DEVELOPING SUSTAINABLE SUPPLY CHAINS IN REGIONAL AUSTRALIA CONSIDERING DEMAND UNCERTAINTY, GOVERNMENT SUBSIDIES AND CARBON TAX REGULATION

A Thesis submitted by

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For the award of

Doctor of Philosophy

2020

Abstract

There is a tremendous opportunity to implement sustainable supply chain management practices in terms of logistics, operations, and transport network in regional Australia. Unfortunately, this opportunity has not been investigated and there is a lack of academic studies in this body of knowledge. This thesis is made up by three related, but independent models designed to efficiently distribute products from a regional hub to other part of the country. This research aims to develop efficient and sustainable supply chain practices to deliver regional Australian products across the country and overseas. As the airports of most Australian capital cities are over-crowded while many regional airports are under-utilised, the first model examines the ways to promote the use of regional airports. Australia is a significant food producer and the agricultural products are primarily produced in regional areas. In the other two models, we focus on the distribution of perishable products from regional Australia.

The first model presented in Chapter 2 outlines how different government subsidy schemes can be used to influence airfreight distributions that favour the use of regional airports and promote regional economic development. The model simultaneously considers time-window and release-time constraints as well as the heterogeneous fleet for ground distribution where fuel consumption is subject to load, travel distance, speed and vehicle characteristics. A real-world case study in the state of Queensland, Australia is used to demonstrate the application of the model. The results suggest that the regional airport's advantages can be promoted with suitable subsidy programs and the logistics costs can be reduced by using the regional airport from the industry’s perspective.

The second model presented in Chapter 3 examines the impacts of carbon emissions arising from the storage and transportation of perishable products on logistical decisions in the cold supply chain considering carbon tax regulation and uncertain demand. The problem is formulated as a two-stage stochastic programming model where Monte Carlo approach is used to generate scenarios. The aim of the model is to determine optimal replenishment policies and transportation schedules to minimise both operational and emissions costs. A matheuristic algorithm based on the Iterated Local Search (ILS) algorithm and a mixed integer programming is developed to solve the problem in realistic sizes. The proposed model was implemented in a real-world

case study in the state of Queensland, Australia to demonstrate the application of the model. The results highlight that a higher emissions price does not always contribute to the efficiency of the cold supply chain system.

The third model presented in Chapter 4 investigates the impacts of two different transport modes - road and rail - on the efficiency and sustainability of transport network to deliver meat and livestock from regional Queensland to large cities and seaports. The model is formulated as a mixed-integer linear programming model that considers road traffic congestions, animal welfare, quality of meat products and environmental impacts from fuel consumption of different transport modes. The aim of the model is to determine an optimal network configuration where each leg of journey is conducted by the most reliable, sustainable and efficient transport mode. The results indicate that it would be possible to significantly decrease total cost if a road-rail intermodal network is used. Considering animal welfare, product quality and traffic congestion can have a significant effect on the decisions related to transport mode selection.

CERTIFICATION OF THESIS

This Thesis is the work of Mahla Babagolzadeh except where otherwise acknowledged, with the majority of the authorship of the papers presented as a Thesis by Publication undertaken by the Student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: Associate professor Shane Zhang

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Acknowledgements

I would like to express my sincere gratitude to my supervisors Assoc. Prof. Shane Zhang, Dr Anup Shrestha and Prof. Alice Woodhead for their supervisions, their valuable advice and providing motivation throughout the course of my PhD studies. It has been a pleasure to collaborate with them.

I would like to thank my Advisor Prof. Babak Abbasi for his invaluable support, encouragement, sharing his knowledge and guidance in all the time of research. I have been extremely fortunate to have the opportunity to learn from and collaborate with him.

Special thanks and sincere gratitude must also go to faculty and staff in School of Management and Enterprise at University of Southern Queensland to help and support me during my PhD. I acknowledge Mr Bernard O'Neil for his professional proofreading advice.

I would like to thank my family and friends for encouragement and motivation. Most of all, I would like to give my appreciation to my parents, Eshrat and Naser and my brothers Mahdi and Milad for their great support and love that gave me confidence to pursue my dreams.

This research has been supported by an Australian Government Research Training Program Scholarship.

List of publications arising

- Babagolzadeh, M., Zhang, Y., Abbasi, B., Zhang, A., and Shrestha, A., 2020. Promoting regional airports with subsidy schemes: A case study in Australia. Transportation Research Part A: Policy and Practice (under review).

  The overall contribution of Mahla Babagolzadeh was 75% to the concept development, analysis, drafting and revising the final submission; Yahua Zhang, Babak Abbasi, Anup Shrestha and Anming Zhang contributed the other 25% to concept development, analysis, editing and providing important technical inputs.

- Babagolzadeh, M., Shrestha, A., Abbasi, B., Zhang, Y., Woodhead, A. and Zhang, A., 2020. Sustainable cold supply chain management under demand uncertainty and carbon tax regulation. Transportation Research Part D: Transport and Environment, 80, p.102245.

  The overall contribution of Mahla Babagolzadeh was 75% to the concept development, analysis, drafting and revising the final submission; Anup Shrestha, Babak Abbasi, Yahua Zhang, Alice Woodhead and Anming Zhang contributed the other 25% to concept development, analysis, editing and providing important technical inputs.

- Babagolzadeh, M., Zhang, Y., Abbasi, B., Zhang, A., Shrestha, A., and Yong, J., 2020. Sustainable intermodal meat supply chain: Moving cattle from outback Queensland to the Port of Brisbane. Transportation Research Part E: Logistics and Transportation Review (under review).

  The overall contribution of Mahla Babagolzadeh was 75% to the concept development, analysis, drafting and revising the final submission; Yahua Zhang, Babak Abbasi, Hang Yu, Anup Shrestha and Jianming Yong contributed the other 25% to concept development, analysis, editing and providing important technical inputs.

- Babagolzadeh, M., Shrestha, A., Abbasi, B., Zhang, S., Atefi, R. and Woodhead, A., 2019. Sustainable Open Vehicle Routing with Release-Time and Time-Window: A Two-Echelon Distribution System. IFAC-PapersOnLine, 52(13), pp.571-576.

  The overall contribution of Mahla Babagolzadeh was 85% to the concept development, analysis, drafting and revising the final submission; Anup Shrestha, Babak Abbasi, Shane Zhang, Reza Atefi and Alice Woodhead contributed the other 15% to concept development, analysis, editing and providing important technical inputs.

- Babagolzadeh, M., Shrestha, A., Abbasi, B., Zhang, Y., and Woodhead, A., 2018. A two-stage stochastic programming model to optimize logistical decisions in cold supply chain under government regulations. In 2018 AMSI Optimise Mathematical Innovation Conference, University of Melbourne, 18-22 June, Melbourne, Australia.

  The overall contribution of Mahla Babagolzadeh was 85% to the concept development, analysis, drafting and revising the final submission; Anup Shrestha, Babak Abbasi, Yahua Zhang and Alice Woodhead contributed the other 15% to concept development, analysis, editing and providing important technical inputs.

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Chapter 1: Introduction

1.1 Background

In an increasingly competitive global economic environment, a prompt response to the customer's needs and cutting the operational costs along a supply chain are vital. In Australia the recent rises in population and congestion in metropolitan areas have increased operational costs and waiting times as well as business challenges to meet customer demands for fast and reliable deliveries in supply chains. In addition, there have been challenges related to environmental sustainability and green supply chain management has been called for and required in recent years.

A supply chain is a system consisting of suppliers, manufacturers, distributors, retailers and customers in which products are transferred from a supplier to an end user. Management of the entire processes and practices in this system is known as supply chain management. The focus of supply chain management used to be on economic performance only. However, the recent impact in sustainability issues such as the environment and a drop in the quality of products have begun to permeate corporate thinking towards developing sustainable supply chain management. Hence, there has been a growing body of literature on the topic of sustainable supply chain management (see, for example, (Mota et al., 2015; Sheu et al., 2005)). Researchers have been studying the wide range of matters that can influence a sustainable supply chain. Using energy efficiently and keeping the quality of the product at the level necessary to maintain or increase customer satisfaction are two examples.

One of the main challenges in the area of sustainability relates to carbon and other greenhouse gas (GHG) emissions from supply chain activities (Fichtinger et al., 2015). There has been growing attention in this area as result of the introduction of carbon tax regulation in some parts of the world (Li et al., 2017). According to a recent survey, the transportation sector is one of the major contributors to GHG emissions, accounting for 17% of Australia's total emissions (Australian Government, 2017). The significant growth in traffic congestion in metropolitan cities in Australia contributes to this. Another sustainability issue is related to the quality of the product which can impact on customer satisfaction. Product quality can significantly deteriorate due to long waiting times caused by traffic congestion and over-crowded facilities in metropolitan areas in Australia. Given the high freight volume and the growth in traffic congestion in metropolitan areas, decision makers, particularly in the three forms of government in Australia, have a great interest in the potential for regional areas, which usually have underused capacity, to be used as distribution hubs to improve the efficiency and reliability of distribution along supply chains with an emphasis on sustainability issues.

Australia is a significant food producer in the world and exports more than 70% of its agricultural production (Michael, 2018). Transporting value-added agricultural products along supply chains is important because of the associated high levels of employment, personal income and government tax revenue (Woodhead et al., 2017). Notwithstanding the recent political issues between Australia and China, there has been a steadily increasing demand for Australian agricultural products across Asia, especially for dairy, food and natural health products (Michael, 2018). Studies have proposed establishment of food clusters in Australian regional areas that are close to food production regions. This will improve the efficiency and reliability of supply chains and support regional economic development (Zhang and Woodhead, 2016). There would likely be positive impacts of the sustainability of the supply chains. To support regional areas as distribution hubs, the Australian government has introduced regional subsidy schemes (Zhang et al., 2017).

Despite the important role that regional Australia could play in operational efficiency and reliability improvement along the supply chains, designing a sustainable supply chain from a regional hub to other parts of Australia has failed to attract the attention of scholars to any great extent. This research aims to work on this topic that is worthy of scholarly investigation as well as includes significant policy and practical implications.

1.2. Motivation for the Study

As a PhD student at the University of Southern Queensland (USQ) at Toowoomba which is located in the regional, city of Toowoomba, in Australia, it was recognized there was a significant effort of the Toowoomba local government (Toowoomba Regional Council) and USQ scholars to investigate the viability of Toowoomba as a distribution hub. The city is in a strategic location for the surrounding region and has excellent transport connectivity across Australia and key overseas locations.

The Darling Downs region, where Toowoomba is situated, is the second largest agricultural production area in Australia, and the largest in Queensland and accounts for about a quarter of the state’s agricultural production (Zhang and Woodhead, 2016).

Toowoomba was also identified by Australian government agencies and industry as a potential agricultural distribution centre of perishable products (Zhang and Woodhead, 2016).

Toowoomba is 120 km west of Brisbane, the capital city of the state of Queensland, and is the largest non-capital inland city in Australia. It is situated at the junction of main national highways and is connected to the Western Rail line, providing it with a good opportunity to become a distribution hub. The position of Toowoomba was further strengthened when the Wellcamp Airport in Toowoomba was put into commercial freight use in November 2014 and it became a gateway for distributing cargo to domestic and international markets.

Due to the location and position of Toowoomba as a regional area for both production and distribution of perishable products, it provided an excellent opportunity to embark on this research study to use decision support tools and evaluate the suitability of Toowoomba as a distribution hub and how it can affect efficiency and sustainability of supply chains in presence of government regional schemes from practical and theoretical point of views. Furthermore, the strategic positioning of Toowoomba provides a suitable platform and motivation to design a transport network to distribute products from a regional area to other parts of the country in a sustainable way.

1.3 Rational and knowledge gap

This thesis examines three topics. The rational and knowledge gap of each topic is discussed as follows:

Topic 1 (addressed in Chapter 2) examines how government regional subsidy schemes may influence the structure of cargo distribution network and logistics decisions. The propose research links with three strands of literature, namely, the regional air transport, open vehicle routing problems and multimodal transport network. There has been a growing body of literature on these areas since 2000 (Rezaei et al., 2017; Atefi et al., 2018; Kundu and Sheu, 2019; Li and Zhang, 2020). However, most of these studies focus on metropolitan airports and regional airports have received little attention. In addition, the existing literature mainly explores the effect of government subsidy schemes to promote a specific transport mode. There is a lack of studies examining the effect of regional subsidy schemes to reduce the volume of cargo traffic at the increasing congested metropolitan airports. To the best of our knowledge, our study is the first one that integrates logistics decisions and government regional subsidies for cargo distribution network.

Topic 2 (discussed in Chapter 3) explores the impacts of carbon tax regulation and uncertain demand on logistics decisions in the cold supply chain. We develop an optimisation model based on a two-stage stochastic programming to capture the uncertainty of demand, accounting for a heterogenous fleet and carbon tax regulation. There are many studies focusing on the distribution planning in cold supply chain. However, only a few studies incorporate environmental impacts into the distribution planning in cold supply chains (Chen and Hsu, 2015; Hsiao et al., 2017; Hariga et al., 2017; Stellingwerf et al., 2018b). Among these studies, some studies considered stochastic parameters in modelling in the cold supply chains. For example, Soysal et al. (2015) presented an integrated IRP model for distribution of a perishable product that contains load dependent distribution costs for evaluation of carbon emissions, perishability and service level constraint for satisfying stochastic demand. Firoozi and Ariafar (2017) developed a Lagrangian relaxation-based heuristics algorithm to solve a stochastic model presented for distribution of perishable products. Although these studies considered models for distribution perishable products in stochastic environment, the energy consumption of cold facilities and emissions from storage were largely neglected. To the best of our knowledge, no existing research has addressed the replenishment policy and transportation schedules in an integrated model for the cold supply chain sector with a consideration of demand uncertainty, carbon tax regulations and a heterogeneous fleet simultaneously. This research will fill this literature gap.

Topic 3 (addressed in Chapter 4) examines the opportunity of expanding the use of an intermodal road-rail transport network for a meat supply chain. We present an intermodal transport network model for a meat supply chain that takes into account traffic congestion, animal welfare and the quality of meat products during transport operations in presence of a carbon tax regulation. In recent years, there has been growing body of literature in the area of intermodal transport network as such network offers an opportunity to facilitate international trade and to mitigate road congestion (Kumar and Anbanandam, 2020; Baykasoglu and Subulan, 2016; Sorensen et al., 2012). Good surveys of the development of intermodal transport networks can be found in Bontekoning et al. (2004), Mathisen and Hanssen (2014) and Abbassi et al. (2018). However, studies addressing the intermodal transport problem in food supply chains are still small in number. Soysal et al. (2014) proposed a linear programming model for a multimodal beef supply chain to minimise the economic costs and emissions during beef's distribution. Abbassi et al. (2018) presented an intermodal transport model for agriculture products that accounts for the quality loss during transport operations in order to minimise total costs. Although these studies addressed the intermodal transport network in food supply chains, the animal welfare issue has been neglected, which is a key aspect to be addressed in Chapter 4.

1.4. Research aim and objectives

The aim of this study is twofold. First, to investigate how to improve the performance of supply chains in Australia by using a regional area as a distribution hub in line with government regional support schemes. Second, to design a distribution network to move products efficiently and reliably from the regional hub to other parts of the country under both carbon tax regulation and uncertain demand. This research addresses the following questions:

RQ 1: *How different government subsidy schemes can be used to influence airfreight distribution that favours the use of regional airports and to promote regional economic development?*

RQ 2: *What is the effect of government regional support schemes on logistics decisions and economic costs?*

RQ3: *What are the impacts of carbon tax regulation and the uncertainty of demand on logistics decisions in the supply chain with perishable products?*

RQ 4: *How can the investigation of two different transport modes (road and rail) affect the efficiency and reliability of the transport network in transporting meat and livestock from regional Queensland to large cities and seaports?*

RQ 5: *How can animal welfare and the quality of products affect transport mode selection decisions in the meat supply chain considering traffic congestion?*

These questions gave rise to the following objectives for this research:

- To develop a mathematical model to determine the best distribution network under government regional support schemes.
- To establish a model to analyse the effect of different regional support schemes (linear subsidy and non-linear subsidy) on logistics decision making and economic costs to identify the most effective scheme.

- To develop a stochastic model to determine cost-efficient and environment-friendly replenishment policies and transport schedules in a cold supply chain under both carbon tax regulation and uncertain demand.
- To establish a model to select the most reliable, sustainable and efficient transport mode to conduct each leg of the journey in a meat supply chain while considering animal welfare issues, the quality of the products and traffic congestion.

1.5 Contribution of research

As mentioned, the increasing traffic congestion in metropolitan areas in Australia has brought challenges for efficient and reliable deliveries in supply chains. This can have a significant impact on the sustainability of a supply chain. Thus, decision makers such as those at all levels of government and in industry have a great interest in the potential for regional areas with underused capacity to be distribution hubs to avoid the suburban heavy traffic congestion which results in inefficient, unreliable and unsustainable supply chains. Using hubs in regional areas will not only lead to improved efficiency, reliability and sustainability in a supply chain, but they can also help to promote regional economic development. To implement this strategy for effective regional schemes, it is essential to design efficient, reliable and sustainable distribution networks between the regional and metropolitan areas. Although an increased amount of research has focussed on regional areas as a result of the Australian government's recent regional support schemes, few researchers have used decision support tools to provide quantitative evidence (most of studies in this field are proposals and discussion based). Also, the existing research does not focus on designing an efficient, reliable and sustainable distribution network between regional and metropolitan areas, especially in a cold supply chain. This study seeks to fill this gap. This research uses decision support tools to answer how government regional support schemes may influence freight distribution in and from regional areas and so promote regional economic development. It also presents models to help design an efficient, reliable and sustainable network for distributing products, especially livestock and perishable agricultural ones, from a regional area to other parts of Australia.

1.6 Thesis structure

This thesis is a composition of three models that offer solutions to answer the research questions listed in section 1.3 in three chapters.

The first model (presented in Chapter 2) is presented to explore how the government regional subsidy schemes influence freight distribution decisions that favour the use of regional airports and promote regional economic development, with a consideration of the optimal ground distribution network from those airports to the consignees. The proposed model considers the subsidy schemes as linear and non-linear functions. The model simultaneously considers the time window, release time constraints and the heterogeneous fleet for ground distribution where fuel consumption is subject to load, travel distance, speed and vehicle characteristics. This model is applied to the situation in Australia where the metropolitan airports are operating close to their full capacity while the vast majority of the regional airports are underutilised.

A case study in Australia is presented to demonstrate the application of the proposed framework. The results illustrate that introducing subsidies can promote the viability of regional airport's as a logistics hub and have a positive effect on the reduction of total costs. The results also suggest that the framework under a linear subsidy provides a better performance from the economic and delivery time perspectives. However, in terms of promoting a regional airport and economic growth, a non-linear subsidy is preferred.

The second model (presented in Chapter 3) investigates the impact of carbon emissions arising from storage and transportation on logistics decisions in a cold supply chain under a carbon tax regulation. The model also determines the impact of uncertain demand on the operational decisions related to storage and transportation. The model is developed based on a two-stage stochastic programming to determine cost-efficient and sustainable replenishment policies and transport schedules in which energy consumption and emissions are determined by load, distance, speed and vehicle characteristics. Given a statistical distribution for the demand uncertainty, scenarios are generated using the Monte Carlo approach. Moreover, stability tests are conducted to make sure that the scenario size is adequate with a reliable representation of the demand. A matheuristic algorithm based on an Iterated Local Search algorithm and a mixed integer programming are used to solve the proposed problem in an efficient computational time. The performance of the matheuristic algorithm is analysed using test instances with various sizes.

A real world case study in a regional area of Queensland is used to demonstrate the application of the proposed model; the area is one of the main producers of cold products in Australia. The results highlight that a higher emissions price does not always contribute to the efficiency of the cold supply chain system.

The third model (presented in Chapter 4) investigates how integrating different transport modes (road and rail) can affect the efficiency, reliability and sustainability of the distribution of meat products and livestock from regional Queensland to large cities and seaports. The proposed model simultaneously considers road traffic congestion, animal welfare issues, the quality of the meat products and environmental impacts from fuel consumption in the different transport modes. The aim of the model is to determine an optimal transport network where each leg of the journey is conducted by the most efficient, reliable and sustainable transport mode. The cost function comprises transport, animal welfare reduction, quality loss and emissions costs.

To evaluate the performance of the model, a real world case study is used to illustrate how the proposed model could help decision makers to develop a sustainable, reliable and cost-efficient intermodal transport network in a meat supply chain. The proposed model is implemented in a case study in Queensland which has the largest beef cattle herd in Australia. The results illustrate that it would be possible to decrease the total cost significantly if a road–rail intermodal network is used in conjunction with a unimodal network in the meat supply chain. The results indicate that using road–rail intermodal network for long distances can provide a better performance in terms of animal welfare and the quality of the products.

Finally, Chapter 5 discusses the research findings and demonstrates the contribution of this research to the academic literature. This chapter also offers recommendation for future research in this area and implications of research to policy and practice.

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Chapter 2: Promoting regional airports with subsidy schemes: A case study in Australia

2.1 Introduction

As the largest island nation which is far from the dense business centres and markets such as China and the US, airfreight has become increasingly important for Australia (Hamal, 2011). The airfreight sector is one of the largest dollar value contributors to Australia's international trade: *AUD* 1 in every *AUD* 5 of Australia's imports and exports are transported by air (Adrian et al., 2019). Worldwide, airfreight accounts for 36% of the value of global trade annually (Feng et al., 2015), which makes it a vital component in global supply chains (Tan and Tsui, 2017). According to (Boeing, 2014), the market for airfreight is likely to grow at a rate of 4.2% per year throughout the world. An increase in the demand for fast deliveries is one of the main drivers of this growth (Li et al., 2016). Most airfreight is transported in the cargo hold of passenger aircrafts and some airlines operate a dedicated fleet of freight (Zhang and Zhang, 2002; Hong and Zhang, 2010). With major international airports becoming increasingly congested, it is difficult for them to accommodate more all-cargo carriers. The congestion problem in metropolitan airports also leads to increased operational costs and longer waiting times before the freight can be released to clients. Thus, decision makers such as governments and airport managements have a great interest in shifting significant volumes of airfreight to regional airports. This has motivated us to do this research.

In recent years there has been a high demand in Asia for Australian agricultural products, especially for dairy, food and natural health products. There have been proposals for food clusters to be established in Australian regional cities close to food production areas (Zhang and Woodhead, 2016). Therefore, the three levels of government in Australia are keen to develop regional airports as cargo distribution hubs which can assist in increasing operational efficiencies in cargo distribution system. In contrast to the high airfreight volumes at metropolitan airports, the current low volumes at regional airports are not adequate to support the high costs of both maintenance and upgrading infrastructure (Zhang et al., 2017; Donehue and Baker, 2012). Almost 50% of the regional airports in Australia operate at a loss each year and have to rely on subsidies from their local government. To support regional airports, the Australian government has introduced regional subsidy schemes. However, they have not stopped regional airports from losing services in recent years (Zhang et al., 2017).

The airfreight network is a multi-echelon one, from the shippers who supply the cargo to consignees through to airports and freight forwarders (Derigs et al., 2009). The shipper is the supplier of the freight; the airports are the depots that receive the cargo from the shipper, store the pelletised cargo in terminals and place them on pallets for distribution to the freight forwarders; and the forwarders are responsible for delivering the cargo to the consignees (Leung et al., 2009). The consignee is the last to receive the shipment and then distributes the goods to its clients and customers. Companies involved in cargo distribution usually deals with third parties for transport operations which can be cost-effective to ship cargo as vehicles do not need to return their starting points at the end of the route. In other words, cargo companies do not (explicitly) pay for vehicles return trip. We refer to this situation as the open vehicle routing problem. In the open vehicle routing problem, a solution contains a set of Hamiltonian paths connected to the depots instead of Hamiltonian cycles existing in the vehicle routing problem.

Shifting cargo traffic from metropolitan airports to regional airports, would substantially reduce the length of time that cargo is held at an airport. However, the ground transport time may increase as most consignees are located at a distance from regional airports. Therefore, an efficient ground transport system is needed. This research attempts to answer how government subsidy schemes may influence airfreight distribution through regional airports to reduce the volume of cargo traffic at metropolitan airports, with a consideration of the optimal performance of distributing cargo from the airport to the consignees.

This paper evaluates the effect of different subsidy schemes on network structure and logistics decisions for cargo distribution. Specifically, we propose a mixed integer linear programming model for open vehicle routing problem that accounts for the time-window and release-time constraints under subsidy schemes to support regional areas. The proposed model considers subsidy schemes as linear and non-linear functions. In the proposed model a heterogeneous fleet is used for downstream distribution, and fuel consumption is determined by the load, speed, distance and vehicle characteristics. Release-time refers to the time at which the cargo becomes ready for downstream distribution, and it is influenced by the airfreight traffic volume. This model is applied to the situation in Australia where the metropolitan airports are operating close to their full capacity while the vast majority of the regional airports are underutilised.

The proposed model can help make decisions to minimise operational cost, including air transport costs, ground transport costs and penalty cost as a result of time-window violations, in presence of regional subsidy schemes. To the best of our knowledge, research integrating logistics decisions and government subsidies for airfreight distribution is rare, and so this research can generate significant policy implications for promoting the use of regional airports by the transport industry.

This research reveals that the introduction of subsidy schemes provides more benefits in reducing the total costs from the perspective of the industries involved in the cargo distribution. The results indicate that the framework under subsidy scenario 2 can provide a better performance in terms of costs and delivery time as compared to that of under subsidy scenario 1. Moreover, we observed that increasing the volume of cargo traffic at a regional airport under subsidy scenario 1 is almost linear with an increase in the government subsidy budget cap, while it increases at different rates under subsidy scenario 2. Therefore, policy makers can seek advantages from the proposed framework to determine an appropriate government subsidy budget cap and subsidy rates.

The remainder of this chapter is structured as follows. Section 2.2 reviews the literature relevant to this research. In Section 2.3, we present a framework to examine the regional subsidy schemes. Section 2.4 provides a description of the case study for which the model was implemented, and the results obtained. Sensitivity analyses on subsidy values and managerial implications are also presented in Section 2.4. In section 2.5, we present managerial insights and policy implications. Section 2.6 provides conclusions and is followed by appendices of supporting material.

2.2 Literature review

The proposed framework in this research links with three strands of literature, namely, the regional air transport, open vehicle routing problems, Multi modal transport network. We review recent papers relevant to these three problems in sub-sections 2.2.1, 2.2.2 and 2.2.3 respectively.

2.2.1 The regional air transport problem

Air transport enables nations to access global markets and supply chains in a reliable and cost-efficient manner. Thus, effective air transport services in today's fast-cycle logistics era can greatly improve a region's connectivity and thereby give businesses in that region a competitive advantage (Zhu et al., 2019b). Unfortunately, compared with the numerous studies dedicated to aviation activities in metropolitan areas, research on regional airports and regional air transport services is sparse (Zhang et al., 2017). Graham and Guyer (2000) argue that the UK aviation policy focuses on capacity shortages at large airports in southeast England and that issues affecting regional airports such as sustainability and pro-competition policy receive little attention. As the performance of regional airport is affected by the decisions of airlines, in many countries the government provides some financial incentive to encourage airlines to serve regional airports.

Humphreys and Francis (2002) studied the UK regional aviation market and found that the pattern of regional airport utilisation is dependent on decisions by airlines. Therefore, it is important to take into account the interest of all stakeholders when formulating airport planning and regulatory policies. Donehue and Baker (2012) identify challenges faced by regional airports in Australia, which mainly stem from the interrelating factors of infrastructure costs, the high cost of maintenance and security infrastructure upgrades. Baker and Donnet (2012) examined the relationship between regional economic growth and regional air transport services and found a significant bi-directional relationship between them. They suggested that public financial support such as subsidy schemes should be in place to ensure that the level of services is maintained in Australia's regional areas. Yuen et al. (2017) provided an analytical framework to capture the competition (and cooperation) between gateway and hinterland (regional) airports. They found that the introduction of a regional cargo airport is likely to lead to an improvement in the aggregate welfare of the gateway and the hinterland.

To support small and remote communities, the Australian government introduced the Air Services Australia Enroute Charges Payment Scheme, which offers subsidies to air operators that provide aeromedical services to these areas (Zhang et al., 2017). The Chinese government has had a subsidy program on regional routes and uses a fee collected from all passengers for airport construction (now the Civil Aviation Development Fund), although the amount is relatively small. To develop itself into an airport city, Zhengzhou, a city in central China, provides financial subsidies and incentives to airlines for setting up at Zhengzhou Airport and operating new routes. Logistics firms conducting business at Zhengzhou Airport such as importing and distributing cargo also receive subsidies from the government (Zhang and Woodhead, 2016). Sometimes the manufactured goods are even trucked for more than 10 hours from South China to Zhengzhou Airport because of the subsidy incentives, which has ensured a high freight load factor for flights out of Zhengzhou Airport.

Some researchers have studied airport selection and fleet routing problems. Gardiner et al. (2005) conducted a survey to identify the factors that influence the airfreight companies' decisions on airport selection. They found that airport charges, financial incentives and customes' clearance times were among the significant factors influencing the freight operators' decisions. Yan et al. (2006) presented a mixed integer programming model to solve the problems of airport selection, fleet routing and timetable setting in order to maximise profits for airfreight. They found that effective cargo transfers not only reduce operating costs but also increase profitability.

Chao and Yu (2013) assessed airfreight competitiveness at major Asia-Pacific airports. They considered internal factors (e.g., airport facilities, charges and opening hours) and economic development (e.g., annual cargo growth and cargo volumes) in their evaluation. The results indicate that Changi Airport is the most competitive airport in terms of airport facilities and operations, while Hong Kong has the number one ranked airport in terms of airfreight capacity and economic development (see also Zhang (2003), for an in-depth analysis of Hong Kong's competitiveness in air cargo in the context of Asia-Pacific airports). Rezaei et al. (2017) used a multi-criteria tool to determine the optimal strategy for planning freight shipment from outstations to hub airports with a consideration of the cost, loading time and quality. They found that vehicles costs and freight handling tariffs are the main factors in determining the optimal freight bundling configuration. Customers today have become more demanding for fast delivery and prefer to obtain the right goods at the right time. One of few studies to consider the freight forwarding companies' optimisation problem is that by Archetti and Peirano (2020). Again, much of the research discussed here focuses on metropolitan airports and little attention has been given to airfreight operations at regional airports. This research aims to fill this gap.

2.2.2 The open vehicle routing problem

When a regional airport is used, the freight needs to be transported to the clients in various locations and often at some distance from the airport. Thus, the open vehicle routing problem (OVRP) arises. OVRP is a variant of the vehicle routing problem (VRP) (Dantzig and Ramser, 1959), in which vehicles do not return to the starting node. Schrage (1981) was a pioneer in introducing the idea of open routes in VRP, which was defined as OVRP by Sariklis and Powell (2000).

There are a number of heuristic methods used to solve OVRP including simulated annealing (Tarantilis et al., 2004), ant colony optimisation (Li et al., 2009), neighbourhood-based search (Şevkli and Güler, 2017), particle swarm optimisation (MirHassani and Abolghasemi, 2011), genetic and evolutionary computing (Yu et al., 2011) and the tailored iterated local search algorithm (Atefi et al., 2018). However, in these approaches, it should be noted that most of these approaches only addressed a simple variation of OVRP without considering the time-window constraints.

The time-window constraints bring more complexity to the modelling of OVRP (Xia and Fu, 2019). Repoussis et al. (2007) presented a model for OVRP with time-window constraints (OVRPTW) and developed a route-construction insertion-based sequential approach to find a good quality solution. Brandão (2018) developed a local search algorithm for solving the OVRPTW in an efficient computational time. Another variation of VRP relevant to this research is the vehicle routing problem with release date (VRPRD), which is how soon can an order be dispatched from the depot after it is released. The challenge in this is that the release-time has a significant impact on the travel time and is negatively associated with customer satisfaction. The delivery time may be longer than is desired given the release-time.

Archetti et al. (2015) and Reyes et al. (2018) are among the few researchers to study the complexity of VRPRD. Archetti et al. (2015) addressed this problem when special topologies were considered for the distribution network. The network can be a star structure when the depot is at the centre of the distribution area or a line structure when the customers are located along a road. The authors considered two scenarios. The total distance travelled in a given delivery deadline was minimised in the first problem, while the second problem focused on minimising the total distribution time. Reyes et al. (2018) addressed the complexity of VRPRD where the delivery to each customer was only allowed in a window between the release-time and the distribution deadline. Their model ensures that the completion time of the last route and the distance travelled were minimised simultaneously.

Cattaruzza et al. (2016) addressed a multi-trip VRP which accounted for hard time-window and release-time constraints. They developed a hybrid genetic algorithm using Solomon's instances (Solomon, 1987) to evaluate the proposed algorithm. Shelbourne et al. (2017) investigated a VRP that considers release-time and due date constraints with the aim of minimising transport costs and high customer service level, represented by total weighted delivery tardiness and total travel distance. Although these studies considered release-time constraints in the VRP models, the fuel consumption in the transportation was largely neglected. Nor did they take into account the subsidisation policy and its impact on route configurations. Moreover, these models only focused on a single transport model, i.e., ground distribution.

2.2.3 Multi modal transport network

Multi modal transport is defined as shipment of cargo from shipper to consignee using two or more transport modes such as air, rail, road and waterways (Hayuth, 1987). Multi modal transport has become an interesting area of research due to globalisation and growth of international trade (Abbassi et al., 2019; Baykasoglu and Subulan, 2016). There has been a wide range of applications for multi modal transport including the import/export of freight (Baykasoglu and Subulan, 2016), the shipment of hazardous material (Assadipour et al., 2016) and passenger movement (Zhu et al., 2019b). Good reviews on multi modal transport network can be found in Bontekoning et al. (2004) and SteadieSeifi et al. (2014).

Arnold et al. (2004) developed an integer linear programming model to find an optimal location for rail/road terminals for freight transport. The model was applied to the rail/road transport system in Iberian Peninsula. The results demonstrated that the modal shares of the goods are subject to the variation of rail cost. Resat and Turkay (2015) developed a bi-objective optimisation model accounting for time dependent traffic congestion constraints to design a reliable transport network by integrating different transport modes. Baykasoglu and Subulan (2016) presented a mixed-integer programming model for multi mode sustainable load planning problem that accounts for transport mode selection, outsourcing and load allocation decisions simultaneously. The model seeks to determine the optimal import and export load flow with an aim of minimising economic costs and CO_2 emission and maximising customer satisfaction.

Abbassi et al. (2019) presented three robust optimisation models for multi modal transport network to capture uncertainties of using costs of terminals, capacities of terminals and transport costs. They developed a hybrid algorithm based on a population-based simulated annealing and exact approach to solve the model. Kelle et al. (2019) proposed a simulation model to measure the benefits of mode changes and to evaluate the trade-off between environmental goals and other performance measures. The results indicated that changing transport mode from road to rail can provide better environmental performance. It should be noted that these studies addressed multi modal transport network, however, they mainly focus more on rail, waterways and road.

Chang (2008) proposed a bi-objective optimisation model accounting time-window to identify the best route for shipments on an international multi modal network. They developed a heuristic algorithm based on relaxation and decomposition techniques to solve the model. The results indicated that if transport cost is of major concern, waterway is the desirable transportation mode, while air is the preferred transport mode in terms of travel time. Cho et al. (2012) designed a dynamic programming algorithm for bi-objective multi modal routing problem to find the optimal solution considering every possible modality (rail, air, waterway and road). A real case study related to shipment from Busan to Rotterdam was used to evaluate the efficiency of the algorithm. Etemadnia et al. (2015) proposed a mixed integer linear programming model to find the optimal facilities location within fruit and vegetable supply chain system for efficient transfer of food where they examined the multi modal (road and air) transport system. The results can help policy makers to identify whether the current network connecting producers and customers is optimal or not and to find the potential opportunity for future investment in transport infrastructure.

Archetti and Peirano (2020) presented a mixed integer linear programming model for air transport freight forwarder service problem in international multi modal transport network. The model seeks to select the best options over the wide offer of transport services for international transport with an aim of minimising the total costs. Huang et al. (2020) proposed a model to help airfreight forwarders make an optimal routing and consolidation decisions in air-road multi modal transport network. They designed an approximate algorithm based on Lagrangian Relaxation to solve the model. The performance of the algorithm was examined using different text problem in terms of problem scale. These studies addressed road-air multi modal transport network, however the effect of subsidy schemes towards efficiency improvement of transport network was largely neglected.

Some multi modal research have analysed the effect of subsidy schemes on the development multi modal transport network (Yin et al., 2020). Santos et al. (2015) proposed a mixed integer programming model to examine the impact of three freight transport policies on promoting rail-road multi modal transport Belgium. The model seeks to determine the optimal location of rail-road terminals and optimal allocation of freight flows between modes with an aim of minimising transport costs from shippers perspective. The results indicated that subsidies are critical to the success of multi modal transport in Belgium. Larranaga et al. (2017) addressed the logistics manager's preference for freight transport services in Brazil using a stated preference analysis of freight mode choice (road, rail and waterways) and presented sustainable policies that could increase the competitiveness of the region. The results suggested that increasing the reliability of intermodal alternatives is more effective in encouraging intermodality than cost reduction.

