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

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Abstract

Increasing awareness of sustainability in supply chain management has prompted organizations and individuals to consider environmental impacts when managing supply chains. The issues concerning environmental impacts are significant in cold supply chains due to substantial carbon emissions from storage and distribution of temperature-sensitive product. This paper investigates the impact of carbon emissions arising from storage and transportation in the cold supply chain in the presence of carbon tax regulation, and under uncertain demand. A two-stage stochastic programming model is developed to determine optimal replenishment policies and transportation schedules to minimize 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 performance and robustness of the matheuristic algorithm are analyzed using test instances in various sizes. A real-world case study in Queensland, Australia is used to demonstrate the application of the model. The results highlight that higher emissions price does not always contribute to the efficiency of the cold supply chain system. Furthermore, the analyses indicate that using heterogeneous fleet including light duty and medium duty vehicles[1] can lead to further cost saving and emissions reduction.

Keywords: Sustainable cold supply chain; Two-stage stochastic programming; Carbon tax regulations; Demand uncertainty; Matheuristic algorithm.

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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

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

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 (EPA, 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). Energy consumption of cold supply chains accounted for around 30% of total world energy consumption (Kayfeci et al., 2013). Refrigeration is a major contributor to global energy consumption, accounting for 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 AU$ 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 AU$ 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 AU$ 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 minimizing 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 paper investigates the impacts of carbon emissions arising from storage and transportation in the cold supply chain in the presence of carbon tax regulation. The paper also considers the impact of uncertain demand on the operational decisions associated with storage and transportation. We develop an optimization 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 minimize 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 can provide a better balance between cost and emissions in 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 paper is organized as follows. In section 2, the literature relevant for this research is reviewed. Section 3 presents a description of our model and assumptions. In section 4, we formulate the proposed problem as a two-stage stochastic programming model. Section 5 presents the proposed matheuristic algorithm. The evaluation of the matheuristic algorithm, practical context and case study data are presented in Section 6. We also conduct sensitivity analyses and discuss findings and managerial implications in section 6. Finally, section 7 contains concluding remarks.

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 optimization.

Bozorgi et al. (2014) presented a new inventory model for a cold product with a capacitated refrigerated unit for both holding and transportation. The aim of their model was to find the optimal order quantity while minimising cost and emissions functions. These authors provided an analysis which identified the trade-off between the objective functions, and found that the emissions function is more sensitive to deviation from optimality than the cost function. In a later work, Bozorgi (2016) developed a variation of the economic order quantity (EOQ) model for a family of cold products. The aim of the model was to determine the inventory level that minimizes cost while considering emissions. The results indicate the effectiveness of the proposed model in comparison with the EOQ model and the sustainable order quantity (SOQ) model proposed by Bouchery et al. (2012).

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 optimization 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 optimization was developed to solve the model in their study. Stellingwerf et al. (2018a) presented an optimization model for a load dependent vehicle routing problem to minimize 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 leads 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 optimization 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 analyze 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 optimization 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 optimization 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 modeling).

Stochastic parameters brings more complexity in modeling 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 analyze 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 minimize 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 optimization model for cold supply chain management aiming to minimize 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 contributions of this paper to the existing cold supply chain literature can be summarised as follows: (1) providing an integrated optimisation model as a two-stage stochastic programming considering demand uncertainty and fuel consumption and consequently emissions from transportation and cold facilities under carbon tax regulation; (2) developing a computationally efficient matheuristic algorithm based on an Iterated Local Search and mixed integer programming to solve the proposed problem. Finally from the practical point of view, we show how the proposed model could be implemented in a real-world case study based on data from Queensland, Australia that leads to managerial insights regarding how cold supply chain participants enable to make cost-efficient and environment-friendly decisions under carbon tax regulation and demand uncertainty.

3. Problem description

The main objective of this research is to develop an optimization 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 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

[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.

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 minimize 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 realization of the uncertain demand. At the end of the period, the actual demand of retailers are 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 realized 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:

- There 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_k) 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 back 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-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 optimization 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 minimize 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 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 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] 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.

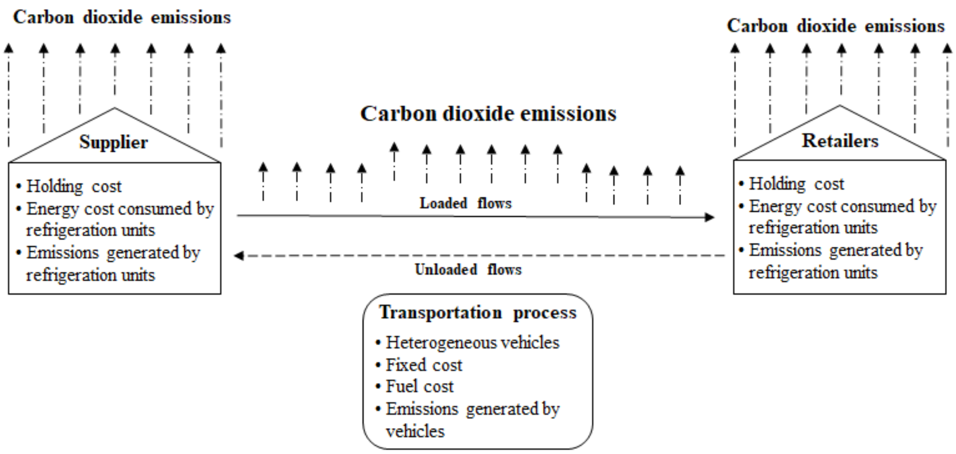


Figure 1: A simple scheme of the proposed problem

3.1. *Modeling approach*

The cold supply chain can alter and extend the shelf life of cold products, which increases the uncertain nature of the demand for perishable products. It is thus believed that projecting the demand for a longer period may not be accurate but it can be much more accurate for shorter periods (Sazvar et al., 2014). In our modelling, we focus on planning for two stages which each stage may contain some periods of time and delivery is assumed to be conducted at the beginning of each period. For illustration purpose, we set the planning horizon to two periods following Sazvar et al. (2014); Mirzapour Al-e hashem et al. (2017) which is sufficient for this study.

In the two-stage stochastic programming model, the decision variables are categorized 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 realization 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 scenarios. The main decisions relevant to each stage in our modelling are summarized in Table 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 minimize the costs related to the first-stage decisions and expected costs of the second-stage decisions.

Table 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 4.3)	Optimal speed of vehicles when traveling on arc (i, j) in the second period under each scenario (related to extended model, section 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 the each period under each scenario

The problem is considered as a complete graph $G = (\nu, E)$, where $\nu = \{0, 1, ..., N\}$ 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 paper to develop the mathematical model are summarized in Tables 2, 3 and 4. We use Greek letters and upper case letters to represent parameters, while lower-case letters are used to denote variables.

Table 2: Indices

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

Table 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_S	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

3.2. Fuel consumption

We utilize 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_κ) of vehicle type κ over distance D_{ij} at a speed of S can be calculated as follows.

$$G_\kappa = \Gamma(\frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S} + (W_\kappa + L_\kappa)\gamma_\kappa \alpha D_{ij} + \beta_\kappa \gamma_\kappa D_{ij} S^2) \tag{1}$$

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

Table 4: Variables

$i_{R_n t}(\xi)$	Inventory level in retailer n at the end of period t under scenario ξ
i^f_S	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
$f^f_{i\kappa m}$	Product flow entered to node i by m^{th} vehicle of type κ in the first period
$f^s_{i\kappa m}(\xi)$	Product flow entered to node i by m^{th} vehicle of κ in the second period, under scenario ξ
q^f_n	Quantity of product delivered to retailer n in the first period
$q^s_n(\xi)$	Quantity of product delivered to retailer n in second period under scenario ξ
$x^f_{ij\kappa m}$	*1* if arc (i,j) is visited by m^{th} vehicle of type κ in the first period; $\emptyset$ otherwise
$x^s_{ij\kappa m}(\xi)$	*1* if arc (i,j) is visited by m^{th} vehicle of type κ in the second period under scenario ξ; $\emptyset$ otherwise
$s^f_{ij\kappa m}$	Speed of m^{th} vehicle of type κ when traveling on arc (i,j) in the first period
$s^s_{ij\kappa m}(\xi)$	Speed of m^{th} vehicle of type κ when traveling on arc (i,j) in the second period under scenario ξ
$g^{fr}_{ij\kappa m}$	*1* if m^{th} vehicle of type κ travels from i to j at speed level r in the first period; $\emptyset$ otherwise
$g^{sr}_{ij\kappa m}(\xi)$	*1* if m^{th} vehicle of type κ travels from i to j at speed level r in the second period under scenarios ξ; $\emptyset$ otherwise
$y^f_{ij\kappa m}$	Auxiliary variable linked fuel cost to vehicles' load at the first period
$y^s_{ij\kappa m}(\xi)$	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^f_S	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
$z^f_{n\kappa m}$	Auxiliary variable using for linearization in the first period
$z^s_{n\kappa m}(\xi)$	Auxiliary variable using for linearization in the second period under scenario ξ

