who can be easily confined to their respective fleets, shippers are the primary demand generators in the system. Assuming they use their own fleet for deliveries would render the entire iMAS static. Thus, during each learning period, the assignment of deliveries from shippers to other agents is randomised using a uniform distribution function, generating numbers between 0 and 100. Lastly, carriers or the PI-Manager are selected randomly with equal chances in each learning period.

Table 7.4. Parameters used in simulations.

Parameter used in simulations	Parameters' value
Working hours	7 am – 5 pm
Working day	300 days
Van capacity	100 parcel per vehicle
MCV capacity	450 parcel per vehicle
Van lease cost	$ 5503
MCV lease cost	$ 5688
Van goods insurance cost	$ 160
MCV goods insurance cost	$ 240
Van operational cost	$ 0.29 per km
MCV operational cost	$ 0.46 per km
PI-hub rental cost	$ 940 per square meter per month[1]
PI-hub fee	$ per parcel
PI-Manager's profit margin range	0-9%
MAS Q-learning discount rate	0.8
MAS Q-learning learning rate	0.2

7.5.2 iMAS Simulation Results: Distribution Network Performance

This chapter aims to evaluate the effectiveness of the simulated DNs in reducing total VKT across different simulations. The inclusion of PI-hubs within the DN fosters a two-tiered operational model. In this scenario, carriers and shippers use the PI-hubs. Conversely, when PI-Manager services are not utilised, the network operates under a single-tier structure.

Establishing a baseline scenario is customary in logistics and transportation to evaluate the efficiency and performance of introduced alternatives. Since network configuration and agent learning abilities vary in this chapter's simulations, choosing a baseline is challenging. By removing PI-hubs from the network and eliminating interactions between carriers and shippers, our focus shifts solely to order fulfilment rather than the specifics of the delivery firm. This allows us to concentrate solely on the VKT required to deliver goods to the final customers. This base-case simulation is a non-learning single-tier distribution system without any decision-making processes.

Figure 7.6 illustrates the average VKT driven in one learning period in tier 1, tier 2, single-tier network, and the total VKT. In the base-case simulation, VKT is calculated based on the single-tier network, as we assumed the absence of PI-hubs in this simulation. The findings indicate that the lowest VKT is achieved in S3, where the PI-Manager acts as the sole Q-learning agent. This is attributed to its capability to quickly discern and adapt to the patterns

[1] https://soho.com.au/

of other agents, who have static behaviour, thereby adjusting its fees accordingly. Furthermore, all simulations involving the PI-Manager utilising Q-learning (S5, S6, and S7) also exhibit lower VKT compared to simulations where the PI-Manager does not engage in learning. The percentages in Figure 7.6 represent the VKT reduction relative to the base case simulation.

It has been observed that in simulations involving the PI-Manager as a learning agent, the PI-hubs utilisation is higher compared to other simulations. Simulations employing a learning PI-Manager, namely S3, S5, S6, and S7, demonstrated 92%, 90%, 87%, and 85% PI-hubs utilisation, respectively. Conversely, simulations where the PI-Manager is non-learning, including S1, S2, and S4, exhibit lower PI-hubs utilisation at 81%, 81%, and 83%, respectively. The incorporation of PI-hubs in the DN is crucial as it transforms the single-tier DN into a two-tier structure. This transformation promotes the use of lighter freight vehicles and subsequently reduces the total VKT.

7.5.3 iMAS Simulation Results: Individual Agent

This section analyses the performance of each agent, rather than the overall network, across the defined simulations. The average cost per day of carriers and shippers is assessed for all simulations, whereas the performance of the PI-Manager, including the PI-hub fee and their profits, is evaluated only when this agent is learning.

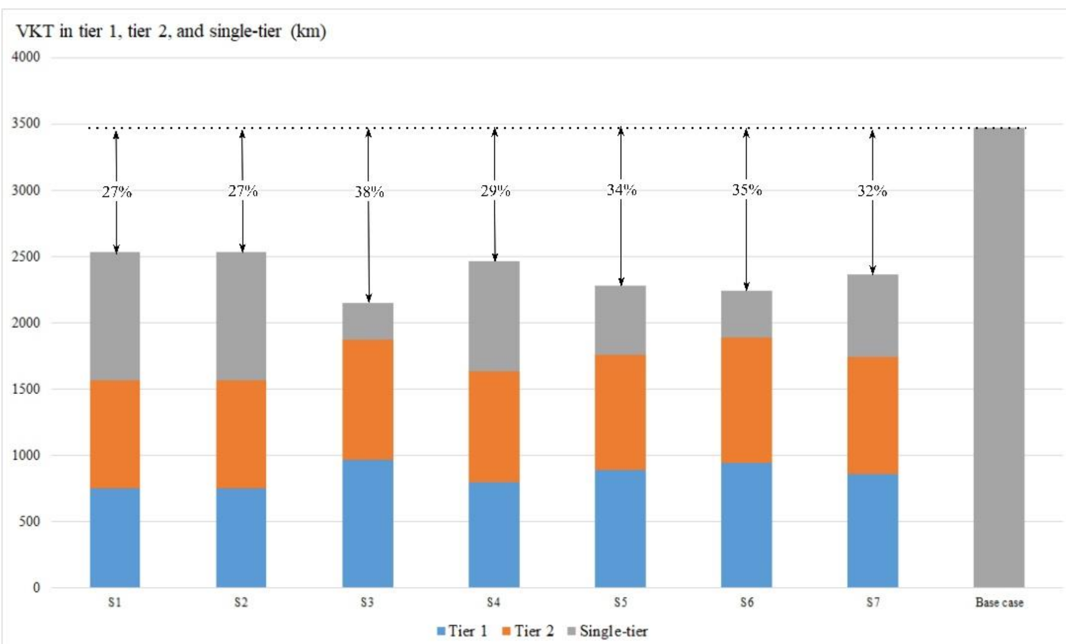


Figure 7.6. VKT across tiers 1, 2, single-tier, and total VKT.

Carriers' cost is illustrated in Figure 7.7 across seven simulations and compared with the base case simulation. The results reveal that when carrier agents are treated as learning agents, simulations S1, S4, S5, and S7, their costs are lower compared to when they function as non-learning agents, S2, S3, and S6. Such outcomes align with the overarching objective of MAS

Q-learning, wherein learning agents engage with the environment and other agents, receiving feedback from them. Leveraging previous experiences and the consequences of their actions, they iteratively refine their decision-making processes so that their objectives will be achieved. Additionally, the lowest overall cost for carriers is observed in scenario S1, characterised by carriers as the only learning agent. Conversely, the highest cost for carriers is noted in scenario S3, where the PI-Manager operates as the sole learning agent. Figure 7.7 also includes the cost associated with each carrier and the percentage of total cost reduction relative to the base case simulation.

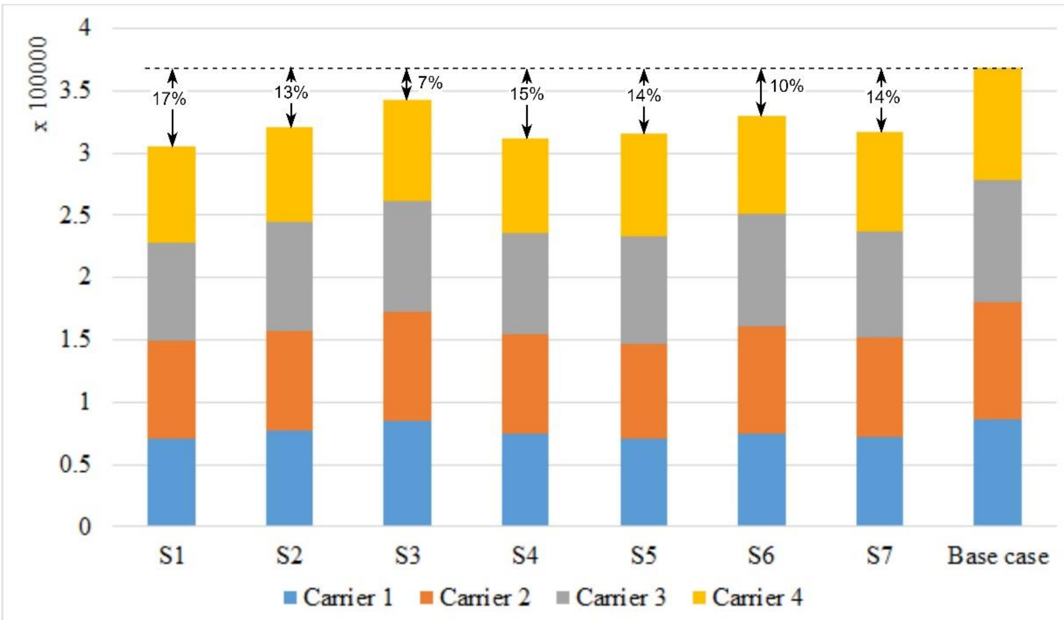


Figure 7.7. Transportation cost of carriers in different simulations.

Figure 7.8 illustrates shippers' overall costs across all simulations in one learning period. In S2, S4, S6, and S7, where shippers are learning agents, they achieve lower transportation costs compared to other simulations. While the lowest transportation cost for shippers occurs in S6, in S7, the transportation cost of Shipper 1 is slightly lower than its cost in S6, highlighting the dynamic nature of the learning process among agents. The highest cost for shippers is observed in S1, where carriers are the sole learning agents. The percentage of shippers' cost reduction compared to the base case simulation is also displayed in Figure 7.8.

In scenarios where the PI-Manager is not designated as a learning agent, the PI-hub fee remains consistent throughout the simulation period. Consequently, in our evaluation of the PI-Manager agent's performance, we concentrate exclusively on simulations where they are a learning agent, namely S3, S5, S6, and S7. Figures 7.9 – 7.12 illustrate the fluctuations in fees observed throughout the entirety of the learning process, spanning one year. In contrast to S5, S6, and S7, where the fee gradually stabilises and reaches a steady state by the end of the learning period, S3 exhibits a distinctly increasing PI-hub fee even at the final learning stages. The contrast highlights the varying dynamics when the PI-Manager is the only learning agent. Lastly, Figures 7.13 – 7.16 show the profit of PI-Manager agent in each learning period, with an interpretation similar to that of the PI-hub fee.

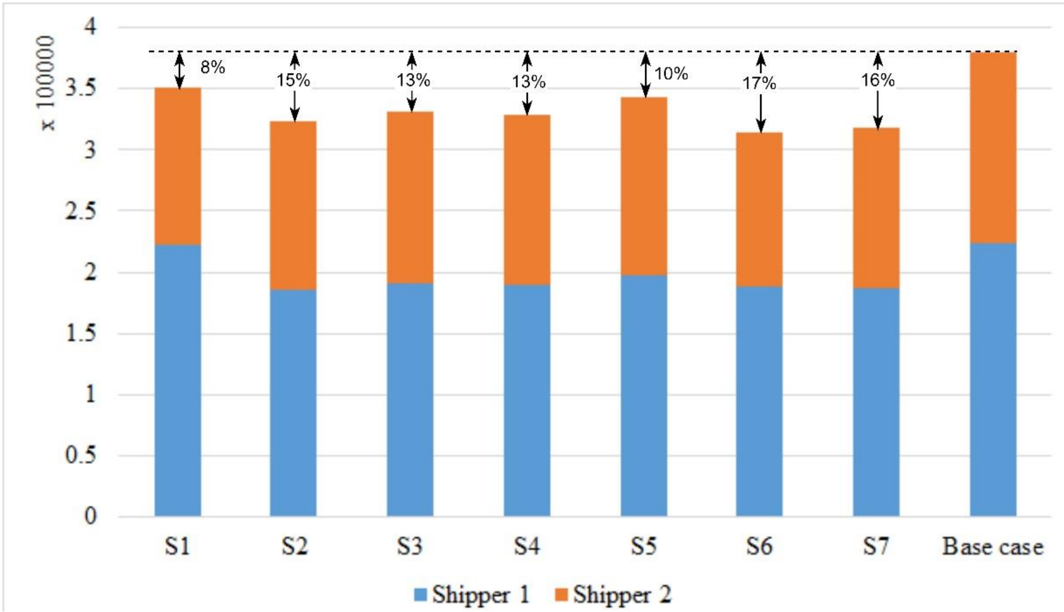


Figure 7.8. Shippers' transportation costs across various simulations.

In simulations where the PI-Manager agent operates as a learning agent, it adeptly adjusts its actions to increase the PI-hub fee and generate larger profits, which aligns with their desired objective. Across various simulations, the agent's behaviour exhibits more pronounced variability during the early and middle stages of learning. However, during the final steps of the learning period, it consistently demonstrates a similar pattern across all simulations.

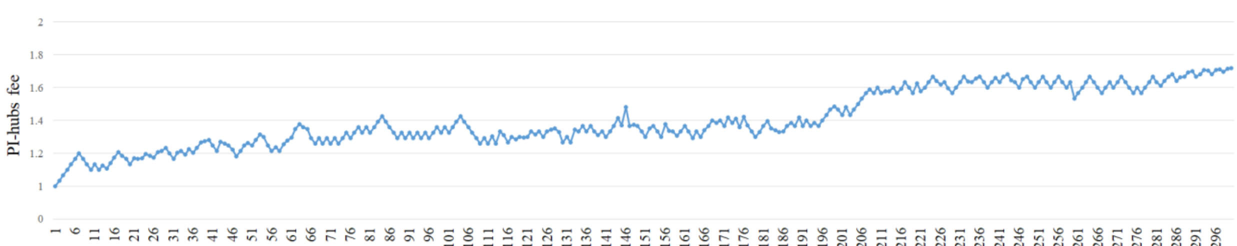


Figure 7.9. PI-hub fee adjustment during S3.

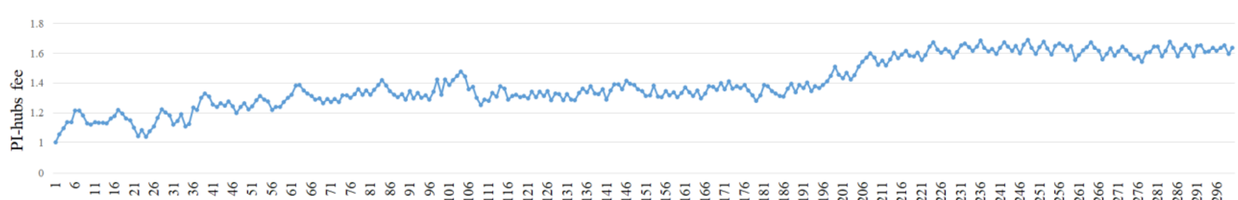


Figure 7.10. PI-hub fee adjustment during S5.

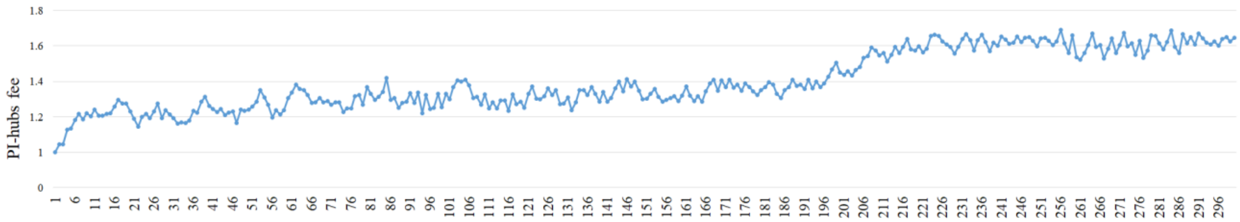


Figure 7.11. PI-hub fee adjustment during S6.

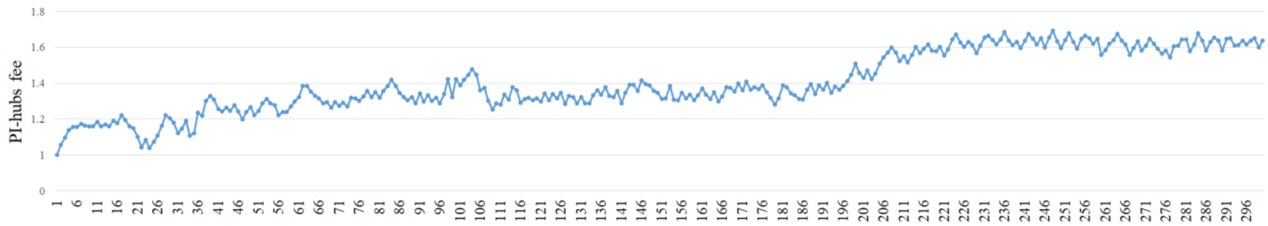


Figure 7.12. PI-hub fee adjustment during S7.

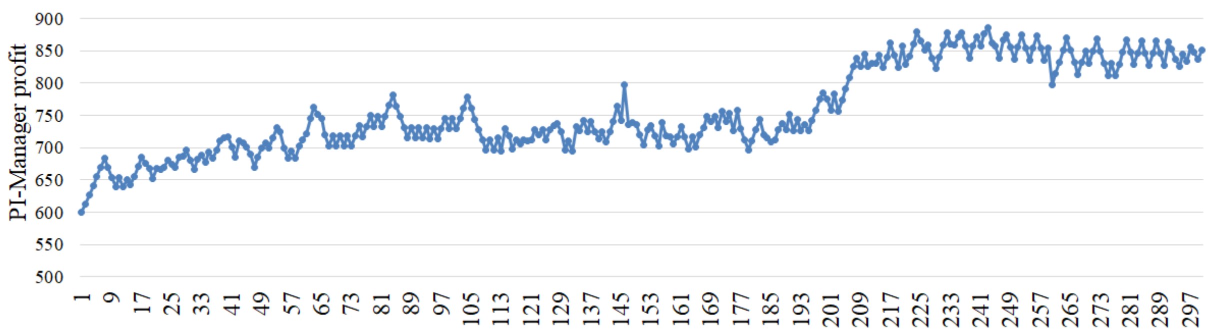


Figure 7.13. PI-Manager profits across S3.

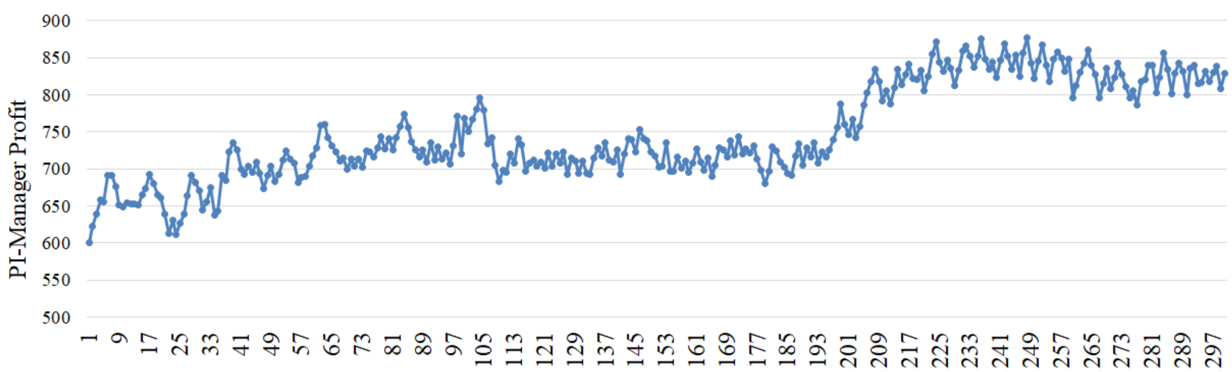


Figure 7.14. PI-Manager profits across S5.

