Decision Support Modeling for Sustainable Food Logistics Management

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Chapter 1

General introduction

1.1 Introduction to the research project

Logistics systems in different sectors currently face the challenge of improving their sustainability performance induced by the increasing environmental and social concerns such as population growth, climate change, environmental pollution, resource scarcity and food safety. The trend towards being more sustainable has caused the fact that companies have to meet the challenges that sustainability brings to their business. A universally accepted definition of sustainable logistics or transportation systems, however, does not exist (Janic, 2006; Mihyeon Jeon and Amekudzi, 2005). The definitions often capture attributes of logistics system effectiveness and efficiency, and impacts of operations on the economy, environment, and social quality of life (Mihyeon Jeon and Amekudzi, 2005). In this context, sustainable logistics is concerned with not only economic issues, but also with environmental and social ones associated with the movement of goods through a supply chain.

From the point of food logistics, the increasing world population along with growth of international food trade necessitates attention to avoidable product waste in Food Supply Chains (FSCs) (Jedermann et al., 2014). According to the estimation of the Food and Agriculture Organization of the United Nations, 32% of all food produced in the world was lost or wasted in 2009 (Lipinski et al., 2013). Another study (Jenny et al., 2011) points out that the industrialized world wastes more food per-capita than the developing countries. Their estimations indicate that the per capita food waste by consumers in Europe and North-America is 95-115 kg/year, whereas it is only 6-11 kg/year in sub-Saharan Africa and South/Southeast Asia. In order to curb food waste, Tesco in the UK has started to alter its supply chain logistics by using new packaging options[1], and tracking food loss and waste in its value chains[2]. Wal-Mart undertook a pilot project to avoid food waste at its Japanese stores in 2013. In order to achieve this goal, the company strived to accurately estimate, order and stock the required products, and performed regular freshness checks to guarantee freshness and reduce throwaway[3]. As can be seen from these examples, leading companies in developed economies have already started to search for opportunities to control food waste in their supply chains.

Addressing food waste reduction also contributes to the improvement of sustainability (Kaipia et al., 2013; Chabada et al., 2013). Wasted food represents a waste of resources

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[1] http://fruitnet.com/fpj/article/161057/tesco-alters-its-supply-chain-logistics-to-cut-food-waste,Onlineaccessed:October2014

[2] http://reports.weforum.org/enabling-trade-from-valuation-to-action/enabling-trade-from-farm-to-fork/a4-benefits-of-improved-agricultural-supply-chains/,Onlineaccessed:October2014

[3] http://joc.com/international-logistics/cool-cargoes/wal-mart-turns-attention-reducing-food-waste_20140804.html,Onlineaccessed:December2014

used in production such as land, water, energy or inputs together with the emissions generated during the course of producing and distributing that food (Jenny et al., 2011; Garnett, 2011). Studies in logistics literature, therefore, address food waste not only to improve economic performance but also to reduce the resultant potential environmental and societal impacts (see Bourlakis et al. (2014); Govindan et al. (2014); Rijpkema et al. (2014)). Correspondingly, food waste is regarded as one of the influential indicators of sustainable development and its importance has been acknowledged by society. For instance, the year 2014 has been designated "European year against food waste" by the European Parliament[4]. Therefore, the need to reduce food waste throughout the FSCs to improve economic, environmental and social performance is rising on the agenda of all involved companies.

Logistics activities, especially transportation, are significant sources of air pollution affecting human health and greenhouse gas emissions that are responsible for global warming (Wang et al., 2011). Emissions result in other environmental threats as well, such as depletion of the ozone layer, broken biological cycles, and increased acidification of ground and water (Jonsson, 2008). These issues have increased the awareness of the need to reduce transportation energy use and emissions, which are naturally treated as the main Key Performance Indicators (KPIs) to assess sustainability performance in logistics management literature (see Kolb and Wacker (1995); Léonardi and Baumgartner (2004); Kamakaté and Schipper (2009); Coley et al. (2009); Kamakaté and Schipper (2009)). With regard to food logistics, food transport is growing due to increasing global food consumption and distances between production and consumption, and is therefore an important source of CO_2 emissions (Whitelegg, 2005).

Energy use and emissions from transportation operations are also among the most popular indicators used to assess the sustainability performance of logistics systems in practice. The transport sector is responsible for nearly 25% of European Union (EU) greenhouse gas emissions[5]. According to the European Environment Agency, CO_2 emissions from transport activities are projected to grow to 25-28% above the 1990 level by 2030 due to the steady increase in passenger and freight demand (Whitelegg, 2005). The survey conducted by the Deutsche Post DHL in six key global markets (India, China, the U.S., Brazil, the UK, and Germany) with 3600 business and end consumers presents insights on how the logistics industry would develop in terms of sustainability (DHL, 2010). Some of the conclusions drawn in this study are that: (1) almost two-thirds of business customers believe that transportation will be used by companies as a key lever to reduce

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[4]http://www.europarl.europa.eu/RegData/bibliotheque/briefing/2014/130678/LDM_BRI(2014)130678_REV1_EN.pdf,Onlineaccessed:December2014
[5]http://ec.europa.eu/clima/policies/transport/index_en.htm,Onlineaccessed:September2014

their carbon footprint, (2) 51% of the end customers prefer green transport solutions rather than cheaper solutions, and 57% of business customers will go for being a greener provider rather than a cheaper one in the coming years, and (3) more than two-thirds of the respondent companies already have carbon reduction targets or plans, which shows that transportation energy use and emissions are among the most prominent logistical environmental issues in practice. For instance, companies such as Deutsche Post DHL and UPS set long term objectives to increase carbon efficiency and transform the way they do businesses along the way (DHL, 2010; UPS, 2013). A study (Piecyk and McKinnon, 2010) conducted in the UK on specialists from a broad range of organizations involved in logistics, e.g., producers, retailers, logistics service providers and trade bodies, can be given as another example to reflect the logistics sector awareness on global warming in practice. It is estimated in this study that the global warming concern will exert a significant influence on freight transport operations over 80% of the businesses by 2020. To conclude, as shown through these examples, the logistics sector will be shaped by not only economic forces, but also by environmental and social concerns.

Management of transportation energy efficiency improvement and emission reduction opportunities have already been put on the agenda of (logistics) companies. Emission reduction targets set, and policy measures and strategies devised by governments and the EU to reduce environmental externalities of freight transport force companies to take measures against environmental degradation. Examples of environmental regulations are: (i) eco-labelling systems to environmentally approve transportation such as EU flower within the EU, (ii) emission rights trading that ensures to have a system which rewards companies for having reduced emissions, and (iii) specific regulations for heavy vehicles to drive in bus lanes in cities, e.g., only heavy vehicles which comply with specific environmental requirements are allowed to drive in environmental zones, whereas older vehicles are not allowed to drive into inner-city areas (Jonsson, 2008). These examples show that authorities have multiple means of control to reduce the energy use and emissions from transportation activities. In response to that companies have to re-evaluate their operations with respect to externalities.

In summary, reducing the amount of food waste and raising transportation energy efficiency to reduce greenhouse gas emissions are recent challenges confronted by the food industry (Defra, 2006). These challenges require the development of innovative logistics systems that are able to balance economic factors with environmental and social concerns. In response, this research develops models that give decision makers the opportunity to incorporate additional environmental and social concerns besides cost into the logistics decision making process. Accordingly, section 1.2 briefly discusses the progress towards

Sustainable Food Logistic Management. Section 1.3 discusses the need for decision support models. Section 1.4 describes the research design including research objectives and methodologies employed. Section 1.5 provides the thesis outline. The last section (Section 1.6) presents the included publications.

1.2 Towards Sustainable Food Logistics Management

Logistics Management (LM) provides competitive advantage to companies. According to the Council of Supply Chain Management Professionals, it is a part of supply chain management, and plans, implements, and controls the forward and reverse flow and storage of goods, services, and related information to meet requirements requested by customers[6] and imposed by stakeholders such as the government (new rules and regulations such as the General Food Law) and the retail community (e.g., Global Food Safety Initiative) (Van der Vorst et al., 2005). For the last two decades food logistics systems have seen the transition from traditional LM to Food Logistics Management (FLM), and successively, to Sustainable Food Logistics Management (SFLM). Figure 1.1 illustrates the transition towards SFLM through these three sequential phases.

As shown in Figure 1.1, LM coordinates and optimizes logistics activities such as transportation, inventory management, storage and warehousing, materials handling, packaging, information processing, demand forecasting, procurement, facility location, production planning, customer service, packing and loading, etc. (Chopra and Meindl, 2010; Jonsson, 2008). These activities require several decisions to be made: determining inventory levels, delivery quantities and schedules, production quantities and schedules, routes to deliver products, and selecting transport mode and places for unloading-reloading products. Traditional LM addresses these decisions mainly to achieve cost reduction and responsiveness improvement, though this is changing due to increasing food related concerns and sustainability awareness.

FSCs are composed of organizations that produce and distribute vegetable or animal-based products to consumers (Van der Vorst et al., 2005). An additional challenge of food logistics compared to most of the other sectors is that products can be discarded once they are non-compliant with quality standards or are not sold before the "best before" dates (Lipinski et al., 2013). Specific characteristics of FSCs mainly related to the high perishability of food products require different management approaches that result in the development of FLM. The objectives in LM has been broadened through the inclusion of new key logistics issues, among which improved food quality and reduction

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[6]http://www.cscmp.org,Onlineaccessed:February2014
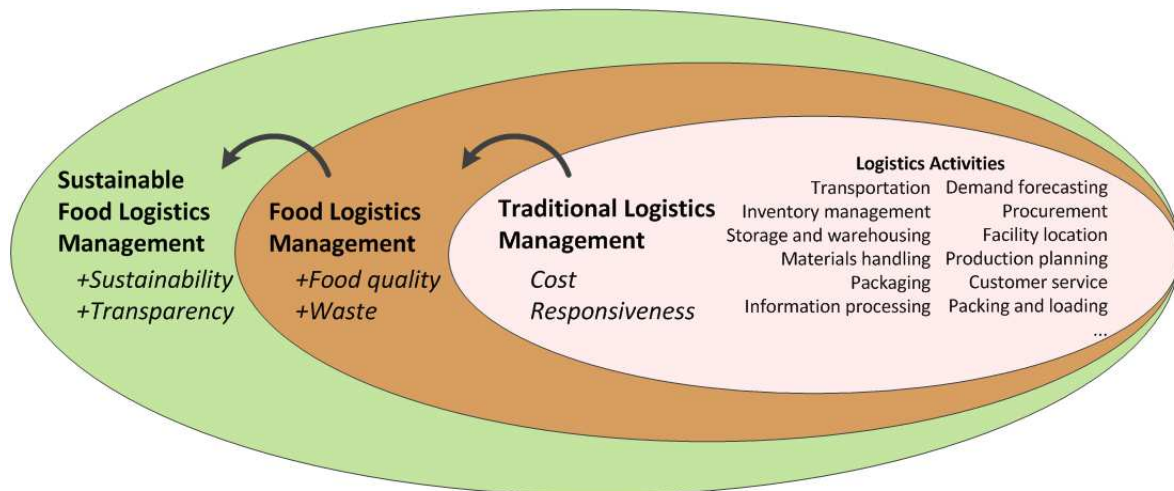
FIGURE 1.1: Towards Sustainable Food Logistics Management (Ovals indicate the key logistics issues that are taken into account.)

of food waste are the main ones (Van der Vorst et al., 2011), as shown in Figure 1.1. Apart from the transition due to the food related concerns, there is still progress in the development of logistics systems which are more sustainable or resource efficient.

Supply chain sustainability is the consideration of environmental factors and social aspects of operations in Supply Chain Management in addition to the traditional economic concerns (Brandenburg et al., 2014). Improving supply chain sustainability has become one of the major topics for researchers and practitioners in the last decade. Pressures from various stakeholders such as customers and non-governmental organizations, global competition and economic concerns, and legislation are among the main reasons for the increased interest in the field (see respective references in Frota Neto et al. (2008); Ashby et al. (2012); Andiç et al. (2012); Hassini et al. (2012)). Commitment to sustainability practices might give benefits to organizations such as improved brand reputation, new products and markets, and enhanced customer satisfaction (Bettley and Burnley, 2008; Abdallah et al., 2012). The mentioned reasons and drivers have affected almost all supply chains including FSCs and pushed companies to search for opportunities to mitigate negative environmental and social impacts, become more transparent and at the same time retain profitability.

The fast evolution of sustainability leads to the development of a new fast-growing concept called Sustainable Food Logistics Management. SFLM mainly aims to improve the supply chain sustainability and the ability to track a product through the whole chain (traceability) along with the previous objectives of LM and FLM phases (see Fig. 1.1). Accordingly, this transition has given rise to practical necessities of taking additional KPIs into account while managing FSCs in a sustainable way. Total amount of land use,

total energy use and emissions generated can be given as examples of indicators for environmental performance that reflect the state of the physical environment affected by the FSC operations. In this context, SFLM enables the organizations in FSCs to fulfil market demand by getting the right food product, in the right quantity and quality, at the right time, to the right place, with the right cost while being as sustainable as possible.

Acknowledging the importance of the transition towards being more sustainable, the EU has launched several research projects to improve the economic, environmental and social performance of the FSCs. Two of these projects, SALSA and SCALE, have supported this research:

- SALSA (2010-2013) is a collaborative project funded by the European Commission under the theme FP7 KBBE (Knowledge-Based Bio-Economy)[7]. Partners from industry, research institutes, and universities collaborated in this project to improve the Latin American and European Union soy bean and beef chains sustainability by balancing the three aspects of sustainability: Profit, People and Planet. The SALSA project comprised seven work packages, each of which was characterized by different tasks (e.g., assessment of sustainability and market performance for the selected food chains, implementation of eco-innovative tools or development of a web-based platform supporting the creation of sustainable value added food chains).

- SCALE (2012-2015) is a collaborative project partly funded by INTERREG IVB North-West Europe, which is a financial instrument of the European Union's Cohesion Policy[8]. The SCALE project has partners from industry and academy to increase economic competitiveness and improve environmental and social sustainability of food and drink supply chain logistics across North-West Europe. To achieve that objective, three interconnecting work packages were defined (i.e., development of frameworks and tools to measure and then optimize the economic, environmental and social costs of each unit of food delivered to the consumer, development of frameworks that can support multi-party collaborative relationships, development of ICT tools to underpin the activities of the previous two work packages).

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[7]Knowledge-based sustainable value-added food chains: innovative tools for monitoring ethical, environmental and socio-economical impacts and implementing EU-Latin America shared strategies (FP7/2007-2013) under grant agreement number 265927. For more information: http://www.salsaproject.eu/,Onlineaccessed: August2014

[8]Step change in agri-food logistics ecosystems. The SCALE is a collaborative project partly funded by INTERREG IVB North-West Europe, which is a financial instrument of the European Union's Cohesion Policy. For more information: http://www.projectscale.eu/,Onlineaccessed:August2014.

This research has contributed to the SALSA and SCALE projects by (i) conducting literature reviews that reflect the state of the art in quantitative models for SFLM, and (ii) developing logistics decision support tools that were applied in case studies to contribute to the sustainability performance of the FSCs.

1.3 Decision support models for better logistics performance

The main challenge of SFLM is to determine how to incorporate additional dimensions (KPIs) into the decision making process, given the fact that trade-offs often exist among these indicators. The trend towards ensuring sustainability in food logistics requires companies to change the way they manage their supply chains (Abdallah et al., 2012) and to find innovative ways for improving their operations to gain a competitive advantage. In particular, cost optimization of logistics operations without showing respect to environmental and social externalities does not guarantee long-term success for companies. Sustainability objectives, thus, have to be considered alongside with other performance objectives when devising an operations strategy (Bettley and Burnley, 2008). Additionally, the perishability factor that makes decision making more challenging in food logistics systems needs to be taken into account while the relevant decisions are being made. These aspects increase the need for advanced decision support models which can capture current food supply chain dynamics.

Operations Research (OR) models can support decision making in food logistics which have increased complexity due to the aforementioned progression in FSCs. Especially in the last decade, researchers' tendency to address food logistics problems has increased. Common interest is to improve the performance in food logistics systems by means of developing advanced models that incorporate the environmental and social KPIs besides the traditional ones, cost and responsiveness. There exist some recent studies (Meneghetti and Monti, 2014; Validi et al., 2014; Govindan et al., 2014; Sazvar et al., 2014) on designing and operating sustainable food distribution networks. The reviewed literature on SFLM shows that research on the topic is, however, still scarce and the food industry needs more advanced models for the entire chain to support business decisions and capture SC dynamics (Akkerman et al., 2010; Dabbene et al., 2008). Even in broad terms, not specific to food logistics, OR models are mainly interested in economic concerns (e.g., profit maximization or cost minimization) and often do not recognize operations impact to environment or society (Dekker et al., 2012). However, it is an evolving field, and the interest in how to incorporate environmental and social considerations and practices into the OR models to improve sustainability of operations has started to appear in

research papers more than before. This movement is beneficial for society and industry, as improvement of quantitative decision support models will contribute to the development of Sustainable Supply Chain Management (Bloemhof, 2005).

As discussed in the previous sections, making food logistics systems more sustainable through paying more attention to transportation energy use and emissions, and product waste is one of the current trends. Perusal of the literature shows that researchers propose various logistics improvement opportunities to better manage the aforementioned KPIs. Table 1.1 shows the main logistics improvement opportunities for transportation energy use and emissions, and product waste. The review of literature on the logistics OR models reveals that not sufficient attention has been given to exploit these improvement opportunities to have more sustainable logistics systems. Therefore, there is potential to improve logistics OR models by incorporating the indicated logistic improvement opportunities. This way of improvement will allow decision makers to assess logistics performance not only based on cost but also on other key sustainability indicators.

TABLE 1.1: Logistics improvement opportunities for transportation energy use and emissions, and product waste

KPIs	Improvement opportunities	Respective references
Transportation energy use and emissions	Use of environmentally friendly vehicles Better logistics network management Use of multi-modality and/or intra-modality Vehicle utilisation improvement (average payload) Better route planning Less exposure to traffic congestion Use of alternative distribution systems Better vehicle sharing (collaboration) Use of bio-fuels Avoiding empty hauls Use of comprehensive fuel estimation models	WEF (2009); McKinnon and Edwards (2010); Garnett (2011); McKinnon (2011); Pieters et al. (2012); Wakeland et al. (2012); Qu et al. (2014).
Product waste	Tracking inventory age (shelf life information) Better inventory planning More efficient information sharing (VMI system) Better control of product waste and quality loss Monitoring temperature history Use of specific quality decay models Enabling food redistribution to redirect edible food that would otherwise be discarded Forecasting development to utilize demand data Improved food labelling	Parfitt et al. (2010); European-Commission (2011); Rong et al. (2011); Kaipia et al. (2013); Aung and Chang (2014); Coelho and Laporte (2014); Jedermann et al. (2014).

1.4 Research design

The discussion provided so far in this chapter points out two issues. First, reducing food waste, and transportation energy use and emissions are the recent challenges of the

food industry. Second, the resultant transition from a focus on traditional LM to FLM, and successively, to SFLM adds to the complexity of logistics operations and restricts the usage of traditional OR models in practice. From this point forth, this PhD thesis is concerned with decision support for SFLM through enhanced models that can account for energy use and carbon emissions from transportation operations, and/or product waste, and logistics cost.

Stakeholders in the SALSA and SCALE projects also showed interest in transportation energy use, emissions and food waste besides logistics cost as key sustainability indicators. These additional environmental and social indicators are mainly related to the logistics activities of transportation and inventory management, which have been introduced in Figure 1.1. Growing food consumption along with increasing distances between production and consumption contribute to growth in transportation which consumes energy and is one of the main sources of emissions in logistics systems. In contrast to most of the other supply chains, inventory management in FSCs is confronted with the additional problem of product waste. Therefore, transportation and inventory management in FSCs require special attention to control transportation energy use and emissions, and product waste. Accordingly, the focus in this thesis is on transportation and inventory management activities in FSCs. These activities comprise the following three key decisions:

- *Inventory levels:* How much inventory to keep at each actor?

- *Delivery quantity and schedule:* When to deliver to each actor and how much to deliver to each actor each time it is served?

- *Routes to deliver products:* How to combine several customer deliveries into vehicle routes?

In this research context, the research on our problem necessitates adopting logistics decision support models to accommodate the transportation energy use and emissions, and product waste concerns which change FSCs beyond recognition. The enhanced decision support models can be used by decision makers to improve the performance of the sustainable food logistics systems in terms of logistic cost, transportation energy use and carbon emissions, and/or product waste. Accordingly, the overall objective of this thesis was defined as follows:

> Overall Objective: To obtain insight in how to improve the sustainability performance of food logistics systems by developing decision support models that can address the concerns for transportation energy use and consequently carbon emissions, and/or product waste, while also adhering to competitiveness.

In line with this overall objective, we have defined five main research objectives which are introduced in the following subsections.

1.4.1 Research opportunities

The progression to SFLM has changed the key logistical aims and accordingly raised the interest in better decision support models that are able to address the additional sustainability concerns. Much research, including both quantitative and qualitative approaches, is devoted to improve performance of food logistics systems. Literature review studies such as Ahumada and Villalobos (2009a); Akkerman et al. (2010); James et al. (2006); Seuring and Muller (2008); Beske et al. (2014) aim to reflect the state of the art and present research opportunities in the fields of FSCs and/or sustainability. Among these studies, Akkerman et al. (2010) and Beske et al. (2014) address both FSCs and sustainability issues together. These studies, however, do not cover the contributions regarding the development from LM to FLM towards SFLM, which would be useful to reveal the research progress on the topic. Moreover, they do not discuss in detail the key logistical aims, KPIs and logistics system scope issues taken into account in the models. Such kind of information would enable to better evaluate the practical usability of the models and to better present the related modelling challenges. This resulted in the first research objective (RO) of this thesis:

> RO1: To identify key logistical aims, analyse available quantitative models and point out modelling challenges in SFLM.

RO1 is investigated through a conducted literature review on quantitative and qualitative studies in FLM. As will be described in Chapter 2, the main findings of the literature review indicate that (i) most studies rely on a completely deterministic environment, (ii) the food waste challenge in logistics has not received sufficient attention, (iii) traveled distance is often used as a single indicator to estimate related transportation cost and emissions, and (iv) most studies propose single objective models for the food logistics problems. These findings motivated us to work on the following research objectives RO2, RO3, RO4 and RO5.

Each of these research objectives addresses different logistics problems. The two main reasons for selecting these logistics problems are: (i) they deal with transportation and/or inventory management activities, which form the focus of this thesis, and (ii) they comprise some of the intrinsic improvement opportunities for the transportation energy use

and emissions, and product waste introduced in Table 1.1. Note that transportation energy use and emissions, and product waste are respected as the environmental and social concerns in this research.

1.4.2 Environmentally friendly network management for perishable products

Increased distances between partners in supply chains due to globalization (Elhedhli and Merrick, 2012) have boosted the importance of logistics network management. A network problem generally comprises two main decisions: inventory amounts at the supply chain partners and product allocation decisions among them. Traditional OR models on the problem (e.g., Bilgen and Gunther (2010) and Verderame and Floudas (2009)) aim to ensure better network management and inventory planning to reduce logistics cost. The common assumption is that there is a centralized system in which chain partners are collaborating vertically and horizontally. From another point of view, better network management and inventory planning, and intrinsic vertical and horizontal collaboration options can also serve as improvement opportunities for the indicators of transportation energy use and emissions, and product waste as well (see Table 1.1). These inherently existing improvement opportunities further increase the value of network management.

Several issues need to be addressed to better assist decision makers in solving network problems. First, network problems in practice usually involve more than one transportation alternative between chain partners through the development of multi-modal (rail, road, air, etc.) and multi-vehicle (vehicles different in age, size, type, etc.) transportation systems. Evaluation of all transportation alternatives between partners while making network decisions can contribute to both economic and environmental performance of the whole supply chain, if the environmental externalities of these options are considered along with economic factors. Second, fuel consumption for road freight transportation depends not only on distance, as commonly assumed, but also on other factors such as road structure, vehicle and fuel types, and vehicle loads (see Hsu et al. (2007) and Bektaş and Laporte (2011)). Ignoring this fact might lead to missing economic and environmental opportunities. For instance, in a network problem, empty legs can occur before getting to sites for service and during the return to vehicle rental firms, or road structures (motorway, rural, urban) can be different in each network arc. For these kinds of cases, the use of comprehensive fuel estimation models which are able to explicitly estimate transportation energy use can be useful to make more sustainable decisions. Third, products can have limited shelf lives which have potential to affect network decisions. Therefore, the perishability nature of the products might restrict the usage of the decision support tools that assume unlimited product shelf lives. Even though many studies have been

conducted on network planning, the review of previous research showed that none of these addressed the above mentioned issues simultaneously. Following this, second RO of this thesis was defined:

RO2: To analyse the relationship between economic (cost) and environmental (transportation carbon emissions) performance in a network problem of a perishable product.

RO2 is investigated in Chapter 3 through a developed deterministic multi-objective linear programming (MOLP) model of a Network Problem. The developed model was applied to an international beef logistics chain operating in Brazil and exporting beef to the European Union.

1.4.3 Environmentally friendly routing with time-dependent speed

To alleviate the environmental (e.g., energy usage and congestion) and social (e.g., traffic-related air pollution, accidents and noise) consequences of logistics operations, multi-echelon distribution strategies are becoming popular. For instance, to address issues in two-echelon distribution systems and to manage freight transportation in urban areas, several projects (e.g., CIVITAS[9] and ELCIDIS[10]) have been undertaken in recent years. The two-echelon capacitated vehicle routing problem (2E-CVRP) is a distribution system in which intermediate capacitated depots are placed between a supplier and final customers (Feliu et al., 2007). In such a system, large trucks are used to transport freight over long-distances from suppliers to intermediate depots where consolidation takes place. Afterwards, the products are transferred to destination points using small and environmentally-friendly vehicles.

The basic 2E-CVRP assumes that distribution costs and travel times between nodes are known in advance and are constant (Feliu et al., 2007; Perboli et al., 2011). As discussed previously, fuel consumption and therefore distribution cost can change based on vehicle load, since it is dependent on the visiting order of the customers. Vehicle speed can change according to the traffic density at a certain time and location as well, which makes it impossible to know the total travel time in advance (see Figliozzi (2011) and Jabali et al. (2012)). The 2E-CVRP aims to manage freight transportation in urban areas, therefore speed changes due to traffic congestion at certain times and locations might affect the routing decisions. The review of previous research showed that such an

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[9]An initiative which was launched in 2002 to redefine transport measures and policies in order to create cleaner, better transport in cities. http://www.civitas.eu/index.php?id=79&sel_menu=23&measure_id=620, Onlineaccessed:August2013

[10]A project about electric vehicle city distribution system in Rotterdam, Netherlands. http://www.managenergy.net/resources/779,Onlineaccessed:August2013

attempt had not been made for the 2E-CVRP with time-dependent travel times. This was the motivation behind RO3 of this thesis:

RO3: To investigate the performance implications of accommodating explicit transportation energy use and traffic congestion concerns in a 2E-CVRP.

RO3 is addressed in Chapter 4 through a developed deterministic mixed integer linear programming (MILP) model of a 2E-CVRP. The developed model was applied to a supermarket chain operating in the Netherlands.

1.4.4 Environmentally friendly inventory routing for perishable products with demand uncertainty

Vendor Managed Inventory (VMI), which is an effective strategy to gain competitive advantage in a supply chain, refers to a collaboration between a vendor and its customers in which the vendor takes on the responsibility of managing inventories at customers (Hvattum and Løkketangen, 2009). The vendor has to bear the responsibility that the customers do not run out of stock in return for having an opportunity to decide on quantity and time of the shipments to the customers (Andersson et al., 2010). This integrated problem comprising inventory, distribution and routing decisions fits to the well-known problem structure in inventory literature called inventory routing problem (IRP) with one-to-many (single supplier and multiple customers) distribution structure (Andersson et al., 2010; Coelho et al., 2012b). Studies on the IRP contribute to the improvement of sustainable logistics systems as well, since they aim to ensure better route planning, better vehicle sharing through vertical collaboration, better inventory planning, and more efficient information sharing through a VMI system. Note that these issues are listed as some of the improvement opportunities for the indicators of transportation energy use and emissions, and product waste in Table 1.1.

Some traditional assumptions in the IRP literature can be relaxed to better benefit from the application of the proposed models in current food logistics systems. These assumptions are summarized as follows. First, a common assumption of constant and foreknown distribution costs between nodes ignores the effect of vehicle load on fuel consumption. Vehicle load is dependent on the visiting order of the customers and can change the fuel consumption and therefore fuel cost (Kara et al., 2007; Kuo and Wang, 2011). As shown in the literature (e.g., Bektaş and Laporte (2011) and Franceschetti et al. (2013)), reductions on operational costs and environmental externalities can be obtained through an explicit consideration of fuel consumption. Second, IRP models often disregard the potential product waste that can occur during inventory keeping due to the perishability

nature of some products. Ignoring product perishability might result in undesired stock outs at customers and therefore is one of the main obstacles for the application of the basic IRP models in food logistics management. Third, the deterministic customer demand assumption, which is commonly made in the literature, can be regarded as doubtful from a practical point of view. These weaknesses of existing attempts motivated us to enhance the traditional models for the IRP and accordingly RO4 of this thesis was defined:

RO4: To investigate the performance implications of accommodating explicit transportation energy use, product waste and demand uncertainty concerns in an IRP.

RO4 is addressed in Chapter 5 through a developed chance-constrained programming model of an IRP with one-to-many distribution structure and demand uncertainty. The developed model was applied to the fresh tomato distribution operations of a supermarket chain.

1.4.5 Environmentally friendly inventory routing for perishable products with horizontal collaboration and demand uncertainty

An IRP with many-to-many distribution structure concerns the transportation of products between a number of suppliers and customers (Andersson et al., 2010; Coelho et al., 2012b). It has thus a horizontal collaboration option among suppliers as distinct from its previously introduced one-to-many case. Horizontal collaboration, along with vertical collaboration, contributes to better vehicle sharing, which increases the value of IRP with many-to-many distribution structure.

Some studies have analysed the potential savings through the application of horizontal collaboration in different logistics problems such as a routing problem (Krajewska et al., 2008), a bin-packing problem (Vanovermeire et al., 2013) and a distribution problem (van Lier et al., 2014). Apart from these quantitative attempts, according to the large-scale survey of Cruijssen et al. (2007) in LSPs, companies strongly believe that horizontal collaboration can improve their quality of services and profitability. A review of the literature showed that researchers did not explicitly address horizontal logistics collaboration in IRP. The findings in other logistics problems encouraged us to explicitly address the horizontal logistics collaboration in IRP as well. Following this, RO5 of this thesis was defined:

RO5: To analyse the benefits of horizontal collaboration in a green IRP for perishable products with demand uncertainty.

RO5 is addressed in Chapter 6 through a developed chance-constrained programming model of an IRP with many-to-many distribution structure and demand uncertainty.

The developed model was applied to the distribution operations of two suppliers, where the first supplier produces figs and the second supplier produces cherries.

1.5   Thesis outline

The thesis starts with a literature review of quantitative and qualitative studies in FLM in Chapter 2. In the subsequent chapters, the following four decision support models have been presented for different logistics problems. Chapter 3 presents a MOLP model on Network problem with direct shipment. Chapter 4 presents a MILP model on 2E-CVRP. Chapter 5 presents a chance-constrained programming model on IRP with single supplier and multiple customers. Chapter 6 presents a chance-constrained programming model on IRP with multiple suppliers and multiple customers.

Figure 1.2 summarizes the research framework followed in this PhD thesis. It shows that the studied logistics problems deal with transportation and/or inventory management activities and comprise several intrinsic improvement opportunities for transportation energy use and emissions, and product waste. The literature review in Chapter 2 identifies key logistical aims, analyses available quantitative models and points out modelling challenges in SFLM. The subsequent chapters (Chapters 3, 4, 5 and 6) focus on developing enhanced decision support models by incorporating logistics improvement opportunities to make them more useful for decision makers in SFLM and to better manage a set of KPIs in food logistics. The incorporated logistics improvement opportunities and considered KPIs are presented in Figure 1.2.

In the last chapter (Chapter 7) the conclusions and main findings following from the conducted studies are presented. Additionally, limitations of the conducted studies and recommendations on further research, as well as managerial implications are provided.
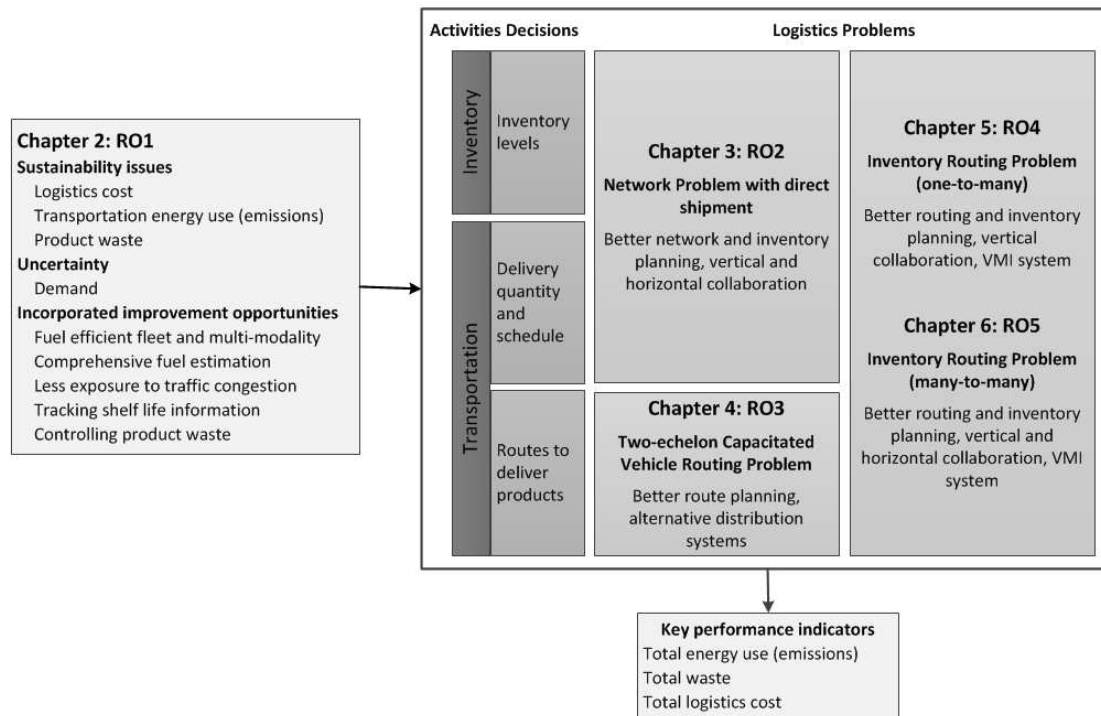
FIGURE 1.2: Research framework

1.6 Included publications

This thesis is a collection of five papers that all aim at the improvement of sustainable food logistics systems. The papers are either published, accepted for publication, or under review for journal publication. The chapters contain the following papers:

Chapter 2: Soysal, M., Bloemhof-Ruwaard, J.M., Meuwissen, M.P., Van der Vorst, J.G.A.J. (2012). A review on quantitative models for sustainable food logistics management. *International Journal on Food System Dynamics*, 3(2), 136-155.

Chapter 3: Soysal, M., Bloemhof-Ruwaard, J.M., Van der Vorst, J.G.A.J. (2014). Modelling food logistics networks with emission considerations: The case of an international beef supply chain, *International Journal of Production Economics*, 152, 57-70.

Chapter 4: Soysal, M., Bloemhof-Ruwaard, J.M., Bektaş, T. (2015a). The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations, *International Journal of Production Economics*, 164, 366-378.

Chapter 5: Soysal, M., Bloemhof-Ruwaard, J.M., Haijema, R., Van der Vorst, J.G.A.J. (2015b). Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty. *International Journal of Production Economics*, 164, 118-133.

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Chapter 6: Soysal, M., Bloemhof-Ruwaard, J.M., Haijema, R., Van der Vorst, J.G.A.J. Modeling a green inventory routing problem for perishable products with horizontal collaboration and demand uncertainty. Submitted to an international journal on Nov 30, 2014. (Under review)

Chapter 2

A review on quantitative models for sustainable food logistics management

This chapter is based on the published journal article:

In this chapter, we investigate RO1:
To identify key logistical aims, analyse available quantitative models and point out modelling challenges in sustainable food logistics management.

2.1 Introduction

Food Supply Chains (FSCs) are composed of organizations that produce and distribute vegetable or animal-based products to consumers. Due to food related diseases (e.g. EHEC, BSE) and globalisation of food production (Nepstad et al., 2006), consumers have become more aware of the origin and nutritional content of their food. This leads to a growing interest in traceability, freshness and quality of products. At the same time, producers expand product assortments to satisfy consumer's broadening desires. This results in more complicated lot sizing decisions and increased transportation costs. An expected continuous increase in world population brings forward another important concern, food security, regarding the availability of food in different parts of the world. The aforementioned developments explain why Food Supply Chain Management (FSCM) has become an important issue in both public and business agendas.

In addition to traditional Supply Chain Management[1] (SCM) objectives, such as cost reduction and responsiveness improvement, FSCM requires a different management approach that also considers intrinsic characteristics of food products and processes (Van der Vorst et al., 2011). Over the last few decades, scholars and practitioners have emphasized FSCM more than ever before. Additionally, FSCs just as other supply chains have recently been confronted with another trend, a request for sustainability, necessitating new and advanced approaches in FSCM. Sustainability is improving the quality of life not only for the current generation but also for the future generations (Brundtlandt, 1987). Sustainable development deals with balancing between ecological, economic and social impacts at the level of society in the long term (Aiking and Boer, 2004). This means that it stresses the importance of key issues closely related to human welfare and the natural environment. Therefore, a product needs to be socially fair and environmentally friendly in addition to being produced efficiently, competitively and profitably (Euclides Filho, 2004). The fast evolution of sustainable development changes the goals in almost every supply chain (SC) including FSCs and makes traditional strategies inappropriate. This has led to the development of a new fast-growing concept: Sustainable Food Supply Chain Management (SFSCM) (c.f. Seuring and Muller, 2008; Ahumada and Villalobos, 2009a).

The major factors contributing to the increased interest in SFSCM are: raising consciousness of the importance of sustainable system dynamics and, related to that, changing regulations set by governments that enact strict rules on food safety and sustainability issues. The main aim of these legislations is to impose firms taking necessary precautions against any negative social and environmental impacts of their operations. Companies operating

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[1]Further on in the text, the terms Supply Chain Management and Logistics Management will be used interchangeably.

in the agriculture and food sector are confronted with the following: (1) accelerating environmental and social impact assessment policies and standards such as HACCP, BRC or ISO22000 enacted by governments; (2) the emerging concept of extended producer responsibility supporting the shift from "cradle to grave" to "cradle to cradle" perspective (Frota Neto et al., 2009) pushed by either governments or influential private institutions, and (3) gradually increasing preoccupation in society to live well without compromising future generation's rights to prosper.

Unsurprisingly, this progression from traditional SCM to FSCM and now to SFSCM increases the complexity of supply chains and results in more challenging logistics management. As defined by the Council of Supply Chain Management Professionals: *"Logistics management is that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers' requirements"*[2]. The aforementioned developments have stimulated companies and researchers to consider multiple Key Performance Indicators (KPIs) such as cost, perishability and sustainability in food logistics management (FLM) projects. Companies often have to invest in a redesign of their logistics network to manage those KPIs simultaneously. As a result, the traditional performance indicator "cost" is replaced by the emerging triple bottom line concept in which Profit, People and Planet are the simultaneous drivers towards performance (Van der Vorst et al., 2005). It is apparent that this change evokes the need for an integrated approach that links food supply chain (FSC) logistics decisions to the three pillars (economic, environmental and social pillars) of sustainability (Chaabane et al., 2012) and at the same time manage product quality; an approach called sustainable food logistics management (SFLM).

Sustainability in itself is not a new research area and much literature is devoted to this subject (e.g. Klassen and Whybark (1999)). However, FSC systems are complex, comprising a wide diversity of products with different characteristics and quality management requirements, enterprises, dynamic interactions and markets. This makes logistics decisions concerning FSCs such as production, inventory and distribution decisions more challenging. Quantitative models can support management decision making in these areas. At present the literature lacks an overview of the state of the art concerning these models on SFLM (Akkerman et al., 2010).

The main aim of this study is to identify key logistical aims, analyse currently available quantitative models and point out modelling challenges in SFLM. We conduct an academic literature review on quantitative studies in FLM that includes journal articles

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[2] http://www.clm1.org/digital/glossary/glossary.asp,Onlineaccessed:August2012

and books. Primary (e.g. research articles) and Secondary Sources (e.g. literature reviews) concerning Operations Research and Operations Management disciplines are used. Quantitative studies published within the past 25 years are covered and also qualitative studies are consulted to broaden the discussion and to understand key logistical aims more clearly. Literature search is carried out within well-known databases, Thomson Reuters (formerly ISI) Web of Knowledge, Google Scholar, EBSCO, and followed by reference and citation analyses to find related contributions. The following search criteria are employed: SFLM, FSC production planning, FSC distribution planning, FSC quantitative models, sustainability in FSCs, food safety/security issues in FSCs, transport management in FSCs.

Previous literature review studies have also focussed on FSCs and/or sustainability (Ahumada and Villalobos, 2009a; Akkerman et al., 2010; James et al., 2006; Seuring and Muller, 2008). Among these studies, only Akkerman et al. (2010) consider both FSCs and sustainability issues together. However, in contrary to this study, we cover the contributions considering the development from SCM to FSCM towards SFSCM. Furthermore, we present detailed information with respect to key logistical aims and related models to generate a structured linkage between the practical requirements and the current modelling literature using the KPIs and logistics system scope issues considered in models.

The rest of the paper is organized as follows. Section 2.2 describes the key logistical aims in SFLM. Section 2.3 discusses the currently available quantitative models in related literature. Section 2.4 presents the quantitative modelling challenges. Finally, section 2.5 provides the conclusions of this study.

2.2 Key logistical aims

In this section, we cover the key logistical aims in SFLM in three groups: (1) cost reduction and improved responsiveness (SCM phase), (2) improved food quality and reduction of food waste (FSCM phase), and (3) improved sustainability and traceability (SFSCM phase). As it is shown, these groups can also be regarded as sequential phases towards SFSCM. We also discuss the drivers and enablers of the key logistical aims to provide the potential research intentions in the different phases (Table 2.1). Additionally, we present generic logistics system scope issues of each phase that need to be considered in quantitative models to adequately manage the related key logistical aims. Discussing the drivers and enablers, and the generic logistics system scope issues, allows us to evaluate and assess respectively the KPIs and the logistics system scope of the models in the further sections.

	Key aims		Drivers & Enablers	Explanation of Key Aims	Logistics System Scope Issues	Literature
SCM phase	Cost reduction		Economic crisis resulting in low prices, Globalisation resulting in world-wide competition, Automation resulting in more efficient processes.	The ability to minimize total global network costs from the source of supply to its final point of consumption.	Network design, Distribution channel choice, Outsourcing, Operational excellence, Inventory positions choice, Transportation alternatives and constraints, Production choices, Incorporation of uncertainty, Use of information technology.	(Beamon, 1998) (Cachon and Fisher, 2000) (Christopher and Juttner, 2000) (Chopra, 2003) (Chopra and Meindl, 2010) (Fisher, 1997) (Gunasekaran *et al.*, 2008) (Lambert and Cooper, 2000) (Simchi-Levi *et al.*, 2009)
	Improved responsiveness		Demand for more product variety, high frequent deliveries with short lead times and small batches, Increased demand uncertainty, New ICT tools that facilitate more advanced information exchange.	The ability to have a flexible and robust system that satisfies customer orders in time and responds quickly to the dynamics of the global marketplace. Additionally, to cooperate and collaborate with the other supply chain members in a way that facilitates movement of information in timely, reliable and accurate manner.		
FSCM phase	Improved food quality		Demand for safe and high quality food products, Health consciousness of consumers, Year round availability of food, Demand for more convenience products, Technological improvements.	The ability to control product quality in the supply chain and deliver high quality food products in various forms to final consumers by incorporating product quality information in logistics decision making.	**All the above +** Homogeneity controls, Dynamic inventory management, Dynamic control of goods flow, Cold chain management, Multiple temperature consideration for multiple products, Product interferences consideration, Monitoring temperature history, Customer requirements consideration, Use of specific quality decay models, Waste management.	(Akkerman *et al.*, 2010) (Blackburn and Scudder, 2009) (Dabbene *et al.*, 2008) (Hafliðason *et al.*, 2012) (Trienekens and Zuurbier, 2008) (Van der Vorst *et al.*, 2000) (Van der Vorst *et al.*, 2007) (Van der Vorst *et al.*, 2011) (Van Donselaar *et al.*, 2006)
	Reduction of food waste		Demand for high quality products with long shelf lives, Increased food security concerns, Pressure from global organizations.	The ability to collaborate in the supply chain network to reduce food that is discarded or lost uneaten because the quality has deteriorated.		
SFSCM phase	Improved sustainability	Environmental concerns	Growth of world population, Climate change, Limited natural resources, Escalating sustainability awareness.	The ability to reduce environmental impacts (e.g. GHG emission, energy use, water use, air pollution, deforested land, land availability and noise) of operations and to facilitate new energy sources such as biofuels.	**All the above +** Use of impact assessment tools, Sustainable food production consideration, Sustainable inventory management consideration, Sustainable transportation management consideration, Traceability possibility of products.	(Bettley and Burnley, 2008b) (Chaabane *et al.*, 2012) (Dekker *et al.*, 2012) (Fritz and Schiefer, 2009) (Helms, 2004) (Linton *et al.*, 2007) (Nepstad *et al.*, 2006) (Wang *et al.*, 2011) (Wognum *et al.*, 2011)
		Societal concerns	Increased child labour, Employment, Escalating sustainability awareness.	The ability to reduce societal impacts (e.g. nutritional content of products, employment opportunities, farm income) of operations.		
	Improved traceability		Recent food crises, Legislation.	The ability to have complete visibility of all relevant product and process characteristics in the chain allowing to track and trace products throughout all stages in a supply chain.		

TABLE 2.1: Key logistical aims in SFLM

2.2.1 Cost reduction and improved responsiveness

Cost reduction and responsiveness improvement aims are the two main traditional concerns in SCM. SCM aims for better customer service with less cost while satisfying the requirements of other stakeholders in the chain (Van der Vorst and Beulens, 2002; Van der Vorst et al., 2005). Cost refers to the total global network costs from the source of supply to its final point of consumption[3]. Cost reduction and control efforts have been already a central focus in many sectors. However, economic crises and ongoing globalisation have boosted the importance of achieving lowest cost in almost all supply chains including FSCs. Unlike the past, food industries are heading towards international markets for sourcing necessary products for their operations and serving products. The (compulsory) network extension for facilitating economies of scale increases complexity in FSCs. This results in problems that are more sophisticated than in the past (Bilgen and Ozkarahan, 2007). Automation resulting in more efficient processes enables companies to some extent to cope with these problems. Nevertheless, the changing system still leads to the need of advanced models and tools for planning SC operations (Mula et al., 2010). Additionally, global coordination and optimization of geographically dispersed facilities is necessary (Brown et al., 2001) to quickly and accurately determine the distribution options and costs (Chopra, 2003; Simchi-Levi et al., 2009).

The second major concern, establishing improved SC responsiveness, has two main dimensions: the time between placing and receiving an order, and how quickly companies respond to the dynamics of the global marketplace such as customer's unique and rapidly changing needs, new product introductions and new sourcing opportunities (Beamon, 1998; Fisher, 1997). Responsiveness and flexibility are key issues to maintain customer satisfaction in the food industry (Lambert and Cooper, 2000). Nowadays consumers ask for more product variety and high frequent deliveries with short lead times that forces fast production in small batches. Also, demand uncertainty has increased due to increased product variety and competition. Gunasekaran et al. (2008) state that the key factors for forming a responsive SC are: timely information sharing, shortening the total cycle time, coordinating the workflow, implementing good decision support systems, reducing lead times, integrating information about operations, reducing redundant echelons and creating flexible capacity. In parallel, new ICT tools that facilitate more advanced information exchange (Cachon and Fisher, 2000) and collaboration (Christopher and Juttner, 2000) help companies to improve their responsiveness. Companies are also confronted with trade-offs between the cost of the SC (efficiency) and its responsiveness, resulting in discussions on the position of the customer order decoupling point (Van der Vorst et al.,

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[3]http://www.scdigest.com/assets/Reps/SCDigest_Global_Logistics_Excellence.pdf, Onlineaccessed:August2012

2005; Van Donk, 2001). On one hand, increased product diversity and competition leads to a make to order production system with a decrease in inventories to reduce inventory costs; on the other hand producing to stock and keeping more inventory (buffer/safety) in the SC guarantees quick customer response. Therefore, FSCs have the challenge to maintain a reasonable balance between these two issues: reducing cost versus improving customer service.

The literature review identified a number of generic logistics system scope issues that need to be considered while managing the aforementioned key logistical aims of the SCM phase (see Table 2.1). In terms of network design, crucial issues are: the roles and the types of operations performed in facilities, locations of facilities, capacities allocated to each facility, markets that facilities will serve and sources that will feed facilities (Chopra and Meindl, 2010). Additional generic issues identified are (see Table 2.1): (i) distribution channel choice among several distribution options, (ii) outsourcing possibility, (iii) operations excellence with respect to time, quantity and invoice, (iv) strategic inventory positions choice, (v) transportation alternatives and constraints (e.g. time windows, number of vehicles, capacity of carriers), (vi) production choices (e.g. workforce scheduling, multiple product handling, batch size consideration), (vii) incorporation of uncertainty and (viii) use of information technologies (e.g. Geographic Information System or Wireless Sensor Network).