4. Mathematical model

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

$$\min z = SC + TC + LC + EC \tag{2}$$

(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:

$$SC = H_S i_S^f + \phi_E \lceil \frac{i_S^f}{C_S} \rceil E_S + \sum_{\xi} P(\xi) \Bigg(H_S i_S^s(\xi) + \phi_E \lceil \frac{i_S^s(\xi)}{C_S} \rceil E_S +$$

$$\sum_t \sum_n \big(H_R i_{R_n t}(\xi) + \phi_E \lceil \frac{i_{R_n t}(\xi)}{C_R} \rceil E_R \big) \Bigg) \tag{2.i}$$

Where $\lceil . \rceil$ refers to ceiling function. The first two parts in the function (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 (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:

$$TC = \sum_{\kappa} \sum_{m} \Bigg(\sum_{n} F_\kappa x_{0n\kappa m}^f + \overbrace{\phi_F \Gamma \sum_{i,j,i \neq j} \Big(\frac{x_{ij\kappa m}^f \Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}}}^{\text{Fuel cost at the first-stage}}$$

$$\underbrace{+ W_\kappa x_{ij\kappa m}^f \gamma_\kappa \alpha D_{ij} + x_{ij\kappa m}^f \beta_\kappa \gamma_\kappa D_{ij} S_{ij}^2 + y_{ij\kappa m}^f \gamma_\kappa \alpha \Big)}\Bigg) +$$

$$\sum_{\xi} P(\xi) \Bigg(\sum_{\kappa} \sum_{m} \Big(\sum_{n} F_\kappa x_{0n\kappa m}^s(\xi) + \overbrace{\phi_F \Gamma \sum_{i,j,i \neq j} \Big(\frac{x_{ij\kappa m}^s(\xi) \Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} +}^{\text{Fuel cost at the second-stage}}$$

$$\underbrace{W_\kappa x_{ij\kappa m}^s(\xi) \gamma_\kappa \alpha D_{ij} + x_{ij\kappa m}^s(\xi) \beta_\kappa \gamma_\kappa D_{ij} S_{ij}^2 + y_{ij\kappa m}^s(\xi) \gamma_\kappa \alpha \Big)}\Big)\Bigg) \tag{2.ii}$$

Parts 1 and 2 in the function (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 (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 $y_{ij\kappa m}^f$, $y_{ij\kappa m}^s(\xi)$ and constraints (33) - (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:

$$LC = \sum_{\xi} P(\xi) \sum_{t} \sum_{n} \pi s_{nt}(\xi) \tag{2.iii}$$

The function (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.

$$\begin{aligned}
EC = \mu \Bigg(& \Big(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,j,i \neq j} \big(\frac{x^f_{ij\kappa m} \Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m} \gamma_\kappa \alpha D_{ij} + x^f_{ij\kappa m} \beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^f_{ij\kappa m} \gamma_\kappa \alpha \big)\Big) \\
& \times \sigma + \lceil \frac{i^f_S}{C_S} \rceil E_S \times \delta + \\
& \sum_{\xi} P(\xi) \Bigg(\Big(\Gamma \sum_{\kappa} \sum_{m} \sum_{i,j,i \neq j} \big(\frac{x^s_{ij\kappa m}(\xi) \Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^s_{ij\kappa m}(\xi) \gamma_\kappa \alpha D_{ij} + \\
& x^s_{ij\kappa m}(\xi) \beta_\kappa \gamma_\kappa D_{ij} S^2_{ij} + y^s_{ij\kappa m}(\xi) \gamma_\kappa \alpha \big)\Big) \times \sigma + \big(\lceil \frac{i^s_S(\xi)}{C_S} \rceil E_S + \\
& \sum_{t} \sum_{n} \lceil \frac{i_{R_n t}(\xi)}{C_R} \rceil E_R \big) \times \delta \Bigg) \Bigg)
\end{aligned} \tag{2.iv}$$

Where $\lceil . \rceil$ refers to ceiling function. Parts 1 and 2 in the function (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 (2.iv) represent expected carbon emissions cost arising from transportation and storage under all possible scenarios.

Constraints and their explanation are discussed as follows:

S.t.

$$i^f_S = Q - \sum_{n} q^f_n \tag{3}$$

$$i^s_S(\xi) = i^f_S + Q - \sum_{n} q^s_n(\xi) \qquad \forall \xi \tag{4}$$

$$i_{R_n 1}(\xi) = q^f_n - D_n(\xi) + s_{n1}(\xi) \qquad \forall n, \xi \tag{5}$$

$$i_{R_n t}(\xi) = i_{R_n (t-1)}(\xi) + q^s_n(\xi) - D_n(\xi) + s_{nt}(\xi) \qquad \forall n, \xi, t \geq 2 \tag{6}$$

$$i_{R_n t}(\xi) \leq \Upsilon \qquad \forall n, \xi, t \tag{7}$$

Constraints (3) - (7) relate to the inventory decisions. In particular, constraints (3) - (6) are inventory balances at the supplier and retailers at the end of each period respectively. Constraint set (7) ensures that the remaining inventory of each retailer at the end of each period does not exceed its maximum storage capacity.

$$q_n^f \leq \sum_j \sum_\kappa x_{jn\kappa m}^f \Upsilon \qquad \forall n \tag{8}$$

$$q_n^s(\xi) \leq \sum_j \sum_\kappa x_{jn\kappa m}^s(\xi) \times (D_n(\xi) + \Upsilon) \qquad \forall n, \xi \tag{9}$$

$$q_n^s(\xi) \leq D_n(\xi) + \Upsilon - i_{R_n(t-1)}(\xi) \qquad \forall n, \xi, t \geq 2 \tag{10}$$

Constraints (8) - (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 (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

$$. \sum_n x_{0n\kappa m}^f \leq 1 \qquad \forall \kappa, m \tag{11}$$

$$\sum_n x_{0n\kappa m}^s(\xi) \leq 1 \qquad \forall \kappa, m, \xi \tag{12}$$

$$\sum_i \sum_\kappa \sum_m x_{in\kappa m}^f \leq 1 \qquad \forall n \tag{13}$$

$$\sum_i \sum_\kappa \sum_m x_{in\kappa m}^s(\xi) \leq 1 \qquad \forall n, \xi \tag{14}$$

Constraints (11) - (14) associate with the routing decisions. In particular, Constraints (11) - (12) denote that each vehicle departs from the supplier at most once per period to visit retailers. Constraints (13) - (14) represent that each retailer is visited at most once at each period by only one vehicle, split delivery is not allowed.

$$\sum_i x_{in\kappa m}^f - \sum_i x_{ni\kappa m}^f = 0 \qquad \forall n, \kappa, m \tag{15}$$

$$\sum_i x_{in\kappa m}^s(\xi) - \sum_i x_{ni\kappa m}^s(\xi) = 0 \qquad \forall n, \kappa, m, \xi \tag{16}$$

$$M \sum_n x_{0n\kappa m}^f - \sum_n \sum_j x_{nj\kappa m}^f \geq 0 \qquad \forall \kappa, m \tag{17}$$

$$M \sum_n x_{0n\kappa m}^s(\xi) - \sum_n \sum_j x_{nj\kappa m}^s(\xi) \geq 0 \qquad \forall \kappa, m, \xi \tag{18}$$