The diagram in Figure 7.17 illustrates the reduction percentages in costs for shippers, carriers, and VKT compared to the base case simulation. Additionally, it signifies the proportion of learning periods during which the DN operates as a single tier without using PI-hubs. While there isn't an optimal simulation, the focus is on reducing freight vehicle movement in metropolitan areas. Notably, S3 represents the maximum VKT reduction, attributed to the effectiveness of PI-hubs in addressing this issue. However, the highest cost reductions for carriers and shippers are seen in S1 and S2, respectively. It has also been observed that there is an average reduction of 31.7% in VKT, which surpasses the average reductions in carriers' and shippers' costs, standing at 12.8% and 13.1%, respectively. This success in VKT reduction can be attributed to the implementation of PI-hubs in metropolitan areas. These hubs not only store goods closer to the final customers, thus preventing unnecessary VKT from shippers' warehouses to customers, but they also enhance delivery consolidation levels.

Achieving a balanced approach across all key performance indicators (KPIs) necessitates identifying the optimal policy for the PI-manager, given their decisions significantly impact PI-hub utilisation, VKT reduction, and the DN's structure. However, conducting a sensitivity analysis is crucial to gain a deeper understanding of how their policy influences KPIs.

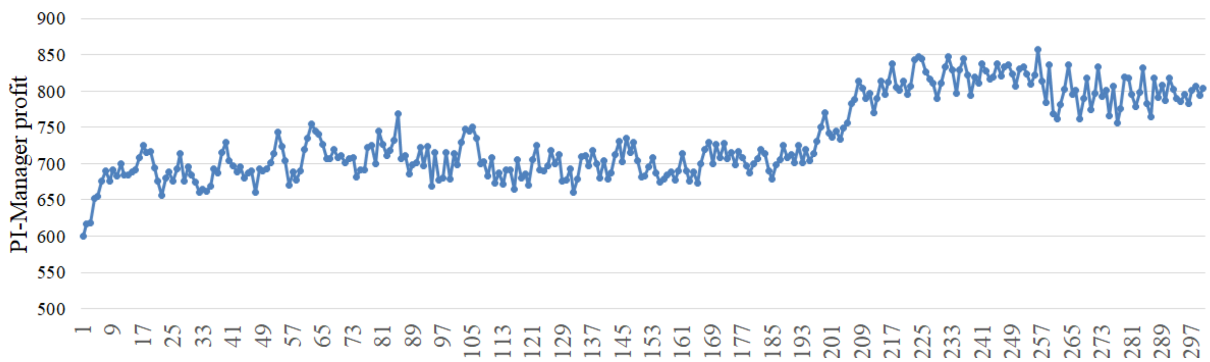


Figure 7.15. PI-Manager profits across S6.

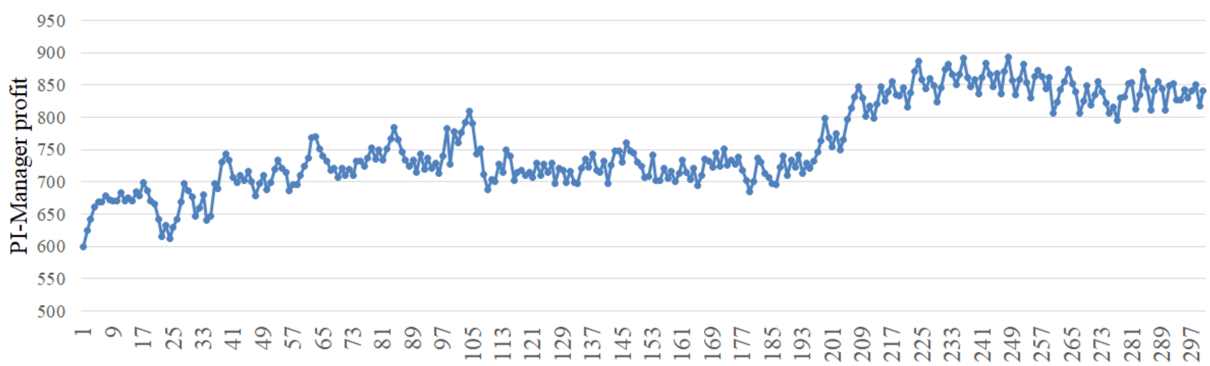


Figure 7.16. PI-Manager profits across S7.

7.6 Sensitivity Analysis

In this section, we aim to evaluate the impact of PI-hub fee on simulation results. The initial PI-hub fee is changed to assess its impact on carrier and shipper decisions regarding PI-Manager utilisation. In Section 7.5, it was assumed that the initial fee for PI-hub is $1 per parcel. This section explores adjustments to the PI-hub fee by ±5%, ±10%, and ±20%. Subsequently, the calculations include the VKT of tier 1 and tier 2 when PI-hubs are utilised, the VKT of a single-tier network when PI-hubs are not utilised, and the overall VKT of each simulation. Additionally, the overall cost for carriers and shippers is computed. Tables 7.5 –

7.10 present the detailed results. To facilitate easier comprehension, Figures 7.18 –7.20 visually represent the total VKT, carriers' cost, and shippers' cost.

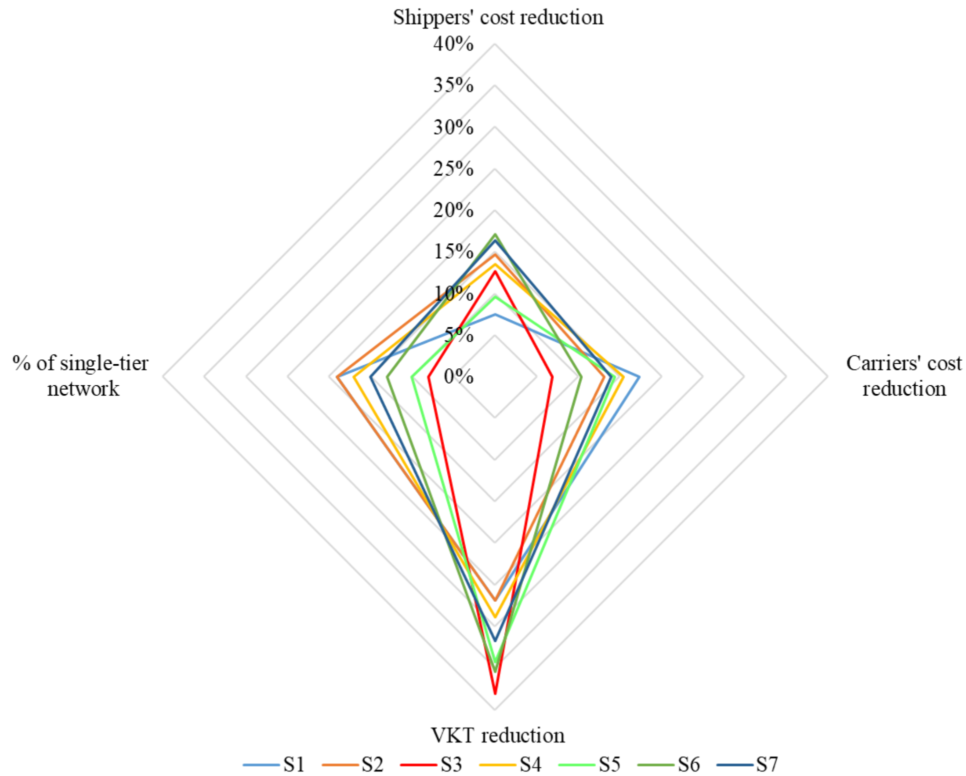


Figure 7.17. Comparison of KPIs across simulations.

Table 7.5. Impact of increasing PI-hub initial fee by 5%.

KPIs	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	-2.74%	-2.34%	-1.67%	-3.22%	-2.08%	-2.12%	-2.41%
Tier 1 VKT	772.87	772.86	985.71	816.26	911.70	965.67	880.07
Tier 2 VKT	826.07	826.06	923.22	854.46	884.04	968.30	901.85
Single-tier VKT	978.74	979.89	284.54	852.70	528.52	356.52	635.51
Total VKT	2577.68	2578.80	2193.46	2523.42	2324.26	2290.49	2417.43
Carriers' cost	305999	350442	329073	326183	348323	343284	334529
Shippers' cost	378809	324998	329413	330657	329917	347868	339189

Table 7.6. Impact of decreasing PI-hub initial fee by 5%.

KPIs	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	3.39%	4.01%	5.36%	3.87%	4.18%	4.20%	4.26%
Tier 1 VKT	723.29	723.95	927.42	763.21	855.82	905.98	824.87
Tier 2 VKT	735.08	739.47	837.89	767.82	793.39	871.73	800.86
Single-tier VKT	1014.96	1014.11	289.06	870.23	542.59	361.80	651.65
Total VKT	2473.33	2477.53	2054.37	2401.27	2191.81	2139.50	2277.39
Carriers' cost	309547	316255	297553	288485	297840	289557	286558
Shippers' cost	346413	307372	338618	318017	346626	277260	321369

Table 7.7. Impact of increasing PI-hub initial fee by 10%.

KPIs	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	-11.3%	-9.44%	-8.14%	-10.32%	-8.41%	-8.28%	-9.71%
Tier 1 VKT	779.65	779.63	994.20	823.25	919.39	973.06	887.60
Tier 2 VKT	854.52	854.48	953.29	883.94	913.34	999.26	932.43
Single-tier VKT	924.69	914.98	266.00	780.97	494.57	331.36	597.34
Total VKT	2558.87	2549.09	2213.49	2488.16	2327.31	2303.68	2417.37
Carriers' cost	321717	359922	360657	356428	359498	345297	331778
Shippers' cost	381257	332001	321216	339206	345321	356169	351149

Table 7.8. Impact of decreasing PI-hub initial fee by 10%.

	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	14.09%	14.23%	11.77%	14.51%	12.03%	13.38%	12.94%
Tier 1 VKT	676.89	676.96	873.54	712.79	802.36	849.45	770.89
Tier 2 VKT	726.27	732.36	812.65	747.49	786.47	855.45	798.41
Single-tier VKT	1129.69	1129.56	318.95	971.04	602.27	401.57	726.25
Total VKT	2532.85	2538.87	2005.15	2431.32	2191.10	2106.48	2295.55
Carriers' cost	292081	302815	312716	278244	266503	314271	304523
Shippers' cost	315563	315253	274217	293166	332707	273999	311783

Table 7.9. Impact of increasing PI-hub initial fee by 20%.

KPIs	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	-26.21%	-22.91%	-21.54%	-24.16%	-22.36%	-24.91%	-26.03%
Tier 1 VKT	825.91	825.92	1046.31	873.18	970.96	1028.10	940.10
Tier 2 VKT	946.33	946.35	1043.91	981.00	1006.21	1101.76	1032.33
Single-tier VKT	753.24	743.70	240.30	638.94	406.47	269.06	481.75
Total VKT	2525.48	2515.97	2330.52	2493.12	2383.64	2398.93	2454.18
Carriers' cost	344513	341921	344328	335592	329706	370585	359649
Shippers' cost	357655	329253	332888	328916	347870	320435	328810

Table 7.10. Impact of decreasing PI-hub initial fee by 20%.

KPIs	Simulation						
	S1	S2	S3	S4	S5	S6	S7
% PI-hub usage	27.06%	24.47%	23.70%	26.35%	25.61%	24.10%	25.54%
Tier 1 VKT	628.03	627.33	817.75	659.47	746.41	792.36	718.53
Tier 2 VKT	708.46	707.29	792.07	729.97	746.21	834.61	775.00
Single-tier VKT	1226.30	1227.68	343.62	1056.66	652.47	433.83	784.67
Total VKT	2562.79	2562.30	1953.44	2446.09	2145.09	2060.80	2278.21
Carriers' cost	268753	299403	310662	293365	301486	276074	267198
Shippers' cost	338798	260255	290713	309474	298290	256275	290470

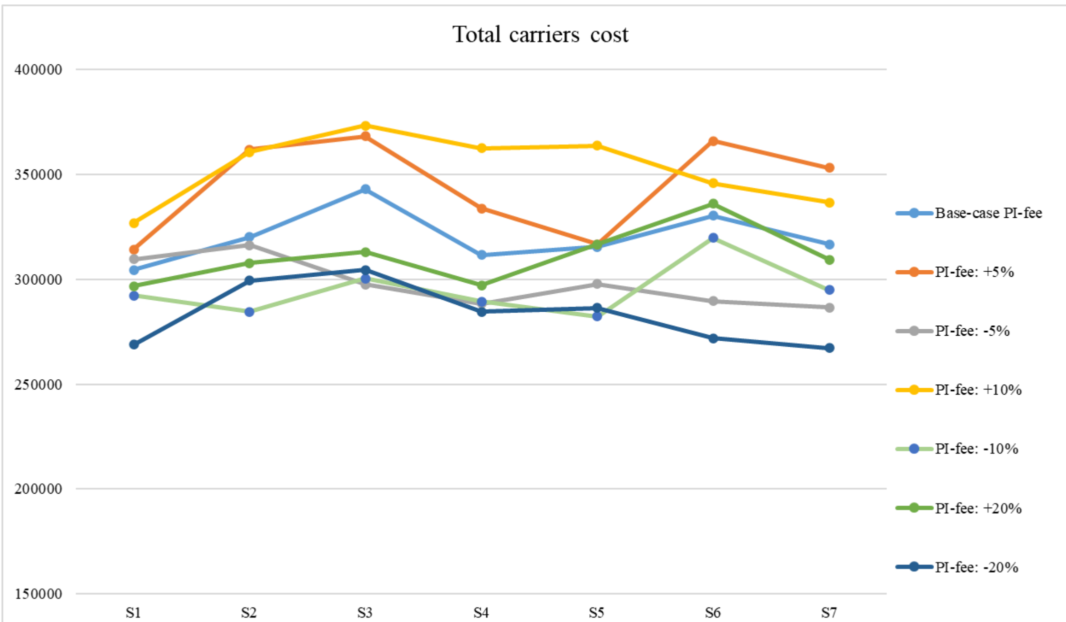


Figure 7.18. Impact of different initial PI-hub fee on carriers' cost.

PI-hubs usage sensitivity is evaluated in specified simulations by varying the initial fee from a baseline. As expected, higher fees led to decreased PI-hub usage, while lower fees resulted in increased usage. As the percentage change in the initial fee increases, both positive and negative changes, the response of carriers and shippers to PI-hub usage also intensifies. Notably, reactions to decreased initial fees are more perceptible than those to increased fees. A 10% fee increase is feasible for PI-Manager, as PI-hub usage only decreased by 8% on average, indicating potential financial gains from this policy shift. Conversely, a fee reduction, while likely not financially feasible for PI-Manager, could be implemented through government support aimed at increasing PI-hub usage in metropolitan areas to reduce VKT and its negative consequences.

The lowest shippers' cost occurs when the PI-hub fee is reduced by 20%, indicating their high responsiveness to lower fees offered by the PI-Manager. Conversely, a 10% increase in the PI-hub fee leads to the highest shippers' costs. A similar pattern is also observed for carriers, as their lowest cost occurs when the PI-hub fee is reduced by 20%, followed by a

10% reduction in the fee. Moreover, when the fee is increased by 10%, carriers experience the highest cost. The lowest and highest total VKT also occur when the PI-hub fee is decreased by 20% and increased by 10%, respectively.

The influence of initial PI-hub fees on the PI-Manager's cumulative profit during learning simulations is depicted in Figure 7.21. This figure presents profit values in dollars, with each bar accompanied by a percentage reflecting the profit change relative to a baseline initial PI-hub fee.

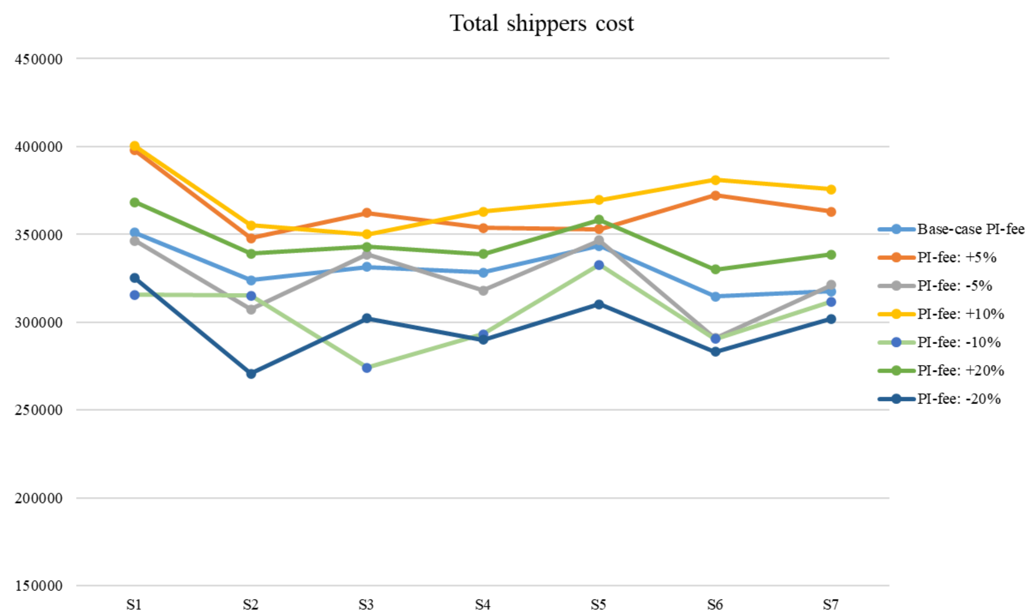


Figure 7.19. Impact of different initial PI-hub fee on shippers' cost.

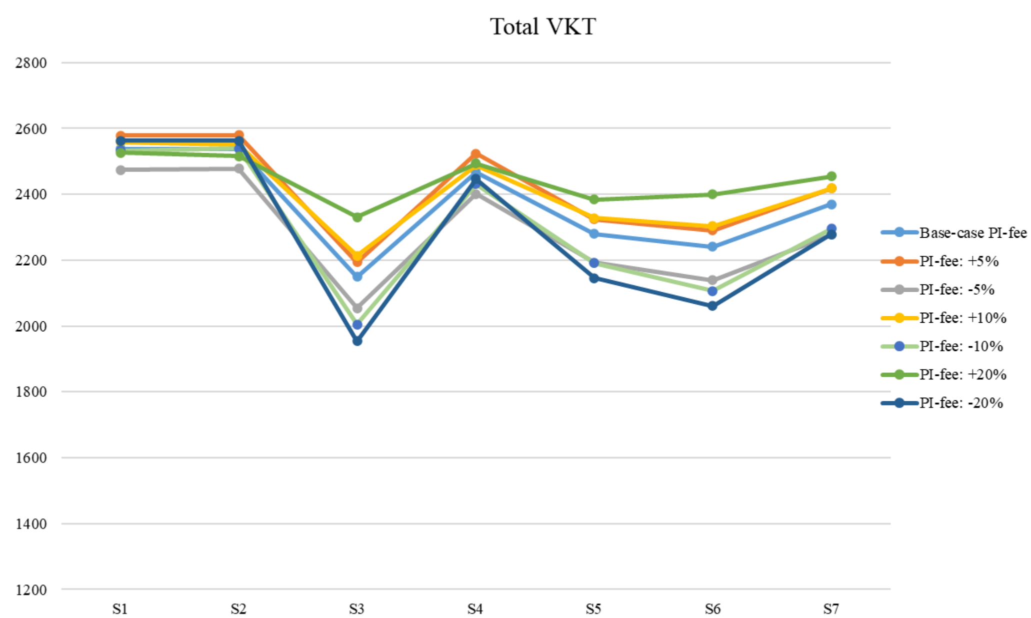
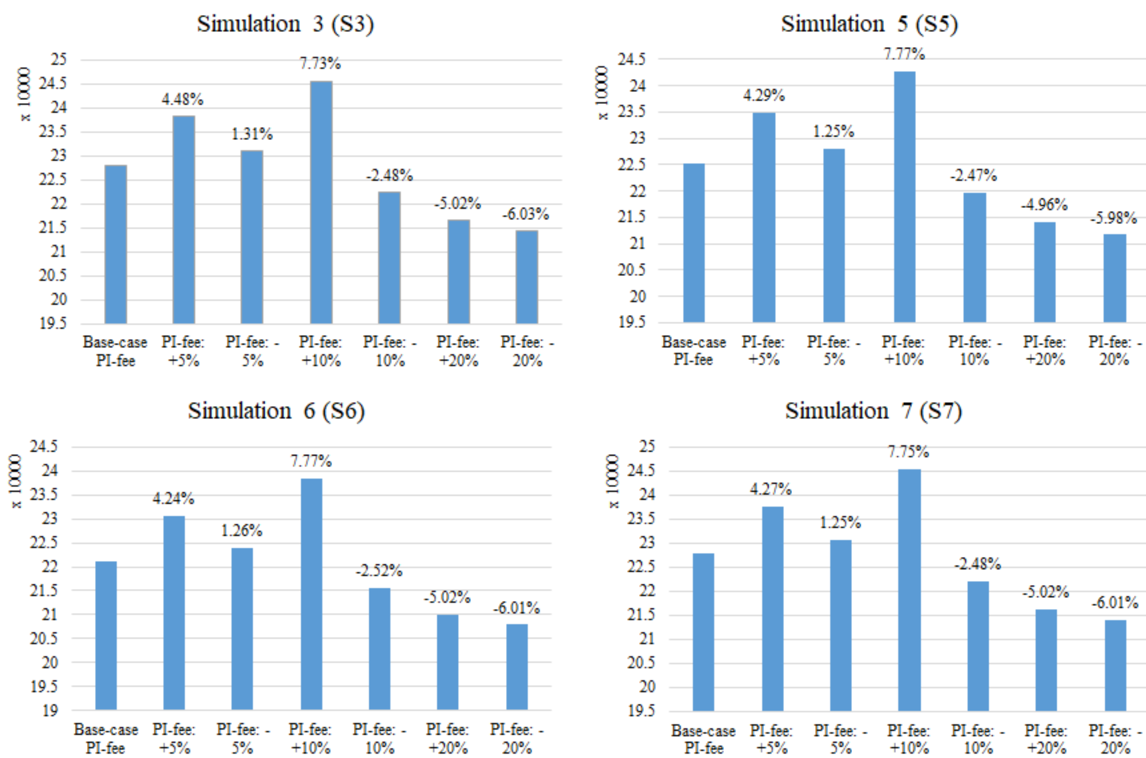


Figure 7.20. Impact of different initial PI-hub fee on total VKT.