2.2.2 Improved food quality and reduction of food waste

Addition of food quality and food waste concerns to the key logistical aims of SCM phase triggers the transition from SCM to FSCM. Nowadays, consumers ask for safe and high quality products with a competitive price throughout the year (Apaiah and Hendrix, 2005; Trienekens and Zuurbier, 2008). Increasing attention on food safety shows that health consciousness of consumers has been increasing. In FSCs, the quality of the product continuously changes starting from the time the raw material leaves the grower (or the slaughter for meat products) to the time the product reaches the consumer (Dabbene et al., 2008). This quality change (often degradation) necessitates keeping track of and preserving perishable product quality along the FSC to increase its freshness. These changes in product value make conventional SC strategies, not taking perishability into account, inappropriate (Blackburn and Scudder, 2009). Perishable products require management approaches and models that can cope with additional challenges such as temperature controls, quality decay or waste reduction methods (Hafliason et al., 2012; Van Donselaar et al., 2006). Technological improvements (e.g. temperature controlled facilities and trucks) enable FSCs to manage food quality throughout the chain. Van der Vorst et al.

([2011](), [2007]()) propose the innovative concept of Quality Controlled Logistics (QCL) and claim that the establishment of better FSC designs depends on the availability of real time product quality information and the use of that information in advanced logistics decision making along the chain. Apart from this work, also other studies in literature are devoted to the special planning of perishable food products ([Adachi et al., 1999](); [Lutke Entrup et al., 2005](); [Tarantilis and Kiranoudis, 2001]()). Additionally, consumers have started to desire more convenient products that require minimal preparation such as ready to eat or just heating before eating. This tendency also requires special attention in FSCM.

The second major concern, reducing food waste, deals with preventing or reducing food spoilage in FSCs. Throughout the FSCs among the world, food waste is progressively increasing because of the mismanagement of perishable food products. Consumers' desire for high quality products with long shelf lives also contributes to the increase of food waste. Due to being close to best before dates, many products are lost in FSCs without reaching the consumers as consumers are not willing to buy them. For example, the annual loss in the agro chain from the Netherlands is approximately 2,000 million €and this is 30% up to even 50% in some sectors. Of this, 10% to 20% is lost in production, 2% to 10% in industry and trade and 3% to 6% in the retail and out-of-home market[4].

The relevant logistics system scope covers the generic issues that need to be considered while managing the aforementioned key logistical aims of FSCM phase. Generic issues regarding SCM phase need to be considered beforehand. The additional issues commonly related with the specific characteristics of FSCM phase (given in Table 2.1) are: (i) batch homogeneity controls along the chain, (ii) dynamic inventory management that tracks the quality of products, (iii) dynamic control of goods flow that adopts conditions and logistics to optimize market fulfilment (e.g. redirecting products to other markets having lower quality requirements), (iv) cold chain management that considers temperature or enthalpy controlled carriers, depots, (v) multiple temperature consideration for multiple products, (vi) product interferences consideration (e.g. bananas produce ethylene that accelerates the ripening process of other fruits), (vii) monitoring temperature history for accurate quality predictions, (viii) customer requirements consideration for specific markets, (ix) use of specific quality decay models, and (x) waste management that considers spoilages.

2.2.3 Improved sustainability and traceability

Addition of sustainability and traceability concerns to the key logistical aims of the FSCM phase leads to the need for a new approach, SFSCM. The Kyoto Protocol setting binding

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[4]`www.minlnv.nl/txmpub/files/?p_file_id=2001236,Onlineaccessed:September2012`

targets for industrialized countries can be given as a recent step of governments towards achieving sustainable development[5]. The European Union is also an influential proponent of sustainability (Linton et al., 2007). Consciousness of consumers towards environmental and societal issues put pressure on companies to use sustainable practices, since world population is growing, climates are changing and natural resources are depleting. Also, nutritional content of products (Helms, 2004), increased child labour and employment conditions are under discussion as societal issues. Seuring and Muller (2008) summarize the pressures and incentives for sustainability in supply chains (not only for FSCs) as follows: legislations, customer demands, response to stakeholders, competitive advantage, pressure groups and reputation loss. As a consequence, increasing sustainability awareness of stakeholders (Bettley and Burnley, 2008) inevitably affects the (logistics) decision making process and operations in FSCs. As such, the concept of sustainable SC design has emerged and aims to incorporate economic, environmental as well as societal decisions into SCs in the design phase (Chaabane et al., 2012; Wang et al., 2011). However, it is obvious that the environmental and social dimensions of SFSCM must be undertaken with a clear and explicit recognition of the economic goals of the firm (Carter and Rogers, 2008; Wognum et al., 2011).

The second key logistical aim, improving traceability, has also growing impact on FSCs. Consumers want to get more insight in production processes as well as what happened to the product as it moves through the SC (Mogensen et al., 2009). This places emphasis on especially the people and planet aspects of sustainability. Legislations from governments or pressures from non-profit organizations aim to stimulate improved SC visibility in FSCs. A good traceability system can contribute to improved transparency by offering specific information regarding product and related processes to consumers (Fritz and Schiefer, 2009; Wognum et al., 2011). Additionally, Fritz and Schiefer (2008) stress the importance of intensified cooperation and collaboration between the actors of the chain and improved monitoring of activities to achieve transparency and tracking and tracing of products and services throughout the value chain. This integration and monitoring can be enhanced with the use of new ICT tools to redirect the pattern of logistics operations[6].

The relevant logistics system scope covers the generic issues that needs to be considered while managing the aforementioned key logistical aims of SFSCM phase. Generic issues regarding the SCM and the FSCM phase need to be considered beforehand. The additional issues commonly related with the specific characteristics of SFSCM phase (given in Table 2.1) are: (i) use of impact assessment tools (e.g. Life Cycle Assessment Analysis (LCA) assesses impacts of operations associated with all stages of a product's life

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[5] http://unfccc.int/kyoto_protocol/items/2830.php,Onlineaccessed:June2012
[6] http://www.internationaltransportforum.org/pub/pdf/02LogisticsE.pdf,Onlineaccessed:June2012

starting from-cradle-to-grave), (ii) sustainable food production consideration (e.g. using efficient machines that can reduce water use consumption or choosing production locations considering deforestation, land use issues), (iii) sustainable inventory management consideration (e.g. controlling energy use of cooling stocks in facilities (Akkerman et al., 2010)), (iv) sustainable food transportation management consideration (e.g. considering GHG emissions, fuel consumptions of different transportation modes, new energy sources such as biofuels or noise, air pollution caused by vehicles (Dekker et al., 2012)), and (iv) traceability possibility of products for improving transparency in FSCs (e.g. use of safety focused traceability systems).

2.3 Currently available quantitative models on (S)FLM

After identifying key logistical aims and related generic logistics system scope issues, this section focuses on quantitative models for FLM and SFLM. Following the paper selection method given in section 2.1, 36 relevant papers were selected that were used for the analysis. First, we present the main characteristics of the reviewed models (Table 2.2), followed by an analysis of the KPIs (Table 2.3) and logistics system scope issues (Table 2.4) considered in the models for each of the key logistical aims.

2.3.1 Modelling characteristics

In recent years Operations Management and Operations Research literature has shown a growing interest in FSCM (Akkerman et al., 2010). Correspondingly, the number of studies using food logistics models is increasing. In this study, we investigate the quantitative models with respect to the main characteristics (Table 2.2) summarized below:

Modelling type: Researchers develop various types of models to facilitate the decision making process and enable companies' operations to be carried out in a systematic way. The distribution of model types used in the batch of 36 papers are as follows: (i) Mixed Integer Programming (54% of all models), (ii) Analytical (20%), (iii) Simulation (11%), (iv) Linear Programming (6%), (v) Multi Objective Programming (6%), and (vi) Goal Programming (3%).

(Non)linearity: Except for a few studies that have non-linear terms in their models, most researchers use linear models. Investigating extensions of the same approach to nonlinear cost structures (Ahuja, 2007) or building a different approach for tackling with dynamic problems (Dabbene et al., 2008) are reasons to include nonlinear terms.

Solution approaches and tools: Apart from standard software programs (e.g. Cplex, Lindo), various heuristics have been developed to solve the models. Complexity of the problem (Eksioglu and Jin, 2006), large problem instances (Ahuja, 2007) or possibility to generate fast solutions (Rong and Grunow, 2010) lead researchers to consider heuristic approaches.

Application area: Almost all contributions have case studies. FSCs such as meat, dairy, and fruit are taken as application areas.

Real vs. Hypothetical: Proposed models are implemented either by considering real or hypothetical data.

2.3.2   Models for cost reduction and improved responsiveness

The reviewed literature shows that total logistics cost incurred and variance of the total logistics cost are the main KPIs considered in models aimed at cost reduction (Table 2.3). All quantitative studies try to redesign logistics operations with the aim of minimizing SC costs in the food logistics system. Costs can be classified as production, inventory, distribution and other costs. Other costs represent food-specific costs such as milk collection, biomass drying or by-product credit costs. Additionally, authors (Ahumada and Villalobos, 2009b; Blackburn and Scudder, 2009; Rong et al., 2011) regard costs of food quality decay, cooling, wastage and product loss as part of the main cost groups. Apart from the main cost groups, Rong and Grunow (2010) also incorporate batch dispersion costs into their model to solve the trade-offs between reducing production costs of products and reducing the concerns for food safety. Distinct from other studies, Azaron et al. (2008) also adopt the minimization of the variance of the total cost into a multi-objective model to increase the robustness of the model.

According to the literature review, the following KPIs are considered in models to improve responsiveness: on-time delivery, late delivery, missed sales, order cycle time (lead time) and transport carriers utilised (Table 2.3). Most models in literature aim to ensure on-time delivery of customer orders using deterministic assumptions and known demand without incorporating uncertainty (Table 2.4). Constraints on production time are discussed by Ahumada and Villalobos (2009b) and Bilgen and Gunther (2010), including strict deadlines such as a specific production lot that has to be finished up to a particular day or maximum order cycle time. Moreover, Van der Vorst et al. (2000) emphasise shortening cycle times (lead times) and increasing the execution frequency of business processes.

Reference	Model Type	(Non)linearity	Solution Approaches and Tools	Application Area	Real/Hypothetical
(1) Gelders et al. (1987)	MIP	L	Fortran	Large brewery	R+H
(2) Zuo et al. (1991)	MIP	L	MPSX/MIP packages, Fortran, Heuristic	Corn	R
(3) Van der Vorst et al. (1998)	Simulation	U	U	U	R
(4) Van der Vorst et al. (2000)	Simulation	U	U	Chilled salads	R
(5) Brown et al. (2001)	MIP	L	Heuristic	Cereal and convenience foods	R
(6) Gebresenbet and Ljungberg	Analytical	U	Route LogiX	Agriculture	R
(7) Jansen et al. (2001)	Simulation	U	Arena	Catering	R
(8) Tarantilis and Kiranoudis (2002)	Analytical	U	Mic.Visual C++, Heuristic	Meat	R
(9) Wouda et al. (2002)	MIP	L	U	Dairy	R
(10) Apaiah and Hendrix (2005)	LP	L	Gams	Pea-based novel protein foods	R
(11) Ioannou (2005)	LP	L	Lindo, Excel solver	Sugar	R
(12) Eksioglu and Jin (2006)	MIP	L	Cplex 9, Heuristic	U	H
(13) Higgins et al. (2006)	MIP	L	Fortran 95, Heuristic	Sugar	R
(14) Ahuja (2007)	MIP	NL	Cplex 7.0, Greedy heuristic	U	H
(15) Bilgen and Ozkarahan (2007)	MIP	L	ILOG's OPL - Cplex 8.0	Wheat	R
(16) Hsu et al. (2007)	MIP	L	Several Algorithms	Lunch box	H
(17) Zanoni and Zavanella (2007)	MIP	L	Cplex 6.6, Heuristic	U	H
(18) Azaron et al. (2008)	MOP	NL	Goal attainment technique-Lingo	Wine	H
(19) Dabbene et al. (2008)	Analytical	NL	A specific optimisation algorithm	N	N
(20) Osvald and Stirn (2008)	Analytical	L	Heuristic	Vegetables	H
(21) Ahumada and Villalobos (2009b)	MIP	L	AMPL - Cplex 10	Pepper-tomatoes	H
(22) Akkerman et al. (2009)	MIP	L		N	N
(23) Blackburn and Scudder (2009)	Analytical	U	U	Melons and sweet corn	R
(24) Chen et al. (2009)	MIP	NL	Mic.Visual C++ 6, Lingo 10.0	U	N
(25) Van der Vorst et al. (2009)	Simulation	U	ALADIN TM	Pineapples	R
(26) Bilgen and Gunther (2010)	MIP	L	ILOG's OPL - Cplex 11.2	Fruit juices and soft drinks	H
(27) Oglethorpe (2010)	GP	U	MS Excel Solver	Pork	R+H
(28) Rong and Grunow (2010)	MIP	U	Cplex 10.2, Heuristic	U	H
(29) Wang et al. (2010)	MIP	NL	Heuristic	Cooked meat-bakery	R
(30) Ahumada and Villalobos (2011)	MIP	U	Cplex	Bell peppers and tomato	H
(31) Bosona and Gebresenbet (2011)	Analytical	U	GIS- Route LogiX	Local food producers	R
(32) Rong et al. (2011)	MIP	L	ILOG's OPL - Cplex 10.2	Bell peppers	R
(33) Yan et al. (2011)	Analytical	U	U	U	H
(34) Zucchi et al. (2011)	MIP	L	Gen. Alg. Mod. Sys. 22.5 with Cplex	Beef	R
(35) You et al. (2012)	MOP	L	E-constrained method, Cplex 12	Cellulosic, Ethanol sector	R
(36) Zanoni and Zavanella (2012)	Analytical	L	U	Fried potato	R

MIP: Mixed integer programming, LP: Linear programming, MOP: Multi objective programming, GP: Goal programming, U:Unspecified, N:None, L:Linear, NL: Nonlinear, R:Real, H:Hypothetical

TABLE 2.2: Main characteristics of quantitative models in (S)FLM

Researchers use different approaches for managing the late deliveries and missed sales found in models under stochastic assumptions. Some examples are (1) keeping track of percentage delivered on agreed time (Jansen et al., 2001), (2) considering losses in goodwill for violation of delivery time (Chen et al., 2009) and (3) number of missed sales caused by stock-outs (Van der Vorst et al., 1998). Regarding late deliveries, Blackburn and Scudder (2009) also introduce the Marginal Value of Time (MVT) rate to measure the cost of a unit time delay in a SC. This means that researchers want to control backorders or missed sales that lead to decreased responsiveness. Opposite to this, Dabbene et al. (2008) consider cost of earliness from early delivering to demand points as this may lead to stocking problems. In literature time windows constraints are set for managing the challenges of late or early deliveries (Chen et al., 2009; Osvald and Stirn, 2008).

Another KPI, order cycle time (lead time), refers to the time that elapses from the moment an order is placed to the moment ordered goods are received (Van der Vorst et al., 1998). Researchers incorporate lead time into models by considering parameters such as transportation distances (e.g. Gebresenbet and Ljungberg (2001), Osvald and Stirn (2008)), required transportation times (e.g. Hsu et al. (2007), Dabbene et al. (2008)) or required production times (e.g. Wang et al. (2010)).

Utilisation of transport carriers can also improve responsiveness by shortening cycle times for customer deliveries. Gebresenbet and Ljungberg (2001) consider empty driving, load capacity utilization level in terms of volume and motor idling times during stoppage. Moreover, Akkerman et al. (2009), and Gebresenbet and Ljungberg (2001) refer to the contribution of transport utilization on environmental impact in terms of CO_2 emissions.

Researchers put logistics system scope boundaries in accordance with the logistics problem under consideration and their objectives. Logistics system scope issues considered in quantitative models for SCM phase are presented in Table 2.4. Our analysis is as follows:

- Production, transportation and inventory, which are the main logistical drivers in a SC (Chopra and Meindl, 2010), can be regarded as main modelling decisions. Most studies use an integrated approach of production, transportation and inventory management with the aim of generating synergy, building an integrated view and improving the efficiency of all interrelated processes (Eksioglu, 2002; Mula et al., 2010).

- In quantitative models the main question to be answered in terms of production is: how much to produce in each production plant? Apart from that, a few studies incorporate decisions such as workers required in a specific period for cultivating product (Ahumada and Villalobos, 2009b) or available labour restrictions (Ahumada

and Villalobos, 2011) as workforce scheduling issues. Additionally, some studies manage multiple products with the same model (e.g. Brown et al. (2001), You et al. (2012)). Researchers also consider batch size/setup number decisions to get more insight in the problem (e.g. Rong et al. (2011), Wang et al. (2010)). Furthermore, a few studies incorporate production facility location decisions into their models (e.g. Gelders et al. (1987), Zucchi et al. (2011)).

- The foremost issue in terms of transportation is determining transportation amounts in each channel. In response to the evaluation of multi-mode transportation networks, some studies consider different transportation alternatives such as road, train, air simultaneously (e.g. Apaiah and Hendrix (2005), Bilgen and Ozkarahan (2007)). These kinds of models offer decision makers more flexibility and ease of cost minimization and on-time delivery opportunities while managing the whole network. In addition to that, dual sourcing (e.g. Ioannou (2005), Zuo et al. (1991)), transhipment between facilities (e.g. Wouda et al. (2002)) and indirect shipments (e.g. Higgins et al. (2006), Tarantilis and Kiranoudis (2002)) are also possible.

- A few studies incorporate stochastic elements into their models. Demand (e.g. Ahuja (2007)), lead time (e.g. Van der Vorst et al. (2000)), supply and costs (e.g. Azaron et al. (2008)), and SC behaviour (e.g. Dabbene et al. (2008)) are the stochastic elements considered in the studies.

2.3.3 Models for improved food quality and reduction of food waste

The reviewed literature shows that degraded food quality, temperature level changes and enthalpy level changes are the KPIs considered in models for the key logistical aim of improved food quality (Table 2.3). The problem of perishability, sometimes even leading to food waste, affects almost all operations along the FSCs. Lutke Entrup et al. (2005) give an example to illustrate this challenge. Increasing yoghurt freshness requires producing as close as possible to the demand date. At best, each product is produced daily. However, this type of production causes smaller lot sizes and higher costs, since significant set-up costs occur in yoghurt production. For these kinds of effects, attempts have been made to incorporate product quality decay in food logistics models (Table 2.3). The aim of these studies is coping with the quality decay challenge while managing the logistics operations.

Most studies in literature, such as Zanoni and Zavanella (2007); Eksioglu and Jin (2006), assume that product quality diminishes linearly and is deemed useless after a specific time period. This means that as long as products are above the pre-specified minimum levels,

they are regarded as acceptable. Additionally, the model does not penalize the product deliveries with a short remaining shelf life. However, either part of the purchased goods cannot be sold on the market or only with a lower price because of continuous quality degradation (Osvald and Stirn, 2008). To avoid these problems and to encourage the freshness of deliveries, a few studies consider the cost of inventory lost while being transported (Ahumada and Villalobos, 2009b, 2011; Osvald and Stirn, 2008). Additionally, Van der Vorst et al. (2009) measure the product quality when the product arrives at the retail store as a KPI by checking the remaining selling time at the retail outlet. Moreover, rather than assuming simple linear decay, for instance Rong et al. (2011) use a quantitative quality decay model based on the Arrhenius equation, which is a remarkably accurate formula for the temperature dependence (Chang, 1981), to manage quality changes.

Among the studies that handle the perishability problem in their models, some studies (e.g. Rong and Grunow (2010) and Van der Vorst et al. (2009)) also include temperature control of the products to determine optimal temperature settings in a supply network (Table 2.3). In these studies, product quality decays depend on the temperature levels. This means that the magnitude of quality change for alternative temperature conditions is assumed to be known in advance as a parameter. Moreover, Akkerman et al. (2009) state that enthalpy level control is easier than temperature controls. Therefore, they include enthalpy level tracking to their models in addition to temperature control.

According to the literature review, the KPI considered in models to improve the key logistical aim of food waste reduction is food waste occurred (Table 2.3). A few of the studies in literature refer to the potential food waste problem (Table 2.3). Among those studies, You et al. (2012) and Rong et al. (2011) explicitly integrate the food waste calculations into their models. In these aforementioned studies, products that lose their suitable freshness are discarded and food waste or waste disposal costs are incurred.

Logistics system scope issues considered in quantitative models for the FSCM phase are presented in Table 2.4. Our analysis is as follows:

- In order to manage continuous quality change in FSCs, quality tracking possibility is considered and incorporated into the models (e.g. Eksioglu and Jin (2006), Yan et al. (2011)). This consideration unsurprisingly affects the logistics decisions, because of shelf life constraints (Ahumada and Villalobos, 2011; Rong et al., 2011).

- Studies that track quality and consider inventory decisions mostly employ dynamic inventory management. This allows them to manage a real-time inventory system (Van der Vorst et al., 2000) that tracks the quality levels of inventories in each period (Ahumada and Villalobos, 2011).

- Some studies consider temperature or enthalpy controlled carriers or depots (e.g. Akkerman et al. (2009), Blackburn and Scudder (2009)). This leads them to consider additional factors such as energy usage rates of those carriers or additional costs. Additionally, only Bosona and Gebresenbet (2011) attempt to manage multiple products by considering different temperature levels.

- Different quality decay models are used depending on the specifications of the related product (e.g. Hsu et al. (2007), Dabbene et al. (2008)), in order to manage perishable products more efficiently.

- Although handling quality decay, most studies assume that products are delivered before spoilage. However, a few studies incorporate possibility of quality fall below the minimum levels that results in food waste (e.g. Van der Vorst et al. (2009)). In addition to that, one study (You et al., 2012) also considers waste treatment units.

2.3.4 Models for improved sustainability and traceability

For the key logistical aim of improved sustainability, the reviewed literature shows that GHG emitted, fuel consumed, energy used and water used (as environmental dimensions), and nutritional content of products (health impacts) and number of accrued jobs (as societal dimensions) are the KPIs considered in the models (Table 2.3). Although sustainability is not a new concept for both business world and society, research in this field is regarded as in its infancy period by scholars (Linton et al., 2007). Our literature review also supports that argument as we found only a small number of quantitative studies dealing with SFLM (Table 2.3). Studies that consider the new emerging sustainability goals in FLM attempt to deal with the above mentioned environmental and/or societal concerns in addition to economic objectives.

All of the studies (see Table 2.3) measure GHG emissions by a single indicator in terms of either carbon dioxide emissions (CO_2/year) (e.g. Akkerman et al. (2009)) or carbon dioxide-equivalent (CO_2, CH_4, and NO_x) emissions (CO_2-eq/year) (e.g. You et al. (2012)) (Table 2.4). The common aim of these studies is controlling and reducing the CO_2 emitted to the environment from the logistical operations. Vehicles during transportation (Gebresenbet and Ljungberg, 2001; Van der Vorst et al., 2009) or processes related with production management such as blending, drying, storing (You et al., 2012) can be given as examples for those logistical operations that cause CO_2 emissions (Table 2.4). For instance, Gebresenbet and Ljungberg (2001) consider transport distance, speed, load, road conditions with respect to slope and motor idling time. The related environmental impact is expressed in kg CO_2 per mile travelled or per product. You et al. (2012) point to the

importance of life cycle stages of products to be included in emission rates estimations. For this reason, they integrate LCA analysis with multi objective optimization.

Energy use in models, usually expressed in MJ per second/per ton km, relates to operations in logistics system. Those models either focus on energy consumption from maintaining temperature (e.g. Zanoni and Zavanella (2012)) or operations such as heating, lightening or machine use (e.g. Oglethorpe (2010)) (Table 2.4). The common aim of the studies is reducing the energy consumption throughout the chain while maintaining operations (Table 2.3). Additionally, Oglethorpe (2010) links the energy use with emission calculations by assuming that energy use of processing operations equals a specific amount of CO_2 emission per kg of output. A few studies also include controlling the consumption of water, an important natural resource, in the chain (Table 2.3) using water restriction constraints (Ahumada and Villalobos, 2009b; You et al., 2012). As a final environmental KPI, only Bilgen and Ozkarahan (2007) consider fuel consumed during logistics operations. They take fuel consumption as one of the transportation cost input among others i.e. hire cost of vehicle, government charges.

In literature, only two studies aim to manage nutritional contents of products. Apaiah and Hendrix (2005) consider protein content and Oglethorpe (2010) consider fat content of products. In addition, in (Oglethorpe, 2010; You et al., 2012), the number of accrued jobs, which is expressed as hours and full-time equivalent jobs per year respectively, is used as a societal objective.

According to the literature review, batches traced is the KPI considered in models to improve the key logistical aim of improved traceability (Table 2.3). Bilgen and Gunther (2010) emphasize a need in FSCs to assign demand to daily delivery periods rather than weeks because of shortened replenishment cycles and quicker replenishment times. For this reason, they stress that completion of production lots has to be traced on a daily time scale. They introduce auxiliary binary decision variables, which indicate that the specific production lot has been finished on a specific line up to a particular day. Rong and Grunow (2010) work on a different problem and support the idea that traceability systems have to be complemented with suitable production and distribution planning approaches. They include a parameter called batch ID to their models, allowing the model to get information on batch number, product type, production time, and production location for each product. They aim to determine the number of batches, the batch sizes and which batches are delivered to which retailers in each period with this information.

Logistics system scope issues considered in quantitative models for SFSCM phase are presented in Table 2.4. Our analysis is as follows:

- Except for one study (You et al., 2012), researchers do not use any tool such as LCA for defining more accurately the related environmental and societal impacts of logistics operations. This results in omitting or mishandling effects of some operations to the environment and/or society.

- Although fuel consumption rate is one of the most important competitive factors in logistics management, it is not modelled. Only one study (Bilgen and Ozkarahan, 2007) implicitly mention fuel consumption. Apparently, models consider fuel consumption calculations under the total transport cost, however this leads to losing the chance to assess explicitly the amount of fuel used which is crucial in terms of environmental sustainability.

- Societal issues are less addressed than environmental issues in quantitative models. The main reason for this is the challenge of measurement and quantification of societal issues.

- Some studies (e.g. Ahuja (2007), Rong et al. (2011)), assume that models can trace product batches of different quality throughout the logistics network.

2.4 Quantitative modelling challenges

Section 2.2 first identified key logistical aims and related generic logistics system scope issues in FLM (Table 2.1). Then, section 2.3 analysed currently available quantitative models with respect to their general characteristics (Table 2.2), KPIs (Table 2.3) and relevant logistics system scope issues (Table 2.4). In this section, we aim to point out modelling challenges based on the assessment of the above mentioned models.

Most literature studies rely on a completely deterministic environment (Table 2.4). This assumption allows decision makers to achieve 100% on-time delivery (Table 2.3). Researchers have not shown yet interest in late deliveries or missed sales, which are crucial KPIs of logistics management in terms of improving responsiveness (Table 2.3). This approach is understandable since deterministic models can be developed and solved relatively easy. However, in the real world most SC members in the food industry are confronted with several uncertainties i.e. information availability and data timeliness, supply, process and demand uncertainties (Van der Vorst et al., 2000) (Table 2.1). Therefore, deterministic assumptions do not fully capture the complexity of real world problems, which might hinder their applicability. For instance, a model with deterministic demand will allow inventory reductions. Assuming no demand variation will result in minimized

Phase	Category		1*	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
SCM Phase	Cost reduction and improved responsiveness	Total logistics costs incurred	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Variance of the total logistics cost	✓	✓																																		
		On-time delivery		✓				✓		✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Late delivery				✓			✓							✓		✓		✓	✓				✓	✓	✓											
		Missed sales			✓		✓																															
		Order cycle time (lead time)			✓	✓	✓	✓	✓	✓						✓		✓		✓	✓		✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
		Transport carriers utilised			✓	✓	✓	✓	✓	✓																							✓					
FSCM Phase	Improved food quality and reduction of food waste	Degraded food quality	✓		✓	✓								✓		✓		✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓
		Temperature level changes			✓													✓			✓			✓	✓		✓		✓	✓	✓	✓	✓	✓				✓
		Enthalpy level changes																						✓														
		Food waste occurred																	✓			✓					✓				✓			✓			✓	
SFSCM Phase	Improved sustainability and traceability	GHG emitted						✓																✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓
		Energy used																✓						✓			✓		✓									
		Water used																					✓						✓							✓	✓	
		Fuel consumed															✓																					
		Nutritional content of products										✓																	✓									
		Number of accrued jobs																									✓		✓		✓							
		Batches traced			✓	✓																						✓		✓	✓	✓	✓	✓	✓		✓	✓

*Numbers refer to studies listed in Table 2.2

TABLE 2.3: Key performance indicators in (S)FLM

	Phase		1*	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
SCM Phase	Cost reduction and improved responsiveness	Production amounts	✓	✓	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Production capacity		✓	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓	✓	✓			✓				✓	✓		✓	✓	
		Workforce scheduling																					✓									✓						
		Multiple product			✓	✓	✓	✓	✓		✓	✓			✓		✓		✓				✓			✓	✓	✓		✓		✓	✓		✓		✓	✓
		Batch size/setup number				✓								✓											✓													
		Production facility location determination	✓								✓									✓																		
		Transportation amounts	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
		Transportation capacity	✓	✓	✓	✓		✓	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓			✓	✓				✓	
		Multi-mode transportation		✓			✓					✓					✓						✓		✓		✓			✓		✓	✓	✓		✓	✓	
		Dual sourcing possibility		✓			✓				✓	✓	✓				✓						✓															
		Transhipment possibility between facilities																																				
		Indirect shipment possibility	✓	✓				✓	✓		✓		✓		✓	✓	✓	✓	✓			✓				✓		✓				✓			✓		✓	✓
		Inventory levels			✓	✓	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓		✓		✓	✓			✓	✓		✓	✓	✓	✓	✓	✓		✓	✓
		Inventory storage capacity in facilities			✓	✓		✓	✓				✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓				✓				✓	✓
		Incorporation of uncertainty			✓	✓			✓							✓		✓		✓						✓	✓											
FSCM Phase	Improved food quality and reduction of food waste	Quality tracking possibility		✓	✓	✓								✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓		✓	✓
		Dynamic inventory management			✓	✓								✓		✓			✓			✓	✓							✓	✓	✓	✓		✓		✓	✓
		Temperature or enthalpy controlled carriers, depots																											✓	✓	✓	✓	✓					✓
		Multiple temperature for multiple products															✓																✓					
		Use of specific quality decay models									✓							✓			✓				✓	✓	✓			✓		✓		✓				✓
		Possibility of quality fall below the minimum level																					✓				✓				✓			✓			✓	
		Waste treatment units																										✓	✓								✓	
SFSCM Phase	Improved sustainability and traceability	LCA analyses																									✓	✓	✓		✓	✓	✓				✓	
		Emissions from transportation				✓										✓					✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
		Emissions from other operations e.g. production, storing.																						✓		✓	✓	✓	✓	✓	✓	✓	✓				✓	
		CO² emissions																												✓								
		CO²-equivalent (CO², CH⁴, and NO^x) emissions															✓																					
		Fuel consumption																✓								✓	✓	✓	✓									
		Energy consumption for maintaining temperature																										✓	✓									
		Energy consumption for heating, lightning and ext.																										✓	✓									
		Water use										✓											✓						✓									
		Product content consideration																											✓									
		Employment consideration																																				
		Traceability possibility of products			✓	✓	✓		✓					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓

*Numbers refer to studies listed in Table 2.2

TABLE 2.4: Logistics system scope issues of quantitative models in (S)FLM

cost solutions by reducing inventory levels. However, SC responsiveness requires adaptation to changes in customer demand or in the marketplace, so attention should be paid to incorporating variabilities in the model's relevant logistics system scope issues. In addition to that, companies need to evaluate trade-offs between cost and responsiveness, so losses in goodwill or costs of time delays should be carefully studied.

One of the main concerns of FSCs, continuous quality degradation, appears in almost two third of all reviewed literature with an increasing rate in recent years (Table 2.3, 2.4). The challenge of including food quality decay shows itself in models. Most models roughly take product perishability into account by using linear quality decay models, solely depending on time. However, increasing customer concerns on food safety necessitates more sensitive and detailed quality decay models that consider the intrinsic product conditions. In response to that, only a limited number of researchers employ quality decay models that explicitly include product parameters, time, and environmental factors (Table 2.4). Integrating those kinds of quality models into the logistics models will enhance the value of models, since they will provide more reliable results to the decision makers. Furthermore, almost no researchers show interest in the food waste problem, occurring at almost all stages of the FSC (Table 2.3). Incorporating the option that product quality falls below the minimum level will help these models to approach real life problems and issues much better than before.

So far, research in sustainable logistics has received insufficient attention (Table 2.3, 2.4). Approximately, only one third of the studies has environmental or societal repercussion considerations. As expected, the researchers' tendency to incorporate sustainability into logistics models has increased in recent years, but this has been insufficient. Only a few models incorporate sustainability KPIs into their models but ignore other relevant indicators (Table 2.3) and/or logistics system scope issues (Table 2.4). For instance, in terms of GHG emission reduction, researchers mostly focus on CO_2 emissions (Table 2.4). However, integrating also other GHGs such as methane (CH_4), nitrous oxide (N_2O) and fluorinated gases will improve the applicability of the proposed solutions[7]. Furthermore, the use of environmental and societal impact assessment analyses such as LCA has a huge potential to improve the validity of the sustainable logistics models (Table 2.1). After determining the key impact categories and relevant logistics system scope issues for reducing negative repercussions of operations on the environment and society, researchers can incorporate them into models and search for the improvement opportunities.

Most literature studies propose single objective models for the related logistical problems in FSCs (Table 2.2). However, real life problems consist of multi objectives, which are

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[7]http://www.epa.gov/climatechange/emissions/index.html#ggo,Onlineaccessed:June2012

in conflict with each other. For instance, it is common to see attempts, which are either obligatory or voluntary due to carbon taxes or environmental awareness, for decreasing GHG emissions from logistics operations. Unsurprisingly, those attempts in either case come at a cost to companies. The challenge is managing the additional objective of reducing emission levels together with SC cost. It is also possible to give other examples incorporating multi-goals such as cost vs. responsiveness, cost vs. quality, quality vs. sustainability. These examples present the necessity of multi objective perspectives in logistics models and researchers could use multi objective programming models to deal with such cases.

Finally, determining the system boundary is a careful job in FLM. If the target of a model is to improve the sustainability performance of logistics operations, the proposed solutions should also satisfy economic expectations of stakeholders. This means that the ideal model for SFLM generally should incorporate all of the key logistical aims that are explained in detail in the previous sections (Table 2.1). A few attempts to simultaneously deal with challenges regarding the three phases (SCM, FSCM and SFSCM) have been found in literature. However, those attempts have not fully captured the relevant KPIs and logistics system scope issues (Table 2.3, 2.4). Even, we have observed that some logistics system scope issues (outsourcing possibility, product interferences consideration, Table 2.1) are not handled by any of the quantitative models. Thereby, performances of the proposed models can be improved by incorporating more KPIs and more logistics system scope issues related to the problem.

2.5   Conclusion

FSCM is in general a complex process owing to the intrinsic characteristics of food product and processes of FSCs and the fast moving and highly competitive food sector. Especially in last years, in addition to the existing challenges, FSCs have been confronted with the increased attention for sustainable development. Many drivers such as legislation, customers' awareness and non-profit organizations' pressure have pushed companies to seek ways to reduce their environmental and societal impacts. Unsurprisingly, addition of sustainability concerns into the FSCM decision making process has made it more complicated and challenging than before. Inevitably, food logistics systems are also affected by the progress starting from traditional SCM to FSCM and now further progressing to SFSCM.

In this paper, we have reviewed quantitative studies in FLM in a structured way. To the best of our knowledge, this is the first literature review on SFLM that has covered the

contributions considering the development from SCM to FSCM towards SFSCM. We can conclude from this work that the research on SFLM has been developing according to the needs of the food industry. The number of studies that consider KPIs and logistics system scope issues regarding recent needs of the food sector has been increasing. However, are these studies adequate to aid decision making process and capture FSC dynamics? We highlight that current FLM literature is insufficient to respond to these practical needs. Generally, the intrinsic characteristics of food products and processes have not been handled properly in the studies. The majority of the works reviewed have not contemplated on sustainability problems, apart from a few recent studies. To conclude, new and advanced models for SFLM are needed that take specific requirements from practice into consideration to support business decisions and capture FSC dynamics. Better logistics models can improve food quality and safety, availability of food, and create sustainable and efficient business networks, which are the main issues faced by stakeholders in FSCs.

Acknowledgement

Chapter 3

Modeling food logistics networks with emission considerations: the case of an international beef supply chain

This chapter is based on the published journal article:

M. Soysal, J.M. Bloemhof-Ruwaard, J.G.A.J. van der Vorst (2014) "Modeling food logistics networks with emission considerations: the case of an international beef supply chain" *International Journal of Production Economics*, Vol. 152, pp. 57-70.

In this chapter, we investigate RO2:

To analyse the relationship between economic (cost) and environmental (transportation carbon emissions) performance in a network problem of a perishable product.

3.1 Introduction

The progressive increase of food consumption due to growing world population and wealth stimulates higher food production. A recent way for managing the increased production is globalization of food supply chains (FSCs) with the help of improvements in transport technologies, cheaper transportation, reductions in tariffs and other barriers to trade. Globalization has improved the chance of profitability from cross-border operations as well; however it has led to increased distances between partners in supply chains (Elhedhli and Merrick, 2012). The increased distances have enhanced the strategic importance of logistics network decisions such as selection of suppliers, distribution channels and transportation modes, determining production and inventory amounts at each plant and allocation of products (Cordeau et al., 2006; Harris et al., 2011). The need for a well organized logistics network thus has increased in the food sector, which is producing more than ever on a global scale.

Traditional logistics management considers mainly two key logistical aims, cost reduction (efficiency) and improved responsiveness while dealing with the logistics network problem. However, intrinsic characteristics of food products and processes such as product perishability and food quality, and a growing sustainability trend require extension of the key logistical aims with quality and environmental considerations. This necessity leads to the need for decision support tools that can integrate economic considerations with quality preservation as well as environmental protection in FSCs. Accordingly, literature review shows that there is a need for models that are able to deal with the key challenges in managing quality and sustainability (Akkerman et al., 2010; Soysal et al., 2012). The need in practice and in research forms our main motivation to develop a model that allows to consider perishability of goods and emissions from transportation operations along with cost concerns in food logistics network.

We take the beef sector as a representative of a food supply chain that has both food and environment related challenges. Shelf life for beef that includes several quality factors (e.g. juiceness, tenderness, nutritive value, appearance and palatability) puts an additional pressure on logistics decisions, since the product may become undesirable, even it is not unsafe (Delmore, 2009). Apart from quality concerns, appreciation grows for the idea of a carbon-constrained economy in the livestock sector with the growing awareness towards environment conservation (Robinson et al., 2011). Especially, transportation is one of the main sources of livestock related carbon dioxide (CO_2) emissions (Delgado et al., 1999) and increasing global beef trade results in more fuel consumption for beef related

transportation. Therefore, it is wise to address product perishability and emissions from transportation while managing beef logistics chains.

We develop a multi-objective linear programming (MOLP) model for a generic beef logistics network problem. The objectives of the model are (i) minimizing total logistics cost and (ii) minimizing total amount of greenhouse gas (GHG) emissions from transportation operations. Duration of inventory keeping is limited due to the perishability nature of the product. The environmental effect of freight transportation is measured in CO_2 emissions. We provide a case study of the international beef logistics chain operating in Nova Andradina, Mato Grosso do Sul, Brazil and exporting beef to the European Union (EU) to illustrate the applicability of the proposed model for real logistics systems. The rationales for the selected beef chain are: (1) Brazil ranks as the largest beef exporter in the world by holding an approximately 21% share of the global beef trade in 2011 (Abiec, 2012d), (2) Brazil has potential to keep its position in the global market, and (3) Beef trade relationship exists ($47,693$ ton for fresh-chilled beef in 2010) between Brazil and the EU (Abiec, 2012a,b). In this case study, we put the main focus on road transportation, which is the only delivery option till the export ports, as rail, inland ship or air need infrastructure that is not available yet. The logistical challenges in the case of Brazil are mainly related to usage of old trucks, inefficient road infrastructure or deficiency of available trucks.

The structure of the remaining of the paper is as follows. Section 3.2 presents a literature review on logistics models that take product perishability and/or emissions into account. Section 3.3 presents a formal definition of the generic problem, the methodology used for emission estimations and the proposed MOLP model for the generic beef logistics network problem. Section 3.4 presents the case study description, data gathering and the computational analysis of the model. The last section presents conclusions and directions for further research.

3.2 Literature review

The logistics network problem that has transportation and inventory decisions under capacity constraints for a multi-period planning horizon has been widely studied in the literature (see Ahn et al., 1994; Bilgen and Gunther, 2010; Verderame and Floudas, 2009). However, quality degradation of products puts additional challenges on logistics decisions in food sector. Literature review studies present the state of the art in product perishability consideration in FSCs (Ahumada and Villalobos, 2009a; Akkerman et al., 2010; James et al., 2006; Soysal et al., 2012). As pointed out in these studies, the number

of proposed decision support tools which are able to control products according to their quality levels has been increasing in recent years (e.g. Bosona and Gebresenbet, 2011; Rong et al., 2011; Wang et al., 2010; Ahuja, 2007). Ahuja (2007) controls the quality of products by constraining the number of periods that a good is stored at a facility. In this study, we use this approach to account for the perishable nature of beef.

Similar to raising awareness on quality decay, sustainability is an emerging area in FSCs (Akkerman et al., 2010; Seuring and Muller, 2008). The main reasons for the growing interest are stakeholder pressure and the need for adopting increasing environmental regulations. GHG emissions reduction, the most prominent environmental issue in practice, is one of the most significant sustainability objectives considered in logistics management literature (Soysal et al., 2012). Researchers have developed quantitative logistics models that can manage economic issues along with emission controls in response to the need for practice. Literature search is carried out within Thomson Reuters (formerly ISI) Web of Knowledge and followed by reference and citation analysis to find related contributions that have quantitative models with emission consideration for logistics management. We investigate the models with respect to main characteristics (Table 3.1) summarized below:

- *Model type:* Mixed Integer Linear Programming and Multi-Objective (Non)Linear Programming approaches are the most used modeling types.

- *Decisions:* The main logistical drivers in a supply chain are production/processing, transportation and inventory management decisions (Chopra and Meindl, 2010). The reviewed models manage one or more of the aforementioned decisions. All models aim to reduce emissions from transportation. Additionally, some studies consider emissions from production/processing and/or inventory holding together with transportation emissions.

- *GHG emissions calculation approaches:* The crucial stage during model development is calculating emissions from predetermined emission sources. Researchers employ basically two approaches to measure the emissions from transportation operations. First approach, which is preferred most, is using fixed emission or environmental impact factors per distance unit and/or per weight unit (e.g. Chaabane et al., 2008; Wang et al., 2011), per product (e.g. You et al., 2012), per vehicle (e.g. Paksoy et al., 2011b), which are obtained through other environmental studies. The second approach is estimating emissions indirectly by calculating total energy consumed from transportation operations while considering the aforementioned parameters such as distance, speed or weight (e.g. Bektaş and Laporte, 2011; Bauer et al., 2010). For production and inventory related emissions, either fixed emission factor

per unit produced or stocked (e.g. Oglethorpe, 2010) or energy consumption from production and/or inventory related operations is considered (e.g. Abdallah et al., 2012).

- *GHG consideration:* Studies in the literature either take only CO_2 gas emissions (e.g. Bauer et al., 2010) or group emissions of different GHG gases, such as CO_2, CH_4, and NO_x, together in a single indicator in terms of carbon dioxide equivalent (CO_2eq) emissions (e.g. You et al., 2012).

- *Application area:* Researchers implement the proposed models on different areas such as automotive, steel and plastic waste.

We found three quantitative models that manage product perishability while considering GHG emissions (Akkerman et al., 2009; Van der Vorst et al., 2009; You et al., 2012). Among these studies only You et al. (2012) propose a MOLP model that can be used to gain insight in the the trade-off between multiple objectives. In contrast to that study, we also consider the effects of return hauls on transportation cost and emissions. Furthermore, we adopt a different methodology based on a distance-based formulation, (Defra, 2005), to estimate road transport emissions. Under this methodology, road structure, vehicle and fuel types, weight loads of vehicles and traveled distances are taken into account. This approach has been also used by Harris et al. (2011), who integrated the approach into a simulation model without considering perishability and return hauls (see Table 3.1). Therefore, this study breaks away from the literature on logistics network models by simultaneously considering the aforementioned issues. Consequently, contributions of the study can be summarized as follows: (1) integrating food transport emissions into a MOLP model for the generic beef logistics network problem while considering road structure, vehicle and fuel types, weight loads of vehicles, traveled distances, return hauls and product perishability, (2) presenting the applicability of the model in an international beef logistics network based on real data, multiple scenarios, and analysis.

3.3 Modelling a generic beef logistics network

3.3.1 Formal definition of the generic problem

Our modeling approach is based on a generic multi-echelon beef logistics network problem that consists of a number of third party logistics (3PL) firms, production regions, slaughterhouses, export departure and import arrival points at fixed locations (Fig. 3.1). In the generic beef logistics chain, production regions are responsible for providing livestock to

TABLE 3.1: Logistics models that incorporate GHG emissions

	Model type	Decisions	GHG emissions calculation approaches	GHG consideration	Application area
Frota Neto et al., 2008	MOLP	(PT)*	Environmental impact factor for producing one product unit and transporting one shipment of product is used.	U	Pulp and Paper
Akkerman et al., 2009**	MILP	(PT)I	Environmental impact factor for producing one product unit and transporting one shipment of product is used.	CO_2eq	Meal elements
Van der Vorst et al., 2009**	Sim.	P(TI)	Energy consumption for transportation and inventory is calculated and converted to realized emissions.	CO_2	Pineapples
Oglethorpe, 2010	GP	(PTI)	Emission factor per weight of output produced and stocked and per distance unit travaled is used. Energy used for refrigeration of product, machine use, heating and lightening is calculated and converted to realized emissions from inventory.	CO_2	Pork
Bauer et al., 2010	MILP	(T)I	Energy consumption for transportation is calculated with a model and converted to realized emissions. The main parameters for the model are: vehicle type and utilization ratio.	CO_2	U
Bektaş and Laporte, 2011	ILP	(T)	Energy consumption for transportation is calculated with a model and converted to realized emissions. The main parameters for the model are: vehicle type, speed and utilization ratio.	CO_2	U
Paksoy et al., 2011b	MOLP	(T)	Emission factor per truck is used.	CO_2	U
Harris et al., 2011	Sim.	(TI)	A formulation (Defra, 2005)*** that estimates emissions from amount of fuel consumed is used. The effect of road structure on emissions is also considered. Electricity consumption in depots are estimated and converted to realized emissions from inventory.	CO_2	Automotive
Wang et al., 2011	MOP-NL	P(T)	Emission factor per distance unit is used. Emissions from each unit of flow in facilities is also considered. There is possibility for making environmental investment on a facility to lower emissions.	CO_2	U
Chaabane et al., 2011	MOLP	(PT)	Emission factor per weight unit and per distance unit is used.	CO_2eq	Steel
Paksoy et al., 2011a	LP	P(T)	Emission factor per weight unit and per distance unit is used. Age of the vehicles are considered due to decreasing engine efficiency.	CO_2	U
Ubeda et al., 2011	MILP	(T)	A formulation (Defra, 2005)*** that estimates emissions from amount of fuel consumed is used. Amount of empty-running reduction during backhauls is also considered.	CO_2	Food distribution
Abdallah et al., 2012	MILP	(PT)	Emission factor per weight unit and per distance unit is used. Energy consumption in facilities is also considered and converted to realized emissions.	CO_2	U
Bing et al., 2012	MILP	(T)	Amount of fuel consumed is calculated and converted to realized emissions.	CO_2eq	Plastic waste
Chaabane et al., 2012	MILP	(PT)I	Emission factor per output produced and distributed is used.	CO_2eq	Aluminum
Elhedhli and Merrick, 2012	MIP-NL	P(T)	Emission factor per vehicle is used. The relationship between emissions and vehicle weight is modeled using a concave function.	CO_2	U
Mallidis et al., 2012	MILP	(T)	Emission factor per weight unit and per distance unit is used.	CO_2eq	U
You et al., 2012**	MOLP	(PTI)	Emission factor per output produced, distributed and stored is used. Life Cycle Assessment methodology is employed for identifying and quantifying the emissions.	CO_2eq	Cellulosic, Ethanol sector

P: Production/Processing, T: Transportation, I: Inventory, CO_2: Carbon dioxide, CO_2eq: Carbon dioxide equivalent, MILP: Mixed-integer linear programming, MOP-NL: Non-linear multi objective programming, Sim: Simulation, GP: Goal programming, MOLP: Multi objective linear programming, ILP: Integer linear programming, LP: Linear programming, MIP-NL: Non-linear mixed integer programming, U: Unspecified
* Parentheses refers emission source, for instance (P) refers emissions from production or (PT) refers emissions from production and transportation.
** Those studies have product perishability consideration.
*** Detailed information about this model is given in coming section.

slaughterhouses. Slaughterhouses can be supplied from more than one production region and after the slaughtering process, beef can be send to more than one export departure point from the same slaughterhouse. Slaughterhouses can keep limited amount of livestock inventory. Different types of rented trucks from 3PL firms are used for livestock transportation between production regions and slaughterhouses, and for beef transportation between slaughterhouses and export departure points. Each truck rented from a 3PL firm turns back again to the same firm (see Fig. 3.1) and trucks do not need to be fully loaded during service. It is also worth to mention that trucks are empty before getting to the sites for service and during return stage to the 3PL firms. Transportation capacity restrictions are imposed on export departure points. There are multiple transport options such as sea, train or air transportation, between export departure and import arrival points. Import arrival points have also a multi-source option that allows receiving beef from different export departure points.
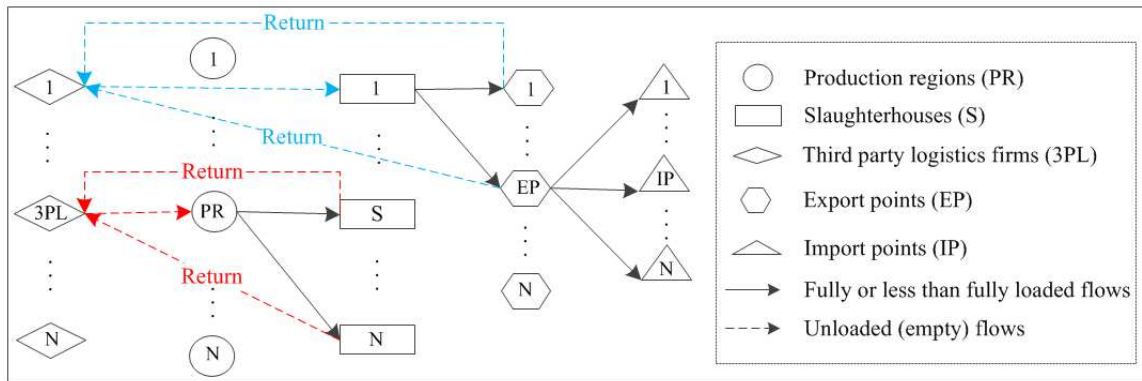
FIGURE 3.1: Representation of the generic beef logistics network

The demand for beef is assumed to be known a priori. CO_2 emissions occur due to the transportation between the actors. Slaughterhouses and export departure points can keep certain amounts of beef inventory. However, it is not possible to keep long term beef inventory in those facilities due to quality considerations. Therefore, maximum number of periods that beef can be stored in facilities needs to be restricted. Additionally, indirect flows between actors are not allowed. That means each facility sends livestock or beef directly to its destination location.