Kundu and Sheu (2019) presented a competition model based on the game-theory to examine the effects of subsidy on shippers' mode preferences and switching behaviour from maritime to rail mode. The results indicated that offering subsidies based on shipper types seems to be the best response strategy to increase the use of rail-road. Li and Zhang (2020) proposed the model for jointly optimising railway freight prices and operation plan in the presence of government subsidy for rail operators. The results indicate that combining the use of dynamic pricing with subsidy scheme for rail operator can reduce CO_2 emissions by up to 26.12%. It should be noted that although these studies considered the effects of government subsidy schemes to promote a certain transport mode particularly rail, none of them have taken into account any regional subsidy scheme towards shifting cargo traffic from metropolitan to regional area.

The following aspects distinguish this paper from previous studies. First, we consider a multi-modal transport system, including airfreight and ground distribution, using an open vehicle routing optimisation model to solve the airfreight distribution problem in the presence of regional subsidy schemes. Second, we explore the impact of different regional financial support schemes on the structure of the transport network and the cargo flows in the network. In sum, our model seeks to minimise airfreight costs, ground distribution costs and penalties as a result of time-window violations at the consignees' locations. The real-world case study presented in this paper can generate significant insights for policy makers to design appropriate regional subsidy schemes to achieve reduction in cargo traffic at metropolitan areas without substantially increasing compliance costs for the cargo industries.

2.3 A framework for subsidy schemes evaluation

Some governments across the world have launched regional subsidy schemes to encourage industries to use regional areas as distribution hubs with the dual aims of reducing cargo traffic volumes in metropolitan cities and developing regional areas. To examine the impact of different subsidy schemes on logistics decisions and economic costs, we propose a framework comprising an optimisation model and sensitivity analysis. First, we explain the different subsidy schemes that support regional areas. Second, we evaluate the implementation of subsidy schemes and investigate their effect on logistics decisions and economic costs. Finally, we conduct sensitivity analyses on the government subsidy limit and the subsidy value to determine the best value which can lead to the most benefits for the prospective industries and the economic development of the regional area.

2.3.1 Subsidy schemes

In this research, we consider different subsidy schemes to support the airfreight and ground transport industries in regional areas. We present the subsidies as forms of linear and multiple breakpoint functions. They are the most popular subsidy functions used in the existing literature (Lu and Shao, 2016; Liu et al., 2019; Chen et al., 2019). The subsidy rates are treated as exogenous in this study because in reality once approved, they would not be changed in the short run given that government expenditures are constrained by the annual budget. We assume a subsidy rate of (ϑ_V) per kilogram of cargo distributed from a regional area by vehicles. We also assume a subsidy value for plane flights as follows: 1) a subsidy value for flights landing at a regional area expressed as a linear function with a subsidy rate of (ϑ_F) per kilogram of cargo; 2) a subsidy value for flights based on a multiple breakpoint function. The multiple breakpoint subsidy function $g_h(o_m)$ is formulated as follows:

$$g_h(o_m) = \begin{cases} \vartheta_1 + r_1(o_m - L_1), & L_1 \leq o_m \leq U_1 \\ \vartheta_2 + r_2(o_m - L_2), & L_2 = U_1 \leq o_m \leq U_2 \\ \vdots & \\ \vartheta_h + r_h(o_m - L_h), & L_h = U_{(h-1)} \leq o_m \leq U_h \end{cases} \tag{2.1}$$

where r_i is the slope (subsidy rate) when the quantity of cargo carried by a flight is between L_i and U_i, and h means that there are h line segments in $g_h(o_m)$. The slope of the function is assumed to gradually decrease by the cargo flow as it is logical from the perspective of a government which has a limited budget. A baseline scenario and two subsidy scenarios are summarised as follows:

- Baseline: no subsidy for vehicles dispatched from a regional area, and no subsidy for flights landing in this area.
- Scenario 1: the implementation of a linear subsidy function for vehicles dispatched from a regional area, and the implementation of a linear subsidy function for flights landing at a regional area.
- Scenario 2: the implementation of a linear subsidy function for vehicles dispatched from a regional area, and the implementation of a multiple breakpoint subsidy function for flights landing at a regional area.

2.3.2 Optimisation model

In this section we present an optimisation model to evaluate the effect of different subsidy scenarios on the network structure and the economic costs. Our research focuses on an airfreight distribution problem which incorporates the choice of the best options within the various route configurations in the presence of subsidy schemes to minimise costs and adhere to delivery times. The research considers international airfreight distribution in which cargo is shipped from an origin airport to destination airports (regional or metropolitan) and then distributed to consignees through forwarder warehouses. Minimum load ($minload$) and maximum load ($maxload$) are assumed for the aircraft. Once the cargo is at the destination airports, it is stored in cargo terminals and pelletised before being released for delivery to the forwarders' warehouses. As these operations are time consuming and depend on the volume of cargo traffic at the airports, we define a release-time (R_{Ai}) at each airport i. The cargo then has to be transported to the forwarders' warehouses.

A forwarders warehouse is the point where the cargo is held temporarily for customs clearance and tagging and sorting for the consignees. A release-time (R_F) is assumed for each forwarder warehouse. Heterogeneous vehicles with a maximum capacity (C_K) are assumed for ground distribution from destination airports to consignees. In the proposed model the vehicles do not return to the beginning points as a result of an outsourcing strategy. The transportation cost comprises a fixed cost component (F_K) when the vehicle is used and a variable cost component that is a function of travel distance, load, speed and vehicle characteristics. Each consignee i is served by only one vehicle and split delivery is not allowed. The cycle of planning is assumed to be equal to the maximum number of flights (TM) required between the originating and destination airports.

Each consignee j has a certain demand (Q_j) which needs to be delivered during a soft time-window indicated by $[E_i, T_i]$. Due to the fact that each consignee is assumed to be a distribution centre with limited resources, including manpower, unloading cargo at a consignee's location needs to be prearranged and conducted during the window period. Therefore, if a vehicle arrives at the consignee's location before E_i, it needs to wait. However, late arrival at the consignee's location, say after T_i, is penalised by (π). The aim of the model is to determine the optimal routes and cargo volume flow in each route in order to minimise the operational costs and to respect delivery times. A simple configuration of the proposed network is shown in Figure 2-1.

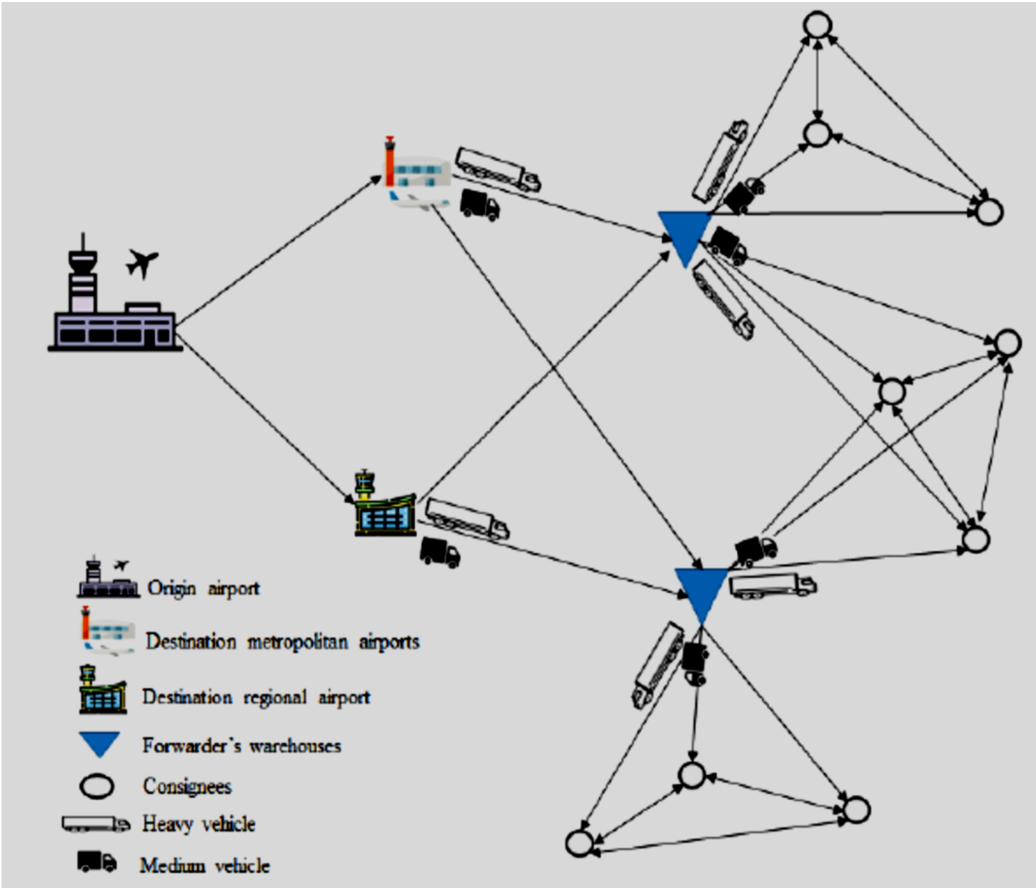


Figure 2-1:A simple schematic diagram of the proposed network

The proposed problem is defined as a directed graph $G = (\nu, E)$, where ν is the set of nodes and E is the set of arcs. The set of nodes comprises 0 representing an origin airport, N_A represents the set of destination airports at metropolitan (N_{A1}) and regional (N_{A2}) areas ($N_A \in N_{A1} \cup N_{A2}$), N_F represents the set of forwarder warehouses, and N_C is the set of consignees, $\nu \in N_A \cup N_F \cup N_C \cup \{0\}$. The arc set E represents the available links between nodes. In the proposed model we define an origin route as a vehicle starting from a destination airport, finishing its trip either at a forwarder's warehouse or at its last consignee location. A sub-route starts from a forwarder's warehouse which has been visited by an origin route, visits a set of consignees and ends at its last consignee location. We consider N_T as total number of nodes and $\{N_T + 1\}$ as a dummy point for modelling purposes. Without loss of generality, we assume that we have access to an unlimited number of heavy and medium duty vehicles for ground distribution. The notations used to develop the mathematical formulation are defined in Appendix A (see Tables A-1, A-2 and A-3).

2.3.3 Fuel consumption

We utilise the same method as Bektaş and Laporte (2011) and Babagolzadeh et al. (2020) to estimate fuel consumption of the vehicle FC_k. The fuel consumption over distance D_{ij} at a constant speed can be estimated as follows:

$$FC_k = \Gamma(\frac{\mu_\kappa D_{ij}}{speed} + \beta_\kappa D_{ij}(speed)^2 + (W_\kappa + TW_\kappa)\gamma D_{ij} \qquad (2.2)$$

where $\Gamma = \tau / \phi\psi$, $\mu_k = \Phi_k N_k \iota_k$, $\gamma = 1/(1000\zeta\omega)(G \sin\theta + GC_e \cos\theta)$, β_k= $(0.5Cd_k \rho A_k)/(1000\zeta\omega)$. $(W_k + TW_k)$ denotes the total vehicle weight *(kg)*, including the sum of curb weight and payload. Expression (2.2) comprises three terms: the first term is called the *engine-module* which is linear with travel time; the second term is called the *speed-module* in which the speed takes a quadratic form; and the last term is referred to as the *weight-module* which is independent of the vehicle speed.

2.3.4 Model under subsidy scenario 1

In this section the subsidy rate per kilogram of cargo ϑ_F is assumed to calculate the subsidy value granted for a flight landing at a regional airport. The proposed model (z_L) is defined as follows:

$$\min z_L = ATC - TSI + GTC + PC \qquad (2.3)$$

Expression (2.3) refers to the objective function which comprises four parts: air transport cost *(ATC)*, total subsidy income *(TSI)*, ground transportation cost *(GTC)* and penalty cost *(PC)*. These parts are discussed as follows:

Air transport cost

The air transport cost *(ATC)* includes the landing costs and the variable costs of operating the aircraft and are presented as follows:

$$ATC = \sum_{m} \sum_{i \in N_A} \left(\sum_{j \in N_F} \sum_{\kappa} f_{ij\kappa m} CL_i + D_{0i} A y_{im} \right) \qquad (2.3.i)$$

The first part of function (2.3.i) presents the landing cost at the destination airports and the second part of the function computes the variable cost (fuel cost) of the aircraft.

Total subsidy income

The total subsidy income is the minimum of both the total subsidy value granted by the government for cargo distribution and the government subsidy limit. In the proposed model z_L, we consider a subsidy value for a flight as a linear function with a subsidy rate per kilogram of cargo ϑ_F. The total subsidy income is linked to the subsidy scenario 1 and the government subsidy limit by constraints (2.45) and (2.46). The total subsidy income is formulated as follows:

$$TSI = ms \tag{2.3.ii}$$

Ground transport cost

The ground transport cost (GTC) comprises the vehicles' fixed costs, the vehicles' variable costs (fuel cost) and the driver costs. It is formulated as follows:

$$\begin{aligned}GTC = \sum_{m}\sum_{\kappa}\Bigg(\sum_{i\in N_A}\sum_{j\in N_F} F_\kappa x_{ij\kappa m} \\ + \phi_F \Gamma \sum_{i\in N_A\cup N_F\cup N_C}\ \sum_{j\in N_F\cup N_C, j\neq i} x_{ij\kappa m} D_{ij}\Big(\frac{\mu_\kappa}{S_R} + W_\kappa \gamma + \beta_\kappa S_R^2\Big)\Bigg) + \\ \sum_{m}\sum_{\kappa}\Bigg(\sum_{i\in N_F}\sum_{j\in N_C} F_\kappa z_{ij\kappa m} + \phi_F \Gamma \sum_{i\in N_F\cup N_C}\ \sum_{j\in N_C, j\neq i} z_{ij\kappa m} D_{ij}\left(\frac{\mu_\kappa}{S_R} + W_\kappa \gamma + \beta_\kappa S_R^2\right)\Bigg) \\ + \\ +\phi_F \Gamma \sum_{m}\sum_{\kappa}\sum_{i\in N_A\cup N_F\cup N_C}\ \sum_{j\in N_F\cup N_C, j\neq i} av_{ij\kappa m}\gamma + \sum_{m}\sum_{\kappa}(wc_{\kappa m}^{o} + wc_{\kappa m}^{s})\end{aligned} \tag{2.3.iii}$$

Parts 1 and 2 in function (2.3.iii) represent the vehicles' fixed costs and the variable costs (fuel cost) of the vehicles on their origin routes. Parts 3 and 4 of function (2.3.iii) compute a vehicles' fixed cost and the variable costs (fuel cost) of the vehicles on sub-routes. Part 5 of function (2.3.iii) considers a vehicle's load in the transportation costs on routes. The last part of function (2.3.iii) is related to driver costs. In this function the variable cost is dependent on speed, load, travel distance and the vehicle's characteristics. Note that transportation costs are linked to the vehicle's load by auxiliary variables av_{ijkm} and constraint set (2.47).

The driver salary costs on the origin routes are linked to the departure time of vehicles from the last node of the origin routes and the departure time of the vehicles from a destination airport by constraint set (2.48). The driver salary costs are linked to the departure time of vehicles from the last node of sub-routes and the departure time of the vehicles from the first node of sub-routes (the forwarder's warehouse) by constraint set (2.49). Note that the departure time of a vehicle from the dummy point is equal to the departure time of the vehicle from the last node on its trip.

Penalty cost

The penalty cost *(PC)* is considered in the proposed model when the time-window constraint is violated at each consignee's location. It is modelled as follows:

$$PC = \sum_{i \in N_C} p_i \tag{2.3.iv}$$

Each consignee i must be visited during a soft time-window indicated by $[E_i, T_i]$. A penalty applies if a vehicle arrives at consignee's location after T_i. The penalty cost is calculated at a consignee's location by constraint set (2.44).

The constraints are explained and discussed in Appendix B.

Similarly, we construct a model (z_B) assuming that the subsidy is treated as a multiple breakpoint function for airfreight arriving at a regional airport. The objective of model (z_B) is the same as model (z_L). However, we add new constraints to model (z_B). The details of model (z_B) are presented in Appendix C.

2.4 Computational results

The aim of this section is threefold: 1) to demonstrate the application of the models formulated in Section 2.3 using a real-world case study in Australia; 2) to explore the impact of introducing different regional subsidy scenarios on operational decisions; and 3) to conduct sensitivity analyses on some parameters. We used a real-world case study related to importing airfreight to Australia due to the high volume of cargo and the high operation costs at metropolitan airports in this country. The case study description is presented in Section 2.4.1. Section 2.4.2 presents the results of implementing the framework proposed in the real-world case study under the different subsidy scenarios. The sensitivity analyses on the government subsidy limit and subsidy value are conducted in Section 2.4.3.

2.4.1 Description of the case study

The use of decision support tools for minimising the operational costs and the waiting times for cargo at metropolitan airports in Australia can be justified due to the high volume of airfreight at those airports and the long queues for cargo handling too. Our research is motivated by a new strategy adopted by the Australian government to use regional airports, which usually have underused capacity as distribution hubs, in order to reduce the operational costs and the waiting times for cargo at metropolitan airports and to develop regional areas.

In this study we use a regional international airport, officially known as the Brisbane West Wellcamp Airport (BWWA) (hereafter referred to as the Toowoomba Airport) as an example. This airport is located in Toowoomba in Queensland, the largest non-capital inland city in Australia. Toowoomba Airport was put into commercial use in November 2014 as a gateway for importing cargo from China to Australia in order to reduce the operational costs and the high volume of cargo at Sydney's international airport. Toowoomba is 120 km west of Brisbane, the capital city of Queensland. Toowoomba was identified by Australian agencies and transport industry as a major hub for importing and exporting freight due to its strategic location and excellent transport connectivity (Zhang and Woodhead, 2016). We examine how regional subsidy schemes can promote the use of this regional airport.

China is Australia's largest trading partner. Cathy Cargo Pacific operates regular cargo flights between Hong Kong and Toowoomba, so we consider Hong Kong as the main shipper. We assume Sydney's international airport and Toowoomba Airport are the importing hubs in our model. The cargo is first stored in the airport cargo terminals before it is released to forwarders for distributions. For illustration purposes, we consider a real-world distribution network containing four consignees who are located in three mainland capital cities, namely Sydney, Melbourne and Brisbane.

The distance between the nodes is calculated using Google Maps. Table 2-1 reports the demand of each consignee (Q_j), service time (ST_i) at each node and the latest time of starting services at each consignee's location T_i. The time-window violation cost is assumed to be AUD 0.03/s at each consignee's location. The release-times at Sydney International Airport and Toowoomba Airport are assumed to be 6 hours and 2 hours, respectively. As customs clearance and tagging operations are completed in the forwarder's warehouses, we assume a release-time of 1.5 hours at the forwarder's warehouse.

Table 2-1:Demand, service time and the latest time of starting services

Parameters	Consignees			
	1	2	3	4
Demand (Q_i) kg	6500	7500	9000	8500
Service time (ST_i) s	1950	2250	27000	2550
The latest time of starting services T_i	68000	105000	100000	107000

We assume a Boeing 747 aircraft is used for the movement of cargo from Hong Kong to Australia, and we consider its minimum capacity (*Minload*) to be 15 tons and its maximum capacity (*Maxload*) to be 90 tons. As we test the framework provided in Section 3 for the small real-world example, we assume a one-third use of the aircraft's capacity, i.e., *Minload* = 5 tons and *Maxload* = 30 tons. Consequently, in this example we consider the total aircraft fuel cost to be 30% of the air transportation cost. The fuel cost for this aircraft is assumed to be *AUD 6/km*: a Boeing 747 consumes 12 *L/km* while 1*L* of jet fuel is costed at *AUD* 0.50 (Administration, 2019). The landing costs at Sydney International Airport and at Toowoomba Airport are assumed to be *AUD* 20 and *AUD*12 per tons of cargo, respectively, based on our discussion with air transport industry professionals. The flight time from Hong Kong to Sydney International Airport and to Toowoomba Airport are assumed to be 9 hours and 32 minutes and 9 hours, respectively. A heterogeneous vehicle fleet is assumed to be used for cargo distribution from the airports. We consider an unlimited number of two different vehicle types – heavy and medium duty – for the distribution operation. As the data regarding the characteristics of vehicles are not available, the parameters used to calculate the fuel cost of each type of vehicle are taken from previous research and are summarised in Tables 2-2 and 2-3. The average speed is assumed to be 80 *km/h* for both types of vehicles.

Table 2-2:Definition of vehicle specific parameters

Notation	Description	Medium duty	Heavy duty
W_κ	Curb weight	6328	14000
C_κ	The capacity of vehicle	17000	24000
F_κ	Fixed cost of vehicle	97.53	154.43
Φ_κ	Engine friction factor	0.2	0.15
N_κ	Engine speed	36.67	30
ι_κ	Engine displacement	6.9	10.5
$C_{d\kappa}$	Coefficient of aerodynamics drag	0.7	0.9
A_κ	Frontal surface area	8	10

Source: Koç et al. (2014) and Cheng et al., (2017),1 Pound(£)=1.63 AUD dollars (04 Oct 2019)

Table 2-3:Definition of vehicle typical parameters

Notation	Description	Value
τ	Fuel-to-air mass ratio	1
G	Gravitational constant	9.81
ρ	Air density	1.2041
C_e	Coefficient of rolling resistance	0.01
ω	Efficiency parameter for diesel engines	0.45

ϕ_F	Unit fuel cost	1.46
φ	Heating value of a typical diesel fuel	44
ψ	Conversion factor	737
ζ	Vehicle drive train efficiency	0.45
F_d	Driver salary	0.0055

Source: Koç et al. (2014) and Cheng et al. (2017)

As the data related to subsidy schemes are not available in Australia, we use subsidy rates offered by Zhengzhou Airport in China for cargo distribution. One of the authors visited Zhengzhou Airport and acquired the first-hand freight subsidy information which is applied in our case study. The subsidy rate per kilogram of cargo distributed from Toowoomba Airport to the forwarder's warehouse by vehicles is assumed to be ϑ_V = AUD 0.09 based on the case of Zhengzhou Airport. We also assume that the government subsidy limit is AUD 20,000. In the first scenario, we assume a linear subsidy function for flights landing at the Toowoomba Airport with a subsidy rate of $\vartheta_F = AUD\ 0.55/kg$. However, under the second scenario we consider a multiple breakpoint subsidy function with two segments: flights with cargo load ranges of 22,000 kg or higher and of 15,000 - 22,000 kg. The data related to this function is summarised as follows:

$$g_h(o_m) = \begin{cases} 6000 + 1.286(o_m - 15000), & 15000 \le o_m \le 22000 \\ 15000 + 1(o_m - 22000), & 22000 \le o_m \le 30000 \end{cases} \quad (2.4)$$

2.4.2 Computational experiments and analysis

In this section an application of the framework proposed in Section 2.3 is presented by implementing the framework for the data of real-world example provided in Section 2.4.1.

We use the exact method to explore the effect of introduction of different regional subsidy schemes on logistics decisions in airfreight distribution. We attempt to show how the introduction of regional subsidy schemes can change cargo volumes at the regional level. To do so, we used a commercial optimisation solver (Cplex) which is based on branch and cut algorithms. All experiments were coded on an Intel i7 CPU with a 3.6 GHz processor and 16 GB RAM.

We focus on the following key performance indicators: (i) air transportation costs that consist of landing costs and the aircraft's fuel cost; (ii) subsidy incomes that include the subsidy achieved from landing flights at the regional airport and the subsidy granted for vehicles dispatched from the regional airport; (iii) ground transportation costs that consist of fixed costs, fuel costs and driver costs; and (iv) penalty costs as a result of time-window violations. The results are used to compare the effect of two different subsidy scenarios to identify the most effective scenarios. We also present the results of the framework under the baseline scenario and compare this with the two subsidy scenarios to investigate the effect of introducing subsidies on the network structure. Finally, sensitivity analyses are performed on the government subsidy limit and the subsidy value to determine the best value which can lead to a better performance of the proposed framework.

We report the optimal network structure and the optimal values of the objective functions under the baseline scenario in Table 2-4 and Figure 2-2, respectively. Two aircraft are used to transport cargo from Hong Kong to Australia in the optimal solution, which means that there are two planning cycles ($m = 2$). The optimal solution under the baseline scenario includes an origin route and a sub-route which are traversed by heavy and medium duty vehicles, respectively, in the first planning cycle and which contains an origin route that uses a medium duty vehicle to distribute cargo in the second planning cycle. In the first planning cycle of the optimal solution the capacity utilisation of the heavy duty vehicle is 100% at the beginning of the origin route, but it decreases to 70.83% after visiting the forwarder's warehouse. The capacity utilisation of the medium duty vehicle is 38.23% on the sub-route in the first planning cycle and is 44.11% on the origin route in the second planning cycle. As can be observed from the results, the metropolitan airport is selected as the only distribution hub under the baseline scenario and this choice can easily meet the time-window requirement with less ground transportation needed.

Table 2-4:Optimal values of the objective functions under the baseline scenario in AUD

Air transportation		Ground transportation			Penalty costs	Subsidy incomes	Total costs
Fuel cost	Landing cost	Fuel cost	Fixed cost	Driver cost			
26535.60	630	2146	349.49	706.21	104.16	0	30471.46

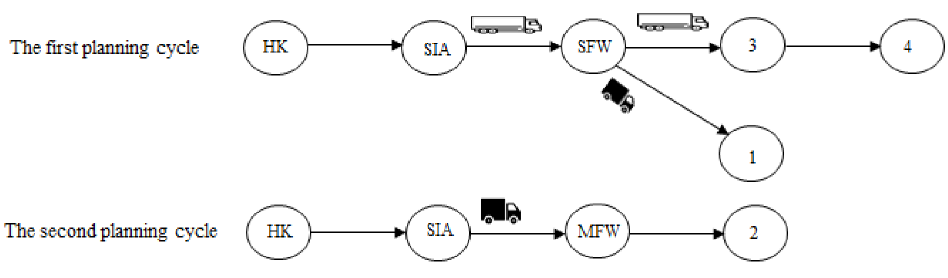
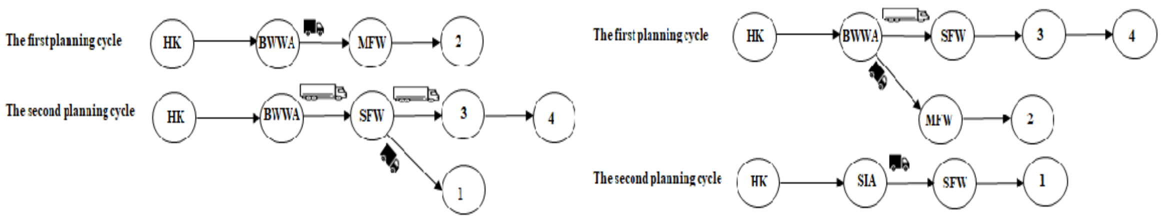


Figure 2-2: Unique view of optimal routes under the baseline scenario (HK: Hong Kong, SIA: Sydney International Airport, SFW: Sydney Forwarder Warehouse, MFW: Melbourne Forwarder Warehouse)

To evaluate the behaviour of the framework under the two subsidy scenarios presented in Section 2.3.1, we implemented the framework under the two scenarios for the real-world example and compared the results of these scenarios together and with those obtained from the baseline scenario. The optimal configuration of the network and the optimal values of objective function of the model under two subsidy scenarios are reported in Table 2-5 and Figure 2-3, respectively.

Table 2-5:Optimal values of the objective functions under the baseline scenario in AUD

	Air transportation		Ground transportation			Penalty costs	Subsidy incomes	Total costs
	Fuel cost	Landing cost	Fuel cost	Fixed cost	Driver cost			
Subsidy scenario 1	24724.80	378	4024.52	349.49	1087.57	5457.38	20000	16021.76
Subsidy scenario 2	25630.20	430	3924.55	349.49	1128.49	4091.93	20000	15554.66



(a) Subsidy scenario 1 (b) Subsidy scenario 2

Figure 2-3:Unique view of optimal routes under two subsidy scenarios

As can be seen from the results, the regional airport is selected as the only distribution hub under subsidy scenario 1, while a combination of the regional and metropolitan airports is used for distributing cargo under subsidy scenario 2. The regional airport is still the main distribution hub under subsidy scenario 2 as a significant volume of cargo is sent to this airport for distribution. Tables 2-4 and 2-5 demonstrate that introducing subsidy schemes provides more benefits in reducing the total costs from the perspective of the industries involved in the cargo distribution. Compared to the baseline scenario, the introduction of subsidies in scenarios 1 and 2 can decrease the total operating cost by 47.42% and 48.95%, respectively. Under subsidy scenarios 1 and 2 the air transportation costs, including the aircraft's fuel costs and landing costs, decrease by 7.59% and 4.07%, respectively, compared with those in the baseline scenario, while the ground transportation costs and the penalty costs increase significantly in both subsidy scenarios.

The results suggest that subsidy scenario 2 is more desirable from the economics and delivery time points of view. However, subsidy scenario 1 is preferred for reducing the volume of cargo traffic at the metropolitan airport and increasing it at the regional airport. It can be seen that subsidy scenario 1 can reduce air transportation costs by almost 3.67% compared with that obtained under subsidy scenario 2. However, it leads to 1.09% higher ground transportation costs. In summary, although all of the cost savings come at the cost of government subsidies, if the goals are to develop regional economies and to increase regional airport connectivity, then subsidy scenario 1 can generate a more desirable outcome as the regional airport is selected as only distribution hub.

2.4.3 Sensitivity analysis

This section analyses the impact of changing parameters on the total cost, subsidy income and volume of cargo traffic at metropolitan and regional airports in Australia. We perform sensitivity analyses with changes in the government subsidy limit and the subsidy values.

2.4.3.1 Impact of changes in the government subsidy limit under the two subsidy scenarios

In this section we investigate the effect of changes in the government subsidy limit on the total cost and the volume of cargo traffic at the regional airport. According to the results, the reduction in the total cost is driven exclusively by granting subsidies and partially offset by a decrease in air transportation costs. Figure 2-4 indicates that an increase in the government subsidy limit can lead to a reduction in the total cost and an increase in the volume of cargo traffic at a regional airport to the point where the government subsidy limit is relaxed (i.e., Budget>20160 under scenario 1 and Budget>20250 under scenario 2 in our example) and thereafter further changes in this parameter do not impact on the optimal solution.

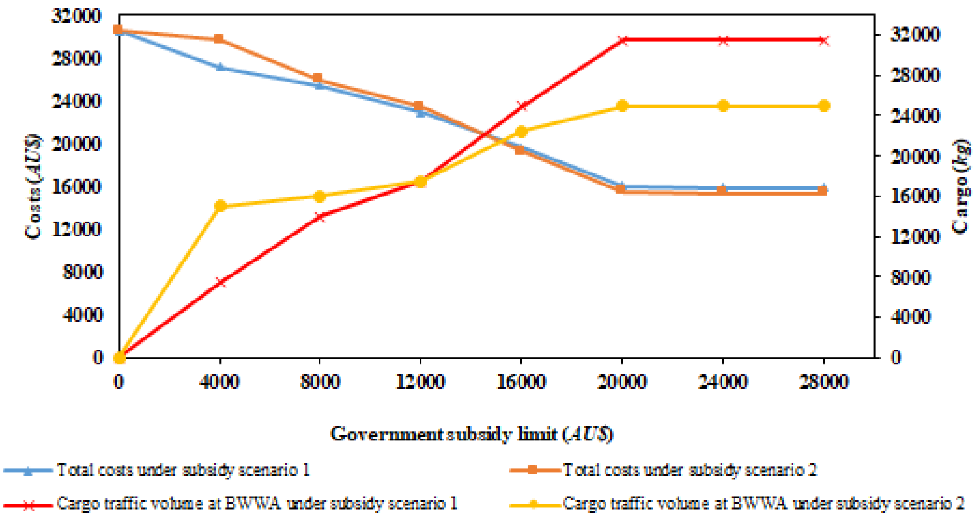


Figure 2-4:Impact of government subsidy limit on the total cost and cargo traffic at Toowoomba Airport under two subsidy scenarios

As can be seen from Figure 2-4, if there is no opportunity to introduce regional subsidies (Budget=0) then the transport industry would incur the maximum of the total cost for cargo distribution. In our example, with the increase of the government subsidy limit from *AUD* 0 to *AUD* 4000, subsidy scenario 1 provides a better result from the total cost reduction perspective. It can lead to further reduction in total costs of 308.17% compared with that obtained under subsidy scenario 2. However, in terms of the volume of cargo traffic, much more cargo is shifted to the regional airport under subsidy scenario 2. Thus, changes in the government subsidy limit can lead to a reduction of 23.8% and 47.6% in the volume of cargo traffic at the metropolitan airport under subsidy scenarios 1 and 2, respectively.

It can be observed that extending the government subsidy limit from *AUD* 4000 to *AUD* 12000 under subsidy scenario 2 can lead to an increase in subsidy income of 169.3%, but it does not have a significant effect in shifting the cargo traffic from the metropolitan airport to the regional airport. That is, only 15.1% of the volume of cargo traffic would be shifted to the regional airport. Further increases in the government subsidy limit, say, from *AUD* 12000 to *AUD* 20000 can decrease total costs by 30.08% and 33.5% under subsidy scenarios 1 and 2, respectively. It can also lead to an increase of 42.85% cargo traffic at the regional airport under subsidy scenario 2, while the increase in cargo traffic is 80% under subsidy scenario 1

2.4.3.2 Impact of changes in subsidy rate under subsidy scenario 1

This section analyses the impact of subsidy value changes on the total cost and the volume of cargo traffic at the regional airport under subsidy scenario 1. Figure 2-5 indicates that overall the total cost trend experiences a decreasing pattern with the increase in the value of the subsidy rate under scenario 1, while the volume of cargo traffic at Toowoomba Airport does not change linearly. If subsidy scheme was not considered for the regional area (subsidy value = 0), Toowoomba Airport would not be selected as a distribution hub as the industries involved in cargo distribution would incur the maximum level of the total cost. The results also indicate that a continued increase in the subsidy rate does not always lead to an increased volume of cargo traffic at Toowoomba Airport due to the government subsidy limit.

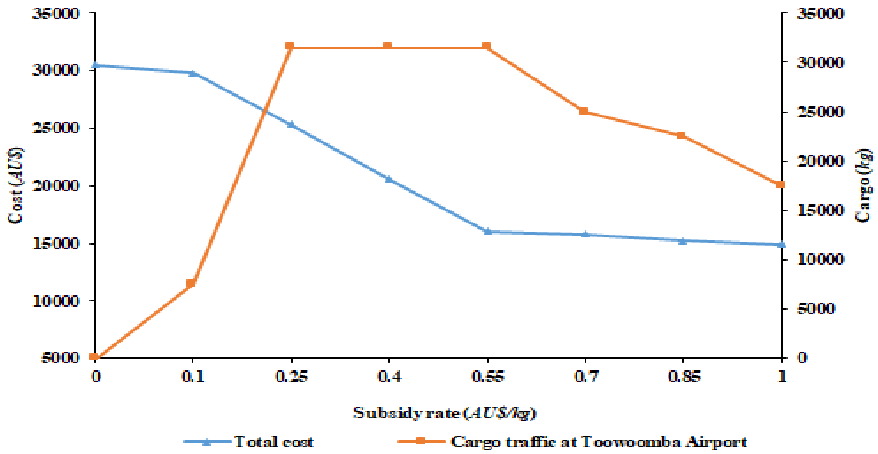


Figure 2-5:Impact of changing in subsidy rate on the total cost and cargo traffic at Toowoomba Airport under scenario 1

As can be seen from Figure 2.5, the increase of the subsidy rate from *AUD* 0 *to AUD* 0.25 per kilogram decreases the total cost by 16.9% and a considerable growth in cargo traffic is achieved at Toowoomba Airport. A further increase in the subsidy rate from *AUD* 0.25 to *AUD* 0.55 per kilogram does not lead to additional growth in the traffic at Toowoomba Airport. It can only provide a significant reduction in the total cost by 36.7%. It can be observed that with the continued increase of subsidy rate from *AUD* 0.55 to *AUD* 1 per kilogram decreases the volume of cargo traffic at Toowoomba Airport by 44.44% because of the constraint of the government subsidy limit, while the total cost decreases by only 6.9%.