Figures 7.21. Impact of initial PI-hub fee on profit of the PI-Manager.

Figure 7.22 illustrates the impact of the initial Pi-hub fee policy on each simulation from the KPIs perspective. In general, the observed trend is that the direction of KPIs changes is opposite to the initial Pi-hub fee changes. However, there are exceptions noted during the 20% increase in fees in simulations S1, S2, S3, and S4. In these instances, while carriers' costs decrease, shippers' costs increase. This indicates that carriers benefit from higher Pi-hub fees in their interactions with other agents.

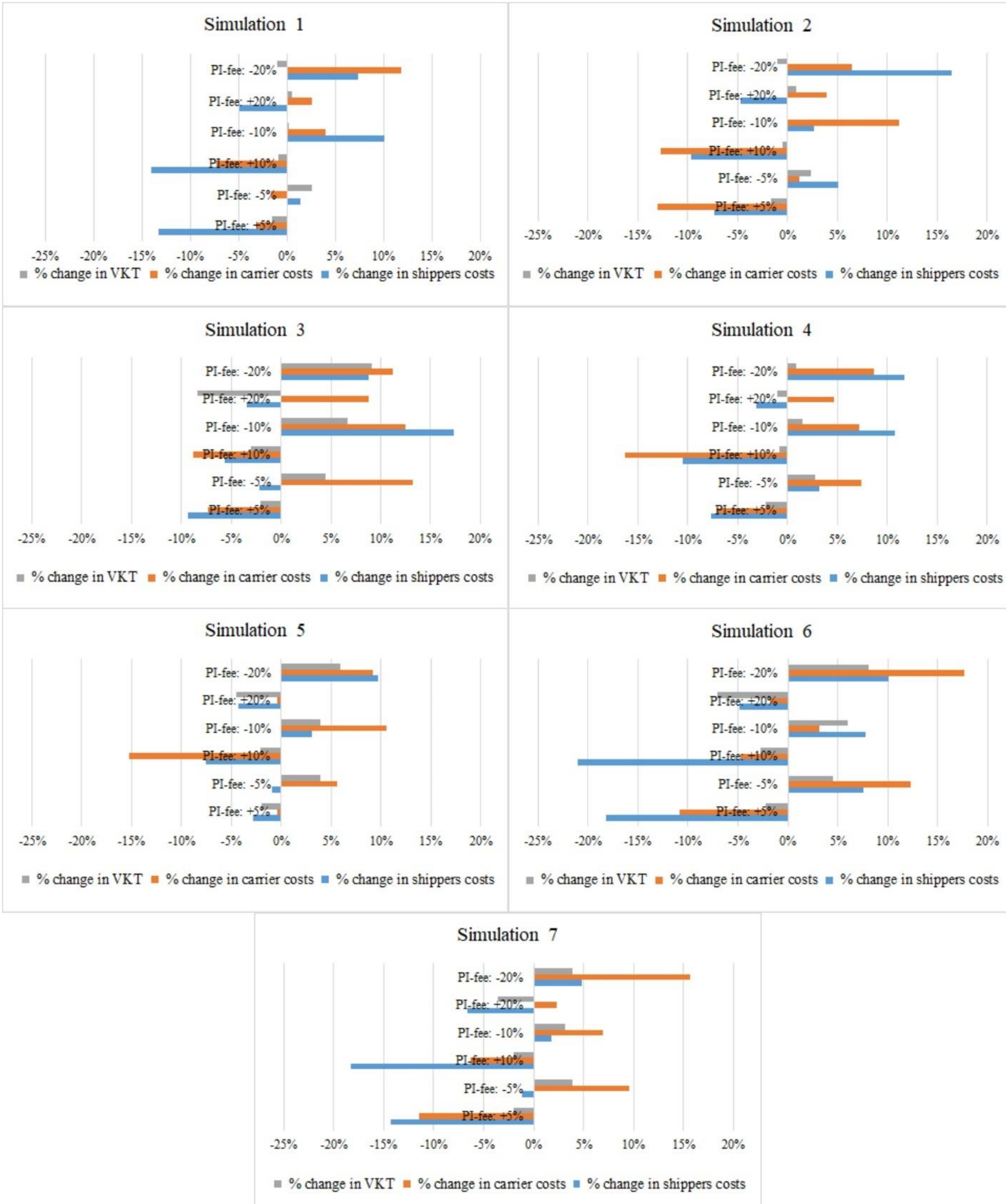


Figure 7.22. Impacts of varying initial Pi-hub fees on the KPIs.

7.7 Chapter Summary

In this chapter, we design a machine learning-based intelligent multi-agent system (iMAS) functioning as a decision support system (DSS). iMAS presents a platform for assessing the ramifications of diverse stakeholders' policies on last-mile logistics (LML). This is achieved by identifying stakeholders and establishing an interactive decision-making milieu. The findings of the literature review outlined in Section 2.5 have revealed the principal stakeholders in the LML. The comprehensive information, which encompasses decisions, policies, and requests among stakeholders, is illustrated in Figure 7.3. Among the six stakeholders identified, carriers, shippers, and PI-Managers are considered learning agents. The learning process, delineated in Figure 7.4, is formulated based on the interactions among stakeholders and their aim elucidated in Section 2.5. Another crucial component of the DSS is an environment wherein learning agents can engage with one another. To this end, we leverage the near-optimal DN conceived through the hub covering problem expounded in Chapter 5, coupled with the state-of-the-art vehicle routing problem model introduced in Chapter 6.

The iMAS employs MAS Q-learning, a variant of reinforcement learning, as its methodological approach, specifically designed for simulation purposes based on the objectives of the agents. Seven simulations, as outlined in Table 7.3, were conducted to evaluate the effectiveness of the agents. The primary performance metric, VKT, for different DN segments is calculated in all scenarios (Figure 7.5). The results indicate that the lowest total VKT occurs in S3 when the PI-Manager is the sole learning agent, while the highest total VKT is observed in S7 when all agents are engaged in learning.

When carriers, shippers, and PI-Managers are considered learning agents, they outperform than when they are not learning. Across all simulations wherein carriers and shippers are learning agents, their cumulative costs exhibit a reduction compared to instances where they are non-learning agents (Figures 7.7 and 7.8). Furthermore, when the PI-Manager is not engaged in the learning process, carriers exhibit lower transportation costs, as observed in S1 and S4. This trend is similarly observed for shippers in S2 and S4. Notably, in S3, where the PI-Manager operates as the only learning agent, there is more increase in the PI-hub fee and PI-Manager’s profit throughout the learning process (Figures 7.9 and 7.13), indicating the agent's adeptness in addressing its objectives.

Extensive sensitivity analysis was performed by adjusting the initial PI-hub fee by ±5%, ±10%, and ±20%. PI-hub utilisation increased as PI-hub fees decreased, reaching their peak at a 20% reduction. Conversely, usage declined as fees increased, with the most significant drop observed at a 20% fee increase. The variations in VKT across all distribution network (DN) segments compared with the base PI-hub fee, as illustrated in Figure 7.20. The lowest and highest total VKT was observed, with a 20% decrease and a 10% increase in the PI-hub fee, respectively. Carriers' and shippers' costs were calculated across all scenarios and simulations, as shown in Figures 7.18 - 7.19. Additionally, the sensitivity analysis included the PI-Manager's profit evaluation, revealing a 7.77% increase in profit with a 10% fee increase. For more detailed information about the sensitivity analysis, please refer to Section 7.6.

The transition from a single-tier system to a two-tier system in the DN is achieved through the utilisation of PI-Managers' services. A key advantage of incorporating PI-hubs into the network is the reduction in VKT facilitated by consolidation at these hubs and the decreased distance between goods depots and customers. This VKT reduction contributes to mitigating environmental impacts by lowering fuel consumption and emissions. Furthermore, the implementation of a two-tier DN enables more efficient and streamlined delivery processes by storing goods in closer proximity to customers, resulting in improved customer satisfaction through faster deliveries. Finally, a network facilitated by PI-hubs bolsters road safety by minimising the presence of heavy vehicles on roads, as second-tier delivery is conducted using vans.

The sensitivity analysis underscores the significant influence of PI-hub fee variations on agents' costs, profits, and VKT within the DN. Understanding potential real-world scenarios that could lead to fluctuations in the PI-hub fee is crucial. For example, an increase may stem from heightened demand or increased costs associated with implementing and maintaining these facilities, such as a rise in the rental price of PI-hubs. Conversely, a decrease could be influenced by external factors like government initiatives, such as subsidies or tax incentives.

Furthermore, our simulations highlight the significant advantages of utilising iMAS in the LML ecosystem. These findings not only confirm the effectiveness of the MAS Q-learning approach but also emphasis the value of collaborative decision-making among stakeholders. By creating an environment where stakeholders can continuously refine their strategies, the iMAS framework shows potential for addressing inefficiencies, cutting operational expenses, and ultimately improving the overall performance of LML networks. Importantly, this chapter marks the first assessment of the impact of the Physical Internet (PI) on the network and its stakeholders within a learning environment in the LML context.

While this chapter highlights the promising uses of iMAS in LML, additional studies are necessary to investigate the potential of other machine learning methods. Moreover, varying the environment in which agents interact could provide insight into their responses in new settings. By addressing these factors, iMAS has the potential to transform decision-making and collaboration within the constantly evolving landscape of LML.

Lastly, to enhance the realism of the simulation environment, introducing auctions between agents could be a viable solution. Auction-based simulations have the potential to facilitate a comprehensive evaluation of each agent's impact on the system, including the competition dynamics among agents within the same group (e.g., between carriers). This approach allows for a more nuanced understanding of how various factors influence system performance and competitiveness.

Chapter 8: Conclusion

8.1 Introduction

This chapter offers a comprehensive summary of the research findings, delineates the research questions, and examines how they were answered in pursuit of the research aim, thereby enriching the existing body of knowledge on last-mile logistics (LML). Furthermore, it provides insights into potential avenues for future research on this topic.

8.2 Research Contribution

The thesis significantly contributed to the design of a novel and realistic urban goods distribution network, especially in LML. It began by conducting extensive literature reviews, which identified key unsustainable trends, for instance disruptive events. These findings laid the groundwork for understanding the challenges faced by stakeholders in LML. Moreover, the thesis mapped out key stakeholders involved in LML, such as carriers and shippers, while also proposing the integration of Physical Internet managers (PI-Managers) to oversee shared and collaborative logistics hubs. This integrated approach aimed to enhance coordination and collaboration within the logistics network, potentially leading to more efficient and sustainable last-mile delivery operations.

In addition to contributing to the existing literature, the e-commerce data used in this research provides a realistic understanding of current parcel delivery demand in metropolitan areas. At the strategic level, a hub covering problem (HCP) model is developed, incorporating various factors such as single allocation, spatial conditions, local regulations relevant to the case study, and road traffic pattern analysis. The operational procedure of parcel delivery is optimised by creating a novel, realistic vehicle routing problem (VRP) that integrates features like collaboration, environmental sustainability, capacity constraints, and multiple freight hubs in the distribution network.

An intelligent multi-agent system (iMAS) is also developed, integrating literature review findings to describe agents, applying the HCP results to locate hubs in the simulation, and using the developed methodology to solve the VRP and evaluate agents' responses to different policies. The novelty of the iMAS lies in its use of three learning agents, which significantly expand the solution space. For more details about the contribution, this section will restate the research questions introduced in Chapter 1, followed by a summary of the key outcomes achieved in addressing each question.

8.2.1 Research Question 1

The first research question was “What factors and trends cause unsustainability in city logistics, particularly in the last-mile logistics?”. A literature review was conducted to answer this question and the following results were obtained:

- ✓ Results showed that four key unsustainable trends are: urban population growth, increasing popularity of e-commerce, fast delivery, and disruptive events.

- ✓ The main unsustainable impacts of urban population growth are air pollution, noise pollution, and GHG emissions.
- ✓ The main unsustainable impacts of the increasing popularity of e-commerce are rising service costs, failed delivery, increase in vehicles movement, return of products and reverse logistics, small shipment sizes, highly competitive market.
- ✓ The main unsustainable impacts of fast delivery are smaller truckload, more frequent fleet movements, increase in transportation costs, restricting retailers to accept future orders.
- ✓ The main unsustainable impacts of disruptive events are supply risk, demand risk, transportation risk, infrastructure risk, and socio-political risk
- ✓ SDGs′ goals and targets related to city logistics and LML were identified.

8.2.2 Research Question 2 and its Outcome

The second research question was "What are the existing and newly emerged stakeholders in the last-mile logistics? And how are their interactions with themselves and the environment from the strategic, tactical, and operational decision perspectives?" To answer this question another literature review was conducted which resulted in following findings:

- ✓ Identification of five key stakeholders in LML: residents, customers, carriers, shippers, and governments.
- ✓ Introduction of Physical Internet managers (PI-Managers) as new stakeholders to address the growing needs of shared and open logistics facilities.
- ✓ Identification of stakeholders' objectives.
- ✓ Identification of strategic, tactical, and operational decisions regarding distribution network design in LML.
- ✓ Mapping stakeholders' interactions based on their objectives and the decisions they can make.

8.2.3 Research Question 3 and its Outcome

The third research question was defined as "What impact has the COVID-19 pandemic had on e-commerce delivery patterns in the Sydney metropolitan area?". To answer this question data from a major carrier in Australia was used and parcel demand changes were evaluated spatially and statistically. Key findings of this study include:

- ✓ The impact of the COVID-19 pandemic on the level of e-commerce demand and last-mile delivery varied depending on geographical location and type of business.
- ✓ The pandemic potentially changed both the pattern and amount of home delivery.
- ✓ While in some countries, both B2B and B2C carriers experienced a drastic increase in delivery demand, in others, only B2C's demand grew, while that for B2B's declined.

- ✓ Based on the results of analysing Australia's largest business-to-customer carrier, demand for parcel delivery in Sydney was correlated to levels of employment, internet access, and population.
- ✓ Delivery demand shifts from inner postcodes to outer postcodes, highlighting the need for multiple logistics hubs to meet customer requirements effectively.

8.2.4 Research Question 4 and its Outcome

The fourth research question was "What is the optimal configuration of micro-consolidation centres in a collaborative last-mile distribution network?". To answer the question, we developed a new spatial methodology to solve an uncapacitated single allocation hub covering problem. This study revealed the following findings:

- ✓ Designing a collaborative last-mile distribution network that incorporates micro-consolidation centres (MCCs) servicing parcel lockers (PLs) by addressing the uncapacitated single allocation hub covering problem (USAHCP).
- ✓ Integrating MCCs and PLs, where customers retrieve their parcels, to establish more efficient and sustainable urban distribution systems by minimising failed deliveries and vehicle kilometres travelled (VKT) while maximising customer accessibility to PLs.
- ✓ Assessing diverse scenarios, considering two key variables: 1) maximum driving time constraints to evaluate various city accessibility policies; and 2) operating at different times of the day as proxies for variations in road traffic patterns.
- ✓ Evaluating 15 distribution configurations aligned with 15-minute city concept, providing valuable insights for stakeholders, particularly carriers, shippers, and governments, for their planning endeavours.

8.2.5 Research Question 5 and its Outcome

The fifth research question was defined as "What is the impact of optimising the allocation of urban delivery vehicles on the last-mile logistics? If a collaborative distribution network of micro-consolidation centres is used, how can this optimisation be achieved?". By answering this question, the following findings were obtained:

- ✓ Developing a collaborative multi-depot green vehicle routing problem incorporating MCCs and Comprehensive Modal Emission Model (CMEM).
- ✓ Bi-objective optimisation minimising both VKT and CO_2 emissions.
- ✓ Proposing a state-of-the-art self-adaptive metaheuristic algorithms hybridising intelligent water drops and simulated annealing for solution methodology.
- ✓ Directing algorithm convergence towards the global minimum via a feedback control system.
- ✓ Directing the algorithm towards the global optimum by implementing two knowledge-based systems through a mathematically proven approach.

- ✓ 43% and 25% reduction in VKT and CO_2, respectively, comparing the current distribution network and the collaborative one.

8.2.6 Research Question 6 and its Outcome

The last research question was "What is the impact of creating a DSS using an intelligent multi-agent system in line with sustainable urban distribution on stakeholders' interaction and last mile efficiency?". Following findings were achieved by answering this question:

- ✓ Developing an intelligent multi-agent system (iMAS) by focusing on stakeholder interactions in LML.
- ✓ Considering three learning agents in simulations: carriers, shippers, and PI-Managers.
- ✓ Designing a novel learning process based on agents' characteristics to represent the flow of information and diverse decision-making among agents.
- ✓ Formulating the learning process, including agents' actions and rewards aligning with the learning method, Q-learning, towards optimal actions based on environmental rewards.
- ✓ Integrating all major models of this research, including the hub covering problem and vehicle routing problem, into the iMAS as the environment where agents can interact.
- ✓ Varying agent combinations undergoing the learning process and creating seven simulations for a deeper understanding of the agents' reactions.
- ✓ Validating the learning methodology based on the results showing that learning agents exhibit a greater tendency to achieve desired objectives.
- ✓ Enabling stakeholders to evaluate various policies and actions for enhancing efficiency by using the iMAS as a decision support system.
- ✓ Acting as a comprehensive decision support system by integrating studies from other chapters, including LML stakeholder analysis, CMPGVRP, and USAHCP.

8.3 Future Directions

Potential research directions are discussed in this section. While the primary novel developed models of this thesis are the hub covering problem (HCP) presented in Chapter 5, the vehicle routing problem (VRP) mentioned in Chapter 6, and the intelligent multi-agent system summarised in Chapter 7, the recommendations for future work will commence with the data analysis conducted in Chapter 4.