Constraints (15) - (16) ensure that the incoming arcs must be equal to departing arcs at each node and related to subtour elimination. Constraints (17) - (18) ensure that retailers can be visited by a vehicle when the vehicle departs from the supplier.

$$f^f_{n\kappa m} \leq O_\kappa \sum_i x^f_{in\kappa m} \qquad \forall n, \kappa, m \tag{19}$$

$$f^s_{n\kappa m}(\xi) \leq O_\kappa \sum_i x^s_{in\kappa m}(\xi) \qquad \forall n, \kappa, m, \xi \tag{20}$$

$$\sum_\kappa \sum_m f^f_{o\kappa m} = 0 \tag{21}$$

$$\sum_\kappa \sum_m f^s_{0\kappa m}(\xi) = 0 \qquad \forall \xi, \tag{22}$$

Constraints (19) - (22) indicate the product's flow balance. In particular, constraints (19) - (20) confirm that the vehicle's capacity is respected. Constraints (21) - (22) ensure that vehicles are empty when returning to the supplier.

$$f^f_{n\kappa m} \geq \sum_i \sum_\chi x^f_{i\chi\kappa m} \times q^f_\chi - M(1 - x^f_{0n\kappa m}) \qquad \forall n, \kappa, m \tag{23}$$

$$f^f_{n\kappa m} \leq \sum_i \sum_\chi x^f_{i\chi\kappa m} \times q^f_\chi + M(1 - x^f_{0n\kappa m}) \qquad \forall n, \kappa, m \tag{24}$$

$$f^s_{n\kappa m}(\xi) \geq \sum_i \sum_\chi x^s_{i\chi\kappa m}(\xi) \times q^s_\chi(\xi) - M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \tag{25}$$

$$f^s_{n\kappa m}(\xi) \leq \sum_i \sum_\chi x^s_{i\chi\kappa m}(\xi) \times q^s_\chi(\xi) + M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \tag{26}$$

$$f^f_{n\kappa m} \leq M \sum_i x^f_{in\kappa m} \qquad \forall n, \kappa, m \tag{27}$$

$$f^s_{n\kappa m}(\xi) \leq M \sum_i x^s_{in\kappa m}(\xi) \qquad \forall n, \kappa, m, \xi \tag{28}$$

Constraints (23) - (26) determine the total load when a vehicle departs from the supplier. Constraints (27) - (28) set the product's flow entering to a retailer as a non-zero value if there is a link to the retailer.

$$f^f_{n\kappa m} - f^f_{j\kappa m} \leq q^f_n + M(1 - x^f_{nj\kappa m}) \qquad \forall n, j, \kappa, m \tag{29}$$

$$f^f_{n\kappa m} - f^f_{j\kappa m} \geq q^f_n - M(1 - x^f_{nj\kappa m}) \qquad \forall n, j, \kappa, m \tag{30}$$

$$f^s_{n\kappa m}(\xi) - f^s_{j\kappa m}(\xi) \leq q^s_n(\xi) + M(1 - x^s_{nj\kappa m}(\xi)) \qquad \forall n, j, \kappa, m, \xi \tag{31}$$

$$f^s_{n\kappa m}(\xi) - f^s_{j\kappa m}(\xi) \geq q^s_n(\xi) - M(1 - x^s_{nj\kappa m}(\xi)) \qquad \forall n, j, \kappa, m, \xi \tag{32}$$

$$y^f_{n\kappa m} \geq f^f_{n\kappa m} \times D_{in} - M(1 - x^f_{in\kappa m}) \qquad \forall i, n, \kappa, m \tag{33}$$

$$y^s_{n\kappa m}(\xi) \geq f^s_{n\kappa m}(\xi) \times D_{in} - M(1 - x^s_{in\kappa m}(\xi)) \qquad \forall i, n, \kappa, m, \xi \tag{34}$$

Constraints (29) - (32) decrease product's flow on a route after visiting a retailer by its demand. By (33) - (34) transportation cost is dependent on product's flow on a route.

$$i_{R_n t}(\xi) \times s_{nt}(\xi) = 0 \qquad \forall n, t, \xi \tag{35}$$

$$x^f_{ii\kappa m} = x^s_{ii\kappa m}(\xi) = 0 \qquad \forall i, n, \kappa, m, \xi \tag{36}$$

$$i^f_S, i^s_S(\xi), f^f_{i\kappa m}, f^s_{i\kappa m}(\xi), q^f_n, q^s_n(\xi) \geq 0 \qquad \forall i, n, \kappa, m, \xi \tag{37}$$

$$i_{R_n t}(\xi), s_{nt}(\xi) \geq 0 \qquad \forall n, t, \xi \tag{38}$$

$$x^f_{ij\kappa m}, x^s_{ij\kappa m}(\xi) \in (0, 1) \qquad \forall i, j, i \neq j, \kappa, m, \xi \tag{39}$$

Constraint set (35) represents that $i_{nt}(\xi)$ and $s_{nt}(\xi)$ cannot take positive values simultaneously. Constraint set (36) indicates the impossible arcs and constraints (37) - (39) define the types of decision variables.

4.1. ***Symmetry breaking constraints***

In this section, we add symmetry breaking constraints as valid inequalities to strengthen the formulation and tighten feasible solution region resulting in accelerating of the convergence to an optimal solution. The symmetry breaking constraints for each type of vehicle are defined as follows:

$$\sum_n x^f_{0n\kappa m} \leq \sum_n x^f_{0n\kappa(m-1)} \qquad \forall \kappa, m = 2, ..., \eta_\kappa \tag{40}$$

$$\sum_n x^s_{0n\kappa m}(\xi) \leq \sum_n x^s_{0n\kappa(m-1)}(\xi) \qquad \forall \kappa, m = 2, ..., \eta_\kappa, \xi \tag{41}$$

$$\sum_n x^f_{nj\kappa m} \leq \sum_n \sum_{i<j} x^f_{ni\kappa(m-1)} \qquad \forall i, \kappa m = 2, ..., \eta_\kappa \tag{42}$$

$$\sum_n x^s_{nj\kappa m}(\xi) \leq \sum_n \sum_{i<j} x^s_{ni\kappa(m-1)}(\xi) \qquad \forall i, \kappa, m = 2, ..., \eta_\kappa, \xi \tag{43}$$

Constraints (40) - (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 (42) - (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).

4.2. *Linearization of the model*

The proposed base case model (z) contains several nonlinear expressions. We utilize linearization techniques to develop an equivalent linear mathematical model and to achieve optimal solutions. To linearize constraint (35), we define a binary variable $av_{nt}(\xi)$ and constraints (44) - (45). $av_{nt}(\xi) = 1$ if $i_{R_nt}(\xi)$ 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.

$$s_{nt}(\xi) \leq Mav_{nt}(\xi) \qquad \forall n, t, \xi \qquad (44)$$

$$i_{R_nt}(\xi) \leq M(1 - av_{nt}(\xi)) \qquad \forall n, t, \xi \qquad (45)$$

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 $u_{R_nt}(\xi)$ in constraints (46), (49) and (52), respectively, and constraints (47) - (48), (50) - (51) and (53) - (54) as follows:

$$u_S^f = \lceil \frac{i_S^f}{C_S} \rceil \qquad (46)$$

$$u_S^f \geq \frac{i_S^f}{C_S} \qquad (47)$$

$$u_S^f \leq \frac{i_S^f}{C_S} + 1 - \epsilon \qquad (48)$$

$$u_S^s(\xi) = \lceil \frac{i_S^s(\xi)}{C_S} \rceil \qquad (49)$$

$$u_S^s(\xi) \geq \frac{i_S^s(\xi)}{C_S} \qquad \forall \xi \qquad (50)$$

$$u_S^s(\xi) \leq \frac{i_S^s(\xi)}{C_S} + 1 - \epsilon \qquad \forall \xi \qquad (51)$$

$$u_{R_nt}(\xi) = \lceil \frac{i_{R_nt}(\xi)}{C_R} \rceil \qquad (52)$$

$$u_{R_nt}(\xi) \geq \frac{i_{R_nt}(\xi)}{C_R} \qquad \forall n, t, \xi \qquad (53)$$

$$u_{R_nt}(\xi) \leq \frac{i_{R_nt}(\xi)}{C_R} + 1 - \epsilon \qquad \forall n, t, \xi \qquad (54)$$