2.4.3.3 The impact of changes in the subsidy rate under subsidy scenario 2

In terms of the total cost and the volume of cargo traffic at the regional airport, the results of the sensitivity analysis on the value of the subsidy rate under subsidy scenario 2 are reported in Figure 2-6. With a reduction of 60% to 80% in the subsidy rate in the multiple breakpoint function, the volume of cargo traffic at Toowoomba Airport remains unchanged (at the maximum level), but it leads to an increase of 1.82%

in the total cost as a result of the decrease in the subsidy value granted by the government. Decreasing the subsidy rate from 40% to 60% results in a considerable growth in the volume of cargo traffic at the regional airport, with only a 4.79% increase in the total cost.

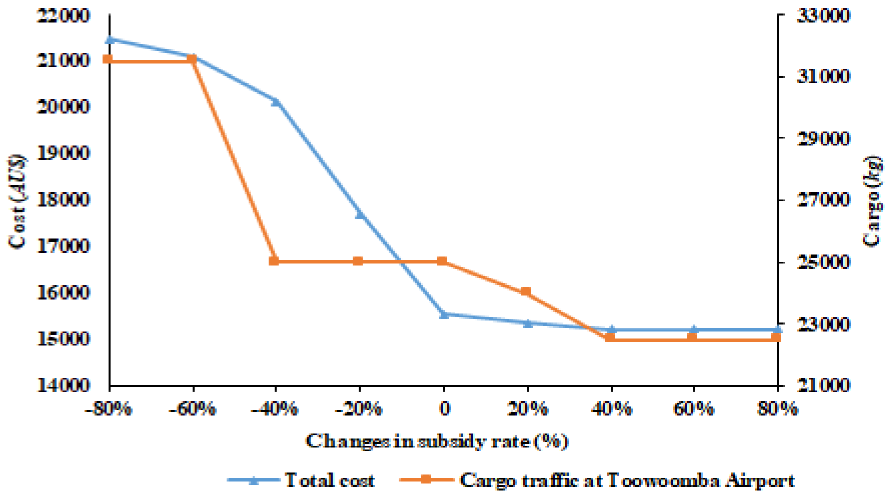


Figure 2-6:Impact of changing subsidy rate on the total cost and cargo traffic at Toowoomba Airport under scenario 2

As can be seen from the results, decreasing the subsidy rates by up to 40% does not have any impact on the volume of cargo traffic at the regional airport, while it can lead to an increase in the total cost by 29.4% . In contrast to the significant impact of reducing subsidy rates on the total cost, an increase in subsidy rates in this case does not lead to a considerable improvement in the volume of cargo traffic and the total cost. For instance, an increase in the subsidy rate of up to 40% can lead to a less than 2.2% improvement in the total cost, while it decreases the volume of cargo traffic at Toowoomba Airport by around 10%. As can be observed, a further increase in the subsidy rate of up to 80% does not lead to additional operational modifications towards system improvements as a result of the government subsidy limit. The results suggest that, in this case, lower subsidy rates are more beneficial in terms of increasing the volume of cargo traffic at Toowoomba Airport and of decreasing the government's expense in granting the subsidies. However, it would not be a cost-efficient decision from the perspective of the industries involved in distributing the cargo.

2.5 Managerial insights

The proposed framework in this research provides valuable insights into the possible solutions to the congestion problem at metropolitan airports and underutilisation problem at regional airports. Specifically, this research can help policy makers to design proper regional subsidy schemes that can be used to shift cargo traffic from metropolitan airports to regional airports without significantly increasing economic costs for cargo industries. As subsidy schemes will also impose a financial burden on the government, the effectiveness of subsidy schemes must be evaluated with assistance of the framework proposed in this research before implementation.

The results obtained from the case study demonstrate that the cargo industries might be willing to use the regional airport as a distribution hub in the presence of regional subsidy schemes. This can lead to significant reduction in the volume of cargo traffic at the metropolitan airport and increasing in the efficiency of cargo distribution. The introduction of regional subsidy schemes can reduce total cost from the prospective of cargo industries. For example, in our case study, the introduction of subsidy schemes can reduce the operation costs by up to 48.98% for cargo industries compared with the situation without subsidies.

A regional subsidy scheme cannot be an optimal for all purposes. In our case study, we observed that the introduction of regional subsidy scheme in the form of non-linear function is more desirable from economic costs and delivery time perspectives. However, regional subsidy scheme under linear function can generate a more desirable outcome if our goals are to reduce the volume of cargo traffic at the metropolitan airport and to promote the regional airport. Therefore, it is critical to evaluate the effectiveness of the subsidy schemes for the intended goals before they are implemented.

The results indicated that increasing the volume of cargo traffic at a regional airport under subsidy scenario 1 is almost linear with an increase in the government subsidy budget cap, while it increases at different rates under subsidy scenario 2. Hence, it is important for policy makers to determine an appropriate government subsidy budget cap in such a way that it can motivate cargo industries to use regional airport without imposing an excessive financial burden on the government.

2.6 Summary

Since the airfreight sector is one of the largest value contributors to Australia’s international trade, the major metropolitan airports in Australia have become increasingly congested resulting in substantial increases in operational costs and waiting times at these airports. As such, decisions that focus on shifting a considerable volume of airfreight traffic to regional airports are significant considerations for airport management and all levels of government in Australia. Shifting airfreight traffic from metropolitan airports will not only reduce the length of time that cargo is held at airports, but it can also help to promote regional airports, which should result in regional economic development. Hence, to encourage the industries involved in cargo distribution to use regional airports as distribution hubs, the Australian government has introduced subsidy schemes. Using regional airports as distribution hubs through the subsidy schemes results in increased efficiency at metropolitan airports and promotes regional airports, but it may lead to an increase in ground transportation costs and the time required because most of the consignees are located closer to metropolitan areas.

This chapter has presented a mixed integer linear programming model that accounts for the time-window and release-time constraints. The model seeks to explore how different government subsidy schemes influence freight distribution that favours the use of regional airports and promotes regional economic development, with a consideration of the optimal ground distribution network from those airports to the consignees. The proposed model considers subsidy schemes as linear and non-linear functions. The model simultaneously considers the government subsidy limit and the heterogeneous fleet for ground distribution where fuel consumption is subject to load, travel distance, speed and vehicle characteristics. The aim of the model is to minimise airfreight costs, ground transportation costs and penalty costs as a result of time-window violations.

To evaluate the performance of the proposed framework, a real-world case study in Australia was investigated to demonstrate how the proposed model could be used as a decision support tool to assist policy makers to develop optimal subsidy schemes. The computational experiments illustrated that metropolitan airports can be used as distribution hubs without introducing any subsidy schemes as this choice needs less ground transportation to distribute the cargo to the consignees. We observed that it would be possible to decrease airfreight costs by 7.59% and 4.07% by introducing the subsidy scenarios 1 and 2, respectively. However, this can lead to a significant increase in ground transportation costs and penalty costs. The results indicated that subsidy scenario 1 has a better performance in shifting cargo traffic from a metropolitan airport to a regional airport, while subsidy scenario 2 is recommended in terms of cost efficiency and delivery time

We conducted sensitivity analyses on the government subsidy limit and the subsidy values to provide meaningful insights for policy makers to make the best decisions to improve the efficiency of cargo distribution. We observed that increasing the volume of cargo traffic at a regional airport under subsidy scenario 1 is almost linear with an increase in the government subsidy limit, while it increases at different rates under subsidy scenario 2. Therefore, policy makers can seek advantages from the proposed framework to determine an appropriate government subsidy limit. Our analysis on the subsidy rate identified that an increase in the subsidy rates does not always result in a considerable improvement because of the government subsidy limit. Moreover, our experiments indicated that a reduction of about 54% and 60% in the subsidy rates in scenarios 1 and 2 would provide better performances, respectively, in terms of increasing the volume of cargo traffic at a regional airport and in promoting regional economic development. This finding may have significant value for policy makers who may be introducing airfreight subsidy schemes.

Chapter 3: Sustainable cold supply chain management under demand uncertainty and carbon tax regulation

3.1 Introduction

Increasing human awareness of environmental impacts has encouraged researchers to make greater efforts toward improving sustainability during the operations of supply chain (Zhu et al., 2008). As a result, there has been a growing body of literature on the area of sustainable supply chain management since 2000 (see, for example, Mota et al. (2015); Sheu et al. (2005)). Researchers have been working on a wide range of topics that can influence sustainable supply chain. The efficient use of energy and environmental impact are two examples. These issues are also of great concerns to many supply chain participants and operators. One of the main challenges in the area of environmental sustainability relates to carbon and other greenhouse gases (GHG) emissions from supply chain activities. According to a recent survey, transportation and storage are main drivers of environmental issues in supply chains (Fichtinger et al., 2015).

The transportation sector is one of the major contributors to the GHG emissions. GHG emissions from this sector accounted for 27% of total US emissions in 2013 (United States Environmental Protection Agency, 2014) and 17% of Australia's total emissions (Australian Government, 2017). In Australia, transport costs are very high as a result of the long distances between widely spread production and consumption points in the country. The fuel cost accounts for 30% of the total costs during long distance road freight transport in Australia (MacGowan, 2010). Given the high freight volume and road length in Australia, government and industry have agreed on the need to manage the transportation sector efficiently to reduce energy consumption and consequently emissions (Australian Government, 2019). Since the transport sector plays a major role in generating GHG emissions, many countries often incorporate this sector in their sustainability initiatives in order to achieve emissions goals (Estrada-Flores, 2011; Zhang et al., 2004)

The handling, storing and transporting temperature-sensitive products involve consumption of large amount of energy and thus contribute to the increase in GHG emissions. Temperature-sensitive products are perishable products, that require cold facilities to maintain freshness and usability. Cold facilities, especially refrigeration, use a large amount of energy and therefore have significant environmental impacts (Gwanpua et al., 2015). The energy consumption of cold supply chains accounted for around 30% of total world energy consumption (Kayfeci et al., 2013). Refrigeration contributed to 15% of the electricity consumed worldwide (Coulomb, 2008). Cold storage has been recognized as one of the top 10 processes in the UK cold supply chain for energy saving potential (James et al., 2009). It is estimated that refrigeration uses around 178 *petajoule* of energy in the Australian cold supply chain, costing around *AUD* 2.6 billion each year (Jutsen et al., 2017). Jutsen et al. (2017) reported even a 1% reduction in refrigeration energy consumption in both stationary and truck refrigeration in the Australian cold supply chain can lead to around *AUD* 25 million reduction in annual energy cost in the cold supply chain. Saving this amount of energy can lead to a reduction in GHG emissions by 180,000 tonnes, which is worth more than *AUD* 2.1 millions (Jutsen et al., 2017).

Sustainability of supply chain cannot be substantiated without the help of proper incentives and public policies (Sheu, 2008, 2011). As a response to this challenge, legislations on minimising carbon emissions from firms' operations have been developed by many governments around the world (Mohammed et al., 2017). The carbon tax policy is a cost-effective way to curb carbon emissions which is highly recommended by many researchers and economists (Li et al., 2017; Oreskes, 2011; Zhang and Baranzini, 2004). Under carbon tax regulations, firms are charged a tax rate for a unit of carbon emitted (Rezaee et al., 2017). The main practical advantages of using carbon tax regulation over alternative emission regulations include: it may be more beneficial from the perspective of uncertainty (Wittneben, 2009; Zakeri et al., 2015); it is quicker to implement with less negative impact on economic growth (Lu et al., 2010) and needs lesser administration in its implementation (Ma et al., 2018); and it can also be modified easily when new information becomes available (Pearce, 1991). The carbon tax does not only benefit the environment but also all participants in the cold supply chain as a result of the reduction in high-cost energy consumption (Hariga et al., 2017; Tsai et al., 2017).

This chapter investigates the impacts of carbon emissions arising from storage and transportation in the cold supply chain in the presence of carbon tax regulation. The study also considers the impact of uncertain demand on the operational decisions associated with storage and transportation. We develop an optimisation model based on a two-stage stochastic programming to determine cost-efficient and environment-friendly replenishment policies and transportation schedules in which energy consumption and emissions are determined by load, distance, speed and vehicle characteristics. We present a matheuristic algorithm based on an Iterated Local Search algorithm and a mixed integer programming to solve the model in efficient computational time. The proposed model is also evaluated using a real-world case study in Queensland, Australia since the road length and high energy consumption of the cold supply chains are the two major challenging issues in this region.

The proposed model can help make decisions to minimise operational costs, including holding costs, transportation costs, energy costs and shortage costs as well as emission costs, taking into account the carbon tax regulation, uncertain demand and a heterogeneous fleet. To the best of our knowledge, no existing research has addressed replenishment policy and transportation schedules in an integrated model in a cold supply chain that considers demand uncertainty, carbon tax regulations and a heterogeneous fleet.

This research reveals that a heterogeneous fleet comprising light duty and medium duty vehicles[1] can provide a better balance between cost and emissions as compared to a homogeneous fleet, either light duty or medium duty vehicles. Moreover, we observed that carbon price plays a significant role in the successful implementation of carbon tax regulations. Therefore, it is critical for policy makers to determine an appropriate carbon price in such a way that the environmental improvement can be achieved without compromising economy.

The remainder of this chapter is organised as follows. In Section 3.2, the literature relevant for this research is reviewed. Section 3.3 presents a description of our model and assumptions. In Section 3.4, we formulate the proposed problem as a two-stage stochastic programming model. Section 3.5 presents the proposed matheuristic algorithm. The evaluation of the matheuristic algorithm, practical context and case study data are presented in Section 3.6. We also conduct sensitivity analyses and discuss findings and managerial implications in Section 3.6. Finally, Section 3.7 contains concluding remarks.

[1] In this research, two types of vehicle including light and medium duties vehicles were used for product distributions. The light duty vehicle has 258 units capacity with 3500 kg curb weight, while the medium duty one has 508 units capacity with 6550 kg curb weight (see Table 7)

3.2 Literature review

Recent research on cold supply chains concentrates on the effect of sustainability decisions on the performance of cold supply chains. James and James (2010) conducted a survey on cold supply chains to examine their impacts on climate change. The authors estimated that about 50% of total energy consumption in the food industry is related to cold facilities. Soysal et al. (2012) reviewed quantitative models in sustainable food logistics management. It has been found that apart from a few studies (.e.g Akkerman et al. (2009); Oglethorpe (2010)), there is a lack of advanced quantitative models that study sustainable food logistics management. Xu et al. (2015) reviewed the methods to reduce the carbon footprint at each stage of a food system from the perspective of technical, consumption behavior and environmental policies. They reported that improving management techniques and adopting advanced technologies are critical for every stage of a good food system. Carbon emissions can be substantially reduced with proper process control of carbon emissions and process optimisation.

Bozorgi et al. (2014) presented a new inventory model for a cold product with a capacitated refrigerated unit for both holding and transportation. The authors provided an excellent analysis of the trade-off between the objective functions, and found that the emissions function is more sensitive to deviation from optimality than the cost function. This model was extended in Bozorgi (2016) by introducing multiple types of cold product items and considering the compatibility of the items for sharing storage and transportation units. Distribution planning is one of the main activities in cold supply chains. Hu et al. (2017) addressed the problem of scheduling distribution of fresh products in a refrigerated vehicle and proposed a mixed integer programming model to reduce total transportation cost including routing, time penalty, cargo damage and refrigeration costs. Zhang and Chen (2014) presented an optimisation model involving delivering a variety of frozen products with the aim of achieving minimum delivery costs. They modified a genetic algorithm to solve the model and considered inside and outside temperatures to calculate refrigeration costs during the transportation process. However, the contribution of environmental impacts towards sustainability improvement of the cold supply chain was neglected in both these studies.

Some cold supply chain research incorporates environmental impacts into the distribution planning of cold items in cold supply chains. For example, Chen and Hsu

(2015) compared two transportation systems - namely; traditional multi-vehicle distribution and multi-temperature joint distribution, and their environmental impacts arising from energy consumption and refrigerant leakages during the transportation process. Soysal et al. (2014) proposed a multi-objective linear programming model for the beef logistics network problem considering both logistics cost and the total amount of emissions. In this study, an ϵ-constraint approach was used as a solution method. Hsiao et al. (2017) formulated a cold supply chain distribution model with the aim of determining a distribution plan to fulfill customer requirements for preferred food quality levels at the lowest distribution cost including emissions costs caused by vehicles. An algorithm based on adapted biogeograph-based optimisation was developed to solve the model in their study. Stellingwerf et al. (2018a) presented an optimisation model for a load dependent vehicle routing problem to minimise emissions in a temperature-controlled transportation system. The authors found that considering emissions generated by refrigeration in road transportation can lead to different routes and speeds compared with the traditional vehicle routing problem. Stellingwerf et al. (2018b) formulated an IRP model to examine the economic and environmental benefits of cooperation in a temperature-controlled supply chain. The authors found that vendor managed inventory (VMI) cooperation can lead to further cost and emissions savings. These studies addressed the environmental impact into the distribution scheduling in the cold supply chain without considering environmental regulations.

As a result of increasing awareness regarding environmental impacts and the need for adapting to changes in environmental regulations, a recent focus has been established in supply chain management literature to incorporate carbon emissions regulations. Marufuzzaman et al. (2014a) presented a bi-objective optimisation model accounting for economic and environmental considerations to identify location and planning decisions, simultaneously, in a biodiesel supply chain. They explored the impact of different carbon emissions regulations in the performance of the supply chain. Palak et al. (2014) extended a variation of the classical economic lot sizing model to analyse the impact of carbon emissions regulations on replenishment and transportation mode selection decisions. The results indicate that the buyer has tendency to use local suppliers to reduce costs-related carbon emissions as a result of tighter carbon emissions regulations. Park et al. (2015) focused on the last-mile distribution network design and investigated how carbon tax affects the supply chain structure and social welfare. The authors found that a change in carbon cost has a greater effect on supply chain structures when market competition is more intense. These studies investigated the impact of different carbon emissions regulations on the performance of the supply chains without considering perishable products and their requirements. Hariga et al. (2017) addressed the lot sizing and transporting problem for a single cold product in a three-echelon cold supply chain comprising a plant, a distribution center and a retailer. These authors proposed a mathematical optimisation model and considered the impacts of carbon emissions resulting from transportation and storage activities of a cold product in a deterministic environment under carbon tax regulations. There was no consideration for parameters uncertainty as relevant in practice in these studies.

The uncertain nature of parameters adds more complexity to the system, even in the traditional supply chain management. Yu et al. (2012) presented a stochastic model for an inventory-routing problem (IRP) with split delivery in which unsatisfied demands due to the lack of stock influence the customer service level. The model was formulated as an approximate stochastic IRP where initial uncertain demands are transformed into deterministic demands. Solyalı et al. (2012) used a robust mixed-integer programming for IRP in which the probability distribution of uncertain demands of customers was not specified. Marufuzzaman et al. (2014b) presented a two-stage stochastic programming model to manage biodiesel supply chain that accounts for the impact of various carbon emissions regulations and uncertainties on the supply chain decisions. The authors used Lagrangian relaxation method within L-shaped algorithm to solve the model and added valid cuts to improve the algorithm performance. Cardona-Valdés et al. (2014) presented a bi-objective stochastic programming model to design a two-echelon production-distribution network under uncertain demand. The authors developed a tabu search within the framework of multi-objective adaptive memory programming to solve the proposed model. Bertazzi et al. (2015) adopted a stochastic dynamic programming for an IRP in which the supplier has a limited production capacity and deliveries are conducted using transportation procurement to satisfy uncertain demands. Mohajeri and Fallah (2016) presented an optimisation model for closed-loop supply chain that accounts for carbon emissions constraints, uncertain demand and return rate. The authors developed a fuzzy programming to capture the uncertain nature of parameters. It should be noted that these studies only considered non-perishable products (i.e. perishable products were not included in their modelling).

Stochastic parameters bring more complexity in modelling supply chain problems for perishable/cold items. Acknowledging that the design of a distribution network for perishable inventory is different and more challenging than for non-perishables, Firoozi and Ariafar (2017) proposed a stochastic distribution network model for perishable products using a Lagrangian relaxation-based heuristics algorithm to solve the model. The model considers uncertain demand and deals with the uncertainty of product lifetime by defining worst-case scenarios. Soysal et al. (2015) proposed an IRP model for a single perishable product that contains load dependent distribution costs for evaluation of carbon emissions, perishability and service level constraint for satisfying stochastic demand. They implemented the model for fresh tomato distribution and the results indicated that the integrated model could help achieve cost savings without compromising the service quality. Soysal et al. (2018) presented an IRP model with demand uncertainty, which addressed carbon emissions arising from distribution of perishable products, in order to analyse the benefit of horizontal collaboration related to perishability, energy consumption and logistics cost. Although these studies considered perishable products in a stochastic environment, the energy consumption of cold facilities and emissions from storage were not considered.

Galal and El-Kilany (2016) and Saif and Elhedhli (2016) are two of the few studies that simultaneously address the issues of uncertain demand, energy consumption and emissions of cold supply chains. Galal and El-Kilany (2016) presented a simulation model of cold inventory replenishment policy that considers economic and environmental aspects of changing the order quantity in the food supply chain. Their results indicate that reducing the order quantities can lead to a decrease in costs and emissions without sacrificing the service levels. The authors also considered demand and lead time uncertainty in their model. Saif and Elhedhli (2016) examined the cold supply chain design problem with a simulation approach and considered the economic and environmental effects. Their model aims to minimise the capacity, inventory and transportation costs and at the same time assumes stochastic demand. The authors show that it is possible to reduce the global warming effect of cold supply chains without incurring a large increase in cost. However, these studies did not take into account carbon regulation, nor examined its impact on cold supply chain operational decisions.

The research by Hariga et al. (2017) might be the most relevant study to our research in terms of research objectives and scope. They presented an optimisation model for cold supply chain management aiming to minimise both operation costs and emissions costs. However, their model operates in a deterministic environment while we consider the uncertain nature of demand, hence a two-stage stochastic programming model is developed. In Hariga et al. (2017), vehicles were assumed to be homogeneous, while in this study we consider heterogeneous vehicles, which is more realistic. The model proposed by Hariga et al. (2017) assumes a one-to-one distribution network, while our research uses a one-to-many distribution network, which is more realistic and challenging in finding the optimal route and ways to integrate retailers into vehicle routes.

The main scientific contribution of this chapter is the development of an integrated optimisation model for the cold supply chain considering demand uncertainty under carbon tax regulations, which is an under-researched area in the existing supply chain literature. The computationally efficient matheuristic algorithm provided in this research, based on an Iterated Local Search and mixed integer programming, is useful for researchers examining similar issues. The real-world case study presented in this chapter can generate significant policy implications in terms of designing appropriate carbon tax policies to achieve emissions reductions without substantially increasing compliance costs for cold supply chain participants.

3.3 Problem description

The main objective of this research is to develop an optimisation model for sustainable cold supply chain management with a consideration of demand uncertainty. Our research focuses on a cold supply chain in which a central supplier serves a set of retailers, under uncertain demand over a finite planning horizon. Heterogeneous vehicles are assumed to be dispatched from the supplier, visit the retailers and return to the supplier on the same day. Each retailer is served by only one vehicle in each period, split delivery is not allowed. The transportation costs[2] comprise

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[2] Decisions related to determining the optimal number of vehicles required in the distribution system toward reducing vehicles idling costs are interesting from the management perspective. Such decisions are strategic decisions which are often made at the initial planning stage, well ahead of the operational stage, which is the focus of this study. Furthermore, in the operational decisions planning considered in this study, we did not consider the vehicle idling costs as the vehicle idling costs are much less than the costs associated with operating the vehicles. Indeed, the distribution system incurs different costs such as fixed vehicle cost, fuel cost and emissions cost when using the vehicles which far outweigh the vehicle idling costs.

the fixed cost component when the vehicle is used, and the variable cost component that is a function of travel distance, load, speed and vehicle characteristics.

We assume that the supplier has a limited quantity available cold product *(Q)* at each period. The storage cost for both supplier (H_S) and retailers (H_R) are associated with storing a unit of cold product to maintain the quality of the product at the desired level. Carbon emissions from the transportation operation as well as the storage operations at the supplier and retailers are incorporated into the proposed model. We regard shortage as a lost sale. In order to minimise lost sales, a penalty per unit (π_κ) is applied whenever the quantity of product delivered is less than the actual demand. The supplier needs to decide on the quantities delivered to the retailers before realisation of the uncertain demand. At the end of the period, the actual demand of retailers is revealed and then shortage or inventory levels in the retailers and cold facilities requirements will be specified accordingly. At the beginning of the next period, considered the realised demand, the next quantities delivered to the retailers and consequently suitable vehicle types and vehicle routes must be determined. We also assume that the cold supply chain operates under the carbon tax regulation. Before formulating the proposed model, we state the following assumptions:

- here are *K* types of refrigeration vehicles with a maximum capacity (O_κ) at the supplier to distribute cold products to a set of retailers. The number of available vehicles (η_κ) for each type is limited.
- Retailer demand is assumed to be stochastic and follows a statistical distribution.
- All shipments happen at the beginning of each period. The vehicles depart the supplier at the beginning of each period and return to the supplier after visiting retailers within the same period, which is normally takes several hours[3] .
- The quantity of products delivered to a retailer is determined such that the maximum inventory capacity in the retailer is not exceeded.
- The number of refrigerators required to maintain cold products at the supplier and retailers is determined by the remaining inventory after satisfying the demand at each period. Each retailer is assumed to be a central distributor which serves sub-

[3] In this research, our focus is on a distribution system in which the distribution time is less than a day. With the support of an effective cold supply chain and new technology, the perishable products will have a longer shelf-life, which is usually a few weeks or more. Compared with the extended shelf-life, the distribution time is relatively small, which is ignored in this research. However, if the distribution involves an area that takes a longer time, the distribution time should be considered

retailers immediately after receiving the products. Hence, only the excess quantities from the daily demand are sent to the storage that needs a refrigeration system in our modelling at each retailer at each period and will be used in the next period.

The optimisation model seeks to determine the optimal configuration of the routes and vehicle types, the quantity of cold product to be delivered to retailers, and the number of refrigerators used for storage under uncertain demand and carbon tax regulation in order to minimise the operation costs and lost sale cost as well as the costs of emissions. The model aims to capture the trade-off between cost and emissions. The configuration of the proposed problem in our study is depicted in Figure 3-1. The scheme illustrates a cold supply chain including a supplier that distributes a cold product to a number of retailers. As can be seen from Figure 3-1, both the supplier and retailers are responsible for the growth of environmental impacts, especially carbon emissions, as a result of energy consumption of different logistical operations, transportation and inventory, along the chain.

3.3.1 Modelling approach

As we focus on cold products that have variable demand, projecting the demand may not be accurate for the long-term period. The demand forecasting for such types of products could be much more accurate for the short-term period (Sazvar et al., 2014). Our modelling framework contains only two stages, but each stage can encompass one or more than one period depending on the nature of the problem. This is similar to Sazvar et al. (2014); Mirzapour Al-e hashem et al. (2017) in which two periods are used and considered sufficient for illustration purposes.

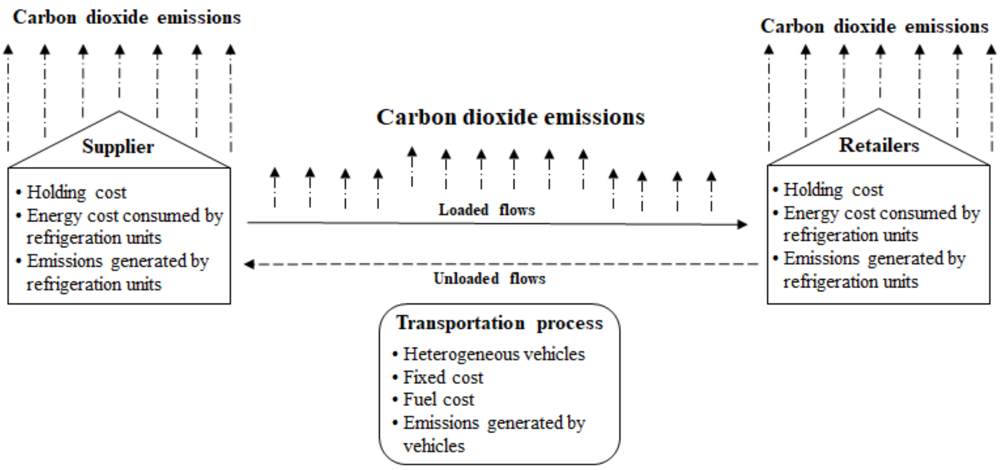


Figure 3-1: A simple scheme of the proposed problem

In the two-stage stochastic programming model, the decision variables are categorised into two stages. The stage changes when the information related to the actual demand is updated with newly available data represented by the scenarios. In our modelling, the first-stage decision variables are decisions that are not affected by the scenarios and must be made prior to the realisation of uncertainty at the first period, and are referred to as "here and now" decisions. It means that these decision variables are made based on existing information and would be fixed after being made under all scenarios. For the proposed problem, the first-stage decisions contain decisions that the supplier makes at the beginning of the first period without having exact information related to the actual demand. However, the second-stage decision variables depend on the scenarios, also known as "wait and see" decisions, and must be made after the uncertain parameters (demand value) are revealed. It means that these decision variables are changed based on each scenario. In our model, the second-stage decision variables constitute decisions that the supplier and retailers make after unveiling the demand based on each scenario. The main decisions relevant to each stage in our modelling are summarised in Table 3-1.

In our modelling, we calculate the operational costs related to the first-stage separately from those associated with the second-stage. Hence, some costs are computed twice. The objective functions aim to minimise the costs related to the first-stage decisions and expected costs of the second-stage decisions.

Table 3-1:Main decisions at each stage

First-stage decisions	**Second-stage decisions**
Optimal quantity delivered to each retailer in the first period	Optimal quantity delivered to each retailer in the second period under each scenario
Optimal number of refrigeration systems that requires to be turned on at the supplier based on the remaining inventory in the first period	Optimal number of refrigeration systems that requires to be turned on at the supplier based on the remaining inventory in the second period under each scenario
The optimal route for distribution of products in the first period	The optimal route for distribution of products in the second period under each scenario
Optimal speed of vehicles when traveling on arc *(i, j)* in the first period (related to extended model, Section 3.4.3)	Optimal speed of vehicles when traveling on arc *(i, j)* in the second period under each scenario (related to extended model, Section 3.4.3)
Optimal selection vehicle type for distribution of products on each route in the first period	Optimal selection of vehicle type for distribution of products on each route in the second period under each scenario
	Optimal number of refrigeration systems that requires to be turned on at each retailer based on

	the remaining inventory in each period under each scenario

The problem is considered as a complete graph $G = (\upsilon, E)$, where $\upsilon = \{0,1,\dots,N\}$ is the set of nodes and E is the arc set. The set of nodes comprises 0 representing the supplier, and N representing the total number of retailers. Arcs also present the available roads between nodes. The notations used in the chapter to develop the mathematical model are summarised in Tables 3-2, 3-3 and 3-4. We use Greek letters and upper-case letters to represent parameters, while lower-case letters are used to denote variables.

Table 3-2:Indices

ξ	Index of scenario, $\xi = 1, \dots, \Xi$
κ	Index of transportation type, $\kappa = 1, \dots, K$
t	Index of time period, $t = 1,2$
n, χ	Index of retailer, $n, \chi = 1, \dots, N$
i, j	Index of node including supplier and retailers, $i, j \in \upsilon = \{0, \dots, N\}$
m	Index of the number of vehicles available for type κ at supplier, $m = 1, \dots, \eta_\kappa$
r	Index of speed level, $r = 1, \dots, \Lambda$

Table 3-3:Parameters

Q	Available quantity of product at the supplier in each period
H_R	Unit cost of holding inventory at retailers per period
H_S	Unit cost of holding inventory at the supplier per period
Υ	Maximum inventory capacity at retailers
η_κ	Total number of vehicles available for type κ at the supplier
O_κ	Capacity of vehicle type κ
D_{ij}	The distance from node *i* to *j*
S_{ij}	The speed of vehicles on arc *(i,j)*
S^r	Speed of vehicles at level *r* (related to the extended model)
ϕ_F	Fuel cost per liter
F_κ	Fixed cost of vehicle type κ
σ	Fuel conversion factor *(g/s to L/s)*
C_R	Capacity of refrigerator at retailers
C_S	Capacity of refrigerator at the supplier
ϕ_E	Electricity cost per *kWh*
E_R	Energy consumption of refrigeration system at retailers *(kWh/day)*
E_R	Energy consumption of refrigeration system at the supplier *(kWh/day)*
δ	The amount of carbon emissions for 1 *kWh* energy generation *(kg/kWh)*
Γ	Technical parameter
Φ_κ	Engine friction factor of vehicle type κ *(kJ/rev/L)*
N_κ	Engine speed of vehicle type κ *(rev/s)*

ι_κ	Engine displacement of vehicle type κ *(L)*
τ	Fuel-to-air mass ratio
ψ	Conversion factor from *(g/s)* to *(L/s)*
ζ_κ	Vehicle drive train efficiency
ω	Efficiency parameter for diesel engines
g	Gravitational constant *(m/s^2)*
θ	Road angle
C_e	Coefficient of rolling resistance
$C_{d\kappa}$	Coefficient of aerodynamics drag
ρ	Air density *(kg/m^3)*
A_κ	Frontal surface area *(m^2)*
W_κ	Curb weight of vehicle type κ *(kg)*
ϑ	Weight of each unit of product
L_κ	Total payload of vehicle type κ *(kg)*
φ	Heating value of a typical diesel fuel *(kj/g)*
π	Lost sale cost per unit at retailer
$D_n(\xi)$	Forecasted demand at retailer *n* at each period under scenario ξ
μ	Unit CO_2 emissions price *(AU$/kg)*
$P(\xi)$	Probability of scenario ξ
M	A large number
ε	A small number

3.3.2 Fuel consumption

We utilise the same approach as Barth and Boriboonsomsin (2009) and Bektaş and Laporte (2011) to estimate fuel consumption based on the comprehensive emissions model of Barth et al. (2005). The fuel consumption $G_\kappa$of vehicle type κ over distance D_{ij}at a speed of S can be calculated as follows:

$$G_k = \Gamma(\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S} + (W_\kappa + L_\kappa)\gamma_\kappa \alpha D_{ij} + \beta_\kappa \gamma_\kappa D_{ij} S^2) \tag{3.1}$$

Where $\Gamma = \tau/\varphi\psi, \gamma_\kappa = 1/(1000\zeta_\kappa \omega), \alpha = gsin\theta + gC_e cos\theta, \beta_\kappa = 0.5C_{d\kappa}\rho A_\kappa$. $(W_\kappa + L_\kappa)$ denotes the total vehicle weight *(kg),* including the sum of curb weight and pay load. Expression (3.1) comprises three terms: the first term is called the *engine module* which is linear with travel time; the second term is referred to as the *weight module* which is independent of the vehicle speed; and the last term is called the *speed module* in which the speed is taken a quadratic form.

Table 3-4:Variables

$i_{R_n t}(\xi)$	Inventory level in retailer n at the end of period *t* under scenario ξ
i_S^f	Inventory level in the supplier in the first period
$i_S^s(\xi)$	Inventory level in the supplier at end of second period under scenario ξ
$s_{nt}(\xi)$	Amount of shortage in retailer n at end of period *t* under scenario ξ

$f_{i\kappa m}^{f}$	Product flow entered to node *i* by m^{th}vehicle of type κ in the first period
$f_{i\kappa m}^{f}(\xi)$	Product flow entered to node *i* by m^{th}vehicle of κ in the second period, under scenario ξ
q_{n}^{f}	Quantity of product delivered to retailer *n* in the first period
$q_{n}^{s}(\xi)$	Quantity of product delivered to retailer *n* in second period under scenario ξ
$x_{ij\kappa m}^{f}$	1 if arc *(i,j)* is visited by m^{th} vehicle of type κ in the first period; ∅ otherwise
$x_{ij\kappa m}^{s}(\xi)$	1 if arc *(i,j)* is visited by m^{th} vehicle of type κ in the second period under scenario ξ; ∅ otherwise
$s_{ij\kappa m}^{f}$	Speed of m^{th} vehicle of type κ when traveling on arc *(i,j)* in the first period
$s_{ij\kappa m}^{s}(\xi)$	Speed of m^{th} vehicle of type κ when traveling on arc *(i,j)* in the second period under scenario ξ
$g_{ij\kappa m}^{fr}$	1 if m^{th} vehicle of type κ travels from *i* to *j* at speed level *r* in the first period; ∅ otherwise
$g_{ij\kappa m}^{fr}(\xi)$	1 if m^{th} vehicle of type κ travels from *i* to *j* at speed level *r* in the second period under scenarios ξ; ∅otherwise
$y_{ij\kappa m}^{f}$	Auxiliary variable linked fuel cost to vehicles' load at the first period
$y_{ij\kappa m}^{s}(\xi)$	Auxiliary variable inked fuel cost to vehicles' load at the second period under scenario ξ
$av_{nt}(\xi)$	Auxiliary variable using for linearization in each period under scenario ξ
u_{S}^{f}	Auxiliary variable using for linearization in the first period
$u_{S}^{s}(\xi)$	Auxiliary variable using for linearization in the second period under scenario ξ
$u_{R_n t}(\xi)$	Auxiliary variable using for linearization in each period under scenario ξ
$z_{n\kappa m}^{f}$	Auxiliary variable using for linearization in the first period
$z_{n\kappa m}^{s}(\xi)$	Auxiliary variable using for linearization in the second period under scenario ξ

3.4 Mathematical Model

We propose a mathematical model, denoted by base case model *(z),* based on a two-stage stochastic programming as follows:

$$Min\ z = SC + TC + LC + EC \tag{3.2}$$

Expression (3.2) refers to the objective function which comprises four costs: storage costs (*SC*), transportation costs (*TC*), lost sale cost (*LS*) and carbon emissions costs (*EC*). These costs are discussed as follows:

Storage costs

The storage costs (*SC*) include holding cost and energy cost of refrigeration units and are presented as follows:

$$\begin{aligned} SC = H_S i_S^f + \phi_E \left\lceil \frac{i_S^f}{C_S} \right\rceil E_S \\ + \sum_{\xi} P(\xi) \Bigg(H_S i_S^s(\xi) + \phi_E \left\lceil \frac{i_S^s(\xi)}{C_S} \right\rceil E_S \\ + \sum_{t} \sum_{n} \left(H_R i_{R_n t}(\xi) + \phi_E \left\lceil \frac{i_{R_n t}(\xi)}{C_R} \right\rceil E_R \right) \Bigg) \end{aligned} \tag{3.2.i}$$

Where $\lceil . \rceil$ refers to ceiling function. The first two parts in the function (3.2.i) are the holding cost, and energy cost consumed by refrigeration units at the supplier in the first period, respectively, which are not dependent on scenarios (first-stage decision variables). The remain parts of the function (3.2.i) are associated with the expected value of the second-stage costs. The expected holding cost and energy cost in the supplier under scenario ξ in the second period are represented by parts 3 and 4, respectively. Parts 5 and 6 represent the respective expected holding cost and energy cost consumed by refrigeration units at retailers under scenario ξ in each period.