Here, the e-commerce data is solely utilised as input for various models. Extensive literature and methodologies exist for predicting future demand by employing machine learning algorithms and artificial intelligence. Predicting e-commerce demand has the potential to assist stakeholders in strategic planning and enhance the efficiency of the distribution network.

While this research tackles the USAHCP with realistic constraints, it is worth to acknowledge that the HCP is a well-explored area in transportation, featuring numerous refinements and additions in the existing literature. Subsequent studies could thus explore incorporating additional details like multi-period or stochastic elements to broaden the research's scope and applicability. Moreover, this research primarily focuses on LML, thus excluding assessment of the upper level of goods transportation from manufacturers to urban areas. Addressing this aspect could potentially introduce additional criteria for locating hubs, as well as transform the problem into a multimodal HCP, thereby unveiling various opportunities to enhance network efficiency.

Similar to the HCP, various types of the VRP exist in transportation literature, offering a distinct opportunity to refine the developed model. Particularly, significant enhancements that could render the model more realistic involve incorporating time-window and stochastic features. Additionally, combining HCP and VRP could result in a location-routing problem, effectively addressing both strategic and operational challenges concurrently.

Regarding the iMAS, the domain of reinforcement learning (RL) is rapidly evolving, presenting opportunities for incorporating advanced RL algorithms like deep Q-networks (DQNs) or proximal policy optimisation (PPO). Additionally, enhancing existing machine learning methods, such as exploring transfer learning techniques from related domains, could further improve the efficiency and adaptability of the iMAS in complex LML scenarios. Future research could also explore the integration of domain knowledge or expert systems to complement the learning capabilities of the iMAS, further improving its performance and applicability in complex real-world scenarios.

Lastly, the utilisation of auctions in LML and MAS contributes to improving collaboration and establishing a realistic simulation environment in the logistics sector. Auctions are advantageous for fostering collaboration by creating a simulation environment that closely mirrors real-world logistics scenarios. This auction-based simulation can target either task assignment among diverse agents or task reallocation among companies within the same agent category. Such an approach is well-suited to meet the needs of multiple stakeholders and enhance logistics operations.

Appendix A

Identified decisions at operational, tactical, and strategic levels are presented in Table A.1.

Table A.1. Operational (O), tactical (T), and strategic (S) decision in the last-mile logistics

Decision level	Decision code	Description	Reference
Operational	O1	Load factor of delivery vehicles	(Awad et al., 2020; Cagliano et al., 2017; Panah et al., 2022)
	O2	Vehicle routing, sequences, time window, pick-up and delivery, etc.	(Baghali et al., 2023; İnanlı et al., 2015; Le et al., 2022; Liu & Lin, 2019)
	O3	Inventory problems, including holding, shortage, ordering and purchase	(Habibi et al., 2018; Panah et al., 2022; Sanada & Ishigaki, 2023)
Tactical	T1	Service schedules	(Le et al., 2022; Wisittipanich & Hengmeechai, 2015)
	T2	Fleets size and type	(Ivanov et al., 2019; VicRoads & Transport for Victoria, 2019)
	T3	Traffic routing	(Baghali et al., 2023; Wu et al., 2022)
	T4	defining allowed externalities, including emissions, noise	(Arvidsson et al., 2013; GUO et al., 2023; Liu & Lin, 2019)
	T5	H-containers	(Krommenacker et al., 2016; Sallez et al., 2016)
	T6	defining condition of deliveries, such as temperature, and required humidity	(Awad et al., 2020; Mvundura et al., 2015)
	T7	managing allocation of pi-containers to pi-vehicles, including sorting, and loading and unloading process	(Krommenacker et al., 2016; Sallez et al., 2016)
Strategic	S1	single type vs. multitype logistics facility	(Bozkaya et al., 2010; Ruiz-Meza et al., 2021; Shahanaghi & Yazdian, 2010)
	S2	Centralised vs decentralised facility	(Milewski & Wiśniewski, 2022; D. Zhang et al., 2023)
	S3	Serve in-store shoppers: conventional stores	
	S4	Attended home delivery	(Arnold et al., 2018)
	S5	Unattended home delivery	(McKinnon & Tallam, 2003)
	S6	Pick-up points	(Arnold et al., 2018)
	S7	Click and collect	(Arnold et al., 2018)
	S8	Locker boxes	(Grabenschweiger et al., 2021)
	S9	P-containers	(Matusiewicz, 2024)
	S10	Single commodity vs. multicommodity	(Boerkamps et al., 2000; Pujawan et al., 2015)
	S11	Collaboration (collaborative network)	(Miranda et al., 2009) (Tang et al., 2019)
	S12	Interaction among facilities	(Dreischerf & Buijs, 2022; Dupas et al., 2023)
	S13	Dominant flow (single echelon vs. multi-echelon)	(Guerrero Campanur et al., 2018; Ruiz-Meza et al., 2021)
	S14	Delivery policies	(Dreischerf & Buijs, 2022)
	S15	location problems	(Dupas et al., 2023; Long & Grasman, 2012)
	S16	Retail location	(Dupas et al., 2023; Long & Grasman, 2012)
	S17	T-containers	(Krommenacker et al., 2016; Sallez et al., 2016)
	S18	containers' security	(Krommenacker et al., 2016)

Appendix B

B2B demand changes in the Sydney metropolitan area are compared for the twelve-month periods spanning March 2019-February 2020 and March 2020-February 2021 (Figures A.1 and A.2).

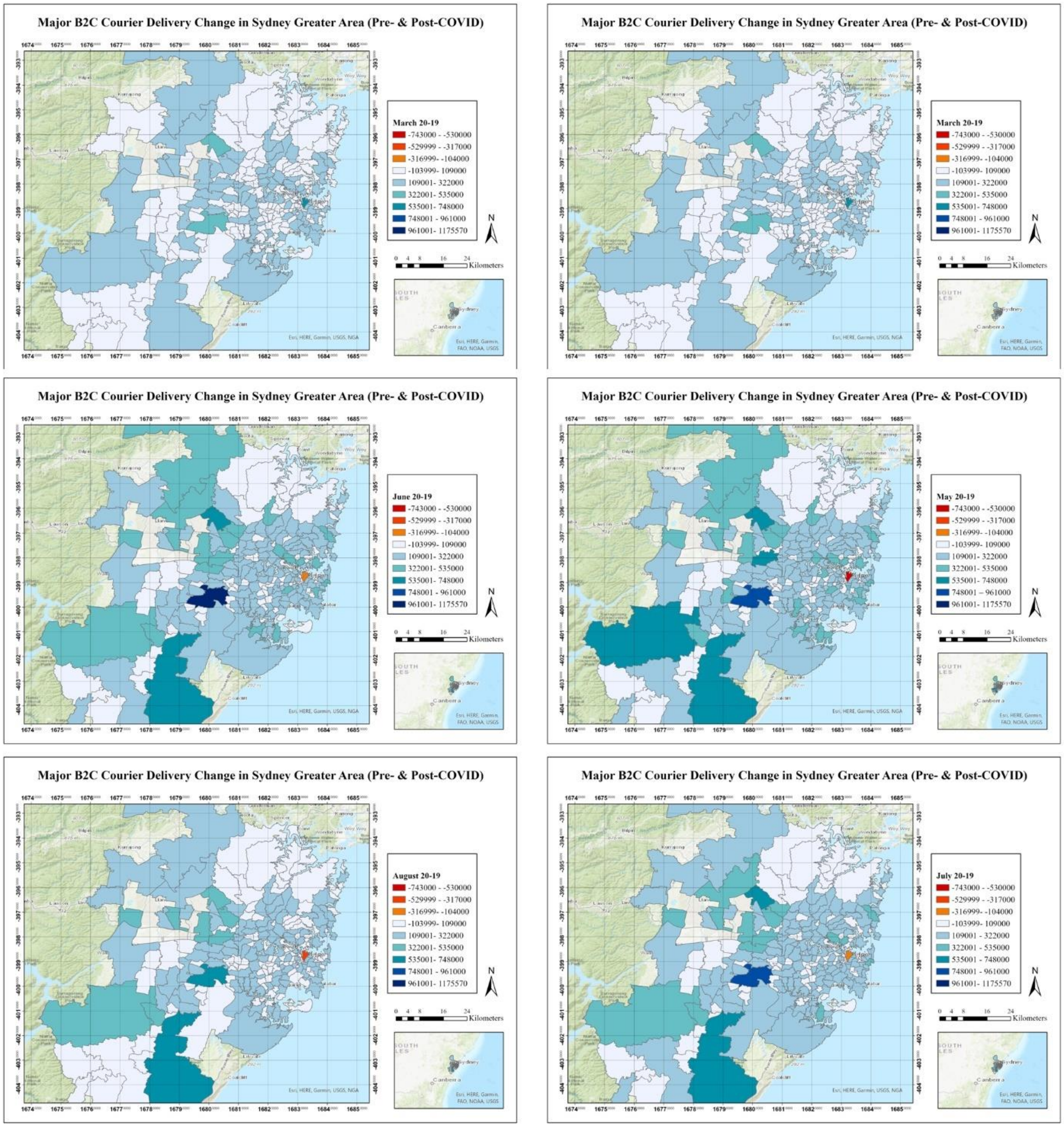


Figure A.1. Comparison of B2B demand changes from March 2019 to August 2020, and the corresponding months in the subsequent year.

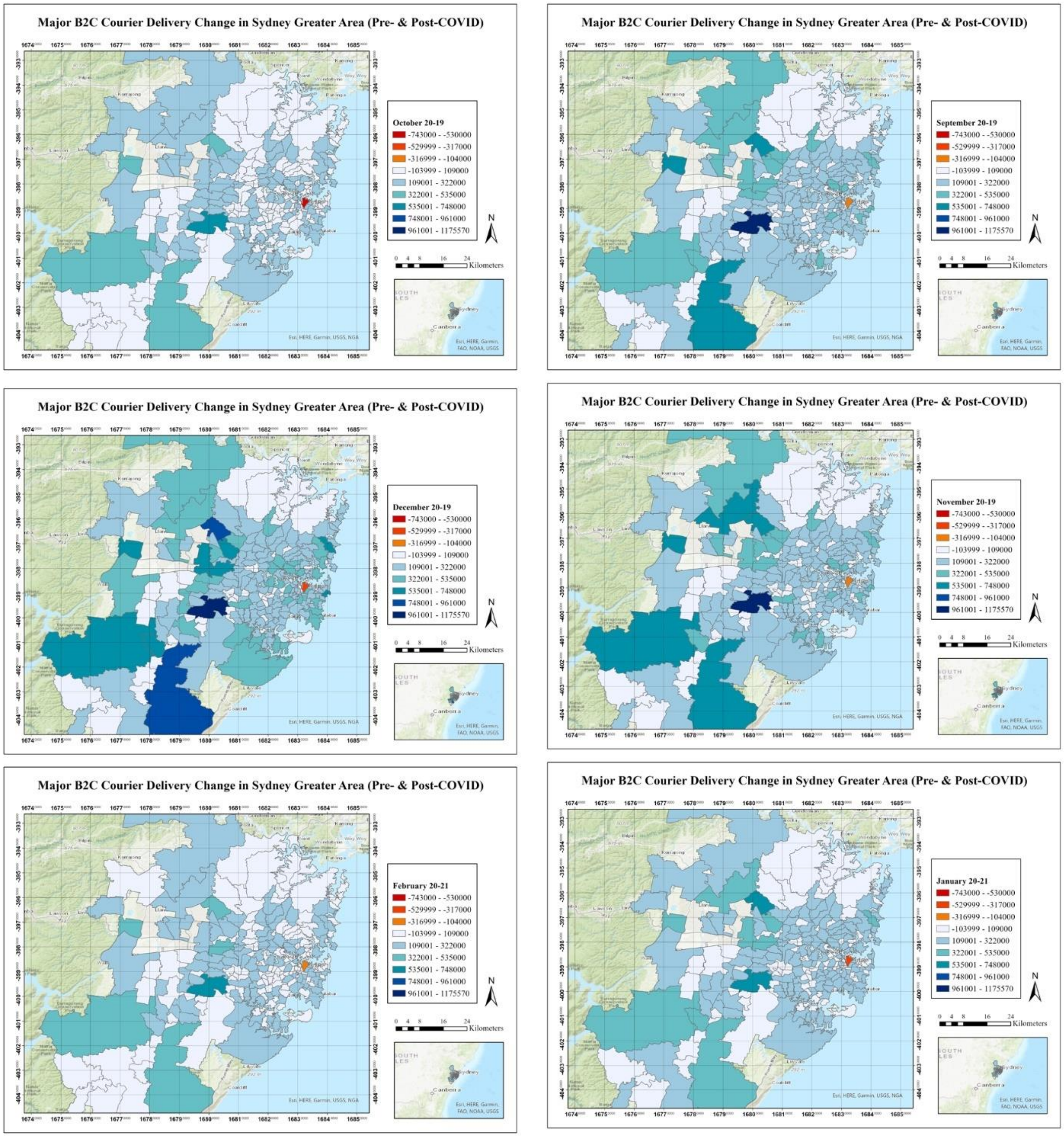


Figure A.2. Comparison of B2B demand changes from September 2019 to February 2020, and the corresponding months in the subsequent year.

Appendix C

The location of selected MCCs in different scenarios and time of day is presented in Table C.1. This table also presents the total driving time (TDT) and total weighted driving time (TWDT).

Table C.1. Detailed results of the USAHCP in three different scenarios.

Scenario	Time period	MCCs location (SA3 code)	Total driving time (minute)	Total weighted driving time	Vehicle kilometre travelled (km)
15-minute	Midnight	Baulkham Hills (11501)	135	0.658	108.2
		Rouse Hill - McGraths Hill (11504)	44	0.03	45.7
		Mount Druitt (11603)	77	0.265	73
		Botany (11701)	76	0.406	47.9
		Sydney Inner City (11703)	311	1.652	213.9
		Eastern Suburbs - North (11801)	73	0.318	43.4
		Bankstown (11901)	217	1.094	183.7
		Ku-ring-gai (12103)	148	0.731	127.5
		Manly (12201)	106	0.489	77.4
		Richmond - Windsor (12404)	24	0.125	25.7
		Auburn (12501)	274	1.199	233.8
		Bringelly - Green Valley (12701)	78	0.351	88.2
		Fairfield (12702)	78	0.424	67.3
		Cronulla - Miranda - Caringbah (12801)	93	0.336	78.7
	Morning peak	Baulkham Hills (11501)	11	0.147	6.3
		Rouse Hill - McGraths Hill (11504)	18	0.036	20
		Blacktown (11601)	46	0.179	24.3
		Blacktown - North (11602)	46	0.168	29.4
		Botany (11701)	94	0.485	50.8
		Sydney Inner City (11703)	128	1.184	52.2
		Eastern Suburbs - North (11801)	104	0.459	43.5
		Bankstown (11901)	91	0.289	52.5
		Hurstville (11903)	54	0.217	29
		Leichhardt (12002)	80	0.269	39.6
		Strathfield - Burwood - Ashfield (12003)	129	0.460	70.3
		Chatswood - Lane Cove (12101)	90	0.501	51.1
		Ku-ring-gai (12103)	43	0.156	25.8
		North Sydney - Mosman (12104)	34	0.163	13.7
		Manly (12201)	32	0.096	16.6
		Warringah (12203)	30	0.191	17
		Richmond - Windsor (12404)	26	0.134	25.7
		St Marys (12405)	33	0.093	21.5
		Auburn (12501)	80	0.291	45.6
		Carlingford (12502)	62	0.270	34.6
		Merrylands - Guildford (12503)	59	0.327	34
		Pennant Hills - Epping (12601)	56	0.177	35
		Bringelly - Green Valley (12701)	58	0.140	58
		Fairfield (12702)	81	0.342	55.5
		Cronulla - Miranda - Caringbah (12801)	100	0.390	62.1
	Off peak	Baulkham Hills (11501)	48	0.338	28.5
		Rouse Hill - McGraths Hill (11504)	19	0.037	20
		Blacktown - North (11602)	44	0.151	32.8
		Mount Druitt (11603)	77	0.308	63.5
		Botany (11701)	79	0.427	39
		Sydney Inner City (11703)	176	1.339	77.6

Table C.1. Detailed results of the USAHCP in three different scenarios.

		Eastern Suburbs - North (11801)	100	0.434	44.4
		Bankstown (11901)	100	0.312	59.8
		Hurstville (11903)	64	0.253	37.8
		Strathfield - Burwood - Ashfield (12003)	226	0.814	123.7
		Chatswood - Lane Cove (12101)	171	0.724	107.4
		Ku-ring-gai (12103)	56	0.201	37.6
		Manly (12201)	72	0.380	39.6
		Richmond - Windsor (12404)	27	0.135	25.7
		Carlingford (12502)	131	0.575	83.9
		Merrylands - Guildford (12503)	86	0.456	51.3
		Bringelly - Green Valley (12701)	71	0.210	71.9
		Fairfield (12702)	65	0.319	45.9
		Cronulla - Miranda - Caringbah (12801)	96	0.376	62.1
	Afternoon peak	Baulkham Hills (11501)	25	0.187	14
		Rouse Hill - McGraths Hill (11504)	19	0.036	20
		Blacktown (11601)	35	0.187	17.8
		Blacktown - North (11602)	57	0.163	39.6
		Botany (11701)	82	0.435	39.5
		Sydney Inner City (11703)	117	1.119	44.2
		Eastern Suburbs - North (11801)	101	0.445	43.2
		Bankstown (11901)	106	0.324	58.7
		Hurstville (11903)	65	0.258	37.5
		Leichhardt (12002)	96	0.379	45.8
		Strathfield - Burwood - Ashfield (12003)	119	0.377	63.6
		Chatswood - Lane Cove (12101)	114	0.470	61.5
		Ku-ring-gai (12103)	57	0.205	35.7
		Manly (12201)	75	0.401	39.9
		Richmond - Windsor (12404)	26	0.134	25.7
		St Marys (12405)	33	0.095	21.6
		Auburn (12501)	105	0.408	59.4
		Merrylands - Guildford (12503)	73	0.460	40
		Pennant Hills - Epping (12601)	126	0.563	83.3
		Bringelly - Green Valley (12701)	85	0.302	85.1
		Fairfield (12702)	66	0.244	46.8
		Cronulla - Miranda - Caringbah (12801)	89	0.371	54
	Night	Baulkham Hills (11501)	150	0.729	106.4
		Rouse Hill - McGraths Hill (11504)	46	0.036	45.7
		Mount Druitt (11603)	84	0.284	73
		Botany (11701)	92	0.421	56
		Marrickville-Sydenham-Petersham (11702)	250	0.887	142.4
		Eastern Suburbs - North (11801)	120	1.112	69.4
		Bankstown (11901)	198	1.048	151.4
		Chatswood - Lane Cove (12101)	152	0.683	106
		Ku-ring-gai (12103)	88	0.297	69.1
		Manly (12201)	89	0.468	58.2
		Richmond - Windsor (12404)	26	0.132	25.7
		Auburn (12501)	254	1.192	196.5
		Bringelly - Green Valley (12701)	82	0.365	87.5
		Fairfield (12702)	85	0.465	65.9
		Cronulla - Miranda - Caringbah (12801)	102	0.367	79.5
20-minute	Midnight	Blacktown – North (11602)	169	0.570	168.3
		Bankstown (11901)	283	1.483	233.8
		Kogarah – Rockdale (11904)	434	1.955	324.6
		Ku-ring-gai (12103)	224	0.766	206.9

Table C.1. Detailed results of the USAHCP in three different scenarios.