We convert the nonlinear constraints (23) - (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 (55) - (62).

$$z_{n\kappa m}^f \leq q_n^f + M(1 - \sum_{j \in \nu \setminus \{0\}} \sum_j x_{jn\kappa m}^f) \qquad \forall n, \kappa, m \qquad (55)$$

$$z_{n\kappa m}^f \geq q_n^f - M(1 - \sum_{j \in \nu \setminus \{0\}} \sum_j x_{jn\kappa m}^f) \qquad \forall n, \kappa, m \qquad (56)$$

$$f_{n\kappa m}^f \geq \sum_{\chi} z_{\chi\kappa m}^f - M(1 - x_{0n\kappa m}^f) \qquad \forall n, \kappa, m \qquad (57)$$

$$f^f_{n\kappa m} \leq \sum_{\chi} z^f_{\chi\kappa m} + M(1 - x^f_{0n\kappa m}) \qquad \forall n, \kappa, m \tag{58}$$

$$z^s_{n\kappa m}(\xi) \leq q^s_n(\xi) + M(1 - \sum_{j\in\nu\setminus\{0\}} x^s_{jn\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \tag{59}$$

$$z^s_{n\kappa m}(\xi) \geq q^s_n(\xi) - M(1 - \sum_{j\in\nu\setminus\{0\}} x^s_{jn\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \tag{60}$$

$$f^s_{n\kappa m}(\xi) \geq \sum_{\chi} z^s_{\chi\kappa m}(\xi) - M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n, \kappa, m, \xi \tag{61}$$

$$f^s_{n\kappa m}(\xi) \leq \sum_{\chi} z^s_{\chi\kappa m}(\xi) + M(1 - x^s_{0n\kappa m}(\xi)) \qquad \forall n, \kappa m, \xi \tag{62}$$

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

$$\min z =$$

$$H_S i^f_S + \phi_E u^f_S E_S + \sum_{\xi} P(\xi)\Big(H_S i^s_S(\xi) + \phi_E u^s_S(\xi) E_S + \sum_t \sum_n (H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R)\Big) \tag{63.i}$$

$$+ \sum_{\kappa}\sum_{m}\Big(\sum_n F_\kappa x^f_{0n\kappa m} + \phi_F \Gamma \sum_{i,j,i\neq j}\Big(\frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa\gamma_\kappa D_{ij} S^2_{ij} + y^f_{ij\kappa m}\gamma_\kappa\alpha\Big)\Big) + \sum_{\xi} P(\xi)\Big(\sum_{\kappa}\sum_{m}\Big(\sum_n F_\kappa x^s_{0n\kappa m}(\xi) + \phi_F\Gamma\sum_{i,j,i\neq j}\Big(\frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa\iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha D_{ij} + x^s_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}S^2_{ij} + y^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha\Big)\Big)\Big) \tag{63.ii}$$

$$+ \sum_{\xi} P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) \tag{63.iii}$$

$$+ \mu\Big(\Gamma\sum_{\kappa}\sum_{m}\sum_{i,j,i\neq j}\Big(\frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa\iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa\alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa\gamma_\kappa D_{ij}S^2_{ij} + y^f_{ij\kappa m}\gamma_\kappa\alpha\Big) \times \sigma + u^f_S E_S \times \delta + \sum_{\xi} P(\xi)\Big(\Gamma\sum_{\kappa}\sum_{m}\sum_{i,j,i\neq j}\Big(\frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa\iota_\kappa D_{ij}}{S_{ij}} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha D_{ij} + x^s_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}S^2_{ij} + y^s_{ij\kappa m}\gamma_\kappa\alpha\Big) \times \sigma + \Big(u^s_S(\xi)E_S + \sum_t\sum_n u_{R_n t}E_R\Big) \times \delta\Big)\Big) \tag{63.iv}$$

Subject to:

Constraints (3) - (22), (27) - (34), (36) - (45), (47) - (48), (50) - (51) and (53) - (62).

*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 $s^f_{ij\kappa m}$ and $s^s_{ij\kappa m}(\xi)$ 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:

$\min z_v =$

$$H_S i^f_S + \phi_E u^f_S E_S + \sum_{\xi} P(\xi)\Big(H_S i^s_S(\xi) + \phi_E u^s_S(\xi) E_S + \sum_t \sum_n \left(H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R\right)\Big) \tag{64.i}$$

$$+ \sum_\kappa \sum_m \Big(\sum_n F_\kappa x^f_{0n\kappa m} + \phi_F \Gamma \sum_{i,j,i\neq j} \Big(\frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{s^f_{ij\kappa m}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa\gamma_\kappa D_{ij}(s^f_{ij\kappa m})^2 + y^f_{ij\kappa m}\gamma_\kappa\alpha\Big)\Big) + \sum_\xi P(\xi)\Big(\sum_\kappa\sum_m \Big(\sum_n F_\kappa x^s_{0n\kappa m}(\xi) + \phi_F\Gamma \sum_{i,j,i\neq j}\Big(\frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa\iota_\kappa D_{ij}}{s^s_{ij\kappa m}(\xi)} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha D_{ij} + x^s_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}(s^s_{ij\kappa m}(\xi))^2 + y^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha\Big)\Big)\Big) \tag{63.ii}$$

$$+ \sum_\xi P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) \tag{64.iii}$$

$$+ \mu\Big(\Gamma \sum_\kappa \sum_m \sum_{i,j,i\neq j} \Big(\frac{x^f_{ij\kappa m}\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{s^f_{ij\kappa m}} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa\alpha D_{ij} + x^f_{ij\kappa m}\beta_\kappa\gamma_\kappa D_{ij}(s^f_{ij\kappa m})^2 + y^f_{ij\kappa m}\gamma_\kappa\alpha\Big) \times \sigma + u^f_S E_S \times \delta + \sum_\xi P(\xi)\Big(\Gamma\sum_\kappa\sum_m\sum_{i,j,i\neq j}\Big(\frac{x^s_{ij\kappa m}(\xi)\Phi_\kappa N_\kappa\iota_\kappa D_{ij}}{s^s_{ij\kappa m}} + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha D_{ij} + x^s_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}(s^s_{ij\kappa m})^2 + y^s_{ij\kappa m}\gamma_\kappa\alpha\Big) \times \sigma + \Big(u^s_S(\xi)E_S + \sum_t\sum_n u_{R_n t}E_R\Big)\times\delta\Big)\Big) \tag{64.iv}$$

Subject to:

Constraints (3) - (22), (27) - (34), (36) - (45), (47) - (48), (50) - (51) and (53) - (62). The objective function of the extended model (z_v) contains non-linear terms. To linearize these terms, the linearization approach presented by Bektaş 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 $g^{fr}_{ij\kappa m}$ and $g^{sr}_{ij\kappa m}(\xi)$ as auxiliary variables and link them with $x^f_{ij\kappa m}$ and $x^s_{ij\kappa m}(\xi)$ through the following expressions.

$$\sum_r g^{fr}_{ij\kappa m} = x^f_{ij\kappa m} \qquad \forall i,j,\kappa,m \tag{65}$$

$$\sum_r g^{sr}_{ij\kappa m}(\xi) = x^s_{ij\kappa m}(\xi) \qquad \forall i,j,\kappa,m,\xi \tag{66}$$