Transportation costs

The transportation costs (TC) comprise vehicles' fixed cost and variable cost (fuel cost) and are formulated as follows:

$$
\begin{aligned}
TC = \sum_{\kappa}\sum_{m}\Bigg(\sum_{n} F_\kappa x^f_{0n\kappa m} \\
&+ \phi_F \Gamma\Big(\sum_{i,i,i\neq j} \frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} \\
&+ x^f_{ij\kappa m}\beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^f_{ij\kappa m}\gamma_\kappa \alpha\Big)\Bigg) + \\
\sum_{\xi} P(\xi)\Bigg(\sum_{\kappa}\sum_{m}\Bigg(\sum_{n} F_\kappa x^s_{0n\kappa m}(\xi) \\
&+ \phi_F \Gamma\Big(\sum_{i,i,i\neq j} \frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa \alpha D_{ij} \\
&+ x^s_{ij\kappa m}(\xi)\beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^s_{ij\kappa m}(\xi)\gamma_\kappa \alpha\Big)\Bigg)\Bigg)
\end{aligned}
\tag{3.2.ii}
$$

Parts 1 and 2 in the function (3.2.ii) present vehicles' fixed cost and variable cost (fuel cost) at the first period, respectively, which are not subject to uncertainty. The remain parts of the function (3.2.ii) are used to compute the expected value of the second-stage costs. The expected vehicles' fixed cost and variable cost under scenario ξ at the second period are computed separately by parts 3 and 4. In this function, the variable cost is dependent on speed, load, travel distance and vehicle's characteristics. Note that transportation costs are linked to the vehicles' load by auxiliary variables $y^f_{ij\kappa m}$, $y^s_{ij\kappa m}(\xi)$ and constraints (3.33) - (3.34).

Lost sale cost

The lost sale cost (LC) is subject to uncertainty. In other words, the lost sale cost (LC) is specified after the uncertain demands are revealed at the first period. The lost sale cost (LC) is modelled as follows:

$$LC = \sum_{\xi} P(\xi) \sum_{t} \sum_{n} \pi s_{nt}(\xi) \tag{3.2.iii}$$

The function (3.2.iii) represents the expected lost sale cost incurred by the retailers due to its inability to meet uncertain demand at the second-stage. The lost sale cost under scenario ξ is calculated by multiplying the total amount of lost sale by the unit lost sale cost.

Carbon emissions costs

The carbon emissions costs (EC) comprise the amount of carbon emissions from transportation and storage processes. The total amount of carbon emissions is computed by multiplying the total amount of energy consumption in transportation and storage processes, with carbon emissions coefficients and emissions price.

$$\begin{aligned} EC = \mu \Bigg(\Bigg(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,i,i \neq j} \frac{x^{f}_{ij\kappa m} \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{S_{ij}} + W_{\kappa} x^{f}_{ij\kappa m} \gamma_{\kappa} \alpha D_{ij} + x^{f}_{ij\kappa m} \beta_{\kappa} \gamma_{\kappa} D_{ij} S^{2}_{ij} \\ + y^{f}_{ij\kappa m} \gamma_{\kappa} \alpha \Bigg) \times \sigma + \left\lceil \frac{i^{f}_{S}}{C_{S}} \right\rceil E_{S} \times \delta \Bigg) + \\ \mu \sum_{\xi} P(\xi) \Bigg(\Bigg(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,i,i \neq j} \frac{x^{s}_{ij\kappa m}(\xi) \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{S_{ij}} + W_{\kappa} x^{s}_{ij\kappa m}(\xi) \gamma_{\kappa} \alpha D_{ij} \\ + x^{s}_{ij\kappa m}(\xi) \beta_{\kappa} \gamma_{\kappa} D_{ij} S^{2}_{ij} + y^{s}_{ij\kappa m}(\xi) \gamma_{\kappa} \alpha) \Bigg) \times \sigma \\ + \left(\left\lceil \frac{i^{s}_{S}(\xi)}{C_{S}} \right\rceil E_{S} + \sum_{t} \sum_{n} \left\lceil \frac{i_{R_{n}t}(\xi)}{C_{R}} \right\rceil E_{R} \right) \times \delta \Bigg) \end{aligned} \tag{3.2.iv}$$

Where $\lceil . \rceil$ refers to ceiling function. Parts 1 and 2 in the function (3.2.iv) represent the carbon emissions costs arising from transportation and storage at the first period, respectively, which is not affected by scenarios. The remaining parts in expression (3.2.iv) represent expected carbon emissions cost arising from transportation and storage under all possible scenarios.

S.t.

$$i^{f}_{S} = Q - \sum_{n} q^{f}_{n} \tag{3.3}$$

$$i_S^s(\xi) = i_S^f + Q - \sum_n q_n^s(\xi) \qquad \forall\xi \qquad (3.4)$$

$$i_{R_n1}(\xi) = q_n^f - D_n(\xi) + s_{n1}(\xi) \qquad \forall n, \xi \qquad (3.5)$$

$$i_{R_nt}(\xi) = iRn(t-1)\xi + qns(\xi) - Dn\xi + snt(\xi) \qquad \forall n, \xi, t \geq 2 \qquad (3.6)$$

$$i_{R_nt}(\xi) \leq \Upsilon \qquad \forall n, \xi, t \qquad (3.7)$$

Constraints (3.3) - (3.7) relate to the inventory decisions. In particular, constraints (3.3) - (3.6) are inventory balances at the supplier and retailers at the end of each period respectively. Constraint set (3.7) ensures that the remaining inventory of each retailer at the end of each period does not exceed its maximum storage capacity.

$$q_n^s(\xi) \leq \sum_j \sum_\kappa x_{jn\kappa m}^f \Upsilon \qquad \forall n \qquad (3.8)$$

$$q_n^s(\xi) \leq \sum_j \sum_\kappa x_{jn\kappa m}^s(\xi) \times (D_n(\xi) + \Upsilon) \qquad \forall n, \xi \qquad (3.9)$$

$$q_n^s(\xi) \leq D_n(\xi) + \Upsilon - i_{R_n(t-1)}(\xi) \qquad \forall n, \xi, t \geq 2 \qquad (3.10)$$

Constraints (3.8) - (3.9) indicate that if a retailer n is not visited by vehicle type κ, the quantity of product delivered to the retailer *n* by vehicle type κ is zero. Constraint set (3.10) indicates that the cold product is delivered to a retailer as long as the inventory does not exceed maximum inventory capacity at each period.

$$\sum_n x_{0n\kappa m}^f \leq 1 \qquad \forall \kappa, m \qquad (3.11)$$

$$\sum_n x_{0n\kappa m}^s(\xi) \leq 1 \qquad \forall \kappa, m, \xi \qquad (3.12)$$

$$\sum_i \sum_\kappa \sum_m x_{in\kappa m}^f \leq 1 \qquad \forall n \qquad (3.13)$$

$$\sum_i \sum_\kappa \sum_m x_{in\kappa m}^s(\xi) \leq 1 \qquad \forall n, \xi \qquad (3.14)$$

Constraints (3.11) - (3.14) associate with the routing decisions. In particular, constraints (3.11) - (3.12) denote that each vehicle departs from the supplier at most once per period to visit retailers. Constraints (3.13) - (3.14) represent that each retailer is visited at most once at each period by only one vehicle, split delivery is not allowed.

$$\sum_i x_{in\kappa m}^f - \sum_i x_{ni\kappa m}^f = 0 \qquad \forall n, \kappa, m \qquad (3.15)$$

$$\sum_i x_{in\kappa m}^s(\xi) - \sum_i x_{ni\kappa m}^s(\xi) = 0 \qquad \forall n, \kappa, m, \xi \qquad (3.16)$$

$$M \sum_n x_{0n\kappa m}^f - \sum_n \sum_j x_{nj\kappa m}^f \geq 0 \qquad \forall \kappa, m \qquad (3.17)$$

$$M \sum_n x_{0n\kappa m}^s(\xi) - \sum_n \sum_j x_{nj\kappa m}^s(\xi) \geq 0 \qquad \forall \kappa, m, \xi \qquad (3.18)$$

Constraints (3.15) - (3.16) ensure that the incoming arcs must be equal to departing arcs at each node and related to subtour elimination. Constraints (3.17) - (3.18) ensure that retailers can be visited by a vehicle when the vehicle departs from the supplier.

$$f^{f}_{n\kappa m} \leq O_{\kappa} \sum_{i} x^{f}_{in\kappa m} \qquad \forall n, \kappa, m \qquad (3.19)$$

$$f^{s}_{n\kappa m}(\xi) \leq O_{\kappa} \sum_{i} x^{s}_{in\kappa m}(\xi) \qquad \forall n, \kappa, m, \xi \qquad (3.20)$$

$$\sum_{\kappa} \sum_{m} f^{f}_{0\kappa m} = 0 \qquad (3.21)$$

$$\sum_{\kappa} \sum_{m} f^{s}_{0\kappa m}(\xi) = 0 \qquad \forall\, \xi \qquad (3.22)$$

Constraints (3.19) - (3.22) indicate the product's flow balance. In particular, constraints (3.19) - (3.20) confirm that the vehicle's capacity is respected. Constraints (3.21) - (3.22) ensure that vehicles are empty when returning to the supplier.

$$f^{f}_{n\kappa m} \geq \sum_{i} \sum_{\chi} x^{f}_{i\chi\kappa m} \times q^{f}_{\chi} - M(1 - x^{f}_{0n\kappa m}) \qquad \forall n, \kappa, m \qquad (3.23)$$

$$f^{f}_{n\kappa m} \leq \sum_{i} \sum_{\chi} x^{f}_{i\chi\kappa m} \times q^{f}_{\chi} + M(1 - x^{f}_{0n\kappa m}) \qquad \forall n, \kappa, m \qquad (3.24)$$

$$f^{s}_{n\kappa m}(\xi) \geq \sum_{i} \sum_{\chi} x^{s}_{i\chi\kappa m}(\xi) \times q^{s}_{\chi}(\xi) - M(1 - x^{s}_{0n\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \qquad (3.25)$$

$$f^{s}_{n\kappa m}(\xi) \leq \sum_{i} \sum_{\chi} x^{s}_{i\chi\kappa m}(\xi) \times q^{s}_{\chi}(\xi) + M(1 - x^{s}_{0n\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \qquad (3.26)$$

$$f^{f}_{n\kappa m} \leq M \sum_{i} x^{f}_{in\kappa m} \qquad \forall n, \kappa, m \qquad (3.27)$$

$$f^{s}_{n\kappa m}(\xi) \leq M \sum_{i} x^{s}_{in\kappa m}(\xi) \qquad \forall n, \kappa, m, \xi \qquad (3.28)$$

Constraints (3.23) - (3.26) determine the total load when a vehicle departs from the supplier. Constraints (3.27) - (3.28) set the product's flow entering to a retailer as a non-zero value if there is a link to the retailer.

$$f^{f}_{n\kappa m} - f^{f}_{j\kappa m} \leq q^{f}_{n} + M(1 - x^{f}_{nj\kappa m}) \qquad \forall n, j, \kappa, m \qquad (3.29)$$

$$f^{f}_{n\kappa m} - f^{f}_{j\kappa m} \geq q^{f}_{n} - M(1 - x^{f}_{nj\kappa m}) \qquad \forall n, j, \kappa, m \qquad (3.30)$$

$$f^{s}_{n\kappa m}(\xi) - f^{s}_{j\kappa m}(\xi) \leq q^{s}_{n}(\xi) + M(1 - x^{s}_{nj\kappa m}(\xi)) \qquad \forall n, j, \kappa, m, \xi \qquad (3.31)$$

$$f^{s}_{n\kappa m}(\xi) - f^{s}_{j\kappa m}(\xi) \geq q^{s}_{n}(\xi) - M(1 - x^{s}_{nj\kappa m}(\xi)) \qquad \forall n, j, \kappa, m, \xi \qquad (3.32)$$

$$y^{f}_{n\kappa m} \geq f^{f}_{n\kappa m} \times D_{in} - M(1 - x^{f}_{in\kappa m}) \qquad \forall i, n, \kappa, m \qquad (3.33)$$

$$y^{s}_{n\kappa m}(\xi) \geq f^{s}_{n\kappa m}(\xi) \times D_{in} - M(1 - x^{s}_{in\kappa m}(\xi)) \qquad \forall i, n, \kappa, m, \xi \qquad (3.34)$$

Constraints (3.29) - (3.32) decrease product's flow on a route after visiting a retailer by its demand. By (3.33) - (3.34) transportation cost is dependent on product's flow on a route.

$$i_{R_n t}(\xi) \times s_{nt}(\xi) = 0 \qquad \forall n, t, \xi \qquad (3.35)$$

$$x^{f}_{ii\kappa m} = x^{s}_{ii\kappa m}(\xi) = 0 \qquad \forall i, n, \kappa, m, \xi \qquad (3.36)$$

$$i^{f}_{S}, i^{s}_{S}(\xi), f^{f}_{i\kappa m}, f^{s}_{i\kappa m}(\xi), q^{f}_{n}, q^{s}_{n}(\xi) \geq 0 \qquad \forall i, n, \kappa, m, \xi \qquad (3.37)$$

$$i_{R_n t}(\xi), s_{nt}(\xi) \geq 0 \qquad \forall n, t, \xi \qquad (3.38)$$

$$x^{f}_{ij\kappa m}, x^{s}_{ij\kappa m}(\xi) \in \{0,1\} \qquad (3.39)$$

Constraint set (3.35) represents that $i_{nt}(\xi)$ and $s_{nt}(\xi)$ cannot take positive values simultaneously. Constraint set (3.36) indicates the impossible arcs and constraints (3.37) - (3.39) define the types of decision variables.

3.4.1 Symmetry breaking constraints

In this section, we add symmetry breaking constraints as valid inequalities to strengthen the modelling and tighten the feasible solution regions, which will result in the acceleration of the convergence to an optimal solution. The symmetry breaking constraints for each type of vehicle are defined as follows:

$$\sum_{n} x^{f}_{0n\kappa m} \leq \sum_{n} x^{f}_{0n\kappa(m-1)} \qquad \forall \kappa, m = 2, \dots, \eta_{\kappa} \qquad (3.40)$$

$$\sum_{n} x^{s}_{0n\kappa m}(\xi) \leq \sum_{n} x^{s}_{0n\kappa(m-1)}(\xi) \qquad \forall \kappa, \xi, m = 2, \dots, \eta_{\kappa} \qquad (3.41)$$

$$\sum_{n} x^{f}_{nj\kappa m} \leq \sum_{n} \sum_{i \leq j} x^{f}_{ni\kappa(m-1)} \qquad \forall i, \kappa, m = 2, \dots, \eta_{\kappa} \qquad (3.42)$$

$$\sum_{n} x^{s}_{nj\kappa m}(\xi) \leq \sum_{n} \sum_{i \leq j} x^{s}_{ni\kappa(m-1)}(\xi) \qquad \forall i, \kappa, m = 2, \dots, \eta_{\kappa}, \xi \qquad (3.43)$$

Constraints (3.40) - (3.41) ensure that the m^{th}vehicle of type κ cannot leave the supplier if vehicle $(m-1)^{th}$of the same type is not used. This symmetry breaking rule is applied for the retailer nodes by constraints (3.42) - (3.43). These constraints imply that if a retailer *n* is visited by m^{th} vehicle type κ in period *t*, then $(m-1)^{th}$ vehicle of the same type must serve a retailer with an index smaller than *n* in the same period. These constraints have been derived from the valid inequalities used for the capacitated vehicle routing problem in Fischetti et al. (1995) and the plant location problem in Albareda-Sambola et al. (2011). These constraints are also used in Coelho and Laporte (2013).

3.4.2 Linearisation of the model

The proposed base case model *(z)* contains several nonlinear expressions. We utilise linearisation techniques to develop an equivalent linear mathematical model and to achieve optimal solutions. To linearise constraint (3.35), we define a binary variable $av_{nt}(\xi)$ and constraints (3.44) - (3.45). $av_{nt}(\xi) = 1$ if $i_{R_n t}(\xi)$is equal to zero;

$av_{nt}(\xi) = 0$ if $s_{nt}(\xi)$ is equal to zero for the n^{th} retailer at each period under each scenario ξ.

$$s_{nt}(\xi) \leq Mav_{nt}(\xi) \qquad \forall n, t, \xi \qquad (3.44)$$

$$i_{R_n t}(\xi) \leq M(1 - av_{nt}(\xi)) \qquad \forall n, t, \xi \qquad (3.45)$$

There are a number of non-linear terms in the objective function related to the number of refrigeration units used for storing cold products at the supplier and retailers. In order to formulate these terms as a linear expression, we define integer variables u_S^f, $u_S^s(\xi)$ and $u_{R_n t}^s(\xi)$ in constraints (3.46), (3.49) and (3.52), respectively, and constraints (3.47) - (3.48), (3.50) - (3.51) and (3.53) - (3.54) as follows:

$$u_S^f = \left\lceil \frac{i_S^f}{C_S} \right\rceil \qquad (3.46)$$

$$u_S^f \geq \frac{i_S^f}{C_S} \qquad (3.47)$$

$$u_S^f \leq \frac{i_S^f}{C_S} + 1 - \varepsilon \qquad (3.48)$$

$$u_S^s(\xi) = \left\lceil \frac{i_S^s(\xi)}{C_S} \right\rceil \qquad (3.49)$$

$$u_S^s(\xi) \geq \frac{i_S^s(\xi)}{C_S} \qquad \forall \xi \qquad (3.50)$$

$$u_S^s(\xi) \leq \frac{i_S^s(\xi)}{C_S} + 1 - \varepsilon \qquad \forall \xi \qquad (3.51)$$

$$u_{R_n t}(\xi) = \left\lceil \frac{i_{R_n t}(\xi)}{C_R} \right\rceil \qquad (3.52)$$

$$u_{R_n t}(\xi) \geq \frac{i_{R_n t}(\xi)}{C_R} \qquad \forall n, t, \xi \qquad (3.53)$$

$$u_{R_n t}(\xi) \leq \frac{i_{R_n t}(\xi)}{C_R} + 1 - \varepsilon \qquad (3.54)$$

We convert the nonlinear constraints (3.23) - (3.26) to linear expressions with the help of non-negative variables, $z_{n\kappa m}^f$ and $z_{n\kappa m}^s(\xi)$, and add constraints (3.55) - (3.62).

$$z_{n\kappa m}^f \leq q_n^f + M(1 - \sum_{j \in \upsilon \backslash \{0\}} x_{jn\kappa m}^f) \qquad \forall n, \kappa, m \qquad (3.55)$$

$$z_{n\kappa m}^f \geq q_n^f - M(1 - \sum_{j \in \upsilon \backslash \{0\}} x_{jn\kappa m}^f) \qquad \forall n, \kappa, m \qquad (3.56)$$

$$f_{n\kappa m}^f \geq \sum_{\chi} z_{\chi\kappa m}^f - M(1 - x_{0n\kappa m}^f) \qquad \forall n, \kappa, m \qquad (3.57)$$

$$f_{n\kappa m}^f \leq \sum_{\chi} z_{\chi\kappa m}^f + M(1 - x_{0n\kappa m}^f) \qquad \forall n, \kappa, m \qquad (3.58)$$

$$z_{n\kappa m}^s(\xi) \leq q_n^s(\xi) + M(1 - \sum_{j \in \upsilon \backslash \{0\}} x_{jn\kappa m}^s(\xi)) \qquad \forall n, \kappa, m, \xi \qquad (3.59)$$

$$z^s_{n\kappa m}(\xi) \geq q^s_n(\xi) - M(1 - \sum_{j\in\upsilon\setminus\{0\}} x^s_{jn\kappa m}(\xi)) \qquad \forall n,\kappa,m,\xi \qquad (3.60)$$

$$f^s_{n\kappa m}(\xi) \geq \sum_{\chi} z^s_{\chi\kappa m}(\xi) - M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n,\kappa,m,\xi \qquad (3.61)$$

$$f^s_{n\kappa m}(\xi) \leq \sum_{\chi} z^s_{\chi\kappa m}(\xi) + M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n,\kappa,m,\xi \qquad (3.62)$$

Finally, the linear equivalent of the proposed base case model (*z*) is rewritten as follows:

$$\min z = H_S i^f_S + \phi_E u^f_S E_S + \sum_{\xi} P(\xi)\left(H_S i^s_S(\xi) + \phi_E u^s_S(\xi) E_S + \sum_t \sum_n \left(H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R\right)\right) + \qquad (3.63.i)$$

$$\sum_{\kappa}\sum_{m}\left(\sum_{n} F_\kappa x^f_{0n\kappa m} + \phi_F \Gamma(\sum_{i,i,i\neq j} \frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^f_{ij\kappa m}\gamma_\kappa \alpha)\right) + \qquad (3.63.ii)$$

$$\sum_{\xi} P(\xi)\left(\sum_{\kappa}\sum_{m}\left(\sum_{n} F_\kappa x^s_{0n\kappa m}(\xi) + \phi_F \Gamma(\sum_{i,i,i\neq j} \frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa \alpha D_{ij} + x^s_{ij\kappa m}(\xi)\beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^s_{ij\kappa m}(\xi)\gamma_\kappa \alpha)\right)\right) +$$

$$\sum_{\xi} P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) \qquad (3.63.iii)$$

$$\mu\left(\left(\Gamma \sum_{\kappa}\sum_{m}\sum_{i,i,i\neq j} \frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^f_{ij\kappa m}\gamma_\kappa \alpha\right) \times \sigma + u^f_S E_S \times \delta\right) + \qquad (3.63.iv)$$

$$\mu \sum_{\xi} P(\xi) \Bigg(\bigg(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,i,i\neq j} \frac{x_{ij\kappa m}^{s}(\xi) \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{S_{ij}} + W_{\kappa} x_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha D_{ij}$$

$$+ x_{ij\kappa m}^{s}(\xi) \beta_{\kappa} \gamma_{\kappa} D_{ij} S_{ij}^{2} + y_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha \bigg) \times \sigma$$

$$+ \left(u_{S}^{s}(\xi) E_{S} + \sum_{t} \sum_{n} u_{R_{n}t}(\xi) E_{R} \right) \times \delta \Bigg)$$

Subject to:

Constraints (3.3) - (3.22), (3.27) - (3.34), (3.36) - (3.45), (3.47) - (3.48), (3.50) - (3.51) and (3.53) - (3.62).

3.4.3 Model extension with variable speed consideration

In this section, we modify the proposed base case model (z) and consider speed as a decision variable, denoted by z_{v}. Let $s_{ij\kappa m}^{f}$ and $s_{ij\kappa m}^{s}(\xi)$ be the speeds of m^{th} vehicle type κ when traveling from node i to node j at the first and second stages, respectively. The mathematical model is then rewritten as follows:

$$\min z = H_{S} i_{S}^{f} + \phi_{E} u_{S}^{f} E_{S} \tag{3.64.i}$$

$$+ \sum_{\xi} P(\xi) \Bigg(H_{S} i_{S}^{s}(\xi) + \phi_{E} u_{S}^{s}(\xi) E_{S}$$

$$+ \sum_{t} \sum_{n} \left(H_{R} i_{R_{n}t}(\xi) + \phi_{E} u_{R_{n}t}(\xi) E_{R} \right) \Bigg)$$

$$+ \sum_{\kappa} \sum_{m} \Bigg(\sum_{n} F_{\kappa} x_{0n\kappa m}^{f} \tag{3.64.ii}$$

$$+ \phi_{F} \Gamma (\sum_{i,i,i\neq j} \frac{x_{ij\kappa m}^{f} \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{s_{ij\kappa m}^{f}} + W_{\kappa} x_{ij\kappa m}^{f} \gamma_{\kappa} \alpha D_{ij}$$

$$+ x_{ij\kappa m}^{f} \beta_{\kappa} \gamma_{\kappa} D_{ij} (s_{ij\kappa m}^{f})^{2} + y_{ij\kappa m}^{f} \gamma_{\kappa} \alpha) \Bigg) +$$

$$\sum_{\xi} P(\xi) \Bigg(\sum_{\kappa} \sum_{m} \bigg(\sum_{n} F_{\kappa} x_{0n\kappa m}^{s}(\xi)$$

$$+ \phi_{F} \Gamma (\sum_{i,i,i\neq j} \frac{x_{ij\kappa m}^{s}(\xi) \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{s_{ij\kappa m}^{s}(\xi)} + W_{\kappa} x_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha D_{ij}$$

$$+ x_{ij\kappa m}^{s}(\xi) \beta_{\kappa} \gamma_{\kappa} D_{ij} (s_{ij\kappa m}^{s}(\xi))^{2} + y_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha) \bigg) \Bigg) +$$

$$\sum_{\xi} P(\xi) \sum_{t} \sum_{n} \pi s_{nt}(\xi) \tag{3.64.iii}$$

$$\mu\left(\left(\left(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,i,i \neq j} \frac{x_{ij\kappa m}^{f} \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{s_{ij\kappa m}^{f}} + W_{\kappa} x_{ij\kappa m}^{f} \gamma_{\kappa} \alpha D_{ij} + x_{ij\kappa m}^{f} \beta_{\kappa} \gamma_{\kappa} D_{ij} (s_{ij\kappa m}^{f})^{2} + y_{ij\kappa m}^{f} \gamma_{\kappa} \alpha\right) \times \sigma + u_{S}^{f} E_{S} \times \delta\right) + \right. \tag{3.64.iv}$$

$$\mu \sum_{\xi} P(\xi) \left(\left(\left(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,i,i \neq j} \frac{x_{ij\kappa m}^{s}(\xi) \Phi_{\kappa} N_{\kappa} \iota_{\kappa} D_{ij}}{s_{ij\kappa m}^{s}(\xi)} + W_{\kappa} x_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha D_{ij} + x_{ij\kappa m}^{s}(\xi) \beta_{\kappa} \gamma_{\kappa} D_{ij} (s_{ij\kappa m}^{s}(\xi))^{2} + y_{ij\kappa m}^{s}(\xi) \gamma_{\kappa} \alpha\right) \times \sigma + \left(u_{S}^{s}(\xi) E_{S} + \sum_{t} \sum_{n} u_{R_{n}t}(\xi) E_{R}\right) \times \delta\right)\right.$$

Subject to:

Constraints (3.3) - (3.22), (3.27) - (3.34), (3.36) - (3.45), (3.47) - (3.48), (3.50) - (3.51) and (3.53) - (3.62). The objective function of the extended model z_v contains non-linear terms. To linearize these terms, the linearisation approach presented by Bektas and Laporte (2011) is used. We consider a set (Λ) associated with different speed levels, *r,* at which vehicles can travel on arc (*i,j*) with respect to a speed standard, $S^r \leq S$. We then define $g_{ij\kappa m}^{fr}$and $g_{ij\kappa m}^{sr}(\xi)$as auxiliary variables and link them with $x_{ij\kappa m}^{f}$and $x_{ij\kappa m}^{s}(\xi)$ through the following expressions.

$$\sum_{r} g_{ij\kappa m}^{fr} = x_{ij\kappa m}^{f} \qquad \forall i, j, \kappa, m \tag{3.65}$$

$$\sum_{r} g_{ij\kappa m}^{sr}(\xi) = x_{ij\kappa m}^{s}(\xi) \qquad \forall i, j, \kappa, m, \xi \tag{3.66}$$

The extended linearised model z_v is presented as follows:

$$\min z = H_S i_S^f + \phi_E u_S^f E_S + \sum_{\xi} P(\xi) \left(H_S i_S^s(\xi) + \phi_E u_S^s(\xi) E_S + \sum_{t} \sum_{n} \left(H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R \right) \right) \tag{3.67.i}$$

$$+\sum_{\kappa}\sum_{m}\left(\sum_{n}F_\kappa x^{f}_{0n\kappa m}\right. \tag{3.67.ii}$$

$$+\phi_F\Gamma\sum_{i,i,i\neq j}(\sum_{r}\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r}g^{fr}_{ij\kappa m}+W_\kappa x^{f}_{ij\kappa m}\gamma_\kappa \alpha D_{ij}$$

$$\left.+\sum_{r}g^{fr}_{ij\kappa m}\,\beta_\kappa\,\gamma_\kappa D_{ij}(S^r)^2+y^{f}_{ij\kappa m}\gamma_\kappa\alpha)\right)+$$

$$\sum_{\xi}P(\xi)\left(\sum_{\kappa}\sum_{m}\left(\sum_{n}F_\kappa x^{s}_{0n\kappa m}(\xi)\right.\right.$$

$$+\phi_F\Gamma\sum_{i,i,i\neq j}(\sum_{r}\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r}g^{sr}_{ij\kappa m}(\xi)+W_\kappa x^{s}_{ij\kappa m}(\xi)\gamma_\kappa \alpha D_{ij}$$

$$\left.\left.+\sum_{r}g^{sr}_{ij\kappa m}(\xi)\,\beta_\kappa\gamma_\kappa D_{ij}(S^r)^2+y^{s}_{ij\kappa m}(\xi)\gamma_\kappa\alpha)\right)\right)+$$

$$\sum_{\xi}P(\xi)\sum_{t}\sum_{n}\pi s_{nt}(\xi) \tag{3.67.iii}$$

$$\mu\left(\Gamma\sum_{\kappa}\sum_{m}\sum_{i,i,i\neq j}(\sum_{r}\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r}g^{fr}_{ij\kappa m}+W_\kappa x^{f}_{ij\kappa m}\gamma_\kappa \alpha D_{ij}\right. \tag{3.67.iv}$$

$$\left.+\sum_{r}g^{fr}_{ij\kappa m}\,\beta_\kappa\gamma_\kappa D_{ij}(s^{f}_{ij\kappa m})^2+y^{f}_{ij\kappa m}\gamma_\kappa\alpha\times\sigma+u^{f}_{S}E_S\times\delta\right)+$$

$$\mu\sum_{\xi}P(\xi)\left(\Gamma\sum_{\kappa}\sum_{m}\sum_{i,i,i\neq j}(\sum_{r}\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r}g^{sr}_{ij\kappa m}(\xi)+W_\kappa x^{s}_{ij\kappa m}(\xi)\gamma_\kappa \alpha D_{ij}\right.$$

$$+\sum_{r}g^{sr}_{ij\kappa m}(\xi)\,\beta_\kappa\gamma_\kappa D_{ij}(S^r)^2+y^{s}_{ij\kappa m}(\xi)\gamma_\kappa\alpha)\times\sigma$$

$$\left.+\left(u^{s}_{S}(\xi)E_S+\sum_{t}\sum_{n}u_{R_{n}t}(\xi)E_R\right)\times\delta\right)$$

Subject to:

Constraints (3.3) – (3.22), (3.27) – (3.34), (3.36) – (3.45), (3.47) – (3.48), (3.50) – (3.51) and (53) – (62) and (65) – (66).

The deterministic version of the model is a variant of the vehicle routing problem which is known as NP-hard (Coelho et al., 2012; Dabia et al., 2013). Therefore, our model is an NP-hard problem. In our model, a typical instance of the base case (z) had 63,612 constraints and 23,778 variables including 7,158 integer variable decisions, meaning that the optimisation solver (Cplex) is not able to obtain an optimal solution in a reasonable running time. This is confirmed in Section 3.6.1 where the majority of the test instances could not reach optimal values. Therefore, the matheuristic algorithm was also developed in this chapter to obtain good quality solutions in a reasonable computational time.

3.5 An Iterated Local Search algorithm

In this section, we present a matheuristic algorithm based on an Iterated Local Search (ILS) algorithm and a mixed integer programming for the proposed problem. The ILS method is an extension of the classical local search that includes shaking procedure as a diversification mechanism (Sabar and Kendall, 2015). ILS is a single solution based method that searches in the neighbourhood of the local optimum found by local search to generate a new solution instead of restarting completely from another initial solution (Cuervo et al., 2014). Although simple, ILS has been an effective method in solving optimisation problems (Costa et al., 2012; Cuervo et al., 2014; Vansteenwegen et al., 2009). We were also motivated to use the ILS algorithm by the fact that its framework is very adaptable as we intended to combine it with a mixed integer programming to present matheuristic. We first discuss the main components of this algorithm in Sections 3.5.1 – 3.5.7, and the outline of the matheuristic algorithm is provided in Section 3.5.8. The efficiency of the algorithm is demonstrated using multiple test instances in Section 3.6.1.

3.5.1 Initialisation

The initialisation procedure is composed of three phases and is presented in Algorithm 1 (Figure 3-2). In the first phase, we only focus on constructing routes simply to serve the retailers. We relax the heterogeneous fleet assumption and assume that each retailer is visited by a single route using the medium duty vehicle, $\eta_2 = N$. In other words, a retailer i is served with vehicle κ_i, $\kappa = 2$ and $i = 1, \ldots, N$. Then, in the second phase, we use a modified model presented in Section 3.4 (model *z*) in which the routing variables are fixed and considered as the parameters of the model (see Appendix D). The modified model is solved using Cplex to determine the quantity delivered to the retailers. In the third phase, routes are re-built to serve retailers with heterogeneous fleet. This phase focuses on routing decisions and uses the delivered quantities obtained from the second phase as input parameters. In this phase, the first retailer is randomly selected and assigned with a vehicle with a consideration of the vehicle's capacity. Then a next retailer will be randomly selected and inserted into the best position in the route. If no feasible insertion can be found, the retailer is assigned with a next available vehicle. The procedure is repeated until all retailers have been assigned with available vehicles.

```
Algorithm 1: The initialization procedure
Route index κ=0;
Construct single routes to serve the retailers considering
  homogeneous fleet;
Solve the modified model using Cplex to determine the optimal
  quantity delivered to the retailers;
repeat
  | κ=κ + 1;
  | Select a retailer randomly and assign it as the first node to a
  |   vehicle κ;
  | repeat
  | | Select a retailer randomly and insert it into the best position
  | |   in the vehicle route κ;
  | until ((there is an un-routed retailer) and (the capacity
  |   constraint is met));
until (there is an un-routed retailer);
```

Figure 3-2:The initialisation procedure

3.5.2 Swap procedure within the same route

In this procedure, a classical swap procedure is implemented under a best improvement strategy. This procedure seeks to improve the solution's cost by exchanging the positions of the retailers visited in the same route. Let $n_1$be the number of visited retailers on route κ. The procedure starts from retailer i, $i < n_1$, and exchange its positions with another retailer j, $j < n_1$,. All possible exchanges are evaluated for retailer *i,* and then the best one is implemented. This procedure is repeated for all retailers over all routes. The search is stopped whenever the swapping offers no additional improvement.

3.5.3 Swap procedure between routes

This procedure follows the classical swap procedure which is executed under a best improvement strategy. In this procedure customer i from route $\kappa_1$exchange with customer j from route κ_2 considering the vehicles' capacity. The procedure generates all possible combinations of i and j between each pair of routes, and the best feasible one is implemented. In contrast to the previous swap procedure, this procedure may provide unfeasible solutions due to the vehicles' capacity. The procedure stops when no additional improvement is found.