The described generic problem allows us to present the integration of emissions generated from beef and livestock transportation into a mathematical logistics network model. We acknowledge that different beef logistics networks can be characterized in several ways in terms of product flows, truck flows and ownership or even number of chain layers. However, it is possible to employ the same emission estimation methodology, which is described in section 3.3.2, and same approach to incorporate emissions into the model, which is described in section 3.3.4, while adapting the model to different logistics structures.

The decisions that need to be made are: (i) number of livestock slaughtered per slaughter-house per period, (ii) amount of livestock and beef inventories, (iii) flows between actors (allocation decisions), (iv) number of trucks used (rented) from 3PL firms considering also the possibility of less than fully loaded truck shipments. The planning horizon comprises N periods. Transportation lead time between the actors in the chain is assumed to be zero; however, it can be easily incorporated into the model. The aim of the model is minimizing total logistics costs comprising inventory and transportation costs together with the total CO_2 emissions from transportation operations.

3.3.2 Emissions estimations

We follow the methodology presented in Figure 3.2 to calculate CO_2 emissions from road transportation, which is based on a distance-based formulation (Defra, 2005, 2011). The main required parameters for the formulation are liters fuel per km ($Lfpk$) for empty and full trips. Vehicle and fuel type, and road structure affect these parameters. The distance-based formulation assumes that load linearly affects fuel consumption. Therefore, we calculate $Lfpk$ for trucks by considering their load weights, and $Lfpk$ for empty and full trips as follows (Defra, 2005, 2011):

$$Lfpk = Lfpk(empty) + \big(Lfpk(full) - Lfpk(empty)\big) * (weight\ load/load\ capacity)$$
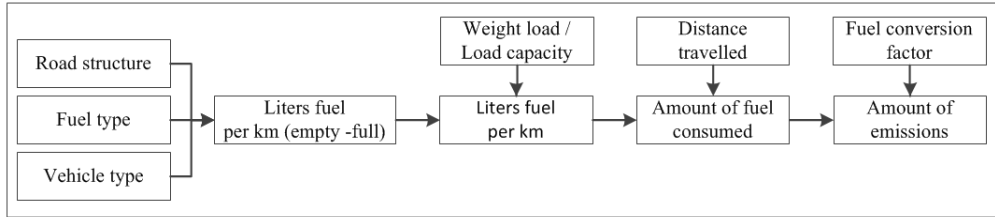
FIGURE 3.2: Emissions estimation methodology for road transportation

Then, multiplication of $Lfpk$ with traveled distances gives us total fuel consumption amounts. After calculating total fuel consumption amounts, we estimate CO_2 emissions by taking into account amount fuel consumed and fuel conversion factor as follows (Defra, 2005, 2011):

$$TotalCO_2(kg) = Amount\ of\ fuel\ consumed\ (Total\ km\ travelled * Lfpk)\ * Fuel\ conversion\ factor$$

This approach allows us to consider the effects of empty drives and less than fully loaded truck shipments on logistics cost and CO_2 emissions. We use unit CO_2 emissions (kg/ton-km) to calculate emissions from other transportation modes such as sea, train or air transportation.

3.3.3 Notation

For the mathematical description of the model the following notation is introduced:

Indices:

i	node index for facilities including production regions, slaughterhouses, export departure and import arrival points,
k	node index for 3PL firms,
i, j	index pair referring to an arc from node i to node j,
m	vehicle type index,
f	transportation mode index,
t	time index referring to a period,

Sets:

F	set of production regions,
S	set of slaughterhouses,
P	set of export departure points,
C	set of import arrival points,
FS	set of production regions and slaughterhouses,
FS_a	set of arcs between production regions and slaughterhouses,
SP	set of slaughterhouses and export departure points,
SP_a	set of arcs between slaughterhouses and export departure points,
PC	set of export departure points and import arrival points,
PC_a	set of arcs between export departure points and import arrival points,
O	set of 3PL firms,
OF_a	set of arcs between 3PL firms and production regions,
OS_a	set of arcs between 3PL firms and slaughterhouses,
OP_a	set of arcs between 3PL firms and export departure points,
$M_{i,j}$	set of truck types that can be used for arc $i, j \in FS_a \cup SP_a$,
$TM_{i,j}$	set of transportation modes that can be used for arc $i, j \in PC_a$,
T	set of periods and L refers the length of a future planning cycle,

Monetary Parameters:

$liveinvcost_i$	cost for storing one livestock unit for one period in facility $i \in S$,
$beefinvcost_i$	cost for storing one ton beef (bone free meat) for one period in facility $i \in SP$,
$rentcost_{k,i,j,m}$	fixed renting cost from 3PL firm $k \in O$, to use in arc $(i, j) \in FS_a \cup SP_a$, for truck type $m \in M_{i,j}$,
$fuelcost$	fuel cost per liter,
$unitcost_{i,j,f}$	cost per ton for transportation on arc $(i, j) \in PC_a$ with transportation mode $f \in TM_{i,j}$,

Technical Parameters:

max	maximum number of periods that beef can be stored in facilities, $max \leq L - 1$
$weight$	average carcass weight of one livestock, in tons,
$yield$	yield of one livestock, 1 ton carcass weight = 0.7 (yield ratio) ton beef,
$emptyfuel_{i,j,m}$	the liter fuel consumption amount (l/km) of empty truck in arc $(i, j) \in FS_a \cup SP_a \cup OF_a \cup OS_a \cup OP_a$ with truck type $m \in M_{i,j}$,
$fullfuel_{i,j,m}$	the liter fuel consumption amount (l/km) of full truck in arc

$(i, j) \in FS_a \cup SP_a \cup OF_a \cup OS_a \cup OP_a$, with truck type $m \in M_{i,j}$,

$conversion$	fuel conversion factor,
$capacity_m$	transportation capacity of truck type $m \in M_{i,j}$, in tons / heads,
$distance_{i,j}$	distance between node $i \in FS \cup P \cup O$ and node $j \in FS \cup P \cup O$, in km,
$demand_{i,t}$	demand from import arrival point $i \in C$, in period t, in tons
$livecap_{i,t}$	number of available livestock in production region $i \in F$, at the beginning of period $t \in T$, in tons
$liveinvcap_i$	total livestock inventory capacity of slaughterhouse $i \in S$ for the whole planning horizon, in tons
$slaughtercap_i$	total livestock slaughtering capacity of slaughterhouse $i \in S$ for the whole planning horizon, in tons
$beefinvcap_i$	total beef inventory capacity of facility $i \in SP$ for the whole planning horizon, in tons
$transcap_i$	total beef transportation capacity of export departure point $i \in P$ for the whole planning horizon, in tons
$emissions_{i,j,f}$	CO_2 emissions factor (kg/ton-km) for transportation on arc $(i, j) \in PC_a$ with transportation mode $f \in TM_{i,j}$, in kg/ton-km

Main Decision Variables:

$L_{i,j,t,m}$	flow quantities of livestock on arcs $(i, j) \in FS_a$, in period $t \in T$, with truck type $m \in M_{i,j}$, in number of heads,
$BT_{i,j,t,m}$	flow quantities of beef on arcs $(i, j) \in FS_a \cup SP_a$, in period $t \in T$, with truck type $m \in M_{i,j}$, in tons,
$BS_{i,j,t,f}$	flow quantities of beef on arcs $(i, j) \in PC_a$, in period $t \in T$, with transportation mode $f \in TM_{i,j}$, in tons,
$N_{k,i,j,t,m}$	number of fully loaded trucks rented from 3PL firm $k \in O$, used on arcs $(i, j) \in FS_a \cup SP_a$, in period t, with truck type $m \in M_{i,j}$,
$C_{i,t}$	number of livestock slaughtered in slaughterhouse $i \in S$, in period $t \in T$,
$IL_{i,t}$	inventory level of livestock in slaughterhouse $i \in S$, at the beginning of period $t \in T$, in number of heads,
$IB_{i,t}$	inventory level of beef in facility $i \in SP$, at the beginning of period $t \in T$, in tons,
$LT_{k,i,j,t,m}$	amount of load carried with less than fully loaded truck rented from 3PL firm $k \in O$, on arcs $(i, j) \in FS_a \cup SP_a$, in period $t \in T$, with truck type $m \in M_{i,j}$, in number of heads or tons,

Derived Decision Variables:

$Z_{k,i,j,t,m}$	binary variable that equals 1, if less than full truck load is carried with a truck rented from 3PL firm $k \in O$, on arc $(i, j) \in FS_a \cup SP_a$, in period t, with truck type $m \in M_{i,j}$, otherwise 0,
$U_{k,i,j,t,m}$	utilisation rate (load factor) of less than fully loaded truck rented from 3PL firm $k \in O$, used on arc $(i, j) \in FS_a \cup SP_a$, in period $t \in T$, with truck type $m \in M_{i,j}$,
$LF_{k,i,j,t,m}$	the liter fuel consumption amount (l/km) of less than fully loaded truck rented from 3PL firm $k \in O$, used on arc $(i, j) \in FS_a \cup SP_a$, in period $t \in T$, with truck type $m \in M_{i,j}$,

3.3.4 Multi objective linear programming (MOLP) model for the generic beef logistics network problem

The generic logistics network problem is formulated mathematically as a MOLP model. The objectives of the model are: (i) an economic objective to minimize total logistics cost and (ii) an environmental objective to minimize total CO_2 emissions from transportation operations. The model constraints include the following: inventory and product flow balance, demand satisfaction, flow structure, truck utilization rate, fuel consumption amount, capacity of transport, inventory and slaughtering, and decision variable constraints.

Economic Objective (OF_1): The economic objective is measured by the total logistics cost that consists of the sum of four parts:

$$\textbf{min} \; OF_1 = IC + TC_1 + TC_2 + TC_3. \tag{3.1}$$

- Inventory costs (IC) for livestock and beef.

$$IC = \sum_{t=1}^{L} \sum_{i \in S} liveinvcost_i * IL_{i,t} + \sum_{t=1}^{L} \sum_{i \in SP} beefinvcost_i * IB_{i,t}.$$

- Transportation costs of fully loaded trucks (TC_1) considering also empty arrivals to sites and returns to 3PL firms.

$$
\begin{aligned}
TC_1 = \sum_{t=1}^{L} \sum_{(i,j) \in FS_a \cup SP_a} \sum_{m \in M_{i,j}} \sum_{k \in O} &\Big(N_{k,i,j,t,m} * \big(rentcost_{k,i,j,m} + (distance_{i,j} \\
&* fullfuel_{i,j,m} * fuelcost + distance_{k,i} * emptyfuel_{k,i,m} * fuelcost + distance_{j,k} \\
&* emptyfuel_{j,k,m} * fuelcost) \big) \Big).
\end{aligned}
$$

- Transportation costs of less than fully loaded trucks (TC_2) considering also empty arrivals to sites and returns to 3PL firms.

$$
\begin{aligned}
TC_2 = \sum_{t=1}^{L} \sum_{(i,j) \in FS_a \cup SP_a} \sum_{m \in M_{i,j}} \sum_{k \in O} &\big((Z_{k,i,j,t,m} * rentcost_{k,i,j,m}) + (distance_{i,j} \\
&* LF_{k,i,j,t,m} * fuelcost) + Z_{k,i,j,t,m} * (distance_{k,i} * emptyfuel_{k,i,m} * fuelcost \\
&+ distance_{j,k} * emptyfuel_{j,k,m} * fuelcost) \big).
\end{aligned}
$$

- Transportation costs of other transportation modes such as sea, train or air (TC_3) between export departure and import arrival points.

$$TC_3 = \sum_{t=1}^{L} \sum_{(i,j) \in PC_a} \sum_{f \in TM_{i,j}} BS_{i,j,t,f} * unitcost_{i,j,f}.$$

Environmental Objective (OF_2): The environmental objective is measured by the total CO_2 emissions that consists of the sum of three parts:

$$\min \ OF_2 = TE_1 + TE_2 + TE_3. \tag{3.2}$$

- Transportation emissions from fully loaded trucks (TE_1) considering also empty arrivals to sites and returns to 3PL firms.

$$TE_1 = \sum_{t=1}^{L} \sum_{(i,j) \in FS_a \cup SP_a} \sum_{m \in M_{i,j}} \sum_{k \in O} \big(N_{k,i,j,t,m} * (distance_{i,j} * fullfuel_{i,j,m} * conversion$$
$$+ distance_{k,i} * emptyfuel_{k,i,m} * conversion + distance_{j,k} * emptyfuel_{j,k,m} * conversion)\big).$$

- Transportation emissions from less than fully loaded trucks (TE_2) considering also empty arrivals to sites and returns to 3PL firms.

$$TE_2 = \sum_{t=1}^{L} \sum_{(i,j) \in FS_a \cup SP_a} \sum_{m \in M_{i,j}} \sum_{k \in O} \big(distance_{i,j} * LF_{k,i,j,t,m} * conversion + Z_{k,i,j,t,m}$$
$$* (distance_{k,i} * emptyfuel_{k,i,m} * conversion + distance_{j,k} * emptyfuel_{j,k,m} * conversion)\big).$$

- Transportation emissions from other transportation modes such as sea, train or air (TE_3) between export departure and import arrival points.

$$TE_3 = \sum_{t=1}^{L} \sum_{(i,j) \in PC_a} \sum_{f \in TM_{i,j}} BS_{i,j,t,f} * emissions_{i,j,f} * distance_{i,j}.$$

Constraints: The model consists of the following sets of constraints.

- Constraints (3.3) and (3.4) ensure capacity restrictions on livestock transportation from production regions to slaughterhouses and balanced livestock inventories in slaughterhouses.

$$\sum_{j \in S} \sum_{m \in M_{i,j}} L_{i,j,t,m} \leq livecap_{i,t}, \qquad \forall i \in F, \forall t \in T \tag{3.3}$$

$$IL_{i,t} + \sum_{j \in F} \sum_{m \in M_{i,j}} L_{j,i,t,m} - C_{i,t} = IL_{i,t+1}, \qquad \forall i \in S, \forall t \in T. \tag{3.4}$$

- Constraints (3.5) to (3.8) ensure balanced beef inventories in slaughterhouses and export departure points while adhering to maximum storage time constraint of beef.

$$IB_{i,t} + (C_{i,t} * weight * yield) - \sum_{j \in P} \sum_{m \in M_{i,j}} BT_{i,j,t,m} = IB_{i,t+1}, \qquad \forall i \in S, \forall t \in T \tag{3.5}$$

$$IB_{i,t} \leq \sum_{a=t}^{t+max} \sum_{j \in P} \sum_{m \in M_{i,j}} BT_{i,j,a,m}, \qquad \forall i \in S, \forall t \in T \tag{3.6}$$

$$IB_{i,t} + \sum_{j \in S} \sum_{m \in M_{i,j}} BT_{j,i,t,m} - \sum_{j \in C} \sum_{f \in TM_{i,j}} BS_{i,j,t,f} = IB_{i,t+1}, \qquad \forall i \in P, \forall t \in T \qquad (3.7)$$

$$IB_{i,t} \leq \sum_{a=t}^{t+max} \sum_{j \in C} \sum_{f \in TM_{i,j}} BS_{i,j,a,f}, \qquad \forall i \in P, \forall t \in T. \qquad (3.8)$$

- Constraints (3.9) enforce that the total rate of flow from the export departure points must be higher than the corresponding market demand of import arrival points.

$$\sum_{j \in P} \sum_{f \in TM_{i,j}} BS_{j,i,t,f} \geq demand_{i,t}, \qquad \forall i \in C, \forall t \in T. \qquad (3.9)$$

- Constraints (3.10) to (3.13) represent that flows between nodes comprise fully and less than fully loaded truck trips. However, only one less than fully loaded truck can be on an arc at the same period and truck load needs to be less than truck capacity.

$$L_{i,j,t,m} = \sum_{k \in O} N_{k,i,j,t,m} * capacity_m + LT_{k,i,j,t,m}, \quad \forall (i,j) \in FS_a, \forall t \in T, \forall m \in M_{i,j} \qquad (3.10)$$

$$BT_{i,j,t,m} = \sum_{k \in O} N_{k,i,j,t,m} * capacity_m + LT_{k,i,j,t,m}, \quad \forall (i,j) \in SP_a, \forall t \in T, \forall m \in M_{i,j} \qquad (3.11)$$

$$\sum_{k \in O} \sum_{m \in M_{i,j}} Z_{k,i,j,t,m} \leq 1, \qquad \forall (i,j) \in FS_a \cup SP_a, \forall t \in T \qquad (3.12)$$

$$LT_{k,i,j,t,m} < capacity_m * Z_{k,i,j,t,m}, \forall (i,j) \in FS_a \cup SP_a, \forall t \in T, \forall m \in M_{i,j}, \forall k \in O. \qquad (3.13)$$

- Constraints (3.14) ensure that utilisation rates of less than fully loaded trucks are calculated based on less than full truck loads and capacities.

$$U_{k,i,j,t,m} = LT_{k,i,j,t,m}/capacity_m, \qquad \forall (i,j) \in FS_a \cup SP_a, \forall t \in T, \forall m \in M_{i,j}, \forall k \in O. \qquad (3.14)$$

- Constraints (3.15) ensure that the liter fuel consumption amount (l/km) of less than fully loaded trucks are calculated based on the distance based formulation (Defra, 2005, 2011) described in section 3.3.2.

$$LF_{k,i,j,t,m} = (Z_{k,i,j,t,m} * emptyfuel_{i,j,m}) + ((fullfuel_{i,j,m} - emptyfuel_{i,j,m}) * U_{k,i,j,t,m}),$$
$$\forall (i,j) \in FS_a \cup SP_a, \forall t \in T, \forall m \in M_{i,j}, \forall k \in O. \qquad (3.15)$$

- Constraints (3.16) to (3.19) ensure capacity restrictions on livestock slaughtering, livestock and beef stocking, and beef transportation to ports.

$$\sum_{t=1}^{L} C_{i,t} \leq slaughtercap_i, \qquad \forall i \in S \qquad (3.16)$$

$$\sum_{t=1}^{L} IL_{i,t} \leq liveinvcap_i, \qquad \forall i \in S \qquad (3.17)$$

$$\sum_{t=1}^{L} IB_{i,t} \leq beefinvcap_i, \qquad\qquad \forall i \in SP \qquad (3.18)$$

$$\sum_{t=1}^{L} \sum_{j \in S} \sum_{m \in M_{i,j}} BT_{j,i,t,m} \leq transcap_i, \qquad\qquad \forall i \in P. \qquad (3.19)$$

- Constraints (3.20) to (3.26) represent the nonnegativity, integrality and binary restrictions imposed upon the decision variables.

$$L_{i,j,t,m} \geq 0, \qquad \forall (i,j) \in FS_a, \forall t \in T, \forall m \in M_{i,j} \qquad (3.20)$$

$$BT_{i,j,t,m} \geq 0, \qquad \forall (i,j) \in SP_a, \forall t \in T, \forall m \in M_{i,j} \qquad (3.21)$$

$$BS_{i,j,t,f} \geq 0, \qquad \forall (i,j) \in PC_a, \forall t \in T, \forall f \in TM_{i,j} \qquad (3.22)$$

$$C_{i,t}, IL_{i,t} \geq 0, \qquad \forall i \in S, \forall t \in T \qquad (3.23)$$

$$IB_{i,t} \geq 0, \qquad \forall i \in SP, \forall t \in T \qquad (3.24)$$

$$LT_{k,i,j,t,m}, U_{k,i,j,t,m}, LF_{k,i,j,t,m} \geq 0, \quad \forall (i,j) \in FS_a \cup SP_a, \forall t \in T, \forall m \in M_{i,j}, \forall k \in O \qquad (3.25)$$

$$N_{k,i,j,t,m} \in \mathbb{Z}^+, Z_{k,i,j,t,m} \in \{0,1\}, \qquad \forall (i,j) \in FS_a \cup SP_a, \forall t \in T \forall m \in M_{i,j}, \forall k \in O. \qquad (3.26)$$

3.4 Case study

3.4.1 Description and data gathering

This section presents an implementation of the proposed model in a real-life fresh-chilled beef logistics network operating in Nova Andradina, Mato Grosso do Sul, Brazil and exporting beef to the EU. The overview of the whole network and the zoomed view of the area that covers production regions, 3PL firms, slaughterhouses and export ports are presented in Figure 3.3. Mato Grosso do Sul ranks third out of 26 states in terms of contribution (11.74%) to total area used for cattle in hectares in Brazil (Nzte, 2010). Mato Grosso do Sul has 11 micro-regions. The reasons for selecting Nova Andradina among other micro-regions are: (1) It has three slaughterhouses that have certification to export cattle meat to EU out of 11 in Mato Grosso do Sul and (2) It has a high density of cattle production. Nova Andradina has five cities (Table 3.C). We consider each city as a production region, since there are hundreds of small and medium sized farms in the region. We have a planning horizon of six months and use the first six months of 2010's trade data between Brazil and EU in our analysis (Abiec, 2012a,b; Nzte, 2010).

Fleet age is one of the major issues for logistics management, since age of the vehicles apparently has an important effect on fuel consumptions because of new technologies. The average fleet age used in logistics activities is more than eight years in Brazil (World-Bank, 2012). Due to this fact, rather than considering different types of vehicles used, we
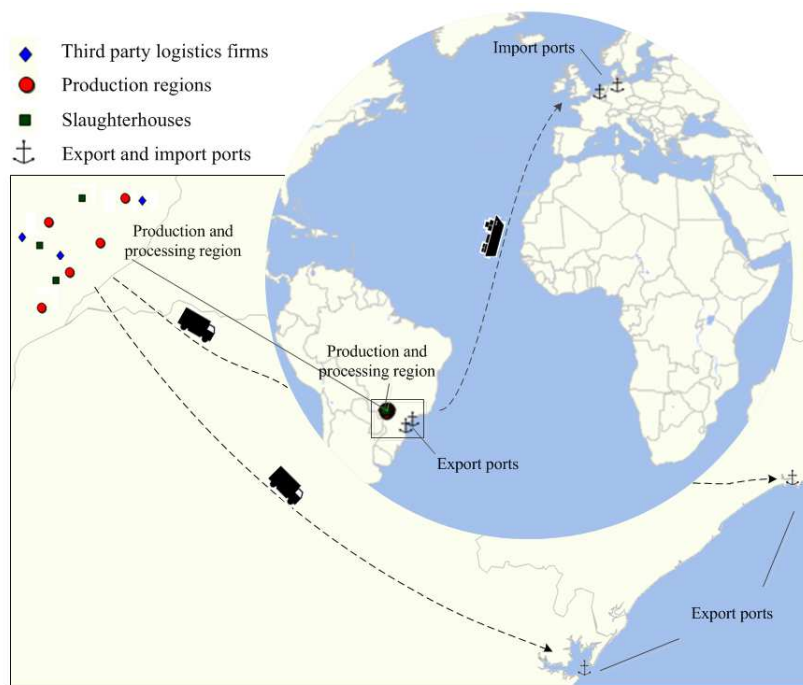
FIGURE 3.3: The analysed beef logistics network between Nova Andradina and the EU

prefer to consider the issue of fleet ages that can be also handled with our model. The difference in the model is that $M_{i,j}$, set of truck types, is interpreted as set of truck age categories and m, vehicle type indices, are interpreted as vehicle age category indices. The fleet in Brazil includes tractor-trailers, fixed bed, bulk goods, and special goods vehicles such as tankers (World-Bank, 2012). We assume that livestock and beef are carried to the slaughterhouses and export ports with standard trucks (Tractor semi-trailers) that have two age categories (old and new) and rented from one of the three 3PL firms in Nova Andradina. Transportation capacities of trucks are: 20 ton beef and 20 cattle (Cederberg et al., 2009).

We calculate cost of operations of trucks by considering fixed renting costs ($€$/truck) from the 3PL firms and variable costs ($€$/km) over distances. We estimate fixed renting costs for trucks considering related capital investment of 3PL firms depending on the age of the truck. So, it is a reasonable assumption to take fixed renting costs for the new truck higher than the old truck. Basically, two stages exist in the beef logistics network: 1st Stage consisting all routes that start from a 3PL firm, visit a production region and a slaughterhouse and turn back to the same 3PL firm; 2nd Stage consisting all routes that start from a 3PL firm, visit a slaughterhouse and an export port and turn back to the same 3PL firm. Therefore, fixed costs cover the period that starts when a truck departs from a 3PL firm and ends when the empty truck returns to the 3PL firm after finalizing the service. Fixed renting costs (240 $€$/old truck, 420 $€$/new truck) for the routes in 2nd

Stage are higher than the costs (40 €/old truck, 70 €/new truck) for the routes in 1st Stage because of the distance differences (see Fig. 3.3).

Unfortunately, no data is available on Brazilian fuel consumption amounts of trucks for different road types. Therefore, we use the data given by Hoen et al. (2010) for the trucks in Europe's conditions. The data is presented in Table 3.2 as a base case. We assume that the data of Hoen et al. (2010) relate to refrigerated trucks and an old truck consumes 10% higher and a new truck consumes 10% lower than the base case amounts (Table 3.2). It is assumed that road structures of 3PL-production regions, production regions-slaughterhouses and slaughterhouses-3PL are the same: 40% motorway, 50% rural and 10% urban. Road structures of slaughterhouses-export ports, and export ports-3PL are also the same: 70% motorway, 10% rural and 20% urban. Related fuel consumption amounts between actors based on the aforementioned road structures are presented in Table 3.2. We use 2.63 kg/l for fuel conversion factor (Defra, 2007) and €1 for fuel cost in Brazil[1] to calculate emissions and operational cost.

TABLE 3.2: Fully loaded and unloaded (empty) fuel consumption amounts (l/km) calculation

Road Type	Motorway		Rural		Urban		3PL-PR / PR-S/ S-3PL		S-EP / EP-3PL	
Load Factor (%)	0	100	0	100	0	100	0	100	0	100
Base case	0.226	0.360	0.230	0.396	0.288	0.504	-	-	-	-
Old vehicle (+10 %)	0.249	0.396	0.253	0.436	0.317	0.554	**0.258**	**0.432**	**0.263**	**0.432**
New vehicle (-10 %)	0.203	0.324	0.207	0.356	0.259	0.454	**0.211**	**0.353**	**0.215**	**0.353**

3PL: Third party logistics firms, PR: Production regions, S: Slaughterhouses, EP: Export Ports
Source: Based upon the study of Hoen et al. (2010).

Inventory holding costs for livestock (22.05€/head-month) and beef (105€/ton-month) are expressed as a percentage (3%) of the approximate market values of the items and same for all facilities. We take the market price for one ton bone-free beef as €3500[2], average carcass weight of one livestock as 300 kg and use the factor 0.7; i.e. from 1 kg carcass weight (meat with bone), 0.7 kg bone-free beef is produced (Cederberg et al., 2009). Correspondingly, inventory costs are calculated as follows: (i) Livestock inventory cost per head: Market price * Carcass weight * Yield ratio * Percentage (3%) and (ii) Beef inventory cost per ton: Market price * Percentage (3%).

The Nova Andradina region uses Porto de Paranagua and Santos Ports for beef export to EU ports which are in Rotterdam and Hamburg. Unit ton cost for transporting between ports with ship (PS-type container vessel: 11,000 TEU) is taken as 0.12 €/kg[3]. Related CO_2 emissions factor is 0.007 kg/ton-km (Dekker et al., 2012). EU share in

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[1] http://data.worldbank.org/indicator/EP.PMP.SGAS.CD,Onlineaccessed:August2013
[2] http://swineweb.com/brazilian-exports-for-3-main-meat-sectors-take-major-fall-in-june/ ,Onlineaccessed:August2013
[3] http://www.globalshippingcosts.com,Onlineaccessed:August2013

Brazil exports is 5% for fresh-chilled beef (Abiec, 2012b). State of Mato Grosso do Sul's participation is taken as 11.74% (Nzte, 2010). Finally, Nova Andradina's contribution to total export is estimated as 27% (# of export slaughterhouses in Nova Andradina/# of export slaughterhouses in Mato Grosso do Sul). Monthly European demand satisfied from Nova Andradina for fresh-chilled beef in the first six month of 2010 is presented in Table 3.A and it is assumed that demand of EU is satisfied equally from the two import ports, Rotterdam and Hamburg.

Distances between actors (Table 3.B) are calculated via web based distance measurement tools[4]. Locations of production regions are defined as approximately center of each city. Available livestock numbers in production regions are estimated considering their contributions to cattle production in 2010 (Table 3.C) and the demand satisfied from the region (Table 3.A). Slaughtering capacities (300 ton) are taken as the same for all slaughterhouses and estimated considering the demand satisfied from the region. Another assumption is that slaughterhouses can keep livestock (300 head) and beef (200 ton) inventory, whereas export ports can keep only beef (100 ton) inventory. Maximum storage time, k is restricted to two months because of perishability nature of the beef. Export ports' transportation capacities used by Nova Andradina region are estimated (Porto de Paranagua, 124 tons, Santos Port, 676 tons) considering the amounts of Brazilian beef exports by sea ports in 2010 (Abiec, 2012c). Summary for all the values and estimations of the input parameters along with the relevant data sources are presented in Table 3.D.

3.4.2 Model solution

We solved the MOLP model with the ϵ - constraint method (Andersson, 2000). This method has been also employed in other recent studies which have multiple objective models (Chaabane et al., 2011; Nikbakhsh et al., 2013; Zhang et al., 2010). Under the ϵ - constraint method, one objective is selected for optimization, whereas the others are reformulated as constraints. In our solution methodology, OF_1 was selected for optimization and OF_2 was formulated as an additional constraint. The right hand side value of the additional constraint is ϵ, which represents the limit on CO_2 emissions. We derived a Pareto frontier to observe the dependency between the two objectives. While deriving the Pareto frontier, initially, the model that has OF_1 was solved without the additional constraint and the total amount of generated emissions in that instance was set as a highest value of the ϵ. Afterwards, the additional constraint was activated and the right hand side value of the ϵ was progressively reduced in each instance starting from its highest value. Therefore, a set of models that differ with respect to the right hand side value of the additional constraints is required. Consequently, progressively changing the ϵ value

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[4]http://maps.google.nl/ and http://www.searates.com/,Onlineaccessed:July2013

allowed us to obtain different points on the Pareto frontier.

$$\textbf{min } OF_1$$
$$s.t.$$
$$Constraints \ (3.3) \ to \ (3.26),$$
$$OF_2 \leq \epsilon, \ \ (additional \ constraint)$$

We used the ILOG-OPL development studio and Cplex 12.2 optimization solver to solve the MOLP model. The model has 2637 continuous, 756 binary and 756 integer variables, and 2806 constraints. We could not find optimal solutions within a time limit of 1000 seconds because of the size of the problem. However, we calculated lower bounds for each model through a relaxation technique, where all binary variables related with less than fully loaded truck usage were replaced by continuous variables, constrained in the $[0, 1]$ interval. Our computational tests showed that the average difference between our feasible solutions and the lower bounds is less than approximately 2%. Therefore, we used the feasible solutions in our analysis that are sufficiently close to the optimal solutions and obtained within reasonable times.

3.4.3 Analysis and discussion

3.4.3.1 Solutions of base cases

We defined two base cases: Lowest Cost (LC) and Lowest emission (LE). Summary results for these base cases are presented in Table 3.3. The effect of reducing emissions can be seen from the total cost difference between LC and LE base cases. Inventory and road transportation cost items increase in LE base case. The reasons for the cost change in LE base case are: (i) decreasing the number of less than fully loaded trucks that result an increase in inventories, and (ii) using new trucks rather than old ones that result an increase in transportation costs.

Emission differences in different parts of the logistics network in both cases are due to road conditions, distances and vehicle loads. Ship transportation related cost and emissions do not change between the base cases, since it is the single alternative for transportation between export and import ports and age of the vehicles for ship transportation is not considered in our problem.

Results suggest to keep 55 and 5.2 tons of beef inventory for the whole planning horizon in the LE and LC cases respectively. Although maximum storage time is restricted to two months, under the suggested strategy beef would not be held in inventory longer than

one month (Table 3.3). This indicates that constraints (3.6) and (3.8) are non-binding constraints as a result of the parameter setting of our case study. However, these two constraints will restrict the maximum storage time for FSCs where keeping inventory more than one month is advantageous.

TABLE 3.3: Summary results for base cases

Case		Lowest cost	Lowest emission
Logistics cost (€)	Inventory	546	7,004
	Road transportation	44,642	51,801
	Ship transportation	93,720	93,720
	Total	138,908	152,525
Transportation emissions (kg)	Third party logistics firms - Production regions	4,000	3,100
	Production regions - Slaughterhouses	7,196	5,554
	Slaughterhouses - Third party logistics firms	5,160	4,264
	Slaughterhouses - Export ports	34,514	27,856
	Export ports - Third party logistics firms	20,672	16,485
	Export ports - Import ports	56,374	56,374
	Total	127,917	113,633
General	Less than fully loaded trucks	12%	6%
	Old truck usage	100%	0%
	New truck usage	0%	100%
	Total livestock inventory (heads)	0	56
	Total beef inventory (ton)	5.2	55
	Maximum time beef held in inventory (month)	1	1

The structure of the analysed logistics network and the aggregated values (sum of all planning horizon) of the decision variables for the LC case are visualized in Figure 3.4. In order to not complicate the figure, the returns from slaughterhouses and export ports to 3PL firms, and the number of less than fully loaded trucks in each route are not shown. However, regarding the returns, it is already known that each truck rented from a 3PL firm turns back again to the same firm (see Fig. 3.1) due to the given assumption. The total beef inventory for the whole planning horizon (5.2 tons), which is also not presented in the figure, is kept in the Santos Port.

3.4.3.2 Trade-offs between multiple objectives

In our problem due to different features of trucks in terms of fixed renting cost and fuel consumption rates, trade-offs occur between logistics cost and amount of CO_2 emissions from transportation. This means that decreasing emissions from transportation comes at a cost. In addition to the aforementioned two base cases, we generated 10 additional instances by lowering ϵ value (limit on CO_2 emissions) 1% from the highest emission level at each instance. The derived Pareto frontier represents the trade-off relationships between cost and emissions (Fig. 3.5a).
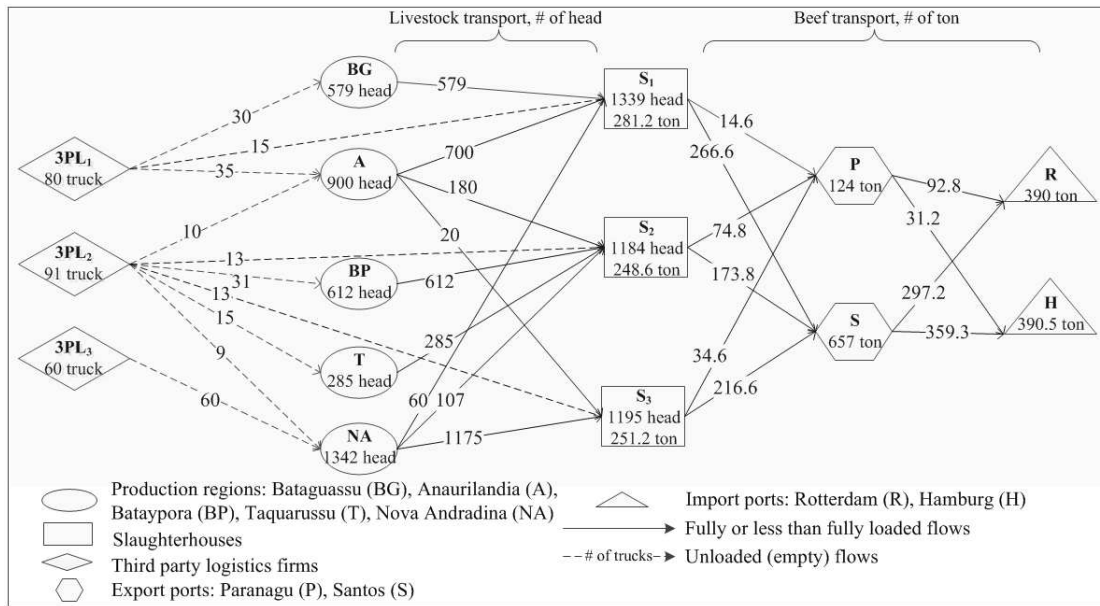
FIGURE 3.4: Logistics network structure and related decision variables for the LC case

(a) Trade-offs between total cost and CO_2 emissions

(b) Old and new truck usage ratios in all instances
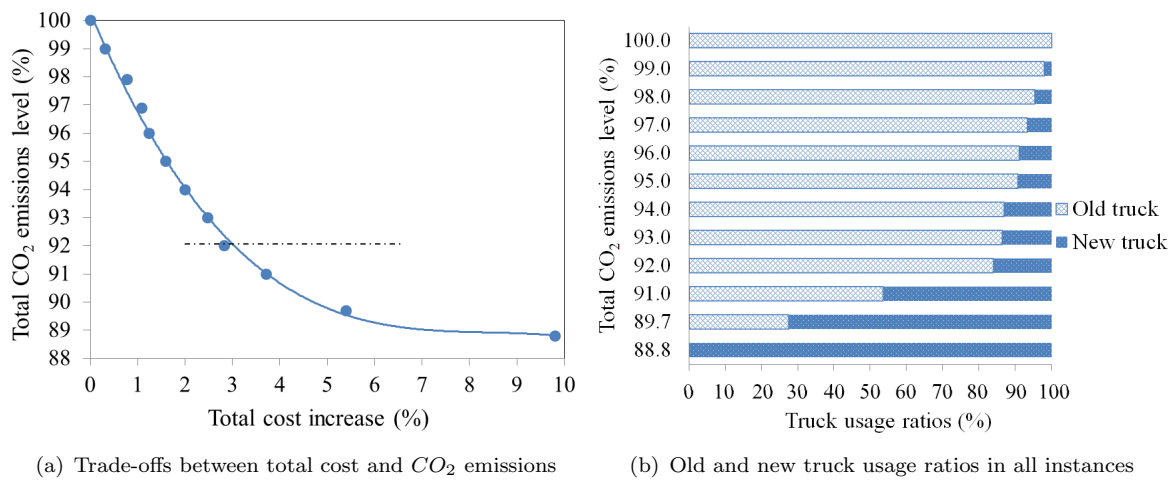
FIGURE 3.5: Results obtained from the trade-offs analysis

As it is observed from Figure 3.5a, the slope of the Pareto frontier is clearly decreasing after a point where emissions level is around 92%. The dotted horizontal line in Figure 3.5a shows approximately the point where slope decrease starts. This slope change indicates that cost of achieving the same percentage of emissions reduction is increasing. This is because of the logistics network structure. In Nova-Andradina, the distances (average: 190 km) for the routes (3PL firms-production regions-slaughterhouses-3PL firms) in 1st stage are less than the distances (average: 1497 km) for the routes (3PL firms-slaughterhouses-export ports-3PL firms) in 2nd stage (see Fig. 3.3). Results show that new trucks are firstly rented for longer distances, in our case for the routes in 2nd stage, to reduce emissions. This is reasonable, since the total emissions effect of using a new truck will be higher for long distances compared to short distances. Model results suggest that

emissions can be reduced by renting new trucks for the 1st stage after the trucks in the 2nd stage have been completely renewed. However, more new trucks need to be rented in the 1st stage to achieve the same emissions reduction, because of the distance differences between the 1st stage and the 2nd stage (see Fig. 3.3). This necessity results in higher cost increase for the same percentage of emissions decrease. Figure 3.5b presents the truck usage rates in all instances. This figure also confirms that the ratio of new trucks is increasing more while achieving the same percentage of emissions decrease in further instances.

The trade-off analysis provides managerial insights on improving sustainability of the analysed logistics network. The cost of being sustainable from the point of reducing transportation emissions was determined by means of the Pareto frontier (see Fig. 3.5a) obtained through the trade-off analysis. This information is especially useful when setting sustainability targets that need an evaluation of economic and environmental factors. The Pareto frontier can be used for such an evaluation, since it ensures to find a compromise solution between costs and emissions. For instance, after evaluations of cost and emissions in line with economic and environmental objectives, one of the presented solutions in Figure 3.5a can be selected for the analysed logistics network. One of the prominent sustainable suggestion would be selecting the breaking point located around the emissions level of 92% on the Pareto frontier (see Fig. 3.5a). This would ensure in approximate numbers an emission reduction of 8% in return of a cost increase of 3% that necessitates to use 16% new truck for the routes in 2nd stage (see Fig. 3.5a,b). As a result, these kinds of insights can support managerial decisions and improve sustainability performance of the selected chain.

3.4.3.3   Road transport emissions ratios of different parts of the supply chain

Considering all instances including the two base cases, average contributions of each supply chain part to total road transport emissions is presented in Figure 3.6. More or less same amount of emissions are generated from ship transportation between export and import ports, which could raise the discussion of using local food. We know that trucks are either fully or less than fully loaded between production regions and slaughterhouses, and slaughterhouses and export ports, and empty while coming from 3PL firms and turning back to them again in road transportation. Unsurprisingly, loaded trips (58.2%) contribute more than empty trips (41.8%) to total road transportation emissions and in loaded trips the share of slaughterhouses to export ports (47.3%) is higher than the share of production regions to slaughterhouses (10.9%) mainly due to the aforementioned distance differences. However, the remarkable thing is that empty trips constitute nearly

two-fifths of emissions from road transportation. Among those empty trips especially the share of export ports to 3PL firms (28.2%) due to long distances is quite striking. Therefore, cost and emissions effect of decreasing empty legs (return hauls) between export ports and 3PL firms is significant to consider and will definitely improve the added value in logistics chain.
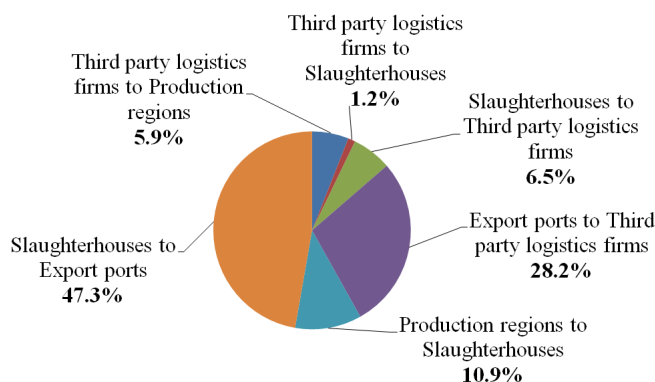
FIGURE 3.6: Road transport emissions ratios in different parts of the supply chain

Addressing the more responsible parts for the road transport emissions in the whole chain helped us to point out some potential sustainable action plans. In our case, total emission contribution of the two parts, which are between slaughterhouses and export ports, and export ports and 3PL firms, is 75.5% due to the long distances (approximately 700 km) between these facilities. Managerial actions for dealing with such long distance operations in road transport might be as follows: (1) increasing the capacity of the vehicles, (2) using fuel efficient vehicles, (3) using alternative ports, (4) using backloading opportunities to reduce empty returns, and (5) shifting market from export to domestic market. Consequently, the managerial implication is that evaluating the road transport emission sources as a whole enables to present the importance of distances between actors in terms of environmental impact.

3.4.3.4   Sensitivity analysis

In order to get more insight, sensitivity analysis was conducted on five different parameters: export port capacities, fuel efficiency levels, inventory holding costs, truck supply capacities and fixed renting cost of new trucks. Practical necessities and challenges learnt from the related literature and Brazilian partners in an EU funded project, SALSA[5], which has an objective of increasing social, environmental and economic sustainability of the Latin American and EU food chains, motivated us to focus on the aforementioned

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[5]Knowledge-based sustainable value-added food chains: innovative tools for monitoring ethical, environmental and socio-economical impacts and implementing Eu-Latin America shared strategies (FP7/2007-2013) under grant agreement number 265927

issues. Each of these analyses enables to explore the effects of possible changes in the current logistics system on cost and emissions. Therefore, the sensitivity analysis serves a supportive role in evaluating and better understanding the analysed beef logistics network in Brazil.

• *Effect of removing capacity restrictions on export ports:* The Porto de Paranagua is more closer (Average: 660km) to slaughterhouses and 3PL firms, than Santos Port (Average: 780km) in Nova Andradina region. However, capacity of the Porto de Paranagua allows for only 15.5% of export from Nova Andradina region to EU (Abiec, 2012c). We knew from the previous analysis that the total emissions share of slaughterhouses to export ports and export ports to 3PL firms constitutes 40.4% of emissions as well. These reasons led us to analyse the potential impact of removing capacity restrictions on the aforementioned export ports. As it is expected, removing capacity restrictions on export ports results in transportation of all European demand from the closer port, Porto de Paranagua. In this case, results show that a cost reduction of 2.0% in LC case, and 4.0% in LE case, and an emissions reduction of 4.2% in LC case, and 4.8% in LE case could be obtained. The satisfaction of all demand from Porto de Paranagua necessitates approximately a 6-fold capacity increase and because of financial issues it might not be possible within the short term. However, it is certain that improvements in port capacity of Porto de Paranagua would have major impacts on reducing cost and emissions in Brazil.

• *Effect of investing in better roads:* Transportation infrastructure has important implications on truck speeds and consequently on fuel efficiency (World-Bank, 2012). Brazil has the third largest road network in the world, at approximately 1.6 million km, but only 196,000 km (around 12%) of it is paved (World-Bank, 2010). This fact shows the inadequacy of road structure, or in general term transportation infrastructure, in Brazil. Correspondingly, actors in Brazil beef logistics chain pay taxes for the improvement of roads. However, we used the fuel consumption data for the trucks in Europe's conditions. This motivated us to analyse the impact of different fuel efficiency levels on both cost and emissions. We considered two fuel efficiency levels in which fuel consumptions were increased by 5% and 10% (Fig. 3.7). Results show that decreasing fuel efficiency due to bad infrastructure shifts the Pareto frontier to the right. This means that the trade-off relationship between the multiple objectives, costs and CO_2 emissions, is not affected, but both of them increase because of the increased fuel consumption. From the other perspective, results confirm that improvement by paying money for better roads has two potential awards: decreasing logistics cost and decreasing emissions. This sensitivity analysis also enables to evaluate the scenarios in which more energy is needed in Brazil for refrigeration, since the reason for the fuel increase might be not only bad infrastructure, but also excess energy usage of truck refrigerators in Brazil as well.
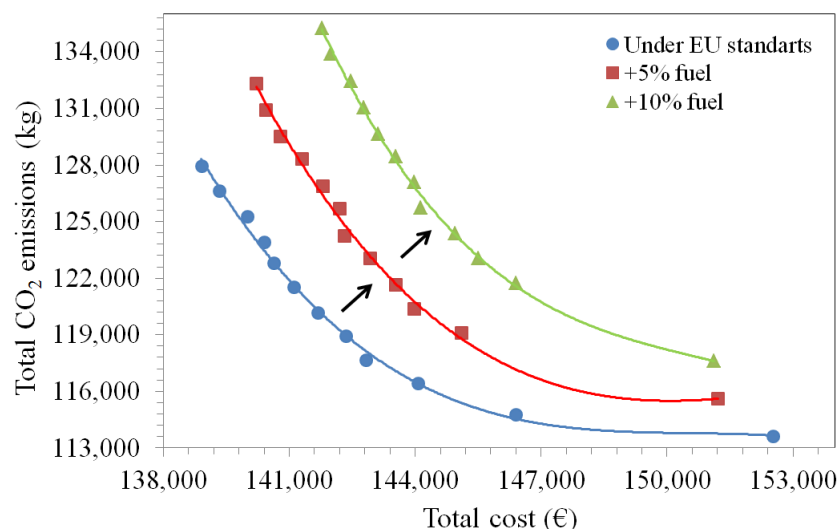
FIGURE 3.7: Effect of increase in fuel consumption

- *Effect of changing inventory holding cost:* Results on LC and LE cases (Table 3.3) show that beef is not held in inventory longer than one month, although maximum storage time is restricted to two months. However, handling of beef products that are one month old might be different for the wholesaler/retailer in terms of distribution and marketing processes required in comparison to that for fresh beef. This fact motivated us to analyse the effects of changes in inventory holding cost. In our previous analysis inventory holding cost for beef was expressed as a percentage, 3%, of the approximate market value of the product. Additionally, we considered 1% and 5% (Table 3.4). The lower inventory cost, 1%, ensures to analyse a scenario in which freshness of the product becomes less important and the higher inventory cost, 5%, ensures to analyse a scenario in which freshness of the product becomes more important. Results for the LC case show that increase in inventory holding cost leads to decrease in inventories and increase in road transportation cost. The reason for that is using less than fully loaded trucks and sending goods before aging become more advantageous rather than keeping items in inventory to increase load size in the next period. This can be observed from the percentages of less than fully loaded trucks for different inventory levels (Table 3.4). Moreover, due to more use of less than fully loaded trucks, total emissions increase as increasing inventory holding cost. In summary, this sensitivity analysis enables to show the effect of changing inventory holding cost depending on the importance given on freshness of the beef.