The extended linearized model (z_v) is presented as follows:

$$\min z_v =$$

$$H_S i^f_S + \phi_E u^f_S E_S + \sum_\xi P(\xi)\Big(H_S i^s_S(\xi) + \phi_E u^s_S(\xi)E_S +$$
$$\sum_t \sum_n (H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R)\Big) \tag{67.i}$$

$$+ \sum_\kappa \sum_m \Big(\sum_n F_\kappa x^f_{0n\kappa m} + \phi_F \Gamma \sum_{i,j,i\neq j} \Big(\sum_r \frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r} g^{fr}_{ij\kappa m}$$
$$+ W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + \sum_r g^{fr}_{ij\kappa m}\beta_\kappa \gamma_\kappa D_{ij}(S^r)^2 + y^f_{ij\kappa m}\gamma_\kappa \alpha\Big)\Big) +$$
$$\sum_\xi P(\xi)\Big(\sum_\kappa \sum_m \Big(\sum_n F_\kappa x^s_{0n\kappa m}(\xi) + \phi_F \Gamma \sum_{i,j,i\neq j} \Big(\sum_r \frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r} g^{sr}_{ij\kappa m}(\xi) +$$
$$W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa \alpha D_{ij} + \sum_r g^{sr}_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}(S^r)^2 + y^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha\Big)\Big)\Big) \tag{67.ii}$$

$$+ P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) \tag{67.iii}$$

$$\mu\Big(\Gamma \sum_\kappa \sum_m \sum_{i,j,i\neq j} (\sum_r \frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r} g^{fr}_{ij\kappa m} + W_\kappa x^f_{ij\kappa m}\gamma_\kappa \alpha D_{ij} + \sum_r g^{fr}_{ij\kappa m}\beta_\kappa\gamma_\kappa D_{ij}(S^r)^2 + y^f_{ij\kappa m}\gamma_\kappa\alpha)$$
$$\times \sigma + u^f_S E_S \times \delta +$$
$$\sum_\xi P(\xi)\Big(\Gamma \sum_\kappa \sum_m \sum_{i,j,i\neq j} \Big(\sum_r \frac{\Phi_\kappa N_\kappa \iota_\kappa D_{ij}}{S^r} g^{sr}_{ij\kappa m}(\xi) + W_\kappa x^s_{ij\kappa m}(\xi)\gamma_\kappa\alpha D_{ij} +$$
$$\sum_r g^{sr}_{ij\kappa m}(\xi)\beta_\kappa\gamma_\kappa D_{ij}(S^r)^2 + y^s_{ij\kappa m}\gamma_\kappa\alpha\Big) \times \sigma + \Big(u^s_S(\xi)E_S + \sum_t\sum_n u_{R_n t}E_R\Big) \times \delta\Big)\Big) \tag{67.iv}$$

Subject to:

Constraints (3) - (22), (27) - (34), (36) - (45), (47) - (48), (50) - (51) and (53) - (62) and (65) - (66).

The models presented in this section are NP-hard even if demand is assumed to be certain as they are an extension of vehicle routing problem which has been proven to be NP-hard (Dabia et al., 2013; Coelho et al., 2012). The stochastic nature of the demand can even increase the complexity of the problem. A typical instance of the base case model (z) had 63,612 constraints and 23,778 variables and feasible region increases significantly with the number of retailers. Hence, optimisation solver (Cplex) is not able to obtain optimal solutions in reasonable running times. This fact is also highlighted by computational results presented in section 6.1 for majority of the test instances. Therefore, in the next section, we developed a matheuristic algorithm to obtain good quality solutions within reasonable computational times.

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. ILS method is an extension of classical local search that includes shaking procedure as a diversification mechanism (Sabar and Kendall, 2015). ILS is a single solution based methodology 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). Despite the simplicity of ILS, it has been an effective methodology to solve optimization problems (Vansteenwegen et al., 2009; Costa et al., 2012; Cuervo et al., 2014). ILS algorithm is able to escape from a local optimum using shaking procedure. We were also motivated to use 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 5.1 - 5.7, and the outline of the matheuristic algorithm is provided in section 5.8. The efficiency of the algorithm is demonstrated using multiple test instances in section 6.1.

5.1. Initialization

The initialization procedure is composed of three phases, and is presented in Algorithm 1. 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 $i = 1, ..., N$. Then, in the second phase, we use a modified model presented in section 4 (model z) in which the routing variables are fixed and considered as the parameters of the model (see Appendix A). 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);
```

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, $j \leq n_1$. 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.

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 κ_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.

5.4. *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.

5.5. *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.

5.6. *Routes integration*

The goal of this procedure is to improve the solution by best utilizing the vehicles' capacity through routes integration. We categorize 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, κ_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 $(\kappa_1, \kappa_2, \kappa_3)$. 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.

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, $S_1 = \{0, 1, ..., \Xi\}$ 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 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.

$Shaking2$: 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 4 (model z) in which the values of routing variables not related to the selected retailer (e.g, x^f_{ijkm}, $i, j \neq$ the selected retailer) and not included in *solution*1 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, *solution*1 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 *solution*1. 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.

*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 optimization 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. The algorithm starts from an initial solution generated by using the initialization procedure in section 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 5.7 followed by local search procedures presented in sections 5.2 - 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