3.5.4 $\boldsymbol{Extraction - Insertion_1}$

The aim of this procedure is to improve the solution by re-positioning the retailers on route κ. This procedure extracts a visited retailer from its location on route κ and re-insert it into the first best position on the route that leads to an improvement in the solution quality by decreasing the visiting cost. If an extracted retailer cannot provide any improvement by inserting in any new position, it is reverted to its original position and a new retailer is evaluated. The procedure is repeated until no improvement is found. During this procedure, the sequence of the visited retailers may change on each route.

3.5.5 $\boldsymbol{Extraction - Insertion_2}$

The goal of this procedure is to improve the solution by re-positioning retailers on another existing route or building a new route. This procedure follows the same idea of the $Extraction - Insertion_1$ procedure with a difference that the extracted retailer is inserted into the best feasible position on an existing route or assigned to an empty vehicle with a consideration of the vehicle's capacity. In this procedure, if the re-positioning of the extracted retailer cannot lead to any improvement in the solution quality, it is inserted back to its original position and a new retailer is evaluated. This procedure may provide unfeasible solutions due to the vehicles' capacity. The procedure stops when no additional improvement is found.

3.5.6 Routes integration

The goal of this procedure is to improve the solution by best utilising the vehicles' capacity through routes integration. We categorise the solution into the sets that include two or three routes in each period. As an example, suppose that we have three routes (κ_1, $\kappa_2$and κ_3), to serve the retailers at the first period. This procedure creates sets including all possible combinations of two or three routes, i.e., (κ_1, κ_2), (κ_1, κ_3), (κ_2, κ_3) and (κ_1, κ_2, κ_3). Then the procedure explores the possibility of the routes integration within each set. In other words, if the total quantity delivered to retailers visited in each set is less than the maximum vehicle capacity, the routes integration will be feasible. In this procedure, all possible integration are evaluated and then the best one is implemented. The procedure is repeated until no improvement is found.

3.5.7 Shaking procedure

To abstain stopping at local optimum, we present two shaking procedures as follows:

Shaking1: Let S_1 be all sub-solutions including the sub-solution of the first period and the sub-solutions of Ξ scenarios in the second period, $S_1 = \{0,1, \dots, \Xi\}$ where 0 represents the sub-solution of the first period and the rest of them represent the sub-solutions of scenarios in the second period. The procedure starts with $S_1 = 0$ and removes the corresponding sub-solution, i.e., the procedure destroys the routes in the sub-solution. Then we use a modified model to re-build new routes for the corresponding period or scenario and update the quantity delivered to retailers. In the modified model, we use the model presented in Section 3.4 (model z) in which all routing variables, except routing variables related to the corresponding period or scenario, are fixed as parameters. We solve then the modified model using Cplex to re-build an optimal sub-solution for the targeted period or scenarios, and update the quantity delivered to retailers in the whole solution. The procedure is repeated until $S_1 \leq \Xi$. If the best solution is improved during this procedure, the procedure starts again from $S_1 = 0$. Hence, the number of times that this procedure is repeated is not constant in algorithm iterations.

Shaking1: A retailer is randomly selected and extracted from the solution, from all sub-solutions in the first and second periods. The solution is updated after extracting the selected retailer and is called *solution1*. We use a modified model to re-insert the selected retailer in the best position, i.e., the position with the minimum extra insertion cost, on routes in *solution1*. The modified model uses the model presented in Section 3.4 (model z) in which the values of routing variables not related to the selected retailer (e.g, $x^{f}_{ij\kappa m}$, $i,j \neq$ the selected retailer) and not included in *solution1* are set to zero. However, the values of other routing variables are determined by the modified model. We illustrate this with an example in which there are 3 retailers serving by two routes. First a retailer is selected randomly (say, retailer 2) and extracted from the solution. Suppose that the solution includes the following routes $\kappa_1 = (0,1,2,0)$, and $\kappa_2 = (0,3,0)$. As a result of the extraction, *solution1* includes the following routes $\kappa_1 = (0,1,0)$, and $\kappa_2 = (0,3,0)$. Second, the modified model is used to re-insert retailer 2 in the best position on the routes in *solution1*. To do so, the following routing variables, $x_{13\kappa_1}$, $x_{31\kappa_1}$, $x_{13\kappa_2}$and $x_{31\kappa_2}$are set to zero in the modified model. Then, the modified model is solved using Cplex to determine the optimal position of the selected retailer on the routes to build new routes accordingly. The quantity delivered to retailers are also updated in the whole solution.

3.5.8 The matheuristic algorithm

This section describes the matheuristic algorithm that we have developed based on an Iterated Local Search and a mixed integer programming to solve the proposed problem. Matheuristics are a kind of heuristic methods that make use of a mathematical programming model inside a heuristics framework to obtain a good quality solution (Bertazzi et al., 2016). They have been successfully implemented in different optimisation problems (e.g., Hemmati et al. (2016); Fonseca et al. (2018); Ghiami et al. (2019)).

The pseudocode of the proposed algorithm is presented in Algorithm 2 (Figure 3-3). The algorithm starts from an initial solution generated by using the initialisation procedure in Section 3.5.1 (lines 1-4 in Algorithm 2). Then the algorithm is executed repeatedly to improve the initial solution by randomly selected a shaking procedure from Section 3.5.7 followed by local search procedures presented in Sections 3.5.2 – 3.5.6 (lines 5-21 in Algorithm 2). In each iteration, if the initial solution is improved, it is updated (lines 14-20 in Algorithm 2). The algorithm stops after a number of consecutive repetitions *(Iter)* without improvement or the time limitation is met.

Algorithm 2: The structure of our matheuristic algorithm

```
Input: Initial − solution;
Best − cost = Cost (Initial − solution);
Current − solution := Initial − solution;
Best − solution := Initial − solution;
repeat
    Randomly select one of the shaking procedures;
    repeat
        Current − solution := Swap(Current − solution);
        Current − solution := Swap2(Current − solution);
        Current − solution :=
          Extraction − Insertion_1(Current − solution);
        Current − solution :=
          Extraction − Insertion_2(Current − solution);
        Current − solution :=
          Routes − Integration(Current − solution);
    until (no more improvement is achieved);
    if (Cost (Current − Solution) < Best − Cost) then
        Best − Cost = Cost (Current − Solution);
        Best − solution := Current − Solution;
    end
    else
        Current − solution := Best − solution;
    end
until (the time limitation is met) or (no improvements are found
  for Iter consecutive iteration);
Output:Best − solution;
```

Figure 3-3:The structure of our matheuristics algorithm

3.6. Computational results

The aim of this section is fourfold: 1) to evaluate the efficiency of the matheuristic algorithm, 2) to demonstrate the application of the model formulated in Section 3.4 using a real-world case study, 3) to analyse the impact of using heterogeneous fleet on economic and environmental aspects, 4) to conduct sensitivity analyses for some parameters and provide managerial insights in order to make cost-effective and environment-friendly decisions. We use a real-world case study in the state of Queensland in Australia to evaluate our proposed model from a practical aspect due to the long distances between production and consumers' sites and high energy consumption of cold supply chain operations in this region (Jutsen et al., 2017; MacGowan, 2010; Tasman, 2004). We evaluate the performance of the matheuristic algorithm using test instances in multiple sizes in Section 3.6.1. Due to the uncertain nature of demand, Monte Carlo sampling approach is used to generate a suitable scenario size to evaluate the model from a practical perspective in Section 3.6.2. The case description and numerical experiments are presented in Sections 3.6.3 and 3.6.4, respectively. Section 3.6.5 presents the impact of using heterogeneous fleet on the economic and emissions costs. The sensitivity analyses for parameters are conducted in Section 3.6.6. Finally, managerial insights are presented in Section 3.6.7.

3.6.1 Analysing the performance of the proposed algorithm

In this section, we perform computational tests to evaluate the efficiency of the proposed algorithm. We generate test instances with multiple sizes using real data of the case study presented in Section 3.6.3. We compare the performance of the proposed algorithm with results obtained from commercial optimization solver (Cplex) within time limit of 7200 s per instance. The proposed algorithm presented in Section 3.5.8 was implemented in Visual Studio C++ and Cplex 12.3 was used to solve the modified mathematical models within the algorithm. All experiments were coded on an Intel i7 CPU with a 3.6 GHz processor and 16 GB RAM. Before presenting the results of algorithm, the main parameter of the algorithm (*Iter*) was carefully tuned as it impacts on the quality of the solution and computational time. To tune *Iter*, one-third of the instances of various sizes have been selected as the test instances. Without loss of generality, we assume different values for *Iter* (e.g., 50, 100, 150 and 200). Then, the algorithm was run ten times for each value on the test instances. The results revealed that the best value for *Iter* is 100 measured by the average optimality gap and CPU time. This experiment indicated that changing *Iter* from 100 to 150 or 200 leads to an increase in the run time with no significant improvement in the quality of the solution.

To evaluate the proposed algorithm, 40 instances in small and medium sizes were generated using real data of the case study. Each instance is labeled “Data-s-n” where “s” represents the total number of scenarios and “n” the total number of retailers. Table 3-5 summarises the results for 40 instances containing up to 65 scenarios and 6 retailers. The column labeled “Cplex”, gives the best solution obtained using commercial optimisation solver (Cplex). The proposed algorithm was run ten times for each instance and the results are reported in the last five columns including average solution, standard deviation, best solution, worst solution and average running time for each instance.

Table 3-5:Performance of the Matheuristic algorithm on small and medium size instances

		Matheuristic				
Ins.	Cplex	Ave. solution	Standard deviation	Best solution	Worst solution	Ave. time (s)
Data-5-3	2111.88*	2,111.88	0	2,111.88	2,111.88	9.33

Data-5-4	3271.05*	3271.05	0	3271.05	3271.05	16.50
Data-5-5	4,635.14	4,635.14	0	4,635.14	4,635.14	37.44
Data-5-6	13,282.59	13,282.59	0	13,282.59	13,282.59	200.00
Data-10-3	2,173.24*	2,173.24	0	2,173.24	2,173.24	11.70
Data-10-4	3,193.60	3,193.60	0	3,193.60	3,193.60	31.97
Data-10-5	4,713.39	4,713.39	0	4,713.39	4,713.39	68.41
Data-10-6	13,033.29	13,028.37	0	13,028.37	13,028.37	251.75
Data-15-3	2,380.98	2,365.81	7.97	2,361.87	2,380.90	17.41
Data-15-4	3,353.71	3,353.71	0	3,353.71	3,353.71	41.47
Data-15-5	4811.80	4,809.16	1.44	4,807.60	4,811.80	88.24
Data-15-6	12,887.92	12,885.29	0.60	12,885.1	12,887.01	341.73
Data-20-3	2,520.65	2,390.57	9.95	2,379.00	2,398.28	24.18
Data-20-4	3,432.47	3,432.47	0	3,432.47	3,432.47	65.86
Data-20-5	4,821.73	4,817.57	2.11	4,815.63	4,820.53	125.07
Data-20-6	12,996.58	12,981.15	1.52	12,980.43	12,984.00	522.67
Ave.	5,851.25	5,840.31	1.48	5,839.07	5,842.38	115.86
Data-40-3	2,771.37	2,455.15	27.24	2,455.15	2,546.85	59.09
Data-40-4	3,544.32	3,450.29	7.88	3,444.05	3,461.22	169.50
Data-40-5	5,003.01	4,939.88	4.63	4,935.74	4,947.64	308.62
Data-40-6	13,191.22	12,951.17	2.10	12,948.68	12,955.92	1,059.66
Data-45-3	2,769.37	2,441.56	9.90	2,434.75	2,457.09	74.69
Data-45-4	3,473.07	3,387.15	3.64	3,384.62	3,395.48	204.38
Data-45-5	4,890.88	4,889.15	1.02	4,888.33	4,890.88	414.31
Data-45-6	12,870.60	12,709.80	3.73	12,706.30	12,715.87	1,204.58
Data-50-3	2,787.34	2,490.80	20.20	2,481.85	2,545.71	91.15
Data-50-4	3,541.63	3,458.72	4.54	3,452.03	3,466.88	212.57
Data-50-5	4,950.26	4,947.80	1.48	4,946.58	4,949.75	448.00
Data-50-6	12,941.92	12,799.11	3.10	12,795.64	12,803.52	1,502.79
Data-55-3	2,734.09	2,478.84	27.34	2,461.22	2,551.99	86.49
Data-55-4	3,515.23	3,440.98	4.31	3,434.62	3,448.03	237.12
Data-55-5	4,920.91	4,916.20	1.63	4,913.81	4,918.37	509.91
Data-55-6	13,309.93	12,761.47	5.11	12,757.56	12,771.15	2,120.22
Data-60-3	2,790.10	2,546.03	10.36	2,527.99	2,563.98	106.75
Data-60-4	3,599.88	3,517.16	4.59	3,512.39	3,527.19	306.40
Data-60-5	4,980.57	4,976.57	2.10	4,974.39	4,980.29	561.70
Data-60-6	13,260.34	12,812.17	2.40	12,808.97	12,815.39	2,220.89
Data-65-3	3,478.42	3,243.66	13.73	3,236.99	3,269.76	116.34
Data-65-4	4,642.97	4,549.68	4.11	4,543.43	4,555.15	296.28
Data-65-5	6,755.82	6,751.29	1.88	6,747.89	6,753.42	585.66
Data-65-6	13,042.71	12,818.46	2.03	12,817.61	12,823.88	2,338.37
Ave.	6,240.25	6,073.01	7.04	6,067.11	6,088.15	634.81
Global Ave.	6,084.65	5979.93	4.82	5,975.89	5,989.84	427.23

* The obtained solutions are optimal.

In Table 3-5, the running times for Cplex are not reported as the time limit of 7200 s has been reached for most of the instances. On these instances, Cplex is able to prove optimality for only 3 of the 40 instances within the time limit. As can be seen from Table 3-5, in 31 instances the matheuristic algorithm, on average, generated better solutions than Cplex. In 9 instances, the two approaches produced the same solutions. In general, the matheuristic algorithm was able to find a good solution faster than Cplex. The results show that the performance of the matheuristic algorithm is more robust as the standard deviation of solutions across ten runs is smaller than the standard deviation from average solution and that found by Cplex. We also generated 12 larger instances containing up to 65 scenarios and 10 customers. Table 3-6 summarises the results for the larger instances. For these 12 instances the performance of the proposed matheuristic algorithm is superior to that of Cplex. The algorithm leads to 54.33% improvement, on average, in the best solution obtained by Cplex. The performance of the solution is also stable on the larger instances as the standard deviation of average solution and that found by Cplex is greater than the standard deviation of solutions found by the matheuristic algorithm across ten runs. As can be observed from the results, increasing in the size of the problem may not always lead to an increase in the running time of the algorithm, as its structure is governed by a randomness mechanism. Moreover, in the proposed algorithm, the number of times which *shaking1* is repeated may be different in algorithm iterations for each instance, as S_1re-starts from zero if the procedure leads to an improvement in the best solution.

Table 3-6:Performance of matheuristic algorithm on large size instances

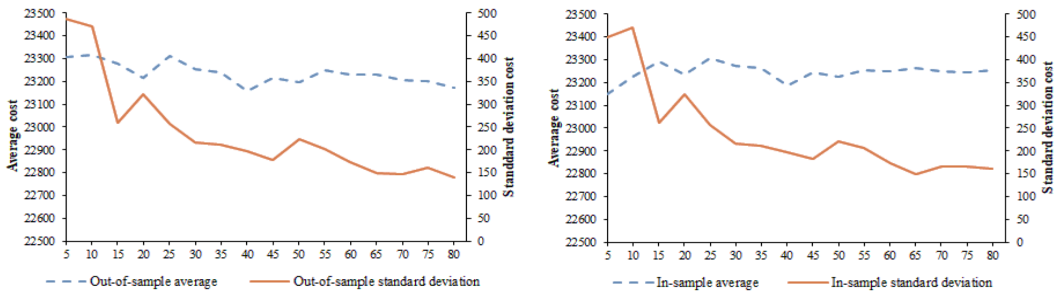
Ins.	Cplex	Matheuristic				
		Ave. solution	Standard deviation	Best solution	Worst solution	Ave. time (s)
Data-50-8	9,413.85	8790.81	11.51	8,782.11	8,822.40	3,913.31
Data-50-9	15,119.22	8,989.58	11.66	8,976.13	9,010.64	4,083.79
Data-50-10	23,736.23	9,932.10	106.45	9,864.97	10,199.41	3,980.58
Data-55-8	9,694.77	8,790.64	3.65	8,783.21	8,795.98	4,319.59
Data-55-9	10,676.35	8,973.51	6.06	8,964.66	8,981.01	4,591.06
Data-55-10	18,583.32	9,933.97	115.93	9,883.42	10,255.86	4,604.49
Data-60-8	13,066.86	8,814.18	4.67	8,808.31	8,820.55	5,225.99
Data-60-9	19,176.27	9,040.19	17.07	9,015.97	9,064.02	5,002.93
Data-60-10	25,634.95	9,912.50	27.65	9,850.64	9,942.13	4,803.97
Data-65-8	15640.86	11,818.85	37.88	11,776.51	11,865.91	5,447.67
Data-65-9	12,689.18	8,968.68	7.60	8,953.26	8,984.14	5,587.15
Data-65-10	80,167.28	11,843.2	235.70	11,530.39	12,119.36	5,604.32
Ave.	21,133.26	9,650.69	48.82	9,599.13	9,738.45	4,763.74

3.6.2 Monte Carlo sampling approach

Using a scenario-based approach to deal with uncertainty in an optimisation model generates a significant challenge due to the need to select an appropriate scenario sample size to balance the effort between optimisations and estimation. Due to demand uncertainty and the variability in solutions, it is crucial to determine the size of the scenario to absorb these variabilities and to avoid time-consuming computations. In this chapter, a Monte Carlo sampling approach is applied to cope with demand uncertainty. This method is suitable to solve a model involving attributes such as expectations and probabilities that cannot be valued exactly (Homem-de-Mello & Bayraksan, 2014).

Once a statistical distribution is defined for the demand, various scenario sample sizes can be generated using a Monte Carlo sampling approach. The in-sample and out-of-sample stability and computational efforts are executed to identify a desirable scenario sample size. The in-sample stability measures the variability of the objective function among different scenarios in the same scenario sample size. The out-of-sample stability considers the variability of objective function observed among various independent scenario sample sizes (Kaut and Wallace, 2007; Dillon et al., 2017).

We created a simple instance, considering the proposed base case model (z) in Section 3.4 and the most parameter values used in Section 3.6.3 to perform the stability of the tests. In order to conduct tests, we generated the sample sizes of 16 scenarios, ranging from 5 to 80 with an increment of 5. For each scenario, 20 replications were performed. Figure 3-4 illustrates the average and the standard deviation of the optimal objective function for all replications, and the average and standard deviation of the optimal objective function for each scenario within a given size. As can be observed from both plots, the average and standard deviation of the objective function converged after 65 scenarios. Hence, we can conclude that choosing 65 scenarios is reasonable in terms of stability measurements.



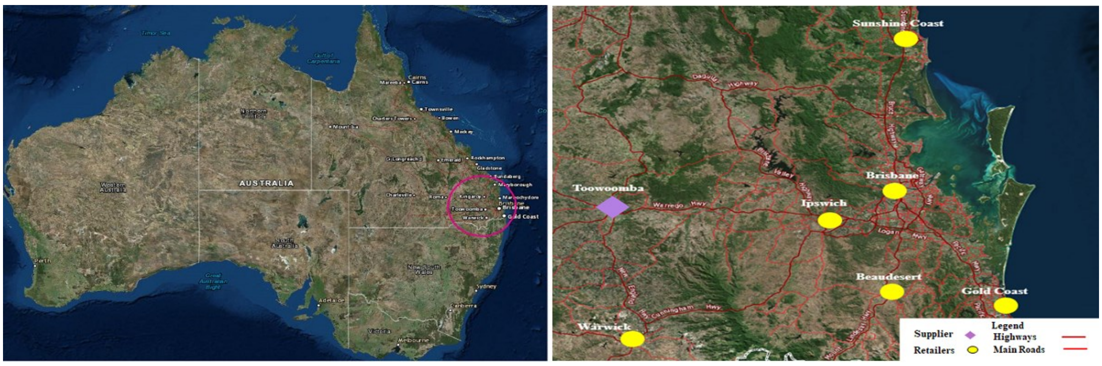
(a) Out-of-sample stability (b) In-sample stability

Figure 3-4:Scenario sample stability for determining reliable scenario size

3.6.3 Description of the case study

The need for Australia to use decision support tools for minimising operational and emissions costs simultaneously can be justified due to the geographical dispersion and subsequent road length as well as energy consumption of transportation and storages in the Australian cold supply chain. We apply the proposed model in Section 3.4 to a real-world case study for distributing perishable products from the region of Toowoomba (an agricultural region in the state of Queensland in Australia) to the retailers in its surrounding areas.

Toowoomba is 120 *km* west of Brisbane, the capital city of the state of Queensland and the largest non-capital inland city in Australia. Toowoomba is situated at the junction of main national highways. Toowoomba was identified by Australian government agencies and industry as a potential agricultural distribution centre of perishable products due to its strategic location, and excellent transport connectivity (Zhang and Woodhead, 2016). Therefore, we used Toowoomba as the supplier in our research that distributes a single type of cold item to retailers. We assume surrounding cities/towns: namely, Brisbane, Gold Coast, Sunshine Coast, Ipswich, Warwick and Beaudesert as retailers in our research. The logistics network consisting of the locations of supplier and retailers is presented in Figure 3-5.



(a) Australia (b) The selected region

Figure 3-5:The logistics network for the case study

We also assume that heterogeneous vehicles are used to distribute the cold product from the supplier to all retailers. We consider two different vehicle types, light and medium duty vehicles. As the data regarding the characteristics of vehicles are not available, the parameters used to calculate the fuel cost of each type of vehicle are taken from previous research and are summarised in Tables 3-7 and 3-8. It should be noted that, these data are associated with normal (unrefrigerated) vehicles. Refrigerated vehicles consume more energy consumption and have higher carbon emissions because of extra fuel requirements for cooling (Stellingwerf et al., 2018a). The data associated with the exact fuel consumption of refrigerated vehicles cannot be computed easily as it is influenced by several factors such as temperature. For the sake of simplicity, we increase the fuel consumption by 20% to account for the further fuel consumption required by refrigeration vehicles.

We considered speed as a fixed parameter over all routes in our real-world case study as we focused on rural distribution across the State of Queensland, Australia which has similar road conditions. The cold supply chain participants should normally observe the speed limits set by the government. Speed limits are enforced by laws, and clearly indicated in traffic signs across roads. We set a speed parameter in such a way that satisfies all speed standards across the roads in our case study. While factors such as traffic conditions and disasters may also impact the speed of vehicles, these problems are rare in the case study considered. It is, therefore, logical and sufficient to consider speed as a fixed parameter in our case study. We used a big-*M* to create some constraints in our modelling. The value of the *M* can impact on the performance of the model. The value of *M* has been determined in such a way that could cover the relevant constraints and was set tomax $\{N, \max\{O_\kappa \times D_{in}\}, \max\{D_n(\xi), \Upsilon\}$. Based on our case study data, the *M* value was taken as $\max\{O_\kappa \times D_{in}\}$.

Table 3-7: Definition of vehicle specific parameters

Notation	Description	Light duty	Medium duty
W_κ	Curb weight	3500	6550
O_κ	The capacity of vehicle	2580 (258 unit)	5080 (508 units)
F_κ	Fixed cost of vehicle	74.19	106.62
Φ_κ	Engine friction factor	0.25	0.2
N_κ	Engine speed	38.34	33
ι_κ	Engine displacement	2.77	5
$C_{d\kappa}$	Coefficient of aerodynamics drag	0.6	0.7
A_κ	Frontal surface area	7	9

Source: Koc et al. (2014) and Cheng et al. (2017)

Table 3-8:Definition of vehicle typical parameters

Notation	Description	Value
τ	Fuel-to-air mass ratio	1
g	Gravitational constant (m/s^2)	9.81
ρ	Air density (kg/m^3)	1.2041
C_e	Coefficient of rolling resistance	0.01
ω	Efficiency parameter for diesel engines	0.45
ϕ_F	Unit fuel cost (AU$/L)	1.46
μ	Unit CO_2emissions price (AU$/kg)	0.44
σ	CO_2 emitted by unit fuel consumption (kg/L)	2.669
φ	Heating value of a typical diesel fuel (kJ/g)	44
S	Speed (km/h)	60
ψ	Conversion factor (g/s to L/s)	737
ζ_κ	Vehicle drive train efficiency	0.4

The emissions (in kg per 100 km) generated by the two types of refrigerated vehicles are shown in Figure 3-6. Figure 3-6 demonstrates the impacts of two important factors, travel speed and payload, on the emissions. It can be seen that refrigerated vehicles generate high emissions in low speed values as a result of inefficiency in fuel consumption. The amount of emissions decreases with the increase in speed until a certain level, after which it goes up again with the increase in speed because of the aerodynamic drag. Figure 3-6 also shows the impact of payload on the resulting emissions.

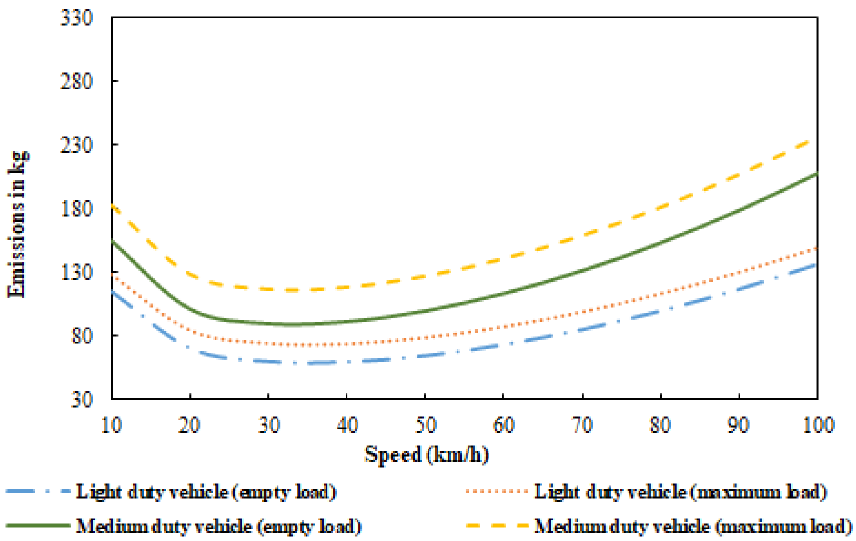


Figure 3-6:Emissions per 100 km depending on speed with different payload settings

In our models, we take vehicle load, speed and distance travelled into account when calculating associated fuel cost. For the distance measure, we considered the centre of Toowoomba as the supplier point. We also aggregated retailers in each city/town and considered the centre of each city/town as the retailer point. The distance between nodes is then estimated using Google Maps and given in Table 3-9. The proposed model is a general model which is not limited to any special statistical distribution as a distribution function is only used to generate demand scenarios. The realistic data presenting the daily demand of the retailers for a cold product was generated by a Poisson distribution, in accordance with Schmidt and Nahmias (1985), Berk and Gürler (2008), and Olsson and Tydesjö (2010). As the demand of each city/town differs significantly, we use different mean values to generate retailer point's demand. In this study, the scenario size was determined using Monte Carlo sampling approach presented in Section 3.6.2. As discussed above, a sample of 65 scenarios was used.

Table 3-9:Distances between nodes in the case study, in km

	T	W	I	BD	GC	SC	B
Toowoomba (T)	0	-	-	-	-	-	-
Warwick (W)	83.8	0	-	-	-	-	-
Ipswich (I)	89.6	118	0	-	-	-	-
Beaudesert (BD)	160	122	68.4	0	-	-	-
Gold Coast (GC)	175	177	92.9	55.3	0	-	-
Sunshine Coast (SC)	219	259	146	175	177	0	-
Brisbane (B)	121	158	44.5	70	71.9	105	0

A unit cold product refers to a packaging unit, which could be a box or a pallet. It is assumed that one packaging has $\vartheta = 10\ kg$ weight and occupies a volumetric space of *volume*= 0.15 m^3. At the supplier end, medium sized refrigeration units are used with a storage capacity of 20 m^{3}each (or equivalently C_S=133 units of the cold item). We consider a refrigeration system with single stage recuperating compressors and evaporative condensers for storing a cold item at both the supplier and retailers. The energy consumption of such refrigeration system type is 57.6 kWh/year/ m^3 (James and James, 2010).

Hence, the total energy consumed by each refrigeration unit at the supplier is $57.6 \times\ 20 = 1152$ kWh/year (or equivalently $E_S = 3.156$ kWh/d. At a retailer, a smaller size of the same type refrigeration units is utilised with a storage capacity of 10 m^3 each (or equivalently C_R=66 units of the cold item). Hence, in the same way, the energy consumption by one refrigeration unit at a retailer is $57.6 \times\ 10 = 576$ kWh/year (or equivalently $E_R\ = 1.58$ kWh/d).

Since the energy cost varies across the level of consumption and countries, we assume the cost to be AUD 0.0928 per kWh. The total carbon emissions per 1 kWh of energy consumption by each refrigeration unit is assumed to be 6.895×10^{-4} tons/kWh (or equivalently $\delta = 6.895 \times 10^{-7}$ kg/kWh) (Hariga et al., 2017). The available quantity of cold product at the supplier facility was assumed to be Q=1200 units in each period and we also assume that the maximum storage capacity at a retailer is ϒ=200 units. The holding cost at the supplier and a retailer are assumed to be $H_S = AUD10$ and $H_R = AUD15$ per packaging unit of cold product per day respectively. We consider shortage as lost sales and its cost is set to be $\pi = AUD100$per packaging unit of cold product.

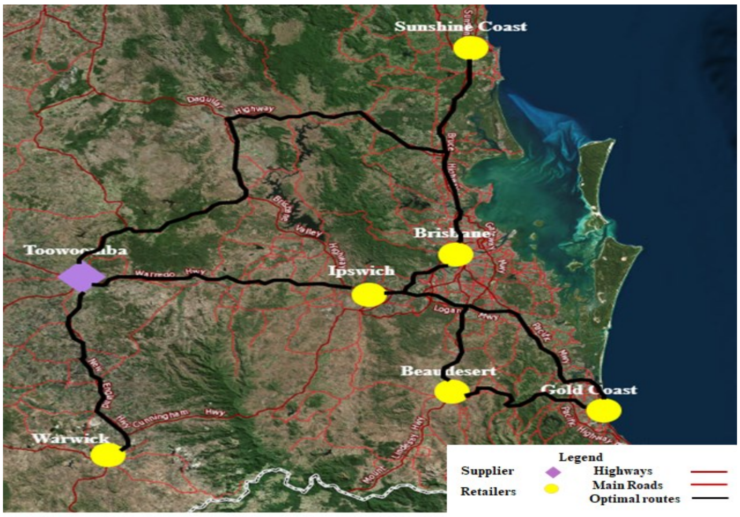
3.6.4 Numerical example and analysis

In this study, we explore the trade-off between logistics operational costs and emissions in the cold supply chain and the benefits of accounting for carbon tax regulation and using a heterogeneous fleet on the proposed framework. We focused on the following KPIs: (i) emissions costs that consist of emissions from transportation and inventory, (ii) storage costs that consist of holding and refrigeration costs, (iii) transportation costs that include fixed and fuel costs, (iv) cost of lost sales, and (v) total cost. In order to evaluate the effects of the parameters on the KPIs, sensitivity analyses were performed for the carbon price, distance and vehicle speed. In addition, the benefits of applying heterogeneous vehicles were examined.

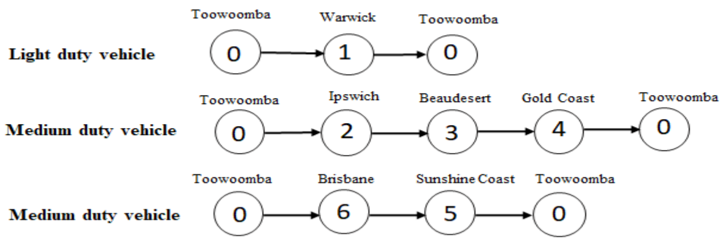
We report the optimal configurations of the first-stage decision variables and optimal expected values of the objective functions of the base case model (z) in Figure 3-7 and Table 3-10, respectively. The optimal solution of the first-stage includes three routes: the first route includes Toowoomba, Warwick and Toowoomba; the second one includes Toowoomba, Ipswich, Beaudesert, Gold Coast and Toowoomba; and the third route visits Toowoomba, Brisbane, Sunshine Coast and Toowoomba. Light duty vehicle is used in the first route, while the other two routes are traversed by medium duty vehicles. Vehicles' capacity utilisation is 57.36%, 98.03% and 78.34% in the first, second and third routes at the first-stage, respectively.

Table 3-10:Optimal values of the objective functions under the base case model in AUD

Inventory cost	Transportation cost	Emissions cost	Lost sale cost	Total cost
7980.15	1741.42	978.53	2117.50	12817.61



(a) The general view of optimal routes



(b) Unique view of optimal routes

Figure 3-7:The general and unique views of the optimal routes at the first-stage under the base case model

To evaluate the behaviour of the extended model $z_v$we implemented it in the case study and compared the results with those obtained from the base case model (z). The optimal configuration of the first-stage is similar to that obtained by the base case model; however the optimal expected values of the objective functions are lower. It appears that better economic and environmental results can be achieved with flexible speed. The optimal expected values of the objective functions of the extended model are summarised in Table 3-11.

Table 3-11:Optimal values of the objective functions under the extended model in AUD

Inventory cost	Transportation cost	Emissions cost	Lost sale cost	Total cost
7995.26	1578.72	848.46	2105.18	12527.62

As can be observed from the results, the vehicles tend to travel at the lowest speed level, 40 *km/h*, to reduce transportation costs and emissions costs as a result of a reduction in fuel consumption. The total emissions generated, and the total cost decreased by around 13.29% and 2.26%, respectively, compared to the results obtained under the fixed speed.

Figure 3-8 presents the frequency of the optimal quantities delivered to each city/town under 65 scenarios in the second-stage. It can be seen that in the second-stage, in 35.38% of the scenarios the amount of quantities delivered to Warwick is in the range of 80-100 pack of cold item, and in 12.3% of the cases it is more than its λ; in 40% of the scenarios the amount of quantities delivered to Ipswich falls within the range of 110-140 pack of cold item, and in 16.9% of the cases is more than its λ; for Beaudesert, in 56.9% of the scenarios the amount of quantities delivered is less than 80, and in 80% is less than its λ; in 37% of the scenarios the amount of quantities delivered to Gold Coast falls in the range 170-200 pack of cold item, and 26.1% of the cases is more than its λ; in more than half of the scenarios the amount of quantities delivered to Sunshine Coast and Brisbane falls in the range 130-160 and 210-240 pack of cold items, respectively, and in 12.3% and 40% of the cases it is more than their λs respectively. The optimal solution of the second-stage includes 26 various routes under 65 scenarios. Figure 3-9 indicates that in the 23.07% of the scenarios, the optimal solution construction in the second-stage includes two routes which are traversed by medium duty vehicles.