- *Effect of restricting truck supply:* We assumed that whenever needed, trucks can be rented from the 3PL firms without any problem. However, the agricultural community in Brazil is concerned about truck shortages due to increased agricultural production and new regulations that restrict the number of hours a truck driver may work. Therefore, we analysed a scenario in which one of the three 3PL firms, $3PL_2$, is confronted with a

TABLE 3.4: Effect of changing inventory holding cost for the LC case

Percentage of the market price	1%	3%	5%
Inventory cost (€)	789	546	37
Road transportation cost (€)	43,965	44,642	45,389
Total cost (€)	138,474	138,908	139,145
Total emissions (kg)	126,872	127,917	128,002
Less than fully loaded trucks	8%	12%	13%
Old truck usage	100%	100%	100%
Total livestock inventory (heads)	0	0	0
Total beef inventory (ton)	22.5	5.2	0.2
Maximum time beef held in inventory (month)	1	1	1

truck shortage and can not provide trucks during the whole planning horizon. Under this circumstance, facilities that rent trucks from $3PL_2$ necessarily go for the other two 3PL firms, $3PL_1$ and $3PL_3$, located comparably far. This supply change leads to increasing travelling distance that results in a cost increase of 1.1% in LC case, and 1.5% in LE case, and an emissions increase of 3.0% in LC case, and 2.7% in LE case. However, if the remaining two 3PL firms did not have enough truck capacity to compensate the supply decrease, trucks would be rented from 3PL firms located in more far away regions to satisfy the livestock and beef demand on time. The effect of that scenario on cost and emissions would be worse. Therefore, this sensitivity analysis on truck supply shows that capacity problems in 3PL firms have negative effects on cost and emissions.

• *Effect of changing fixed renting cost of new trucks:* We took fixed renting costs for the new truck higher than the old one considering related capital investment of 3PL firms depending on the age of the truck. One of the current discussions in logistics management is providing green tax incentives to encourage the purchase of cleaner vehicles consuming less fuel by means of new technologies (McKinnon et al., 2012). These kinds of legislations can reduce the related capital investment cost for the 3PL firms and the indirectly renting prices of new trucks. Therefore, we analysed the effects of reductions on fixed renting cost of new trucks (Table 3.5). According to the results for the LC case, 10% decrease does not affect on cost and emissions, since the model still suggests to use only old trucks in all routes as in the solution of LC base case (see Table 3.3). However, different amounts of reductions on cost and emissions are obtained for the instances where related costs are decreased by 20% and 30%. The reason for the emission decreases is starting to use new trucks. At first sight, cost increase would be expected for the last two instances, 20% and 30%, due to the usage of new trucks, which have still higher fixed renting costs compared to the costs for the old ones. However, less fuel consumption feature of new trucks makes use of them economically advantageous for the long routes even paying more for their rents. As a result, this sensitivity analysis on fixed renting cost of new trucks shows that

green tax incentives can economically and environmentally improve the performance of the logistics systems.

TABLE 3.5: Effect of changing fixed renting cost of new trucks for the LC case

Percentage of decrease in rent	Compared to LC case		New truck usage
	Cost reduction	Emission reduction	
10%	0%	0%	0%
20%	0.1%	3.5%	9%
30%	1%	7.5%	18%

3.5 Conclusions

In this study, we present a MOLP model for the generic beef logistics network problem. It has two competing goals: minimizing total logistics cost and minimizing total CO_2 emissions from transportation operations. Road structure, vehicle and fuel types, weight loads of vehicles, traveled distances, return hauls and product perishability are considered while integrating transportation emissions into the MOLP model. The model is thus important for decision makers who are concerned with logistical network problems of perishable products under emissions consideration. Implementation of the model on the beef export chain between a region of Brazil and the EU shows its applicability to real life logistics networks. The model can easily be further adapted to other emerging value-added food chains as well. The results presented in this study are obtained by means of a ϵ - constraint method used for solving MOLP models.

Different analyses are conducted to support decision making in the selected chain. The question of how much cost to bear to reduce emissions to different levels in the logistics system is answered by the presented Pareto frontier that shows the trade-off relationships between logistics costs and emissions. The next question is where to focus to (re)design a logistics network that is more environmentally-friendly in terms of transportation emissions. Regarding that issue, road transport emission shares of the chain parts are observed by the pie chart. The pie chart results indicate the importance of distances between actors in terms of environmental impact. Moreover, sensitivity analysis on practically important parameters show the potential impacts of several changes to logistics cost and emissions. Some of the most interesting results from the sensitivity analysis can be given as follows: (1) removing capacity constraints on export ports shows that capacities put pressure on the logistics system while selecting the related port for transportation, (2) decreasing fuel efficiency of trucks due to the inefficient infrastructure results in shifts of the Pareto frontier with both increase in logistics cost and emissions, and (3) decreasing fixed renting

cost of new trucks due to the obtained advantage of 3PL firms from green tax incentives result in economic and environmental improvement. In summary, all the analyses show that the proposed model serves as a decision support tool while further improving the environmental position of the selected food logistics chain.

It is possible to extend the proposed model in several ways, which can be suggested as future research areas. First, reverse product flows from the destination nodes and indirect flows between facilities can also be considered. Second, other sources of emissions (e.g. emissions from livestock or refrigeration in more detail) and other sustainability key performance indicators (e.g. energy usage or water consumption) can also be evaluated. Third, quality or age of the products can be tracked through the supply chain in a more detailed way instead of just restricting the maximum number of periods that beef can be stored in facilities.

Acknowledgement

APPENDIX

In this section, we present the remaining data used for the MOLP model.

TABLE 3.A: Estimation of monthly European demand satisfied from Nova Andradina for fresh-chilled beef in the first six months of 2010, in tons

	Total Beef Export	EU Share	Mato Grosso do Sul's Participation	Nova Andradina's Participation (Demand)
January	67,092	3,355	394	**107**
February	74,311	3,716	436	**119**
March	80,720	4,036	474	**129**
April	79,010	3,951	464	**126**
May	90,692	4,535	532	**145**
June	96,856	4,843	569	**155**
Total	953,869	47,693	5,599	**781**

Source: (Abiec, 2012a,b; Nzte, 2010)

TABLE 3.B: Distances between nodes in the beef logistics chain, in km

	BG	A	BP	T	NA	S_1	S_2	S_3	P	S	$3PL_1$	$3PL_2$	$3PL_3$
Bataguassu (BG)	0												
Anaurilandia (A)	-*	0											
Bataypora (BP)	-	-	0										
Taquarussu (T)	-	-	-	0									
Nova Andradina (NA)	-	-	-	-	0								
S_1	42	39	66	99	45	0							
S_2	93	57	12	33	54	-	0						
S_3	93	66	39	54	30	-	-	0					
Porto de Paranagu (P)	-	-	-	-	-	639	640	702	0				
Santos Port (S)	-	-	-	-	-	740	772	825	-	0			
$3PL_1$	15	45	96	129	93	51	99	102	602	710	0		
$3PL_2$	66	48	15	45	45	57	15	24	644	774	-	0	
$3PL_3$	111	90	69	75	30	75	63	33	723	850	-	-	0

S_i: Slaughterhouse i, $3PL_i$: Third party logistics firm i

* Distances which are not necessary for the model are not presented.

TABLE 3.C: Available livestock numbers in cities for each month, in heads

	Jan.	Feb.	March	Apr.	May	June	Contribution* (%)
Bataguassu	88	97	107	105	122	130	16
Anaurilandia	132	145	161	158	183	196	24.1
Bataypora	85	94	104	102	118	127	15.6
Taquarussu	41	45	50	49	56	60	7.4
Nova Andradina	201	222	246	240	279	299	36.8
Total	547	603	668	654	758	812	100

*Contributions of cities in Nova Andradina to cattle production, in 2010 (Ibge, 2012)

TABLE 3.D: Summary for all the values and estimations of the problem's input parameters along with the relevant data sources

Parameters	Values/Estimations	Sources
liveinvcost	22.05€/head-month	http://swineweb.com, Cederberg et al. (2009)
beefinvcost	105€/ton-month	http://swineweb.com, Cederberg et al. (2009)
rentcost	1st Stage: 40 €/old truck, 70 €/new truck	Assumption
	2nd Stage: 240 €/old truck, 420 €/new truck	
fuelcost	€1	http://data.worldbank.org
unitcost	0.12 €/kg	http://globalshippingcosts.com
max	2 months	Assumption
weight	300 kg	Cederberg et al. (2009)
yield	0.7	Cederberg et al. (2009)
emptyfuel	Table 3.2	Hoen et al. (2010)
fullfuel	Table 3.2	Hoen et al. (2010)
conversion	2.63 kg/l	Defra (2007)
capacity	20 ton beef and 20 cattle	Cederberg et al. (2009)
distance	Table 3.B	http://maps.google.nl/ , http://searates.com/
demand	Table 3.A	Abiec (2012b), Nzte (2010),
livecap	Table 3.C	Ibge (2012)
liveinvcap	300 head	Assumption
slaughtercap	300 ton	Assumption
beefinvcap	Slaughterhouses: 200 ton, Export ports: 100 ton	Assumption
transcap	Porto de Paranagua: 124 tons, Santos Port: 676 tons	Abiec (2012c)
emissions	0.007 kg/ton-km	Dekker et al. (2012)

Chapter 4

The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations

This chapter is based on the published journal article:

M. Soysal, J.M. Bloemhof-Ruwaard, Tolga Bektaş (2014) "The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations" *International Journal of Production Economics*, 164, 366-378.

In this chapter, we investigate RO3:

To investigate the performance implications of accommodating explicit transportation energy use and traffic congestion concerns in a two-echelon capacitated vehicle routing problem.

4.1 Introduction

The significant growth in freight traffic and increase in traffic congestion in urban areas necessitate introducing legal restrictions on the use of large-size vehicles with heavy loads. For instance, in some cities of Australia (e.g., Sydney and Melbourne[1]) oversize vehicles are not allowed to travel on designated routes during peak hours (RTA, 2007). The desired objective of keeping large vehicles away from congested areas aims not only to reduce the environmental externalities of freight distribution (e.g., energy usage and congestion), but also to improve the social consequences of such activities (e.g., traffic-related air pollution, accidents and noise). One way of achieving this objective is to use multi-echelon distribution strategies in which freight is delivered to customers via intermediate depots rather than direct shipments from the origin (Crainic et al., 2004; Perboli et al., 2011). In two-echelon distribution systems, large trucks are used to transport freight over long-distances to intermediate depots where consolidation takes place. The products are transferred to destination points using small and environmentally-friendly vehicles. This approach also finds applications in e.g., multi-modal freight transportation, grocery and hypermarket product's distribution, and e-commerce and home delivery services (Feliu et al., 2007). Several projects (e.g., CIVITAS[2] and ELCIDIS[3]) have been undertaken in recent years to address issues in two-echelon logistics systems and to manage freight transportation in urban areas.

The two-echelon capacitated vehicle routing problem (2E-CVRP) is a distribution system where intermediate capacitated depots, called satellites, are placed between a supplier and final customers (Feliu et al., 2007). Direct shipments from suppliers to customers as in Vehicle Routing Problems (VRPs), e.g., Jabali et al., 2012; Kritikos and Ioannou, 2013, are not allowed in this setting. Freight must first be sent from the depot to a satellite and thence to the destination. The 2E-CVRP has two types of vehicle routes: (i) first-echelon routes that start and end at the depot and visiting the satellites, and (ii) second-echelon routes that start and end at the same satellite and visiting the customers (see Fig. 4.1). Satellites usually have limited capacities and are allowed to be serviced by more than one first-echelon route. In the second-echelon, however, each customer is visited exactly once by a route. A homogeneous vehicle fleet is used at each echelon. Second-echelon vehicles are smaller in capacity than the first-echelon vehicles. A handling cost proportional to

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[1] http://www.vicroads.vic.gov.au/NR/rdonlyres/3B9992E3-D9B7-4F5E-B0A6-9AA6ED4E3DE2/0/VRPIN00966.pdf,Onlineaccessed:September2013

[2] An initiative which was launched in 2002 to redefine transport measures and policies in order to create cleaner, better transport in cities. http://www.civitas.eu/index.php?id=79&sel_menu=23&measure_id=620, Onlineaccessed:August2013

[3] A project about electric vehicle city distribution system in Rotterdam, Netherlands. http://www.managenergy.net/resources/779,Onlineaccessed:August2013

the quantity loaded or unloaded is incurred for the satellites due to the unloading of first-echelon vehicles and loading of second-echelon vehicles. Satellites do not perform any other activity, e.g., significant physical installations and warehousing are not required. The objective of the basic 2E-CVRP is to determine two sets of first and second echelon routes that minimize total routing and handling cost.
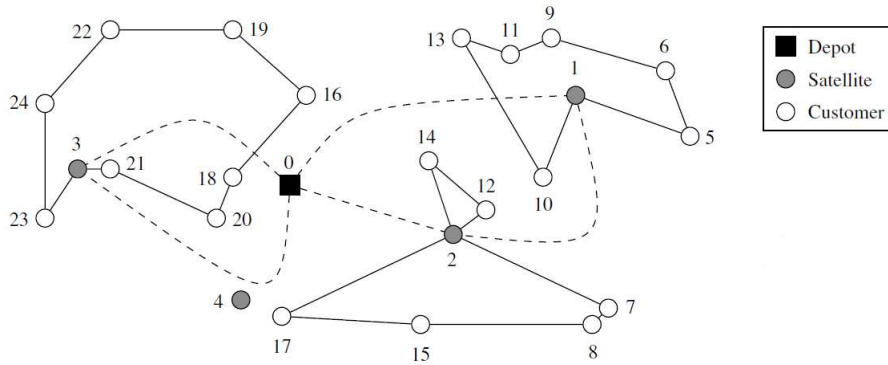
FIGURE 4.1: A solution to the 2E-CVRP (Source: Baldacci et al. (2013))

The basic 2E-CVRP assumes that distribution costs and travel times between nodes are known in advance and are constant (Feliu et al., 2007; Perboli et al., 2011). However, fuel consumption and therefore cost can change based on vehicle speed and load. In particular, vehicle speed can change according to the traffic density at a certain time and location, and load is dependent on the visiting order of the customers. Real-world vehicle routing applications require calculation of distribution costs more accurately, which will also help to reduce relevant operational or environmental related costs. This has been shown in the relevant literature for a number of VRPs considering fuel consumption or emissions (e.g., Bektaş and Laporte, 2011; Franceschetti et al., 2013). Such an attempt has not yet been made for the 2E-CVRP with time-dependent travel times. This is the motivation behind this paper. In particular, we incorporate detailed fuel consumption estimations based on factors such as vehicle type, traveled distance, vehicle speed and vehicle load into the 2E-CVRP.

Our study adds to the literature on VRPs that have fuel consumption or emissions considerations by (1) developing a comprehensive MILP formulation for a time-dependent 2E-CVRP that accounts for vehicle type, traveled distance, vehicle speed, load, emissions and multiple time zones that may occur during the planning horizon, (2) presenting the applicability of the model in a supermarket chain operating in the Netherlands based on mostly real data, multiple scenarios, and analysis.

The rest of the paper is structured as follows. The next section presents a review of the relevant literature on the 2E-CVRP and VRPs with environmental considerations. In

the subsequent section, we present a mathematical formulation of the problem, followed by computational results on a real-life distribution problem. The last section presents conclusions and future research directions.

4.2 Literature review

The 2E-CVRP has recently attracted attention largely because of the growing need for research to manage distribution systems for congested urban areas (Crainic et al., 2004). The 2E-CVRP is an NP-Hard problem due to the fact that it is a special case of the VRP. Feliu et al. (2007) present a commodity-flow formulation for the 2E-CVRP, using which solutions were obtained for different scenarios with a branch & cut algorithm. Perboli et al. (2010, 2011) use valid inequalities to further improve the algorithm of Feliu et al. (2007) and obtain relatively good solutions with limited computational effort. Jepsen et al. (2013) show that the model presented by Perboli et al. (2011) may not provide feasible solutions when there are more than two satellites in the solution. They describe an adjusted formulation and a new mathematical model for a relaxation of the 2E-CVRP but provides optimal solutions for the given problem sizes of 50 customers and five satellites using a specialized branching scheme. Heuristic algorithms for the 2E-CVRP are presented in Crainic et al. (2008), Crainic et al. (2011), Perboli et al. (2011) and Hemmelmayr et al. (2012). Santos et al. (2013) and Baldacci et al. (2013) describe exact algorithms for solving the 2E-CVRP. The algorithm of Santos et al. (2013) is a hybrid branch-and-bound and column-generation, and the one by Baldacci et al. (2013) is based on decomposing the problem into a limited set of multi-depot capacitated VRPs with side constraints. Crainic and Sgalambro (2014) and Crainic et al. (2009) study the 2E-CVRP with various assumptions concerning different operational issues such as the management of the vehicle fleet, the flexibility associated with the delivery of goods and the size of the controlled fleets.

One of the common points of all the studies above is the assumption of constant cost or travel times between the nodes. This is a strong assumption for the 2E-CVRP, since the problem includes second-echelon routes often traveled over congested urban areas with different traffic density levels for different times of a day. Additionally, this assumption is restrictive in that it does not allow for an explicit calculation of the fuel consumed in logistics operations, which is crucial in terms of reducing environmental externalities (Soysal et al., 2012). To the best of our knowledge, the only study that considers fuel consumption in this context is by Crainic et al. (2012), who employ a generalized travel cost function comprising fixed costs for the arcs, operational costs, and environmental

costs. They assess the effect of traffic congestion on travel cost by conducting analyses on different scenarios which vary according to the day-period (time zone) in which vehicles travel. They assume that each day-period has different arc travel costs and all delivery operations are carried out within the same day-period. Therefore, the travel cost of an arc changes in different scenarios, but remains same within each scenario. This approach of changing travel costs according to the day-period in each scenario obviously cannot handle problems with multiple time zones. For instance, there might be an initial congestion period followed by a non-congestion period during the planning horizon. This requires a consideration of the transition period between periods of congested and free-flow traffic. Such changes in arc travel cost within the same planning horizon or transition period between different time zones were not addressed by Crainic et al. (2012).

There exist other studies on the more standard versions of the VRP with an explicit consideration of environmental issues, such as fuel consumption or emissions. The standard VRP and its variants have been extensively studied in the literature, but only relatively few papers have looked at fuel consumption or emissions in the routing decisions. The interested reader is referred to the reviews by Demir et al. (2014b) and Lin et al. (2014) on the topic. We present a short comparison of such studies given in Table 4.1, differentiated with respect to the following factors taken into account in estimating fuel consumption or emissions: (i) distance traveled, (ii) vehicle load, (iii) vehicle speed and (iv) time-dependent speed profiles.

TABLE 4.1: Studies on VRPs that have fuel consumption or emissions considerations

Studies	Distance trav.	Vehicle load	Vehicle speed	Time-dep. speed
Hsu et al. (2007)	✓	✓	✓	✓
Kara et al. (2007)	✓	✓	-	-
Apaydin and Gonullu (2008)	✓	-	-	-
Tavares et al. (2008)	✓	✓	-	-
Tavares et al. (2009)	✓	✓	✓	-
Kuo (2010)	✓	✓	✓	✓
Figliozzi (2010)	✓	-	✓	✓
Maden et al. (2010)	✓	-	✓	✓
Bektaş and Laporte (2011)	✓	✓	✓	-
Figliozzi (2011)	✓	-	✓	✓
Kuo and Wang (2011)	✓	✓	✓	-
Suzuki (2011)	✓	✓	✓	-
Ubeda et al. (2011)	✓	✓	-	-
Crainic et al. (2012)	✓	-	✓	-
Demir et al. (2012)	✓	✓	✓	-
Erdogan and Miller-Hooks (2012)	✓	-	-	-
Jabali et al. (2012)	✓	-	✓	✓
Jemai et al. (2012)	✓	-	-	-
Xiao et al. (2012)	✓	✓	-	-
Eguia et al. (2013)	✓	✓	✓	-
Franceschetti et al. (2013)	✓	✓	✓	✓
Gajanand and Narendran (2013)	✓	✓	✓	-
Kwon et al. (2013)	✓	-	-	-
Pradenas et al. (2013)	✓	✓	✓	-
Ramos et al. (2014)	✓	✓	✓	-
Demir et al. (2014a)	✓	✓	✓	-

According to Table 4.1, all studies take traveled distance into account in estimating the fuel consumption or emissions. However, although, vehicle load and speed are regarded as significant factors affecting fuel consumption and emissions[4] (Demir et al., 2011; Ligterink et al., 2012), not all studies presented in Table 4.1 have taken these factors into account. Some of the studies that employed vehicle speed have considered non-constant travel times between the nodes as well. In these studies, travel speed between the same two nodes can change due to the time of travel (e.g., rush hour or not) and locations of nodes (e.g., urban or rural area).

Our brief review shows that most studies presented in Table 4.1 have not taken all four aforementioned factors into account simultaneously with the exception of Hsu et al. (2007), Kuo (2010) and Franceschetti et al. (2013). These studies, however, consider a single-echelon VRP. Other differences between this study and others are as follows. Hsu et al. (2007) assume that some links in the network have traffic congestion with known probabilities, and do not deal with multiple time zones and use expected travel times. Kuo (2010) proposes a heuristic algorithm for finding the vehicle routes, and the approach therefore does not guarantee optimality. Moreover, fuel consumption amounts are only estimated linearly. In particular, while incorporating load of the vehicles into the fuel consumption estimations, they assume that an extra load in the vehicle would increase fuel consumption by a predetermined percentage. Finally, a recent study by Franceschetti et al. (2013) propose an integer linear programming model for a VRP by considering two time zones starting with an initial congestion period and followed by a free-flow period.

4.3 Problem description

The problem studied here is defined on a complete graph $G = \{V, A \cup A'\}$, where the set of nodes $V = \{V_0 \cup V_S \cup V_C\}$ consists of three subsets: a depot ($V_0 = \{0\}$), a set of satellites (V_S) and a set of customers (V_C). The set of arcs consists of two subsets: those in the first-echelon $A = A(V_0 \cup V_S)$ and in the second-echelon $A' = A(V_S \cup V_C)$ where $A(S)$, $S \subset V$ is the set of all arcs with both endpoints in S. Time-dependent travel times are considered to account for traffic congestion effects when traveling on arcs $(i, j) \in A'_c \subseteq A'$. The index set of first-echelon vehicles located at the depot is $K = \{1, 2..., k\}$, each vehicle with capacity c. Freight is delivered to satellites from the depot through these vehicles. Each satellite can be served by more than one first-echelon

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[4]http://www.goodyear.com/truck/pdf/commercialtiresystems/FuelEcon.pdf,Onlineaccessed: February2013

vehicle, so the total freight assigned to each satellite can be split into two or more vehicles. A fleet of k'_s identical vehicles of capacity $c' < c$ are available at each satellite $s \in V_S$ for serving the customers, where each customer has a known nonnegative demand q_i to be delivered. The total number of second-echelon vehicles is $k' = \sum_{s \in V_S} k'_s$. The demand of each customer cannot be split among different vehicles and each customer is visited exactly once by a second-echelon route. Additionally, each customer has a service time shown by h_i. As in the standard VRP, waiting at customers is not allowed after service has been completed. The distance between two nodes $(i, j) \in A \cup A'$ is denoted by d_{ij}. The unit handling cost of freight in satellite $s \in V_S$ is given as b_s.

The aim of the problem in this study is to determine the first and second echelon routes for all vehicles by respecting the assumptions stated above so as to minimize the total cost of travel and handling. Travel cost includes that of driver and fuel consumption, calculated for each arc in the network. Let w denote the wage for the drivers and p denote the fuel price per liter. The driver of each vehicle is paid from the beginning of the time horizon until the time they return to the starting point. Fuel consumption is mainly dependent on speed, load and distance. The following sections explain the calculation of time-dependent travel times and fuel consumption in greater detail.

4.3.1 Time dependency

The travel time of a vehicle depends on distance, where speed changes according to the departure time and the arc being traversed. Vehicles travel at a free-flow speed f in the first-echelon. The vehicle traversing a congested arc $(i, j) \in A'_c$ has different travel speeds s_l, $l \in T = \{1, 2, 3..., T_e\}$ according to the time zone T in which it travels. Figure 4.2a shows an example of speed profiles for four-time zones. The rest of the arcs, $(i, j) \in A' \backslash A'_c$, are defined as non-congested, for which speed is constant and denoted f' (Figure 4.2b).

(a) For arcs $(i, j) \in A'_c$ (second-echelon)   (b) For arcs $(i, j) \in A' \backslash A'_c$ (second-echelon)
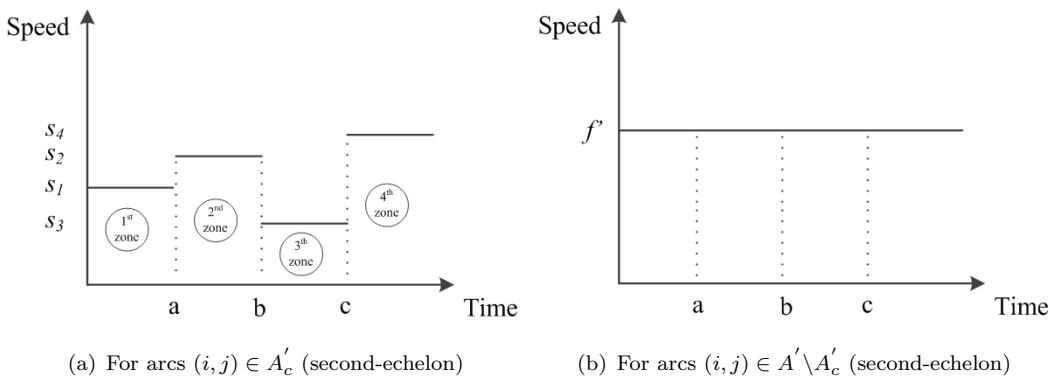
FIGURE 4.2: An example of speed profiles for four-time zones

4.3.2 Fuel consumption and emissions

We employ the same approach as in Bektaş and Laporte (2011), Demir et al. (2012) and Franceschetti et al. (2013) for estimating fuel consumption and emissions that is based on the comprehensive emissions model of Barth et al. (2005). According to this model, the total amount of fuel used *Fuel* (liters) for traversing a distance *distance* (m) at constant speed *speed* (m/s) with load *load* (kg) is calculated as follows:

$$Fuel = \lambda\left(kN_eV\frac{distance}{speed} + \gamma\beta distance(speed)^2 + \gamma\alpha(\mu + load)distance\right)$$

where $\lambda = \frac{\xi}{\kappa\psi}$, $\gamma = \frac{1}{1000\varepsilon\varpi}$, $\beta = 0.5C_dA\rho$, and $\alpha = g\sin\phi + gC_r\cos\phi$. Furthermore, k is the engine friction factor (kJ/rev/liter), N_e is the engine speed (rev/s), V is the engine displacement (liter), μ is the vehicle curb weight (kg), g is the gravitational constant (9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, A is the frontal surface area (m^2), ρ is the air density (kg/m^3), ε is vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines, ξ is fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s). For further details on these parameters, the reader is referred to Demir et al. (2011).

4.3.3 A mixed integer linear programming formulation

This section presents a comprehensive mixed integer linear programming formulation for the studied problem. This formulation is based on the model proposed by Jepsen et al. (2013) for the 2E-CVRP, but extends it to account for the time-dependent speeds and the amount of fuel consumed. The full notation that is needed for the model is presented in Table 4.2.

We now present the formulation, starting with the objective function.

$$Minimize \sum_{(i,j)\in A}\sum_{k\in K}\left(\lambda_1\big(\omega_1(d_{ij}/f)X_{ijk} + \upsilon_1 d_{ij}f^2 X_{ijk} + \varrho_1(\mu_1 X_{ijk} + I_{ijk})d_{ij}\big)\right)p \qquad (4.\text{i})$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}(d_{ij}/f)X_{ijk}w \qquad (4.\text{ii})$$

$$+ \sum_{s\in V_S}T_s b_s \qquad (4.\text{iii})$$

$$+ \sum_{(i,j)\in A'\backslash A'_c}\sum_{s\in V_S}\left(\lambda_2\big(\omega_2 G_{ijs} + \upsilon_2 G_{ijs}f'^3 + \varrho_2(\mu_2 Z_{ijs} + F_{ijs})d_{ij}\big)\right)p \qquad (4.\text{iv})$$

$$+ \sum_{(i,j)\in A'_c}\sum_{s\in V_S}\sum_{m\in T}\left(\lambda_2\big(\omega_2((d_{ij}/s_m)N^{mm}_{ijs}) + \upsilon_2((d_{ij}/s_m)N^{mm}_{ijs})s_m^3 + \varrho_2(\mu_2 N^{mm}_{ijs} + E^{mm}_{ijs})d_{ij}\big)\right)p \qquad (4.\text{v})$$

TABLE 4.2: Parameters and decision variables

Symbol	Meaning
$\delta^-(s)$	entering first-echelon arcs of satellite $s \in V_S$,
$\delta^+(s)$	leaving first-echelon arcs of satellite $s \in V_S$,
$\delta^{'-}(i)$	entering second-echelon arcs of node $i \in V_S \cup V_C$,
$\delta^{'+}(i)$	leaving second-echelon arcs of node $i \in V_S \cup V_C$,
M_i	sufficiently large numbers, $i \in \{1, 2\}$
c	capacity of vehicles in first-echelon,
c'	capacity of vehicles in second-echelon,
k'_s	vehicle limit in satellite $s \in V_S$,
k'	total size of the second-echelon vehicles, is equal to $\sum_{s \in V_S} k'_s$,
q_i	demand of customer $i \in V_C$,
d_{ij}	distance between two nodes $i \neq j \in V$,
b_s	unit handling cost of freight in satellite $s \in V_S$,
h_i	service time in customer $i \in V_C$,
t_l	ending time of zone $l \in T \backslash \{T_e\}$,
s_l	travel speed in time zone $l \in T$,
f	free-flow speed in first-echelon,
f'	free-flow speed in second-echelon,
z_l	max distance that can be traveled in time zone $l \in T \backslash \{1, T_e\}$, $z_l = (t_l - t_{l-1})s_l \quad \forall l \in T \backslash \{1, T_e\}$,
e_l	is calculated as follows, $e_l = (t_l - t_{l-1})s_l^3 \quad \forall l \in T \backslash \{1, T_e\}$,
ω_j	technical parameter, $k_j N_e^j V_j$, for vehicle in echelon $j \in \{1, 2\}$,
v_j	technical parameter, $\gamma_j \beta_j$, for vehicle in echelon $j \in \{1, 2\}$,
ϱ_j	technical parameter, $\gamma_j \alpha_j$, for vehicle in echelon $j \in \{1, 2\}$,
λ_j	technical parameter, $\xi_j / \kappa_j \psi_j$, for vehicle in echelon $j \in \{1, 2\}$,
μ_j	curb-weight of vehicle in echelon $j \in \{1, 2\}$,
p	fuel price per liter,
w	wage rate for the drivers of the vehicles,
X_{ijk}	binary variable equal to 1 if first-echelon vehicle $k \in K$ goes from $i \in V_0 \cup V_S$ to $j \in V_0 \cup V_S$, and 0 otherwise,
W_{sk}	the amount of freight delivered to satellite $s \in V_S$ by vehicle $k \in K$,
T_s	total demand delivered from satellite $s \in V_S$,
Z_{ijs}	binary variable equal to 1 if second-echelon vehicle from satellite $s \in V_S$ goes from $i \in V_S \cup V_C$ to $j \in V_S \cup V_C$, and 0 otherwise,
F_{ijs}	the load on a vehicle from satellite $s \in V_S$ when leaving node $i \in V_S \cup V_C$,
E_{ijs}^{mn}	the load on a vehicle from satellite $s \in V_S$ when leaving node $i \in V_S \cup V_C$, and departure and arrival times are in zones $m, n \in \{T | n \geq m\}$ respectively,
I_{ijk}	the load on a vehicle $k \in K$ when leaving node $i \in V_0 \cup V_S$,
D_{ijs}	departure time from node $i \in V_S \cup V_C$ when departure node is $j \in V_S \cup V_C$, and vehicle origin is $s \in V_S$,
H_{ijs}^{mn}	departure time from node $i \in V_S \cup V_C$ when departure node is $j \in V_S \cup V_C$, and vehicle origin is $s \in V_S$, and departure and arrival times are in zones $m, n \in \{T | n \geq m\}$ respectively,
G_{ijs}	travel time between node $i \in V_S \cup V_C$ and $j \in V_S \cup V_C$ for the vehicle that has an origin $s \in V_S$,
R_i	time at which service starts at node $i \in V_C$,
S_{is}	total time spent on a route that has node $i \in V_C$ as last visited before returning to a satellite $s \in V_S$,
P_{ijs}^m	binary variable equal to 1 if departure time of a vehicle that has an origin $s \in V_S$ to traverse arc $(i, j) \in A'_c$ is higher than the $t_m, m \in T \backslash \{T_e\}$, and 0 otherwise,
L_{ijs}^m	binary variable equal to 1 if time zone during departure for a vehicle that has an origin $s \in V_S$ to traverse arc $(i, j) \in A'_c$ is $m \in T \cup \{0\}$, and 0 otherwise,
Y_{ijs}^{mn}	binary variable equal to 1 if departure time for a vehicle that has an origin $s \in V_S$ is earlier than $t_m, m \in T \backslash \{T_e\}$ and arrival time is later than $t_n, n \in \{T \backslash \{T_e\} | n \geq m\}$ while traversing the arc $(i, j) \in A'_c$, and 0 otherwise,
B_{ijs}^{mn}	max distance that can be traversed on arc $(i, j) \in A'_c$ before $t_n, n \in \{T \backslash \{T_e\} | n \geq m\}$ while departure time is earlier than $t_m, m \in \{T \backslash \{T_e\}\}$, for a vehicle that has an origin $s \in V_S$,
N_{ijs}^{mn}	binary variable equal to 1 if departure and arrival times for a vehicle that has an origin $s \in V_S$ are in zones $m, n \in \{T | n \geq m\}$ respectively, while traversing the arc $(i, j) \in A'_c$, and 0 otherwise,
A_{ijs}^{mn}	travel time of a vehicle that has an origin $s \in V_S$ for the arc $(i, j) \in A'_c$ when departure and arrival times are in zones $m, n \in \{T | n \geq m\}$ respectively,

$$+ \sum_{(i,j)\in A'_c} \sum_{s\in V_S} \sum_{m\in T\setminus\{T_e\}} \sum_{n\in T, n>m} \left(\lambda_2 \left(\omega_2 A_{ijs}^{mn} + \upsilon_2((t_m N_{ijs}^{mn} - H_{ijs}^{mn})s_m^3 \right.\right.$$

$$+ \sum_{p=m+1}^{p<n} e_p N_{ijs}^{mn} + (H_{ijs}^{mn} + A_{ijs}^{mn} - t_{n-1}N_{ijs}^{mn})s_n^3) + \varrho_2(\mu_2 N_{ijs}^{mn} + E_{ijs}^{mn})d_{ij} \Big) \Big) p \tag{4.vi}$$

$$+ \sum_{i\in V_C} \sum_{s\in V_S} S_{is}w. \tag{4.vii}$$

$$\tag{4.1}$$

The objective function (4.1) comprises seven parts: (4.i) fuel cost for the first-echelon, (4.ii) driver cost for the first-echelon, (4.iii) handling fee in the satellites, (4.iv) fuel cost for the non-congested arcs in the second-echelon, (4.v) fuel cost for the congested arcs in the second-echelon if departure and arrival times are in the same time zone, (4.vi) fuel cost for the congested arcs in the second-echelon, if departure and arrival times are in different time zones, (4.vii) driver cost for the second-echelon.

$$\sum_{(i,j)\in\delta^+(s)} X_{ijk} = \sum_{(i,j)\in\delta^-(s)} X_{ijk}, \qquad \forall s \in V_S, k \in K \tag{4.2}$$

$$\sum_{(i,j)\in\delta^+(s)} X_{ijk} \le 1, \qquad \forall s \in V_0 \cup V_S, k \in K \tag{4.3}$$

$$\sum_{(i,j)\in\delta^+(s)} I_{ijk} = \sum_{(i,j)\in\delta^-(s)} I_{ijk} - W_{i,k}, \qquad \forall s \in V_S, k \in K \tag{4.4}$$

$$I_{ijk} \le cX_{ijk}, \qquad \forall (i,j) \in A, k \in K \tag{4.5}$$

$$\sum_{(i,j)\in\delta^-(s)} I_{ijk} \le 0, \qquad \forall s \in V_0, k \in K. \tag{4.6}$$

Constraints (4.2) to (4.6) relate to the first-echelon. In particular, constraints (4.2) ensure flow conservation for each vehicle at each satellite, constraints (4.3) ensure that a vehicle visits a satellite at most once, and constraints (4.4) to (4.6) model the flow on each arc and ensure that vehicle capacities are respected.

$$\sum_{k\in K} W_{sk} = T_s, \qquad \forall s \in V_s. \tag{4.7}$$

Constraints (4.7) link the delivery from all first-echelon vehicles with the total demand delivered from each satellite.

$$\sum_{s\in V_S} \sum_{(a,b)\in\delta'+(i)} Z_{abs} = 1, \qquad \forall i \in V_C \tag{4.8}$$

$$\sum_{(a,b)\in\delta'-(i)} Z_{abs} = \sum_{(a,b)\in\delta'+(i)} Z_{abs}, \qquad \forall i \in V_C, s \in V_S \tag{4.9}$$

$$\sum_{s'\in V_S\setminus\{s\}} \left(\sum_{(a,b)\in\delta'+(s)} Z_{abs'} + \sum_{(a,b)\in\delta'-(s)} Z_{abs'} \right) = 0, \qquad \forall s \in V_S \tag{4.10}$$

$$\sum_{(a,b)\in\delta'+(s)} Z_{abs} \le k'_s, \qquad \forall s \in V_S \tag{4.11}$$

$$\sum_{s \in V_S} \sum_{(a,b) \in \delta'^+(s)} Z_{abs} \leq k', \tag{4.12}$$

$$\sum_{s \in V_S} \sum_{(a,b) \in \delta'^+(i)} F_{abs} = \sum_{s \in V_S} \sum_{(a,b) \in \delta'^-(i)} F_{abs} - q_i, \qquad \forall i \in V_C \tag{4.13}$$

$$F_{abs} \leq c' Z_{abs}, \qquad \forall s \in V_S, (a,b) \in A' \tag{4.14}$$

$$T_s = \sum_{(a,b) \in \delta'^+(i)} F_{abs}, \qquad \forall s \in V_S \tag{4.15}$$

$$\sum_{s \in V_S} T_s = \sum_{i \in V_C} q_i, \tag{4.16}$$

$$\sum_{(i,j) \in \delta'^+(s)} D_{ijs} = 0, \qquad \forall s \in V_S \tag{4.17}$$

$$\sum_{(i,j) \in \delta'^-(i)} \sum_{s \in V_S} (D_{ijs} + G_{ijs}) = R_i, \qquad \forall i \in V_C \tag{4.18}$$

$$\sum_{(i,j) \in \delta'^+(i)} \sum_{s \in V_S} D_{ijs} = R_i + h_i, \qquad \forall i \in V_C \tag{4.19}$$

$$D_{iss} + G_{iss} \leq S_{is}, \qquad \forall i \in V_C, s \in V_S \tag{4.20}$$

$$D_{ijs} \leq M_2 Z_{ijs}, \qquad \forall (i,j) \in A', s \in V_S. \tag{4.21}$$

Constraints (4.8) to (4.21) relate to the second-echelon. Constraints (4.8) ensure that each customer is visited exactly once. Constraints (4.9) ensure conservation of the vehicle origin at each customer. Constraints (4.10) eliminate traffic between the satellites. Constraints (4.11) and (4.12) ensure that the number of vehicles used is not more than the available vehicles. Constraints (4.13) and (4.14) model the flow on each arc and ensure that vehicle capacities are respected. Constraints (4.15) ensure flow balance at each satellite. Constraints (4.16) ensure that total demand is equal to total amount delivered from all satellites. Constraints (4.17) initialize the departure time from the satellites as 0. Constraints (4.18) and (4.19) are used to model the relationship between departure and arrival times at each customer. Constraints (4.20) compute the time at which the vehicle returns to the satellite. Constraints (4.21) are used to set departure times to zero for arcs that do not exist in the route.

$$G_{ijs} = (d_{ij}/f') Z_{ijs}, \quad \forall (i,j) \in A' \backslash A'_c, s \in V_S. \tag{4.22}$$

Constraints (4.22) measure the travel time for the non-congested second-echelon arcs $(i,j) \in A' \backslash A'_c$ that exist in the route.

$$M_2(1 - P^m_{ijs}) + D_{ijs} \geq t_m, \qquad \forall (i,j) \in A'_c, s \in V_S, m \in T \backslash \{T_e\} \tag{4.23}$$

$$D_{ijs} < t_m + P^m_{ijs} M_2, \qquad \forall (i,j) \in A'_c, s \in V_S, m \in T \backslash \{T_e\} \tag{4.24}$$

$$\sum_{m \in T \backslash \{T_e\}} P^m_{ijs} + Z_{ijs} = \sum_{m \in T} m L^m_{ijs}, \qquad \forall (i,j) \in A'_c, s \in V_S \tag{4.25}$$

$$\sum_{m \in T \cup \{0\}} L^m_{ijs} = 1, \qquad \forall (i,j) \in A'_c, s \in V_S. \tag{4.26}$$

Constraints (4.23) to (4.26) compute the time zone when the vehicles depart from node

$i \in V_S \cup V_C$ to node $j \in V_S \cup V_C$, where $(i,j) \in A'_c$, by considering the departure time from node $i \in V_S \cup V_C$ and ending times of zones $m \in T \backslash \{T_e\}$.

$$B_{ijs}^{mn} = \left((t_m L_{ijs}^m - D_{ijs})s_m + \sum_{p=m+1}^{p \leq n} z_p L_{ijs}^m \right) + M_1(1 - L_{ijs}^m), \forall (i,j) \in A'_c, s \in V_S, m, n \in \{T \backslash \{T_e\}|n \geq m\}. \tag{4.27}$$

Constraints (4.27) are used to compute bounds, which are necessary to calculate the time zone when the vehicles arrive at node $j \in V_S \cup V_C$ from node $i \in V_S \cup V_C$, where $(i,j) \in A'_c$. These bounds show the maximum distance that can be traversed before the end of each zone by considering the departure time from node $i \in V_S \cup V_C$ and ending times of zones $m \in T \backslash \{T_e\}$.

$$M_1(1 - Y_{ijs}^{mn}) + d_{ij} \geq B_{ijs}^{mn}, \quad \forall (i,j) \in A'_c, s \in V_S, m, n \in \{T \backslash \{T_e\}|n \geq m\} \tag{4.28}$$

$$d_{ij} < B_{ijs}^{mn} + Y_{ijs}^{mn} M_1, \quad \forall (i,j) \in A'_c, s \in V_S, m, n \in \{T \backslash \{T_e\}|n \geq m\} \tag{4.29}$$

$$\sum_{n \in T \backslash \{T_e\}, n \geq m} Y_{ijs}^{mn} + L_{ijs}^m m = \sum_{n \in T, n \geq m} n N_{ijs}^{mn}, \quad \forall (i,j) \in A'_c, s \in V_S, m \in T \backslash \{T_e\} \tag{4.30}$$

$$\sum_{n \in T \cup \{T_{e+1}\}, n \geq m} N_{ijs}^{mn} = 1, \quad \forall (i,j) \in A'_c, s \in V_S, m \in T \backslash \{T_e\}. \tag{4.31}$$

Constraints (4.28) to (4.31) compute the time zone when the vehicles arrive at node $j \in V_S \cup V_C$ from node $i \in V_S \cup V_C$, where $(i,j) \in A'_c$, by considering the departure time from node $i \in V_S \cup V_C$ and ending times of zones $m, n \in T \backslash \{T_e\}$.

$$E_{ijs}^{mn} \leq N_{ijs}^{mn} c', \quad \forall (i,j) \in A'_c, s \in V_S, m, n \in \{T|n \geq m\} \tag{4.32}$$

$$\sum_{m \in T} \sum_{n \in \{T|n \geq m\}} E_{ijs}^{mn} = F_{ijs}, \quad \forall (i,j) \in A'_c, s \in V_S \tag{4.33}$$

$$H_{ijs}^{mn} \leq N_{ijs}^{mn} M_2, \quad \forall (i,j) \in A'_c, s \in V_S, m, n \in \{T|n \geq m\} \tag{4.34}$$

$$\sum_{m \in T} \sum_{n \in \{T|n \geq m\}} H_{ijs}^{mn} = D_{ijs}, \quad \forall (i,j) \in A'_c, s \in V_S. \tag{4.35}$$

Constraints (4.32) to (4.35) compute the dependent decision variables E_{ijs}^{mn} and H_{ijs}^{mn}, which are used to calculate travel time and fuel consumption amounts.

$$N_{ijs}^{T_e T_e} = L_{ijs}^{T_e}, \quad \forall (i,j) \in A'_c, s \in V_S \tag{4.36}$$

$$A_{ijs}^{mn} = (t_{n-1} N_{ijs}^{mn} - H_{ijs}^{mn}) + \left(d_{ij} N_{ijs}^{mn} - ((t_m N_{ijs}^{mn} - H_{ijs}^{mn})s_m + \sum_{p=m+1}^{p<n} z_p N_{ijs}^{mn}) \right) / s_n,$$

$$\forall (i,j) \in A'_c, s \in V_S, m \in T \backslash \{T_e\}, n \in \{T|n > m\} \tag{4.37}$$

$$\sum_{m \in T \backslash \{T_e\}} \sum_{n \in T, n>m} A_{ijs}^{mn} + \sum_{m \in T} (d_{ij}/s_m) N_{ijs}^{mm} = G_{ijs}, \quad \forall (i,j) \in A'_c, s \in V_S. \tag{4.38}$$

Constraints (4.36) to (4.38) compute the travel time for the congested second-echelon arcs $(i,j) \in A_c'$ by considering time zones during departure and arrival.

$$X_{ijk} \in \{0,1\}, \qquad \forall(i,j) \in A, k \in K \tag{4.39}$$

$$Z_{ijs} \in \{0,1\}, \qquad \forall(i,j) \in A', s \in V_S \tag{4.40}$$

$$P_{ijs}^m \in \{0,1\}, \qquad \forall(i,j) \in A', s \in V_S, m \in T\backslash\{T_e\} \tag{4.41}$$

$$L_{ijs}^m \in \{0,1\}, \qquad \forall(i,j) \in A', s \in V_S, m \in T \cup \{0\} \tag{4.42}$$

$$Y_{ijs}^{mn} \in \{0,1\}, \qquad \forall(i,j) \in A', s \in V_S, m,n \in \{T\backslash\{T_e\}|n \geq m\} \tag{4.43}$$

$$N_{ijs}^{mn} \in \{0,1\}, \qquad \forall(i,j) \in A', s \in V_S, m,n \in \{T|n \geq m\} \tag{4.44}$$

$$W_{sk} \geq 0, \qquad \forall s \in V_S, k \in K \tag{4.45}$$

$$T_s \geq 0, \qquad \forall s \in V_S \tag{4.46}$$

$$F_{ijs}, D_{ijs}, G_{ijs} \geq 0, \qquad \forall(i,j) \in A', s \in V_S \tag{4.47}$$

$$R_i \geq 0, \qquad \forall i \in V_C \tag{4.48}$$

$$S_{is} \geq 0, \qquad \forall i \in V_C, s \in V_S \tag{4.49}$$

$$I_{ijk} \geq 0, \qquad \forall(i,j) \in A, k \in K \tag{4.50}$$

$$E_{ijs}^{mn}, H_{ijs}^{mn}, A_{ijs}^{mn} \geq 0, \qquad \forall(i,j) \in A', s \in V_S, m,n \in \{T|n \geq m\} \tag{4.51}$$

$$B_{ijs}^{mn} \geq 0, \qquad \forall(i,j) \in A', s \in V_S, m,n \in \{T\backslash\{T_e\}|n \geq m\}. \tag{4.52}$$

Constraints (4.39) to (4.52) represent the binary and nonnegativity restrictions imposed on the decision variables.

4.3.4 Strengthening the MILP model

This section presents three groups of valid inequalities to tighten the formulation and accelerate the convergence to an optimal solution. The first set of simple valid inequalities is on the binary variables and is as follows:

$$Z_{ijs} \geq P_{ijs}^m, \qquad \forall(i,j) \in A_c', s \in V_S, m \in T\backslash\{T_e\} \tag{4.53}$$

$$Z_{ijs} \geq L_{ijs}^m, \qquad \forall(i,j) \in A_c', s \in V_S, m \in T\backslash\{T_e\} \tag{4.54}$$

$$Z_{ijs} \geq Y_{ijs}^{mn}, \quad \forall(i,j) \in A_c', s \in V_S, m,n \in \{T\backslash\{T_e\}|n \geq m\} \tag{4.55}$$

$$Z_{ijs} \geq N_{ijs}^{mn}, \quad \forall(i,j) \in A_c', s \in V_S, m,n \in \{T\backslash\{T_e\}|n \geq m\}. \tag{4.56}$$

Constraints (4.53) to (4.56) represent the relationships between the given binary variables, specifically, if a second-echelon vehicle from satellite $s \in V_S$ does not use the route from $i \in V_S \cup V_C$ to $j \in V_S \cup V_C$, the binary variables ($P_{ijs}^m, L_{ijs}^m, Y_{ijs}^{mn}$, and N_{ijs}^{mn}), which are used to calculate related travel time and fuel consumption in the congested second-echelon arcs $(i,j) \in A_c'$, take the value of 0.