```
1  Input: Initial − solution;
2  Best − cost = Cost (Initial − solution);
3  Current − solution := Initial − solution;
4  Best − solution := Initial − solution;
5  repeat
6      Randomly select one of the shaking procedures;
7      repeat
8          Current − solution := Swap(Current − solution);
9          Current − solution := Swap2(Current − solution);
10         Current − solution := Extraction − Insertion1(Current − solution);
11         Current − solution := Extraction − Insertion2(Current − solution);
12         Current − solution := Routes − Integration(Current − solution);
13     until (no more improvement is achieved);
14     if (Cost (Current − Solution) < Best − Cost) then
15         Best − Cost = Cost (Current − Solution);
16         Best − solution := Current − Solution;
17     end
18     else
19         Current − solution := Best − solution;
20     end
21 until ((the time limitation is met) or (no improvements are found for Iter
     consecutive iteration);
22 Output:Best − solution;
```

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 4 using a real-world case study, 3) to analyze 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 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 6.2. The case description and numerical experiments are presented in sections 6.3 and 6.4, respectively. Section 6.5 presents the impact of using heterogeneous fleet on the economic and emissions costs. The sensitivity analyses for parameters are conducted in section 6.6.1. Finally, managerial insights are presented in section 6.7.

6.1. Analyzing 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 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 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 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 instances of various sizes have been selected as the test instances. Without loss of generality, we assume the different values for $Iter$ (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 with respect to 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 5 summarizes the results for 40 instances containing up to 65 scenarios and 6 retailers. The column labeled "*Cplex*", gives the best solution obtained using commercial optimization 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 5: Performance of the Matheuristic algorithm on small and medium size instances

Ins.	Cplex	Matheuristic				
		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*	3,271.05	0	3,271.05	3,271.05	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 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 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 6 summarizes 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_1 re-starts from zero if the procedure leads to an improvement in the best solution.

Table 6: Performance of matheuristic algorithm on large size instances

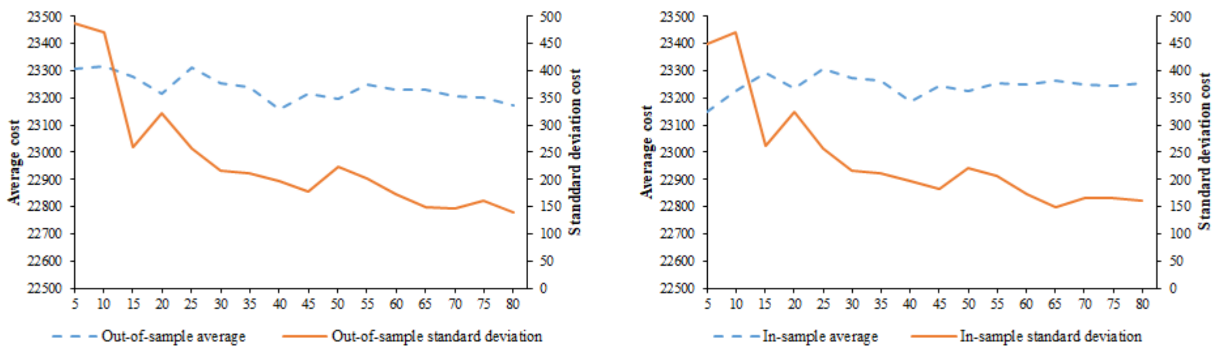
Ins.	Cplex	Matheuristic				
		Ave. solution	Standard deviation	Best solution	Worst solution	Ave. time (s)
Data-50-8	9,413.85	8790.81	11.51	8,782.11	8,822.40	3,913.31
Data-50-9	15,119.22	8,989.58	11.66	8,976.13	9,010.64	4,083.79
Data-50-10	23,736.23	9,932.10	106.45	9,864.97	10,199.41	3,980.58
Data-55-8	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

6.2. ***Monte Carlo sampling approach***

Using a scenario-based approach to deal with uncertainty in an optimization model generates a significant challenge due to the need to select an appropriate scenario sample size to balance the effort between optimizations 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 paper, 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 and 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 4 and the most parameter values used in section 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 2 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

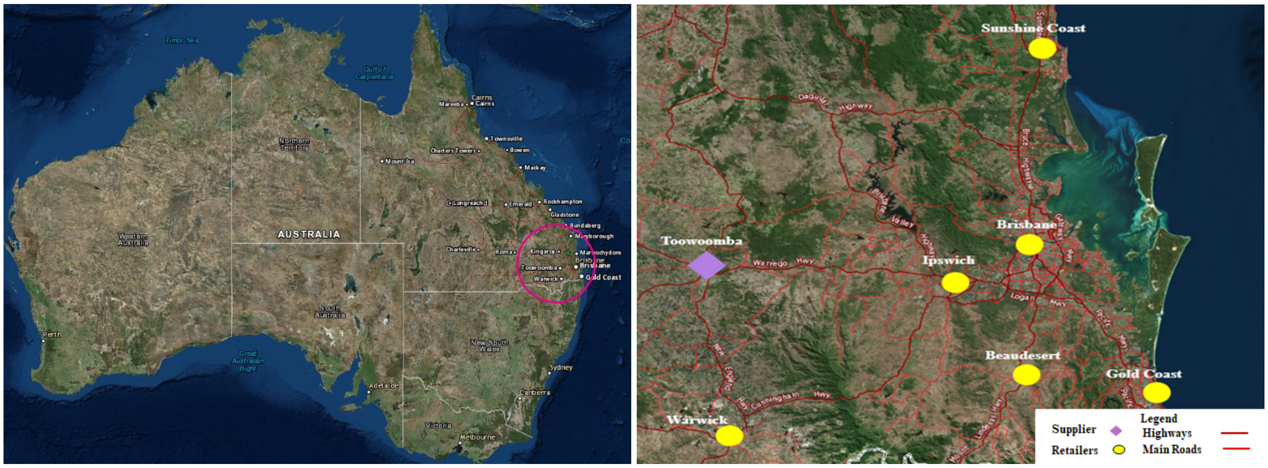
(b) In-sample stability

Figure 2: Scenario sample stability for determining reliable scenario size

6.3. ***Description of the case study***

The need for Australia to use decision support tools for minimizing 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 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.



(a) Australia (b) The selected region

Figure 3: 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 summarized in Tables 7 and 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 focus on rural distribution across the state of Queensland, Australia which has almost the same road condition. The cold supply chain participants also use the speed standard which is set by the government. Speed standards are an enforceable law, and indicated by 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 on this paper. It is therefore logical and sensible to consider speed as a fixed parameter for vehicles 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 to $max\{N, max\{O_\kappa \times D_{in}\}, max\{D_n(\xi)\}, \Upsilon\}$. Based on our case study data, the M value was taken as $max\{O_\kappa \times D_{in}\}$.

Table 7: Definition of vehicle specific parameters

Notation	Description	Light duty	Medium duty
W_κ	Curb weight (kg)	3500	6550
O_κ	The capacity of vehicle (kg)	2580 (258 units)	5080 (508 units)
F_κ	Fixed cost of vehicle ($AU\$$/d)	74.19	106.62
Φ_κ	Engine friction factor (kJ/rev/L)	0.25	0.2
N_κ	Engine speed (rev/s)	38.34	33
ι_κ	Engine displacement (L)	2.77	5
$C_{d\kappa}$	Coefficient of aerodynamics drag	0.6	0.7
A_κ	Frontal surface area (m^2)	7	9

Source: Koç et al. (2014)

Table 8: Definition of vehicle typical parameters

Notation	Description	Typical 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_2 emissions 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

Source: Cachon (2014), Demir et al. (2012), Koç et al. (2014) and Soysal et al. (2015), Cheng et al. (2017), 1 Pound(£)=1.79 AUD dollars (20 Sep 2018)

The emissions (in kg per 100 km) generated by the two types of refrigerated vehicles are shown in Figure 4. Figure 4 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 4 also shows the impact of payload on the resulting emissions.

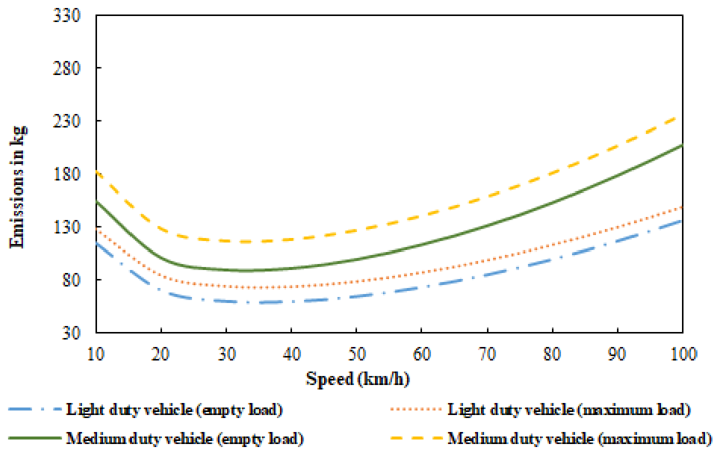


Figure 4: Emissions per 100 km depending on speed with different payload settings

In our models, we take vehicle load, speed and distance traveled 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 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 6.2. As discussed above, a sample of 65 scenarios was used.