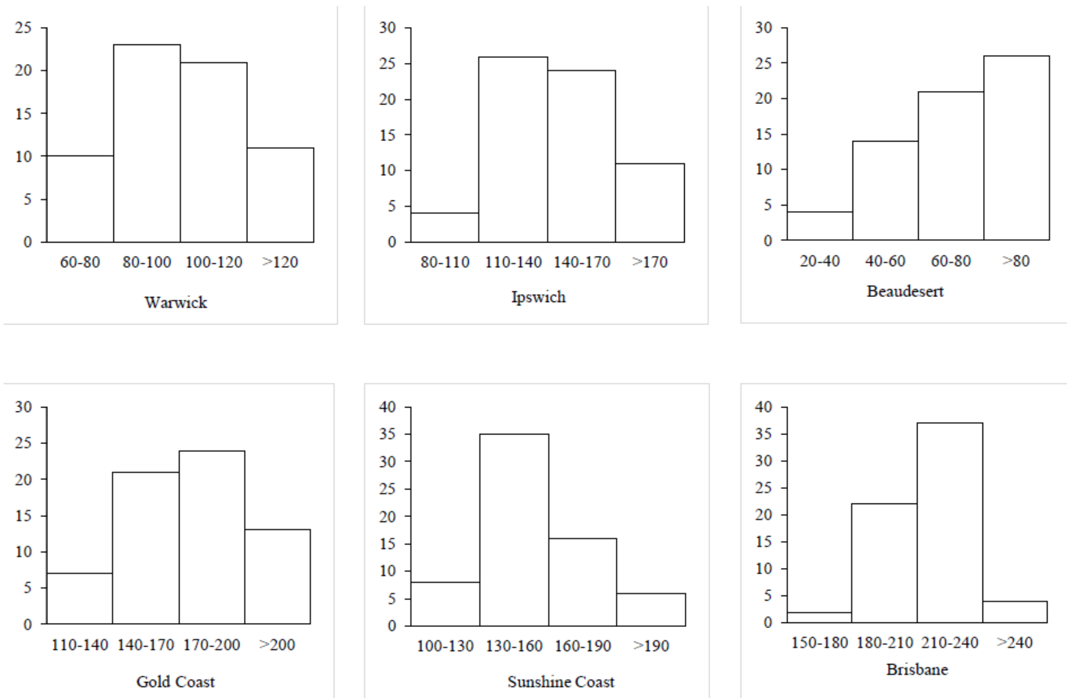


Figure 3-8:Frequency distribution of optimal quantity in the second-stage

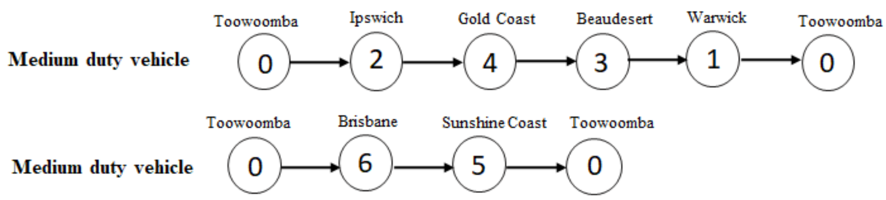


Figure 3-9:Optimal solution construction for 23.07% of scenarios in the second-stage

In our case study, as the cold supply chain participants had access to refrigeration systems greater than their requirements, providing additional refrigeration systems is not a significant issue. However, energy consumption of these refrigeration systems is still a substantial problem. Despite the fact that the number of refrigeration system is high enough to satisfy the requirements of each participant of the chain, different fixed costs for refrigeration systems at the supplier and retailers are assumed to explore the impact of the fixed cost of refrigeration systems on the total cost of the chain. The fixed cost of refrigeration systems at the supplier and retailers are assumed to be $AUD1500$/year (or equivalently $F_S = AUD4.1/day$) and $AUD1000$/year (or equivalently $F_R = AUD2.74/day$), respectively. It contains the cost of having an additional refrigeration system, including its installation. Adding the fixed cost of refrigeration systems into the base case model would increase the total cost by 1.26%.

3.6.5 Impact of a heterogeneous fleet

In this section, we analyse the benefits of applying a heterogeneous fleet to optimise the total cost under the base case model over a homogeneous one. We have conducted experiments by using a heterogeneous fleet (i.e. both light and medium duty vehicles) and a single unique vehicle type (i.e. only light or medium duty vehicle). Table 3.12 represents the result from the comparisons. In Table 3.12, the "Gap" refers to the differences, in percentage, between the status in which a heterogeneous fleet is used and that when a single unique vehicle type is used. Table 3.12 demonstrates that using a heterogeneous fleet renders more benefits in reducing both economic and emissions costs. Compared to the case where a single unique vehicle type is used, the use of heterogeneous vehicles can decrease the total cost by almost 2.28% and 1.88%, respectively. Using a heterogeneous fleet can also reduce the emissions cost by about 4.90% and 9.43% compared with the cases where only light duty or medium duty vehicle is used.

The results suggest when a homogeneous fleet is used, it is desirable to use the medium duty vehicles from the economic point of view, however, in terms of environmental impacts, the light duty vehicles are preferred. Under the travel distance objective, the results imply that using medium duty vehicles is preferable as this can be led to the minimisation of the average distance travelled. In Table 3-12, we also present the range of capacity utilisation of the vehicle fleet for both heterogeneous and homogeneous cases. The average capacity utilisation in the first stage reaches a maximum level of 81.07% when only the light duty vehicle is used, while it reaches a minimum level of 68.5% when only the medium duty vehicle is used.

Table 3-12:Impact of using a heterogeneous fleet on various costs

	Heterogeneous fleet	Only light duty	Only medium duty	Only light duty GAP (%)	Only medium duty GAP (%)
Inventory cost (AUD)	7980.15	7988.86	7980.15	-0.11	0.00
Transportation cost (AUD)	1741.42	1963.20	1884.78	-11.30	-7.61
Lost sale cost (AUD)	2117.5	2135.98	2117.50	-0.87	0.00
Emissions cost (AU)	978.53	1028.93	1080.46	-4.90	-9.43
Total cost (AUD)	12817.61	13116.97	13062.89	-2.28	-1.88
Range of capacity utilisation in the First-stage (%)	57.36-98.03	74.4-99.22	29.13-99.6	-	-
Average loading rate in the first-stage (%)	77.91	81.07	68.50	-	-
Average total travel distance	1017.72	1434.88	1000.68	-	-

3.6.6 Sensitivity analysis

This section analyses the impact of changing parameters on the costs and CO_2emissions with the base case model (z) used as a benchmark. Sensitivity analyses are conducted with changes in unit emission price, distance and vehicle speed.

3.6.6.1 Impact of changes in unit emissions price

This section analyses the impact of unit emissions price on total cost and CO_2emissions. Figure 3-10 indicates that overall the emissions trend experiences a reduction pattern with the increase in the unit emissions price, while the total cost increases steadily. If there were no carbon tax regulation (unit emission price=0), the system would emit the maximum emissions. However, increasing the unit emissions price does not always lead to an environmental improvement as carbon emissions reductions involve substantial economic costs. For instance, with an increase in the unit emissions price from 0.88 (AUD/kg CO_2) to 2.2 (AUD/kg CO_2), the emissions level remains almost unchanged, but the total cost increases from AUD13,789.51 to AUD 16,717.12.

In our case, the reduction in carbon emissions can be achieved through decreases in the number of active refrigeration systems, reduced fuel consumption along the cold supply chain or increased investments in cleaner technologies. Unfortunately, the reduction of active refrigeration systems by one participant can lead to increased sales losses or result in an increased demand for the refrigeration and storage services operated by other participants of the chain. In the latter case, the transportation cost would increase. On the other hand, the reduction of transportation emissions may be achieved by using more light duty vehicles. However, using more light duty vehicles will not always be the best solution as it may increase the distance travelled and the fixed cost due to the increase in transportation frequency. It should also be noted that there is also a limitation of the number of available light duty vehicles in our case.

As can be seen from Figure 3-10, when the unit emissions price increases from 0 to 0.88 (AUD/kg CO_2), the model suggests that there will be a considerable decrease in carbon emissions. However, the extended ranges of the unit emissions prices from 0.88 (AUD/kg CO_2) to 2.2 (AUD/kg CO_2) do not lead to additional operational modifications as any further modifications toward generating lower-emissions are likely to incur a substantial increase in relevant operational costs. Similar findings have been reported in the literature on traditional supply chains (see, Zakeri et al. (2015); Cheng et al. (2017)). Therefore, it appears to be true that a higher carbon price may not always lead to lower carbon emissions in many instances, not just specifically for this case study.

Further increases in the unit emissions prices, say, from 2.2 (AUD/kg CO_2) to 2.64 (AUD/kg CO_2), can lead to a reduction of about only 0.13% in the emissions level. However, it has a higher impact on the total cost. That is, the total cost would increase by about 5.8%. Therefore, to design an optimal carbon tax policy, it is critical to determine the appropriate tax range in which companies are able to decrease emissions without incurring a significant increase in the total cost.

In 2012 the Australian government introduced carbon tax regulations to address increasing emissions that are believed to be associated with the global warming and climate change problems. However, it was repealed in 2014 by the Liberal Government with the excuse that the carbon tax brought high costs to Australian companies and households and was ineffective in reducing emissions. The findings of this research suggest that it is possible for Australian policy-makers to set an appropriate carbon price range to achieve environmental improvements without imposing a significant cost on companies and households.

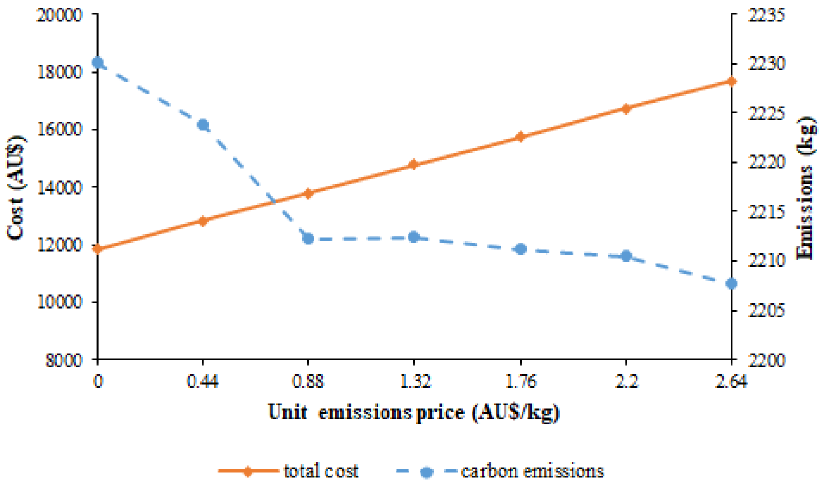


Figure 3-10:Impact of unit emission price on the total cost and emissions

3.6.6.2 Impact of changes in distance

In this section, we examined the effect of an increase in distances on the costs. Figure 3-11 indicates the trend of different components of the objective function with an increase in the distance. As can be seen, a higher travel distance does not have any effect on inventory cost and shortage cost. However, it can lead to an increase in transportation costs and emissions costs and, therefore, the total costs. This is not surprising since distance is one of the main factors affecting fuel consumption and consequently emissions.

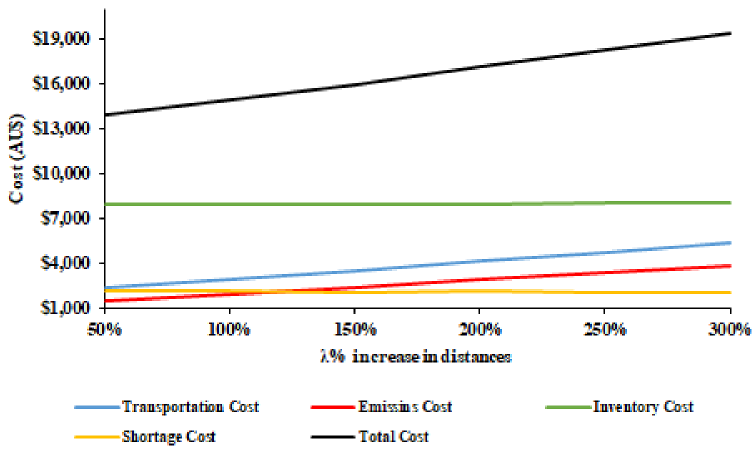


Figure 3-11:Impact of distance on different components of objective function

3.6.6.3 Impact of changes in vehicle speed

Figure 3-12 depicts the impact of changing the vehicle speed on transportation costs and CO_2 emissions. The curves are U-shaped, implying that a very low speed does not always lead to a reduction in transportation cost and emissions due to the inefficient usage of fuel. The transportation cost and CO_2emissions actually decrease when the speed increases from 20 *km/h* to 30 *km/h*. However, further increases in the vehicle speed can lead to higher transportation costs and consequently emissions as speed is one of the main factors impacting on fuel consumption in our model. Similar findings have been reported in the literature on traditional supply chains (see, e.g. Eshtehadi et al. (2017))

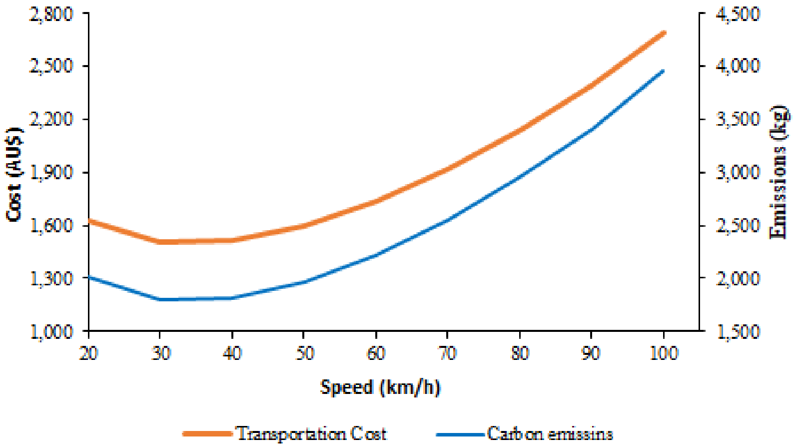


Figure 3-12:Impact of vehicle speed on transportation cost and CO_2 emissions

3.6.7 Managerial insights

In cold supply chain sector, managing storage and distribution of cold products are important due to the high level of energy consumed and consequently emissions generated. Thus, we presented an integrated optimisation model that aims to identify cost-efficient and environmentally-friendly inventory and routing decisions in the cold supply chain. To evaluate the proposed model, a real-world case study was used. The results obtained from the case study demonstrate that using a heterogeneous fleet is more beneficial from an economic and sustainability perspectives than using a homogeneous fleet. Our case study showed that using a homogeneous fleet with only light duty vehicles leads to higher transportation costs and emissions costs. This is largely due to the increased transportation frequency and travel distance. In contrast, when medium duty vehicles are used, total vehicle weight is the main factor that drives up transportation cost and relevant emissions costs.

These observations suggest the following managerial insights. As the energy consumption and emissions from transportation operation of cold products are high and sensitive to load and distance, company managers involved in the cold supply chain should use decision support tools to carefully assess the type of vehicles used and the number of vehicles for each type.

Moreover, the proposed framework in this study can assist the cold supply chain participants to optimise the energy consumption of unique processes across the chain.

For example, the cold supply chain participants are able to circumvent the difficulties of the restrictive energy policy in Australia which often imposes excessive costs on the participants involved in the cold supply chain as a result of the energy-intensive nature of this sector.

Another insight from this research is that emissions improvement is not always achieved by increasing the carbon price. In our case study, with the increase in the unit emissions price from zero, the model modified operations towards the lower-emissions configuration that leads to considerable decrease in the emissions costs. However, with the continued increase of unit emissions price, the amount of generated carbon emissions was almost constant as any further operational modifications to reduce carbon emissions caused further increase in operational costs.

As there has been widespread public debate over the reintroduction of carbon tax in Australia, our sensitivity analysis on carbon price can help the policy makers to make more informed decisions. For example, they can carefully set appropriate price of carbon in order to achieve the environmental goal without significantly damaging the short-term economic growth.

3.7 Summary

Since cold supply chain operations are energy-intensive resulting in substantial increase in CO_2 emissions, adopting sustainable decisions that focus on reducing emissions along cold supply chains is a significant consideration for companies and governments. This chapter proposed a two-stage stochastic programming model to formulate IRP that aims at supporting logistics decisions in the cold supply chain. The proposed model simultaneously considers uncertain demand, which was represented by a set of discrete scenarios, environmental impacts and a heterogeneous fleet where fuel consumption and emissions depend on load, travel distance, speed and vehicle characteristics. To reflect the increasing concern of companies towards the introduction of carbon emissions regulations, the model was also modified to consider the carbon tax regulation. The option of using a two-stage stochastic programming to model the problem guarantees the flexibility and reliability of the proposed framework in terms of being able to adapt itself to real-world applications.

We developed a matheuristic algorithm based on Iterated Local Search algorithm and a mixed integer programming to solve the proposed problem in an efficient computational time. The performance of the matheuristic algorithm was analysed using test instances with various sizes. The results showed that the performance of the matheuristic algorithm was robust and better than Cplex.

In order to evaluate the performance of the model, we used a real-world case study to indicate how the proposed model could assist decisions-makers to develop cost-efficient and environment-friendly replenishment policies and transportation scheduling in the cold supply chain. We implemented the proposed framework for the case study in the state of Queensland in Australia since it is one of the main producers of various cold products. Participants involved in cold supply chains in this area face more challenges as a result of geographical dispersion of suppliers and consumers, and high energy consumption of cold supply chain operations. Given a statistical distribution for the demand uncertainty, scenarios were generated using the Monte Carlo approach. Moreover, stability tests were conducted to make sure that the scenario size was adequate with reliable representation of the demand.

The computational experiments indicated that the optimal solution includes the combination of different vehicle duties. We observed that it would be possible to increase average vehicles' capacity utilisation from 77.91% to around 84.64 %, on average, at the first-stage by removing a third retailer (e.g. Beaudesert) and by adding into the first route. However, this does not lead to optimal solution in terms of cost-efficiency and sustainability-based KPIs, as the energy consumption and consequently emissions from cold supply chain operations are highly influenced by load and distance.

We conducted several analyses to provide meaningful insights for practice that could improve sustainability of the cold supply chain. We observed that using a heterogeneous fleet can generate further potential benefits including cost saving and sustainability improvement than using a homogeneous fleet in the cold supply chain. Therefore, transport managers can use the proposed framework as a decision support tool to control and reduce the environmental impact of transportation operations. Moreover, our experiments on unit emissions price identified that a higher emissions price does not always result in environmental improvement. This finding may have significant value to policy makers, when developing and implementing carbon emissions regulations.

Future research can extend the proposed model in several ways. Interested researchers can consider multi-cold products that need various temperature ranges for storage as a future research area. Incorporating benefits of cold products to customers and hence changing the objective function from cost minimisation to net benefit maximisation would be a natural extension of this research. Considering other parameters of the model to be stochastic would be another interesting area for future research. This study did not consider other exact methods or algorithms, which constitutes a limitation. Future studies can address this issue by developing an exact method such as Dantzig-Wolfe and comparing the results with those produced by the Cplex and matheuristic algorithm, which would add value to the literature. Finally, exploring the impact of alternative emissions regulations on cold supply chain operational decisions would be a potential direction for future studies.

Chapter 4: Sustainable intermodal meat supply chain: Moving cattle from outback Queensland to the Port of Brisbane

4.1 Introduction

Australia is a significant food producer and exports more than 70% of its agricultural production (Michael, 2018). It has a strong track record in producing clean and high quality food products. In the state of Queensland alone the agricultural sector creates more than \$15 billion of value each year. In recent years there has been a high demand for Australian agricultural products from Asia. Queensland's south-east region is well positioned to take advantage of this growing demand and is set to become a major food bowl for Asia given the extensive range of agricultural commodities this region produces, including grain, beef, cotton, eggs and horticultural products (Michael, 2018).

However, agricultural production in Queensland is spread widely as the area of this state is 1.85 million km^2. Livestock travels long distances from remote locations to slaughtering and processing facilities near large cities and then to the Port of Brisbane for export (Woodhead et al., 2016). Rail was the main mode of long-haul transport in Queensland previously, but in the past decade there has been a decline in the use of rail and road transport has become the dominant mode for long-distance transportation. This is because trucks have the advantage of providing a more flexible service in terms of scheduling, route and size of load (Woodhead et al., 2016). With the roads becoming increasingly congested, the Queensland government has expressed an intention to expand the share of transport by rail by reviving the Queensland Western Rail System, thereby increasing regional connectivity and freight market access.

An awareness of environmental issues in food supply chains has been growing (Validi et al., 2014). One of the great challenges in the sustainability of supply chains is the high energy consumption, particularly in transportation and storage (Change, 2007; Fichtinger et al., 2015). Road transport is one of the energy intensive and, consequently, high pollution transport modes (Sörensen et al., 2012). Road transport alone accounts for 71% of the CO_2 emissions generated by the transport sector in the European Union (International Union for Road-Rail Combined Transport, 2009). Fuel cost accounts for 30% of the total costs in long-distance road transport in Australia

(MacGowan, 2010). With the increase in freight demand in recent years, traffic congestion has been a serious issue and road freight has become an unsustainable transport mode (Resat and Turkay, 2019). Hence there is a need to reduce the use of road transport and increase the use of other transport modes to improve the efficiency of agricultural product supply chains.

An intermodal transport network is a promising strategy to achieve this goal as it offers opportunities to reduce transport costs and to mitigate road congestion and environmental impacts (Kumar and Anbanandam, 2020; Baykasoglu and Subulan, 2016; Sorensen et al., 2012) As noted by de Miranda Pinto et al. (2018), an intermodal transport network is less energy intensive and more sustainable than a unimodal transport network. The most common intermodal transport network is road–rail with links to seaports. This is the leading cost-effective and environmentally friendly supply chain. de Miranda Pinto et al. (2018) reported that intermodal road-rail operations can generate 77.4% fewer emissions and 43.48% more energy efficiency than the unimodal network relying on road transport only.

Promoting the sustainability of supply chains needs to be supported by government policies (Sheu, 2008, 2011). Policy makers have introduced incentives and regulations to reduce emissions from supply chain operations (Mohammed et al., 2017). A carbon tax policy can be an effective tool leading to the restructuring of the transport network from unimodal to intermodal operations to improve sustainability (Li et al., 2017; Oreskes, 2011; Zhang and Baranzini, 2004). It has more advantages than other options from a practical perspective: it is easier to implement (Lu et al., 2010) and it can be modified quickly once information is updated (Pearce, 1991).

The transport of livestock and meat products is one of the main contributors to CO_2 emissions in the meat supply chain (Soysal et al., 2014). The stress caused by transport may adversely affect animal welfare and cause economic losses. Meat supply chains face challenges to the quality of the livestock, final products and prices through an increase in delivery time in road transport due to traffic congestion and a decline in the animals' welfare during transportation (Peeters et al., 2008; Gregory and Grandin, 2007). Therefore, it is important to consider animal welfare, the quality of meat products and environmental impact in managing a meat supply chain. This research aims to develop an intermodal transport model for a meat supply chain considering traffic congestion, animal welfare and the quality of meat products during transport operations under a carbon tax policy. We analyse how these factors can affect transport mode selection decisions using a case in Queensland which involves cattle and associated meat products being sent to the Brisbane seaport for export. The results obtained from the case study can help decision makers to design a transport network appropriate for achieving economic and environmental goals.

The remainder of this chapter is organised as follows. In Section 4.2, the literature relevant for this research is reviewed. Section 4.3 presents a description of our model and assumptions. In Section 4.4, we formulate the proposed problem as a mixed integer programming model. Section 4.5 provides a description of the case study for which the model was implemented, and the results obtained. Sensitivity analyses on some parameters and managerial implications are also presented in Section 4.5.3. Section 4.6 contains concluding remarks.

4.2 Literature review

This section reviews literature on the topics of intermodal logistics, a carbon-efficient intermodal network, an intermodal network considering traffic conditions, and an intermodal network considering the quality of the product.

In today's competitive economic environment an efficient transport network is crucial for a country or region to attract tourists, investment and increased international trade (Zhu et al., 2019b; Kumar and Anbanandam, 2020). As reported by Bühler and Jochem (2008) and Kumar and Anbanandam (2020), intermodal transport is one of the strategies with promise to achieve this. An intermodal transport network uses a combination of different transport modes such as rail, road and maritime to distribute products along supply chains (Abbassi et al., 2018). There has been a wide range of applications for intermodal transport networks, including the import/export of freight (Baykasoglu and Subulan, 2016), the shipment of hazardous material (Assadipour et al., 2016) and passenger movement (Kang et al., 2015; Zhu et al., 2019a). Good surveys of the development of intermodal transport networks can be found in Bontekoning et al. (2004) and Mathisen and Hanssen (2014).

Arnold et al. (2004) presented an integer linear model to find the best location for rail-road terminals for freight transport. Limbourg and Jourquin (2009) presented a heuristics model based on a P-median problem and the multimodal assignment problem to solve the intermodal hub location problem in Europe. Ishfaq and Sox (2011) developed a hub location model based on a P-hub median approach to design a road-rail intermodal network that accounts for model connectivity costs and service time requirement. The Lagrangian relaxation approach and a tabu search algorithm are used to solve the model for instances up to 100 nodes. Abbassi et al. (2019) developed a robust optimisation model for a road-maritime intermodal network to capture the uncertainty of terminals' capacities and transport costs.

As CO_2 emissions from transport networks are one of the main contributors to climate change (Demir et al., 2015), some researchers incorporate environmental impacts into their intermodal transport network models. Bauer et al. (2010) proposed an integer linear programming model to address the environmental impacts in intermodal transport networks and used the case of a rail network in Eastern Europe to evaluate their model. Qu et al. (2016) presented a model to explore the effect of environmental considerations and intermodal transfers on an intermodal network design. Their results show that the proposed intermodal transport network provides a better performance than the unimodal network. Demir et al. (2016) presented a stochastic optimisation model to design a 'green' intermodal transport network in the presence of uncertainty. They used a sample average approximation method to capture the uncertainty related to travel time and demand. The results indicate that demand uncertainty has less impact on the optimal solution than travel time uncertainty.

Baykasoğlu and Subulan (2016) presented an optimisation model to address transport mode selection, outsourcing and load allocation decisions in the international intermodal road-maritime-rail network in Turkey. The main focus of the model was to determine the optimal import and export load flow with an aim of minimising costs, transit time and environmental impact. However, these studies incorporated environmental impacts into intermodal network design without considering the design of proper carbon policy. Hoen et al. (2014) examined the effect of carbon emissions policies on transport mode selection decisions in the presence of uncertain demand. Their results demonstrate that even though considerable carbon emissions reduction can be gained by shifting to a different mode, the final decisions are subject to non-monetary and policy considerations. Wang et al. (2015) presented a two-stage Stackelberg gaming model to analyse the effect of carbon taxes on transport mode selection and social welfare. Their results illustrate that social welfare improvement by imposing carbon taxes depends on the social cost of the carbon emissions and the carbon tax rate. However, the challenges presented through traffic issues are not addressed in these studies.

Traffic congestion not only leads to a longer delivery time and the associated customer dissatisfaction, but it also contributes to higher energy consumption and environmental pollution (Resat and Turkay, 2019). Thus, it is important to consider traffic congestion in studying transport mode selection problems. Parola and Sciomachen (2005) developed a simulation model to analyse the impact of traffic growth at a seaport on the land infrastructure and to determine the level of congestion at the truck gates and the degree of saturation of railway lines. Mishra and Welch (2012) presented a model using vehicle emission pricing as an emissions reduction strategy in the intermodal transport network. The results show that the emissions level depends on traffic conditions. Resat and Turkay (2015) presented a mixed integer linear optimisation model that accounts for time-dependent traffic congestion constraints to design a reliable road-maritime-rail intermodal network to increase transport safety by decreasing traffic congestion. They used an ε-constraints method to solve the model with real data from the Marmara region of Turkey.

Lin and Chen (2017) used a simulation-based multimodel traffic assignment model to estimate the traffic volumes generated by a planned special event. Kelle et al. (2019) presented a simulation model accounting for traffic congestion to explore the benefit of mode changes and to evaluate the trade-off between environmental goals and other performance measures such as reliability. They concluded that better environmental performance would be achieved by switching freight from road to rail transport and that this switch would also mitigate road congestion. Resat and Turkay (2019) proposed a bi-objective optimisation model accounting for time-window and traffic congestion constraints to analyse the cost and environmental impact of the intermodal transport network. The results demonstrate the importance of the ports, railway stations and transhipment centres in helping companies to make their additional investment decisions.

As different transport modes lead to different delivery times which can have different impacts on the quality of products, there is a need to consider a quality measurement in the intermodal transport problem in food supply chains to avoid additional costs. Soysal et al. (2014) presented a multi-objective linear programming model for a multimodal beef supply chain to minimise the total costs and emissions for the beef's distribution. The model was solved by an ε-constraints method using a real life international beef supply chain in Brazil. However, they do not address the loss of quality during the transport process. Abbassi et al. (2018) developed a bi-objective optimisation model to design an intermodal transport network for agriculture products in order to minimise total costs and delivery time. They used the data of distributing agricultural products from Morocco to Europe to evaluate the model. They addressed the problem of quality loss during transport operations by considering a constraint that does not allow total transport time to exceed the lifetime of the product. However, rarely has animal welfare been addressed in the transport mode selection literature, and this is a key aspect to be considered in our research. In addition, we will also consider the effect of a carbon tax policy on transport network selection decisions.

4.3 Problem description

In this research we develop an optimisation model for a rail-road intermodal network for managing the meat supply chain with consideration for animal welfare and traffic congestion constraints under a carbon tax policy. Our research focuses on a multi echelon supply chain that comprises production regions, terminals, abattoirs, seaports and distribution centres as destination points. Cattle are transported from production regions to abattoirs for slaughtering and then directly to the seaports for exporting. Or, after slaughtering and processing, meat products are transported to the seaports for exporting or to distribution centres for domestic consumption. Two transport modes – road and rail – are used for carrying cattle from the production regions to the abattoirs or seaports and for meat products from abattoirs to the seaports or distribution centres. Terminals are multimodal network nodes that link the road and rail networks, and animals and meat products are offloaded and uploaded here.

We assume 40-foot cattle trailers are used for transporting the cattle from the production regions to the abattoirs and seaports. Transporting the meat products between the abattoirs and the final destinations (seaports and distribution centres) uses 40-foot normal tailers. In the intermodal network, when trailers arrive at terminal points the trailers will be directly transferred from the trucks to trains. The capacity of a train is assumed to be C^t trailers. A transit time $T$is assumed at each terminal for changing from one transport mode to the other. Transporting animals can have an impact on the animals' welfare and, consequently, on the quality of the meat products, so we consider an animal welfare reduction coefficient for each transport mode.

The carbon emissions from the operations of the different transport modes are incorporated in the proposed model. We consider a threshold for meat products distributed from the abattoir to the seaport or distribution centre. Hence, the quality loss is assumed if meat products arrive at a destination point later than the expected threshold. We also consider that the intermodal meat supply chain operates under a carbon tax policy. The transport cost comprises two components – the fixed cost when a transport mode is used and the variable cost. The following assumptions are applied in formulating the proposed problem:

- Demand at the final destination is assumed to be constant and known in advance.
- Each destination node can be visited by only one vehicle and split delivery is not allowed.
- There is a threshold (T^s) for shipping meat products from the abattoir to the final destination node considering the meat's shelf life. Hence, quality loss (π) is assumed if meat products arrive at the destination point later than the expected threshold.
- Shortage is not allowed.
- 40-foot cattle trailers and 40-foot normal trailers are used for cattle and meat products transports, respectively, in either the unimodal or intermodal network.
- A train with a maximum capacity of C^t trailers is used for transporting cattle and meat products between terminals in the intermodal network.
- We assume a constant speed for the train, while different speeds are considered for vehicles because of the traffic congestion.

The optimisation model seeks to select an effective transport mode and to determine the quantity of cattle and meat products to be shipped through the unimodal and intermodal network that accounts for traffic congestion, meat travel time constraints under a carbon tax policy in order to minimise transport costs, quality loss costs, animal welfare reduction costs and emissions costs. A simple network configuration of the meat supply chain is depicted in Figure 4-1. The figure illustrates a meat supply chain in which products can be shipped by unimodal or intermodal transport at each stage.

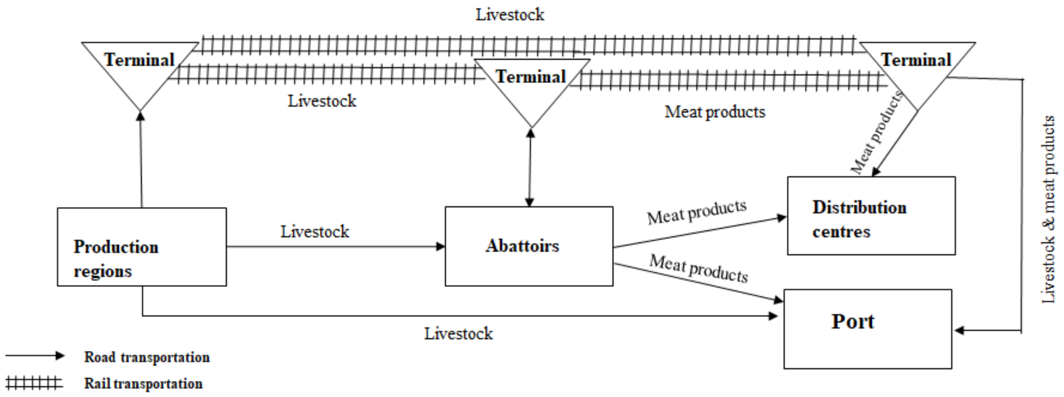


Figure 4-1:A simple network configuration of the proposed meat supply chain

4.4 Optimisation model

In this section a mixed-integer linear programming model is developed for the intermodal transport problem in the meat supply chain. The objective function aims to minimise transport costs, quality loss costs, animal welfare reduction costs and emissions costs. The model is evaluated using data from a real world case study of a meat supply chain in Queensland. We examine the opportunities for expanding the use of rail to ship cattle and meat products to the Brisbane seaport for export and to distribution centres in Brisbane for domestic consumption.

The model considers traffic congestion for road transport and its impact on fuel and emissions costs. We utilise the same approach as Resat and Turkay (2019) and Franceschetti et al. (2013) to simulate traffic congestion in the proposed model. Following these studies, the planning horizon is divided into three time intervals: free flow (m=1), a transient period which is a mixture of free flow and congestion (m=2) and traffic congestion (m=3). The vehicles are assumed to start their travel at the maximum speed level which is equal to speed limit of roads in the free flow interval, i.,e, there is no traffic on the roads. After (Λ) unit of the time a driver applies the break and the vehicle travels at a minimum speed level due to traffic congestions on the roads.

The proposed intermodal problem is defined as a graph $G = (V, A)$, where V is the set of nodes and A is the set of arcs. In V, N_F represents the set of production regions, N_T the set of terminals, N_A the set of abattoirs, N_{DC} the set of distribution centres and N_P the set of seaports – $V = N_F \cup N_T \cup N_A \cup N_{DC} \cup N_P$. The arc set A represents the links available between the nodes. The cattle and meat products can be shipped through either the unimodal or intermodal network using terminals from the production regions to the abattoirs/seaports or from the abattoirs to the distribution centres/seaports. We consider N_S as total number of nodes and $\{N_S + 1\}$ as a dummy point for modelling purposes. Without loss of generality, we assume that we have access to an unlimited number of cattle trailers and normal tailers for distribution in the meat supply chain.

The notation used to develop a mathematical formulation is defined in Tables 4-1, 4-2 and 4-3. We use Greek and upper case letters to represent the parameters, while lower case letters are used to denote the variables.

Table 4-1:The sets and indices for the mathematical formula

i, j, n	Index of nodes, including production regions, terminals, abattoirs, destination points, $i, j \in V \cup \{N_S + 1\}$

$k\ ,l$	Index of trailers
N_F	Set of production region nodes
N_T	Set of terminal nodes
N_A	Set of abattoir nodes
N_{DC}	Set of distribution centre nodes
N_P	Set of seaport nodes
m	Index of time interval, $m = 1, \dots ,3$

Table 4-2:The parameters for the mathematical formula.

W^c	Average carcass weight of one cattle (kg)
W	Average cattle weight (kg)
D_{ij}	Distance from node *i* to *j*
Dm_i	Demand for meat at destination point *i*
Dl_i	Demand for cattle at seaport *i*
C^t	Capacity of train in trailers
C^c	Capacity of cattle trailers (head of cattle)
C^n	Capacity of normal trailers used for shipping meat products (ton)
S^t	Train speed
S_m	Vehicle speed in time interval *m*
T	Transit time at terminals for changing the transport mode
St_i	Service time at node *i*
T^s	Expected threshold for distribution of meat products
B_{ijm}	Time at which the time interval *m* changes to *(m+1)*
θ_{ijm}	Technical parameter to calculate travel time
η_{ijm}	Travel time at time interval *m*
δ	Carbon price (AUD/kg)
π	Unit penalty cost if there is a delay in transport resulting in quality loss (AUD/kg)
ϑ^t	Animal welfare reduction coefficient per *km* by train (*head/km*)
ϑ^v	Animal welfare reduction coefficient per *km* by vehicle (*head/km*)
Cap_i	Cattle supply capacity of a production region *i*
σ	CO_2 emitted by unit fuel consumption ($kg = L$)
F^c	Fixed cost of cattle trailers
F^p	Fixed cost of normal trailers
F^t	Fixed cost of train
U^t	Fuel consumption rate of train per km with a unit of load (kg)
P^f	Fuel price
λ	Technical parameter to calculate vehicles fuel consumption
α	Technical parameter to calculate vehicles fuel consumption
γ	Technical parameter to calculate vehicles fuel consumption
β	Technical parameter to calculate vehicles fuel consumption
μ	Curb-weight (kg)

N^e	Engine speed (rev/s)
Φ	Engine friction factor (kJ/rev/l)
ι	Engine displacement (l)
ζ	Time at which the transient period is finished

Table 4-3:The decision variables for the mathematical formula.

x_{ijk}	1 If vehicle *k* is used for cattle transport on arc (*i,j*); otherwise 0
$x^{'}_{ijk}$	1 If vehicle *k* is used for meat transport on arc (*i,j*); otherwise 0
y_{ik}	1 If cattle are transferred from production region *i* to the corresponding terminal using vehicle *k*; otherwise 0
$y^{'}_{ik}$	1 If cattle are shipped through the unimodal network from production region *i* to the abattoirs/seaport using vehicle k; otherwise 0
z_{ik}	1 If meat products are transferred from the abattoir in region *i* to the corresponding terminal using vehicle *k*; otherwise 0
$z^{'}_{ik}$	1 If meat products are shipped through the unimodal network from the abattoir in region *i* to destination nodes using vehicle *k*; otherwise 0
f_{ijk}	Quantity of cattle (head) transported on arc (*i,j*) using vehicle *k*
$f^{'}_{ijk}$	Quantity of meat products (kg) transported on arc (*i,j*) using vehicle *k*
s_{ijkm}	1 If cattle trailer k departs node *i* toward node *j* in time interval *m*; otherwise 0
$s^{'}_{ijkm}$	1 If normal trailer k departs node *i* to *j* in time interval *m*; otherwise 0
u_j	Starting time of train carrying cattle trailers from terminal *j*
$u^{'}_j$	Starting time of train carrying normal trailers from terminal *j*
t_{jk}	Arrival time of cattle trailer *k* at node *j*
$t^{'}_{jk}$	Arrival time of normal trailer *k* at node *j*
w_{ijkm}	Starting time of cattle trailer k on arc (i,j) in time module m
$w^{'}_{ijkm}$	Starting time of normal trailer k on arc (i,j) in time module m
lq_j	Auxiliary variable using in quality loss cost

4.4.1 Mathematical model

A mathematical formulation for the proposed problem is as follows:

$$minz = TC + QC + WC + EC \tag{4.1}$$

Expression (4.1) refers to the objective function which includes four costs: transport costs (*TC*), quality loss costs (*QC*), animal welfare reduction costs (*WC*) and emissions costs (*EC*). These costs are defined below.