The second set of valid inequalities are on the routing variables, and are presented as follows:

$$X_{ijk} + X_{jik} \leq 1, \quad \forall (i,j) \in \{A | i,j \in V_S\}, k \in K \tag{4.57}$$

$$Z_{ijs} + Z_{jis} \leq 1, \quad \forall (i,j) \in \{A' | i,j \in V_C\}, s \in V_S. \tag{4.58}$$

Constraints (4.57) and (4.58) represent both way flow restrictions on arcs $(i,j) \in \{A | i,j \in V_S\}$ and $(i,j) \in \{A' | i,j \in V_C\}$.

The last set of valid inequalities is related to network flows, and is presented as follows:

$$q_j Z_{ijs} \leq F_{ijs}, \qquad \forall (i,j) \in A', s \in V_S \tag{4.59}$$

$$F_{ijs} \leq (c' - q_i) Z_{ijs}, \qquad \forall (i,j) \in A', s \in V_S \tag{4.60}$$

$$F_{ijs} - \sum_{l \in V_C \cup V_S, l \neq i} F_{jls} \leq q_j Z_{ijs}, \quad \forall i \in V_C \cup V_S, j \in V_C, s \in V_S. \tag{4.61}$$

Constraints (4.59) and (4.60) are restrictions on the total load a vehicle carries by its capacity (Bektaş and Laporte, 2011). Constraints (4.61) model the relationship between each incoming flow and outgoing flows at nodes $i \in V_S \cup V_C$ (Perboli et al., 2010). Our preliminary experimentation has shown that significant reductions in computational time can be obtained from the use of these additional constraints (4.53)–(4.61), as will be shown in the next section.

4.4   Case study

This section presents an implementation of the proposed model on the distribution operations of a supermarket chain operating in the Netherlands. We first describe the data used, then present the results.

4.4.1   Description and data

The underlying transportation network includes one depot, two satellites and 16 supermarket branches (customers) as presented in Figure 4.3. The depot is located in Zaandam. The customers are located in the city center of Utrecht, and satellites are located at the boundary of the city.

There exist two types of vehicles. Large vehicles are used for the deliveries between the depot and the satellites, each with a capacity of 20 tonnes. Small vehicles are used for the deliveries between the satellites and the customers, each with a capacity of 10 tonnes. The parameters used to calculate the total fuel consumption cost are taken from Demir
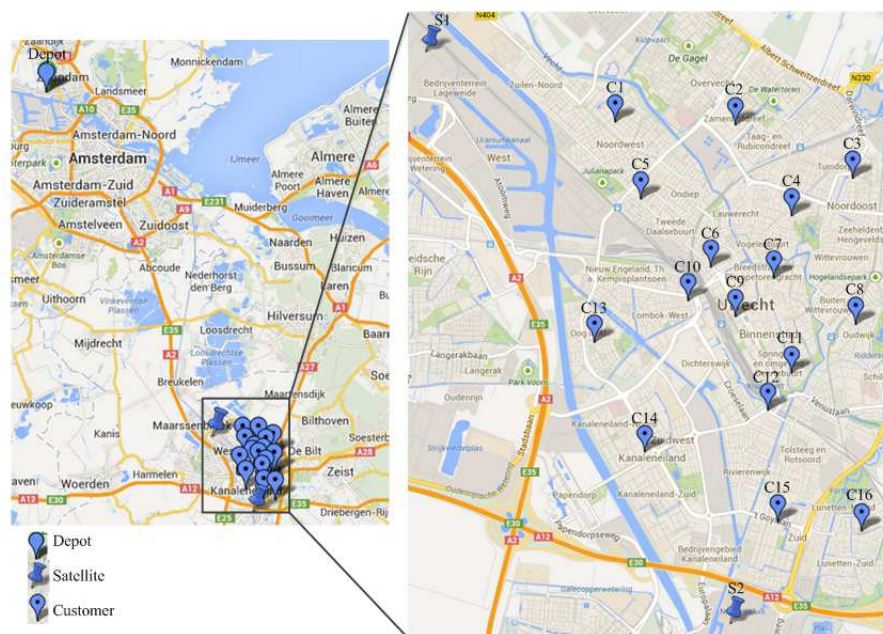
FIGURE 4.3: Representation of the logistics network

et al. (2012) and are given in Table 4.3. It is assumed that small vehicles differ from the large ones in terms of the frontal surface area and curb-weight. For small vehicles, the frontal surface area is 2.5m^2 and the curb weight is 4000kg. For large vehicles, these values are 3.912m^2 and 6350kg, respectively.

TABLE 4.3: Setting of vehicle and emission parameters

Notation	Description	Value
ξ	fuel-to-air mass ratio	1
κ	heating value of a typical diesel fuel (kJ/g)	44
ψ	conversion factor (g/liter)	737
k	engine friction factor (kJ/rev/liter)	0.2
N_e	engine speed (rev/s)	33
V	engine displacement (liter)	5
ρ	air density (kg/m^3)	1.2041
A	frontal surface area (m^2)	3.912
μ	curb-weight (kg)	6350
g	gravitational constant (m/s^2)	9.81
ϕ	road angle	0
C_d	coefficient of aerodynamic drag	0.7
C_r	coefficient of rolling resistance	0.01
ε	vehicle drive train efficiency	0.4
ϖ	efficiency parameter for diesel engines	0.9
p	fuel price per liter (€)	1.7
w	driver wage (€/s)	0.003

Vehicles travel at a fixed speed of 80 km/h between the depot and the satellites. Delivery starts at the same time from a peak-morning period in both satellites. A set of arcs shown in Table 4.4 is assumed to be congested based on the traffic data provided by the Google Maps[5]. The rest of the arcs in the second-echelon are defined to be non-congested and vehicles travel at a free-flow speed in these arcs. We assume that there is an initial period

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[5]http://maps.google.nl/,Onlineaccessed:August2013

of congestion in the congested arcs lasting for an hour[6], followed by a period of free-flow. In the peak period vehicles travel at an average speed of 20 km/h, whereas in the period that follows vehicles travel at an average free-flow speed of 40 km/h.

TABLE 4.4: Congested arcs in the second echelon

From	To	From	To
C1	S1	C11	C9
C2	C4	C12	C8
C2	C3	C12	C9
C3	C4	C12	S2
C3	C7	C13	C14
C3	C2	C14	C15
C4	C2	C14	C13
C4	C3	C14	C10
C5	S1	C14	S2
C7	C3	C15	C14
C8	C12	S1	C1
C9	C11	S2	C12
C9	C12	S2	C14
C10	C14		

Demand is generated randomly for purposes of sensitivity analysis as will be shown in the following section. For the base case, demand (kg) is (2000, 4500, 1500, 3500, 1500, 2500, 1000, 3000, 1500, 3000, 4000, 1000, 500, 1000, 500, 2000) for customers C1–C16, respectively. Distances between nodes (see Table 4.A in the appendix) are calculated using Google Maps[5]. Handling cost at satellites one and two are three and two €/tonne respectively. Service times at customer nodes are assumed to be 10 minutes, regardless of the amount of delivery.

4.4.2 Analysis and discussion

The ILOG-OPL development studio and CPLEX 12.2 optimization package has been used to develop and solve formulation (4.1)–(4.52) for the case study. The resulting model has 2327 continuous and 1106 binary variables, and 3022 constraints. Optimal solutions were obtained on a computer of Pentium(R) i5 2.4GHz CPU with 3GB memory. We focused on four KPIs: (i) total distance, (ii) total time, (iii) total fuel consumption, and (iv) total cost. The proposed model was minimized over each KPI. Each model uses the same set of constraints as shown by (4.2)–(4.52), but has a different objective function as discussed below.

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[6]http://www.forbes.com/sites/jimgorzelany/2013/04/25/the-worlds-most-traffic-congested-cities/,Onlineaccessed:September2014

4.4.2.1 Comparison of different objectives

To obtain a distance-minimizing solution, the following function has been used,

$$Minimize \sum_{(i,j)\in A}\sum_{k\in K} d_{ij}X_{ijk} + \sum_{(i,j)\in A'}\sum_{s\in V_S} d_{ij}Z_{ijs}. \tag{4.62}$$

which minimizes the combined distances traveled in the first and second echelons.

To obtain a time-minimizing solution, the following function has been used,

$$Minimize \sum_{(i,j)\in A}\sum_{k\in K} (d_{ij}/f)X_{ijk} + \sum_{s\in V_S}\sum_{i\in V_C} S_{is}. \tag{4.63}$$

which minimizes the total travel time in the first and second echelons.

To obtain a fuel-minimizing solution, we use the function below.

$$
\begin{aligned}
Minimize \sum_{(i,j)\in A}\sum_{k\in K}& \left(\lambda_1\big(\omega_1(d_{ij}/f)X_{ijk} + \upsilon_1 d_{ij}f^2 X_{ijk} + \varrho_1(\mu_1 X_{ijk} + I_{ijk})d_{ij}\big) \right) \\
+ \sum_{(i,j)\in A'\setminus A'_c}\sum_{s\in V_S}& \left(\lambda_2\big(\omega_2 G_{ijs} + \upsilon_2 G_{ijs}f'^3 + \varrho_2(\mu_2 Z_{ijs} + F_{ijs})d_{ij}\big) \right) \\
+ \sum_{(i,j)\in A'_c}\sum_{s\in V_S}\sum_{m\in T}& \left(\lambda_2\big(\omega_2((d_{ij}/s_m)N_{ijs}^{mm}) + \upsilon_2((d_{ij}/s_m)N_{ijs}^{mm})s_m^3 + \varrho_2(\mu_2 N_{ijs}^{mm} + E_{ijs}^{mm})d_{ij}\big) \right) \\
+ \sum_{(i,j)\in A'_c}\sum_{s\in V_S}\sum_{m\in T\setminus\{T_e\}}\sum_{n\in T, n>m}& \left(\lambda_2\big(\omega_2 A_{ijs}^{mn} + \upsilon_2((t_m N_{ijs}^{mn} - H_{ijs}^{mn})s_m^3 \right.\\
+ \sum_{p=m+1}^{p<n} & e_p N_{ijs}^{mn} + (H_{ijs}^{mn} + A_{ijs}^{mn} - t_{n-1}N_{ijs}^{mn})s_n^3) + \varrho_2(\mu_2 N_{ijs}^{mn} + E_{ijs}^{mn})d_{ij}\big) \Big).
\end{aligned}
\tag{4.64}
$$

The objective function (4.64) is based on the fuel consumption model presented earlier and minimizes the fuel consumption for both the first and second echelon travels.

To obtain a cost-minimizing solution, we use the original objective function (4.1). In summary, we show the differences between the above presented model variations in Table 4.5.

TABLE 4.5: Differences between the model variations

Model variations	Traveled distance	Vehicle speed or Traffic congestion	Vehicle load	Vehicle type	Fuel price and Wage rate (drivers)	Handling fee
Distance-minimization	✓					
Time-minimization	✓	✓				
Fuel-minimization	✓	✓	✓	✓		
Cost-minimization	✓	✓	✓	✓	✓	✓

We present the resulting routes and comparison results for the four objectives in Table 4.6. In this table, we explicitly present the resulting routes both in the first and the second

echelons, yielded by the four formulations. For each solution, we also report the total distance (m), time (s), fuel (liter) and cost (€), both in absolute units and normalized with respect to the smallest value for each performance indicator (in brackets). A graphical visualization of the normalized data is presented in Figure 4.5 as well.

TABLE 4.6: Distance, time, fuel and cost-minimizing solutions

Routes and KPIs	Distance-minimizing	Time-minimizing	Fuel-minimizing	Cost-minimizing
First echelon	D-S1-D	D-S1-D	D-S1-D	D-S2-D
routes	D-S1-D	D-S2-D	D-S1-D	D-S2-D
	S1-13-14-12-15-16-10-S1	S1-13-5-1-3-2-S1	S1-10-12-15-16-14-13-S1	S2-15-16-8-3-7-12-S2
Second echelon	S1-7-8-11-9-S1	S1-10-6-S1	S1-7-8-11-9-S1	S2-11-S2
routes	S1-4-3-2-S1	S2-9-4-7-8-14-S2	S1-6-4-3-1-S1	S2-10-4-6-14-S2
	S1-1-5-6-S1	S2-11-12-15-16-S2	S1-5-2-S1	S2-9-2-1-5-13-S2
Total distance (m)	288600 (1)	293700 (1.02)	291400 (1.01)	302300 (1.05)
Total time (s)	27795 (1.06)	26211 (1)	26984 (1.03)	26358 (1.01)
Total fuel (liter)	64.23 (1.01)	64.92 (1.02)	63.42 (1)	67.33 (1.06)
Total cost (€)	291.57 (1.12)	270.49 (1.04)	287.76 (1.11)	259.53 (1)

The comparison results shown in Table 4.6 indicate that although distance-minimizing solution performs slightly worse in terms of fuel consumption, it yields significantly higher travel times and cost. The resulting routes pass through congested arcs at times of traffic congestion, which results in increased travel time and fuel consumption. The reason for the poor performance with respect to total cost is also due to the higher handling cost in satellite one, which in this solution is used for all deliveries.

In contrast to the distance-minimizing objective, the time-minimizing objective takes vehicle speed, and consequently the traffic congestion, into account (see Table 4.5). The comparison results shown in Table 4.6 indicate that reducing travel time and using the two satellites allow for a better cost performance compared to the distance-minimizing solution.

The fuel-minimizing objective yielded an average of 2.5% reduction in fuel compared to the other objectives. It considers traveled distance, vehicle speed and load (see Table 4.5). Similar to the distance-minimizing solution, the solution proposes to use only satellite one. In comparison with the time-minimizing solution, although it performs better in terms of fuel consumption, it has a higher cost because of longer travel times and higher handling cost. Aiming for less fuel consumption means at the same time minimizing environmental damage in terms of transportation emissions and energy usage, since the amount of emissions and energy usage of a vehicle are directly proportional to the amount of fuel consumed. From this perspective, the solution obtained from the fuel-minimizing objective can be regarded as the most environmentally-friendly one. For the case study, being sustainable (fuel-efficient) comes at a cost increase of 10.8% compared to the most economic solution.

In contrast to the other objectives, the cost-minimizing objective takes travel time due to driver wage, fuel consumption and handling cost into account (see Table 4.5) and achieves, on average, a reduction of 6.9% in cost. The comparison results shown in Table 4.6 indicate that, among other types the cost-minimizing solution has the worst performance with respect to fuel consumption. However, the cost-minimizing solution uses only satellite two for the deliveries that allows to reduce the total handling cost. Additionally, it yields a slightly higher total travel time as compared to the time-minimizing solution, and consequently reduces total driver costs.

4.4.2.2 Effect of valid inequalities on solution time

To evaluate the effect of proposed valid inequalities (4.53)–(4.61), an analysis has been carried out. Table 4.7 presents the results on the computational times required to solve each variation of the model to optimality, with different combinations of the valid inequalities. The results show the efficiency of the valid inequalities.

TABLE 4.7: The effect of the valid inequalities on the computational time (in seconds) to obtain optimal solutions

Types	Distance-minimizing	Time-minimizing	Fuel-minimizing	Cost-minimizing
Model	76	3325	497	3738
Model+(4.53)–(4.58)	230	3293	562	2170
Model+(4.59)–(4.61)	51	1455	342	469
Model+(4.53)–(4.61)	61	1410	210	568

4.4.2.3 Sensitivity analyses

This section presents sensitivity analyses for the model with respect to changes in the handling cost, demand and satellite capacities.

• *Effect of change in the handling cost:* It is clear that changes in the handling cost cannot affect the routing decisions for the distance, time and fuel-minimizing solutions, since this is not considered in the objective function of these variations of the model. However, a change in handling cost in the satellites may affect the resulting cost for all variations of the model. Additionally, handling cost may have an effect on routing decisions for the cost-minimizing solution. This has motivated us to analyze two scenarios that differ with respect to the handling cost structure: (i) Scenario H1: handling cost at satellites one and two are taken as two and three €/tonne respectively, (ii) Scenario H2: handling costs are equal and are set as two €/tonne for both satellites.

The cost-minimizing solution yields same vehicle routes in both scenarios, namely D-S1-D and D-S1-D (first-echelon) and S1-10-6-S1, S1-7-11-12-15-16-14-13-S1, S1-5-1-2-S1, and S1-4-3-8-9-S1 (second-echelon). However this solution is different from that of the base case, which was presented in Table 4.6. In particular, the new solution uses satellite one for product delivery as opposed to using only satellite two as in our base case. Comparisons of the cost-minimizing solutions under different scenarios are presented in Table 4.8. In the new scenarios, the fuel consumption is reduced from 67.33 liters to 63.44 liters due to the usage of satellite one. This reduction also contributes to the decrease in the total cost. One other finding is that although the new scenarios have a shorter total distance, they perform worse in terms of total time compared to the base case. The reason behind this result is the difference in the total distance traveled in and out of the city center. In particular, the total distance traveled out of the city center in the base case is 30600 m shorter than in the new scenarios, whereas, the total distance traveled into the city center is 19900 m longer than that of the new scenarios.

TABLE 4.8: Comparisons of the cost-minimizing solutions under the base case, and scenarios H1 and H2

Scenarios	Total distance (m)	Total time (s)	Total fuel (liter)	Total cost (€)
Base Case	302300	26358	67.33	259.53
Scenario H1	291600	26854	63.44	254.42
Scenario H2	291600	26854	63.44	254.42

The resulting costs of the distance, time and fuel-minimizing solutions change under the new scenarios. The % difference between the results of the distance, time and fuel-minimizing models over the cost-minimizing versions is shown in Table 4.9. For instance, the % difference in total cost between distance-minimizing and cost-minimizing solutions is 12.3% in the base case. However, this reduces to 1.6% in the new scenarios, since handling cost disadvantage of using only satellite one in the distance-minimizing solution disappears. The same holds for the fuel-minimizing solution in which the relative difference reduces from 10.8% to 0.1% due to the change in the handling cost. These results also reveal that the additional cost of being more environmentally-friendly reduces in the new scenarios compared to the base case. The relative difference increases between the time-minimizing and the cost-minimizing solutions in the scenario H1 can be explained in a similar way. The time-minimizing solution proposes to use satellite two as well as it is shown in Table 4.6, however the increased handling cost of the satellite two causes an increase in the total cost. When the handling costs in the satellites are equal, the total cost resulting from the time-minimizing and the cost-minimizing solutions becomes similar.

TABLE 4.9: Cost performances of distance, time, fuel and cost-minimizing solutions under the base case, and scenarios H1 and H2

Model variations	Base Case		Scenario H1		Scenario H2	
Distance-minimizing	291.58	+12.3%	258.58	+1.6%	258.58	+1.6%
Time-minimizing	270.49	+4.2%	272.49	+7.1%	254.99	+0.2%
Fuel-minimizing	287,76	+10.8%	254.76	+0.1%	254.76	+0.1%
Cost-minimizing	259.53	-	254.42	-	254.42	-

• *Effect of change in demand:* The hypothetical demand generated in the base case has a coefficient of variation (CV) equal to 0.6, which represents the ratio of the standard deviation to the mean. In order to test the effect of the variation in the demands, two more demand sets with different CVs have been generated: (i) Scenario D1 with CV=0, where each node has demand equal to 2000 kg, (ii) Scenario D2 with CV=1.32, where demand (kg) is (200, 6000, 100, 250, 5500, 200, 6000, 500, 100, 1500, 100, 7000, 4500, 300, 100, 100) for customers C1–C16, respectively. The results on the performance of distance, time, fuel and cost-minimizing solutions under different scenarios are shown in Figure 4.4.
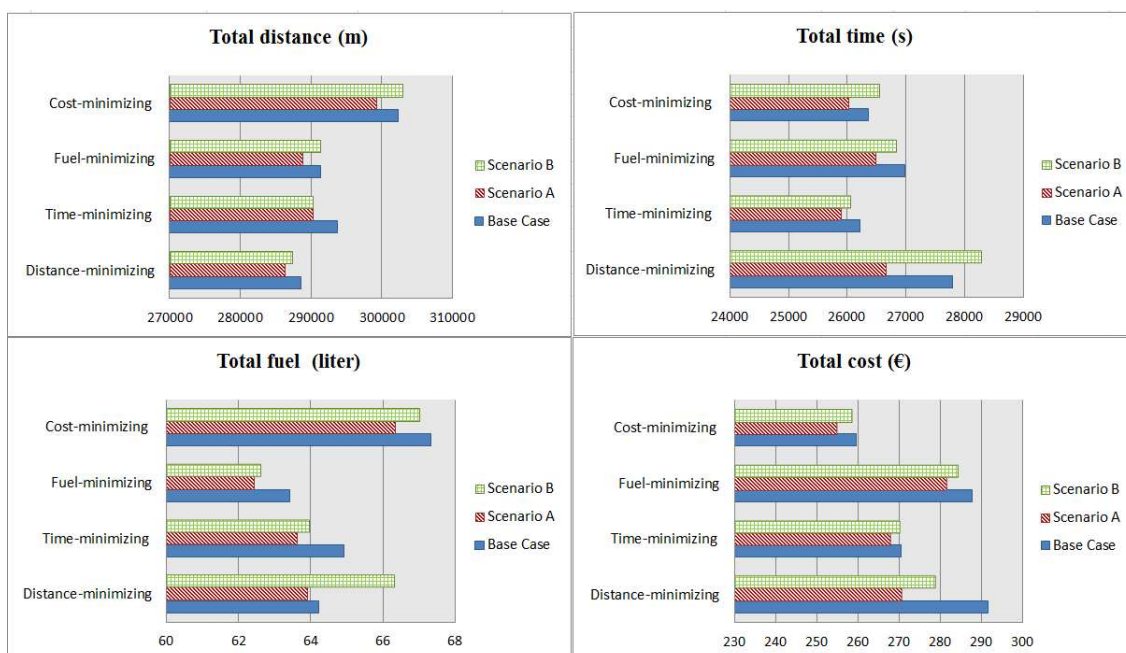
FIGURE 4.4: Comparison of distance, time, fuel and cost-minimizing solutions under the base case, and scenarios D1 and D2

The performances of the distance, time, fuel and cost-minimizing objectives on the KPIs are not the same in each scenario. For instance, the distance-minimizing objective results in a lower fuel consumption than the time-minimizing objective in the base case. However, the time-minimizing objective performs better than the distance-minimizing objective with respect to fuel consumption in scenarios D1 and D2. For each scenario, the amount of potential fuel consumption reduction and its contribution to the total cost can be seen in Figure 4.4. The same figure also shows the potential reduction in total cost.

• *Effect of adding capacity restrictions on the satellites:* With the exception of the time-minimizing solution, all other solutions use a single satellite. These solutions do not impose any limitations on satellite capacity, which implies that all deliveries can be made from a single satellite. To investigate the effect of capacity limitations on satellites, we now analyze Scenario C, which, unlike the base case, assumes that the capacity of a satellite $s \in V_S$ has a finite capacity c_s. This restriction is modeled through the following constraints.

$$T_s \leq c_s, \qquad \forall s \in V_S. \tag{4.65}$$

In Scenario C, we assume that each satellite has two small vehicles to deliver the products to the customers, which makes for a delivery capacity of 20 tonnes. For Scenario C, we present the resulting routes and comparison results for the four objectives in Table 4.10.

TABLE 4.10: Distance, time, fuel and cost-minimizing solutions under the scenario C

Routes and KPIs	Distance-minimizing	Time-minimizing	Fuel-minimizing	Cost-minimizing
First echelon routes	D-S1-D D-S2-D	D-S1-D D-S2-D	D-S1-D D-S2-D	D-S1-D D-S2-D
Second echelon routes	S1-13-4-3-2-S1 S1-1-5-6-10-S1 S2-14-12-15-16-S2 S2-9-7-8-11-S2	S1-13-5-1-3-2-S1 S1-10-6-S1 S2-9-4-7-8-14-S2 S2-11-12-15-16-S2	S1-10-4-3-1-S1 S1-5-2-6-13-S1 S2-9-7-8-14-S2 S2-11-12-15-16-S2	S1-13-5-1-3-2-S1 S1-10-S1 S2-15-16-12-11-6-S2 S2-9-4-7-8-14-S2
Total distance (m)	289700 (1)	293700 (1.014)	294100 (1.015)	295100 (1.019)
Total time (s)	27179(1.037)	26211 (1)	26394 (1.007)	26337(1.005)
Total fuel (liter)	65.38 (1.012)	64.92 (1.005)	64.61 (1)	65.45 (1.013)
Total cost (€)	277.69 (1.031)	270.49 (1.005)	274.02 (1.018)	269.27 (1)

According to the results shown in Table 4.10, the routes for the time-minimizing solution remain the same as before, whereas solutions for the other objectives change. The addition of capacity constraints on satellites has now led to the use of both satellites in all model variations. This change has three main effects on the resulting solutions. First, compared to the base case (see Table 4.6), the total cost performances have improved for the distance- and fuel-minimizing solutions, and worsened for the cost-minimizing solution mainly due to changes in the handling cost. Note that the handling cost at the satellite one is higher than that at the satellite two. Second, the total distance in the distance-minimizing solution, the total fuel consumption in the fuel-minimizing solution and the total cost in the cost-minimizing solution have all increased. Third, the similarity between the four solutions resulting from the four model variations have increased, as shown in Figure 4.5 that shows the graphical visualizations of the normalized data for the base case and scenario C.
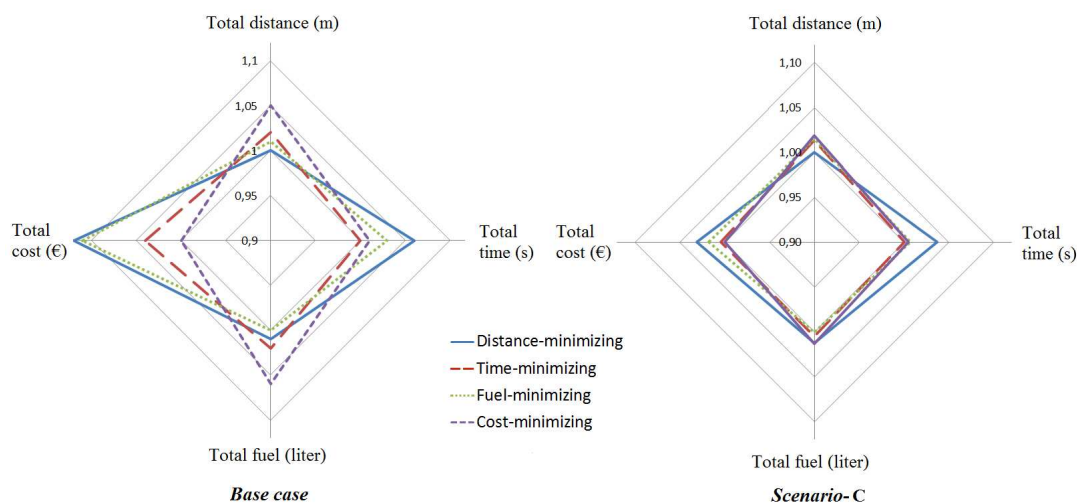
FIGURE 4.5: Comparison of distance, time, fuel and cost-minimizing solutions under the base case and scenario C

4.4.2.4 Comparison of the single-echelon and two-echelon distribution systems

In this section, we analyze the case study assuming a single-echelon distribution system, in order to observe the effect of the type of the distribution system on the selected KPIs. To be able to use the same formulation, the two satellites were removed from the network and a new one was located in the original depot's location. This change has enabled us to omit the first-echelon in the problem and to use the single satellite as a depot. Distances between the satellite (depot) and customers in this case are as presented in Table 4.B. Note that the customer locations and related demands stay as in the base case. Congested arcs presented in Table 4.4 were adapted to the single-echelon case as follows. Congested arcs from/to the second satellite were removed, since that satellite no longer exists. Congested arcs from/to the first satellite were removed, since in the new setting an average of 80% of the total travel between the satellite and customers occurs outside the boundaries of the city. It was assumed that vehicles travel at a speed of 70 km/h between the satellite (depot) and customers. Congested (20 km/h) and free-flow (40 km/h) speeds in the city center were preserved. The length of the rush hour was also kept as one hour. However, the effect of peak-time travel on the KPIs is now diminished, since congestion dissipates by the time vehicles arrive at their first customers from the satellite (depot). Finally, in the single echelon case handling costs were removed as satellite serves as a depot. Figure 4.6 presents the performance of the single-echelon case compared to the base (two-echelon) case.

The results show that the two-echelon system outperforms the single-echelon system in terms of total travel distance, total travel time and total fuel consumption. The main reason for the poor performance of the single-echelon system is the use of small
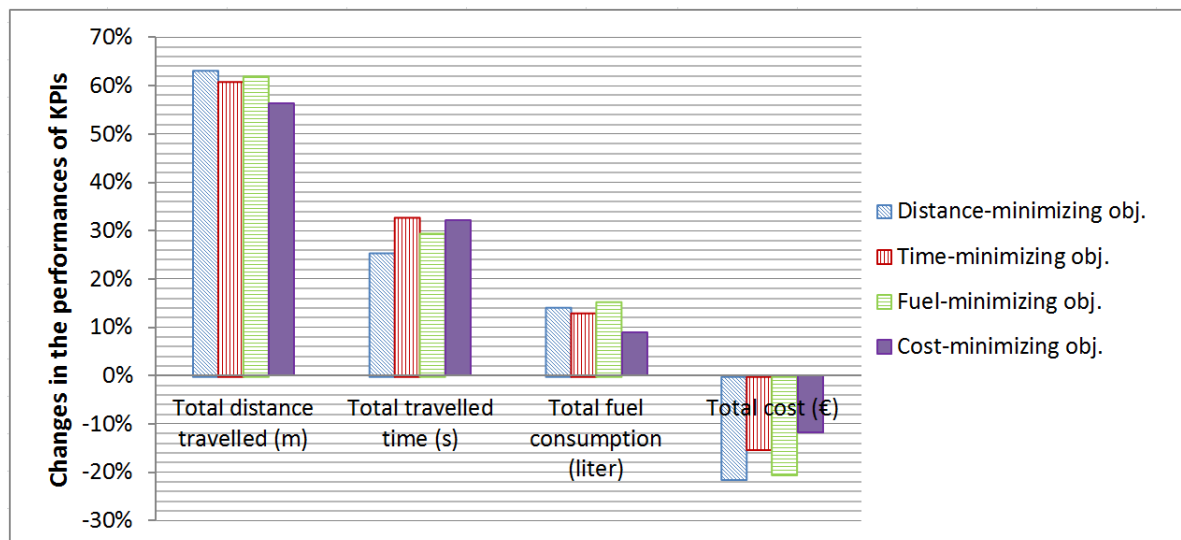
FIGURE 4.6: The performance of the single-echelon case compared to the base (two-echelon) case

vehicles for the long distances, rather than large ones as in the two-echelon system. In particular, four small vehicles were used in the former between the depot (satellite) and the customers, whereas in the latter this was managed through two large vehicles. This load consolidation allowed for reduction in total travel distance, total travel time and total fuel consumption in the two-echelon system. Although the single-echelon system had higher time (increased wage cost) and fuel (increased fuel cost) requirements, the non-existence of handling costs provided comparative advantage over the two-echelon case that led to a better total cost performance. To conclude, for this case study, the two-echelon distribution system enabled to obtain the most environmentally-friendly solution, whereas the least-cost solution was obtained by means of the single-echelon distribution system. However, we note that the single-echelon system will contribute relatively more to congestion due to the need for more vehicles to deliver the same amount of load. Moreover, this system will have worse performance on vehicle and driver utilisation that will reduce the efficiency of the logistics chain.

4.5 Conclusions

In this paper, we have modeled and analyzed the 2E-CVRP to explicitly account for time-dependent speeds in the second-echelon routes and fuel consumption. To the best of our knowledge, this is the first attempt to develop a mathematical model for the time-dependent 2E-CVRP with an explicit consideration of fuel consumption through the use of a comprehensive emission function.

The results of the computational experiments show that the resulting routes and the performances of the solutions with respect to the KPIs change according to the variation of the model. The traditional objectives of distance and time minimization do not ensure minimization of fuel consumption or cost. The comprehensive cost-minimizing objective, which breaks away from the traditional objective functions used in the 2E-CVRP by a detailed estimation of fuel consumption, can achieve average savings in total cost by 6.9%. However, it does not guarantee the best solution in terms of emissions. The use of fuel-minimizing objective can ensure the most environmentally-friendly solution by reducing total fuel consumption on average 2.5% in return for a cost increase of 10.8%. The sensitivity analyses reveal that the performances of the variations of the model on the selected KPIs change according to the handling fee in the satellites, demand of the customers and capacities of the satellites. Additionally, for our case study, the most environmentally-friendly solution is obtained from the use of a two-echelon distribution system, although a single-echelon distribution system provides a solution with lower total cost.

One possible extension of the paper is to develop a heuristic algorithm for the studied problem, which will enable to handle instances that are large in size. The model proposed in this paper can be used to validate and verify the potential of such heuristic algorithms.

Acknowledgement

APPENDIX

In this section, we present the distance data used for the MILP model.

TABLE 4.A: Distances between nodes, in meters

	D	S1	S2	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
D	-	50000	57800	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
S1	51500	-	11000	6900	10000	10800	8400	6700	8000	8800	14000	11900	7100	11000	9700	6300	8200	10100	12200
S2	59000	10600	-	8700	9200	8900	6800	7200	6200	9000	7100	5500	5000	4900	3900	5000	3400	2700	4700
C1	-	7600	8300	-	3100	5300	3800	1500	2800	4100	7200	9200	3900	7600	5500	3700	5600	7400	9500
C2	-	8500	9200	2700	-	3100	2200	2400	2700	2700	4200	6900	3500	5400	5200	4600	6600	8100	9400
C3	-	11700	9200	4600	2800	-	2400	4600	3700	2300	2800	5700	4300	4200	4700	6200	6400	6300	7600
C4	-	8700	9100	3500	1700	1600	-	2700	2000	1200	2700	5400	2600	3900	4200	4400	6100	5700	7900
C5	-	6500	7200	1700	2400	4600	2900	-	1300	3200	4600	6700	2400	6000	4000	2500	4500	6300	8400
C6	-	7200	5600	3400	3000	3100	1600	1700	-	1900	3400	5400	1100	4100	2700	2900	3500	4400	6800
C7	-	14300	7000	5500	4200	3200	2700	4400	3500	-	1500	3300	4100	2500	3200	6000	4900	4500	6500
C8	-	14200	6000	5400	4100	3000	2500	4300	3400	1500	-	3200	4000	1700	2200	5400	3900	3500	5000
C9	-	7500	5700	4300	3700	4000	2400	2800	1800	2700	3400	-	1300	1700	1900	3300	3500	3100	5200
C10	-	6600	5200	4300	3400	3500	2000	2100	1300	2300	3800	5000	-	3600	2300	2400	3000	4000	6400
C11	-	9100	5000	5100	4500	4400	3200	3400	2600	2800	2500	1600	2900	-	1300	4500	2900	2500	4600
C12	-	9600	4000	6200	5600	5700	4300	4500	3700	3300	3200	2700	2900	1300	-	4100	2600	1700	3800
C13	-	6400	4900	4000	4500	6700	4200	2500	3800	4500	6000	5900	2400	5000	3600	-	2100	4100	6100
C14	-	8000	3200	6000	6500	7700	4800	4500	4100	5100	5100	4200	2900	3300	2000	2300	-	2400	4400
C15	-	11800	3700	10000	8200	6300	6100	6200	5400	5300	4000	4400	4500	3300	3000	5000	3500	-	2000
C16	-	13300	5100	9900	9200	7300	7100	7300	6500	6400	5100	5500	5600	4400	4100	6100	4500	2200	-

TABLE 4.B: Distances between nodes (single-echelon case), in meters

S (D)	S (D)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
	-	54500	56000	60600	57000	55700	57000	58200	61800	56000	54800	57200	55900	54200	54200	58500	60500
C1	56200	-	3100	5300	3800	1500	2800	4100	7200	9200	3900	7600	5500	3700	5600	7400	9500
C2	57200	2700	-	3100	2200	2400	2700	2700	4200	6900	3500	5400	5200	4600	6600	8100	9400
C3	58100	4600	2800	-	2400	4600	3700	2300	2800	5700	4300	4200	4700	6200	6400	6300	7600
C4	58200	3500	1700	1600	-	2700	2000	1200	2700	5400	2600	3900	4200	4400	6100	5700	7900
C5	56000	1700	2400	4600	2900	-	1300	3200	4600	6700	2400	6000	4000	2500	4500	6300	8400
C6	55800	3400	3000	3100	1600	1700	-	1900	3400	5400	1100	4100	2700	2900	3500	4400	6800
C7	60700	5500	4200	3200	2700	4400	3500	-	1500	3300	4100	2500	3200	6000	4900	4500	6500
C8	62800	5400	4100	3000	2500	4300	3400	1500	-	3200	4000	1700	2200	5400	3900	3500	5000
C9	56200	4300	3700	4000	2400	2800	1800	2700	3400	-	1300	1700	1900	3300	3900	3100	5200
C10	55300	4300	3400	3500	2000	2100	1300	2300	3800	5000	-	3600	2300	2400	3000	4000	6400
C11	63200	5100	4500	4400	3200	3400	2600	2800	2500	1600	2900	-	1300	4500	2900	2500	4600
C12	60300	6200	5600	5700	4300	4500	3700	3300	3200	2700	2900	1300	-	4100	2600	1700	3800
C13	55600	4000	4500	6700	4200	2500	3800	4500	6000	5900	2400	5000	3600	-	2100	4100	6100
C14	59600	6000	6500	7700	4800	4500	4100	5100	5100	4200	2900	3300	2000	2300	-	2400	4400
C15	59800	10000	8200	6300	6100	6200	5400	5300	4000	4400	4500	3300	3000	5000	3500	-	2000
C16	61200	9900	9200	7300	7100	7300	6500	6400	5100	5500	5600	4400	4100	6100	4500	2200	-

Chapter 5

Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty

This chapter is based on the published journal article:

M. Soysal, J.M. Bloemhof-Ruwaard, R. Haijema, J.G.A.J. van der Vorst (2015) "Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty" *International Journal of Production Economics*, 164, 118-133.

In this chapter, we investigate RO4:
To investigate the performance implications of accommodating explicit transportation energy use, product waste and demand uncertainty concerns in an inventory routing problem.

5.1 Introduction

Ensuring collaborative relationships throughout a supply chain is an effective strategy to gain competitive advantage. Vendor Managed Inventory (VMI) refers to a collaboration between a vendor and its customers in which the vendor takes on the responsibility of managing inventories at customers (Hvattum and Løkketangen, 2009). The vendor decides on quantity and time of the shipments to the customers, but has to bear the responsibility that the customers do not run out of stock (Andersson et al., 2010). The VMI policy is often regarded as a win-win arrangement: suppliers can better coordinate deliveries to customers, since the vehicle routes can be based on the inventory levels observed at the customers rather than the replenishment orders coming from the customers, and customers do not have to dedicate resources to inventory management (Coelho et al., 2012a; Campbell et al., 1998; Raa and Aghezzaf, 2009). Due to such benefits, and the increase in availability of monitoring technologies facilitating the share of accurate and timely information among the chain partners, the VMI policy has received much attention in recent years. However, execution of the VMI policy in an effective way is not a simple task, since under this policy the vendor has to deal with an integrated problem consisting of its own vehicle routing decisions and inventory decisions of customers (Campbell and Savelsbergh, 2004; Raa and Aghezzaf, 2009). This integrated problem, especially arising in VMI systems (Yu et al., 2008), is known in literature as the Inventory Routing Problem (IRP).

The IRP addresses the coordination of two components of the supply chain: the inventory management and the vehicle routing (Jemai et al., 2013). A generic representation of the IRP is illustrated in Figure 5.1. The traditional objective is to minimize total distribution and inventory costs during the planning horizon without causing stock-outs at any of the customers (Aghezzaf et al., 2006). The supplier has to make three simultaneous decisions: (1) when to deliver to each customer, (2) how much to deliver to each customer each time it is served, and (3) how to combine customers into vehicle routes (Bertazzi et al., 2008; Coelho et al., 2012b). In the traditional Vehicle Routing Problems (VRPs), the supplier aims to satisfy the orders given by the customers so as to minimize total distribution cost. On the contrary, in the IRP, orders are determined by the supplier based on input on customers usage (demand). Moreover, in the IRP, the supplier aims to manage inventory of customers such that they do not experience a stock-out, whereas traditional VRPs do not have such a concern. The presence of the inventory component in the IRP adds a time dimension to the related routing problem (Bertazzi et al., 2008). The IRP is thus regarded as a medium-term problem, whereas the VRP is a short term one (Moin and Salhi, 2007). Applications of the IRP arise in a large variety of industries, including the

distribution of liquified natural gas, raw material to the paper industry, food distribution to supermarket chains, automobile components, perishable items, groceries, cement, fuel, blood, and waste organic oil (see respective references in Coelho and Laporte (2013); Coelho et al. (2012b)).
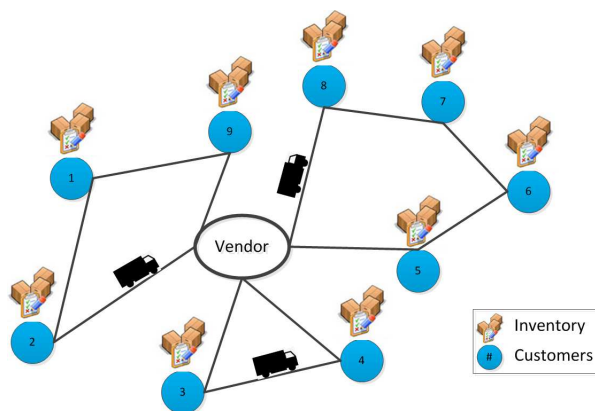
FIGURE 5.1: A generic representation of the Inventory Routing Problem

In the last two decades, food supply chain management has evolved due to various reasons such as demand for safe and high quality food products, increasing health consciousness of consumers, growth of world population, climate change, limited natural resources and escalating sustainability awareness. More specific, food logistics systems have seen the transition from a focus on traditional supply chain management to food supply chain management, and successively, to sustainable food supply chain management (Soysal et al., 2012). This transition has brought new key logistical aims besides the cost minimization objective: (i) the ability to control product quality in the supply chain and deliver high quality food products in various forms to final consumers by incorporating product quality information in logistics decision making, (ii) the ability to collaborate in the supply chain network to reduce food waste and (iii) the ability to reduce environmental and societal impacts of operations (Soysal et al., 2012). The aforementioned developments have stimulated companies and researchers to consider multiple Key Performance Indicators (KPIs) such as cost, food waste and transportation emissions in food logistics management projects (e.g., Zanoni and Zavanella (2012) and Soysal et al. (2014)).

Some traditional assumptions in the IRP literature restrict the usage of the proposed models in current food logistics systems. These assumptions, which can be regarded as doubtful from the practical point of view, are summarized as follows. First, IRP models often assume that distribution costs between nodes are known in advance and are constant (e.g., Vidović et al. (2014) and Qin et al. (2014)). However, fuel consumption and therefore cost can change based on vehicle load which is dependent on the visiting order of the customers (Kara et al., 2007; Kuo and Wang, 2011). The literature for a

number of VRPs shows that an explicit consideration of fuel consumption in logistics operations can help to reduce relevant operational costs and environmental externalities (e.g., Bektaş and Laporte (2011) and Franceschetti et al. (2013)). Second, a common assumption of an unlimited product shelf life in the IRP models is restrictive in that it does not allow for the consideration of quality decay of products. This is one of the main obstacles for the application of the basic IRP models in food logistics management. Third, a widespread tendency is to assume that customer usages are known in advance in the beginning of the planning horizon, which is clearly not the case in reality. These are the main weaknesses of the basic IRP models to be improved.

From this point of view, our interest in this study is to enhance the traditional models for the IRP to make them more useful for the decision makers in food logistics management. In order to achieve that improvement, we do not rely on all common assumptions of the basic IRP models. Therefore, in our problem setting, distribution costs between nodes are not known in advance and can change according to the routing schedule employed, the product is subject to quality decay because of the perishability nature and customer usage is not known a priori. Moreover, we estimate fuel consumption and emissions based on a comprehensive emissions model that allows to incorporate transportation cost and emissions more accurately and explicitly. Consequently, we develop a comprehensive chance-constrained programming model for the multi-period IRP that accounts for perishability, explicit fuel consumption and demand uncertainty. The proposed model manages relevant KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost, simultaneously. To the best of our knowledge, such an attempt has not yet been made for the IRP.

The rest of the paper is structured as follows. Section 5.2 presents a review of the relevant literature on the IRP and clarifies the contribution of our work. Section 5.3 defines the problem and presents the optimization model. Section 5.4 presents three different variations of the proposed model, which are employed to show the benefits of including perishability and explicit fuel consumption considerations in the model. Section 5.5 presents a simulation for the problem to evaluate the solutions of the optimization models. Section 5.6 presents computational results on a real life distribution problem. The last section presents conclusions and future research directions.

5.2   Related literature review

The traditional IRP without perishability and sustainability concerns has been extensively studied in the literature. The interested reader is referred to the reviews by Moin and Salhi

(2007), Andersson et al. (2010) and Coelho et al. (2012b) on the topic. Our focus here is on attempts aimed to incorporate additional KPIs to the IRP. Relatively few studies on the IRP have bothered to introduce new KPIs to the proposed models. We can subdivide the related literature in two groups: (i) studies with perishability considerations, (ii) studies with environmental or societal considerations.

First, we review the studies on IRP with perishability considerations. Federgruen et al. (1986) study the IRP for a perishable product with a fixed lifetime during which it can be used and after which it must be discarded, e.g., human blood, food and medical drugs. They distinguish two age classes, fresh and old, based on the product remaining lifetime and discard the product that reaches the maximum age in inventory. Le et al. (2013) and Al Shamsi et al. (2014) study the IRP for a perishable product with a fixed lifetime as well. Both studies restrict the total amount of time that products can be stored in facilities and do not allow product wastes. Coelho and Laporte (2014) integrate an age tracking approach to the IRP of a perishable product with a fixed shelf life. The age tracking approach ensures to distinguish products according to their shelf lives and has also been used in literature for other logistics problems such as inventory problems (Haijema, 2013), and production and distribution problems (Rong et al., 2011; Van Elzakker et al., 2014). Jia et al. (2014) incorporate quality time windows (shelf life limit) to the IRP of a perishable product with the same objective as the age tracking approach: controlling deteriorating item's quality which has a fixed shelf life. We note that both Coelho and Laporte (2014) and Jia et al. (2014) allow product wastes in the IRP. A number of studies on inventory management deal with products which have limited shelf life as well (e.g., Minner and Transchel (2010) and Rossi et al. (2010)). However, these studies do not take routing decisions into account. The reviews of Nahmias (1982), Amorim et al. (2013), Karaesmen et al. (2011) and Bakker et al. (2012) can be consulted for more information about research on supply chain management of products that are perishable.

Second, we review the studies on IRP with environmental or societal considerations. Treitl et al. (2014) and Al Shamsi et al. (2014) incorporate emissions to the IRP through estimating fuel consumption. Both studies employ the same approach as in Bektaş and Laporte (2011) for estimating fuel consumption and emissions that is based on the comprehensive emissions model of Barth et al. (2005) and Barth and Boriboonsomsin (2009). Mirzapour Al-ehashem and Rekik (2013) and Alkawaleet et al. (2014) incorporate emissions to the IRP as well. However, both studies employ a distance-based emission calculation approach, i.e. emissions produced by vehicle type per unit distance, that does not consider the other factors such as vehicle load and vehicle speed. There exist other studies on a similar problem class, VRPs, with an explicit consideration of environmental issues, such as fuel consumption or emissions (e.g., Bektaş and Laporte (2011) and

Franceschetti et al. (2013)). Note that these studies have interest in routing schedules and do not consider inventory decisions. The interested reader is referred to the reviews by Demir et al. (2014b) and Lin et al. (2014) on this topic.

TABLE 5.1: Studies on IRPs that have perishability or fuel consumption (emissions) considerations

	Perishability		Fuel or emissions considerations			Demand uncertainty
	Shelf life	Waste	Traveled distance	Vehicle load	Vehicle speed	
Federgruen et al. (1986)	✓	✓	-	-	-	✓
Treitl et al. (2014)	-	-	✓	✓	✓	-
Mirzapour Al-ehashem and Rekik (2013)	-	-	✓	-	-	-
Le et al. (2013)	✓	-	-	-	-	-
Alkawaleet et al. (2014)	-	-	✓	-	-	-
Al Shamsi et al. (2014)	✓	-	✓	✓	✓	-
Coelho and Laporte (2014)	✓	✓	-	-	-	-
Jia et al. (2014)	✓	✓	-	-	-	-
This study	✓	✓	✓	✓	✓	✓

Our brief review shows that none of the above mentioned studies presented in Table 5.1, except Al Shamsi et al. (2014), has addressed an IRP with both perishability and sustainability concerns simultaneously. The study of Al Shamsi et al. (2014), however, does not take potential product wastes and demand uncertainty into account. Note that product wastes can be inevitable when the demand is not known in advance. The other given studies, except Federgruen et al. (1986) that take demand uncertainty into account, rely on a completely deterministic environment as well. This diminishes the chance to obtain robust solutions for real-world problems where the actual demand is not known in advance, which is often the case in practice. Some of the studies (e.g., Bertazzi et al. (2013), Hemmelmayr et al. (2010), Huang and Lin (2010) and Yu et al. (2012)) consider demand uncertainty on IRP, however these studies stick to traditional approaches that focus only on a single KPI: cost.

A convenient way to capture the risk associated with uncertain demand is to use a chance-constrained programming approach. Therefore, we formulate the IRP as a chance-constrained programming model. It is first introduced by Charnes and Cooper (1959) and further studied by many authors during the last years, such as Yu et al. (2012) and Abdul Rahim et al. (2014) on IRP, and Hendrix et al. (2012), Rossi et al. (2008) and Pauls-Worm et al. (2014) on inventory problems.