	North Sydney – Mosman (12104)	639	2.995	532.7
	Richmond – Windsor (12404)	56	0.447	59.4
	Carlingford (12502)	395	1.974	346.4
	Bringelly - Green Valley (12701)	228	0.927	251.7
Morning peak	Baulkham Hills (11501)	128	0.566	76.6
	Blacktown - North (11602)	62	0.221	45.2
	Mount Druitt (11603)	83	0.342	63.3
	Botany (11701)	214	1.102	108.4
	Eastern Suburbs - North (11801)	306	1.820	150.1
	Bankstown (11901)	299	1.448	200
	Chatswood - Lane Cove (12101)	243	1.018	156.8
	Ku-ring-gai (12103)	112	0.328	77
	Manly (12201)	110	0.592	58.1
	Richmond - Windsor (12404)	63	0.493	59.4
	Auburn (12501)	469	1.854	322
	Bringelly - Green Valley (12701)	108	0.435	105.4
	Fairfield (12702)	101	0.549	63.8
	Cronulla - Miranda - Caringbah (12801)	126	0.462	79
Off peak	Blacktown - North (11602)	71	0.202	55.4
	Mount Druitt (11603)	89	0.324	73
	Botany (11701)	158	0.799	81.1
	Eastern Suburbs - North (11801)	125	1.259	56.6
	Bankstown (11901)	367	1.710	262.1
	Leichhardt (12002)	463	1.718	285.5
	Ku-ring-gai (12103)	100	0.253	70.8
	Manly (12201)	94	0.417	49.3
	Warringah (12203)	81	0.301	55.8
	Richmond - Windsor (12404)	62	0.489	59.4
	Merrylands - Guildford (12503)	183	1.031	118.7
	Pennant Hills - Epping (12601)	253	1.393	190.1
	Bringelly - Green Valley (12701)	192	0.741	186.8
	Cronulla - Miranda - Caringbah (12801)	121	0.442	79
Afternoon peak	Baulkham Hills (11501)	148	0.655	88.2
	Blacktown - North (11602)	74	0.215	55.4
	Mount Druitt (11603)	97	0.534	79
	Botany (11701)	174	0.843	90.5
	Eastern Suburbs - North (11801)	162	1.339	79
	Bankstown (11901)	319	1.587	212.7
	Leichhardt (12002)	305	1.264	158.3
	Ku-ring-gai (12103)	236	0.965	161.7
	Manly (12201)	81	0.298	40
	Warringah (12203)	99	0.439	66.9
	Richmond - Windsor (12404)	62	0.488	59.4
	Auburn (12501)	286	1.171	172
	Bringelly - Green Valley (12701)	158	0.621	157.1
	Fairfield (12702)	86	0.451	55
	Liverpool (12703)	37	0.060	18.9
	Cronulla - Miranda - Caringbah (12801)	132	0.485	79.1
Night	Baulkham Hills (11501)	202	0.744	154.3
	Canterbury (11902)	391	1.676	276.8
	Kogarah - Rockdale (11904)	333	1.691	234.8
	Ku-ring-gai (12103)	304	1.234	263.7
	North Sydney - Mosman (12104)	625	2.912	484.2
	Richmond - Windsor (12404)	131	0.473	132.7

Table C.1. Detailed results of the USAHCP in three different scenarios.

		Merrylands - Guildford (12503)	413	2.126	340.1
		Bringelly - Green Valley (12701)	219	0.804	229
25-minute		Blacktown - North (11602)	261	1.458	257
		Sydney Inner City (11703)	810	3.806	585
		Hurstville (11903)	549	2.217	446.7
		Ku-ring-gai (12103)	730	2.561	684.9
		Bringelly - Green Valley (12701)	171	0.746	191
		Fairfield (12702)	325	2.055	308.8
	Morning peak	Baulkham Hills (11501)	162	0.611	109.4
		Sydney Inner City (11703)	571	2.885	270.7
		Kogarah - Rockdale (11904)	684	2.959	429.5
		North Sydney - Mosman (12104)	238	1.071	131
		Warringah (12203)	229	0.786	159.2
		Richmond - Windsor (12404)	140	0.495	133.1
		Merrylands - Guildford (12503)	584	3.085	407
		Pennant Hills - Epping (12601)	292	1.066	194.2
		Bringelly - Green Valley (12701)	270	0.956	250.1
	Off peak	Baulkham Hills (11501)	213	0.632	164.2
		Kogarah - Rockdale (11904)	649	2.988	426.5
		North Sydney - Mosman (12104)	626	2.959	417.6
		Warringah (12203)	245	0.817	176
		Richmond - Windsor (12404)	137	0.492	133.1
		Auburn (12501)	579	2.762	409.7
		Pennant Hills - Epping (12601)	282	1.113	211.9
		Bringelly - Green Valley (12701)	393	2.225	382.3
	Afternoon peak	Baulkham Hills (11501)	151	0.639	93.2
		Sydney Inner City (11703)	630	3.293	280.7
		Bankstown (11901)	461	2.120	308.3
		North Sydney - Mosman (12104)	184	0.826	101
		Warringah (12203)	221	0.760	155.9
		Richmond - Windsor (12404)	159	0.491	150.7
		Merrylands - Guildford (12503)	414	1.887	298
		Pennant Hills - Epping (12601)	339	1.264	248.8
		Bringelly - Green Valley (12701)	305	1.378	299.4
		Cronulla - Miranda - Caringbah (12801)	132	0.485	79.1
	Night	Blacktown - North (11602)	163	0.971	149.5
		Mount Druitt (11603)	428	2.547	415.7
		Hurstville (11903)	854	3.736	641.7
		Ku-ring-gai (12103)	628	2.153	558
		North Sydney - Mosman (12104)	877	4.224	694.4
		Bringelly - Green Valley (12701)	244	1.003	252.6

Appendix D

The parameter sensitivity of $F(x, y, z)$ with respect to x can be calculated by applying the partial derivative method shown in equation (D.1):

$$S_x^F = \frac{\partial\, F(x,y,z)}{\partial \text{x}} \times \frac{x}{F(x,y,z)} \qquad (\text{D}.1)$$

Parameter sensitivity analysis determines how a small change in a parameter affects the function value. A high sensitivity value indicates that a small change in the parameter would cause a large change in the function value. In contrast, a low sensitivity value indicates that a small change in the parameter would cause only a small change in the function. A positive sensitivity value also means that as the input parameter increases, the output variable also increases. On the other hand, a negative sensitivity value means that as the input parameter increases, the output variable decreases. Overall, parameter sensitivity analysis provides information about the direction and magnitude of changes in the output variable with respect to specific input parameters.

To calculate the sensitivity of ΔVel_{IWD} with respect to $a_v(t)$, $b_v(t)$, and $c_v(t)$, we assume all parameters are positive and apply (D.1) to equation (23) three times. The sensitivity of ΔVel_{IWD} with respect to $a_v(t)$ $is\ calculated\ in$ equation (A.2)

$$S_{a_v}^F = \frac{\partial\, \Delta Vel_{IWD}}{\partial a_v} \times \frac{a_v}{\Delta Vel_{IWD}} = \frac{1}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2} \times \frac{a_v(t)}{\frac{a_v(t)}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2}} = 1 \qquad (\text{D}.2)$$

Equation (A.3) represents the sensitivity of ΔVel_{IWD} with respect to $b_v(t)$

$$S_{b_v}^F = \frac{\partial\, \Delta Vel_{IWD}}{\partial b_v} \times \frac{b_v}{\Delta Vel_{IWD}} = \frac{-a_v(t)}{\left(\left(b_v(t)+ c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2\right)\right)^2} \times \frac{b_v(t)}{\frac{a_v(t)}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2}} = \frac{-b_v(t)}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2} \qquad (\text{D}.3)$$

Finally, equation (A.4) shows how ΔVel_{IWD} is sensitive to the changes of $c_v(t)$

$$S_{c_v}^F = \frac{\partial\, \Delta Vel_{IWD}}{\partial c_v} \times \frac{c_v}{\Delta Vel_{IWD}} = \frac{-\text{a}_\text{v}(\text{t})\left(\text{Soil}(\text{n}_\text{i},\text{n}_\text{j})\right)^2}{\left(\left(\text{b}_\text{v}(\text{t})+ \text{c}_\text{v}(\text{t})\left(\text{Soil}(\text{n}_\text{i},\text{n}_\text{j})\right)^2\right)\right)^2} \times \frac{c_v(t)}{\frac{a_v(t)}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2}} = \frac{-c_v(t)\left(\text{Soil}(\text{n}_\text{i},\text{n}_\text{j})\right)^2}{b_v(t)+c_v(t)\left(Soil\left(n_i,n_j\right)\right)^2} \qquad (\text{D}.4)$$

Since the result of equation (D.2) is one, ΔVel_{IWD} is highly sensitive to $a_v(t)$ and small changes in this parameter can have a significant impact on ΔVel_{IWD} and consequently on $\Delta GlobalS$. Considering SAIWDSA-1 algorithm, this parameter is suitable to increase when $\Delta GlobalS$ is low.

Based on the results of equations (D.3) and (D.4), and by the fact that $\text{Soil}(\text{n}_\text{i}, \text{n}_\text{j})$ is positive and much larger than $b_v(t)$, and $c_v(t)$, the absolute sensitivity of ΔVel_{IWD} with respect to $c_v(t)$ is larger than $b_v(t)$. Therefore, when $\Delta GlobalS$ is relatively low, $c_v(t)$ should be decreased (because the sensitivity result in (D.4) is negative) to more or less increase the

ΔVel_{IWD}. Finally, when $\Delta GlobalS$ is moderate, we can decrease $b_v(t)$ to have small impact on ΔVel_{IWD}.

Since equation (25) is similar to (23), we do not repeat the parameter sensitivity analysis of $\Delta Soil(i, j)$ with respect to $a_s(t)$, $b_s(t)$, and $c_s(t)$ and so we only state the results. By applying equation (A.1) to equation (21), we have $S_{a_s}^F = 1$, $S_{b_s}^F = \frac{-\mathrm{b}_s(t)}{b_s(t)+c_s(t)\left(Time\left(n_i,n_j;Vel_{IWD}\right)\right)^2}$ and $S_{c_s}^F = \frac{-c_s(t)\left(Time\left(n_i,n_j;Vel_{IWD}\right)\right)^2}{b_s(t)+c_s(t)\left(Time\left(n_i,n_j;Vel_{IWD}\right)\right)^2}$. Based on the results, when $\Delta GlobalS$ is, low, relatively low, and moderate, the best parameter to change is $a_s(t)$, $c_s(t)$, and $b_s(t)$, respectively.

Appendix E

Rules related to the SAIWDSA-1 are presented in Table E.1. To make the self-adaptive algorithm more stable without compromising convergence (Talischi & Paulino, 2013), the maximum parameter changes are limited to 2.5%.

Table E.1. KBS related to the SAIWDSA-1 algorithm.

	if	*then*					
Rules	$\overline{\Delta GlobalS}$	a_v	b_v	c_v	a_s	b_s	c_s
1	VL	+ 2.5%	—	—	+ 2.5%	—	—
2	L	+ 1.25%	—	—	+ 1.25%	—	—
3	M	—	—	- 2.5%	—	—	- 2.5%
4	H	—	- 2.5%	—	—	- 2.5%	—
5	VH	Do not change parameters					

The SAIWDSA-2 rules are listed in Table E.2.

Table E.2. KBS related to the SAIWDSA-2 algorithm.

	if			*then*					
Rules	$\overline{\Delta GlobalS}$	ΔVel	$\Delta Soil$	a_v	b_v	c_v	a_s	b_s	c_s
1	VL	L	—	+ 2.5%	- 2.5%	- 2.5%	—	—	—
2	VL	RL	—	+ 2.5%	-1.25%	—	—	—	—
3	VL	M	—	+ 2.5%	-0.5%	—	—	—	—
4	VL	—	L	—	—	—	+ 2.5%	- 2.5%	- 2.5%
5	VL	—	RL	—	—	—	+ 2.5%	-1.25%	—
6	VL	—	M	—	—	—	+ 2.5%	-0.5%	—
7	L	L	—	+ 1.25%	- 2.5%	—	—	—	—
8	L	RL	—	+ 1.25%	- .25%	—	—	—	—
9	L	M	—	+ 1.25%	-0.5%	—	—	—	—
10	L	—	L	—	—	—	+ 1.25%	- 2.5%	—
11	L	—	RL	—	—	—	+1.25%	-1.25%	—
12	L	—	M	—	—	—	+ 1.25%	-0.5%	—
13	M	L	—	+0.5%	- 2.5%	—	—	—	—
14	M	RL	—	+0.5%	- .25%	—	—	—	—
15	M	M	—	+0.5%	-0.5%	—	—	—	—
16	M	—	L	—	—	—	+ 0.5%	- 2.5%	—
17	M	—	RL	—	—	—	+ 0.5%	-1.25%	—
18	M	—	M	—	—	—	+ 0.5%	- 0.5%	—
19	H	L	—	—	-1.25%	—	—	—	—
20	H	RL	—	—	- 0.5%	—	—	—	—
21	H	M	—	—	-1%	- 2.5%	—	—	—
22	H	—	L	—	—	—	—	-1.25%	—
23	H	—	RL	—	—	—	—	-0.5%	—
24	H	—	M	—	—	—	—	-1%	- 2.5%
25	VH	Do not change parameters							

Appendix F

Table F.1 presents the chosen postcodes for the iMAS simulation. This selection is made for simulation purposes based on their respective population sizes.

Table F.1. Selected postcodes for iMAS simulation.

ID	Postcode	Location		ID	Postcode	Location	
1	2170	150.9193	-33.9332	18	2165	150.9465	-33.87
2	2145	150.9537	-33.8146	19	2154	151	-33.7277
3	2558	150.8052	-34.0308	20	2099	151.2767	-33.7416
4	2255	150.7447	-33.8814	21	2077	151.1013	-33.6776
5	2148	150.8997	-33.7859	22	2567	150.7509	-34.0463
6	2770	150.8138	-33.7555	23	2144	151.0262	-33.8551
7	2259	150.8017	-34.0492	24	2147	150.9368	-33.7677
8	2153	150.9758	-33.7556	25	2160	150.9824	-33.8361
9	2155	150.9381	-33.6935	26	2031	151.2441	-33.9151
10	2166	150.9378	-33.8937	27	2171	150.8413	-33.9156
11	2000	151.2083	-33.8684	28	2035	151.2371	-33.9428
12	2264	150.8943	-33.9964	29	2150	151.0069	-33.8151
13	2176	150.8841	-33.8711	30	2760	150.7813	-33.7608
14	2750	150.6784	-33.7526	31	2220	151.0994	-33.9646
15	2200	151.0144	-33.9222	32	2026	151.2725	-33.8892
16	2168	150.8766	-33.9135	33	2112	151.1103	-33.8117
17	2747	150.7534	-33.732	34	2232	151.0617	-34.0344

References

Abbaspour, M., Karimi, E., Nassiri, P., Monazzam, M. R., & Taghavi, L. (2015). Hierarchal assessment of noise pollution in urban areas - A case study. *Transportation Research Part D: Transport and Environment*, *34*, 95–103. https://doi.org/10.1016/j.trd.2014.10.002

Abdellaoui, M. El, & Pache, G. (2019). Effects of disruptive events within the supply chain on perceived logistics performance. *Economics Bulletin*, *39*(1), 41–54.

Acharya, N., & Singh, S. (2018). An IWD-based feature selection method for intrusion detection system. *Soft Computing*, *22*(13), 4407–4416. https://doi.org/10.1007/s00500-017-2635-2

Adams, W. M. (2006). The Future of Sustainability:Re-thinking Environment and Development in the Twenty-first Century. In *IUCN*.

Adi, T. N., Iskandar, Y. A., Bae, H., & Choi, Y. (2020). Reduction of number of empty-truck trips in inter-terminal transportation using multi-agent Q-learning. *Interconnected Supply Chains in an Era of Innovation - Proceedings of the 8th International Conference on Information Systems, Logistics and Supply Chain, ILS 2020*, 167–172. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85085955113&partnerID=40&md5=43780d4026e03b85c067cbcac2fb81ad

AIT, L.-T. (2020). *Accessibility of goods and services during covid-19 Aiming for better inclusivity through urban logistics services*. CHALMERS UNIVERSITY OF TECHNOLOGY.

Alabajee, M. A. A. K., Ahmed, D. R., & Alreffaee, T. R. (2021). Solving software project scheduling problem using grey wolf optimization. *Telkomnika (Telecommunication Computing Electronics and Control)*, *19*(6), 1820–1829. https://doi.org/10.12928/TELKOMNIKA.v19i6.16758

Aljohani, K., & Thompson, R. G. (2020). A multi-criteria spatial evaluation framework to optimise the siting of freight consolidation facilities in inner-city areas. *Transportation Research Part A: Policy and Practice*, *138*, 51–69. https://doi.org/https://doi.org/10.1016/j.tra.2020.05.020

Aloui, A., Hamani, N., & Delahoche, L. (2021). An integrated optimization approach using a collaborative strategy for sustainable cities freight transportation : A Case study. *Sustainable Cities and Society*, *75*(September), 103331. https://doi.org/10.1016/j.scs.2021.103331

Alumur, S. A., Campbell, J. F., Contreras, I., Kara, B. Y., Marianov, V., & O'Kelly, M. E. (2021). Perspectives on modeling hub location problems. *European Journal of Operational Research*, *291*(1), 1–17. https://doi.org/10.1016/j.ejor.2020.09.039

Alumur, S., & Kara, B. Y. (2008). Network hub location problems : The state of the art. *European Journal of Operational Research*, *190*, 1–21. https://doi.org/10.1016/j.ejor.2007.06.008

Anand, N., Duin, R. Van, & Tavasszy, L. (2010). Multi-Agent Modeling for City Logistics Policy Analysis: Potentials and Challenges. *The 45th Canadian Transportation Research Forum*, 582–596.