Table 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 $57.6 \times 20 = 1152$ kW h/year (or equivalently $E_S = 3.156$ kW h/d). At a retailer, a smaller size of the same type refrigeration units is utilized 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 $57.6 \times 10 = 576$ kW h/year (or equivalently $E_R = 1.58$ kW h/d).

Since the energy cost varies across the level of consumption and countries, we assume the cost to be $AU\$0.0928$ per kWh. The total carbon emissions per $1kWh$ of energy consumption by each refrigeration unit is assumed to be 6.895×10^{-4} tons/kW h (or equivalently $\delta = 6.895 \times 10^{-7}$ kg/kW h) (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 $\Upsilon = 200$ units. The holding cost at the supplier and a retailer are assumed to be $H_S = AU\$10$ and $H_R = AU\$15$ per packaging unit of cold product per day respectively. We consider shortage as lost sales and its cost is set to be $\pi = AU\$100$ per packaging unit of cold product.

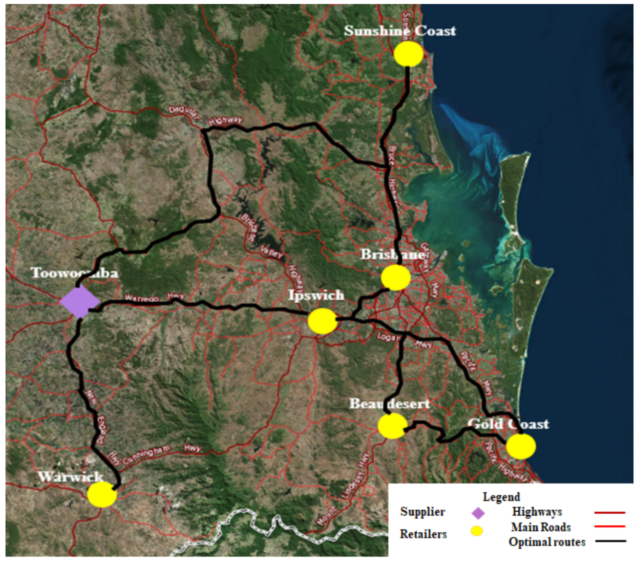
6.4. ***Numerical example and analysis***

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.

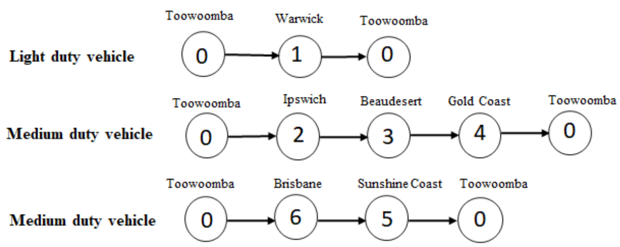
We report the optimal configurations of the first-stage decision variables and optimal expected values of the objective functions of the base case model (z) in Figure 5 and Table 10, respectively. The optimal solution of the first-stage includes three routes: the first route includes Toowoomba, Warwick 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 utilization is 57.36%, 98.03% and 78.34% in the first, second and third routes at the first-stage, respectively.

Table 10: Optimal values of the objective functions under the base case model in $AU\$$

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 5: 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 summarized in Table 11.

Table 11: Optimal values of the objective functions under the extended model in $AU\$$

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 6 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 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 7 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.

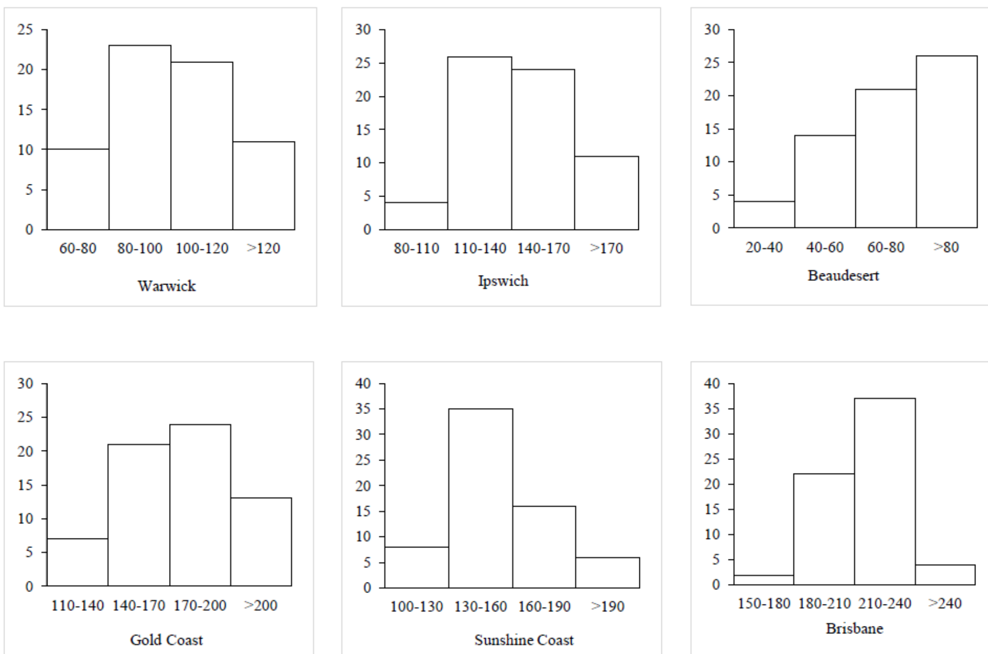


Figure 6: Frequency distribution of optimal quantity in the second-stage

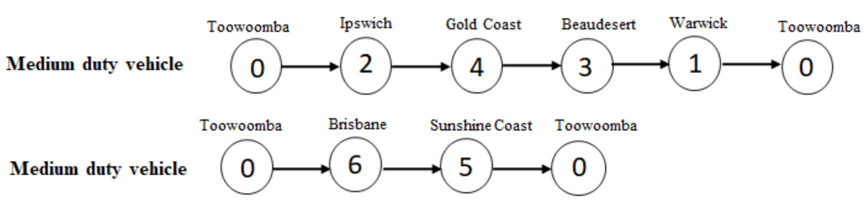


Figure 7: Optimal solution construction for 23.07% of scenarios in the second-stage

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 $1500/year (or equivalently $F_S = \$4.1/day$) and $1000/year (or equivalently $F_R = \$2.74/day$), 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%.

6.5. *The impact of a heterogeneous fleet*

In this section, we analyze the benefits of applying a heterogeneous fleet to optimize 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 12 represents the result from the comparisons. In Table 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 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 lead to the minimization of the average distance traveled. In Table 12, we also present the range of capacity utilization of the vehicle fleet for both heterogeneous and homogeneous cases. The average capacity utilization 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 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 (*AU\$*)	7980.15	7988.86	7980.15	-0.11	0.00
Transportation cost (*AU\$*)	1741.42	1963.20	1884.78	-11.30	-7.61
Lost sale cost (*AU\$*)	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 (*AU\$*)	12817.61	13116.97	13062.89	-2.28	-1.88
Range of capacity utilization 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	-	-

6.6. *Sensitivity analysis*

This section analyses the impact of changing parameters on different components of objective function and CO_2 emissions under the base case model (z). Sensitivity analyses are conducted with respect to changes in unit emission price, distance and vehicle speed.

6.6.1. ***The impact of changes in unit emissions price***

This section analyses the impact of unit emissions price on total cost and CO_2 emissions under the base case model. Figure 8 indicates that on the whole the emissions trend experiences a reduction pattern with the increase of unit emissions price, with the total cost increasing almost linearly. 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 reduction is kind of in conflict with economic costs. For instance, with an increase in unit emissions price from 0.88 ($AU\$/kgCO_2$) to 2.2 ($AU\$/kgCO_2$), the emissions level remains almost constant, but the total cost increases from $AU\$$ 13789.51 to $AU\$$ 16717.12.

In our case, it appears that the carbon emissions reduction can translate to a decrease in the number of active refrigeration systems, fuel consumption reduction across the cold supply chain or investment in cleaner technology. The reduction of active refrigeration systems in one participant may lead to more active refrigeration systems in another participant of the chain, to increase of lost sale costs or transportation costs. On the other hand, the reduction of transportation emissions may be achieved by using more light duty vehicles as fewer emissions are generated than using medium 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 of transportation by increasing the 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 8, when the unit emissions price increases from 0 to 0.88 ($AU\$/kgCO_2$), the model suggests that there will be a considerable decrease in carbon emissions. However, the extended ranges of the unit emissions price from 0.88 ($AU\$/kgCO_2$) to 2.2 ($AU\$/kgCO_2$) do not lead to additional operational modifications as any further modifications toward generating lower-emissions tend to a substantial increase in relevant operational costs. Similar findings have been reported in the literature on traditional supply chain (see, e.g Zakeri et al. (2015); Cheng et al. (2017)). Therefore, the statement that high carbon price may not always lead to lower carbon emissions might be true in many instances, not just specifically for this case study.