To conclude, our study adds to the literature on IRP by: (1) developing a comprehensive chance-constrained programming model with demand uncertainty for a multi-period generic IRP that accounts for the KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost, (2) presenting the applicability of the model on the fresh tomato distribution operations of a supermarket chain operating in Turkey based on mostly real data.

5.3   Problem description

The problem in this study is defined on a complete graph $G = \{V, A\}$, where $V = \{0, ..., |V|\}$ is the set of nodes and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the set of arcs. Node 0 represents the vendor and the remaining nodes $V' = V \backslash \{0\}$ represent customers. The set of vehicles is given as $K = \{1, 2..., |K|\}$, each with capacity c and located at the vendor. Freight is delivered to customers from the vendor through these vehicles that start and end at the vendor's location. Each vehicle can perform at most one route per time period. Each customer can be served by more than one vehicle, hence the total freight assigned to each customer can be split into two or more vehicles. It is assumed that the demand $d_{i,t}$ in each period $t \in T = \{1, ..., |T|\}$ is distributed normally with mean $\mu_{i,t}$ and standard deviation $\sigma_{i,t}$, $\forall i \in V', t \in T$. For each customer, an inventory holding cost $h_i, \forall i \in V'$ occurs at each period. However, the product has a fixed shelf life of $m \geq 2$ periods. Therefore, if a product stays in inventory more than m periods, it becomes spoiled and cost of waste p occurs. The demand of all customers in each period must be satisfied with a probability of at least α. The demand that cannot be fulfilled in one period is backlogged in the next period.

The aim of the problem in this study is to determine the routes and quantity of shipments in each period such that the total cost comprising routing, inventory and waste costs is minimized. Routing cost consists of driver and fuel consumption cost for each arc in the network. Let r denote the wage for the drivers and l denote the fuel price per liter. The driver of each vehicle is paid from the beginning of the time horizon until the time he returns to the starting point. Fuel consumption is mainly dependent on traveled distance, vehicle load and vehicle speed. The following section presents the fuel consumption calculation in greater detail.

5.3.1   Fuel consumption and emissions

We employ the same approach as in Bektaş and Laporte (2011), Demir et al. (2012) and Franceschetti et al. (2013) for estimating fuel consumption that is based on the comprehensive emissions model of Barth et al. (2005). According to this model, the total amount of fuel used, EC (in liters), for traversing a distance a (m) at constant speed f (m/s) with load F (kg) is calculated as follows:

$$EC = \lambda \Big(y(a/f) + \gamma \beta a f^2 + \gamma s(\mu + F)a \Big)$$

where $\lambda = \xi/(\kappa \psi)$, $y = k_e N_e V_e$, $\gamma = 1/(1000 \varepsilon \varpi)$, $\beta = 0.5 C_d A_e \rho$, and $s = g \sin \phi + g C_r \cos \phi$. Furthermore, k_e is the engine friction factor (kJ/rev/liter), N_e is the engine

speed (rev/s), V_e is the engine displacement (liter), μ is the vehicle curb weight (kg), g is the gravitational constant (9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, A_e is the frontal surface area (m^2), ρ is the air density (kg/m^3), ε is the vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines, ξ is the fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s). For further details on these parameters, the reader is referred to Demir et al. (2011). After estimating fuel consumption amounts, we estimate related emission (CO_2) levels by using a fuel conversion factor u (kg/l) for transport activities.

5.3.2 Chance-constrained programming model with demand uncertainty

This section presents a mathematical formulation for the studied problem. Table 5.2 presents the notation for the model.

We now present the formulation, starting with the objective function.

$$Minimise \sum_{i \in V'} \sum_{t \in T} I_{i,t}^+ h_i \tag{5.i}$$

$$+ \sum_{i \in V'} \sum_{t \in \{T|t \geq m\}} E[W_{i,t}]p \tag{5.ii}$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y(a_{ij}/f)X_{i,j,k,t} + \gamma \beta a_{ij} f^2 X_{i,j,k,t} + \gamma s(\mu X_{i,j,k,t} + F_{i,j,k,t})a_{ij} \right) l \tag{5.iii}$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} (a_{ij}/f)X_{i,j,k,t} r. \tag{5.iv}$$

$$\tag{5.1}$$

The objective function (5.1) comprises four parts: (1.i) expected inventory cost, (note that $I_{i,t}^+$ is derived from $E[I_{i,t}]$ through constraints (5.3)), (1.ii) expected waste cost, (1.iii) fuel cost from transportation operations and (1.iv) driver cost.

$$E[I_{i,t}] = \sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t} (E[d_{i,s}] + E[W_{i,s}]), \qquad \forall i \in V', t \in T \tag{5.2}$$

$$I_{i,t}^+ \geq E[I_{i,t}], \qquad \forall i \in V', t \in T \tag{5.3}$$

$$E[W_{i,t}] \geq E[I_{i,t-m+1}] - \sum_{a=t-m+2}^{t} E[d_{i,a}] - \sum_{a=t-m+2}^{t-1} E[W_{i,a}], \qquad \forall i \in V', t \in \{T|t \geq m\} \tag{5.4}$$

$$E[W_{i,t}] = 0, \qquad \forall i \in V', t \in \{T|t < m\} \tag{5.5}$$

$$Pr\left(I_{i,t} \geq 0 \right) \geq \alpha, \qquad \forall i \in V', t \in T. \tag{5.6}$$

Constraints (5.2) to (5.6) relate to the inventory decisions. In particular, constraints (5.2) calculate expected inventory levels for each customer per period by taking the amounts

TABLE 5.2: Parameters and decision variables

Symbol	Meaning
$E[.]$	expectation operator
V	set of all nodes including the vendor 0, $V = \{0, 1, 2..., |V|\}$
V'	set of customers, $V' = V \backslash \{0\}$
A	set of all arcs, $A = \{(i, j) : i, j \in V, i \neq j\}$
T	set of time periods, $T = \{1, 2..., |T|\}$
K	set of vehicle, $K = \{1, 2..., |K|\}$
m	fixed maximum shelf life, $m \geq 2$, in periods,
$d_{i,t}$	demand of customer $i \in V'$ in time period $t \in T$, normal random variable with mean $\mu_{i,t}$, standard deviation $\sigma_{i,t}$, in kg,
α	pre-defined satisfaction level of probabilistic inventory constraint,
c	capacity of a vehicle, in kg,
$a_{i,j}$	distance between node i and j, $(i, j) \in A$, in m,
f	vehicle speed, (m/s),
λ	technical parameter, $\xi/\kappa\psi$, see section 5.3.1,
y	technical parameter, $k_e N_e V_e$, see section 5.3.1,
γ	technical parameter, $1/(1000\varepsilon\varpi)$, see section 5.3.1,
β	technical parameter, $0.5C_d A_e \rho$, see section 5.3.1,
s	technical parameter, $g\sin\phi + gC_r\cos\phi$, see section 5.3.1,
μ	curb-weight of vehicle, in kg,
l	fuel price per liter, €/l,
p	penalty cost for the wasted product, €/kg,
r	wage rate for the drivers of the vehicles, €/s,
h_i	holding cost per period at customer $i \in V'$, €/kg,
$I_{i,t}$	the amount of inventory at customer $i \in V'$ at the end of period $t \in T \cup \{0\}$, in kg, where $I_{i,0} = 0, \forall i \in V'$,
$I_{i,t}^+$	derived decision variable to calculate positive inventory levels, in kg,
$Q_{i,k,t}$	the amount of product delivered by vehicle $k \in K$ to customer $i \in V'$ in the beginning of period $t \in T$, in kg,
$X_{i,j,k,t}$	binary variable equal to 1 if vehicle $k \in K$ goes from $i \in V$ to $j \in V$ in period $t \in T$, and 0 otherwise,
$F_{i,j,k,t}$	the load on vehicle $k \in K$ which goes from $i \in V$ to $j \in V$ in period $t \in T$, in kg,
$W_{i,t}$	the amount of waste at customer $i \in V'$ at the end of period $t \in T$, in kg.

of total product delivered, expected demand and expected waste into account. Hereby, we assume $I_{i,0} = 0, \forall i \in V'$. Constraints (5.3) define variables which are used for the calculation of inventory costs in the objective function. Constraints (5.4) and (5.5) calculate expected waste at each customer per period. Constraints (5.6) are the service-level constraints on the probability of a stock-out at the end of each period.

$$\sum_{i \in V, i \neq j} X_{i,j,k,t} = \sum_{i \in V, i \neq j} X_{j,i,k,t}, \qquad \forall j \in V', k \in K, t \in T \qquad (5.7)$$

$$\sum_{j \in V, i \neq j} X_{i,j,k,t} \leq 1, \qquad \forall i \in V, k \in K, t \in T \qquad (5.8)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,t} = \sum_{j \in V, i \neq j} F_{j,i,k,t} - Q_{i,k,t}, \qquad \forall i \in V', k \in K, t \in T \qquad (5.9)$$

$$F_{i,j,k,t} \leq cX_{i,j,k,t}, \qquad \forall (i,j) \in A, k \in K, t \in T. \qquad (5.10)$$

Constraints (5.7) to (5.10) relate to the routing decisions. In particular, constraints (5.7) ensure flow conservation for each vehicle at each node in each period. Constraints (5.8)

ensure that each vehicle can perform at most one route per time period. Constraints (5.9) and (5.10) model the flow on each arc and ensure that vehicle capacities are respected in each period. Constraints (5.9) provide also the benefit of eliminating subtours that do not include the vendor, since the load on each vehicle is monotonically decreasing as customers are visited (Bard and Nananukul, 2009; Treitl et al., 2014).

$$X_{i,j,k,t} \in \{0,1\}, \qquad\qquad \forall (i,j) \in A, k \in K, t \in T \qquad (5.11)$$

$$F_{i,j,k,t} \geq 0, \qquad\qquad \forall (i,j) \in A, k \in K, t \in T \qquad (5.12)$$

$$-\infty < I_{i,t} < +\infty, \qquad\qquad \forall i \in V^{'}, t \in T \qquad (5.13)$$

$$I_{i,t}^{+}, W_{i,t} \geq 0, \qquad\qquad \forall i \in V^{'}, t \in T \qquad (5.14)$$

$$Q_{i,k,t} \geq 0, \qquad\qquad \forall i \in V^{'}, k \in K, t \in T. \qquad (5.15)$$

Constraints (5.11) to (5.15) represent the restrictions imposed on the decision variables.

5.3.3 Deterministic approximation of the chance-constrained programming model with demand uncertainty

Solving the above chance constrained model is complicated as the product have a fixed expiration date. In line with Pauls-Worm et al. (2014), we therefore consider a deterministic approximation. The deterministic constraints for the stochastic chance constraints (5.6) are rewritten as follows.

Constraints (5.6) ensure the inventory level at the end of every period to be nonnegative with a probability of service level α. Therefore, starting inventory level of every period should be higher than the demand of that period, with a probability higher than the service level. These constraints now can be rewritten as,

$$Pr\Big(I_{i,t-1} + \sum_{k \in K} Q_{i,k,t} \geq d_{i,t} \Big) \geq \alpha, \qquad\qquad \forall i \in V^{'}, t \in T. \qquad (5.16)$$

Applying constraints (5.2) to constraints (5.16), we have

$$Pr\Big(\underbrace{\sum_{s=1}^{t-1} \sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t-1}(d_{i,s} + E[W_{i,s}])}_{I_{i,t-1}} + \sum_{k \in K} Q_{i,k,t} \geq d_{i,t} \Big) \geq \alpha, \qquad \forall i \in V^{'}, t \in T. \qquad (5.17)$$

Rearranging the constraints (5.17) yields

$$Pr\Big(\sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq \sum_{s=1}^{t} d_{i,s} \Big) \geq \alpha, \qquad\qquad \forall i \in V^{'}, t \in T. \qquad (5.18)$$

If $G_{d_{i,1}+d_{i,2}+...+d_{i,t}}(y)$ is the cumulative distribution function of $D_i(t) = d_{i,1}+d_{i,2}+...+d_{i,t}$, then

$$\sum_{s=1}^{t}\sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq G_{D_i(t)}^{-1}(\alpha), \qquad \forall i \in V^{'}, t \in T. \qquad (5.19)$$

$D_i(t) = \sum_{s=1}^{t} d_{i,s}, \quad \forall i \in V^{'}$ will be normally distributed if the $\{d_{i,s}\}$, $\forall i \in V^{'}, s \in T$ with mean $\mu_{i,s}$ and standard deviation $\sigma_{i,s}$ are each normally distributed, and pairwise uncorrelated (Bookbinder and Tan, 1988). Therefore,

$$G_{D_i(t)}^{-1}(\alpha) = \sum_{s=1}^{t} \mu_{i,s} + \sqrt{(\sum_{s=1}^{t}(\mu_{i,s})^2)CZ_{\alpha}}, \qquad \forall i \in V^{'}, t \in T. \qquad (5.20)$$

where C is the coefficient of variation which is assumed to be constant and Z_{α} is a standard normal random variate with cumulative probability of α. Therefore,

$$\sum_{s=1}^{t}\sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq \sum_{s=1}^{t} \mu_{i,s} + \sqrt{(\sum_{s=1}^{t}(\mu_{i,s})^2)CZ_{\alpha}}, \qquad \forall i \in V^{'}, t \in T. \qquad (5.21)$$

As a result, the model is simplified through transforming the stochastic terms by replacing constraints (5.6) with constraints (5.21). Then, the resulting deterministic linear formulation, which is the approximation of the chance-constrained programming model with demand uncertainty, is: (5.1)–(5.5), (5.7)–(5.15) and (5.21). This integrated model that takes perishability, explicit fuel consumption and demand uncertainty into account is denoted by M_{PF}.

5.4 Variations of the integrated model M_{PF}

In this section, we derive from model M_{PF}, three models (M, M_F and M_P) to present the benefits of including perishability and explicit fuel consumption considerations in the model. Table 5.3 presents the considered aspects in the model variations.

TABLE 5.3: Considered aspects in the model variations

	Perishability		Fuel or emissions considerations				Demand uncertainty
	Shelf life	Waste	Traveled distance	Vehicle load	Vehicle speed	Vehicle characteristics	
M	-	-	✓	-	-	-	✓
M_F	-	-	✓	✓	✓	✓	✓
M_P	✓	✓	✓	-	-	-	✓
M_{PF}	✓	✓	✓	✓	✓	✓	✓

Model M does not take perishability into account. Fuel consumption is calculated based on only traveled distance in M, therefore it does not have explicit fuel consumption concern as well. Model M_F also disregards perishability. However, it calculates fuel

consumption explicitly through taking traveled distance, vehicle load, vehicle speed and vehicle characteristics into account. Model M_P has perishability concern. However, it considers only traveled distance while calculating fuel consumption, and therefore does not have explicit fuel consumption concern. The integrated model, M_{PF}, presented in the previous section has both perishability and explicit fuel consumption concerns. Lastly, note that all models take demand uncertainty into account. The following subsections present models M, M_F and M_P.

5.4.1 Model without perishability and without explicit fuel consumption concerns (M)

We adapt M_{PF} by making some changes so that the new model, M, ignores perishability and explicit fuel consumption, as shown in Table 5.3. Initially, the fuel cost component (5.iii) in the objective function (5.1) is replaced with the following fuel cost calculation equation based on only traveled distance:

$$\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}(a_{ij}/1000)X_{i,j,k,t}bl. \tag{5.22}$$

where a new introduced parameter, b, refers to fuel consumption per km. The other components (5.i, 5.ii and 5.iv) in the objective function (5.1) are not changed. Afterwards, the maximum shelf life parameter, m, needs to be set a number which is larger than the length of the planning horizon $|T|$. Model M thus determines an IRP plan as if the products are non-perishable. In reality the product is perishable with a maximum shelf life of say $m' < m$. To evaluate within the MILP what the resulting inventory and waste costs would be if the plan for non-perishables is applied to a perishable product with a shelf life of m' periods, constraints (5.23)–(5.30) are added to the formulation. These constraints do not influence the solution of M, as the constraints are not used in the objective function.

$$E[I'_{i,t}] = \sum_{s=1}^{t}\sum_{k\in K}Q_{i,k,s} - \sum_{s=1}^{t}(E[d_{i,s}] + E[W'_{i,s}]), \qquad \forall i \in V', t \in T \tag{5.23}$$

$$E[W'_{i,t}] = max\big(E[I'_{i,t-m'+1}] - \sum_{a=t-m'+2}^{t}E[d_{i,a}] - \sum_{a=t-m'+2}^{t-1}E[W'_{i,a}],0\big), \ \forall i \in V', t \in \{T|t \ge m'\}$$
$$\tag{5.24}$$

$$E[W'_{i,t}] = 0, \qquad \forall i \in V', t \in \{T|t < m'\} \tag{5.25}$$

$$Waste = \sum_{i\in V'}\sum_{t\in\{T|t\ge m'\}}E[W'_{i,t}]p, \tag{5.26}$$

$$Inv = \sum_{i\in V'}\sum_{t\in T}max\big(I'_{i,t},0\big)h_i, \tag{5.27}$$

$$-\infty < I'_{i,t} < +\infty, \qquad \forall i \in V', t \in T \tag{5.28}$$

$$W'_{i,t} \ge 0, \qquad \forall i \in V', t \in T \tag{5.29}$$

$$Waste, Inv \geq 0. \tag{5.30}$$

where m' refers to the maximum shelf life. Furthermore, $Waste$ and Inv auxiliary variables refer to the total waste and total inventory costs calculated using the inventory and waste tracking auxiliary variables $I'_{i,t}$ and $W'_{i,t}$, $\forall i \in V', t \in T$. In particular, constraints (5.23) calculate expected inventory levels, and constraints (5.26) and (5.27) calculate expected waste at each customer per period. Constraints (5.26) and (5.27) calculate respectively total waste and inventory costs. Constraints (5.28)–(5.30) represent the restrictions imposed on the decision variables.

Apart from these constraints, to calculate total fuel cost explicitly for the comparison purposes with the other types, constraints (5.31)–(5.33) are added to the formulation.

$$\sum_{j \in V'} F_{j,0,k,t} \leq 0, \qquad \forall k \in K, t \in T \tag{5.31}$$

$$Fuel = \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y(a_{ij}/f)X_{i,j,k,t} + \gamma\beta a_{ij}f^2 X_{i,j,k,t} + \gamma s(\mu X_{i,j,k,t} + F_{i,j,k,t})a_{ij} \right)l, \tag{5.32}$$

$$Fuel \geq 0. \tag{5.33}$$

where $Fuel$ auxiliary variable refers to total fuel consumption cost calculated based on the explicit fuel consumption model that considers traveled distance, vehicle load and vehicle speed. In particular, constraints (5.31) ensure that vehicles do not carry load which is more than the total amount delivered to the customers. Note that M_{PF} penalizes carrying more than enough load through explicit fuel consumption cost component existing in its objective function (5.1). Constraint (5.32) does not affect solutions and is used to estimate total fuel consumption cost. Constraint (5.33) represents the restriction imposed on the decision variable. As a result, the resulting constraints for M are (5.2)–(5.15), (5.21), and (5.23)–(5.33).

5.4.2 Model with explicit fuel consumption concern (M_F)

We adapt M_{PF} by making some changes so that the new model, M_F, ignores perishability, as shown in Table 5.3. Same as we do for M, first, the maximum shelf life parameter, m, needs to be set a number which is larger than the length of the planning horizon $|T|$ to ignore the possibility of waste during the whole planning horizon. Afterwards, constraints (5.23)–(5.30) are employed to calculate total inventory and total waste costs for the comparison purposes with the other types. Then, the resulting constraints for M_F are (5.2)–(5.15), (5.21), and (5.23)–(5.30). Note that no changes occur in the objective function (5.1).

5.4.3 Model with perishability concern (M_P)

We adapt M_{PF} by making some changes so that the new model, M_P, does not take fuel consumption explicitly into account, as shown in Table 5.3. Same as we do for M, first, fuel cost from transportation operations component (5.iii) in the objective function (5.1) is replaced with the equation (5.22). The other components (5.i, 5.ii and 5.iv) in the objective function (5.1) are not changed. Apart from that, constraints (5.31)–(5.33) are employed to calculate total fuel cost for the comparison purposes with the other types. Then, the resulting constraints for M_P are (5.2)–(5.15), (5.21), and (5.31)–(5.33).

So far in this section, we present optimization models that differ in terms of considered aspects. In the next section, we present a simulation model which is used for a performance evaluation of the model solutions.

5.5   Performance evaluation by simulation

As it is already mentioned, the optimization models M, M_F, M_P and M_{PF} are the deterministic approximations of the related stochastic models. Therefore, solutions of the formulations can be readily obtained with a commercial MILP solver. In this section, we have proposed a simulation model to evaluate the solutions of these models in terms of inventory and waste performances, and to check whether these solutions are feasible.

The simulation model obtains the delivery schedules from the optimization models and calculates achieved average service level for each customer per period, and average total inventory and waste costs according to the realized demand and maximum shelf life of the product. Due to the fact that the delivery schedules are obtained from the optimization models, we do not calculate emissions, driving time and routing cost amounts by the simulation model to prevent double calculation. The pseudocode of the simulation model is presented in Algorithm 1.

Algorithm 1: Simulation model algorithm

Data: Delivery schedule from the optimization model, $Q_{i,k,t}$ in kg, $\forall i \in V', k \in K, t \in T$;

Fixed maximum shelf life parameter, $m \geq 2$;

Demand mean $\mu_{i,t}$ and standard deviation $\sigma_{i,t}$ in kg, $\forall i \in V', t \in T$;

Penalty cost for the wasted product, p (€/kg) and holding cost per period at customers, h (€/kg);

Result: Average total inventory cost, Average total waste cost, Average service level;

Initialization: set all arrays $\leftarrow 0$;

for *sim = 1 to S (simulation number)* **do**

    for *i = 1 to $|V'|$* **do**

        for *t = 1 to $|T|$* **do**

            Generate random demand, $d_{i,t} \sim N(\mu_{i,t}, \sigma_{i,t})$;

            Compute inventory-I (waste not included), $IB_{i,t} = \sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t} d_{i,s}$;

            if $t < m$ **then**

                Set inventory-II (waste included), $I_{i,t} \leftarrow IB_{i,t}$;

            else

                Compute waste, $W_{i,t} = I_{i,t-m+1} - \sum_{a=t-m+2}^{t} d_{i,a} - \sum_{a=t-m+2}^{t-1} max(W_{i,a}, 0)$;

                Compute inventory-II (waste included), $I_{i,t} = IB_{i,t} - \sum_{s=1}^{t} max(W_{i,s}, 0)$;

            if $I_{i,t} > 0$ **then**

                Keep track of total inventory for computing inventory costs, $SI+ = I_{i,t}$;

            if $I_{i,t-1} + \sum_{k \in K} Q_{i,k,t} < d_{i,t}$ **then**

                Keep track of # of stock outs for computing achieved average service levels, $SA_{i,t} + +$;

            if $W_{i,t} > 0$ **then**

                Keep track of total waste for computing waste costs, $SW+ = W_{i,t}$;

Compute achieved average service level for customer i in period t, $AAS_{i,t} = (SA_{i,t}/S)$;

Compute average total inventory cost, $TI = (SI/S)h$;

Compute average total waste cost, $TW = (SW/S)p$.

5.6 Case study

This section presents an implementation of the proposed model, M_{PF}, and its above described variations, M, M_F and M_P, on the fresh tomato distribution operations of a supermarket chain operating in Turkey. We first describe the data used, then present the results.

5.6.1 Description and data

The underlying transportation network includes one distribution center (DC) and 11 supermarkets (customers) as presented in Figure 5.2. The DC is responsible for providing fresh tomatoes to the supermarkets. We note that in some places there exist multiple supermarkets which are relatively close to each other (e.g., Izmir, Kusadasi and Didim). In these circumstances, we aggregate customers and select one supermarket according to size and/or location. The planning horizon length is four weeks.

FIGURE 5.2: Representation of the logistics network

We assume that homogeneous vehicles are used for the deliveries, each with a capacity of 10 tonnes. The parameters used to calculate the total fuel consumption cost are taken from Demir et al. (2012) and are given in Table 5.4. The fuel consumption per km parameter, b, which is required for M and M_P, is calculated as 0.21 l/km with the fuel consumption calculation model introduced previously based on the assumption that vehicle is assumed as half-loaded. Note that M and M_P disregard the effect of vehicle load on fuel consumption and take only traveled distance into account as a parameter while estimating related fuel consumption amounts. We use 2.63 kg/l as a fuel conversion factor to estimate CO_2 emissions from transportation operations (Defra, 2007). Distances between nodes (see Table 5.A in the appendix) are calculated using Google Maps[1]. Vehicles travel at a fixed speed of 80 km/h.

Demand means (see Table 5.B) are generated randomly for purposes of sensitivity analysis as will be shown in the following section. The coefficient of variation for the demand is assumed to be constant and equal to 0.1 for all supermarkets in each week. The demand for each supermarket in each week must be satisfied with a probability of at least 95%. Holding cost at supermarkets is taken as 10% of the average marketplace selling price of tomatoes[2] in that region of Turkey, and is equal to 0.06 €/kg-week. Shelf life of fresh tomatoes is nearly two weeks (Aguayo et al., 2004). Therefore, if a fresh tomato stays in inventory more than two weeks, it becomes spoiled and cost of waste occurs. The cost of waste is estimated as 0.6 €/kg based on the average marketplace selling price of tomatoes. The aim of the problem is to determine the routes and quantity of shipments in each week such that the total cost is minimized.

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[1]http://maps.google.nl/,Onlineaccessed:February2014
[2]http://halfiyatlari.org/izmir.html,Onlineaccessed:February2014

TABLE 5.4: Setting of vehicle and emission parameters

Notation*	Description	Value
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/liter)	737
k_e	Engine friction factor (kJ/rev/liter)	0.2
N_e	Engine speed (rev/s)	33
V_e	Engine displacement (liter)	5
ρ	Air density (kg/m^3)	1.2041
A_e	Frontal surface area (m^2)	3.912
μ	Curb-weight (kg)	6350
g	Gravitational constant (m/s^2)	9.81
ϕ	Road angle	0
C_d	Coefficient of aerodynamic drag	0.7
C_r	Coefficient of rolling resistance	0.01
ε	Vehicle drive train efficiency	0.4
ϖ	Efficiency parameter for diesel engines	0.9
l	Fuel price per liter (€)	1.7
r	Driver wage (€/s)	0.003

Source: Demir et al. (2012)

* See section 5.3.1 for the description of the notation.

5.6.2 Analysis and discussion

The ILOG-OPL development studio and CPLEX 12.6 optimization package has been used to develop and solve the presented formulations for the case study. The resulting integrated model, M_{PF}, has 1321 continuous and 1056 binary variables, and 1548 constraints. Optimal solutions were obtained on a computer of Pentium(R) i5 2.4GHz CPU with 3GB memory. Our experimentation shows that it takes on average nearly one and half hour to get optimal solutions. The simulation model is implemented in Visual C++ programming language. The simulation number (S) is set to 1000000.

We focus on six KPIs: (i) total emissions, (ii) total driving time, (iii) total routing cost comprised of fuel and wage cost, (iv) total inventory cost, (v) total waste cost, and (vi) total cost. Optimization models M, M_F, M_P and M_{PF} are assessed with respect to these KPIs.

5.6.2.1 Base case solution

Table 5.5 presents performance of the models with respect to all KPIs. According to the results, M and M_F, which neglect perishability, provide relatively lower total emissions, driving time and routing cost than M_P and M_{PF}. As it is shown in Table 5.7, M and M_F solutions propose different routes for the deliveries, i.e., resulting routes for the first period are different. However, total quantity of shipments to each supermarket in each period is the same that leads to the same inventory, waste and service level performances for the two models (see Table 5.6). In our problem, the demand for each customer in each week has to be satisfied with a probability of at least 95%. The achieved average

service levels obtained from the simulation analysis show that M and M_F cannot always meet the desired service level, i.e., service level falls below 95% for supermarkets 1, 3, 9 and 10 in the last period (see Table 5.6). Therefore, optimal solutions obtained from M and M_F do not guarantee feasible solutions for our problem. These two models perform poor in terms of service level as they plan delivery amounts as if there is no chance of product wastes at customers. In the simulation analysis, waste occurrences nevertheless cause to encounter such cases where inventory falls below zero. Both optimization and simulation results presented in Table 5.5 confirm as well that the perishability ignorance in M and M_F leads to poor waste cost performance compared to the other two models, M_P and M_{PF}, which consider perishability of products. For instance, according to the simulation results, this ignorance causes more than five-fold increase in waste cost. To conclude, M and M_F outperforms M_P and M_{PF} in some KPIs, however, the simulation analysis show that M and M_F fail to generate a feasible plan for our problem.

TABLE 5.5: Summary results for base case

	KPIs	M	M_F	M_P	M_{PF}
	Average vehicle load (kg\km)	3506.0	3222.1	3493.3	2618.6
	# of vehicles used	7	7	8	8
	Total emissions (kg)	1449.0	1436.5	1898.4	1862.5
	Total driving time (h)	35.6	35.8	46.7	47.6
Optimization	Total fuel cost (€)	936.6	928.6	1227.1	1203.9
Results	Total wage cost (€)	385.0	386.7	504.0	514.5
	Total routing cost (€)	1321.6	1315.3	1731.1	1718.4
	Total inventory cost (€)	904.9	904.9	805.2	792.9
	Total waste cost (€)	1208.8	1208.8	61.4	61.4
	Total cost (€)	3435.3	3429.0	2597.6	2572.7
	Average total inventory cost (€)	895.8	895.8	790.6	774.5
Simulation	Average total waste cost (€)	1276.7	1276.7	198.9	198.9
Results	Average total cost (€)	3494.1	3487.8	2720.6	2691.8
	Achieved average service levels are presented in Table 5.6.				

Table 5.7 shows that M_P and M_{PF} solutions propose different routes for the deliveries. However, except for two supermarkets, 8 and 9, total quantity of shipments to the supermarkets in each period is the same, as shown in Table 5.6. M_P and M_{PF} meet the service level targets for all supermarkets in each period, since both of them account for product waste. These two models' solutions still cannot completely avoid waste occurrences due to the service level constraints. The service level constraints require to keep a certain amount of inventory at customers in all periods according to the demand means and coefficient of variation to satisfy the desired service level targets. In some circumstances, such as at supermarket 4 in period four, the desired service level requirement causes product wastes as a result of too much inventory. In particular, the vendor, who is responsible for the inventories at customers in our problem, bears waste risk to satisfy demand with a probability of at least 95%. It is a crucial task to balance product waste and out-of-stock in practice as well.

TABLE 5.6: Delivery, inventory, waste quantities and achieved average service levels for supermarkets during the whole planning horizon

Models	Cust. #	Delivery (kg) Weeks				Inventory (kg) Weeks				Waste (kg) Weeks				Achieved Service (%) Weeks			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
$M\&M_F$	1	1462	-	1689	-	562	-	689	-	-	162	-	89	100.0	95.0	100.0	77.1
	2	1630	1273	1817	1237	230	303	421	457	-	-	-	-	95.0	95.0	95.3	95.0
	3	1116	-	1990	-	616	-	740	-	-	116	-	140	100.0	95.0	100.0	84.1
	4	1281	2768	912	-	181	449	861	-	-	-	-	461	95.0	95.0	99.9	95.0
	5	1223	955	1608	1146	173	227	336	381	-	-	-	-	95.0	95.0	95.0	95.0
	6	1397	516	410	1497	197	214	224	321	-	-	-	-	94.9	94.9	94.9	94.9
	7	932	743	1035	-	132	175	710	-	-	-	-	210	95.0	95.0	100.0	95.0
	8	2213	407	304	1364	313	319	304	368	-		19	-	95.0	95.0	95.0	94.9
	9	932	1155	-	1397	132	887	-	97	-	-	187	-	95.0	100.0	95.0	76.6
	10	1281	2449	-	-	181	1030	-	-300	-	-	630	-	95.0	100.0	99.9	0.0
	11	3028	3451	2615	3359	428	678	793	952	-	-	-	-	95.0	95.0	95.0	95.0
$M_P\&M_{PF}$	1	1048	414	1069	620	148	162	231	251	-	-	-	-	95.0	95.0	95.0	95.0
	2	1630	1273	1809	1245	230	303	413	457	-	-	-	-	95.0	95.0	95.0	95.0
	3	582	534	1370	620	82	116	236	256	-	-	-	-	94.9	95.0	95.0	95.0
	4	1281	2768	507	405	181	449	457	405	-	-	-	57	95.0	95.0	95.0	95.0
	5	1223	955	1608	1146	173	228	336	381	-	-	-	-	95.0	95.0	95.0	95.0
	6	1397	516	410	1497	197	214	224	321	-	-	-	-	94.9	94.9	94.9	94.9
	7	932	743	518	517	132	175	193	210	-	-	-	-	95.0	95.0	95.0	95.0
	10	1281	1738	407	304	181	319	326	304	-	-	-	26	95.0	95.0	95.0	95.0
	11	3028	3451	2615	3359	428	678	793	952	-	-	-	-	95.0	95.0	95.0	95.0
M_P	8	2213	407	323	1364	313	300	323	388	-	19	-	-	95.0	95.0	96.0	95.7
	9	932	416	944	1193	132	147	391	284	-	-	-	-	95.0	95.1	100.0	95.1
M_{PF}	8	2213	407	304	1384	313	319	304	388	-	-	19	-	95.0	95.0	95.0	95.8
	9	932	416	740	1397	132	147	187	284	-	-	-	-	95.0	95.1	95.1	95.1

Vehicle load is dependent on the visiting order of the customers. We track the average vehicle load (kg\km) to investigate the effect of vehicle load size on the defined KPIs. M_F and M_{PF} take explicit fuel consumption concern into account and therefore account for vehicle load in addition to traveled distance while estimating fuel consumption amounts. According to the results presented in Table 5.5, M and M_F solutions propose to use seven vehicles for deliveries. Although M_F has worse total driving time or distance performance, it performs better than M in terms of total emissions due to the fact that M_F has less average vehicle load (see Table 5.5). M_P and M_{PF} solutions propose to use eight vehicles for deliveries. Similarly, less total driving time of M_P cannot guarantee less total emissions compared to M_{PF} due to the fact that M_P has higher average vehicle load. Explicit fuel consumption consideration in M_F and M_{PF} affects not only total emissions, but also the other KPIs, and routing and delivery decisions as shown in Tables 5.5, 5.6 and 5.7. In summary, results show that vehicle load affects fuel consumption and emissions and therefore it needs to be considered while making decisions in logistics. The effect of vehicle load on fuel consumption has also been shown in, e.g., Bektaş and Laporte (2011) and Demir et al. (2012), and our results confirm that the previous findings also hold in our problem.

Both optimization and simulation results reveal that M_{PF} including perishability and explicit fuel consumption concerns performs better than the other models in terms of total cost. M_F neglecting perishability concern has slightly better total cost performance than M neglecting perishability and explicit fuel consumption concerns. Resulting total

TABLE 5.7: Resulting routes from the models

Models	Routes	Weeks			
		1	2	3	4
M	1st	0-7-6-5-2-3-4-0	0-11-10-9-8-7-6-5-0	0-4-3-2-0	0-11-8-9-6-5-2-0
	2nd	0-1-8-9-10-11-0	0-4-2-0	0-1-11-8-7-6-5-0	-
M_F	1st	0-11-7-6-5-2-3-4-0	0-11-10-9-8-7-6-5-0	0-4-3-2-0	0-11-8-9-6-5-2-0
	2nd	0-1-8-9-10-11-0	0-4-2-0	0-1-11-8-7-6-5-0	-
M_P	1st	0-7-6-5-2-3-4-0	0-1-11-10-9-8-7-6-5-0	0-4-3-2-0	0-4-3-2-0
	2nd	0-1-8-9-10-11-0	0-4-3-2-0	0-1-11-10-9-8-7-6-5-0	0-1-11-10-9-8-7-6-5-0
M_{PF}*	1st	0-11-7-6-5-2-3-4-0	0-11-10-9-6-5-7-8-1-0	0-4-3-2-0	0-1-8-9-10-0
	2nd	0-1-8-9-10-11-0	0-4-3-2-0	0-1-11-10-9-8-7-6-5-0	0-11-7-6-5-2-3-4-0

* Resulting routes from M_{PF} are also visualised in the Figure 5.3.

FIGURE 5.3: Representation of the resulting routes from M_{PF} for each period

cost of the M_{PF} solution is better than that of M and M_F on average 33.4% according to the optimization results and on average 29.7% according to the simulation results. Additionally, as it is discussed before, M and M_F do not guarantee feasible solution for our problem. On one hand, M_P solutions meet service levels that show the benefit of perishability incorporation to the model. On the other hand, it performs nearly 1.1% worse than M_{PF} in terms of total cost in both optimization and simulation analysis that shows the cost of not incorporating explicit fuel consumption to the model. To conclude, results present the importance of perishability and explicit fuel consumption issues on the studied problem.

Our analysis on the base case show the consequences of perishability and/or explicit fuel consumption ignorance. M_{PF} takes these two aspects into account simultaneously. The models M, M_F and M_P that account for none of the aspects or only a single aspect provide optimal plans for our problem that are higher in cost compared to M_{PF}. Moreover, M and M_F that disregard quality decay cannot meet the desired service level. The managerial implication of these results is that use of the proposed integrated model, M_{PF}, can provide least cost solutions for the studied problem while satisfying the service level requirements.

In the coming section, we carry out further analysis to observe the performances of these models under different scenarios.

5.6.2.2 Sensitivity analysis

This section presents sensitivity analysis for the models with respect to changes in the demand means, coefficient of variation, maximum shelf life, holding cost, service level, fuel price and vehicle speed. In particular, 17 scenarios have been formulated for the sensitivity analysis. In each scenario, different model parameters (demand means, $d_{i,t}$: Demand 1,2, coefficient of variations: $C = 0.05, 0.15, 0.2$, fixed shelf lives, weeks,: $m = 3, 4$, holding costs per period,€/kg,: $h = 0.03, 0.09, 0.12$, service levels, %, : $\alpha = 90, 92.5, 97.5$, fuel price,€/l,: $l = 1.2, 2.2$ and vehicle speed, km/h,: $f = 40, 120$) are employed to observe the effects of changes in the related parameters on the defined KPIs. Results of the optimization sensitivity analysis are presented in Table 5.8.

- *Comparison among models in terms of total cost:*

In all scenarios, M_{PF} performs better than M in terms of total cost. Average total cost gap between the two model solutions is 24.3% according to the optimization results and 21.7% according to the simulation results. The results do not indicate a systematic total cost gap change between M and M_{PF} as l or f changes, whereas the total cost gap between the two model solutions increases as C or α increases. The C or α increase leads to waste cost increase in both model solutions. However, the waste cost increase in M solution is more than that in M_{PF} solution. For instance, the waste cost of M solution is €689 more than that of M_{PF} solution when $C = 0.05$, whereas this cost difference increases to €1807 when $C = 0.2$. Similarly, the waste cost of M solution is €975 more than that of M_{PF} solution when $\alpha = 90\%$, whereas this cost difference increases to €1253 when $\alpha = 97.5\%$. The differences in waste cost changes thus mainly causes extension of the total cost gap between these two models as C or α increases.

In a similar, but reverse way, the total cost gap between M_{PF} and M solutions decreases as m or h increases. The reason is that the waste cost decrease in M solution due to the m or h increase is more than that in M_{PF} solution. For instance, the waste cost of M solution is €1147 more than that of M_{PF} solution when $m = 2$, whereas this cost difference decreases to €0 when $m = 4$. Similarly, the waste cost of M solution is €1838 more than that of M_{PF} solution when $h = 0.03$, whereas this cost difference decreases to €182 when $h = 0.12$. The differences in waste cost changes thus mainly causes reduction of the total cost gap between these two models as m or h increases.

TABLE 5.8: Results of optimization sensitivity analysis

Scenarios	Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
Base case	M	1449.0	35.6	936.6	385.0	1321.6	904.9	1208.8	3435.3
	M_F	1436.5	35.8	928.6	386.7	1315.3	904.9	1208.8	3429.0
	M_P	1898.4	46.7	1227.1	504.0	1731.1	805.2	61.4	2597.6
	M_{PF}	1862.5	47.6	1203.9	514.5	1718.4	792.9	61.4	2572.7
Demand 1*	M	1585.7	39.1	1025.0	421.9	1446.9	769.9	915.2	3132.0
	M_F	1552.5	39.5	1003.5	426.8	1430.3	769.9	915.2	3115.4
	M_P	1909.5	46.7	1234.3	503.9	1738.2	767.5	107.5	2613.2
	M_{PF}	1856.0	47.5	1199.7	513.1	1712.8	767.5	107.5	2587.8
Demand 2*	M	1653.7	39.6	1069.0	427.9	1496.8	895.5	495.9	2888.3
	M_F	1685.1	41.4	1089.2	446.7	1535.9	861.4	495.9	2893.3
	M_P	1914.6	46.7	1237.6	503.9	1741.5	842.5	0.0	2584.0
	M_{PF}	1891.6	46.9	1222.7	506.7	1729.4	842.5	0.0	2571.9
$C = 0.05$	M	1439.6	35.6	930.5	385.0	1315.5	585.4	688.6	2589.5
	M_F	1422.0	35.8	919.2	386.2	1305.3	585.4	688.6	2579.3
	M_P	1886.9	46.7	1219.6	504.0	1723.6	399.5	0.0	2123.1
	M_{PF}	1846.9	47.3	1193.8	511.2	1705.0	399.5	0.0	2104.5
$C = 0.15$	M	1458.3	35.6	942.6	385.0	1327.6	1207.8	1813.2	4348.6
	M_F	1506.0	37.8	973.5	408.8	1382.2	1179.4	1380.0	3941.6
	M_P	1942.4	47.0	1255.5	507.5	1763.0	1159.4	392.0	3314.5
	M_{PF}	1874.5	47.7	1211.7	515.4	1727.1	1159.4	392.0	3278.5
$C = 0.2$	M	1487.7	36.1	961.6	389.6	1351.2	1469.8	2546.6	5367.6
	M_F	1559.7	39.2	1008.2	422.9	1431.1	1447.3	1752.1	4630.5
	M_P	1950.7	47.0	1260.9	507.6	1768.5	1524.2	739.4	4032.0
	M_{PF}	1882.2	48.0	1216.6	518.3	1734.9	1524.2	739.4	3998.4
$m = 3$ weeks	M	1449.0	35.6	936.6	385.0	1321.6	1071.5	197.9	2591.0
	M_F	1436.5	35.8	928.6	386.7	1315.3	1071.5	197.9	2584.7
	M_P	1515.2	37.2	979.4	402.0	1381.4	1056.7	0.0	2438.1
	M_{PF}	1538.8	39.0	994.7	421.1	1415.8	997.5	15.7	2429.0
$m = 4$ weeks	M	1449.0	35.6	936.6	385.0	1321.6	1091.3	0.0	2412.9
	M_F	1436.5	35.8	928.6	386.7	1315.3	1091.3	0.0	2406.6
	M_P	1449.1	35.6	936.7	385.0	1321.6	1091.3	0.0	2413.0
	M_{PF}	1436.5	35.8	928.6	386.7	1315.3	1091.3	0.0	2406.6
$h = 0.03$ €/kg	M	1264.4	30.5	817.3	329.4	1146.8	538.9	1899.8	3585.4
	M_F	1304.6	32.2	843.2	347.6	1190.9	518.1	1533.7	3242.7
	M_P	1898.3	46.7	1227.0	504.0	1731.0	402.6	61.4	2194.9
	M_{PF}	1855.6	47.4	1199.4	511.7	1711.1	402.6	61.4	2175.1
$h = 0.09$ €/kg	M	1746.9	43.2	1129.2	466.6	1595.7	1197.8	410.6	3204.1
	M_F	1765.7	44.8	1141.3	484.1	1625.4	1181.1	340.8	3147.3
	M_P	1927.1	47.0	1245.7	507.5	1753.2	1189.4	61.4	3003.9
	M_{PF}	1862.4	47.6	1203.9	514.5	1718.3	1189.4	61.4	2969.1
$h = 0.12$ €/kg	M	1850.6	45.7	1196.2	493.4	1689.6	1583.5	243.6	3516.7
	M_F	1818.4	46.2	1175.4	498.9	1674.3	1583.5	243.6	3501.4
	M_P	1927.3	47.0	1245.8	507.5	1753.3	1585.8	61.4	3400.4
	M_{PF}	1862.4	47.6	1203.9	514.5	1718.3	1585.8	61.4	3365.5

TABLE 5.8(continued): Results of optimization sensitivity analysis

Scenarios	Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
$\alpha = 90\%$	M	1444.9	35.6	934.0	385.0	1319.0	766.1	974.6	3059.6
	M_F	1430.4	35.8	924.6	386.7	1311.3	766.1	974.6	3052.0
	M_P	1893.2	46.7	1223.7	504.0	1727.7	629.8	0.0	2357.5
	M_{PF}	1850.6	47.3	1196.2	511.2	1707.4	629.8	0.0	2337.2
$\alpha = 92.5\%$	M	1446.7	35.6	935.1	385.0	1320.1	826.6	1070.4	3217.1
	M_F	1433.1	35.8	926.3	386.7	1313.1	826.6	1070.4	3210.1
	M_P	1895.3	46.7	1225.1	504.0	1729.1	707.9	0.0	2437.0
	M_{PF}	1858.0	47.6	1201.0	513.9	1714.9	699.5	0.0	2414.4
$\alpha = 97.5\%$	M	1452.9	35.6	939.1	385.0	1324.1	1024.3	1440.3	3788.7
	M_F	1501.3	37.8	970.4	408.8	1379.2	1001.8	1046.8	3427.8
	M_P	1932.1	47.0	1248.9	507.5	1756.4	933.3	188.0	2877.7
	M_{PF}	1868.4	47.6	1207.7	514.5	1722.2	933.3	188.0	2843.4
$l = 1.2$ €/l	M	1560.8	38.6	712.1	416.5	1128.6	868.0	657.8	2654.4
	M_F	1587.4	40.3	724.3	435.4	1159.7	839.2	573.9	2572.8
	M_P	1927.1	47.0	879.3	507.5	1386.8	792.9	61.4	2241.1
	M_{PF}	1866.4	47.4	851.6	512.2	1363.8	792.9	61.4	2218.1
$l = 2.2$ €/l	M	1449.0	35.6	1212.1	385.0	1597.1	904.9	1208.8	3710.8
	M_F	1436.6	35.8	1201.7	386.7	1588.4	904.9	1208.8	3702.1
	M_P	1898.4	46.7	1588.0	504.0	2092.0	805.2	61.4	2958.5
	M_{PF}	1862.4	47.6	1557.9	514.5	2072.4	792.9	61.4	2926.6
$f = 40$ km/h	M	1401.6	71.3	906.0	770.0	1675.9	904.9	1208.8	3789.6
	M_F	1388.9	71.6	897.8	773.4	1671.2	904.9	1208.8	3784.9
	M_P	1836.2	93.3	1186.9	1007.9	2194.8	805.2	61.4	3061.3
	M_{PF}	1803.4	94.9	1165.7	1024.4	2190.1	792.9	61.4	3044.4
$f = 120$ km/h	M	1973.6	23.8	1275.7	256.7	1532.4	904.9	1208.8	3646.0
	M_F	1963.5	23.9	1269.2	257.8	1527.0	904.9	1208.8	3640.7
	M_P	2585.0	31.1	1670.9	336.0	2006.9	805.2	61.4	2873.4
	M_{PF}	2564.3	31.6	1657.5	341.5	1999.0	792.9	61.4	2853.2

C: Coefficient of variation, m: fixed maximum shelf life, h: holding cost, α: service level.
* Demand mean set is presented in Table 5.B.

M_F and M_{PF} provide the same solutions in scenario $m = 4$ where fixed shelf life is equal to the planning horizon length. In this scenario, these models have thus the same total cost performances, whereas M_{PF} has better cost performance than M_F in the rest of the scenarios. Average total cost gap between the two model solutions is 20.5% according to the optimization results and 18.2% according to the simulation results. The results do not indicate a systematic total cost gap change between M_F and M_{PF} as C, α, l or f changes. However, similar with the case between M and M_{PF}, the total cost gap between M_F and M_{PF} solutions decreases as m or h increases. This is mainly due to the fact that the waste cost decrease in M_F solution is more than that in M_{PF} solution.

In all scenarios, M_{PF} performs better than M_P in terms of total cost. However, the total cost gaps, on average 0.9% according to the optimization results and 0.8% according to the simulation results, are relatively smaller than those observed between M_{PF} and M or M_F. The results do not indicate a systematic total cost gap change between M_{PF} and M_P as C, h or f changes. However, the total cost gap between M_{PF} and M_P solutions slightly increases as α or l increases and the gap slightly decreases as m increases without a systematic waste cost change as it has been observed in the previous analysis.

The simulation analysis indicate parallel results with the optimization results except a case in the scenario $m = 3$. According to the optimization results, M_{PF} performs 0.4% better than M_P in terms of total cost, whereas simulation results indicate that total cost performance of M_P is 1.1% better than M_{PF}. This is mainly due to the difference in waste cost performances. According to the optimization results, waste cost of M_{PF} solution is €15.7 more than that of M_P solution, whereas the realized difference observed from the simulation analysis is €55. This waste cost increase causes M_{PF} to perform worse than M_P. Therefore, if only optimization results are considered, a decision maker may disregard M_P solution that shows better performance in the simulation analysis. This case reveals the benefit of conducting simulation analysis on the delivery schedules obtained from the optimization models, which are the approximations of the stochastic problems.

So far in this subsection relative total cost performances of the models are presented. We now present the effects of changes in the C, m, h, α, l and f to the total costs of models as follows: (i) Total costs of all model solutions increase as C increases. The main drivers of the increase in total costs are growths in inventory and waste amounts. (ii) Total costs of all model solutions decrease as m increases. The main drivers of the decrease in total costs are reductions in routing and waste costs. (iii) Total costs of M_P and M_{PF} solutions increase as h increases. The main contribution to these growths comes from increasing inventory costs. However, the results do not indicate a systematic total cost change for M and M_F as h changes. (iv) Total costs of all model solutions except M_F increase as α increases. The main contribution to these growths comes from increasing inventory costs. (v) Total costs of all model solutions increase as l increases. The main contribution to these growths comes from increasing routing costs. (vi) The results do not indicate a systematic total cost change for all models as f changes.