Arnold, F., Cardenas, I., Sörensen, K., & Dewulf, W. (2018). Simulation of B2C e-commerce distribution in Antwerp using cargo bikes and delivery points. *European Transport Research Review*, *10*(1). https://doi.org/10.1007/s12544-017-0272-6

Arrieta-Prieto, M., Ismael, A., Rivera-Gonzalez, C., & Mitchell, J. E. (2022). Location of urban micro-consolidation centers to reduce the social cost of last-mile deliveries of cargo: A heuristic approach. *Networks*, *79*(3), 292–313. https://doi.org/https://doi.org/10.1002/net.22076

Arvianto, A., Sopha, B. M., Asih, A. M. S., & Imron, M. A. (2021). City logistics challenges and innovative solutions in developed and developing economies: A systematic literature review. *International Journal of Engineering Business Management*, *13*(2), 1–18. https://doi.org/10.1177/18479790211039723

Arvidsson, N., Woxenius, J., & Lammgård, C. (2013). Review of Road Hauliers' Measures for Increasing Transport Efficiency and Sustainability in Urban Freight Distribution. *Transport Reviews*, *33*(1), 107–127. https://doi.org/10.1080/01441647.2013.763866

Australia Post. (2020). *"2020-2022 Group Corporate Responsibility Plan."* https://auspost.com.au/content/dam/auspost_corp/media/documents/australia-post-group-corporate-responsibility-plan-2020-2022.pdf

Australian Bureau of Statistics. (2023). *1270.0.55.001 - Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016*. https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by Subject/1270.0.55.001~July 2016~Main Features~Statistical Area Level 3 (SA3)~10015

Australian Government. (2021). *Australian Government Department of Health*. https://www.health.gov.au/

Awad, M., Ndiaye, M., & Osman, A. (2020). Vehicle routing in cold food supply chain logistics: a literature review. *International Journal of Logistics Management*, *32*(2), 592–617. https://doi.org/10.1108/IJLM-

02-2020-0092
Ayough, A., Khorshidvand, B., & Adibrad, F. (2022). A genetic algorithm for integrated hub covering-routing problem considering forbidden paths. *International Journal of Logistics Systems and Management*, *43*(2), 177–192. https://doi.org/10.1504/IJLSM.2022.126014
Baghali, S., Guo, Z., Wei, W., & Shahidehpour, M. (2023). Electric Vehicles for Distribution System Load Pickup Under Stressed Conditions: A Network Equilibrium Approach. *IEEE Transactions on Power Systems*, *38*(3), 2304–2317. https://doi.org/10.1109/TPWRS.2022.3185605
Ballot, E., Gobet, O., & Montreuil, B. (2012). Physical internet enabled open hub network design for distributed networked operations. In *Studies in Computational Intelligence* (Vol. 402). https://doi.org/10.1007/978-3-642-27449-7_21
BCI-Business Continuity Institute. (2019). “Supply chain resilience 10 year trend analysis. 2009 - 2018.” In *Zurich Insurance Group*. https://www.thebci.org/uploads/assets/uploaded/6bd728bd-bf0e-4eb7-b15fa67164eb9484.pdf
Becerril-arreola, R. (2013). *Digital Commons @ Lingnan University Online retailers ’ promotional pricing , free-shipping threshold , and inventory decisions : a simulation-based analysis*. *230*, 272–283. https://doi.org/10.1016/j.ejor.2013.04.006
Bektaş, T., & Laporte, G. (2011). The Pollution-Routing Problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250. https://doi.org/https://doi.org/10.1016/j.trb.2011.02.004
Benenson, I. (2014). Agent-Based Modelling. *GeoComputation, Second Edition*, 203–239. https://doi.org/10.1201/b17091-16
Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, *13*(2).
Bertsekas, D. (2019). *Reinforcement learning and optimal control*. Athena Scientific.
Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization : overview and conceptual comparison. *ACM Computing Surveys*, *35*(3), 268–308. https://doi.org/10.1145/937503.937505
Boerkamps, J. H. K., Van Binsbergen, A. J., & Bovy, P. H. L. (2000). Modeling behavioral aspects of urban freight movement in supply chains. *Transportation Research Record*, *1725*, 17–25. https://doi.org/10.3141/1725-03
Borkowski, P., Jażdżewska-Gutta, M., & Szmelter-Jarosz, A. (2021). Lockdowned: Everyday mobility changes in response to COVID-19. *Journal of Transport Geography*, *90*(November 2020). https://doi.org/10.1016/j.jtrangeo.2020.102906
Boysen, N., Fedtke, S., & Schwerdfeger, S. (2020). research perspective. In *OR Spectrum* (Issue 0123456789). Springer Berlin Heidelberg. https://doi.org/10.1007/s00291-020-00607-8
Bozkaya, B., Yanik, S., & Balcisoy, S. (2010). A GIS-based optimization framework for competitive multi-facility location-routing problem. *Networks and Spatial Economics*, *10*(3), 297–320. https://doi.org/10.1007/s11067-009-9127-6
Bräysy, O., Dullaert, W., & Nakari, P. (2009). The potential of optimization in communal routing problems : case studies from Finland. *Journal of Transport Geography*, *17*(6), 484–490. https://doi.org/10.1016/j.jtrangeo.2008.10.003
Brochu, E., Cora, V. M., & De Freitas, N. (2010). A tutorial on Bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. *ArXiv Preprint ArXiv:1012.2599*.
Browne, M., Allen, J., & Leonardi, J. (2011). Evaluating the use of an urban consolidation centre and electric vehicles in central London. *IATSS Research*, *35*(1), 1–6. https://doi.org/https://doi.org/10.1016/j.iatssr.2011.06.002
Cagliano, A. C., Carlin, A., Mangano, G., & Rafele, C. (2017). Analyzing the diffusion of eco-friendly vans for urban freight distribution. *International Journal of Logistics Management*, *28*(4), 1218–1242. https://doi.org/10.1108/IJLM-05-2016-0123
Calık, H., Alumur, S. A., Kara, B. Y., & Karasan, O. E. (2009). A tabu-search based heuristic for the hub covering problem over incomplete hub networks. *Computers & Operations Research*, *36*(12), 3088–3096. https://doi.org/https://doi.org/10.1016/j.cor.2008.11.023
Calle, E. Á. A. De. (2017). *Sustainable practices in urban freight distribution in Bilbao*. *October 2011*. https://doi.org/10.3926/jiem.2011.v4n3.p538-553
Campbell, J. F. (1994a). Integer programming formulations of discrete hub location problems. *European Journal of Operational Research*, *72*(2), 387–405. https://doi.org/https://doi.org/10.1016/0377-2217(94)90318-2

Campbell, J. F. (1994b). *Theory and Methodology Integer programming formulations of discrete hub location problems*. *72*, 387–405.
Chaabani, A., Bechikh, S., & Said, L. Ben. (2018). A new co-evolutionary decomposition-based algorithm for bi-level combinatorial optimization. *Applied Intelligence*, *48*(9), 2847–2872. https://doi.org/10.1007/s10489-017-1115-9
Chen, G., Wu, X., Li, J., & Guo, H. (2020). Green vehicle routing and scheduling optimization of ship steel distribution center based on improved intelligent water drop algorithms. *Mathematical Problems in Engineering*, *2020*. https://doi.org/10.1155/2020/9839634
Chen, Q., & Zhang, N. (2015). Does e-commerce provide a sustained competitive advantage? An investigation of survival and sustainability in growth-oriented enterprises. *Sustainability (Switzerland)*, *7*(2), 1411–1428. https://doi.org/10.3390/su7021411
Chopra, S. (2018). The Evolution of Omni-Channel Retailing and its Impact on Supply Chains. *Transportation Research Procedia*, *30*, 4–13. https://doi.org/10.1016/j.trpro.2018.09.002
Ciardiello, F., Genovese, A., Luo, S., & Sgalambro, A. (2023). A game-theoretic multi-stakeholder model for cost allocation in urban consolidation centres. *Annals of Operations Research*, *324*(1–2), 663–686. https://doi.org/10.1007/s10479-021-04013-3
Clausen, U., Geiger, C., & Pöting, M. (2016). Hands-on Testing of Last Mile Concepts. *Transportation Research Procedia*, *14*, 1533–1542. https://doi.org/10.1016/j.trpro.2016.05.118
Contardo, C., & Martinelli, R. (2014). A new exact algorithm for the multi-depot vehicle routing problem under capacity and route length constraints. *Discrete Optimization*, *12*, 129–146. https://doi.org/10.1016/j.disopt.2014.03.001
Cordeau, J. F., Gendreau, M., & Laporte, G. (1997). A tabu search heuristic for periodic and multi-depot vehicle routing problems. *Networks: An International Journal*, *30*(2), 105–119. https://doi.org/https://doi.org/10.1002/(SICI)1097-0037(199709)30:2%3C105::AID-NET5%3E3.0.CO;2-G
Cordeau, J. F., & Maischberger, M. (2012). A parallel iterated tabu search heuristic for vehicle routing problems. *Computers & Operations Research*, *39*(9), 2033–2050. https://doi.org/https://doi.org/10.1016/j.cor.2011.09.021
Crainic, T. G., & Montreuil, B. (2016). Physical Internet Enabled Hyperconnected City Logistics. *Transportation Research Procedia*, *12*(June 2015), 383–398. https://doi.org/10.1016/j.trpro.2016.02.074
Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management Science*, *6*(1), 80–91.
de Oliveira, I. R. L., de Carvalho, K. B., & Brandão, A. S. (2023). Curriculum-based Reinforcement Learning for an Effective Multi-Agent Path Planning Algorithm in Warehouse Scenarios. *2023 15th IEEE International Conference on Industry Applications, INDUSCON 2023 - Proceedings*, 471–477. https://doi.org/10.1109/INDUSCON58041.2023.10374605
de Oliveira, L. K., Lessa, D. A., Oliveira, E., & Gregório Calazans, B. F. (2017). Multi-agent modelling approach for evaluating the city logistics dynamic in a vulnerability situation: An exploratory study in Belo Horizonte (Brazil). *Transportation Research Procedia*, *25*, 1046–1060. https://doi.org/10.1016/j.trpro.2017.05.478
Demir, E., Bektaş, T., & Laporte, G. (2014). A review of recent research on green road freight transportation. *European Journal of Operational Research*, *237*(3), 775–793. https://doi.org/10.1016/j.ejor.2013.12.033
Department of Climate Change, Energy, the E. and W. (2024). *Consultation hub | National Electric Vehicle Strategy - National Electric Vehicle Strategy: consultation paper - Climate*. https://consult.dcceew.gov.au/national-electric-vehicle-strategy/submission/view/354
Department of Industry, Science, E. and R. (2021). *“AUS GHG quarterly update of Australias national greenhouse gas inventory march 2021.”*
Dorf, R. C., & Bishop, R. H. (2017). *Modern control systems* (13th ed.).
Dreischerf, A. J., & Buijs, P. (2022). How Urban Consolidation Centres affect distribution networks: An empirical investigation from the perspective of suppliers. *Case Studies on Transport Policy*, *10*(1), 518–528. https://doi.org/10.1016/j.cstp.2022.01.012
Du, T. C., Li, E. Y., & Chou, D. (2005). Dynamic vehicle routing for online B2C delivery. *Omega*, *33*(1), 33–45. https://doi.org/10.1016/j.omega.2004.03.005
Dupas, R., Deschamps, J. C., Taniguchi, E., Qureshi, A. G., & Hsu, T. (2023). Optimizing the location selection of urban consolidation centers with sustainability considerations in the city of Bordeaux.

Research in Transportation Business and Management, *47*(December 2022). https://doi.org/10.1016/j.rtbm.2022.100943
Ecopostale. (2024). *Ecopostale, smarter deliveries*. https://www.ecopostale.be/index-en.html
Edwards, J., Mckinnon, A., Cherrett, T., Mcleod, F., & Song, L. (2009). The impact of failed home deliveries on carbon emissions. *Logistics Research Network Conference*, *14*(September), 102–108.
Eiselt, H. A., & Marianov, V. (2009). A conditional p-hub location problem with attraction functions. *Computers and Operations Research*, *36*(12), 3128–3135. https://doi.org/10.1016/j.cor.2008.11.014
Enthoven, D. L. J. U., Jargalsaikhan, B., Roodbergen, K. J., uit het Broek, M. A. J., & Schrotenboer, A. H. (2020). The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers. *Computers & Operations Research*, *118*, 104919. https://doi.org/https://doi.org/10.1016/j.cor.2020.104919
Environmental Protection Agency. (2017). *Climate Impacts on Agriculture and Food Supply | Climate Change Impacts | US EPA*. https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-agriculture-and-food-supply_.html
Erdem, M. (2022). Optimisation of sustainable urban recycling waste collection and routing with heterogeneous electric vehicles. *Sustainable Cities and Society*, *80*(November 2021), 103785. https://doi.org/10.1016/j.scs.2022.103785
Ernst, A. T., & Krishnamoorthy, M. (1998). Exact and heuristic algorithms for the uncapacitated multiple allocation p-hub median problem. *European Journal of Operational Research*, *00*(96), 100–112.
Escobar, J. W., Linfati, R., Toth, P., & Baldoquin, M. G. (2014). A hybrid Granular Tabu Search algorithm for the Multi-Depot Vehicle Routing Problem. *Journal of Heuristics*, *20*(5), 483–509. https://doi.org/10.1007/s10732-014-9247-0
Esri. (2022). *Location-allocation analysis layer—ArcGIS Pro | Documentation*. https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/location-allocation-analysis-layer.htm
European Environment Agency. (2022). *Greenhouse gas emissions from transport in Europe*. https://www.eea.europa.eu/ims/greenhouse-gas-emissions-from-transport#:~:text=The transport sector is responsible,since 1990 as other sectors.
Ewedairo, K., Chhetri, P., & Jie, F. (2018). Estimating transportation network impedance to last-mile delivery a case study of maribyrnong city in melbourne. *International Journal of Logistics Management*, *29*(1), 110–130. https://doi.org/10.1108/IJLM-10-2016-0247
Ezugwu, A. E., Akutsah, F., Olusanya, M. O., & Adewumi, A. O. (2018). Enhanced intelligent water drops algorithm for multi-depot vehicle routing problem. In *PLoS ONE* (Vol. 13, Issue 3). https://doi.org/10.1371/journal.pone.0193751
Fazili, M., Venkatadri, U., Cyrus, P., & Tajbakhsh, M. (2017). Physical Internet , conventional and hybrid logistic systems : a routing optimisation-based comparison using the Eastern Canada road network case study. *International Journal of Production Research*, *7543*, 1–28. https://doi.org/10.1080/00207543.2017.1285075
Feng, X., Murray, A. T., & Church, R. L. (2021). Drone service response: Spatiotemporal heterogeneity implications. *Journal of Transport Geography*, *93*(April), 103074. https://doi.org/10.1016/j.jtrangeo.2021.103074
Fisher, R. A. (1950). *Statistical methods for research workers*. Oliver and Boyd Pub.
Floyd, R. W. (1962). Algorithm 97: Shortest Path. *Commun. ACM*, *5*(6), 345. https://doi.org/10.1145/367766.368168
Frederik, J. L., Margaretha, S., Richard, G., Spaan, M. T. J., & Negenborn, R. R. (2022). Large-scale collaborative vehicle routing. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04504-3
Friedrich, C., & Elbert, R. (2022). Adaptive large neighborhood search for vehicle routing problems with transshipment facilities arising in city logistics. *Computers and Operations Research*, *137*(August 2020).
Ganji, M., Kazemipoor, H., Hadji Molana, S. M., & Sajadi, S. M. (2020). A green multi-objective integrated scheduling of production and distribution with heterogeneous fleet vehicle routing and time windows. *Journal of Cleaner Production*, *259*. https://doi.org/10.1016/j.jclepro.2020.120824
Gansterer, M., & Hartl, R. F. (2018). Collaborative vehicle routing : A survey. *European Journal of Operational Research*, *268*(1), 1–12. https://doi.org/10.1016/j.ejor.2017.10.023
García, S., & Marín, A. (2015). Location Science. In *Location Science* (pp. 93–114). https://doi.org/10.1007/978-3-319-13111-5

Glynn, M. S., & Woodside, A. G. (Eds.). (2012). Business-to-Business Marketing Management: Strategies, Cases, and Solutions. In *Business-to-Business Marketing Management: Strategies, Cases, and Solutions* (Vol. 18, p. i). Emerald Group Publishing Limited. https://doi.org/10.1108/S1069-0964(2012)0000018019

Grabenschweiger, J., Doerner, K. F., Hartl, R. F., & Savelsbergh, M. W. P. (2021). The vehicle routing problem with heterogeneous locker boxes. *Central European Journal of Operations Research*, *29*(1), 113–142. https://doi.org/10.1007/s10100-020-00725-2

Guerrero Campanur, A., Olivares-Benitez, E., Miranda, P. A., Perez-Loaiza, R. E., & Ablanedo-Rosas, J. H. (2018). Design of a Logistics Nonlinear System for a Complex, Multiechelon, Supply Chain Network with Uncertain Demands. *Complexity*, *2018*. https://doi.org/10.1155/2018/4139601

Gulc, A. (2021). Multi-stakeholder perspective of courier service quality in B2C e-commerce. *PLoS ONE*, *16*(5 May), 1–18. https://doi.org/10.1371/journal.pone.0251728

GUO, X., LI, X., Mohammed, F. A. H., Alenizi, F. A., Alasedi, K. K., Mohsen, K. S., Alsaalamy, A., El-Shafai, W., Uktamov, K. F., Mehbodniya, A., & Bostani, A. (2023). Green Certificate-Driven Photovoltaic Promotion in Distribution Networks Hosting Hydrogen Fueling Stations for Future Sustainable Transportation: A Risk-Adjusted Dominance Analysis. *Sustainable Cities and Society*, *99*(April), 104911. https://doi.org/10.1016/j.scs.2023.104911

Guo, X., Zhang, W., & Liu, B. (2022). Low-carbon routing for cold-chain logistics considering the time-dependent effects of traffic congestion. *Transportation Research Part D: Transport and Environment*, *113*(October 2022), 103502. https://doi.org/10.1016/j.trd.2022.103502

Gupta, R. K. (1992). *Operations research*. Krishna Prakashan Media.

Habibi, F., Asadi, E., & Sadjadi, S. J. (2018). A location-inventory-routing optimization model for cost effective design of microalgae biofuel distribution system: A case study in Iran. *Energy Strategy Reviews*, *22*(June), 82–93. https://doi.org/10.1016/j.esr.2018.08.006

Hacardiaux, T., & Tancrez, J.-S. (2020). Assessing the environmental benefits of horizontal cooperation using a location-inventory model. *Central European Journal of Operations Research*, *28*(4), 1363–1387. https://doi.org/10.1007/s10100-018-0599-7

Halldórsson, Á., & Wehner, J. (2020). Last-mile logistics fulfilment: A framework for energy efficiency. *Research in Transportation Business and Management*, *37*(January). https://doi.org/10.1016/j.rtbm.2020.100481

Hasanzadeh, H., Bashiri, M., & Amiri, A. (2018). A new approach to optimize a hub covering location problem with a queue estimation component using genetic programming. *Soft Computing*, *22*(3), 949–961. https://doi.org/10.1007/s00500-016-2398-1

He, Z., & Haasis, H. D. (2020). A theoretical research framework of future sustainable urban freight transport for smart cities. *Sustainability (Switzerland)*, *12*(5), 1–28. https://doi.org/10.3390/su12051975

Hillsman, E. L. (1979). *A system for location–allocation analysis* [University of Iowa]. https://www.proquest.com/docview/302905993?pq-origsite=gscholar&fromopenview=true

Ho, W., Ho, G. T. S., Ji, P., & Lau, H. C. W. (2008). A hybrid genetic algorithm for the multi-depot vehicle routing problem. *Engineering Applications of Artificial Intelligence*, *21*(4), 548–557.

Holland, J. H. (1992). *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. MIT press.

Hong, Y., Yan, W., & Ge, Q. (2023). Designing sustainable logistics networks for classified municipal solid wastes collection and transferring with multi-compartment vehicles. *Sustainable Cities and Society*, *99*, 104921. https://doi.org/https://doi.org/10.1016/j.scs.2023.104921

Huang, D., Chen, X., Liu, Z., Lyu, C., Wang, S., & Chen, X. (2020). A static bike repositioning model in a hub-and-spoke network framework. *Transportation Research Part E: Logistics and Transportation Review*, *141*(July). https://doi.org/10.1016/j.tre.2020.102031

Hyperconnected Development Program. (2022). A vision for the European hyperloop network. In *Hyperconnected Europe*. https://www.hyperconnected.eu/

İnanlı, A., Ünsal, B., & Eliiyi, D. T. (2015). Route Optimization for the Distribution Network of a Confectionary Chain. *PROMET - Traffic&Transportation*, *27*(6), 497–503. https://doi.org/10.7307/ptt.v27i6.1645

Industrial Relations Victoria Department of Premier and Cabinet. (2023a). *Rates and costs schedule 2023-24 1 Tonne Vehicle - General Freight Road Transport and Distribution Award 2022* (Issue September).

Industrial Relations Victoria Department of Premier and Cabinet. (2023b). *Rates and costs schedule 2023-24 4 . 5 Tonne Rigid Vehicle (GVM) Road Transport and Distribution Award 2022* (Issue September).