Transport costs

Transport costs (*TC*) are defined as follows:

$$TC = FC^v + FC^t + VC^v + VC^t \tag{4.2}$$

The transport costs include the fixed costs of vehicles (FC^v), the fixed costs of trains (FC^t), the fuel costs of vehicles (VC^v) and the fuel costs of trains (VC^t). These costs are formulated as follows:

$$FC^v = \sum_k \left(\sum_{i \in N_F} \sum_{j \in N_T \cup N_A \cup N_P, i \neq j} F^c x_{ijk} + \sum_{i \in N_T} \sum_{j \in N_A \cup N_P, i \neq j} F^c x_{ijk} + \sum_{i \in N_A} \sum_{j \in N_T \cup N_{DC} \cup N_P} F^p x'_{ijk} + \sum_{i \in N_T} \sum_{j \in N_{DC} \cup N_P} F^p x'_{ijk} \right) \quad (4.3)$$

The first two parts of function (4.3) represent the fixed costs related to the cattle trailers and the remaining parts compute the fixed costs of using normal trailers.

The fixed costs of using trains are presented by function (4.4).

$$FC^t = \sum_k \sum_{i \in N_T} \sum_{j \in N_T} F^t (x_{ijk} + x'_{ijk}) \quad (4.4)$$

We use the same approach as Bektas and Laporte (2011) and Franceschetti et al. (2013) to calculate the fuel consumption of vehicles as a function of load and travel speed. The fuel costs of vehicles are formulated as follows:

$$VC^v = P^f V^v \quad (4.5)$$

Function (4.5) represents the fuel costs of vehicles in which V^v refers to the fuel consumption of vehicles. It comprises three components: the *enginemodule* which is linear with travel time; the speed module, which is quadratic in vehicle speed; the *weightmodule* which is independent of the vehicle speed and travel time. The fuel consumption is defined as follows:

$$V^v =$$

$$\sum_k \sum_i \sum_j \sum_m \lambda \phi \left(\theta_{ijm} (w_{ijkm} + w'_{ijkm}) + \eta_{ijm} (s_{ijkm} + s'_{ijkm}) \right) \quad (4.5.i)$$

$$\sum_k \sum_i \sum_j \sum_{m=1,3} \lambda \Gamma (S_m)^3 \times \left(\theta_{ijm} (w_{ijkm} + w'_{ijkm}) + \eta_{ijm} (s_{ijkm} + s'_{ijkm}) \right) \quad (4.5.ii)$$

$$\sum_k \sum_i \sum_j \lambda \; \Gamma (S_2)^3 \left(\zeta (s_{ijk2} + s'_{ijk2}) - w_{ijk2} - w'_{ijk2} \right) \quad (4.5.iii)$$

$$\sum_k \sum_i \sum_j \lambda \; \Gamma (S_3)^3 \left(w_{ijk2} + w'_{ijk2} + \theta_{ij2} (w_{ijk2} + w'_{ijk2}) + \eta_{ij2} (s_{ijk2} + s'_{ijk2}) - \zeta (s_{ijk2} + s'_{ijk2}) \right) \quad (4.5.iv)$$

$$\sum_k \sum_i \sum_j \lambda \gamma \alpha D_{ij} \left(\mu (x_{ijk} + x'_{ijk}) + f_{ijk} * W + f'_{ijk} \right) \quad (4.5.v)$$

Where $\phi = \Phi N^e \iota$ and $= \gamma\beta$, $\lambda = \tau / \varphi\psi$, $\gamma = 1/(1000\chi\omega)$, $\beta = 0.5 C^d \rho A$ and $\alpha = g sin\theta + g C^e cos\theta$ which are taken from Franceschetti et al. (2013). Function (4.5.*i*) calculates the fuel consumption generated by *enginemodule*. Functions (4.5.*ii*)-(4.5.*iv*) compute the fuel consumption generated by the *speedmodule*. The fuel consumption related to the *speedmodule* in all congestion and free flow intervals is presented by function (4.5.*ii*), while functions (4.5.*iii*) and (4.5.*iv*) compute the fuel consumption generated by the *speedmodule* in the transient interval. Fuel consumption is linked to the vehicles' load by the *weightmodule* in function (4.5.*v*). The fuel consumption of the trains is represented by function (4.6).

$$VC^t = P^f \sum_{k} \sum_{i \in N_T} \sum_{j \in N_T} D_{ij} U^t \left(W f_{ijk} + f'_{ijk} \right) \tag{4.6}$$

Quality loss costs

Quality loss cost (*QC*) is considered in the proposed model when a threshold considered for meat distribution is violated, and is modelled as follows:

$$QC = \pi \sum_{j \in N_{DC} \cup N_P} lq_j \; Dm_j \tag{4.7}$$

The distribution of meat products must be completed before a threshold is reached. A penalty applies as result of quality loss of meat products if the products are distributed to their final destinations later than the threshold. The quality loss cost is computed at each final destination by constraint set (4.52) (see below).

Animal welfare reduction costs

Animal welfare reduction costs (*WC*) comprise the animal welfare reduction cost during the road and rail transport, and is defined as follows:

$$\begin{aligned} WC = & \sum_{i \in N_F \cup N_T \cup N_P} \sum_{j \in N_A \cup N_P, i \neq j} \sum_{k} f_{ijk} \times D_{ij} \times \vartheta^v + \sum_{i \in N_F} \sum_{j \in N_T} \sum_{k} f_{ijk} \times D_{ij} \times \vartheta^v \\ & + \sum_{i \in N_T} \sum_{j \in N_T, i \neq j} \sum_{k} f_{ijk} * D_{ij} * \vartheta^t \end{aligned} \tag{4.8}$$

As we are focusing on cattle transport as a part of the proposed supply chain, we consider animal welfare reduction cost due to the negative impact of travel time on animal welfare which has a direct impact on the quality of the meat products. Parts 1 and 2 in function (4.8) represent the animal welfare reduction cost incurred by road transport and the last part computes it for transport by rail.

Emission costs

Emissions costs (*EC*) include the carbon emissions arising from the road and rail transport. The total carbon emissions costs are calculated by multiplying the amount of energy consumption during transportation by the carbon emissions coefficients and the carbon price.

$$EC = \delta \times \sigma \times \left(V^v + \sum_k \sum_{i \in N_T} \sum_{j \in N_T} U^t D_{ij} \left(W * f_{ijk} + f'_{ijk} \right) \right) \quad (4.9)$$

The first part in function (4.9) computes the emission cost induced by road transport and the second part computes it for transport by rail.

The constraints of the proposed model are as follows:

$$\sum_{j \in N_T} x_{ijk} = y_{ik} \qquad \forall i \in N_F, \forall k \qquad (4.10)$$

$$\sum_{i \in N_F} \sum_{j \in N_T} x_{ijk} = \sum_{i \in N_F} y_{ik} \qquad \forall k \qquad (4.11)$$

$$\sum_{i \in N_T} \sum_{j \in N_T} x_{ijk} \le C^t \qquad \forall k \qquad (4.12)$$

$$\sum_{j \in N_A \cup N_P} x_{ijk} = y'_{ik} \qquad \forall i \in N_F, \forall k \qquad (4.13)$$

$$\sum_{i \in N_F} (y'_{ik} + y_{ik}) \le 1 \qquad \forall k \qquad (4.14)$$

$$\sum_{j \in N_T} x'_{ijk} = z_{ik} \qquad \forall i \in N_A, \forall k \qquad (4.15)$$

$$\sum_{i \in N_A} \sum_{j \in N_T} x'_{ijk} = \sum_{i \in N_A} z_{ik} \qquad \forall k \qquad (4.16)$$

$$\sum_{i \in N_T} \sum_{j \in N_T} x'_{ijk} \le C^t \qquad \forall k \qquad (4.17)$$

$$\textstyle\sum_{j \in N_{DC} \cup N_P} x'_{ijk} = z'_{ik} \qquad \forall i \in N_A, \forall k \qquad (4.18)$$

$$\sum_{i \in N_F \cup T} \sum_{j \in N_P} x_{ijk} + \sum_{i \in N_A} z_{ik} + \sum_{i \in N_A} z'_{ik} \le 1 \qquad \forall k \qquad (4.19)$$

$$\sum_{i \in N_F \cup N_P, i \ne j} x_{ijk} - \sum_{j \in N_P \cup \{N_S+1\}, i \ne j} x_{jik} = 0 \qquad \forall j \in N_P, \forall k \qquad (4.20)$$

$$\sum_{i \in N_T \cup N_A \cup N_{DC} \cup N_P, i \ne j} x'_{ijk} - \sum_{i \in N_{DC} \cup N_P \cup \{N_S+1\}, i \ne j} x'_{jik} = 0 \qquad \forall j \in N_P, \forall k \qquad (4.21)$$

$$\sum_{i \in N_T \cup N_A \cup N_{DC} \cup N_P, i \ne j} x'_{ijk} - \sum_{i \in N_{DC} \cup N_P \cup \{N_S+1\}, i \ne j} x'_{jik} = 0 \qquad \forall j \in N_{DC}, k \qquad (4.22)$$

$$\sum_{j \in N_T \cup N_A \cup N_P} \sum_k f_{ijk} = Cap_i \qquad \forall i \in N_F \qquad (4.23)$$

$$f_{ijk} \le C^c \times x_{ijk} \qquad \forall i \in N_F \cup N_T, \forall j \in V/N_{DC}, k \qquad (4.24)$$

$$f'_{ijk} \le C^n \times x'_{ijk} \qquad \forall i \in V/N_F, \forall j \in V/N_F \cup \{N_S+1\}, k \qquad (4.25)$$

$$\sum_{i \in N_F \cup N_T, i \ne j} f_{ijk} - \sum_{i \in N_T \cup N_A \cup N_P, i \ne j} f_{jik} = 0 \qquad j \in N_T, \forall k \qquad (4.26)$$

$$\sum_{i\in N_A\cup N_T, i\neq j} f'_{ijk} - \sum_{i\in N_{DC}\cup N_T\cup N_P, i\neq j} f'_{jik} = 0 \qquad \forall j \in N_T, \forall k \tag{4.27}$$

$$\sum_{i\in N_T\cup N_{DC}\cup N_P} \sum_k f'_{jik} = W^c * \sum_{i\in N_F\cup N_T} \sum_k f_{ijk} \qquad \forall j \in N_A \tag{4.28}$$

$$\sum_{i\in N_T\cup N_A\cup N_{DC}\cup N_P, i\neq j} \sum_k f'_{ijk} - \sum_{i\in N_{DC}\cup N_P\cup \{N_S+1\}, i\neq j} \sum_k f'_{jik} = Dm_j \qquad \forall j \in N_{DC}, \forall k \tag{4.29}$$

$$\sum_{i\in N_T\cup N_A\cup N_{DC}\cup N_P, i\neq j} \sum_k f'_{ijk} - \sum_{i\in N_{DC}\cup N_P\cup \{N_S+1\}, i\neq j} \sum_k f'_{jik} = Dm_j \qquad \forall j \in N_P, \forall k \tag{4.30}$$

$$\sum_{i\in N_F\cup N_T} \sum_k f_{ijk} - \sum_{i\in N_P\cup \{N_S+1\}} \sum_k f_{jik} = Dl_j \qquad \forall j \in N_P, \forall k \tag{4.31}$$

$$\sum_k \sum_{i\in V} \left(f'_{i\{N_S+1\}k} + f_{i\{N_S+1\}k}\right) = 0 \tag{4.32}$$

$$\sum_m s_{ijkm} = x_{ijk} \qquad \forall i \in N_F \cup N_T \cup N_P,\ j \in N_T \cup N_A \cup N_P, i \neq j, \forall k \tag{4.33}$$

$$\sum_m s'_{ijkm} = x'_{ijk} \qquad \forall i \in V/N_F, i \neq j, \forall k\ \ j \in V \cup \{N_S+1\}/N_F \cup N_A, \tag{4.34}$$

$$s_{ijkm} * B_{ijm-1} - M\left(1 - s_{ijkm}\right) \le t_{ik} + St_i \le s_{ijkm} * B_{ijm} + M(1 - s_{ijkm}) \qquad \forall i \in N_F \cup N_T \cup N_P,\ j \in N_T \cup N_A \cup N_P, \forall k, m \tag{4.35}$$

$$s'_{ijkm} * B_{ijm-1} - M\left(1 - s'_{ijkm}\right) \le t'_{ik} + St_i \le s'_{ijkm} * B_{ijm} + M(1 - s'_{ijkm}) \qquad \forall i \in V/N_F, \forall k, m\ \ j \in V \cup \{N_S+1\}/N_F \cup N_A \tag{4.36}$$

$$t_{jk} \ge t_{ik} + St_i - M * (1 - x_{ijk}) \qquad \forall i \in N_F \cup N_T \cup N_P\ \ j \in N_T \cup N_A \cup N_P, i \neq j, \forall k \tag{4.37}$$

$$t'_{jk} \ge t'_{ik} + St_i - M * (1 - x'_{ijk}) \qquad \forall i \in V/N_F\ \ j \in V/N_F \cup N_A, i \neq j, \forall k \tag{4.38}$$

$$t_{jk} \ge \left(\theta_{ijm} + 1\right)t_{ik} + St_i + \eta_{ijm} * s_{ijkm} - M * (1 - s_{ijkm}) \qquad \forall i \in N_F \cup N_T \cup N_P, \forall k, m\ \ j \in N_T \cup N_A \cup N_P \cup \{N_S+1\} \tag{4.39}$$

$$t'_{jk} \ge (\theta_{ijm} + 1)t'_{ik} + St_i + \eta_{ijm} * s'_{ijkm} - M * (1 - s'_{ijkm}) \qquad \forall i \in V/N_F, \forall k, m\ \ j \in N_T \cup N_P \cup N_{DC} \cup \{N_S+1\} \tag{4.40}$$

$$u_j \geq t_{jk} + T - M * (1 - \sum_{i \in F} x_{ijk}) \quad j \in N_T, \forall k \quad (4.41)$$

$$u'_j \geq t'_{jk} + T - M * (1 - \sum_{i \in A} x'_{ijk}) \quad j \in N_T, \forall k \quad (4.42)$$

$$t_{jk} \geq u_i + D_{ij}/S^t - M * (1 - x_{ijk}) \quad i \in N_T, j \in N_T, i \neq j, \forall k \quad (4.43)$$

$$t'_{jk} \geq u'_i + D_{ij}/S^t - M * (1 - x'_{ijk}) \quad i \in N_T, j \in N_T, i \neq j, \forall k \quad (4.44)$$

$$t_{jk} \leq M \sum_{i \in N_F \cup N_T \cup N_P} x_{ijk} \quad \forall j \in N_A \cup N_T \cup N_P, \forall k \quad (4.45)$$

$$t'_{jk} \leq M \sum_{i \in V/N_F} x'_{jik} \quad \forall j \in V/N_F, \forall k \quad (4.46)$$

$$t'_{jk} \geq t_{jl} - M\,(1 - \sum_{i \in N_T \cup N_P \cup N_{DC}} x'_{jik}) \quad \forall j \in N_A, k, l \in K \quad (4.47)$$

$$w_{ijkm} \geq t_{ik} + St_i - M * (1 - s_{ijkm}) \quad i \in V/N_A \cup N_{DC}, j \in N_T \cup N_A \cup N_p, i \neq j, \forall k, m \quad (4.48)$$

$$w'_{ijkm} \geq t'_{ik} + St_i - M * (1 - s'_{ijkm}) \quad i \in V/N_F, j \in N_T \cup N_{DC} \cup N_P, i \neq j, \forall k, m \quad (4.49)$$

$$lq_j \geq (t'_{jk} - t'_{ik} - St_i - T^s) - M * (1 - \sum_{n \in V/N_F \cup N_A} x'_{ink}) \quad i \in N_A, j \in N_P \cup N_{DC}, \forall k \quad (4.50)$$

$$x'_{ijk}, s'_{ijkm}, x_{ijk}, s_{ijkm}, y_{ik}, y'_{ik}, z_{ik}, z'_{ik} \in \{0,1\} \quad \forall i, j, k, m \quad (4.51)$$

$$f_{ijk}, f'_{ijk}, u_j, u'_j, t_{jk}, t'_{jk}, lq_j, w_{ijkm}, w'_{ijkm} \geq 0 \quad \forall i, j, k, m \quad (4.52)$$

Constraints (4.10) and (4.11) ensure that the intermodal link is used for cattle distribution if the y_{ik} variable is non-zero. Constraint (4.12) satisfies the capacity limit of a train. Constraint (4.13) ensures that the unimodal link is used to distribute cattle if the y'_{ik} variable is non-zero. Constraint (4.14) ensures that each vehicle can be used either in a unimodal or intermodal link to transport cattle from the production regions. Constraints (4.15) and (4.16) denote that the intermodal link is used for meat distribution from abattoirs to destination nodes if the z_{ik} variable is non-zero. Constraint (4.17) confirms that the train's capacity is satisfied when it is used for the distribution of meat products. Constraint (4.18) indicates that the unimodal link is used for meat product distribution if there is no link from an abattoir to a terminal. Constraint (4.19) notes that each vehicle at a destination point can depart from the abattoir for meat distribution or from a production region for cattle transport.

Constraints (4.20) - (4.22) guarantee the connectivity on routes. The number of cattle available at each production region is satisfied by constraint (4.23).

Constraints (4.24) and (4.25) guarantee that if there is no link between two nodes, the product flow is equal to zero. Constraints (4.26) and (4.27) link the product flow leaving a terminal to the product flow that entered the terminal. Constraint (4.28) balances the cattle flow entering an abattoir with the meat products that leave the abattoir. Constraint (4.29) decreases the flow of meat products on a route after visiting a distribution centre by its demand. Constraints (4.30) and (4.31) ensure that the quantity of cattle and meat products entering a seaport is equal to the demand for exporting them. By (4.32) we ensure that vehicles are empty when arriving at the dummy point. Constraints (4.33) and (4.34) ensure that each travelling on each arc (i, j) can be placed is at most in one time interval. The time interval at which vehicle k travels from node i to node j is determined by (4.35) and (4.36). Constraints (4.37) and (4.38) compute the starting time of vehicle k on arc (i,j).

Constraints (4.39) and (4.40) are used to compute the arrival time at node j which is visited immediately after node i in the unimodal link due to traffic congestion at the corresponding time interval m. The departure time of a train is determined by (4.41) and (4.42). Constraints (4.43) and (4.44) determine the arrival time at terminal j which is visited immediately after terminal i in the intermodal link. Constraints (4.45) and (4.46) indicate that the arrival time at node j is equal to zero if there is no link entering the node j. Constraint (4.47) links the decision variables t'_{jk} with the decision variables t_{jl}. Constraints (4.48) and (4.49) compute the starting time of vehicle k on arc (i,j). A delay as a result of threshold violation at a meat distribution point is determined by (4.50). Constraints (4.51) and (4.52) define the types of decision variables.

4.5 Computational results

The aim of this section is twofold: 1) to demonstrate the application of the models formulated in Section 4.5 using a real world case study involving a meat supply chain in Queensland; and 2) to conduct a sensitivity analysis on some of the parameters and explore their impact on the cattle and meat products distribution network to make good efficiency and environmentally friendly decisions.

4.5.1 Description of the case study

The need for Australia to use an intermodal network for reducing transport costs, emissions costs and animal welfare costs can be justified because of the increasing traffic congestion on roads and the negative impact of road transport on animal welfare. We use a real world case study to evaluate the proposed model from a practical perspective. The case study involves a meat supply chain in Queensland, which is responsible for the distribution of cattle and meat products from production regions to destination nodes for export or domestic consumption. In this research we examine the opportunities of expanding the use of an intermodal road–rail transport network in western Queensland. As the number of cattle in Queensland is more than in any other state or territory in Australia, using rail could improve the efficiency and reliability of the meat supply chain in this area. In addition, the meat industry shares key roads with other sectors of Australian agriculture and so by using rail transport the meat industry may help to improve the road freight network for other agricultural sectors (Fraser, 2017).

Cattle were traditionally loaded on rail transport at two major collection points, Quilpie and Morven, in in this part of Queensland. Hence, we assume these two areas as the production regions for our research. We also consider an abattoir for slaughtering and meat processing which is close to the Toowoomba region. The vast majority of Queensland's cattle and meat products are exported through the Brisbane seaport. So, we use the Port of Brisbane as the destination node for the export of cattle and meat products in the proposed model. We also assume two distribution centres in Brisbane as the destination nodes for the meat products for domestic consumption. In this research, cattle and meat products can be shipped between the production regions, the abattoir and the destination nodes using either unimodal or rail–road networks. Hence, we assume three terminals near rail stations as the transfer points for the transport modes in the intermodal network. Terminal 1 is used for the distribution of cattle from the production regions to the abattoir and Brisbane seaport, terminal 2 is linked to the abattoir for the distribution of cattle and meat products and terminal 3 is used to distribute cattle and meat products to the destination nodes (the distribution centres and Brisbane seaport).

We assume a supply capacity of 50 and 55 heads at the production regions closest to Quilpie and Morven, respectively. We consider the average weight of the cattle to be 1000 *kg*. The average carcass weight depends on different factors such as fat tissues, muscle score and so on. However, we assume the average carcass weight to be 60% of the cattle's weight. Service time is considered at each node which is defined transit time at We also assume a transit time of 30 minutes at each terminal for changing the transport mode, which includes loading, unloading and waiting times. In this research, we are focusing on the distribution of meat products, which have a limited shelf life, from the abattoir to the destination nodes. Thus, the travel time, which is dependent on road traffic condition, may impact on the quality of the meat products and, consequently, their final selling price. To avoid these issues and to keep the quality of the meat products at the desired level, we assume the threshold $T^s$to be $3\frac{1}{2}$ hours for the distribution of the meat products from the abattoir to the destination nodes. The penalty cost of AUD0.005/s is applied for each kilogram of meat products distributed after T^s at each destination node. Table 4-4 summarises the cattle and meat products demand and the service times at the production regions, abattoir and destination nodes.

Table 4-4:The cattle and meat products demand and service time at each node.

Parameters	P1	P2	A	DC 1	DC 2	Brisbane seaport
Cattle demand (head)	–	–	–	–	–	30
Meat products (ton)	–	–	–	10	15	20
Service time (minutes)	30	40	40	15	15	30

Note: P = production region; A = abattoir; DC = distribution centre.

The distance between the nodes is estimated using Google Maps. We assume the 40-foot cattle trailer with a capacity of 30 heads is used for cattle distribution from the production regions to the abattoir and Brisbane seaport, and the 40-foot normal trailer with a capacity of 30 tons for transporting the meat products from the abattoir to the distribution centres and the Brisbane seaport. As we test the model for the small real world example, we assume a train with a capacity of four trailers for cattle and meat products distribution. The fixed cost of using the cattle trailer and the normal trailer are assumed to be AUD150 and AUD130, respectively. We also assume a fixed cost of shipping each cattle or meat products trailer using a train to be AUD300. The parameters used to calculate the fuel costs of the vehicles are taken from previous research and are summarised in Table 4-5.

Table 4-5:The definition of the vehicle parameters

Notations	Description	Typical value
μ	Curb weight	6350

N^e	Engine speed (rev/s)	33
Φ	Engine friction factor (kJ/rev/l)	0.2
ι	Engine displacement (L)	5
τ	Fuel-to-air mass ratio	1
φ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/l)	737
χ	Vehicle drive train efficiency	0.4
ω	Efficiency parameter for diesel engines	0.45
g	Gravitational constant (m/s^2)	9.81
C^e	Coefficient of rolling resistance	0.01
C^d	Coefficient of aerodynamic drag	0.7
ρ	Air density (kg/m^3)	1.2041
A	Frontal surface area (m^2)	9
θ	Road angle	0
P^f	Fuel price (AUD/L)	1.6
δ	Unit CO_2 emissions price (AUD/kg)	1.16

Sources: Cachon (2014), Demir et al. (2012), Babagolzadeh et al. (2020)

We assume the speed level to be 80 *km/h* and 40 *km/h* for vehicles in the free flow interval (m=1) and the traffic congestion interval (m=3), respectively. A constant speed level of 80 *km/h* is considered for the train. We assume the fuel consumption rate for the train to be 0.00002/*kg/km*.

4.5.2 Computational experiments and analysis

In this section we present an application of the proposed model by implementing the model for the data of the real world example provided in section 4.5.1.

We use the exact method to analyse the effect of using intermodal transport. We intend to show how an intermodal transport network can improve efficiency, reliability and economic costs considering the traffic conditions, animal welfare issues and a carbon tax policy. To do so, we use the commercial optimisation solver (Cplex) which is based on a branch and cut algorithm. All experiments were coded on an Intel i7 CPU with a 3.6 GHz processor and 16 GB RAM.

We focused on the following key performance indicators: (i) transportation costs that include fixed and fuel costs of a rail–road intermodal transport network; (ii) quality loss costs as a result of a meat threshold distribution violation; (iii) animal welfare reduction costs that consists of those costs during road and rail transport; and (iv) emission costs arising from fuel consumption on a rail–road network. The results are used to compare the unimodal and intermodal networks to identify the most effective network when considering animal welfare issues, traffic conditions and a carbon tax policy. Finally, sensitivity analyses are conducted on the animal welfare reduction costs and on the unit penalty costs to demonstrate the effect of their changes on the economic costs and the network configuration.

We report the optimal network configuration and the optimal values of the objective functions when the rail–road intermodal network is considered in Table 4-6 and Figure 4-2, respectively. The optimal solution uses mostly vehicles for transporting cattle from the production regions to the abattoir because that occurs mostly in the regional area which does not have heavy traffic congestion. However, the model uses a train to distribute meat products from the abattoir to urban areas and vehicles for distribution in the urban areas because of traffic congestion. As can be seen from the results, shipment consolidation is not applied in the meat products' distribution due to the penalty imposed when vehicles arrive at the destination nodes after the threshold level for meat distribution is reached. A train is used for transporting cattle from a production region to the Brisbane seaport because it consumes less fuel and reduces animal welfare issues over the long distance. Using a vehicle to transport cattle from a production region direct to the Brisbane seaport would increase the animal welfare reduction costs by 10.5% while decreasing transport costs and emission costs by 9.18% and 1.53%, respectively, as a result of a reduction in the fixed cost of vehicles and the travel distance in our example.

Table 4-6:The optimal value of the objective functions under a rail–road intermodal network (AUD).

Transport costs	Quality loss costs	Animal welfare reduction costs	Emission costs	Total cost
5336.9	6209.99	9379.5	5027.41	25953.8

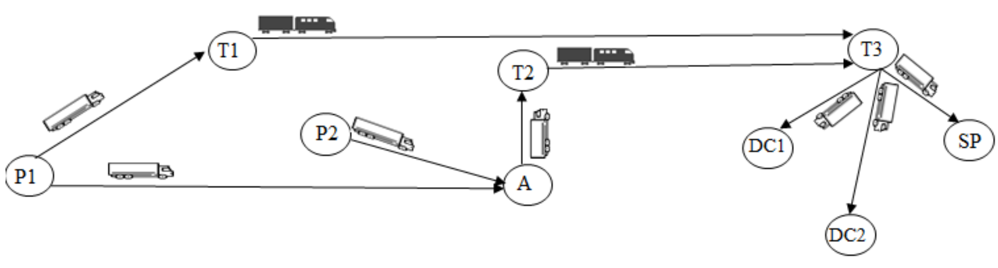


Figure 4-2:The general view of the network configuration in the optimal solution of the intermodal network. (p: production region, T: terminal, A: abattoir, DC: distribution centre and SP: Brisbane seaport)

To evaluate the behaviour of the rail–road intermodal model, we implement the proposed model for the real world example while considering only the unimodal network and comparing those results with those obtained from the rail–road intermodal network. The optimal values of the objective functions obtained from the unimodal network are reported in Table 4-7.

Table 4-7:The optimal value of the objective functions under the unimodal network (AUD).

Transport costs	Quality loss costs	Animal welfare reduction costs	Emission costs	Total cost
3570.52	13500	10363.5	4976.54	32410.56

As can be seen from the results, transport costs decrease by around 33% which is driven exclusively by a reduction in the fixed cost of vehicles. Emission costs reduce by only 1% due to a reduction in the travel distance. However, using only a unimodal network can increase animal welfare reduction costs and quality loss costs by 10.5% and 117.39%, respectively, which leads to increasing the total cost by 24.87%. The results suggest that the rail–road intermodal network is more desirable from the economic and animal welfare points of view. However, the unimodal network is preferred for reducing fuel consumption and, consequently, emissions from the transport operations as the cattle and meat products need to travel additional distances to reach terminals in the intermodal network.

As the Australian government plans to develop a new train line and construct terminals, the findings of this research suggest that it is possible for the government to reduce the cattle and meat products distribution costs and help the participants in the meat supply chain by constructing the terminals closer to the main production regions and the abattoir to reduce vehicle usage and/or the vehicle travel distance.

4.5.3 Sensitivity analysis

In this section we analyse the impact of the parameter changes on the economic costs and the network configuration in the proposed meat supply chain. We also explore how changing the parameters may impact on transport mode selection decisions. A sensitivity analysis is conducted on the differences between the coefficients of the animal welfare reduction costs and the unit penalty costs.

4.5.3.1 Impact of changes in the ratio of road animal welfare reduction costs to the rate for rail

In this section we examine the effect of changing the ratio of the rate of animal welfare reduction costs for road transport to the rate for rail transport on various economic costs and CO_2 emissions.

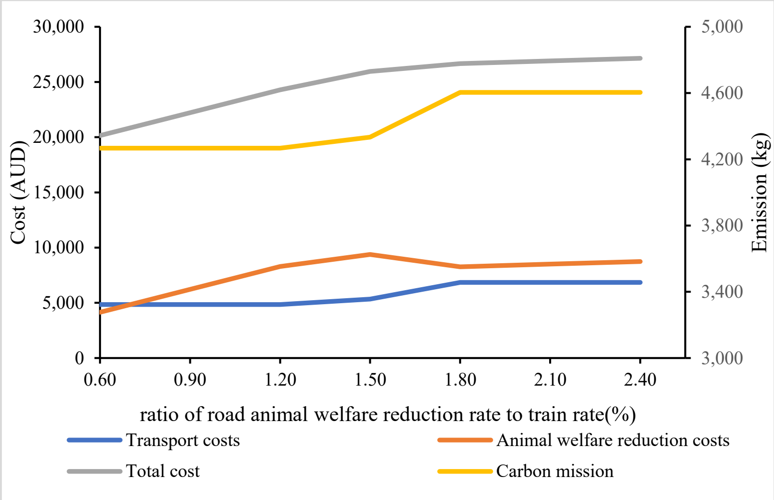


Figure 4-3:The impact of changing the ratio of road animal welfare reduction rate for road transport to the rate for rail transport on different costs and CO2 emissions.

As can be seen from Figure 4-3, increasing the ratio of animal welfare reduction rate for road transport to the rate for rail transport from 0.6 to 1.5 does not lead to any significant changes in transport costs and emissions costs as the network configuration does not change and the model uses the unimodal network to transport cattle. However, it can lead to an increase in animal welfare reduction costs and the total cost by about 126% and 28.7%, respectively.

A further increase in the ratio, say, from 1.5 to 1.8 can change the configuration of the model when using the intermodal network. It results in a considerable growth in emissions costs and transport costs by about 6.2% and 28.3%, respectively, as a result of increases in the travel distance and the fixed cost of vehicles, but only a 2.7% increase in the total cost. However, it provides a reduction of about 11.8% in animal welfare costs.

It can be observed that the continued increase of the ratio from 1.8 to 2.4 does not lead to any changes in the network configuration, transport costs and emissions costs. It would increase total costs by 5.7% as a result of increasing animal welfare reduction costs in the intermodal network. Therefore, it is important to measure the animal welfare reduction coefficient and to consider it when selecting the most suitable transport mode and network configuration.

4.5.3.2 Impact of the changes in unit penalty costs

In this section the sensitivity analysis is conducted on the unit penalty costs to explore its impact on economic costs, the value which is used to calculate quality loss costs (delay multiplied by the load) and to determine the transport network configuration. Figure 4-4 depicts the impact of changes in the unit penalty costs on the transport costs, total cost and quality loss costs. As can be observed from the results, if the penalty was not considered for meat products delivery later than the expected threshold, the unimodal transport network is preferred for meat distribution as it leads to the minimum economic costs as a result of the reduced travel distance, and a smaller number of vehicles required. It also leads to the maximum value involved in quality loss costs as a result of traffic congestion. It also allows the model to consolidate shipments where possible.

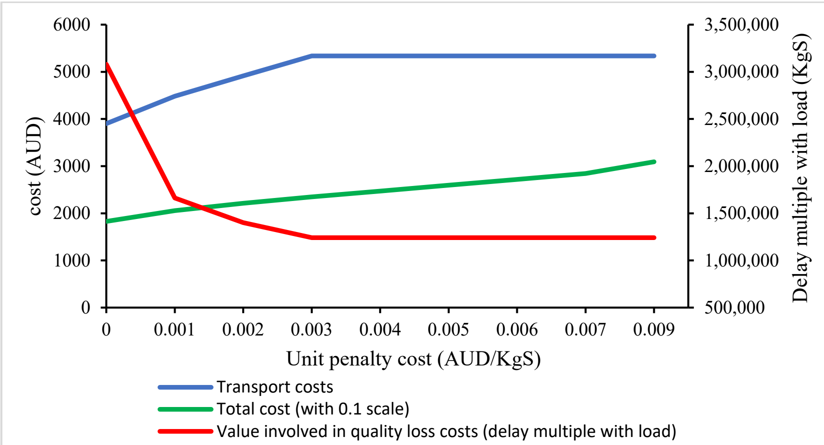


Figure 4-4:The impact of changing the unit penalty costs on different costs and the value involved in the quality loss costs calculation.

In our case, it appears that an increase in unit penalty costs, say, from 0 to $AUD0.002$ can increase the total cost and transport costs by about 21% and 25.9%, respectively, by using the road–rail intermodal network for part of the meat products distribution as this results in longer travel distances and requires more vehicles. However, it has a higher effect on the value involved in calculating the quality loss costs. That is, the value involved in calculating the quality loss costs decreases by about 54.5% as a result of avoiding traffic congestion in some legs of the journey by using the road–rail intermodal network.

As can be seen from the results, the extended range of the unit penalty costs from $AUD0.002$ to $AUD0.003$ can lead to using the road–rail intermodal network only for meat product distribution to avoid a massive increase in quality loss costs as a result of road traffic congestion. It can lead to about a 11.3% reduction in the value of the quality loss costs, while the total cost and transport costs increase by about 8.6% and 6%, respectively.

As can be observed from Figure 4.4, further increases in unit penalty costs cannot lead to any changes in transport costs and the value of quality loss costs. It only has a direct impact on the total cost. The findings of this research suggest that, in this case, a road–rail intermodal network is more beneficial in terms of reducing quality loss costs because heavy road traffic congestion in some legs of the journey may be avoided. However, it would not be a cost-efficient transport network in terms of transport costs and the emissions generated because of the significantly increased travel distances and the number of vehicles required.

4.6 Conclusion

The recent rise in traffic congestion in Australia, due to substantial increases in productivity in different sectors resulting in growing demands for freight transport, has increased delivery time significantly and has brought challenges in satisfying the growing demand for high quality products. Australia is one of the world's main meat producers. The quality of its meat products can also be influenced by animal welfare issues during transportation. To respond to these challenges and to improve the reliability and efficiency of the transport network, it is important to integrate different transport modes when managing the supply chain.