• *Comparison among models in terms of other KPIs:*

In all except three scenarios ($m = 3, 4$ and $h = 0.12$), M and M_F cannot meet the service level requirements for each customer and period, and thus do not guarantee feasible solutions for the studied problem. Note that the resulting waste costs of M and M_F solutions in the scenarios $m = 3, 4$ and $h = 0.12$ are relatively lower than that obtained in the other scenarios, where these two models do not provide feasible solutions. This shows that the stock-out risk increases when the product waste increases. On the contrary, M_P and M_{PF} achieve to satisfy the service targets in all scenarios, since these two models take perishability and therefore waste into account.

In all except one scenario ($m = 4$), M and M_F show relatively better performance with respect to total emissions, total driving time and total routing cost compared to M_P and

M_{PF}. However, note that except the three scenarios ($m = 3, 4$ and $h = 0.12$), M and M_F provide infeasible solutions for the studied problem.

In all except one scenario ($m = 3$), routing and delivery plans obtained from M_{PF} provide less emissions compared to that from M_P. We note that M_{PF} does guarantee less total cost but not less total emissions, since it aims to minimize cost.

• *A general overview:*

The results show that the basic model, M, which does not account for perishability and explicit fuel consumption, has poor cost performance largely due to the higher waste costs compared to the other models. Moreover, M often cannot provide feasible solutions for the problem. Extending M through incorporating explicit fuel consumption has usually slightly improved the total cost performance, but still cannot ensure to have feasible solutions. On the contrary, extension of M through incorporating perishability has significantly improved the total cost performance in all except one scenario ($m = 4$), where perishability is not a crucial issue anymore. Additionally, the new ability of the model to account for product wastes has enabled to have feasible solutions for the problem in all scenarios. Finally, the integrated model, M_{PF}, which is the extended version of M in terms of perishability and explicit fuel consumption, has provided the least cost and feasible solutions in all scenarios. The main managerial implication of the results is that perishability and explicit consideration of fuel consumption are important aspects in the IRP and the proposed integrated model, M_{PF}, which accounts for the both aspects, offers better support to decision makers.

5.6.2.3 Environmental impact minimization

In our problem, total emissions and total waste are the environmental condition indicators that reflect the state of the physical environment affected by the logistics operations. M_{PF} quantifies the total environmental impact in terms of cost through fuel and waste cost components in the objective function (5.1). In this section, the objective function is adapted so that the model can provide an optimal solution which has the lowest total environmental impact cost. In particular, the expected inventory (5.i) and driver (5.iv) cost components are removed from the objective function (5.1), and the formulation is minimized over an environmental objective function that comprises only expected waste (1.ii) and fuel (1.iii) costs. This change ensures to obtain the most environmentally-friendly solution in terms of total emissions and waste. The new variation of M_{PF} that has emphasis only on reducing fuel and waste costs is denoted as M'_{PF}. Figure 5.4 presents the performance of M'_{PF} compared to M_{PF}.
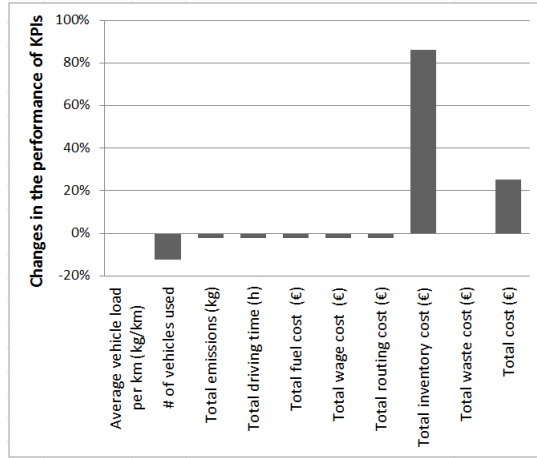
FIGURE 5.4: The performance of M'_{PF} compared to the M_{PF} for the base case.

The results show that M'_{PF} slightly outperforms M_{PF} in terms of number of vehicles used, total emissions, total driving time, and total fuel, wage and routing costs. M'_{PF} solution ensures to have nearly 2% reductions in total emissions (39.6kg), total driving time (one hour), and total fuel (€25.6), wage (€10.6) and routing costs (€36.2) with one less vehicle in total compared to M_{PF} solution. However, M_{PF} performs 86.2% better in terms of total inventory cost (€683.6) and 25.2% in terms of total cost (€647.4) compared to M'_{PF}. Both model solutions have the same total waste costs. This means that nearly 2% total emissions reduction through the use of environmental objective comes at a cost increase of 25.2%. Therefore, additional cost of having a more environmentally-friendly solution is significant for the studied problem. In summary, M_{PF} provides the least cost solution, however, there can be still room to reduce the total environmental impact comprised of emissions and waste by means of M'_{PF}.

5.6.2.4 Modified larger case study

In order to show the performances of the models in a larger problem, we have modified the network. In the new modified setting, nine artificial customers are added (see Figure 5.5) and three vehicles (one more compared to the base case) are employed for the deliveries. Distances between the nodes and customer demands are shown in Tables 5.A and 5.C. The resulting integrated model, M_{PF}, has 5521 continuous and 5040 binary variables, and 6092 constraints for the new relatively large case study.

Table 5.9 presents the results obtained from the models with a solver cut-off time of five hours. The lower bound gap reported in the table shows the percentage gap from the best-known lower bound provided by the solver. In contrast to the base case, where optimal solutions for the integrated model M_{PF} are obtained within nearly one and half hour, for

FIGURE 5.5: Representation of the modified logistics network

TABLE 5.9: Summary results for the large case

Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)	Lower bound gap (%)
M	2380.0	54.0	1538.4	583.0	2121.4	1319.6	574.9	4015.9	1.34
M_F	2362.2	57.5	1526.9	620.6	2147.5	1308.8	549.8	4006.2	4.14
M_P	2489.1	57.7	1608.9	623.1	2232.0	1348.9	114.3	3695.2	2.58
M_{PF}	2362.8	59.3	1527.3	640.4	2167.7	1327.2	114.3	3609.3	2.48

the larger problem, either optimal solutions for the models have not been obtained yet or optimality of the solutions have not been proved yet within five hours. This shows the increasing complexity of the problem as the case size increases.

Regarding performances of the models in terms of the defined KPIs, similar results are obtained with the base case. Results for the larger case confirm the benefit of taking perishability and explicit fuel consumption into account as well. According to the optimization results, integrated model M_{PF} has achieved total cost savings by 11.3% compared to M, 11% compared to M_F and 2.4% compared to M_P. Additionally, simulation results show that M and M_F cannot meet the desired service levels, whereas M_P and M_{PF} satisfy the service levels.

5.7 Conclusions

In this paper, we have modeled and analyzed the IRP to account for perishability, explicit fuel consumption and demand uncertainty. To the best of our knowledge, the model is unique in using a comprehensive emission function and in modeling waste and service level constraints as a result of uncertain demand. The proposed model can be used to aid food logistics decision making process in coordinating inventory and transportation decisions in VMI systems.

We have shown the added value of the proposed model M_{PF} based on case study data and a broad set of experiments. To present the benefits of considering perishability and explicit fuel consumption in the model, the following model variations are employed: (i) M which ignores the perishability of products and explicit fuel consumption, (ii) M_F which ignores the perishability of products and (iii) M_P which ignores explicit fuel consumption. M and M_F cannot meet the desired service levels in all scenarios due to the perishability ignorance which results in relatively higher product wastes. On the contrary, accounting for the perishability allows M_P and M_{PF} to satisfy the service levels in all scenarios. M_{PF} outperforms the other variations of the model in terms of total cost. According to the optimization results, M_{PF} can achieve average savings in total cost by 24.3% compared to M, 20.5% compared to M_F and 0.9% compared to M_P. In the experiments, we have changed the values of the following problem parameters: the demand means, coefficient of variations, fixed shelf lives, holding costs service levels, fuel price and vehicle speed. It appears that the added value of M_{PF} compared to the other model variations in terms of total cost changes according to the parameter values. For instance, the total cost gap between M and M_{PF} solutions increases as C or α increases and decreases as m or h increases. Additionally, the use of more environmentally-friendly objective function (in model M'_{PF}) shows that 2% decrease in total emissions can be obtained in return for a 25.2% significant total cost increase.

The results support the view that the improvement of the IRP model through perishability and explicit fuel consumption incorporation makes it more useful than a basic model that disregards both aspects for the decision makers in food logistics management. One possible extension of the paper is to develop a heuristic algorithm for the studied problem, which will enable to handle instances that are larger in size. The model proposed in this paper can be used to validate and verify the potential of such heuristic algorithms. The other possible extension is to consider a generic logistics network that has many-to-many (multiple suppliers and customers) distribution structure.

Acknowledgement

APPENDIX

In this section, we present the distance and demand data used for the models.

TABLE 5.A: Distances between nodes, in kms

	DC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
DC	-	67	89.2	126	78.1	70.6	106	66.3	64.4	156	151	35.5	139	118	37	49	116	155	52	97	93
1	73.2	-	154	191	143	144	141	101	74.3	166	176	61.5	165	144	110	123	181	221	52	123	119
2	70.8	136	-	65.9	62.9	113	158	118	126	218	212	97.2	201	180	81	66	101	96	51	159	155
3	126	192	69.5	-	98.9	171	233	193	182	274	268	153	259	238	142	129	139	68	119	216	213
4	78.4	144	63.2	99.7	-	123	185	145	134	226	220	105	208	187	91	79	38	95	98	166	162
5	70.9	144	105	163	115	-	50.2	58.4	120	155	220	105	196	114	36	38	106	193	113	167	163
6	106	131	161	222	175	50.9	-	41.6	75.3	105	199	84.4	149	66	87	89	157	264	148	144	135
7	66.5	91.2	121	182	135	58.2	40.1	-	35.3	117	159	44.4	111	78	44	60	169	209	108	104	95
8	67.4	74.9	149	185	137	92.7	74.4	34.5	-	92.1	120	34.8	78	54	78	117	175	215	99	71	62
9	158	166	239	276	228	155	106	116	92.4	-	69.6	126	43	39	160	176	266	306	190	123	89
10	150	176	232	268	220	221	192	152	119	70	-	119	30	109	187	200	258	298	182	95	61
11	35	60.3	116	153	105	106	83.6	43.7	30.6	123	118	-	107	84	72	84	143	182	66	65	61
12	139	165	220	257	209	196	149	110	79	44	30	108	-	83	176	189	247	287	171	84	50
13	120	145	201	238	190	113	66	78	54	40	109	87	83	-	122	133	228	267	151	123	114
14	37	110	84	140	92	36	86	44	77	154	180	71	175	120	-	20	130	170	92	132	129
15	50	127	69	127	79	38	83	60	117	205	198	88	192	171	21	-	117	156	77	150	146
16	115	181	100	137	39	106	222	182	171	258	251	142	245	224	128	116	-	77	135	203	199
17	157	222	95	68	95	201	263	223	212	300	292	183	287	265	170	157	77	-	146	244	240
18	56	52	54	117	99	124	149	109	98	185	178	69	172	151	92	76	137	146	-	130	126
19	96	122	177	214	166	167	143	103	70	123	89	65	83	122	133	146	204	244	128	-	36
20	93	118	174	210	163	163	134	94	61	89	55	61	50	114	129	142	201	240	124	37	-

TABLE 5.B: Demand means (kg) for the supermarkets in each week in different scenarios

Supermarkets	Base case demand set Weeks				Demand set 1 Weeks				Demand set 2 Weeks			
	1	2	3	4	1	2	3	4	1	2	3	4
1	900	400	1000	600	500	1400	1300	300	1500	1000	2600	2000
2	1400	1200	1700	1200	800	1100	1500	1800	2000	500	1200	800
3	500	500	1250	600	1300	600	1000	1900	300	750	900	600
4	1100	2500	500	400	1600	2200	800	600	3000	1150	700	2100
5	1050	900	1500	1100	800	700	900	900	800	550	800	400
6	1200	500	400	1400	2000	800	200	1200	500	3000	1500	1800
7	800	700	500	500	700	300	2500	800	200	1000	400	400
8	1900	400	300	1300	600	1200	1300	1100	1600	600	300	600
9	800	400	700	1300	250	1100	600	600	2200	400	2300	2200
10	1100	1600	400	300	900	300	1100	400	900	900	600	300
11	2600	3200	2500	3200	1800	2200	2500	3400	1400	1100	400	1000
Total	13350	12300	10750	11900	11250	11900	13700	13000	14400	10950	11700	12200

TABLE 5.C: Demand means (kg) for the supermarkets in each week for the large case

Supermarkets	Weeks			
	1	2	3	4
1	900	400	1000	600
2	1400	1200	1700	1200
3	500	500	1250	600
4	1100	2500	500	400
5	1050	900	1500	1100
6	1200	500	400	1400
7	800	700	500	500
8	1900	400	300	1300
9	800	400	700	1300
10	1100	1600	400	300
11	2600	3200	2500	3200
12	700	400	800	600
13	1200	1200	1900	800
14	600	500	1250	600
15	1300	2600	600	400
16	1050	700	1400	900
17	1300	500	400	1400
18	700	800	600	500
19	1500	400	300	1200
20	800	400	1100	600
Total	22500	19800	19100	18900

Chapter 6

Modeling a green inventory routing problem for perishable products with horizontal collaboration and demand uncertainty

In this chapter, we investigate RO5:
To analyse the benefits of horizontal collaboration in a green inventory routing problem for perishable products with demand uncertainty.

6.1 Introduction

Vertical and horizontal collaborations are the two main modes of collaboration commonly applied in logistics. Vertical collaboration involves companies operating at the different levels of the supply chain, e.g., cooperation between a wholesaler and a retailer; whereas horizontal collaboration involves companies from the same level of the supply chain, e.g., cooperation between two wholesalers (Caputo and Mininno, 1996). Relatively more attention has been given to vertical collaboration in logistics literature and the research on horizontal logistics collaboration is accordingly in its infancy (Cruijssen et al., 2007; Leitner et al., 2011; Schulz and Blecken, 2010). The approach of applying only vertical collaboration to a supply chain has been challenged by new drivers such as increased energy costs and awareness on environmental impacts of transportation (Ankersmit et al., 2014). This transition has raised the importance of taking both collaboration opportunities into account simultaneously while tackling logistics problems. One of the problems in literature that incorporates both vertical and horizontal collaboration opportunities is a variant of the Inventory Routing Problem (IRP) where multiple suppliers and customers exist.

The IRP addresses the coordination of inventory management and vehicle routing in a supply chain (Jemai et al., 2013). The variant of the IRP tackled here concerns the transportation of products between a number of suppliers and customers (Andersson et al., 2010). This problem requires vertical collaboration among suppliers and customers, and horizontal collaboration among suppliers. The vertical and horizontal collaborations enable to have a centralized system in which suppliers collectively act as a single entity in their logistics operations and take on the responsibility of managing inventories at customers. Suppliers decide on quantity and time of the shipments to the customers, but have to bear the responsibility that the customers do not run out of stock (Andersson et al., 2010). Such a system offers potential logistics efficiency gains to suppliers through jointly using vehicles. Moreover, suppliers can better coordinate deliveries to customers, since the vehicle routes can be based on the inventory levels observed at the customers rather than the replenishment orders coming from the customers, and customers do not have to dedicate resources to inventory management (Coelho et al., 2012a; Campbell et al., 1998; Raa and Aghezzaf, 2009).

The IRP in this study comprises a 3PL which serves as a rental vehicle company, and multiple suppliers and customers. Figure 6.1 shows a generic representation of the problem. Suppliers provide several product types with fixed shelf lives to the customers. The problem has multiple periods and the customer demand is not known in the beginning

of the planning horizon. The main decisions involved are: (1) when to deliver to each customer, (2) how much to deliver to each customer each time it is served, and (3) how to combine customers into vehicle routes (Bertazzi et al., 2008; Coelho et al., 2012b). The traditional objective is to minimize total distribution and inventory costs during the planning horizon without causing stock-outs at any of the customers (Aghezzaf et al., 2006; Natarajarathinam et al., 2012).
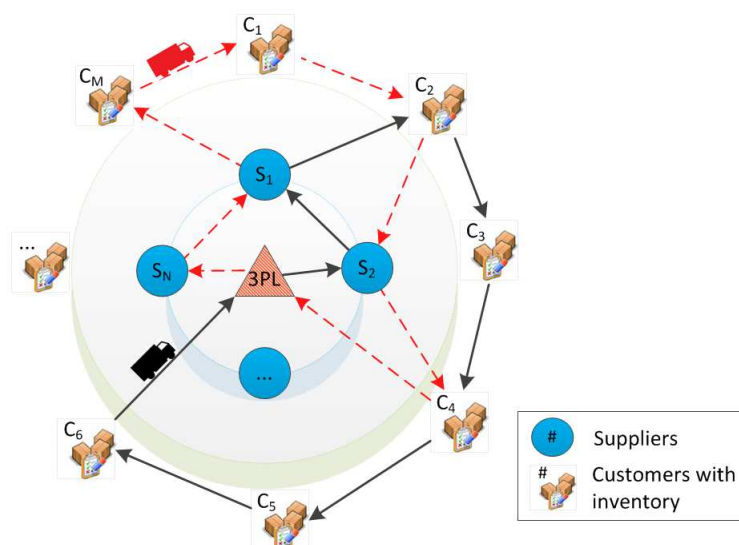
FIGURE 6.1: A generic representation of the Inventory Routing Problem with multiple suppliers and customers

Traditional OR models for the IRP focus mainly on the key logistical aim of cost reduction. However, the need to reduce transportation energy usage, emissions, and product waste require extension of the key logistical aims (Soysal et al., 2014). The traditional models are inadequate to manage these additional key logistical aims. Regarding energy usage, the traditional approaches often rely on distance-based cost calculation, whereas fuel consumption and therefore cost can change based on e.g. vehicle load, which is dependent on the visiting order of the customers (Kara et al., 2007; Kuo and Wang, 2011), vehicle speed or vehicle characteristics (Ramos et al., 2014). The ignorance of explicit fuel consumption may lead to missed opportunities to reduce operational cost and emissions. Regarding perishability, the traditional approaches often assume that products have unlimited shelf lives, whereas this is not the case for all supply chains, especially for food supply chains. The perishability ignorance thus restricts the usage of the traditional approaches in supply chains for perishable products. The need for decision support tools that can incorporate these additional key logistical aims as well as traditional cost concerns has accordingly increased. The need in practice and in research forms the first motivation of this study. That is, to develop a model that allows to consider demand uncertainty, perishability of goods and explicit energy usage (emissions) from transportation

operations along with cost concerns in the IRP with multiple suppliers and customers. The second motivation behind the development of such a model is to use it for analysing the benefits of horizontal collaboration in the IRP, which have above mentioned non-traditional concerns. To the best of our knowledge, our model is the first to address these issues.

The rest of the paper is structured as follows. The next section presents a review of the relevant literature on the IRP and clarifies the contribution of our work. The subsequent section presents the formal description of the problem and related optimization model. This section is followed by computational results on a real life distribution problem. The last section presents conclusions and future research directions.

6.2   Related literature review

The IRP literature describes mainly three types of distribution networks according to the number of suppliers and customers involved: (1) one-to-one: one supplier serves one customer, (2) one-to-many: one supplier serves a set of customers which is the most common case, (3) many-to-many: several suppliers serve a set of customers (Coelho et al., 2012b). Our problem is classified as a many-to-many structure, which is the least studied variant in the literature (Coelho et al., 2012b; Rix et al., 2014). Among the studies on the IRP with many-to-many structure, there are some (e.g., Ronen (2002) and Ramkumar et al. (2012)) that manage multiple products, while some (e.g., Bard et al. (1998) and Savelsbergh and Song (2007)) have concerned with single product (see Table 6.1). All of the studies on the IRP with many-to-many structure do not have perishability and explicit energy usage concerns, which means that these attempts regard only distance while calculating distribution costs and address management of only non-perishable products. Moreover, none of these studies has discussed the effects of horizontal logistics collaboration on logistics Key Performance Indicators (KPIs).

Our review on the other variants of the IRP shows that few studies have bothered to introduce new KPIs to the proposed models (see Table 6.1). These studies therefore can be regarded as non-traditional approaches. Federgruen et al. (1986), Le et al. (2013), Coelho and Laporte (2014), Jia et al. (2014) and Al Shamsi et al. (2014) deal with the IRP of a single perishable product with a fixed shelf life. Among these studies, Federgruen et al. (1986), Coelho and Laporte (2014) and Jia et al. (2014) allow product wastes, whereas in Le et al. (2013) and Al Shamsi et al. (2014), products have to be used within fixed shelf lives before they are spoiled. Treitl et al. (2014), Mirzapour Al-ehashem and Rekik (2013), Alkawaleet et al. (2014) and Al Shamsi et al. (2014) incorporate emissions

to the IRP through estimating fuel consumption from transportation operations. Except the study of Mirzapour Al-ehashem and Rekik (2013) which has a many-to-one structure (a special case of one-to-many structure) and manages multiple products, all given non-traditional approaches have one-to-many structure and manage single product. Therefore, also for the other variants of the IRP, we could not find any attempt, except Al Shamsi et al. (2014), that have addressed both perishability and explicit energy usage concerns simultaneously (see Table 6.1). However, the study of Al Shamsi et al. (2014) does not take potential product wastes and demand uncertainty into account, and note that it addresses one-to-many distribution structure, unlike to our problem. Additionally, none of these non-traditional approaches presented in Table 6.1 has elaborated on issues about horizontal logistics collaboration.

TABLE 6.1: Overview of the related literature on the IRP

	Perishability		Fuel or emissions considerations			Demand uncertainty	Product #	Distribution structure
	Shelf life	Waste	Traveled dist.	Load	Speed			
Federgruen et al. (1986)	✓	✓	-	-	-	✓	Single	One-to-many
Bard et al. (1998)	-	-	-	-	-	✓	Single	Many-to-many
Ronen (2002)	-	-	-	-	-	✓	Multiple	Many-to-many
Persson and Gothe-Lundgren (2005)	-	-	-	-	-	-	Multiple	Many-to-many
Al-Khayyal and Hwang (2007)	-	-	-	-	-	-	Multiple	Many-to-many
Savelsbergh and Song (2007)	-	-	-	-	-	-	Single	Many-to-many
Savelsbergh and Song (2008)	-	-	-	-	-	-	Multiple	Many-to-many
Benoist et al. (2011)	-	-	-	-	-	-	Single	Many-to-many
Ramkumar et al. (2012)	-	-	-	-	-	-	Multiple	Many-to-many
Treitl et al. (2014)	-	-	✓	✓	✓	-	Single	One-to-many
Mirzapour Al-ehashem and Rekik (2013)	-	-	✓	-	-	-	Multiple	Many-to-one
Le et al. (2013)	✓	-	-	-	-	-	Single	One-to-many
Alkawaleet et al. (2014)	-	-	✓	-	-	-	Single	One-to-many
Al Shamsi et al. (2014)	✓	-	✓	✓	✓	-	Single	One-to-many
Coelho and Laporte (2014)	✓	✓	-	-	-	-	Single	One-to-many
Jia et al. (2014)	✓	✓	-	-	-	-	Single	One-to-many
This study	✓	✓	✓	✓	✓	✓	Multiple	Many-to-many

Another key aspect of our problem is that the customer usages are not known in advance in the beginning of the planning horizon, which is usually the case in reality. Some studies on the IRP with many-to-many structure take demand uncertainty into account (Bard et al., 1998; Ronen, 2002). These studies, however, do not have interest on the additional KPIs (see Table 6.1). Among the given non-traditional approaches, except Federgruen et al. (1986) that take demand uncertainty into account, all studies rely on a completely deterministic environment. As shown in Table 6.1, the study of Federgruen et al. (1986) does not have explicit energy usage concern and has a one-to-many distribution structure.

The IRP, except one-to-one structure, inherently involves horizontal logistics collaboration. However, through the review of the studies on the topic, we come to a conclusion that scholars have not explicitly addressed horizontal logistics collaboration in the IRP. Our review on the other logistics problems shows that some studies have analysed the potential savings through the application of horizontal collaboration. For instance, Krajewska et al. (2008) study a routing problem and demonstrate that horizontal cooperation

among freight carriers can yield significant cost savings. In another study (Vanovermeire et al., 2013), a distribution problem is formulated as a bin-packing problem to determine the minimum number of trips necessary to deliver all orders. The results indicate that horizontal collaboration offers a reduction in environmental impacts by reducing the number of trucks employed and it can result in more cost reductions than that of individual companies can achieve. van Lier et al. (2014) address the environmental and societal benefits of bundling outbound freight flows. As a final example, Juan et al. (2014) concentrate on estimating the savings in routing and emissions costs that can be attained by applying backhaul-based horizontal cooperation. Apart from these quantitative attempts, the large-scale survey of Cruijssen et al. (2007) in LSPs operating in Belgium presents the companies' reflections on the potential benefits of and challenges for horizontal cooperation. The survey shows that, in general, LSPs strongly believe that the horizontal collaboration has potential to increase their profitability or to improve the quality of their services. As a result, these findings encourage us to explicitly address the horizontal logistics collaboration in the IRP as well.

This brief survey points out two gaps in the research on this topic: (1) improvement opportunities exist for quantitative models that can be used to support decision makers in sustainable food logistics management and (2) the analysis on exploring the benefits of horizontal logistics collaboration in literature on IRP represents an untouched field of research. Within our knowledge, we could not find any attempt in literature on IRP that take product perishability, explicit energy usage and demand uncertainty into account simultaneously. In particular, we incorporate product perishability, explicit energy usage and demand uncertainty into the IRP with many-to-many structure and multiple products. Afterwards, we analyze the potential savings attained through horizontal collaboration. As distinct from the traditional distance-based cost calculation approaches, we employ detailed fuel consumption estimations based on factors such as vehicle type, traveled distance, vehicle load and vehicle speed. The explicit consideration of fuel consumption ensures to estimate transportation cost and emissions more accurately, and to reduce distribution cost as shown in VRP literature (e.g., Bektaş and Laporte (2011) and Franceschetti et al. (2013)).

To conclude, our study adds to the literature on IRP by: (1) developing a comprehensive chance-constrained programming model with demand uncertainty for a generic IRP with multiple suppliers and customers that accounts for the KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost, (2) analysing the benefits of horizontal collaboration in the IRP with respect to the aforementioned KPIs, and (3) presenting the applicability of the model on the

distribution operations of two suppliers, where the first supplier produces figs and the second supplier produces cherries, based on mostly real data.

6.3 Problem description

The problem in this study is defined on a complete graph $G = \{V, A\}$, where V is the set of nodes that consists of a set of customers $V_C = \{1, 2..., |V_C|\}$, a set of suppliers $V_S = \{1, 2..., |V_S|\}$ and a 3PL (rental vehicle company) node 0, and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the set of arcs. Suppliers provide several product types $P = \{1, 2..., |P|\}$, each with a different fixed shelf life of $m_p \geq 2$ periods. The amount of product $p \in P$ available at supplier $i \in V_S$ in period $t \in T = \{1, ..., |T|\}$ is limited with a given amount, $q_{i,p,t}$. The set of vehicles is given as $K = \{1, 2..., |K|\}$, each with capacity c and located at the 3PL. Freight is picked up from the suppliers and delivered to the customers through these vehicles that start and end at the 3PL's location. Each vehicle can perform at most one route per time period. Each customer can be served by more than one vehicle, hence the total freight assigned to each customer can be split into two or more vehicles. It is assumed that the product demand $d_{i,p,t}$ in each period $t \in T$ is distributed normally with mean $\mu_{i,p,t}$ and standard deviation $\sigma_{i,p,t}$, $\forall i \in V', p \in P, t \in T$. For each customer, an inventory holding cost $h_{i,p}, \forall i \in V_C, p \in P$ occurs at each period. However, if product p stays in inventory more than m_p periods, it becomes spoiled and cost of waste r_p occurs. The demand of all customers in each period must be satisfied with a probability of at least α. The demand that cannot be fulfilled in one period is backlogged in the next period.

The aim of the problem in this study is to determine the routes and quantity of shipments in each period such that the total cost comprising routing, inventory and waste costs is minimized. Routing cost consists of driver and fuel consumption cost for each arc in the network. Let w denote the wage for the drivers and l denote the fuel price per liter. The driver of each vehicle is paid from the beginning of the time horizon until the time he returns to the starting point. Fuel consumption is mainly dependent on traveled distance, vehicle load and vehicle speed. The following section presents the fuel consumption calculation in greater detail.

6.3.1 Fuel consumption and emissions

We employ the same approach as in Bektaş and Laporte (2011), Demir et al. (2012) and Franceschetti et al. (2013) for estimating fuel consumption that is based on the

comprehensive emissions model of Barth et al. (2005). According to this model, the total amount of fuel used EC (liters) for traversing a distance a (m) at constant speed f (m/s) with load F (kg) is calculated as follows:

$$EC = \lambda\left(y(a/f) + \gamma\beta a f^2 + \gamma s(\mu + F)a\right)$$

where $\lambda = \xi/(\kappa\psi)$, $y = k_e N_e V_e$, $\gamma = 1/(1000\varepsilon\varpi)$, $\beta = 0.5 C_d A_e \rho$, and $s = g\sin\phi + gC_r\cos\phi$. Furthermore, k_e is the engine friction factor (kJ/rev/liter), N_e is the engine speed (rev/s), V_e is the engine displacement (liter), μ is the vehicle curb weight (kg), g is the gravitational constant (9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, A_e is the frontal surface area (m^2), ρ is the air density (kg/m^3), ε is the vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines, ξ is the fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s). For further details on these parameters, the reader is referred to Demir et al. (2011). After estimating fuel consumption amounts, we estimate related emission (CO_2) levels by using a fuel conversion factor u (kg/l) for transport activities.

6.3.2 Chance-constrained programming model with demand uncertainty

This section presents a mathematical formulation for the studied problem. Table 6.2 presents the notation for the model.

We now present the formulation, starting with the objective function.

$$Minimise \sum_{i\in V_C}\sum_{p\in P}\sum_{t\in T} I^+_{i,p,t}h_{i,p} \tag{6.i}$$

$$+ \sum_{i\in V_C}\sum_{p\in P}\sum_{t\in\{T|t\geq m_p\}} E[W_{i,p,t}]r_p \tag{6.ii}$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\left(y(a_{ij}/f)X_{i,j,k,t} + \gamma\beta a_{ij}f^2 X_{i,j,k,t} + \gamma s(\mu X_{i,j,k,t} + \sum_{p\in P}F_{i,j,k,p,t})a_{ij}\right)l \tag{6.iii}$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}(a_{ij}/f)X_{i,j,k,t}w. \tag{6.iv}$$

$$\tag{6.1}$$

The objective function (6.1) comprises four parts: (6.i) expected inventory cost, (note that $I^+_{i,p,t}$ is derived from $E[I_{i,p,t}]$ through constraints (6.3)), (6.ii) expected waste cost, (6.iii) fuel cost from transportation operations and (6.iv) driver cost.

$$E[I_{i,p,t}] = \sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,p,s} - \sum_{s=1}^{t}(E[d_{i,p,s}] + E[W_{i,p,s}]), \qquad \forall i\in V_C, p\in P, t\in T \tag{6.2}$$

$$I^+_{i,p,t} \geq E[I_{i,p,t}], \qquad \forall i\in V_C, p\in P, t\in T \tag{6.3}$$

TABLE 6.2: Parameters and decision variables

Symbol	Meaning
$E[.]$	expectation operator
V_C	set of customers, $V_C = \{1, 2..., |V_C|\}$
V_S	set of suppliers, $V_S = \{1, 2..., |V_S|\}$
V	set of all nodes including the 3PL 0, $V = V_C \cup V_S \cup \{0\}$
A	set of all arcs, $A = \{(i,j) : i, j \in V, i \neq j\}$
$A(S)$	$S \subset V$ is the set of all arcs with both endpoints in S
T	set of time periods, $T = \{1, 2..., |T|\}$
P	set of products, $P = \{1, 2..., |P|\}$
K	set of vehicles, $K = \{1, 2..., |K|\}$
m_p	fixed maximum shelf life of product type p, $m_p \geq 2$, in periods,
$d_{i,p,t}$	demand of customer $i \in V_C$ for product type $p \in P$ in time period $t \in T$, normal random variable with mean $\mu_{i,p,t}$, standard deviation $\sigma_{i,p,t}$, in kg,
α	pre-defined satisfaction level of probabilistic inventory constraint,
c	capacity of a vehicle, in kg,
$a_{i,j}$	distance between node i and j, $(i,j) \in A$, in m,
f	vehicle speed, (m/s),
λ	technical parameter, $\xi/\kappa\psi$, see section 6.3.1,
y	technical parameter, $k_e N_e V_e$, see section 6.3.1,
γ	technical parameter, $1/(1000\varepsilon\varpi)$, see section 6.3.1,
β	technical parameter, $0.5 C_d A_e \rho$, see section 6.3.1,
s	technical parameter, $g\sin\phi + gC_r\cos\phi$, see section 6.3.1,
μ	curb-weight of vehicle, in kg,
l	fuel price per liter, €/l,
r_p	penalty cost for the wasted product $p \in P$, €/kg,
w	wage rate for the drivers of the vehicles, €/s,
$q_{i,p,t}$	the amount of product $p \in P$ available at supplier $i \in V_S$ in period $t \in T$, in kg,
$h_{i,p}$	holding cost of product $p \in P$ per period at node $i \in V_C$, €/kg,
$I_{i,p,t}$	the amount of inventory at customer $i \in V_C$ for product $p \in P$ at the end of period $t \in T \cup \{0\}$, in kg, where $I_{i,p,0} = 0, \forall i \in V_C, p \in P$,
$I_{i,p,t}^+$	derived decision variable to calculate positive inventory levels, in kg,
$B_{i,k,p,t}$	the amount of product $p \in P$ picked up from supplier $i \in V_S$ by vehicle $k \in K$ in the beginning of period $t \in T$, in kg,
$Q_{i,k,p,t}$	the amount of product $p \in P$ delivered by vehicle $k \in K$ to customer $i \in V_C$ in the beginning of period $t \in T$, in kg,
$X_{i,j,k,t}$	binary variable equal to 1 if vehicle $k \in K$ goes from $i \in V$ to $j \in V$ in period $t \in T$, and 0 otherwise,
$F_{i,j,k,p,t}$	the load of product $p \in P$ on vehicle $k \in K$ which goes from $i \in V$ to $j \in V$ in period $t \in T$, in kg,
$W_{i,p,t}$	the amount of waste from product $p \in P$ at customer $i \in V'$ at the end of period $t \in T$, in kg,
$U_{i,k,t}$	the position of node $i \in V\backslash\{0\}$ in route $k \in K$ in period $t \in T$.

$$E[W_{i,p,t}] \geq E[I_{i,p,t-m_p+1}] - \sum_{a=t-m_p+2}^{t} E[d_{i,p,a}] - \sum_{a=t-m_p+2}^{t-1} E[W_{i,p,a}], \; \forall i \in V_C, p \in P, t \in \{T | t \geq m_p\}$$

$$(6.4)$$

$$E[W_{i,p,t}] = 0, \qquad \forall i \in V_C, p \in P, t \in \{T | t < m_p\} \tag{6.5}$$

$$Pr\left(I_{i,p,t} \geq 0\right) \geq \alpha, \qquad \forall i \in V_C, p \in P, t \in T. \tag{6.6}$$

Constraints (6.2) to (6.6) relate to the inventory decisions. In particular, constraints (6.2) calculate expected inventory levels of products for each customer per period by taking the amounts of total product delivered, expected demand and expected waste into account.

Hereby, we assume $I_{i,p,0} = 0, \forall i \in V_C, p \in P$. Constraints (6.3) define variables which are used for the calculation of inventory costs in the objective function. Constraints (6.4) and (6.5) calculate expected waste for each product at each customer per period. Constraints (6.6) are the service-level constraints on the probability of a stock-out at the end of each period.

$$\sum_{i \in V, i \neq j} X_{i,j,k,t} = \sum_{i \in V, i \neq j} X_{j,i,k,t}, \qquad \forall j \in V \backslash \{0\}, k \in K, t \in T \qquad (6.7)$$

$$\sum_{j \in V, i \neq j} X_{i,j,k,t} \leq 1, \qquad \forall i \in V, k \in K, t \in T \qquad (6.8)$$

$$X_{i,0,k,t} = 0, \qquad \forall i \in V_S, k \in K, t \in T \qquad (6.9)$$

$$X_{0,j,k,t} = 0, \qquad \forall j \in V_C, k \in K, t \in T \qquad (6.10)$$

$$F_{0,j,k,p,t} = 0, \qquad \forall j \in V_S, k \in K, p \in P, t \in T \qquad (6.11)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} + B_{i,k,p,t}, \qquad \forall i \in V_S, k \in K, p \in P, t \in T \qquad (6.12)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} - Q_{i,k,p,t}, \qquad \forall i \in V_C, k \in K, p \in P, t \in T \qquad (6.13)$$

$$\sum_{p \in P} F_{i,j,k,p,t} \leq c X_{i,j,k,t}, \qquad \forall (i,j) \in A, k \in K, t \in T \qquad (6.14)$$

$$\sum_{k \in K} B_{i,k,p,t} \leq q_{i,p,t}, \qquad \forall i \in V_S, p \in P, t \in T \qquad (6.15)$$

$$U_{i,k,t} + 1 \leq U_{j,k,t} + |V|(1 - X_{i,j,k,t}), \qquad \forall (i,j) \in A(V \backslash \{0\}), k \in K, t \in T. \qquad (6.16)$$

Constraints (6.7) to (6.16) relate to the routing decisions. In particular, constraints (6.7) ensure flow conservation for each vehicle at each node in each period. Constraints (6.8) ensure that each vehicle can perform at most one route per time period. Constraints (6.9) and (6.10) restrict direct flows from the suppliers to the 3PL and from the 3PL to the customers respectively. Constraints (6.11) specify that vehicle is empty while departing from the 3PL. Constraints (6.12) to (6.14) model the flow on each arc and ensure that vehicle capacities are respected in each period. Constraints (6.15) ensure that vehicles cannot pickup a product from a supplier which does not produce that product. Constraints (6.16) eliminate sub-tours (Jepsen et al., 2013).

$$X_{i,j,k,t} \in \{0,1\}, \qquad \forall (i,j) \in A, k \in K, t \in T \qquad (6.17)$$

$$F_{i,j,k,p,t} \geq 0, \qquad \forall (i,j) \in A, k \in K, p \in P, t \in T \qquad (6.18)$$

$$-\infty < I_{i,p,t} < +\infty, \qquad \forall i \in V_C, p \in P, t \in T \qquad (6.19)$$

$$I_{i,p,t}^+, W_{i,p,t} \geq 0, \qquad \forall i \in V_C, p \in P, t \in T \qquad (6.20)$$

$$U_{i,k,t} \geq, 0, \qquad \forall i \in V \backslash \{0\}, k \in K, t \in T \qquad (6.21)$$

$$Q_{i,k,p,t}, B_{i,k,p,t} \geq 0, \qquad \forall i \in V_C, k \in K, p \in P, t \in T. \qquad (6.22)$$

Constraints (6.17) to (6.22) represent the restrictions imposed on the decision variables.

6.3.3 Deterministic approximation of the chance-constrained programming model with demand uncertainty

Solving the above chance constrained model is complicated as products have a fixed expiration date. Pauls-Worm et al. (2014) also use chance-constrained programming approach for an inventory problem of perishable products with fixed shelf lives. In line with their study, we therefore consider a deterministic approximation. The deterministic constraints for the stochastic chance constraints (6.6) are rewritten as follows.

Constraints (6.6) ensure the inventory level for each product at the end of every period to be nonnegative with a probability of service level α. Therefore, starting inventory level of every period should be higher than the demand of that period for each product, with a probability higher than the service level. These constraints now can be rewritten as,

$$Pr\left(I_{i,p,t-1} + \sum_{k \in K} Q_{i,k,p,t} \geq d_{i,p,t}\right) \geq \alpha, \qquad \forall i \in V_C, p \in P, t \in T. \qquad (6.23)$$

Applying constraints (6.2) to constraints (6.23), we have

$$Pr\left(\underbrace{\sum_{s=1}^{t-1}\sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^{t-1}(d_{i,p,s} + E[W_{i,p,s}])}_{I_{i,p,t-1}} + \sum_{k \in K} Q_{i,k,p,t} \geq d_{i,p,t}\right) \geq \alpha, \quad \forall i \in V_C, p \in P, t \in T.$$

$$(6.24)$$

Rearranging the constraints (6.24) yields

$$Pr\left(\sum_{s=1}^{t}\sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^{t-1} E[W_{i,p,s}] \geq \sum_{s=1}^{t} d_{i,p,s}\right) \geq \alpha, \qquad \forall i \in V_C, p \in P, t \in T. \qquad (6.25)$$

If $G_{d_{i,p,1}+d_{i,p,2}+...+d_{i,p,t}}(y)$ is the cumulative distribution function of $D_{i,p}(t) = d_{i,p,1}+d_{i,p,2}+ ... + d_{i,p,t}$, then

$$\sum_{s=1}^{t}\sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^{t-1} E[W_{i,p,s}] \geq G_{D_{i,p}(t)}^{-1}(\alpha), \qquad \forall i \in V_C, p \in P, t \in T. \qquad (6.26)$$

$D_{i,p}(t) = \sum_{s=1}^{t} d_{i,p,s}, \quad \forall i \in V_C, p \in P$ will be normally distributed if the $\{d_{i,p,s}\}$, $\forall i \in V_C, p \in P, s \in T$ with mean $\mu_{i,p,s}$ and standard deviation $\sigma_{i,p,s}$ are each normally distributed, and pairwise uncorrelated (Bookbinder and Tan, 1988). Therefore,

$$G_{D_{i,p}(t)}^{-1}(\alpha) = \sum_{s=1}^{t} \mu_{i,p,s} + \sqrt{\left(\sum_{s=1}^{t}(\mu_{i,p,s})^2\right)C_p Z_\alpha}, \qquad \forall i \in V_C, p \in P, t \in T. \qquad (6.27)$$

where C_p is the coefficient of variation which is assumed to be constant for each product $p \in P$ and Z_α is a standard normal random variate with cumulative probability of α.

Therefore,

$$\sum_{s=1}^{t}\sum_{k\in K}Q_{i,k,p,s} - \sum_{s=1}^{t-1}E[W_{i,p,s}] \geq \sum_{s=1}^{t}\mu_{i,p,s} + \sqrt{\left(\sum_{s=1}^{t}(\mu_{i,p,s})^2\right)C_p Z_\alpha}, \quad \forall i \in V_C, p \in P, t \in T. \quad (6.28)$$

As a result, the model is simplified through transforming the stochastic terms by replacing constraints (6.6) with constraints (6.28). Then, the resulting deterministic linear formulation, which is the approximation of the chance-constrained programming model with demand uncertainty, is: (6.1)–(6.5), (6.7)–(6.22) and (6.28).

6.3.4   Strengthening the MILP model

This section presents valid inequalities to tighten the formulation and accelerate the convergence to an optimal solution. The valid inequalities are related to the routing variables and are as follows:

$$\sum_{j\in V_S}\sum_{k\in K}X_{0,j,k,t} \geq \sum_{i\in V_S}\sum_{k\in K}\sum_{p\in P}B_{i,k,p,t}/c, \qquad \forall t \in T \qquad (6.29)$$

$$\sum_{i\in V_C}\sum_{k\in K}X_{i,0,k,t} \geq \sum_{i\in V_S}\sum_{k\in K}\sum_{p\in P}Q_{i,k,p,t}/c, \qquad \forall t \in T. \qquad (6.30)$$

Constraints (6.29) and (6.30) represent relationships between the given routing variables and decision variables related to pick up and delivery amounts. Our preliminary experimentation has shown that significant reductions in computational time can be obtained from the use of these additional constraints (6.29)–(6.30), as will be shown in the next section.

6.4   Computational analysis

This section presents an implementation of the proposed model on the distribution operations of two suppliers, where supplier S1 produces figs and supplier S2 produces cherries. The performances of the suppliers were assessed with respect to the following defined KPIs: (i) total emissions, (ii) total driving time, (iii) total routing cost comprised of fuel and wage cost, (iv) total inventory cost, (v) total waste cost, and (vi) total cost. Additionally, the benefits of horizontal collaboration between the suppliers were analyzed with respect to the aforementioned KPIs under several scenarios, which are introduced in the following section. We first describe the case and data used, then present the solution method. The results are discussed afterwards.

6.4.1 Description and data

The underlying transportation network includes one 3PL company, two suppliers and five wholesale market halls (customers) as presented in Figure 6.3. The suppliers S1 and S2 are responsible for providing figs and cherries to the customers through two vehicles rented from the 3PL company. These suppliers have the same sizes in terms of total amount of products sent to the customers, however, sensitivity analysis are conducted in the following section to investigate the effect of changes in the suppliers' sizes on the defined KPIs.

We assume that the vehicles used for the deliveries are homogeneous and have a capacity of 10 tonnes. The parameters used to calculate the total fuel consumption cost are taken from Demir et al. (2012) and are given in Table 6.3. We use 2.63 kg/l as a fuel conversion factor to estimate CO_2 emissions from transportation operations (Defra, 2007). Distances between nodes (see Table 6.A in the appendix) are calculated using Google Maps[1]. Vehicles travel at a fixed speed of 80 km/h.

TABLE 6.3: Setting of vehicle and emission parameters

Notation*	Description	Value
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/liter)	737
k_e	Engine friction factor (kJ/rev/liter)	0.2
N_e	Engine speed (rev/s)	33
V_e	Engine displacement (liter)	5
ρ	Air density (kg/m^3)	1.2041
A_e	Frontal surface area (m^2)	3.912
μ	Curb-weight (kg)	6350
g	Gravitational constant (m/s^2)	9.81
ϕ	Road angle	0
C_d	Coefficient of aerodynamic drag	0.7
C_r	Coefficient of rolling resistance	0.01
ε	Vehicle drive train efficiency	0.4
ϖ	Efficiency parameter for diesel engines	0.9
l	Fuel price per liter (€)	1.7
r	Driver wage (€/s)	0.003

Source: Demir et al. (2012)
* See section 6.3.1 for the description of the notation.

The planning horizon length is six weeks. Demand means of products (see Table 6.B) for each week are generated randomly for purposes of sensitivity analysis as will be shown in the following section. The coefficient of variations for the product demands are assumed to be constant and equal to 0.1 for all customers in each week. For both products, the demand for each customer in each week must be satisfied with a probability of at least 95%. Holding costs at customers are taken as 10% of the average marketplace selling prices of the products[2], and are equal to 0.12 €/kg-week for figs and 0.2 €/kg-week for

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[1] http://maps.google.nl/,Onlineaccessed:June2014
[2] http://halfiyatlari.org/izmir.html,Onlineaccessed:June2014

cherries. Shelf life of both products is nearly three weeks. Therefore, if a product stays in inventory more than three weeks, it becomes spoiled and cost of waste occurs. The cost of waste is estimated as 1.2 €/kg for figs and 2 €/kg for cherries based on the average marketplace selling prices. Lastly, it is assumed that the suppliers have enough products to satisfy the related demand during the planning horizon. The aim of the problem is to determine the routes and quantity of shipments in each week such that the total cost is minimized.

TABLE 6.4: Analyzed scenarios

#	Scenario	Description	#	Scenario	Description
0	IS	Initial situation, base cases			
1	S-D1	S1 large and S2 small sized	11	S-HR	Higher routing cost
2	S-D2	S1 small and S2 large sized	12	S-LVS	Lower vehicle speed
3	S-D3	Two common customers	13	S-HVS	Higher vehicle speed
4	S-D4	Zero common customer	14	S-LCV	Lower coefficient of variation
5	S-MN	Modified network	15	S-HCV	Higher coefficient of variation
6	S-LH	Lower holding cost	16	S-LS	Lower service level
7	S-HH	Higher holding cost	17	S-HS	Higher service level
8	S-LW	Lower waste cost	18	S-LMS	Lower maximum shelf lives
9	S-HW	Higher waste cost	19	S-HMS	Higher maximum shelf lives (four weeks)
10	S-LR	Lower routing cost	20	S-HMSa	Higher maximum shelf lives (six weeks)

We defined two base cases: (i) base case BC in which horizontal collaboration does not exist between the suppliers, (ii) base case BC_{HC} in which horizontal collaboration exists between the suppliers. Base cases are represented as Initial situation (IS), as shown in Table 6.4. We also did sensitivity analysis for the model with respect to changes in suppliers' sizes, network structure, number of common customers, cost parameters, vehicle speed, coefficient of variation, service levels and maximum shelf lives. In particular, 20 scenarios have been formulated for the sensitivity analysis (see Table 6.4). We have analyzed two cases in each scenario: (i) a case where the suppliers do not collaborate, (ii) a case where the suppliers collaborate with each other.

In the case where horizontal collaboration exists, vehicles can carry two types of products at the same time. The contributions of the suppliers to the total emissions, driving time, and routing cost in each route were calculated based on the following ratios: total amount of figs carried to total vehicle load for the S1 and total amount of cherries carried to total vehicle load for the S2. Note that vehicles are empty before getting to the suppliers and during return stage from the customers to the 3PL firm. In these arcs, if the vehicle has visited both suppliers, the contributions of the suppliers to the defined KPIs are regarded as equal. Otherwise, if the vehicle has visited a single supplier, the emissions, driving time and routing cost are assigned to that supplier.

6.4.2 Solution method

The ILOG-OPL development studio and CPLEX 12.6 optimization package has been used to develop and solve the presented formulation for the case study. The resulting model has 1777 continuous and 672 binary variables, and 1920 constraints. Optimal solutions were obtained on a computer of Pentium(R) i5 2.4GHz CPU with 3GB memory.