Islam, R. (2017). Deep reinforcement learning technologies. *ArXiv*, 3207–3214. https://ojs.aaai.org/index.php/AAAI/article/view/11694
ITF. (2021). *ITF Transport Outlook: Executive Summary*. OECD. https://doi.org/10.1787/16826a30-en
Ivanov, D., Dolgui, A., Das, A., & Sokolov, B. (2019). Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility. In *International Series in Operations Research and Management Science* (Vol. 276). Springer International Publishing. https://doi.org/10.1007/978-3-030-14302-2_15
Jaegere, N. De, Defraeye, M., & Nieuwenhuyse, I. Van. (2014). The vehicle routing problem: State of the art classification and review. In *KU Leuven -Faculty of Economics and Business*. https://doi.org/10.1016/j.cie.2015.12.007
Janjevic, M., Kaminsky, P., & Ndiaye, A. B. (2013). Downscaling the consolidation of goods-state of the art and transferability of micro-consolidation initiatives. *European Transport - Trasporti Europei*, *54*, 1–23.
Jiang, C., Fu, J., & Liu, W. (2021). Research on Vehicle Routing Planning Based on Adaptive Ant Colony and Particle Swarm Optimization Algorithm. *International Journal of Intelligent Transportation Systems Research*, *19*(1), 83–91. https://doi.org/10.1007/s13177-020-00224-3
Kahalimoghadam, M., Stokoe, M., Thompson, R. G., & Rajabifard, A. (2021). The impact of COVID-19 pandemic on parcel delivery pattern in Sydney. *42nd Australasian Transport Research Forum (ATRF)*.
Kahalimoghadam, M., Thompson, R. G., & Rajabifard, A. (2024). Assessing unsustainable trends in city logistics. In press. *Transportation Research Procedia*.
Kahalimoghadam, M., Thompson, R. G., Rajabifard, A., & Stokoe, M. (2022). Evaluation of governments' role in coping with city logistics problems. *43rd Australasian Transport Research Forum (ATRF)*.
Kamkar, I., Akbarzadeh-T, M. R., & Yaghoobi, M. (2010). Intelligent water drops a new optimization algorithm for solving the vehicle routing problem. *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, 4142–4146. https://doi.org/10.1109/ICSMC.2010.5642405
Kancharla, S. R., & Ramadurai, G. (2018). Incorporating driving cycle based fuel consumption estimation in green vehicle routing problems. *Sustainable Cities and Society*, *40*, 214–221. https://doi.org/https://doi.org/10.1016/j.scs.2018.04.016
Kara, B. Y., & Tansel, B. C. (2003). The single-assignment hub covering problem : Models and linearizations. *Journal of the Operational Research Society*, *54*, 59–64. https://doi.org/10.1057/palgrave.jors.2601473
Kaspi, M., Raviv, T., & Ulmer, M. W. (2022). Directions for future research on urban mobility and city logistics. *Networks*, *79*(3), 253–263. https://doi.org/https://doi.org/10.1002/net.22092
Katsaliaki, K., Galetsi, P., & Kumar, S. (2021). Supply chain disruptions and resilience: a major review and future research agenda. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03912-1
Kawakubo, S., Murakami, S., Ikaga, T., & Asami, Y. (2018). Sustainability assessment of cities : SDGs and GHG emissions. *Building Research and Information*, *46*(5), 528–539. https://doi.org/10.1080/09613218.2017.1356120
Kedia, A., Kusumastuti, D., & Nicholson, A. (2017). Acceptability of collection and delivery points from consumers' perspective : A qualitative case study of Christchurch city ☆. *Case Studies on Transport Policy*, *5*(4), 587–595. https://doi.org/10.1016/j.cstp.2017.10.009
Kiba-Janiak, M. (2016). Key Success Factors for City Logistics from the Perspective of Various Groups of Stakeholders. *Transportation Research Procedia*, *12*(June 2015), 557–569. https://doi.org/10.1016/j.trpro.2016.02.011
Kiba-Janiak, M., Cheba, K., Oliveira, L. K. de, & Marcinkowski, J. (2021). Sustainable last mile delivery on e-commerce market – lesson learned from Covid-19 in Brazil and Poland. *4th VREF Conference on Urban Freight*, 95–96.
Kim, N., Montreuil, B., Klibi, W., & Kholgade, N. (2021). Hyperconnected urban fulfillment and delivery. *Transportation Research Part E: Logistics and Transportation Review*, *145*, 102104. https://doi.org/10.1016/j.tre.2020.102104
Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science*, *220*(4598), 671–680. http://www.jstor.org/stable/1690046
Kober, J., Bagnell, J. A., & Peters, J. (2013). Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, *32*(11), 1238–1274. https://doi.org/10.1177/0278364913495721
Köhler, C., Ehmke, J. F., & Campbell, A. M. (2020). Flexible time window management for attended home deliveries. *Omega (United Kingdom)*, *91*, 1–22. https://doi.org/10.1016/j.omega.2019.01.001

Kovač, M., Tadić, S., Krstić, M., & Bouraima, M. B. (2021). Novel Spherical Fuzzy MARCOS Method for Assessment of Drone-Based City Logistics Concepts. *Complexity*, *2021*, 2374955. https://doi.org/10.1155/2021/2374955

Krommenacker, N., Charpentier, P., Berger, T., & Sallez, Y. (2016). On the usage of wireless sensor networks to facilitate composition/decomposition of physical internet containers. *Studies in Computational Intelligence*, *640*, 81–90. https://doi.org/10.1007/978-3-319-30337-6_8

Kumar, A., Kumar, R., Aggarwal, A., & Bedi, J. (2023). A meta-heuristic-based energy efficient route modeling for EVs integrating start/stop and recapturing energy effect. *Sustainable Cities and Society*, *91*(January), 104420. https://doi.org/10.1016/j.scs.2023.104420

Kumar, V., & Reinartz, W. (2018). *Customer Relationship Management : concept, strategy, and tools.* (3. ed. 201). Springer Berlin Heidelberg. https://search.ebscohost.com/login.aspx?direct=true&AuthType=sso&db=cat00006a&AN=melb.b7188102&site=eds-live&scope=site&custid=s2775460

Lachapelle, U., Burke, M., Brotherton, A., & Leung, A. (2018). Parcel locker systems in a car dominant city : Location , characterisation and potential impacts on city planning and consumer travel access. *Journal of Transport Geography*, *71*(February), 1–14. https://doi.org/10.1016/j.jtrangeo.2018.06.022

Lagorio, A., & Pinto, R. (2020). The parcel locker location issues: An overview of factors affecting their location. *8th International Conference on Information Systems, Logistics and Supply Chain*, *April 2021*, 414–421.

Le, T. D. C., Nguyen, D. D., Oláh, J., & Pakurár, M. (2022). Clustering algorithm for a vehicle routing problem with time windows. *Transport*, *37*(1), 17–27. https://doi.org/10.3846/transport.2022.16850

Lee, S., & Prabhu, V. V. (2016). Just-in-time delivery for green fleets: A feedback control approach. *Transportation Research Part D: Transport and Environment*, *46*, 229–245. https://doi.org/10.1016/j.trd.2016.04.005

Leitner, R., Meizer, F., Prochazka, M., & Sihn, W. (2011). Structural concepts for horizontal cooperation to increase efficiency in logistics. *CIRP Journal of Manufacturing Science and Technology*, *4*(3), 332–337. https://doi.org/10.1016/j.cirpj.2011.01.009

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, *525*(7569), 367–371. https://doi.org/10.1038/nature15371

Leung, A., Lachapelle, U., & Burke, M. (2023). Spatio-temporal analysis of Australia Post parcel locker use during the initial system growth phase in Queensland (2013 – 2017). *Journal of Transport Geography*, *110*(June), 103634. https://doi.org/10.1016/j.jtrangeo.2023.103634

Li, J., Rombaut, E., & Vanhaverbeke, L. (2021). A systematic review of agent-based models for autonomous vehicles in urban mobility and logistics: Possibilities for integrated simulation models. *Computers, Environment and Urban Systems*, *89*(September 2020), 101686. https://doi.org/10.1016/j.compenvurbsys.2021.101686

Lim, S. F. W. T., Jin, X., & Srai, J. S. (2018). Consumer-driven e-commerce: A literature review, design framework, and research agenda on last-mile logistics models. *International Journal of Physical Distribution and Logistics Management*, *48*(3), 308–332. https://doi.org/10.1108/IJPDLM-02-2017-0081

Lim, S. F. W. T., & Srai, J. S. (2018). Examining the anatomy of last-mile distribution in e-commerce omnichannel retailing: A supply network configuration approach. *International Journal of Operations and Production Management*, *38*(9), 1735–1764. https://doi.org/10.1108/IJOPM-12-2016-0733

Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2014). Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications*, *41*(4 PART 1), 1118–1138. https://doi.org/10.1016/j.eswa.2013.07.107

Liu, G.-S., & Lin, K.-P. (2019). A decision support system of green inventory-routing problem. *Industrial Management & Data Systems*, *119*(1), 89–110. https://doi.org/10.1108/IMDS-11-2017-0533

Loayza, N., & Pennings, S. M. (2020). *Macroeconomic Policy in the Time of COVID-19 : A Primer for Developing Countries* (Issue 147291). The World Bank.

Long, S., & Grasman, S. E. (2012). A strategic decision model for evaluating inland freight hub locations. *Research in Transportation Business and Management*, *5*, 92–98. https://doi.org/10.1016/j.rtbm.2012.11.004

Markham, F., & Doran, B. (2015). Equity, discrimination and remote policy: Investigating the centralization of remote service delivery in the Northern Territory. *Applied Geography*, *58*, 105–115.

https://doi.org/https://doi.org/10.1016/j.apgeog.2015.01.020
Matsumoto, M., & Nishimura, T. (1998). Mersenne Twister: A 623-Dimensionally Equidistributed Uniform Pseudo-Random Number Generator. *ACM Transactions on Modeling and Computer Simulation*, *8*(1), 3–30. https://doi.org/10.1145/272991.272995
Matusiewicz, M. (2024). Framework for Physical Internet deployment in cities. *Urban, Planning and Transport Research*, *12*(1). https://doi.org/10.1080/21650020.2024.2303341
Mavhura, E. (2019). Systems Analysis of Vulnerability to Hydrometeorological Threats: An Exploratory Study of Vulnerability Drivers in Northern Zimbabwe. *International Journal of Disaster Risk Science*, *10*(2), 204–219. https://doi.org/10.1007/s13753-019-0217-x
Mchugh, M. L. (2013). The Chi-square test of independence Lessons in biostatistics. *Biochemia Medica*, *23*(2), 143–149. http://dx.doi.org/10.11613/BM.2013.018
McKinnon, A. C., & Tallam, D. (2003). Unattended delivery to the home: An assessment of the security implications. *International Journal of Retail & Distribution Management*, *31*(1), 30–41. https://doi.org/10.1108/09590550310457827
Milewski, D., & Wiśniewski, T. (2022). The Regression Model and the Problem of Inventory Centralization: Is the “Square Root Law” Applicable? *Applied Sciences (Switzerland)*, *12*(10). https://doi.org/10.3390/app12105152
Miranda, P. A., Garrido, R. A., & Ceroni, J. A. (2009). e-Work based collaborative optimization approach for strategic logistic network design problem. *Computers and Industrial Engineering*, *57*(1), 3–13. https://doi.org/10.1016/j.cie.2008.12.007
Miranker, A., & Karplus, M. (1991). Functionality maps of binding sites: a multiple copy simultaneous search method. *Proteins: Structure, Function, and Bioinformatics*, *11*(1), 29–34.
Mommens, K., Buldeo Rai, H., van Lier, T., & Macharis, C. (2021). Delivery to homes or collection points? A sustainability analysis for urban, urbanised and rural areas in Belgium. *Journal of Transport Geography*, *94*(November 2020), 103095. https://doi.org/10.1016/j.jtrangeo.2021.103095
Montreuil, B. (2011). Toward a Physical Internet: meeting the global logistics sustainability grand challenge. *Logistics Research*, *3*(2–3), 71–87. https://doi.org/10.1007/s12159-011-0045-x
Montreuil, B., Meller, R. D., & Ballot, E. (2010). *TOWARDS A PHYSICAL INTERNET : THE IMPACT ON LOGISTICS FACILITIES AND MATERIAL HANDLING SYSTEMS DESIGN AND INNOVATION Benoit Montreuil Russell D . Meller University of Arkansas Eric Ballot*.
Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. (2014). The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transportation Research Procedia*, *4*(0), 178–190. https://doi.org/10.1016/j.trpro.2014.11.014
Morillas, J. M. B., Gozalo, G. R., González, D. M., Moraga, P. A., & Vílchez-Gómez, R. (2018). Noise Pollution and Urban Planning. *Current Pollution Reports*, *4*(3), 208–219. https://doi.org/10.1007/s40726-018-0095-7
Morse, P. M., Kimball, G. E., & Gass, S. I. (2003). Methods of operations research. In *Courier Corporation*. Courier Corporation.
Muñoz-Morera, J., Alarcon, F., Maza, I., & Ollero, A. (2018). Combining a hierarchical task network planner with a constraint satisfaction solver for assembly operations involving routing problems in a multi-robot context. *International Journal of Advanced Robotic Systems*, *15*(3), 1–13. https://doi.org/10.1177/1729881418782088
Muñoz-Villamizar, A., Velázquez-Martínez, J. C., Haro, P., Ferrer, A., & Mariño, R. (2021). The environmental impact of fast shipping ecommerce in inbound logistics operations: A case study in Mexico. *Journal of Cleaner Production*, *283*, 125400. https://doi.org/10.1016/j.jclepro.2020.125400
Mvundura, M., Lorenson, K., Chweya, A., Kigadye, R., Bartholomew, K., Makame, M., Lennon, T. P., Mwangi, S., Kirika, L., Kamau, P., Otieno, A., Murunga, P., Omurwa, T., Dafrossa, L., & Kristensen, D. (2015). Estimating the costs of the vaccine supply chain and service delivery for selected districts in Kenya and Tanzania. *Vaccine*, *33*(23), 2697–2703. https://doi.org/10.1016/j.vaccine.2015.03.084
Nagalakshmi, P., Harish, Y., Kumar, R. K., & Jada, C. (2011). Combined economic and emission dispatch using intelligent water drops-continuous optimization algorithm. *2011 International Conference on Recent Advancements in Electrical, Electronics and Control Engineering, IConRAEeCE'11 - Proceedings*, 168–173. https://doi.org/10.1109/ICONRAEeCE.2011.6129749
Nagarajan, S. M., Deverajan, G. G., Chatterjee, P., Alnumay, W., & Muthukumaran, V. (2022). Integration of IoT based routing process for food supply chain management in sustainable smart cities. *Sustainable Cities and Society*, *76*, 103448. https://doi.org/https://doi.org/10.1016/j.scs.2021.103448

Najwa Ahmad, N., Reddy, M., Dharmendra Chahar, D., & Professor, A. (2013). Analysis of E-Commerce and M-Commerce: Advantages, Limitations and Security issues. *International Journal of Advanced Research in Computer and Communication Engineering*, *2*. www.ijarcce.com

Nathanail, E., Karakikes, I., Mitropoulos, L., & Adamos, G. (2021). A sustainability cross-case assessment of city logistics solutions. *Case Studies on Transport Policy*, *9*(1), 219–240. https://doi.org/10.1016/j.cstp.2020.12.005

Nie, Y., & Li, Q. (2013). An eco-routing model considering microscopic vehicle operating conditions. *Transportation Research Part B: Methodological*, *55*, 154–170. https://doi.org/10.1016/j.trb.2013.06.004

Nikokalam-Mozafar, S. H., Ashjari, B., Tavakkoli-Moghaddam, R., & Omidvar, A. (2014). Solving a multi-objective chance-constrained hub covering location problem by discrete invasive weed optimization. *Cogent Engineering*, *1*(1), 991526. https://doi.org/10.1080/23311916.2014.991526

Niu, Y., Yang, Z., Chen, P., & Xiao, J. (2018). Optimizing the green open vehicle routing problem with time windows by minimizing comprehensive routing cost. *Journal of Cleaner Production*, *171*, 962–971. https://doi.org/10.1016/j.jclepro.2017.10.001

Nsamzinshuti, A., Cardoso, F., Janjevic, M., & Ndiaye, A. B. (2017). Pharmaceutical distribution in urban area: an integrated analysis and perspective of the case of Brussels-Capital Region (BRC). *Transportation Research Procedia*, *25*, 747–761. https://doi.org/https://doi.org/10.1016/j.trpro.2017.05.455

NSW Government. (2022). *State Environmental Planning Policy Amendment (Local Distribution Premises)* (Vol. 2022, Issue 314).

O'Kelly, M. E. (1986). The location of interacting hub facilities. *Transportation Science*, *20*(2), 92–106.

O'Sullivan, D., Rahamathulla, M., & Pawar, M. (2020). The Impact and Implications of COVID-19: An Australian Perspective. *The International Journal of Community and Social Development*, *2*(2), 134–151. https://doi.org/10.1177/2516602620937922

OECD. (2020). *Decarbonising Urban Mobility with Land Use and Transport Policies: The Case of Auckland, New Zealand*. https://doi.org/10.1787/095848a3-en

Olgun, B., Koç, Ç., & Altıparmak, F. (2021). A hyper heuristic for the green vehicle routing problem with simultaneous pickup and delivery. *Computers and Industrial Engineering*, *153*(November 2020). https://doi.org/10.1016/j.cie.2020.107010

Oliveira, L. K. de, Morganti, E., Dablanc, L., & Oliveira, R. L. M. de. (2017). Analysis of the potential demand of automated delivery stations for e-commerce deliveries in Belo Horizonte, Brazil. *Journal of Chemical Information and Modeling*, *01*(01), 1689–1699.

Ouhader, H., & EL kyal, M. (2023). Collaborative location routing problem for sustainable supply chain design with profit sharing. *Environmental Science and Pollution Research*, *30*(39), 90099–90120. https://doi.org/10.1007/s11356-023-27788-3

Pan, S. (2019). Opportunities of product-service system in physical internet. *Procedia CIRP*, *83*, 473–478. https://doi.org/10.1016/j.procir.2019.03.107

Pan, S., Zhang, L., Thompson, R. G., & Ghaderi, H. (2021). A parcel network flow approach for joint delivery networks using parcel lockers. *International Journal of Production Research*, *59*(7), 2090–2115.

Panah, P. G., Bornapour, S. M., Nosratabadi, S. M., & Guerrero, J. M. (2022). Hesitant fuzzy for conflicting criteria in multi-objective deployment of electric vehicle charging stations. *Sustainable Cities and Society*, *85*(July), 104054. https://doi.org/10.1016/j.scs.2022.104054

Pani, A., Sahu, P. K., Patil, G. R., & Sarkar, A. K. (2018). Modelling urban freight generation: A case study of seven cities in Kerala, India. *Transport Policy*, *69*(January 2018), 49–64. https://doi.org/10.1016/j.tranpol.2018.05.013

Peng, J., Weisheng, X., & Jijun, Y. (2009). 2009 Second International Conference on Intelligent Computation Technology and Automation. *2009 Second International Conference on Intelligent Computation Technology and Automation*, *3*, 899–902. https://doi.org/10.1109/ICICTA.2009.682

Perera, L., & Thompson, R. G. (2021). Research in Transportation Business & Management Multi-stakeholder acceptance of optimum toll schemes. *Research in Transportation Business & Management*, *xxxx*, 100654. https://doi.org/10.1016/j.rtbm.2021.100654

Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers and Operations Research*, *34*(8), 2403–2435. https://doi.org/10.1016/j.cor.2005.09.012

Pujawan, N., Arief, M. M., Tjahjono, B., & Kritchanchai, D. (2015). An integrated shipment planning and storage capacity decision under uncertainty: A simulation study. *International Journal of Physical Distribution and Logistics Management*, *45*(9–10), 913–937. https://doi.org/10.1108/IJPDLM-08-2014-0198

Quak, H., Balm, S., & Posthumus, B. (2014). Evaluation of City Logistics Solutions with Business Model Analysis. *Procedia - Social and Behavioral Sciences*, *125*(March), 111–124. https://doi.org/10.1016/j.sbspro.2014.01.1460

Rajabifard, A., Kahalimoghadam, M., Lumantarna, E., Herath, N., Kin, F., Hui, P., & Assarkhaniki, Z. (2021). *Applying SDGs as a systematic approach for incorporating sustainability in higher education*. https://doi.org/10.1108/IJSHE-10-2020-0418

Ranieri, L., Digiesi, S., Silvestri, B., & Roccotelli, M. (2018). A Review of Last Mile Logistics Innovations in an Externalities Cost Reduction Vision. *Sustainability*, 1–18. https://doi.org/10.3390/su10030782

Rodrigue, J. (2020). The distribution network of Amazon and the footprint of freight digitalization. *Journal of Transport Geography*, *88*(August), 102825. https://doi.org/10.1016/j.jtrangeo.2020.102825

Rohmer, S., & Gendron, B. (2020). *A guide to parcel lockers in last mile distribution: Highlighting challenges and opportunities from an OR perspective*. Cirrelt Montreal.