Further increase in the unit emissions price, from 2.2 ($AU\$/kgCO_2$) to 2.64 ($AU\$/kgCO_2$), leads to only around 0.13 % reduction in the emissions level. However, it has higher impact on the total cost. That is, the total cost would increase by about 5.8 %. Therefore, for implementing carbon tax regulation, it is critical to determine the carbon price in such a way under which companies are able to decrease emissions without great burdens on the total cost.

In 2012 Australian government introduced carbon tax regulations as a way to cope with increasing emissions resulting in global warming and climate change. However, it was repealed in 2014 by the Liberal Government for the excuse of the high costs that the carbon tax brought to Australia companies and households and its ineffectiveness in reduce emissions. The findings of this research suggest that it is possible for Australian policy makers to set an appropriate carbon price in such a way that the environmental improvement can be achieved without having a significant cost impact on the economy.

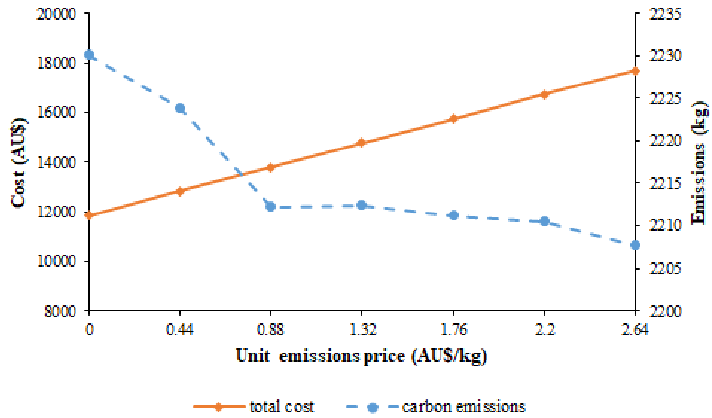


Figure 8: The impact of unit emission price on the total cost and emissions

6.6.2. *The impact of changes in distance*

In this section, we examine the effect of increasing in distances on different costs. We increase all distances through adding $\lambda\%$ of initial distances. Figure 9 indicates the trend of different components of objective function with $\lambda\%$ increase in distances. As can be seen, the higher travel distances does not have any effect on inventory cost and shortage cost. However, it leads to increase in transportation cost and emissions cost and therefore total cost as note that distance is one of the main factors impacting on fuel consumption and consequently emissions.

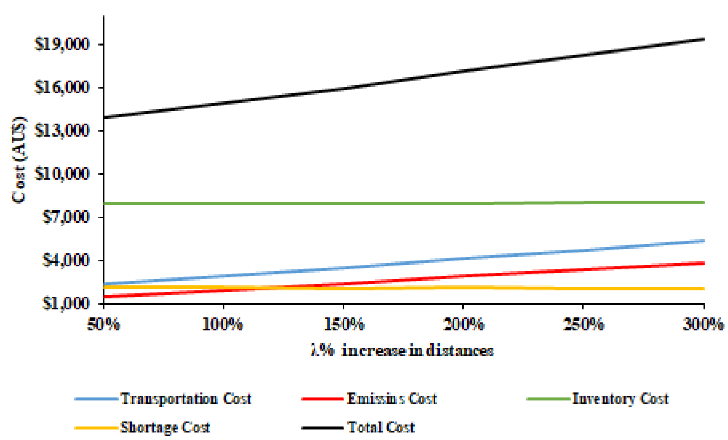


Figure 9: The impact of distance on different components of objective function

In our case, increase in distance does not translate to a decrease in frequency of transportation. Because of decreasing transportation frequency may lead to higher transportation cost and consequently emissions cost as a result of transferring higher load each time and increasing the possibility of using medium duty vehicles which both have a significant impact on fuel consumption and emissions. Furthermore, inventory cost may become higher by reducing frequency of transportation.

6.6.3. *The impact of changes in vehicle speed*

In this section, we have conducted sensitivity analysis on vehicle speed to understand its impact on economic costs and CO_2 emissions. According to the result, vehicle speed has only impact on transportation cost and consequently emissions cost.

Figure 10 depicts the impact of changing vehicle speed on transportation cost and CO_2 emissions. As can be observed, low speed value cannot always lead to reduction in transportation cost and emissions due to the inefficiency usage of fuel. In our case, the transportation cost and CO_2 emissions decrease when speed increases from 20 km/h to 30 km/h as a result of increasing fuel efficiency. However, further increase in vehicle speed leads to higher transportation cost 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 chain (see, e.g. Eshtehadi et al. (2017)).

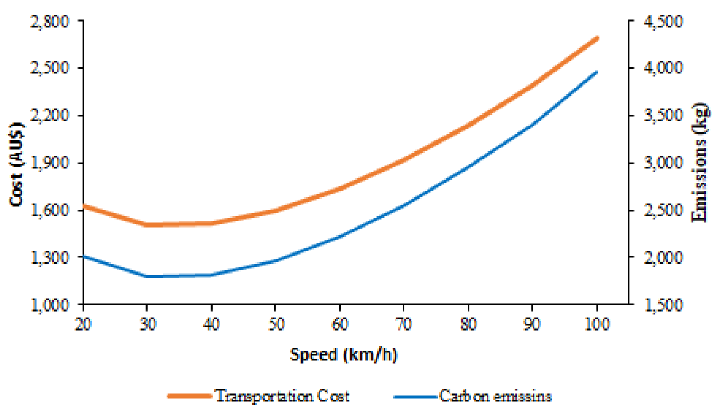


Figure 10: The impact of vehicle speed on transportation cost and CO_2 emissions

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 optimization 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 optimize 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.

The results obtained from sensitivity analyses also show that changes in travel distance and vehicle speed can only impact on transportation cost and consequently emissions cost as travel distance and speed are two important factors to calculate fuel consumption in the proposed model. According to the results, low speed may not lead to reduction in transportation cost and emissions cost as a result of inefficiency in vehicle fuel consumption.

7. Conclusion

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 paper 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 analyzed 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 utilization 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 minimization to net benefit maximization 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. Developing an exact method such as Dantzig-Wolfe would be another suggestion for future researches. Finally, exploring the impact of alternative emissions regulations on cold supply chain operational decisions would be a potential direction for future studies.

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Appendix A. The Modified model

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

$\min z_m =$

$$H_S i_S^f + \phi_E u_S^f E_S + \sum_\xi P(\xi)\Big(H_S i_S^s(\xi) + \phi_E u_S^s(\xi) E_S +$$

$$\sum_t \sum_n \left(H_R i_{R_n t}(\xi) + \phi_E u_{R_n t}(\xi) E_R\right)\Big) + \phi_F \Gamma \sum_n \left(D_{0n} q_n^f \gamma_2 \alpha\right) + \sum_\xi P(\xi)\Big(\phi_F \Gamma \sum_n \left(D_{0n} q_n^s(\xi) \gamma_2 \alpha\right)\Big)$$

$$+ \sum_\xi P(\xi) \sum_t \sum_n \pi s_{nt}(\xi) + \mu\Big(\Gamma \sum_n \left(D_{0n} q_n^f \gamma_2 \alpha\right) \times \sigma + u_S^f E_S \times \delta + \sum_\xi P(\xi)\Big(\Gamma \sum_n \left(D_{0n} q_n^s(\xi) \gamma_2 \alpha\right) \times \sigma$$

$$+ \left(u_S^s(\xi) E_S + \sum_t \sum_n u_{R_n t} E_R\right) \times \delta\Big)\Big) \tag{68}$$

Subject to:

$$i_S^f = Q - \sum_n q_n^f \tag{69}$$

$$i_S^s(\xi) = i_S^f + Q - \sum_n q_n^s(\xi) \qquad \forall \xi \tag{70}$$

$$i_{R_n 1}(\xi) = q_n^f - D_n(\xi) + s_{n1}(\xi) \qquad \forall n, \xi \tag{71}$$

$$i_{R_n t}(\xi) = i_{R_n (t-1)}(\xi) + q_n^s(\xi) - D_n(\xi) + s_{nt}(\xi) \qquad \forall n, \xi, t \geq 2 \tag{72}$$

$$i_{R_n 1}(\xi) \leq \Upsilon \qquad \forall n, \xi \tag{73}$$

$$q_n^s(\xi) + i_{R_n 1}(\xi) \geq D_n(\xi) + \Upsilon \qquad \forall n, \xi \tag{74}$$

$$u_S^f \geq \frac{i_S^f}{C_S} \tag{75}$$

$$u_S^f \leq \frac{i_S^f}{C_S} + 1 - \epsilon \tag{76}$$

$$u_S^s(\xi) \geq \frac{i_S^s(\xi)}{C_S} \qquad \forall \xi \tag{77}$$

$$u_S^s(\xi) \leq \frac{i_S^s(\xi)}{C_S} + 1 - \epsilon \qquad \forall \xi \tag{78}$$

$$u_{R_n t}(\xi) \geq \frac{i_{R_n t}(\xi)}{C_R} \qquad \forall n, t, \xi \tag{79}$$

$$u_{R_n t}(\xi) \leq \frac{i_{R_n t}(\xi)}{C_R} + 1 - \epsilon \qquad \forall n, t, \xi \tag{80}$$

$$i_S^f, i_S^s(\xi), q_n^f, q_n^s(\xi), u_S^f, u_S^s(\xi) \geq 0 \qquad \forall n, \xi \tag{81}$$

$$i_{R_n t}(\xi), s_{nt}(\xi), u_{R_n t}(\xi) \geq 0 \qquad \forall n, t, \xi \tag{82}$$