This chapter proposes an optimisation model to explore the impact of using a road–rail intermodal transport network on economic costs and animal welfare reduction costs in a meat supply chain. The proposed model simultaneously considers road traffic congestion, animal welfare, the quality of meat products and the environmental impact from fuel consumption in different transport modes. It considers the expected threshold for meat products distribution in relation to the quality of those products. The aim of the model is to minimise transport costs, animal welfare reduction costs, quality loss costs and emissions costs.

To evaluate the performance of the model, a real world case study is used to illustrate how the proposed model could help decision makers to develop a reliable and cost-efficient intermodal transport network in a meat supply chain. The model is investigated through a case study in Queensland, the Australian state with the largest beef cattle herd in the country (42% of the national herd).

We observe that it would be possible to decrease the total cost by about 24.87% if a road–rail intermodal network is used along with a unimodal network in the meat supply chain in south-eastern Queensland. The results indicate that using a road–rail intermodal network for long distances can provide a better performance in terms of animal welfare issues and the quality of the products. Using only a unimodal network can increase animal welfare reduction costs and quality loss costs by 10.5% and 117.39%, respectively, compared with road-rail intermodal transport network.

However, a unimodal network is recommended in our example in terms of transport costs and, consequently, emissions costs as using an intermodal network leads to significant increases in travel distances and the number of vehicles required.

We conduct sensitivity analyses on the ratio of animal welfare reduction rate in road transport to the rate for rail transport and unit penalty costs to provide meaningful insights for decision makers to make the best decisions relating to transport mode selection decisions in each part of the meat supply chain in order to improve the reliability and efficiency of the entire chain. We observe that the road–rail intermodal network would benefit more if animal welfare issues were prioritised. Therefore, it is important for decision makers to consider animal welfare, which influences the quality of the meat products, when making transport mode selection decisions. Moreover, our experiments on unit penalty costs identified that higher unit penalty costs lead to using an intermodal network to avoid heavy road traffic congestion with the resultant delays in distribution and consequent increases in quality loss costs. These findings can help the decision makers and meat supply chain participants to make more informed decisions in planning and developing transport networks and logistics facilities. If needed, our model can be easily modified and extended for a wider application with other transport modes and objectives included.

Chapter 5: Conclusions and future research directions

The research undertaken for this thesis developed three models to apply to the efficient, reliable and sustainable distribution of products from regional areas in Australia to other parts of country. The proposed models can be used to help decision makers to make operational and strategic planning decisions. The contributions of this thesis to the research area are:

- It has developed an optimisation model to examine the effects of introducing government regional support schemes on distribution networks in regional areas in Australia and on their economic development.
- It has evaluated the implementation of a linear and a non-linear subsidy scheme and compared their effect on logistics decisions and economic costs to identify the more effective scheme.
- It has developed a two-stage stochastic programming model to determine optimal replenishment policies and transportation schedules for distributing perishable products from a regional area to cities and towns under a carbon tax policy. In addition, a matheuristic algorithm based on the Iterated Local Search algorithm and mixed integer programming was developed to solve the problems in realistic sizes.
- It has developed a mathematical model to explore opportunities of expanding the road–rail intermodal transport network for transporting meat products and livestock from regional Queensland to cities, towns and a seaport while taking into consideration animal welfare issues, the quality of the products, traffic congestion and a carbon tax regime.

The following section reviews the problems addressed in this research, the solution methodologies and the main results. In addition, possible directions for future research for each model are discussed.

5.1 Promoting regional area with subsidy schemes

Chapter 2 explored how government subsidy schemes can influence a freight distribution model that favours the use of regional airports in promoting regional economic development, while taking into account the optimal ground distribution network from those airports to the consignees. The proposed model considered subsidy schemes as linear and multiple breakpoint functions. The model simultaneously considered the government subsidy limit and the heterogeneous fleet for ground distribution where fuel consumption is subject to load, travel distance, speed and vehicle characteristics. The aim of the model was to minimise airfreight costs, ground transportation costs and penalty costs resulting from time-window violations.

A real world case study in Australia was used to demonstrate the application of the proposed framework. The computational experiments illustrated that metropolitan airports can be used as distribution hubs without a subsidy scheme as this option requires less ground transportation to distribute the cargo to the consignees. We observed that it would be possible to decrease airfreight costs significantly in two subsidy scenarios. However, that can lead to a significant increase in ground transportation costs and penalty costs. The results indicated that subsidy scenario 1 has a better performance in shifting cargo traffic from a metropolitan airport to a regional airport, while subsidy scenario 2 is recommended in terms of cost efficiency and delivery time.

Our analysis on the subsidy rate identified that an increase in subsidy rates does not always result in a considerable improvement in cargo volume in the regional area in the presence of the government subsidy limit. The results suggest that, in this case, lower subsidy rates are more beneficial in terms of increasing the volume of cargo traffic at Toowoomba Airport and of decreasing the government's expense in granting the subsidies. However, it would not be a cost-efficient decision from the perspective of the industries involved in distributing the cargo.

5.2 Sustainable cold supply chain, under demand uncertainty and carbon emissions

Chapter 3 described the development of an integrated optimisation model for the cold supply chain that is responsible for the distribution of perishable food products from a regional area to cities and towns. The model formulated was a two-stage stochastic programming model to cope with uncertain demand which was represented by a set of discrete scenarios using the Monte Carlo approach. To reflect the increasing likelihood of the introduction of carbon emissions regulations, the model was also modified to consider possible carbon tax regulations. The proposed model used a heterogeneous fleet for product distribution. The optimisation model seeks to determine the optimal configuration of the routes and vehicle types, the quantity of perishable product to be delivered to retailers, the number of refrigerators used for storage in order to minimise the operation costs and lost sale cost, and the costs of emissions. The model aims to capture the trade-off between costs and emissions. As the model is an NP-hard problem and the optimization solver (Cplex) was not able to obtain an optimal solution in a reasonable running time, a matheuristic algorithm was developed to obtain good quality solutions in a reasonable computational time.

The distribution of perishable products from one of the largest agricultural areas in Australia is used as a case study to demonstrate the application of the model. The results indicated that using a heterogeneous fleet in the cold supply chain can generate potential benefits, including cost saving and sustainability improvement, than if using a homogeneous fleet. Our analysis illustrated that under the travel distance objective, the results imply that using medium duty vehicles is preferable as this can lead to the minimisation of the average distance travelled. Therefore, transport managers can use the proposed framework as a decision support tool to control and reduce the environmental impact of transportation operations.

Our experiments on emissions price also identified that a higher emissions price does not always result in environmental improvement. This finding may be of significant value to policy makers when they are developing and implementing carbon emissions regulations.

5.3 Designing a sustainable intermodal meat supply chain under a carbon emissions regime

Chapter 4 presented a mathematical model within the context of a rail-road intermodal network for a meat supply chain, taking into account the expected distribution threshold, animal welfare issues and traffic congestion constraints under carbon tax regime. The research focused on a multi-echelon supply chain comprising production regions, terminals, abattoirs, seaports and distribution centres as the destinations. The model selected an effective transport mode and determined the quantity of livestock and meat products to be shipped through the unimodal and intermodal links in order to minimise transport costs, quality loss costs, animal welfare reduction costs and emissions costs. The model was implemented for a case study in Queensland, Australia. The results suggested that the rail–road intermodal network is more desirable from the economic and animal welfare points of view. However, the unimodal network was preferred for reducing fuel consumption and, consequently, emissions from the transport operations as the livestock and meat products need to travel additional distances to reach the terminals in the intermodal network.

Our analysis indicated that rail–road intermodal network would be the more beneficial if animal welfare issues are prioritised. Therefore, it is important for decision makers to consider animal welfare, which also influences the quality of the meat products, when making transport mode selection decisions. Moreover, experiments on unit penalty costs identified that a higher unit penalty cost led to using the intermodal network to avoid heavy road traffic congestion which results in delays in product distribution and, consequently, increased quality loss costs.

As the Australian government plans to develop a new train line to the regional area in the case study, which will include new terminals, the findings of this research suggest that it is possible for the government to assist in reducing livestock and meat distribution costs by constructing terminals closer to the main production regions and the abattoirs in order to reduce vehicle usage or the vehicle travel distance in the meat supply chain. This research can motivate participants in the meat supply chain to invest in facility development close to the train terminals in order to facilitate the shipment of livestock and meat products using trains.

5.4 Limitations of the study and possible future research directions

This research investigated a regional distribution network in a situation where the metropolitan cities in Australia are overcrowded and it demonstrated the potential for incorporating sustainability indicators such as energy use, carbon and *GHG* emissions, product quality and animal welfare in three proposed logistics decision support models. While the study has achieved its objectives, there are some limitations which can provide possible future research opportunities.

The model examined in Chapter 2 considered the effect of only two subsidy schemes, which rely on linear and multiple breakpoint functions, on logistics decisions and economic costs. Examining the effects of alternative subsidy schemes on cargo distribution decisions and the promotion of regional economic development would be an interesting line of research in the future. Research on this topic would provide useful insights to help decision makers identify the most effective scheme to manage the supply chain. To reflect the increasing awareness of decision makers about environmental impacts, the emissions arising from air transport and ground transport would be considered so that the proposed model could focus more on improving sustainability. The focus of our model is on transport decisions. However, considering other logistics decisions such as facility location would be another potential direction for future studies. The model considered a constant release time at the facilities. But it can be varied according to the availability of human resources, equipment and the volume of cargo. Therefore, it would be interesting to consider the release time as an uncertain parameter. The model was applied to small real world example. Larger case studies, which are more relevant in practice, will lead to time-consuming computations which may reduce the practical applicability of the proposed model. Developing approaches to appropriate solutions, therefore, would be essential to handle such large case studies.

The model in Chapter 3 assumed the distribution of a single cold product. However, considering the distribution of a number of cold products may have greater applicability in the current competitive global economic environment. Therefore, researchers may be interested in considering several cold products that need various temperature ranges for storage as a future research area. Incorporating the benefits of cold products to customers and, therefore, changing the objective function from cost minimisation to net benefit maximisation would be a natural extension of this research. The model relies on a stochastic environment by taking only demand uncertainty into account. Other parameters such as travel time, which can be influenced by traffic congestion, and supply can be subject to uncertainties in practice as well. Therefore, a direction for future research would be to extend the model to consider uncertainty in other parameters which are not always predictable in practice. However, this extension of the model can add greater complexity and may increase computational times. The proposed model was modified to incorporate a carbon tax regulation because it has different practical advantages. However, exploring the impact of alternative emissions regulations on cold supply chain operational decisions would be another possibility for future studies.

Chapter 4 presented a model which relies on a completely deterministic environment. However, parameters such as travel time, service time at facilities and demand are subject to uncertainty in practice. Therefore, modifying the model to cope with some parameters' uncertainty would be another potential direction for future research. The present research was restricted to using information relating to diesel trains because of the limitation of data availability. To generalise the proposed model, future research should consider electric trains in the model as these may increase the cost efficiency and sustainability of the model. The model focuses on logistics decisions related to the transport network configuration. It would be another line of enquiry for future research on strategic decisions to consider facility location in the model and to investigate the construction of new terminals. The case study in this chapter can be regarded as of small size. Extending the size of the case study to something closer to the reality may increase computational times. But to retain the practical applicability of the proposed model in that situation, an effective approach should be developed to solve the model in reasonable computational time as this would add value to the literature. The model does not consider consolidation at a train terminal. Therefore, it would be interesting to consider the capability of consolidation at train terminals in future research.

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Appendix A: Notations used in mathematical model in Chapter 2

In this appendix we present the notations used in the mathematical model formulation provided in Section 2.3. We use Greek letters and upper-case letters to present the parameters, while lower case letters are used to define the variables.

Table A-1:Indices

κ, l	Index of the number of vehicles, $\kappa, l = 1, \ldots, K$
i, j	Index of node, $i, j \in v \cup \{N_T + 1\}$
m	Index of cycle, $m = 1, \ldots, T_M$
h	Index of segments in breakpoint subsidy function, $h = 1, \ldots, H$

Table A-2:Parameters

CL_i	Landing cost per tonne at a destination airport *i*
A	Air transportation cost per *km* (fuel cost)
ϑ_V	Subsidy value granted per *kg* of cargo distributed from a regional area to other areas
ϑ_F	Subsidy rate granted per *kg* of a flight load if it is landing at a regional airport
ϑ_h	Subsidy value used at multiple breakpoint subsidy function
D_{ij}	The distance from node *i* to *j*
C_κ	Capacity of vehicle κ
F_κ	Fixed cost of vehicle κ
F_d	Driver wage *(AUD/s)*
FT_i	Flight time from origin airport to destination airport *i*
ST_i	Service time at node *i*
η_κ	Fuel cost per litre *(AUD/L)*
Q_j	Demand of consignee *j (kg)*
R_{Ai}	Release-time at a destination airport *i*
R_F	Release-time at a forwarder's warehouse
L_h	Minimum quantity of cargo required the h^{th} segment of subsidy function is granted
U_h	Maximum quantity of cargo required the h^{th} segment of subsidy function is granted
Minload	Minimum load of a flight at cycle *m*
Maxload	Maximum load of a flight at cycle *m*
π	Penalty cost per unit of time for late services at each consignee *(AUD/s)*
T_i	Latest time of starting services at consignee *i (s)*
Ω	loading/unloading time per *kg* cargo
Γ	Technical parameter
Φ_κ	Engine friction factor of vehicle κ *(kJ/rev/L)*
N_κ	Engine speed of vehicle κ (rev/s)
ι_κ	Engine displacement of vehicle κ *(L)*
$C_{d\kappa}$	Coefficient of aerodynamics drag of vehicle κ
ρ	Air density *(kg/m³)*
A_κ	Frontal surface area of vehicle κ (m²)

ζ	Vehicle drive train efficiency
ω	Efficiency parameter for diesel engines
G	Gravitational constant (m/s^2)
θ	Road angle
C_e	Coefficient of rolling resistance
W_κ	Curb weight of vehicle κ *(kg)*
TW_κ	Total payload of vehicle κ *(kg)*
S_R	Average speed of vehicle on origin routes *(m/s)*
Budget	Maximum available budget for granting subsidy for regional areas
M	A large number

Table A-2:Variables

y_{im}	1 if there is a flight from the origin airport to a destination airport *i* at cycle *m*; 0 otherwise
$x_{ij\kappa m}$	1 if κ^{th}vehicle is used to distribute cargoes on arc *(i,j)* at cycle *m* on origin route; 0 otherwise
$z_{ij\kappa m}$	1 If κ^{th} vehicle is used to distribute cargoes on arc *(i,j)* at cycle *m* where $i \in N_F \cup N_C$ is a forwarder warehouse or follows it $j \in N_C$follows a forwarder warehouse
$f_{ij\kappa m}$	Cargo flow carried by κ^{th} vehicle at cycle *m* when travel from node *i* to *j*
o_m	Flight load at cycle *m*
s_{hm}	1 if subsidy is located in h^{th} segment of breakpoint subsidy function at cycle *m*; 0 otherwise
$t_{i\kappa m}$	Departure time from node *i* by vehicle κ in cycle *m*
p_i	Penalty cost at consignee *i* as a result of time-window violation
dt_m	Departure time of an airplane from the origin airport at cycle *m*
$wc_{\kappa m}^{o}$	Driver salary cost of vehicle κ in cycle *m* on origin routes
$wc_{\kappa m}^{s}$	Driver salary cost of vehicle κ in cycle *m* on sub-routes
$av_{ij\kappa m}$	Auxiliary variable linked fuel cost to vehicle's load
$subside_m$	Auxiliary variable using for linearization of subsidy value granted for a flight at each cycle *m*
ms	Auxiliary variable using for linearization of total subsidy value granted by government
$g_h(o_m)$	Multiple breakpoint subsidy function

Appendix B: The constraints under subsidy scenario 1

In this appendix we explain the constraints of the mathematical model formulation provided in Section 2.3.4.

S.t.

$$\sum_{i\in N_A} y_{im} \le 1 \qquad \forall m \qquad (2.5)$$

$$\sum_{i\in N_A} y_{i(m+1)} \le \sum_{i\in N_A} y_{im} \qquad \forall m \qquad (2.6)$$

$$\sum_{i\in N_A} y_{im} \le o_m \qquad \forall m \qquad (2.7)$$

$$x_{ij\kappa m} \le y_{im} \qquad \forall i \in N_A,\ j \in N_F, \kappa, m \qquad (2.8)$$

$$\sum_{i\in N_A}\sum_{j\in N_F} x_{ij\kappa m} + \sum_{i\in N_F}\sum_{j\in N_C\cup\{N_T+1\}} z_{ij\kappa m} \le 1 \qquad \forall \kappa, m \qquad (2.9)$$

$$\sum_{j\in N_C\cup\{N_T+1\}} x_{ij\kappa m} - \sum_{j\in N_F\cup N_C} x_{ji\kappa m} = 0 \qquad \forall i \in N_C, \kappa, m \qquad (2.10)$$

$$\sum_{j\in N_C\cup\{N_T+1\}} z_{ij\kappa m} - \sum_{j\in N_F\cup N_C} z_{ji\kappa m} = 0 \qquad \forall i \in N_C, \kappa, m \qquad (2.11)$$

$$\sum_{j\in N_C\cup\{N_T+1\}} x_{ij\kappa m} - \sum_{j\in N_A} x_{ji\kappa m} = 0 \qquad \forall i \in N_F, \kappa, m \qquad (2.12)$$

$$\sum_{j\in N_A} x_{ji\kappa m} \le \sum_{l,l\ne\kappa}\sum_{j\in N_C} z_{ijlm} + \sum_{j\in N_C} x_{ij\kappa m} \qquad \forall i \in N_F, \kappa, m \qquad (2.13)$$

$$\sum_{l,l\ne\kappa}\sum_{j\in N_C} z_{ijlm} \le M \sum_{\kappa}\sum_{j\in N_A} x_{ji\kappa m} \qquad \forall i \in N_F, m \qquad (2.14)$$

$$\sum_{m}\sum_{\kappa}\sum_{j\in N_C\cup\{N_T+1\}} x_{ij\kappa m} + \sum_{m}\sum_{\kappa}\sum_{j\in N_C\cup\{N_T+1\}} z_{ij\kappa m} = 1 \qquad \forall i \in N_C \qquad (2.15)$$

$$\sum_{i\in N_F}\sum_{j\in N_C} z_{ij\kappa m} + \sum_{j\in N_C} z_{j\{N_T+1\}\kappa m} = 0 \qquad \forall \kappa, m \qquad (2.16)$$

$$\sum_{i\in N_A}\sum_{j\in N_F} x_{ij\kappa m} + \sum_{j\in N_F\cup N_C} x_{j\{N_T+1\}\kappa m} = 0 \qquad \forall \kappa, m \qquad (2.17)$$

Constraints (2.5) - (2.17) are related to routing decisions which are based on vehicle routing problems (Tasan and Gen, 2012; Naji-Azimi and Salari, 2013; Wang et al., 2017). We have modified constraints (2.9) and (2.13) - (2.15) to link the routing variables on the origin routes ($x_{ij\kappa m}$) with the routing variables on the sub-routes ($z_{ij\kappa m}$). Despite the flow conservation constraints in classical vehicle routing problems, we consider incoming arcs may be less than departing arcs at the forwarders' warehouses by modifying constraints (2.13) as a result of creating sub-routes. Constraint set (2.5) enforces that there is at most one route from the origin airport to a destination airport at cycle \$m\$. Constraints (2.6) ensure that a flight cannot leave the origin airport at cycle *(m+1)* if there is no flight from the origin airport at cycle m. Constraints (2.7) ensure that there is no route from the origin airport to the destination airport if a flight load is zero at cycle m. Constraints (2.8) indicate that vehicles depart from a destination airport to forwarders' warehouses only if a flight has landed at that airport at cycle \$m\$. Constraints (2.9) indicate that each vehicle can be used on either an origin route or a sub-route. Constraints (2.10) and (2.11) ensure that the incoming arcs must be equal to the departing arcs at each consignee's location. Constraints (2.12) ensure that the incoming arcs are equal to the departing arcs at each forwarder's warehouse on the origin routes. Constraints (2.13) and (2.14) link the arcs before and after the forwarder's warehouse point. By constraints (2.15) we ensure that each consignee is visited by either an origin route or a sub-route. Constrains (2.16) and (2.17) guarantee the connectivity on sub-routes and origin routes.

$$f_{ij\kappa m} \leq C_\kappa (x_{ij\kappa m} + z_{ij\kappa m}) \qquad \forall i \in N_A \cup N_F \cup N_C \quad \forall i \in N_F \cup N_C, \kappa, m \tag{2.18}$$

$$\sum_\kappa \sum_{i \in N_A} \sum_{j \in N_F} f_{ij\kappa m} = o_m \qquad \forall m \tag{2.19}$$

$$o_m \geq Minload \times \sum_{i \in N_A} y_{im} \qquad \forall m \tag{2.20}$$

$$o_m \leq Maxload \times \sum_{i \in N_A} y_{im} \qquad \forall m \tag{2.21}$$

$$\sum_\kappa \sum_{i \in N_A} f_{ij\kappa m} - \sum_\kappa \sum_{i \in N_C} f_{ji\kappa m} = 0 \qquad \forall j \in N_F, m \tag{2.22}$$

$$\sum_{i \in N_F \cup N_C} f_{ij\kappa m} - \sum_{i \in N_C \cup \{N_T+1\}} f_{ji\kappa m} = Q_j \sum_{i \in N_F \cup N_C} (x_{ij\kappa m} + z_{ij\kappa m}) \qquad \forall j \in N_C, \kappa, m \tag{2.23}$$

$$\sum_m \sum_\kappa \sum_{i \in N_F \cup N_C} f_{i\{N_T+1\}\kappa m} = 0 \tag{2.24}$$

Constraints (2.18) - (2.24) indicate the product flow balances which are based on the capacitated vehicle routing problem (Wang et al., 2017; Soysal et al., 2015). Constraints (2.18) confirm that vehicles' capacity is respected. Constraints (2.19) ensure that the total cargo flow from a destination airport to the forwarders' warehouses is limited to a flight load entering the airport at cycle m. Constraints (2.20) and (2.21) confirm that the minimum load and maximum load of a flight are respected in each cycle m. Constraints (2.22) ensure that the cargo flow entering a forwarder's warehouse is equal to the cargo flow from the forwarder's warehouse at each cycle *m*. Constraints (2.23) decrease the cargo flow on a route after visiting a consignee by its demand. By constraints (2.24) we ensure that vehicles are empty when arriving at the dummy point.

$$dt_m \leq dt_{(m+1)} + M\left(1 - \sum_{i \in N_A} y_{i(m+1)}\right) \qquad \forall\, m \qquad (2.25)$$

$$dt_m \leq \; M \sum_{i \in N_A} y_{im} \qquad \forall\, m \qquad (2.26)$$

$$t_{i\kappa m} \leq M \sum_{j \in N_F} x_{ij\kappa m} \qquad \forall\, i \in N_A, \kappa, m \qquad (2.27)$$

$$t_{i\kappa m} \leq M\left(\sum_{j \in N_C \cup \{N_T+1\}} x_{ij\kappa m} + \sum_{j \in N_C} z_{ij\kappa m}\right) \qquad \forall\, i \in N_F, \kappa, m \qquad (2.28)$$

$$t_{i\kappa m} \leq M * \left(\sum_{j \in N_C \cup \{N_T+1\}} x_{ij\kappa m} + \sum_{j \in N_C \cup \{N_T+1\}} z_{ij\kappa m}\right) \qquad \forall\, i \in N_C, \kappa, m \qquad (2.29)$$

$$t_{i\kappa m} \geq dt_m + FT_i + R_{Ai} - M(1 - y_{im}) - M(1 - \sum_{j \in N_F} x_{ij\kappa m}) \qquad \forall\, i \in N_A, \kappa, m \qquad (2.30)$$

$$t_{i\kappa m} \leq dt_m + FT_i + R_{Ai} + M(1 - y_{im}) + M(1 - \sum_{j \in N_F} x_{ij\kappa m}) \qquad \forall\, i \in N_A, \kappa, m \qquad (2.31)$$

$$t_{j\kappa m} \geq t_{i\kappa m} + {}^{D_{ij}}\!/_{S_R} - M\big(1 - x_{ij\kappa m}\big) + R_F \qquad \forall\, i \in N_A, j \in N_F, \kappa, m \qquad (2.32)$$

$$t_{j\kappa m} \leq t_{i\kappa m} + {}^{D_{ij}}\!/_{S_R} + M\big(1 - x_{ij\kappa m}\big) + R_F \qquad \forall\, i \in N_A, j \in N_F, \kappa, m \qquad (2.33)$$

$$t_{j\kappa m} \geq t_{i\kappa m} + {}^{D_{ij}}\!/_{S_R} - M\big(1 - x_{ij\kappa m}\big) + ST_j \qquad \forall\, i \in N_F, j \in N_C, \kappa, m \qquad (2.34)$$

$$t_{j\kappa m} \leq t_{i\kappa m} + {}^{D_{ij}}\!/_{S_R} + M\big(1 - x_{ij\kappa m}\big) + ST_j \qquad \forall\, i \in N_F, j \in N_C, \kappa, m \qquad (2.35)$$

$$t_{j\kappa m} \geq t_{i\kappa m} + \frac{D_{ij}}{S_R} - M\big(1 - x_{ij\kappa m}\big) + ST_j \qquad \forall\, i \in N_C, j \in N_C, \kappa, m \qquad (2.36)$$

$$t_{j\kappa m} \leq t_{i\kappa m} + \frac{D_{ij}}{S_R} + M\big(1 - x_{ij\kappa m}\big) + ST_j \qquad \forall\, i \in N_C, j \in N_C, \kappa, m \qquad (2.37)$$

$$t_{\{N_T+1\}\kappa m} \geq t_{i\kappa m} - M\big(1 - x_{i\{N_T+1\}\kappa m}\big) \qquad \forall\, i \in N_F \cup N_C,, \kappa, m \qquad (2.38)$$

$$t_{ilm} \geq t_{i\kappa m} - M\left(1 - \sum_{j \in N_C} z_{ijlm}\right) - M\left(1 - \sum_{j \in N_C \cup \{N_T+1\}} x_{ij\kappa m}\right) \qquad \forall\, i \in N_F, l, l \neq \kappa, \kappa, m \qquad (2.39)$$

$$t_{ilm} \leq t_{i\kappa m} + M\left(1 - \sum_{j \in N_C} z_{ijlm}\right) + M\left(1 - \sum_{j \in N_C \cup \{N_T+1\}} x_{ij\kappa m}\right) \qquad \forall\, i \in N_F, l, l \neq \kappa, \kappa, m \qquad (2.40)$$

$$t_{j\kappa m} \geq t_{i\kappa m} + \frac{D_{ij}}{S_R} - M\big(1 - z_{ij\kappa m}\big) + ST_i \qquad \forall\, i \in N_F \cup N_C, j \in N_C, \kappa, m \qquad (2.41)$$

$$t_{j\kappa m} \leq t_{i\kappa m} + \frac{D_{ij}}{S_R} + M\big(1 - z_{ij\kappa m}\big) + ST_i \qquad \forall\, i \in N_F \cup N_C, j \in N_C, \kappa, m \qquad (2.42)$$

$$t_{\{N_T+1\}\kappa m} \geq t_{i\kappa m} - M\left(1 - z_{i\{N_T+1\}\kappa m}\right) \qquad \forall\, i \in N_C, \kappa, m \tag{2.43}$$

$$p_i \geq \pi\left(\sum_m \sum_\kappa t_{i\kappa m} - ST_i - T_i\right) \qquad \forall\, i \in N_C \tag{2.44}$$

Constraints (2.25) - (2.44) are related to the time-windows and guarantee the feasibility of a time schedule for each vehicle based on the vehicle routing problem with time-windows (Cordeau et al., 2007; Kritikos and Ioannou, 2010; Li et al., 2016). Constraint set (2.25) ensures that a flight at the m^{th}cycle cannot depart from the origin airport later than a flight at the $(m+1)^{th}$ cycle. Constraints (2.26) set dt_m as a non-zero value if there is a route between the origin airport and the destination airport. Constraints (2.27) - (2.29) set the $t_{j\kappa m}$ related to node j as a non-zero value if the node is visited by vehicle κ. Constraints (2.30) and (2.31) determine the departure time from a destination airport by vehicle κ at cycle m. Constraints (2.32) and (2.33) compute the departure time from a forwarder's warehouse visited by vehicle κ an origin route. Constraints (2.34) and (2.35) compute the departure time from a consignee visited immediately after a forwarder's warehouse by vehicle κ on an origin route. The departure time from other consignees visited by vehicle κ on origin routes is computed by constraints (2.36) and (2.37). Constraints (2.38) compute the departure time from the dummy point on an origin route which is equal to the departure time at the last node visited by vehicle κ on the origin route. Constraints (2.39) and (2.40) compute the departure time from a consignee visited immediately after a forwarder's warehouse by a sub-route. The departure time from other consignees visited by sub-routes is computed by constraints (2.41) and (2.42). Constraints (2.43) compute the departure time from the dummy point on a sub-route which is equal to the departure time from the last consignee visited on the sub-route. The penalty cost as a result of a time-window violation at each consignee's location is determined by constraints (2.44).

$$ms \leq Budget \tag{2.45}$$

$$ms \leq \sum_m \sum_\kappa \sum_{i \in N_{A2}} \sum_{j \in N_F} f_{ij\kappa m}\left(\vartheta_F + \vartheta_V\right) \tag{2.46}$$

$$av_{ij\kappa m} \geq f_{ij\kappa m} D_{ij} - M\left(1 - x_{ij\kappa m} - z_{ij\kappa m}\right) \qquad \forall\, i \in N_A \cup N_F \cup N_C,\ j \in N_F \cup N_C, m, \kappa \tag{2.47}$$

$$wc^{o}_{\kappa m} \geq Fd\left(t_{\{N_T+1\}\kappa m} - \sum_{i\in N_A} t_{i\kappa m} - \sum_{j\in N_F} x_{j\{N_T+1\}\kappa m} \times R_{Fj} + 2\Omega \sum_{i\in N_A}\sum_{j\in N_F} f_{ij\kappa m} + \Omega \sum_{i\in N_F}\sum_{j\in N_C} f_{ij\kappa m} \right) + M \sum_{i\in N_F} x_{i\{N_T+1\}\kappa m} - M(1 - \sum_{i\in N_C} x_{i\{N_T+1\}\kappa m}) \quad \forall k, m \qquad (2.48)$$

$$wc^{s}_{\kappa m} \geq Fd\left(t_{\{N_T+1\}\kappa m} - \sum_{i\in N_F} t_{i\kappa m} + \Omega \sum_{i\in N_F}\sum_{j\in N_C} f_{ij\kappa m} \right) - M(1 - \sum_{i\in N_C} z_{i\{N_T+1\}\kappa m}) \quad \forall k, m \qquad (2.49)$$

$$y_{im}, x_{ij\kappa m}, z_{ij\kappa m}, \in (0,1) \quad \forall\, i, j, i \neq j, \kappa, m \qquad (2.50)$$

$$f_{ij\kappa m}, t_{i\kappa m}, p_i, av_{ij\kappa m}, dt_m, o_m \geq 0 \quad \forall\, i, j, \kappa, m \qquad (2.51)$$

The total subsidy income is determined based on the government subsidy limit and the subsidy values granted for flights and vehicles at the regional airport under subsidy scenario 1 by constraints (2.45) and (2.46). Constraints (2.47) link the transportation cost to the cargo flow on a route. Constraints (2.48) and (2.49) compute the driver cost on the origin routes and sub-routes, respectively. Constraints (2.50) and (2.51) define the types of decision variables.

Appendix C: The mathematical model under subsidy scenario 2

This appendix presents the model in which the subsidy is considered as a multiple breakpoint function.

$$\min z_B = ATC - TSI + GTC + PC \qquad (2.52)$$

Subject to:

$$\sum_h s_{hm} = \sum_{i \in N_{A2}} y_{im} \qquad \forall m \qquad (2.53)$$

$$L_h - M(1 - s_{hm}) \le o_m \qquad \forall m, h \qquad (2.54)$$

$$o_m \le U_h + M(1 - s_{hm}) \qquad \forall m, h \qquad (2.55)$$

$$subside_m \le g_h(o_m) + M(1 - s_{hm}) \qquad \forall m, h \qquad (2.56)$$

$$subside_m \ge g_h(o_m) - M(1 - s_{hm}) \qquad \forall m, h \qquad (2.57)$$

$$subside_m \le M \sum_h s_{hm} \qquad \forall m \qquad (2.58)$$

$$ms \le \sum_m (subside_m + \sum_\kappa \sum_{i \in N_{A2}} \sum_{j \in N_F} f_{ij\kappa m} \vartheta_V \qquad (2.59)$$

$$s_{hm} \in \{0,1\} \qquad \forall m, h \qquad (2.60)$$

And Constraints (2.5) – (2.45) and (2.47)- (2.51).

Constraints (2.53) ensure that if a flight arrives at a regional area, the subsidy value granted for the flight is set a non-zero value. Constraints (2.54) and (2.55) link flight load with the multiple breakpoint subsidy function. Constraints (2.56) and (2.57) determine the subsidy value granted for a flight based on the multiple breakpoint subsidy function. Constraints (2.58) link the $subside_m$ with the s_{hm} variables. The total subsidy value granted by the government in the regional area under subsidy scenario 2 is determined by constraints (2.59). Constraints (2.60) define the types of decision variables.

Appendix D: The Modified model in Chapter 3

In this appendix the modified model used in the second phase of initialisation procedure is presented to determine quantity delivered to the retailers.

$$\begin{aligned}
\min z_m = {} & H_S i_S^f + \phi_E u_S^f E_S \\
& + \sum_{\xi} P(\xi)\left(H_S i_S^s(\xi) + \phi_E u_S^s(\xi) E_S + \sum_t \sum_n \left(H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R \right) \right) + \\
& \phi_F \Gamma \sum_n (D_{0n} q_n^f \gamma_2 \alpha) + \sum_{\xi} P(\xi)(\phi_F \Gamma \sum_n (D_{0n} q_n^s(\xi) \gamma_2 \alpha)) + \\
& \sum_{\xi} P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) + \\
& \mu \Bigg(\Gamma \sum_n (D_{0n} q_n^f \gamma_2 \alpha) \times \sigma + u_S^f E_S \times \delta \\
& + \sum_{\xi} P(\xi) \Bigg(\Gamma \sum_n (D_{0n} q_n^s(\xi) \gamma_2 \alpha) \times \sigma + (u_S^s(\xi) E_S \\
& + \sum_t \sum_n u_{R_n t}(\xi) E_R) \times \delta \Bigg) \Bigg)
\end{aligned} \tag{3.68}$$

Subject to:

$$i_S^f = Q - \sum_n q_n^f \tag{3.69}$$

$$i_S^s(\xi) = i_S^f + Q - \sum_n q_n^s(\xi) \qquad \forall \xi \tag{3.70}$$

$$i_{R_n 1}(\xi) = q_n^f - D_n(\xi) + s_{n1}(\xi) \qquad \forall n, \xi \tag{3.71}$$

$$i_{R_n t}(\xi) = iRn(t-1)\xi + qns(\xi) - Dn\xi + snt(\xi) \qquad \forall n, \xi, t \geq 2 \tag{3.72}$$

$$i_{R_n 1}(\xi) \leq \Upsilon \qquad \forall n, \xi, t \tag{3.73}$$

$$q_n^s(\xi) + i_{R_n 1}(\xi) \geq D_n(\xi) + \Upsilon \qquad \forall n, \xi \tag{3.74}$$

$$u_S^f \geq \frac{i_S^f}{C_S} \tag{3.75}$$

$$u_S^f \leq \frac{i_S^f}{C_S} + 1 - \varepsilon \tag{3.76}$$

$$u_S^s(\xi) \geq \frac{i_S^s(\xi)}{C_S} \qquad \forall \xi \tag{3.77}$$

$$u_S^s(\xi) \leq \frac{i_S^s(\xi)}{C_S} + 1 - \varepsilon \qquad \forall \xi \tag{3.78}$$

$$u_{R_n t}(\xi) \geq \frac{i_{R_n t}(\xi)}{C_R} \qquad \forall n, t, \xi \tag{3.79}$$

$$u_{R_n t}(\xi) \leq \frac{i_{R_n t}(\xi)}{C_R} + 1 - \varepsilon \qquad \forall n, t, \xi \tag{3.80}$$

$$i_S^f, i_S^s(\xi), q_n^f, q_n^s(\xi), u_S^f, u_S^s(\xi) \geq 0 \qquad \forall n, \xi \tag{3.81}$$

$$i_{R_n t}(\xi), s_{nt}(\xi), u_{R_n t}(\xi) \qquad \forall n, t, \xi \qquad (3.82)$$