Rudolph, C., Nsamzinshuti, A., Bonsu, S., Ndiaye, A. B., & Rigo, N. (2022). Localization of Relevant Urban Micro-Consolidation Centers for Last-Mile Cargo Bike Delivery Based on Real Demand Data and City Characteristics. *Transportation Research Record*, *2676*(1), 365–375. https://doi.org/10.1177/03611981211036351

Ruiz-Meza, J., Meza-Peralta, K., Montoya-Torres, J. R., & Gonzalez-Feliu, J. (2021). Location of urban logistics spaces (ULS) for two-echelon distribution systems. *Axioms*, *10*(3). https://doi.org/10.3390/axioms10030214

Sadati, M. E. H., Çatay, B., & Aksen, D. (2021). An efficient variable neighborhood search with tabu shaking for a class of multi-depot vehicle routing problems. *Computers and Operations Research*, *133*, 105269. https://doi.org/10.1016/j.cor.2021.105269

Sadeghi, M., Jolai, F., Tavakkoli-Moghaddam, R., & Rahimi, Y. (2015). A new stochastic approach for a reliable p-hub covering location problem. *Computers and Industrial Engineering*, *90*, 371–380. https://doi.org/10.1016/j.cie.2015.10.003

Sah, B., Gupta, R., & Bani-Hani, D. (2021). Analysis of barriers to implement drone logistics. *International Journal of Logistics Research and Applications*, *24*(6), 531–550. https://doi.org/10.1080/13675567.2020.1782862

Sallez, Y., Pan, S., Montreuil, B., Berger, T., & Ballot, E. (2016). On the activeness of intelligent Physical Internet containers. *Computers in Industry*, *81*, 96–104. https://doi.org/10.1016/j.compind.2015.12.006

Salmanpour, S., Monfared, H., & Omranpour, H. (2017). Solving robot path planning problem by using a new elitist multi-objective IWD algorithm based on coefficient of variation. *Soft Computing*, *21*(11), 3063–3079. https://doi.org/10.1007/s00500-015-1991-z

Samsuddin, S., Shahizan Othman, M., & Mi Yusuf, L. (2020). Utilizing Ant Colony Optimization and Intelligent Water Drop for Solving Multi Depot Vehicle Routing Problem. *IOP Conference Series: Materials Science and Engineering*, *864*(1), 8–13. https://doi.org/10.1088/1757-899X/864/1/012095

Sanada, T., & Ishigaki, A. (2023). Modeling of Inventory Routing Problem with Intermediate Locations in Emergency Logistics Considering Uncertainty of Road Conditions. In *Lecture Notes in Production Engineering: Vol. Part F1164*. Springer International Publishing. https://doi.org/10.1007/978-3-031-18641-7_5

Sang-To, T., Le-Minh, H., Abdel Wahab, M., & Thanh, C. Le. (2023). A new metaheuristic algorithm: Shrimp and Goby association search algorithm and its application for damage identification in large-scale and complex structures. *Advances in Engineering Software*, *176*(November 2022), 103363. https://doi.org/10.1016/j.advengsoft.2022.103363

Savchenko, L., Grygorak, M., Polishchuk, V., Vovk, Y., Lyashuk, O., Vovk, I., & Khudobei, R. (2022). Complex evaluation of the efficiency of urban consolidation centers at the micro level. *Scientific Journal of Silesian University of Technology.*, *115*(Series Transport), 135–159.

Schervish, M. J. (1996). *P Values : What They are and What They are Not*. *1305*(1996). https://doi.org/10.1080/00031305.1996.10474380

Schett, G., Brunnthaller, G., Hess, C., & Kritzinger, S. (2019). Conceptual Model of a Decentralized Transport Organization in the Increasingly Uncertain Transport Environment of the Physical Internet. *6th International Physical Internet Conference*, *2*(July), 45–60.

Schulte, F., Lalla-Ruiz, E., González-Ramírez, R. G., & Voß, S. (2017). Reducing port-related empty truck emissions: A mathematical approach for truck appointments with collaboration. *Transportation Research Part E: Logistics and Transportation Review*, *105*, 195–212. https://doi.org/https://doi.org/10.1016/j.tre.2017.03.008

Shah-Hosseini, H. (2007). Problem solving by intelligent water drops. *2007 IEEE Congress on Evolutionary Computation, CEC 2007*, 3226–3231. https://doi.org/10.1109/CEC.2007.4424885

Shah-Hosseini, H. (2008). Intelligent water drops algorithm: A new optimization method for solving the multiple knapsack problem. *International Journal of Intelligent Computing and Cybernetics*, *1*(2), 193–212. https://doi.org/10.1108/17563780810874717

Shahanaghi, K., & Yazdian, S. A. (2010). Facility location and distribution decisions in supply chains with fleet sizing considering both tangible and intangible criteria. *International Journal of Management Science and Engineering Management*, *5*(4), 303–309. https://doi.org/10.1080/17509653.2010.10671121

Shahparvari, S., Nasirian, A., Mohammadi, A., Noori, S., & Chhetri, P. (2020). A GIS-LP integrated approach for the logistics hub location problem. *Computers and Industrial Engineering*, *146*(June 2019). https://doi.org/10.1016/j.cie.2020.106488

Shi, Y., Lin, Y., Wang, S., Wen, H., Lim, M. K., & Li, Y. (2023). A simultaneous facility location and vehicle routing problem with recyclable express packaging consideration for sustainable city logistics. *Sustainable Cities and Society*, *98*(May), 104857. https://doi.org/10.1016/j.scs.2023.104857

Shukla, H., Chhadva, J., Jasika, A., Sheth, K., & Malhotra, K. (2017). Application of Operation Research in Logistics and Warehouse Optimization. *International Journal of Innovative Research in Technology & Science(IJIRTS)*, *5*(5), 1–7.

Silva, M. R., & Cunha, C. B. (2017). A tabu search heuristic for the uncapacitated single allocation p-hub maximal covering problem. *European Journal of Operational Research*, *262*(3), 954–965. https://doi.org/https://doi.org/10.1016/j.ejor.2017.03.066

Singh, N., & Davar, S. C. (2004). Noise Pollution-Sources, Effects and Control. *Journal of Human Ecology*, *16*(3), 181–187. https://doi.org/10.1080/09709274.2004.11905735

Singh, S., Kumar, R., Panchal, R., & Tiwari, M. K. (2021). Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research*, *59*(7), 1993–2008. https://doi.org/10.1080/00207543.2020.1792000

Sivazlian, B. D. (2008). Operations Research. In C. A. Floudas & P. M. Pardalos (Eds.), *Encyclopedia of Optimization* (pp. 2847–2858). Springer. https://doi.org/https://doi.org/10.1007/978-0-387-74759-0_465

Stephen, A., Zhou, C., Chew, E. P., & Lee, L. H. (2020). Q-learning based automated guided vehicles recharging scheduling in container terminal. *Proceedings of the 2020 IISE Annual Conference*, 215–220. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85105624291&partnerID=40&md5=b55a43eee49fa23db7f69c0bf6169fb3

Sutton, R. S., & Barto, A. G. (1998). Introduction to reinforcement learning. In *MIT press Cambridge* (Vol. 135). MIT press Cambridge.

Tadić, S., Krstić, M., Kovač, M., & Brnjac, N. (2022). Evaluation of Smart City Logistics Solutions. *Promet-Traffic&Transportation*, *34*(5), 725–738.

Talischi, C., & Paulino, G. H. (2013). A consistent operator splitting algorithm and a two-metric variant: Application to topology optimization. *ArXiv Preprint ArXiv:1307.5100*.

Tampuu, A., Matiisen, T., Kodelja, D., Kuzovkin, I., Korjus, K., Aru, J., Aru, J., & Vicente, R. (2017). Multiagent cooperation and competition with deep reinforcement learning. *PLoS ONE*, *12*(4), 1–15. https://doi.org/10.1371/journal.pone.0172395

Tan, Y., Deng, L., Li, L., & Yuan, F. (2019). The capacitated pollution routing problem with pickup and delivery in the last mile. *Asia Pacific Journal of Marketing and Logistics*, *31*(4), 1193–1215. https://doi.org/10.1108/APJML-06-2018-0217

Tang, X., Lehuédé, F., Péton, O., & Pan, L. (2019). Network design of a multi-period collaborative distribution system. *International Journal of Machine Learning and Cybernetics*, *10*(2), 279–290. https://doi.org/10.1007/s13042-017-0713-5

Taniguchi, E. (2014). Concepts of City Logistics for Sustainable and Liveable Cities. *Procedia - Social and Behavioral Sciences*, *151*, 310–317. https://doi.org/10.1016/j.sbspro.2014.10.029

Taniguchi, E., & Thompson, R. G. (2002). Modeling city logistics. *Transportation Research Record*, *1790*, 45–51. https://doi.org/10.3141/1790-06

Taniguchi, E., & Thompson, R. G. (2014). City logistics: Mapping The Future. In *CRC Press.* (1st ed). https://doi.org/10.4337/9781800370173.00016

Taniguchi, E., Thompson, R. G., & Qureshi, A. G. (2020). Modelling city logistics using recent innovative technologies. *Transportation Research Procedia*, *46*(2019), 3–12. https://doi.org/10.1016/j.trpro.2020.03.157

Taniguchi, E., Thompson, R. G., & Yamada, T. (2016). New Opportunities and Challenges for City Logistics. *Transportation Research Procedia*, *12*(June 2015), 5–13. https://doi.org/10.1016/j.trpro.2016.02.004

Teitz, M. (1968). Heuristic Methods for Estimating the Generalized Vertex Median of a Weighted graph. *Operations Research*, *15*(October 1968), 955–961. https://doi.org/10.1287/opre.16.5.955

The Guardian. (2020). https://www.theguardian.com/world/2020/mar/22/australian-jobseekers-to-get-550-increase-as-part-of-huge-coronavirus-welfare-package

The World Commission on Environment and Development. (1987). "Our Common Future." In *Oxford University Press*. https://doi.org/10.1080/07488008808408783

Thompson, R. G., Zhang, L., Stoke, M., & Ghaderi, H. (2019). Parcel lockers for B2B distribution in central business districts. *IPIC2019, Proceedings, 6th International Physical Internet Conference*, 210–217.

Ting, C.-J., & Chen, C.-H. (2008). Combination of multiple ant colony system and simulated annealing for the multidepot vehicle-routing problem with time windows. *Transportation Research Record*, *2089*(1), 85–92.

TomTom. (2023). *TomTom — Mapping and Location Technology*. https://www.tomtom.com/

Topcuoglu, H., Corut, F., Ermis, M., & Yilmaz, G. (2005). Solving the uncapacitated hub location problem using genetic algorithms. *Computers and Operations Research*, *32*(4), 967–984. https://doi.org/10.1016/j.cor.2003.09.008

Transport for London. (2020). *Delivery and servicing plan guidance* (Issue December). http://content.tfl.gov.uk/delivery-and-servicing-plans.pdf

Transport for NSW. (2017). *"Sustainable Design Guidelines"* (Issue May). https://www.transport.nsw.gov.au/sites/default/files/media/documents/2017/sustainable-design-guidelines-v4.pdf

Transport for NSW. (2023). *1270.0.55.001 - Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016*. https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by Subject/1270.0.55.001~July 2016~Main Features~Statistical Area Level 3 (SA3)~10015

Tu, W., Fang, Z., Li, Q., Shaw, S., & Chen, B. (2014). A bi-level Voronoi diagram-based metaheuristic for a large-scale multi-depot vehicle routing problem. *Transportation Research Part E*, *61*, 84–97. https://doi.org/10.1016/j.tre.2013.11.003

United Nations. (2015a). *Paris agreement*.

United Nations. (2015b). *Transforming our world: the 2030 Agenda for Sustainable Development*. https://sdgs.un.org/2030agenda

United Nations. (2018a). "World Urbanization Prospects 2018." In *Department of Economic and Social Affairs. World Population Prospects 2018.* https://population.un.org/wup/

United Nations. (2018b). *2018 Revision of World Urbanization Prospects | Multimedia Library - United Nations Department of Economic and Social Affairs*. https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html

United Nations. (2021). *Global e-commerce jumps to $26.7 trillion, fuelled by COVID-19 | UN News*. https://news.un.org/en/story/2021/05/1091182

United Nations Statistics Division. (2020). "Global Indicator Framework for the Sustainable Development Goals and Targets of the 2030 Agenda for Sustainable Development." In *Work of the Statistical Commission pertaining to the 2030 Agenda for Sustainable Development*. https://unstats.un.org/sdgs/indicators/Global Indicator Framework after 2022 refinement_Eng.pdf

Van Breedam, A. (1995). Improvement heuristics for the vehicle routing problem based on simulated annealing. *European Journal of Operational Research*, *86*(3), 480–490.

van Duin, J. H. R., Wiegmans, B. W., van Arem, B., & van Amstel, Y. (2020). From home delivery to parcel lockers: a case study in Amsterdam. *Transportation Research Procedia*, *46*, 37–44. https://doi.org/https://doi.org/10.1016/j.trpro.2020.03.161

Vanelslander, T., Deketele, L., & Hove, D. Van. (2013). Commonly used e-commerce supply chains for fast moving consumer goods : comparison and suggestions for improvement. *International Journal of Logistics Research and Applications*, *5567*. https://doi.org/10.1080/13675567.2013.813444

Venkatadri, U., Krishna, K. S., & Ülkü, M. A. (2016). On Physical Internet Logistics : Modeling the Impact of Consolidation on Transportation and Inventory Costs. *IEEE Transactions on Automation Science and*

Engineering, *13*(4), 1517–1527. https://doi.org/10.1109/TASE.2016.2590823
VicRoads, & Transport for Victoria. (2019). *Transport Modelling Guidelines (Volume 4)*. *4*, 213.
Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., & Rei, W. (2012). A Hybrid Genetic Algorithm for Multidepot and Periodic Vehicle Routing Problems. *Operations Research*, *60*(3), 611–624.
Vohra, K., Vodonos, A., Schwartz, J., Marais, E. A., Sulprizio, M. P., & Mickley, L. J. (2021). Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem. *Environmental Research*, *195*, 110754. https://doi.org/10.1016/j.envres.2021.110754
Wang, Y., Assogba, K., Fan, J., Xu, M., Liu, Y., & Wang, H. (2019). Multi-depot green vehicle routing problem with shared transportation resource: Integration of time-dependent speed and piecewise penalty cost. *Journal of Cleaner Production*, *232*, 12–29. https://doi.org/10.1016/j.jclepro.2019.05.344
Wang, Y., Li, Q., Guan, X., Fan, J., Xu, M., & Wang, H. (2021). Collaborative multi-depot pickup and delivery vehicle routing problem with split loads and time windows. *Knowledge-Based Systems*, *231*, 107412. https://doi.org/10.1016/j.knosys.2021.107412
Waßmuth, K., Köhler, C., Agatz, N., & Fleischmann, M. (2023). Demand management for attended home delivery — A literature review. *European Journal of Operational Research*, *xxxx*. https://doi.org/10.1016/j.ejor.2023.01.056
Watkins, C. J. C. H., & Dayan, P. (1992). Q-learning. *Machine Learning*, *8*, 279–292.
Widodo, K. H., Parikesit, D., Purwoto, H., & Soemardjito, J. (2018). Issues and challenges in urban logistics planning in Indonesia. In *City Logistics 3: Towards Sustainable and Liveable Cities* (pp. 317–327). Wiley Online Library.
Wisittipanich, W., & Hengmeechai, P. (2015). A multi-objective differential evolution for Just-In-Time door assignment and truck scheduling in multi-door Cross docking problems. *Industrial Engineering and Management Systems*, *14*(3), 299–311. https://doi.org/10.7232/iems.2015.14.3.299
Woodbridge, M. (2015). "From MDGs to SDGs: What are the Sustainable Development Goals?" In *ICLEI* (Vol. 01, Issue Urban Issues).
Woolworths Group. (2020). *"Sustainability Plan 2021: working together to create a better tomorrow."*
Wu, W., Ma, J., Liu, R., & Jin, W. (2022). Multi-class hazmat distribution network design with inventory and superimposed risks. *Transportation Research Part E: Logistics and Transportation Review*, *161*(May 2021), 102693. https://doi.org/10.1016/j.tre.2022.102693
Xiao, J., Li, Y., Cao, Z., & Xiao, J. (2024). Computers & Industrial Engineering Cooperative trucks and drones for rural last-mile delivery with steep roads. *Computers & Industrial Engineering*, *187*(December 2023), 109849. https://doi.org/10.1016/j.cie.2023.109849
Xu, X., Hao, J., Deng, Y., & Wang, Y. (2017). Design optimization of resource combination for collaborative logistics network under uncertainty. *Applied Soft Computing Journal*, *56*, 684–691. https://doi.org/10.1016/j.asoc.2016.07.036
Xu, X., Jia, Y., Xu, Y., Xu, Z., Chai, S., & Lai, C. S. (2020). A multi-agent reinforcement learning-based data-driven method for home energy management. *IEEE Transactions on Smart Grid*, *11*(4), 3201–3211.
Yan, Y., Chow, A. H. F., Ho, C. P., Kuo, Y. H., Wu, Q., & Ying, C. (2022). Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities. *Transportation Research Part E: Logistics and Transportation Review*, *162*(March), 102712. https://doi.org/10.1016/j.tre.2022.102712
Yang, K., Liu, Y. K., & Yang, G. Q. (2013). Solving fuzzy p-hub center problem by genetic algorithm incorporating local search. *Applied Soft Computing Journal*, *13*(5), 2624–2632. https://doi.org/10.1016/j.asoc.2012.11.024
You, G. (2022). Sustainable vehicle routing problem on real-time roads: the restrictive inheritance-based heuristic algorithm. *Sustainable Cities and Society*, *79*(October 2021), 103682. https://doi.org/10.1016/j.scs.2022.103682
Yuan, M., Kan, X., Chi, C., Cao, L., Shu, H., & Fan, Y. (2022). An adaptive simulated annealing and artificial fish swarm algorithm for the optimization of multi-depot express delivery vehicle routing. *Intelligent Data Analysis*, *26*(1), 239–256.
Zanjirani, R., Hekmatfar, M., Boloori, A., & Nikbakhsh, E. (2013). Computers & Industrial Engineering Hub location problems : A review of models , classification , solution techniques , and applications. *Computers & Industrial Engineering*, *64*(4), 1096–1109. https://doi.org/10.1016/j.cie.2013.01.012
Zhang, D., Zhang, Y., Li, S., Li, S., & Chen, W. (2023). Bi-objective robust optimisation on relief collaborative distribution considering secondary disasters. *International Journal of Production*

Research, 1–20. https://doi.org/10.1080/00207543.2023.2217306
Zhang, H., Yang, N., Huangfu, W., Long, K., & Leung, V. C. M. (2020). Power Control Based on Deep Reinforcement Learning for Spectrum Sharing. *IEEE Transactions on Wireless Communications*, *19*(6), 4209–4219. https://doi.org/10.1109/TWC.2020.2981320
Zhang, Q., Wang, Z., Huang, M., Yu, Y., & Fang, S. (2022). Heterogeneous multi-depot collaborative vehicle routing problem. *Transportation Research Part B*, *160*(December 2021), 1–20.