The model can be used to analyze both cases with and without horizontal collaboration. For the case where horizontal collaboration does not exist, we solved the model separately for each supplier by allowing one vehicle to be used. Note that there exist two suppliers producing different products: S1 produces figs and S2 produces cherries. First, we set the demand for the cherries and supply capacity of the S2 during the whole planning horizon as zero and solved the model for the S1 that aims to satisfy the customer demand for the figs. Afterwards, we did the same for the S2. In particular, we set the demand for the figs and supply capacity of the S1 during the whole planning horizon as zero and solved the model for the S2 that aims to satisfy the customer demand for the cherries. This has removed the chance of joint-vehicle usage with other suppliers and ensured us to investigate the changes in the defined KPIs in the case where suppliers do not collaborate.

6.4.3 Results of base cases (IS)

This section presents first impact of horizontal collaboration in the base cases (IS), then effect of valid inequalities on solution time.

6.4.3.1 Impact of horizontal collaboration

Summary results for the defined base cases with respect to the selected KPIs are presented in Table 6.5. According to the aggregated amounts, 17.1% total cost reduction has been obtained through horizontal collaboration between the suppliers. The total cost difference between the base cases is due to the total routing and inventory cost reductions in the base case BC_{HC}.

TABLE 6.5: Summary results for the base cases

KPIs	BC			BC_{HC}			Gain
	S1	S2	Total	S1	S2	Total	(%)
Total emissions (kg)	2738.6	2888.6	5627.2	1923.0	2057.1	3980.1	29.3
Total driving time (h)	69.5	72.9	142.4	47.5	50.9	98.4	30.9
Total routing cost (€)	2520.4	2654.8	5175.2	1755.9	1879.1	3635.0	29.8
Total inventory cost (€)	1684.2	2606.4	4290.6	1481.7	2556.2	4037.9	5.9
Total waste cost (€)	459.7	538.4	998.1	459.7	538.4	998.1	0.0
Total cost (€)	4664.3	5799.7	10463.9	3697.3	4973.7	8671.0	17.1

The model solution for the base case BC proposes to use 12 vehicles for the deliveries of the products, whereas the required fleet size reduces to 10 in the base case BC_{HC}. Table 6.6 presents the resulting routes for each period in both base cases. The joint vehicle usage of the suppliers in the base case BC_{HC} gives an opportunity to satisfy the demand of the customers for the two products via single visit which clearly contributes to the total routing cost reduction (29.8%). In the base case BC, however, there is no chance to merge deliveries of both suppliers. Moreover, the joint vehicle usage by the help of horizontal collaboration ensures to have total emissions (29.3%), driving time (30.9%) and inventory cost (5.9%) reductions in the base case BC_{HC}.

TABLE 6.6: Resulting routes for the base cases

	BC		BC_{HC}	
Weeks	1st vehicle	2nd vehicle	1st vehicle	2nd vehicle
1st	0-S1-C1-C2-C3-C4-C5-0	0-S2-C5-C4-C3-C2-C1-0	0-S2-S1-C1-C2-0	0-S1-S2-C5-C4-C3-0
2nd	0-S1-C1-C2-C3-C4-C5-0	0-S2-C5-C4-C3-C2-C1-0	0-S2-C5-S1-C1-C2-0	0-S1-S2-C5-C4-C3-0
3rd	0-S1-C1-C2-C3-C4-C5-0	0-S2-C5-C4-C3-C2-C1-0	0-S2-S1-C1-C2-0	0-S1-S2-C5-C4-C3-0
4th	0-S1-C1-C5-C4-C3-0	0-S2-C5-C4-C3-C2-C1-0	0-S2-S1-C1-C2-0	0-S1-S2-C5-C4-C3-0
5th	0-S1-C1-C2-C3-C4-C5-0	0-S2-C3-C5-C1-0	0-S2-S1-C1-C2-C3-C4-C5-0	-
6th	0-S1-C1-C5-C4-0	0-S2-C5-C4-C3-C2-C1-0	0-S2-S1-C1-C2-C3-C4-C5-0	-

The differences in the resulting routes shown in Table 6.6 causes changes in the delivery and inventory amounts between the base cases. These differences can be observed from Table 6.7 which shows delivery, inventory and waste quantities for the customers during the whole planning horizon in both cases.

TABLE 6.7: Delivery, inventory and waste quantities for the customers during the whole planning horizon in both base cases, in kg

	Prod.	Cust. #	Delivery Weeks						Inventory Weeks						Waste Weeks					
			1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
BC	Fig	C1	1165	1746	1586	927	1351	975	165	310	397	423	474	499	-	-	-	-	-	-
		C2	815	1428	1828	823	1462	714	115	243	370	393	456	470	-	-	-	-	-	-
		C3	1514	2635	405	3779	201	150	214	449	454	733	734	351	-	-	-	-	-	383
		C4	3493	507	1132	1235	712	1023	494	500	532	567	579	602	-	-	-	-	-	-
		C5	699	1207	948	1268	2139	923	99	206	254	322	460	483	-	-	-	-	-	-
	Cherry	C1	1747	1159	1587	2788	302	404	247	306	393	581	583	587	-	-	-	-	-	-
		C2	1630	1719	2242	201	292	1238	230	350	492	301	493	531	-	-	-	192	-	-
		C3	1397	3104	302	713	1343	1874	197	501	504	517	559	633	-	-	-	-	-	-
		C4	1630	1495	3152	430	151	1338	230	326	500	581	581	619	-	-	78	-	-	-
		C5	932	1648	1153	614	1306	1192	131	280	333	347	404	446	-	-	-	-	-	-
BC_{HC}	Fig	C1	1165	1746	1586	927	1351	975	165	310	397	423	474	499	-	-	-	-	-	-
		C2	815	1428	2650	-	2176	-	115	243	1193	393	1170	470	-	-	-	-	-	-
		C3	1514	2635	405	3779	351	-	214	449	454	733	884	351	-	-	-	-	-	383
		C4	3943	507	1132	1235	712	1023	494	500	532	567	579	602	-	-	-	-	-	-
		C5	699	1207	948	1268	2138	923	99	206	254	322	460	483	-	-	-	-	-	-
	Cherry	C1	1747	1159	1587	2788	302	404	247	306	393	581	583	587	-	-	-	-	-	-
		C2	1630	1719	2242	301	-	1430	230	350	492	593	301	531	-	-	-	-	192	-
		C3	1397	3104	302	713	1343	1874	197	501	504	517	559	633	-	-	-	-	-	-
		C4	1630	1495	3152	503	-	1416	230	326	578	731	503	619	-	-	-	-	78	-
		C5	932	1648	1153	614	1306	1192	132	280	333	347	404	446	-	-	-	-	-	-

It has been observed that the service level target leads to waste occurrences at some customers in both base cases. In particular, the reason for the related wastes is that the

customers have to hold at least an amount of product in order to not fall into stock-out. Afterwards, when these products are not sold, they perish and waste costs occur.

6.4.3.2 Effect of valid inequalities on solution time

To evaluate the effect of proposed valid inequalities (6.29)–(6.30), an analysis has been carried out. Note that we solved the model separately for each supplier for the base case BC in which horizontal collaboration does not exist between the suppliers. The optimal solutions for the BC have been obtained within seconds even without using the valid inequalities. This is not the case for the BC_{HC} in which horizontal collaboration exists between the suppliers.

TABLE 6.8: The effect of the valid inequalities on the computational time (in seconds) to obtain optimal solutions for the BC_{HC}

|	Solution times	Lower bound gap (%)	Optimality gap (%)
Model	10800	6.04	0.02
Model+(6.29)	835	-	-
Model+(6.30)	5873	-	-
Model+(6.29)–(6.30)	4449	-	-

Table 6.8 presents the results on the computational times required to solve the model for the BC_{HC} to optimality with different combinations of the valid inequalities. Lower bound gap in the table shows the relative gap from the best-known lower bound provided by the software. Optimality gap shows the relative gap from the optimal solution. The results show the efficiency of the valid inequalities. After three hours time limit, the model without valid inequalities gives a feasible solution which is 0.02% above the optimal cost level. However, the gap from the best bound is 6.04%, which shows the fact that it still needs some time to reach the optimal solution and afterwards to prove the solution's optimality.

6.4.4 Sensitivity analysis

This section presents sensitivity analysis for the model with respect to changes in suppliers' sizes, network structure, number of common customers, cost parameters, vehicle speed, coefficient of variation, service levels and maximum shelf lives (see Table 6.4). The results of the sensitivity analysis are shown in Table 6.C. Figure 6.2 shows the gains in terms of routing, inventory, waste and therefore total costs, and emissions from horizontal collaboration in all scenarios. Data labels in the Figures 6.2a and 6.2b indicate the percentage gains.
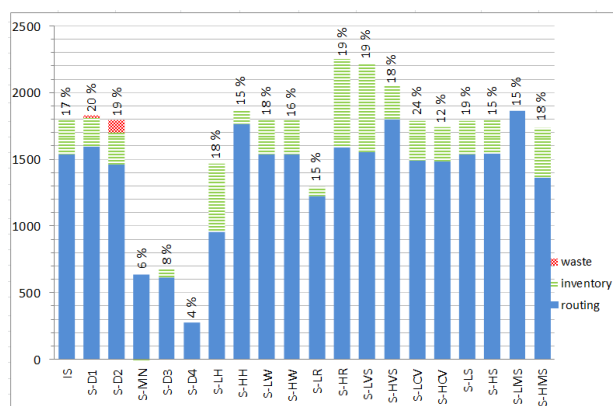
(a) Cost savings, in €and %
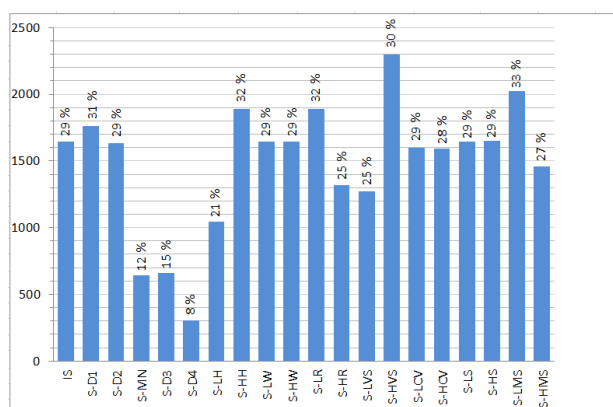
(b) Emissions savings, in kg and %

FIGURE 6.2: Aggregated gains from horizontal collaboration in all scenarios

6.4.4.1 The effect of changes in the suppliers' sizes

In the base cases (IS), both suppliers have the same size in terms of total amount of products sent to the customers. In practice, suppliers could have different sizes as well. This fact motivated us to investigate the effect of changes in suppliers' sizes through two scenarios: (1) S-D1: Total demand for figs produced only by S1 is 70% of the total demand for both products, and total demand for cherries produced only by S2 is 30% of the total demand for both products and (2) S-D2: Large sized supplier, S2, provides 70% of the whole products and the rest, 30%, is provided by the small one, S1.

TABLE 6.9: Total cost gains of the suppliers from horizontal collaboration in different sizes, in €and % (brackets)

Scale	S1	S2
Small sized	982.9 (28%)	1093.8 (26%)
Medium sized	966.9 (21%)	826.0 (14%)
Large sized	734.2 (15%)	814.3 (13%)

Table 6.9 presents the total cost gains of the suppliers from horizontal collaboration in different sizes. According to the results, gains from horizontal collaboration changes based on the supplier size. In particular, as the supplier size decreases, the total cost benefit from cooperation with the other larger supplier increases. This is expected, since smaller firms are tempted to collaborate with larger organizations to improve resource efficiency in practice (Alvarez and Barney, 2001).

Figure 6.2 shows the aggregated gains for both suppliers from cooperation in scenarios S-D1 and S-D2. The results show that total cost and emissions gains from horizontal collaboration change according to the customer demand. The customer demand change also affects the total cost gain structure. For instance, in contrast to the base cases IS, cooperation ensures waste cost gain along with inventory and routing cost gains in the S-D1 and S-D2.

6.4.4.2   The effect of a change in the network structure

The benefits of horizontal collaboration to the suppliers can change based on the logistics network structure. We analysed an additional scenario (MN) which has a different logistics network. In the original logistics network, the suppliers are located in the middle and surrounded by the customers (see Fig. 6.3). In the new modified setting, customers are to some extent clustered and suppliers are taken out through replacing the locations of $S1$ with $C3$ and $S2$ with $C2$, as shown in Figure 6.3.
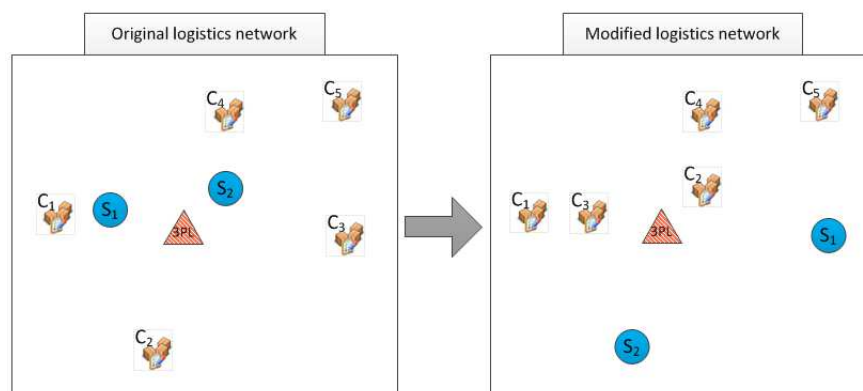

FIGURE 6.3: Representation of the original and modified logistics networks

Table 6.10 presents the gains of the suppliers from horizontal collaboration under different network structures. Note that the original network is the one which has been employed for the base cases. The results show that the benefits from horizontal collaboration in terms of the selected KPIs decrease due to the network structure change in the scenario MN. Especially, in its new location, collaborating with the other supplier does not bring that

much benefit to the S2. In the new setting, the percentage cost gain from cooperation reduces to 2.7% from 14.2% for the S2. For the S1 in its new location, it has been observed that benefits from cooperation have decreased for all the KPIs, and even cooperation leads 2.1% increase in inventory cost. In overall less benefit has been obtained from cooperation compared to the base cases (see Fig. 6.2), and in terms of aggregated amounts, all cost benefit comes from routing cost, as shown in Figure 6.2a.

TABLE 6.10: Gains of the suppliers from horizontal collaboration under base cases IS, and scenarios S-MN, S-D3 and S-D4, in %

		Total emissions	Total driving time	Total routing cost	Total inventory cost	Total waste cost	Total cost
IS: Original	S1	29.8	31.6	30.3	12.0	0.0	20.7
network	S2	28.8	30.2	29.2	1.9	0.0	14.2
S-MN: Modified	S1	21.6	23.9	22.3	-2.1	0.0	11.4
network	S2	3.6	7.7	4.9	1.2	0.0	2.7
S-D3: Two common	S1	11.1	14.9	12.2	4.4	0.0	7.4
customers	S2	18.6	16.4	17.9	0.0	0.0	8.1
S-D4: Zero common	S1	13.1	16.4	14.1	0.0	0.0	6.8
customer	S2	4.8	1.7	3.9	0.0	0.0	1.8

6.4.4.3 The effect of a change in the number of common customers

In the base cases, all customers have demand for both products, which makes them common customers for the suppliers, however, there could be also non-common customers. Here, we analyzed two scenarios: (i) S-D3: It comprises the same customers of which two of them are common and three of them are non-common and (i) S-D4: It comprises the same customers, however none of them are common. New demand structures are presented in Table 6.B.

The results presented in Table 6.10 show that the benefits obtained from working jointly to provide service to the customers decrease as the number of common customers decreases. For instance, total cost gain of the S1 has dropped to 6.8% from 20.7% and for the S2 it has dropped to 1.8% from 14.2% in scenario S-D4 where no common customers exist. Moreover, sharing less common customers also leads to decreases in the aggregated routing and inventory cost gains, and emissions gains from cooperation compared to the base cases IS as shown in Figure 6.2.

6.4.4.4 The effect of changes in cost parameters

We conduct sensitivity analysis on the cost parameters in the model. In particular, the following scenarios have been formulated: (1) S-LH: Lower holding cost (0.06 €/kg for figs and 0.1 €/kg for cherries per period), (2) S-HH: Higher holding cost (0.18 €/kg for figs and 0.3 €/kg for cherries per period), (3) S-LW: Lower waste cost (0.6 €/kg for figs and 1 €/kg for cherries per period), (4) S-HW: Higher waste cost (1.8 €/kg for figs and 3 €/kg for cherries per period), (5) S-LR: Lower routing cost (fuel price is 1.2 €/l and wage rate for the drivers is 0.002 €/s) and (6) S-HR: Higher routing cost (fuel price is 2.2 €/l and wage rate for the drivers is 0.004 €/s).

The results presented in Table 6.C show that the increase and decrease of holding, waste and routing cost parameters lead to, respectively, increased and decreased aggregated total costs in both cases, no matter horizontal collaboration exists or not. Due to the differences in cost changes, the gap representing the benefit of horizontal collaboration has been also affected from the changes in the related cost parameters as shown in Figure 6.2a. For instance, the changes in holding and inventory cost parameters do not have same effects on the aggregated total routing and inventory costs in both cases. That is why cost gain from horizontal collaboration changes in the scenarios S-LH, S-HH, S-LR and S-HR. However, the decrease or increase of waste costs in the scenarios S-LW and S-HW has caused the same absolute changes on the aggregated total routing, inventory and waste costs in both cases, and therefore the cost benefit from horizontal collaboration has stayed same.

The emissions gain from horizontal collaboration has also changed based on the cost parameters' values, as shown in Figure 6.2b. Note that the emission gap in the base cases IS is 29%. The main reasons of the emission gap differences in the scenarios can be discussed as follows. (i) Holding more inventory at the customers has ensured to reduce emissions in cases LH and LH$_{HC}$, whereas the decrease in the LH is more than that of in the LH$_{HC}$. This difference results in a decrease of emission gap to 21% in the scenario S-LH. (ii) Holding less aggregated inventory leads to an increase in emissions in case HH. Emissions level, however, does not change in case HH$_{HC}$, which results in an increase of emission gap between the HH and HH$_{HC}$ to 32%. (iii) Emissions gaps has stayed same in the scenarios S-LW and S-HW, since waste cost changes do not affect emissions. (iv) The higher travel distance and change in the routes lead to an increase in emissions in case LR. Emissions level, however, does not change in case LR$_{HC}$, which results in an increase of emission gap between the LR and LR$_{HC}$ to 32%. (v) The lower travel distance and change in the routes lead to a decrease in emissions in case HR. Emissions level, however,

does not change in case HR_{HC}, which results in a decrease of emission gap between the HR and HR_{HC} to 25%.

6.4.4.5 The effect of changes in other parameters

We also conduct sensitivity analysis on the other parameters in the model. In particular, the following scenarios have been formulated: (1) S-LVS: Lower vehicle speed (40 km/h), (2) S-HVS: Higher vehicle speed (120 km/h), (3) S-LCV: Lower coefficient of variation (0.05), (4) S-HCV: Higher coefficient of variation (0.15), (5) S-LS: Lower service level (92.5%), (6) S-HS: Higher service level (97.5%), (7) S-LMS: Lower maximum shelf lives (two weeks), (8) S-HMS: Higher maximum shelf lives (four weeks) and (9) S-HMSa: Higher maximum shelf lives (six weeks).

The results presented in Table 6.C show that the increase and decrease of vehicle speed lead to increased aggregated total costs in both cases whether horizontal collaboration exists or not. Mainly, aggregated routing cost increases are responsible for the aggregated total cost increases. The aggregated routing costs have increased in the scenario S-LVS due to the increased driving times and therefore wages. However, fuel consumption and therefore emissions levels are decreased in the S-LVS. The increase of vehicle speed in the scenario S-HVS has ensured to reduce driver wages. However, the aggregated routing costs have still increased due to the increased fuel consumption which causes an increase in emissions as well.

The increase and decrease of coefficient of variation and service level parameters lead to, respectively, increased and decreased aggregated total costs and emissions in both cases, no matter horizontal collaboration exists or not (see Table 6.C). The reason is that less demand variation or service level requires to send less products from the suppliers to the customers, which decreases fuel consumption (emissions), inventory and waste costs. High demand variation or service level, however, requires to send more products, which increases fuel consumption (emissions), inventory and waste costs.

The increase and decrease of maximum shelf lives lead to, respectively, decreased and increased aggregated total costs and emissions in both cases whether horizontal collaboration exists or not. The reason is that long shelf lives eliminate waste costs, and allow to reduce fuel consumption and therefore emissions by keeping more inventory at the customers. Less shelf lives, however, increase waste costs, and cause to keep less inventory which increases fuel consumption and therefore emissions.

The experiments show that in terms of aggregated total cost and emissions, changes in vehicle speed, coefficient of variation, service level and maximum shelf lives affect both cases (horizontal collaboration does not exist and exists) in the same way. However, sizes of the changes in the cases are different, which affect the benefits from horizontal collaboration, as shown in Figure 6.2. For instance, the cost gap raises to 24% in the S-LCV and falls to 12% in the S-HCV. Regarding emissions gap, it increases above 30% in the S-HVS and S-LMS, and decreases below 27% in the S-LVS and S-HMS.

6.4.4.6   A general overview

The results show that there can be different circumstances in which horizontal collaboration can be more or less effective. In some cases, gains with respect to the aggregated total cost and emissions decrease (e.g., S-HCV) or increase (e.g., S-HVS) together. However, the aggregated total cost and emissions gains do not always go hand in hand. For instance, the decrease of routing cost has decreased cost gap from 17% to 15%, whereas, increased emissions gap from 29% to 32%. The other way around also happens, such as the decrease of vehicle speed has increased cost gap to 19%, whereas, decreased emissions gap to 25%. The reason for the different effects on cost and emissions benefits is that emissions is dependent only on fuel consumption, however, total cost is calculated based on not only fuel cost, but also wage, inventory and waste costs.

The main managerial implication of the results is that the proposed model can be used to aid decision making processes in IRPs with multiple suppliers and customers, especially confronted in food logistics systems. The model provides routing and delivery plans by considering not only economic concerns, but also product wastes and emissions. In addition to the offered support to the logistics decisions, the model can be used to evaluate the potential economic and environmental benefits of horizontal collaboration, whose importance has been acknowledged in practice and several collaborative projects (e.g., SCALE[3] and CO3[4]).

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[3]Step change in agri-food logistics ecosystems. The SCALE is a collaborative project partly funded by INTERREG IVB North-West Europe, which is a financial instrument of the European Union's Cohesion Policy. For more information: `http://www.projectscale.eu/,Onlineaccessed:August2014`.

[4]Collaboration concept for commodality. The CO3 is a collaborative project funded by the European Union's Seventh Programme for research, technological development and demonstration under grant agreement No 284926. For more information: `http://www.co3-project.eu/,Onlineaccessed:August2014`.

6.5 Conclusions

In this paper, we have modeled and analyzed the IRP with many-to-many distribution structure to account for perishability, explicit fuel consumption and demand uncertainty. The developed model has allowed to analyse the benefits of horizontal collaboration in the IRP with respect to the several KPIs, i.e., total emissions, total driving time, total routing cost comprised of fuel and wage cost, total inventory cost, total waste cost, and total cost.

The results based on a case study data and a broad set of experiments illustrate the potential of horizontal collaboration. Cooperation among suppliers ensures to reduce aggregated total cost by 17% and aggregated total emissions by 29% in the studied case. Extensive sensitivity analysis also confirm that horizontal collaboration among the suppliers contributes to the decrease of aggregated total cost and emissions in the logistics system, whereas the obtained gains are sensitive to the changes in several parameters.

Results of the experimental analysis yield the following important conclusions. As the supplier size decreases, the total cost benefit from cooperation with the larger supplier increases. The logistics network structure change reduces aggregated total cost gap to 6% and emissions gap to 12%. As the number of common customers decreases, the benefits obtained from working jointly to provide service to the customers decrease, e.g., aggregated total cost and emissions gaps fall to 4% and 8% respectively, when there is not any common customer between the suppliers. All analyses show that the aggregated total cost gap varies in a range of about 4-24% and the aggregated total emission gap varies in a range of about 8-33%. As a last remark, it has been observed that the aggregated total cost and emissions gains do not always go hand in hand in the investigated scenarios such that while one increases the other decreases.

Several extensions are possible for the current study. One extension would be to develop a heuristic algorithm to solve the model presented here, which will enable to handle instances that are larger in size. The other possible extension of the paper is to consider heterogeneous vehicles for the deliveries. The last extension worth mentioning here is to tackle uncertainty in supply which can be confronted in practice as well.

Acknowledgement

APPENDIX

In this section, we present the distance and demand data used for the models, and results of sensitivity analysis in detail.

TABLE 6.A: Distances between nodes, in kms

	3PL	S1	S2	C1	C2	C3	C4	C5
3PL	-	86.1	63.6	126	178.8	172	221.6	150.1
S1	85.8	-	137	42.6	187	245	297	173
S2	64	137	-	179	228	161	179	92.2
C1	126	41.7	177	-	175	287	339	214
C2	179	187	228	173	-	285	385	310
C3	172	245	163	288	282	-	169	166
C4	222	297	178	339	383	170	-	112
C5	150	171	91.5	215	312	170	114	-

TABLE 6.B: Demand means (kg) for the customers in each week in different scenarios

	Customers	Fig Weeks						Cherry Weeks					
		1	2	3	4	5	6	1	2	3	4	5	6
Base	C1	1000	1600	1500	900	1300	950	1500	1100	1500	2600	300	400
case	C2	700	1300	1700	800	1400	700	1400	1600	2100	200	100	1200
demand	C3	1300	2400	400	3500	200	150	1200	2800	300	700	1300	1800
set	C4	3000	500	1100	1200	700	1000	1400	1400	2900	350	150	1300
IS	C5	600	1100	900	1200	2000	900	800	1500	1100	600	1250	1150
	Total	6600	6900	5600	7600	5600	3700	6300	8400	7900	4450	3100	5850
	C1	1500	1400	2500	2900	2300	900	500	900	400	2200	300	400
Demand	C2	1200	1100	2200	1800	1750	2400	300	800	1100	200	100	800
set 1	C3	1300	2600	400	2500	200	1250	600	2000	300	700	400	300
S-D1	C4	2800	500	2300	1400	3100	2000	1600	600	2400	350	150	900
	C5	800	1300	1200	1400	2000	1400	500	900	700	400	200	600
	Total	7600	6900	8600	10000	9350	7950	3500	5200	4900	3850	1150	3000
	C1	500	900	400	2200	300	400	1500	1400	2500	2900	2300	900
Demand	C2	300	800	1100	200	100	800	1200	1100	2200	1800	1750	2400
set 2	C3	600	2000	300	700	400	300	1300	2600	400	2500	200	1250
S-D2	C4	1600	600	2400	350	150	900	2800	500	2300	1400	3100	2000
	C5	500	900	700	400	200	600	800	1300	1200	1400	2000	1400
	Total	3500	5200	4900	3850	1150	3000	7600	6900	8600	10000	9350	7950
	C1	1700	2900	3200	1700	2700	1650	0	0	0	0	0	0
Demand	C2	0	0	0	0	0	0	2900	2700	3600	2800	400	1600
set 3	C3	1300	2400	400	3500	200	150	1200	2800	300	700	1300	1800
S-D3	C4	0	0	0	0	0	0	1400	1400	2900	350	150	1300
	C5	3600	1600	2000	2400	2700	1900	800	1500	1100	600	1250	1150
	Total	6600	6900	5600	7600	5600	3700	6300	8400	7900	4450	3100	5850
	C1	1700	2900	3200	1700	2700	1650	0	0	0	0	0	0
Demand	C2	0	0	0	0	0	0	2900	2700	3600	2800	400	1600
set 4	C3	0	0	0	0	0	0	1200	2800	300	700	1300	1800
S-D4	C4	0	0	0	0	0	0	2200	2900	4000	950	1400	2450
	C5	4900	4000	2400	5900	2900	2050	0	0	0	0	0	0
	Total	6600	6900	5600	7600	5600	3700	6300	8400	7900	4450	3100	5850

TABLE 6.C: Results of sensitivity analysis

Scenarios	Cases	Suppliers	Total emissions (kg)	Total driving time (h)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
IS	BC	S1	2738.6	69.5	2520.4	1684.2	459.7	4664.3
		S2	2888.6	72.9	2654.8	2606.4	538.4	5799.7
		Aggr.	5627.2	142.4	5175.2	4290.6	998.1	10463.9
	BC_{HC}	S1	1923.0	47.5	1755.9	1481.7	459.7	3697.3
		S2	2057.1	50.9	1879.1	2556.2	538.4	4973.7
		Aggr.	3980.1	98.4	3635.0	4037.9	998.1	8671.0
S-D1	D1	S1	3139.6	76.5	2855.4	1914.9	0.0	4770.4
		S2	2592.4	68.8	2418.3	1820.6	15.9	4254.8
		Aggr.	5732.0	145.2	5273.8	3735.5	15.9	9025.2
	$D1_{HC}$	S1	2378.3	60.1	2185.9	1850.2	0.0	4036.1
		S2	1593.8	42.6	1490.2	1670.8	0.0	3161.0
		Aggr.	3972.1	102.6	3676.1	3521.0	0.0	7197.1
S-D2	D2	S1	2430.4	63.7	2259.3	1132.5	95.3	3487.1
		S2	3174.4	76.6	2878.8	3191.5	0.0	6070.3
		Aggr.	5604.8	140.3	5138.1	4324.0	95.3	9557.5
	$D2_{HC}$	S1	1611.6	42.6	1501.7	1002.5	0.0	2504.2
		S2	2357.4	60.1	2172.4	3083.6	0.0	5256.0
		Aggr.	3969.1	102.6	3674.1	4086.1	0.0	7760.2
S-D3	D3	S1	1787.6	46.6	1658.3	1501.6	459.7	3619.6
		S2	2493.2	62.5	2286.9	2654.1	155.3	5096.2
		Aggr.	4280.8	109.1	3945.2	4155.7	615.0	8715.8
	$D3_{HC}$	S1	1589.5	39.6	1455.4	1435.0	459.7	3350.2
		S2	2029.8	52.3	1876.5	2654.1	155.3	4685.9
		Aggr.	3619.4	91.9	3332.0	4089.1	615.0	8036.0
S-D4	D4	S1	1423.0	37.0	1318.9	1425.2	0.0	2744.2
		S2	2468.8	61.9	2264.5	2608.7	0.0	4873.1
		Aggr.	3891.8	98.9	3583.4	4033.9	0.0	7617.3
	$D4_{HC}$	S1	1236.1	30.9	1132.5	1425.2	0.0	2557.7
		S2	2351.3	60.8	2176.9	2608.7	0.0	4785.6
		Aggr.	3587.4	91.7	3309.4	4033.9	0.0	7343.3
S-MN	MN	S1	2522.5	63.8	2319.2	1481.7	459.7	4260.6
		S2	2628.3	66.7	2419.1	2586.4	538.4	5543.9
		Aggr.	5150.8	130.5	4738.3	4068.0	998.1	9804.5
	MN_{HC}	S1	1976.9	48.5	1801.8	1513.5	459.7	3775.0
		S2	2532.8	61.5	2301.6	2556.2	538.4	5396.2
		Aggr.	4509.7	110.0	4103.4	4069.8	998.1	9171.3
S-LH	LH	S1	2102.0	51.5	1914.9	1252.1	459.7	3626.7
		S2	2784.5	70.2	2558.1	1373.8	538.4	4470.3
		Aggr.	4886.5	121.7	4472.9	2625.9	998.1	8096.9
	LH_{HC}	S1	1829.6	45.6	1675.4	828.6	459.7	2963.7
		S2	2011.4	50.0	1840.0	1288.2	538.4	3666.6
		Aggr.	3841.1	95.6	3515.4	2116.7	998.1	6630.2
S-HH	HH	S1	2982.0	75.6	2744.1	2249.6	459.7	5453.5
		S2	2888.6	72.9	2654.8	3909.6	538.4	7102.9
		Aggr.	5870.6	148.5	5399.0	6159.2	998.1	12556.3
	HH_{HC}	S1	1914.5	47.3	1747.8	2222.5	459.7	4430.0
		S2	2065.5	51.1	1887.2	3834.4	538.4	6260.0
		Aggr.	3980.1	98.4	3635.0	6056.9	998.1	10690.1
S-LW	LW	S1	2738.6	69.5	2520.4	1684.2	229.9	4434.4
		S2	2888.6	72.9	2654.8	2606.4	269.2	5530.5
		Aggr.	5627.2	142.4	5175.2	4290.6	499.1	9964.9
	LW_{HC}	S1	1923.6	47.5	1756.5	1481.7	229.9	3468.1
		S2	2056.4	50.9	1878.5	2556.2	269.2	4703.9
		Aggr.	3980.1	98.4	3635.0	4037.9	499.1	8172.0
S-HW	HW	S1	2738.6	69.5	2520.4	1684.2	689.6	4894.1
		S2	2888.6	72.9	2654.8	2606.4	807.6	6068.9
		Aggr.	5627.2	142.4	5175.2	4290.6	1497.2	10963.0
	HW_{HC}	S1	1923.0	47.5	1755.9	1481.7	689.6	3927.2
		S2	2057.1	50.9	1879.1	2556.2	807.6	5242.9
		Aggr.	3980.1	98.4	3635.0	4037.9	1497.2	9170.1

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TABLE 6.C(continued): Results of sensitivity analysis

Scenarios	Cases	Suppliers	Total emissions (kg)	Total driving time (h)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
S-LR	LR	S1	2982.0	75.6	1905.0	1499.7	459.7	3864.5
		S2	2888.6	72.9	1843.1	2606.4	538.4	4987.9
		Aggr.	5870.6	148.5	3748.1	4106.2	998.1	8852.4
	LR_{HC}	S1	1914.5	47.3	1213.8	1481.7	459.7	3155.2
		S2	2065.5	51.1	1310.5	2556.2	538.4	4405.1
		Aggr.	3980.1	98.4	2524.2	4037.9	998.1	7560.3
S-HR	HR	S1	2409.6	59.5	2872.9	2095.6	459.7	5428.2
		S2	2888.6	72.9	3466.6	2606.4	538.4	6611.4
		Aggr.	5298.2	132.5	6339.5	4702.0	998.1	12039.6
	HR_{HC}	S1	1922.4	47.5	2291.8	1481.7	459.7	4233.2
		S2	2057.6	50.9	2454.0	2556.2	538.4	5548.6
		Aggr.	3980.1	98.4	4745.8	4037.9	998.1	9781.9
S-LVS	LVS	S1	2330.4	119.1	2792.3	2095.6	459.7	5347.6
		S2	2791.6	145.9	3379.8	2606.4	538.4	6524.6
		Aggr.	5121.9	264.9	6172.1	4702.0	998.1	11872.2
	LVS_{HC}	S1	1849.7	94.4	2215.0	1481.7	459.7	4156.4
		S2	1999.5	102.4	2397.8	2556.2	538.4	5492.4
		Aggr.	3849.2	196.7	4612.8	4037.9	998.1	9648.9
S-HVS	HVS	S1	3760.7	46.3	2931.0	1684.2	459.7	5074.9
		S2	3961.9	48.6	3086.0	2606.4	538.4	6230.8
		Aggr.	7722.6	94.9	6017.0	4290.6	998.1	11305.7
	HVS_{HC}	S1	2609.8	31.5	2027.2	1481.7	459.7	3968.6
		S2	2817.7	34.1	2189.4	2556.2	538.4	5284.0
		Aggr.	5427.6	65.6	4216.6	4037.9	998.1	9252.6
S-LCV	LCV	S1	2725.5	69.5	2511.9	962.1	19.9	3493.8
		S2	2769.9	70.0	2546.8	1415.3	0.0	3962.1
		Aggr.	5495.4	139.5	5058.6	2377.4	19.9	7455.9
	LCV_{HC}	S1	1912.1	47.5	1748.6	779.6	19.9	2548.1
		S2	1984.8	49.3	1815.7	1305.0	0.0	3120.7
		Aggr.	3897.0	96.8	3564.3	2084.7	19.9	5668.8
S-HCV	HCV	S1	2751.8	69.5	2528.9	2406.3	899.6	5834.7
		S2	2906.8	72.9	2666.6	3770.3	1950.3	8387.3
		Aggr.	5658.6	142.4	5195.5	6176.6	2849.9	14222.0
	HCV_{HC}	S1	1915.9	47.0	1746.1	2201.5	899.6	4847.2
		S2	2150.8	52.9	1962.0	3720.1	1950.3	7632.4
		Aggr.	4066.7	99.9	3708.1	5921.6	2849.9	12479.6
S-LS	LS	S1	2735.3	69.5	2518.3	1504.2	350.1	4372.5
		S2	2884.1	72.9	2651.9	2307.8	271.9	5231.6
		Aggr.	5619.4	142.4	5170.2	3812.0	622.0	9604.1
	LS_{HC}	S1	1921.6	47.5	1755.3	1302.3	350.1	3407.7
		S2	2052.9	50.8	1876.1	2257.6	271.9	4405.6
		Aggr.	3974.5	98.4	3631.4	3559.9	622.0	7813.3
S-HS	HS	S1	2743.7	69.5	2523.6	1960.7	628.2	5112.5
		S2	2895.6	72.9	2659.4	3065.3	947.9	6672.5
		Aggr.	5639.2	142.4	5183.0	5026.0	1576.0	11785.1
	HS_{HC}	S1	1913.7	47.1	1745.8	1757.4	628.2	4131.4
		S2	2074.9	51.3	1894.7	3015.1	947.9	5857.7
		Aggr.	3988.6	98.4	3640.5	4772.5	1576.0	9989.1
S-LMS	LMS	S1	3024.3	76.5	2780.9	1451.7	759.4	4992.0
		S2	3026.8	76.6	2783.4	2349.0	2610.4	7742.8
		Aggr.	6051.2	153.1	5564.4	3800.8	3369.7	12734.9
	LMS_{HC}	S1	1945.4	48.5	1781.1	1451.8	759.4	3992.3
		S2	2083.7	52.8	1917.3	2349.0	2610.4	6876.7
		Aggr.	4029.1	101.3	3698.3	3800.8	3369.7	10868.9
S-HMS(a)	HMS	S1	2738.6	69.5	2520.4	1730.2	0.0	4250.5
		S2	2698.3	67.8	2476.8	2780.9	0.0	5257.7
		Aggr.	5436.9	137.3	4997.1	4511.0	0.0	9508.2
	HMS_{HC}	S1	1925.2	47.6	1758.1	1527.7	0.0	3285.8
		S2	2053.0	50.8	1875.8	2610.1	0.0	4485.9
		Aggr.	3978.2	98.4	3633.9	4137.8	0.0	7771.6

IS: Initial situation, S-D1: S1 large and S2 small sized, S-D2: S1 small and S2 large sized,
S-D3: two common customers, S-D4: zero common customer,
S-MN: Modified network, S-LH: Lower holding cost, S-HH: Higher holding cost,
S-LW: Lower waste cost, S-HW: Higher waste cost,S-LR: Lower routing cost,
S-HR: Higher routing cost, S-LVS: Lower vehicle speed, S-HVS: Higher vehicle speed,
S-LCV: Lower coefficient of variation, S-HCV: Higher coefficient of variation,
S-LS: Lower service level, S-HS: Higher service level,
S-LMS: Lower maximum shelf lives, S-HMS(a): Higher maximum shelf lives

Chapter 7

Conclusions and general discussion

7.1   Conclusions

In this PhD thesis, we concentrated on decision support modelling for Sustainable Food Logistics Management (SFLM). The overall objective of the research was to obtain insight in how to improve the sustainability performance of food logistics systems by developing decision support models that can address the concerns for transportation energy use and consequently carbon emissions, and/or product waste, while also adhering to competitiveness. The developed models incorporate several logistics improvement opportunities regarding transportation energy use and emissions, and/or product waste as distinct from the traditional approaches in the literature. In line with the overall objective, five research objectives were set as follows:

• RO1: To identify key logistical aims, analyse available quantitative models and point out modelling challenges in SFLM.

• RO2: To analyse the relationship between economic (cost) and environmental (transportation carbon emissions) performance in a network problem of a perishable product.

• RO3: To investigate the performance implications of accommodating explicit transportation energy use and traffic congestion concerns in a two-echelon capacitated vehicle routing problem (2E-CVRP).

• RO4: To investigate the performance implications of accommodating explicit transportation energy use, product waste and demand uncertainty concerns in an inventory routing problem (IRP).

• RO5: To analyse the benefits of horizontal collaboration in a green IRP for perishable products with demand uncertainty.

The thesis includes a collection of five papers, each of which is devoted to a different RO and contributes to the overall objective. RO1 was confronted in Chapter 2 presenting a literature review on quantitative studies in Food Logistics Management (FLM) to understand the state of the art and modelling challenges. RO2 was confronted in Chapter 3 introducing a multi-objective linear programming (MOLP) model for a logistics network problem. RO3 was confronted in Chapter 4 introducing a mixed integer linear programming (MILP) model for a 2E-CVRP. RO4 was confronted in Chapter 5 introducing a chance-constrained programming model with demand uncertainty for an IRP with one-to-many distribution structure. RO5 was confronted in Chapter 6 introducing a chance-constrained programming model with demand uncertainty for an IRP with many-to-many distribution structure.

In the following, we summarize the main findings and conclusions for each chapter included in the thesis. Afterwards, the integrated findings, managerial implications, limitations of the study and general future research directions are discussed.

7.1.1 Research opportunities

Chapter 2 concentrated on identifying key logistical aims in the three successive phases, which are Logistics Management (LM), FLM and SFLM, and analysing available quantitative models to point out modelling challenges in SFLM. We conducted a literature review on quantitative studies in FLM. Qualitative studies were also consulted to understand the key logistical aims more clearly and to identify relevant logistics system scope issues. To the best of our knowledge, ours was the first literature review on SFLM covering the contributions by taking the development from LM to FLM towards SFLM into account. We presented detailed information with respect to the key logistical aims and related models to generate a structured linkage between the practical requirements and the current modelling literature. The key logistical aims in SFLM were covered in three groups: (1) cost reduction and improved responsiveness (LM phase), (2) improved food quality and reduction of food waste (FLM phase), and (3) improved sustainability and traceability (SFLM phase). Additionally, we investigated the quantitative models with respect to the main characteristics such as modelling type and application area, and incorporated Key Performance Indicators (KPIs) and logistics system scope issues.

Results show that research on SFLM has been progressively developing according to the needs of the food industry. However, the intrinsic characteristics of food products and processes have not yet been handled properly in the identified studies. Some of the main modelling challenges based on the assessment of the analysed models can be summarized as follows:

• Most studies in literature rely on a completely deterministic environment; however, supply chain members in food industry are confronted with several uncertainties. Due to this fact, we proposed models in Chapters 5 and 6 which are able to capture the risk associated with uncertain demand.

• Researchers do not show sufficient interest in food waste problem occurring at different stages of the food supply chains (FSCs). We believe that incorporating the option that product quality falls below the minimum level will help these models to approach real life problems and issues much better than before. From this point of view, we incorporated product waste into the models in Chapters 5 and 6.

• The majority of the works reviewed have not considered sustainability problems, apart from a few recent studies. Regarding emissions, most studies calculate fuel consumption based only on traveled distance. However, this restrictive approach does not allow an explicit calculation of the fuel consumed in logistics operations, which is crucial in terms of reducing environmental externalities. This fact motivated us to explicitly estimate fuel consumption amount in Chapters 3, 4, 5 and 6.

• Most literature studies propose single objective models for the related logistical problems in FSCs. However, real life problems consist of multiple objectives, which are in conflict with each other. Therefore, we proposed a multi-objective model in Chapter 3 which ensures to present the trade-offs between logistics cost and transportation carbon emissions. Moreover, we compared the use of different objectives in Chapter 4 mainly to present the trade-offs between logistics cost and transportation carbon emissions. To reveal the trade-offs among transportation carbon emissions, product waste and logistics cost, different model variations were employed in Chapter 5, and cases with and without horizontal collaboration were analyzed in Chapter 6.

This chapter concludes that new and advanced quantitative models are needed that take specific SFLM requirements from practice into consideration to support business decisions and capture food supply chain dynamics. By this means better logistics decision support models can create sustainable and efficient business networks.

7.1.2 Environmentally friendly network management for perishable products

Chapter 3 addressed a generic multi-echelon beef logistics network problem that consists of a number of third party logistics (3PL) firms, production regions, slaughterhouses, export departure and import arrival points. The main decisions involved are: number of livestock slaughtered, amount of livestock and beef inventories, allocation decisions, and number of trucks used, also taken into consideration the possibility of less than fully loaded truck shipments. The problem aims to minimize the total logistics costs comprising inventory and transportation costs together with the total CO_2 transportation emissions. A MOLP model was developed for the problem. As distinct from the network models in the literature, the proposed model incorporates several aspects simultaneously. The model regards road structure, vehicle and fuel types, weight loads of vehicles and traveled distances while calculating fuel consumption and CO_2 emissions. This approach ensures the assessment of the effects of empty drives, which occur before getting to the sites for service and during return hauls, and less than fully loaded truck shipments on logistics cost and emissions. The beef product is subject to quality decay and duration of inventory

keeping is therefore limited in the model. We provided a case study of the international beef logistics chain operating from a region in Brazil to the European Union (EU) to illustrate the applicability of the proposed model for real logistics systems.

In our case study, the 3PL firms provide trucks that have two age categories (old and new). The old truck is less efficient in terms of fuel consumption; however, its fixed renting cost is lower than that of the new one. Due to these different features of trucks, trade-offs occur between logistics cost and transportation emissions. The trade-off relationships between logistics costs and transportation emissions were revealed in a Pareto frontier, which enables us to answer the question of how much it costs to reduce emissions to different levels in the logistics system. In the following analysis, the road transport emissions shares of the chain parts indicated the importance of distances between actors in terms of environmental impact. Moreover, practical necessities, and challenges learnt from the related literature and Brazilian partners in the EU funded project, SALSA, motivated us to explore the effects of possible changes in the current logistics system on cost and emissions. Some of the most interesting results from the sensitivity analysis on parameters important in practice are as follows: (1) removing capacity constraints on export ports showed that capacities put pressure on the logistics system while selecting the port for transportation, (2) decreasing fuel efficiency of trucks due to the inefficient infrastructure resulted in shifts of the Pareto frontier with increase in both logistics cost and transportation emissions, and (3) decreasing fixed renting cost of new trucks due to the obtained advantage of 3PL firms from green tax incentives resulted in economic and environmental improvement. All the analyses in this chapter show that the proposed model serves as a decision support tool while further improving the environmental performance of the selected food logistics chain.

The model allows only direct flows between the supply chain actors. Therefore, an important direction for our next studies in Chapters 4, 5, and 6 was to consider indirect flows between facilities by tackling routing decisions. Moreover, product waste possibility is ignored in the study, since the model only restricts the maximum number of periods that beef can be stored in facilities. Tracking quality or age of the products through the supply chain in a more detailed way, which will allow control of product waste, was given as another research direction. Starting from this point of view, we regarded potential of product wastes in Chapters 5 and 6.

7.1.3 Environmentally friendly routing with time-dependent speed

Chapter 4 addressed a time-dependent 2E-CVRP that consists of a depot, and a set of satellites and customers. In two-echelon distribution systems, large trucks are used to transport freight over long-distances to satellites where consolidation takes place; afterwards, the products are transferred to destination points using small and environmentally-friendly vehicles. In our problem, time-dependent travel times are considered to account for traffic congestion effects when traveling on the defined arcs in the second-echelon. The objective of the basic 2E-CVRP is to determine two sets of first and second echelon routes that minimize total routing and satellite handling cost. We developed a comprehensive MILP formulation for a time-dependent 2E-CVRP that accounts for vehicle type, traveled distance, vehicle speed, load, emissions and multiple time zones that may occur during the planning horizon. To the best of our knowledge, this was the first attempt to develop a mathematical model for the time-dependent 2E-CVRP with an explicit consideration of fuel consumption through the use of a comprehensive emission function. A case study was provided to present an implementation of the proposed model on the distribution operations of a supermarket chain operating in the Netherlands. We focused on four KPIs: total distance, total time, total fuel consumption, and total cost. The proposed model was minimized over each Key Performance Indicator.

The results of the computational experiments showed that the resulting routes and the performances of the solutions with respect to the KPIs change according to the variation of the model. The traditional objectives of distance and time minimization did not ensure minimization of fuel consumption or cost. The comprehensive cost-minimizing objective, which breaks away from the traditional objective functions used in the 2E-CVRP by a detailed estimation of fuel consumption, could achieve average savings in total cost by 6.9%. However, it did not guarantee the best solution in terms of emissions. The use of fuel-minimizing objective could ensure the most environmentally-friendly solution by reducing total fuel consumption on average 2.5% in return for a cost increase of 10.8%. The sensitivity analyses revealed that the performances of the variations of the model on the selected KPIs changed according to the handling fee in the satellites and demand of the customers. Additionally, for our case study, the most environmentally-friendly solution was obtained by the use of a two-echelon distribution system, although a single-echelon distribution system provides a solution with lower total cost.

The results presented in this chapter confirmed the benefit of explicitly accounting for time-dependent speeds and fuel consumption in a routing problem. Inventory decisions were not incorporated in the problem. However, growing vertical collaboration between suppliers and customers increases the suppliers' responsibility to manage inventory at the

customers besides controlling deliveries. This has resulted in an integrated IRP consisting of suppliers' own vehicle routing decisions and inventory decisions of their customers. Therefore, we focused on IRP in Chapters 5 and 6.

7.1.4 Environmentally friendly inventory routing for perishable products with demand uncertainty

Chapter 5 addressed a generic IRP that consists of a single supplier (depot) and a number of customers. Under the Vendor Managed Inventory (VMI) policy, the supplier has to make three simultaneous decisions: when to deliver to each customer, how much to deliver to each customer each time it is served, and how to combine delivery to customers into vehicle routes. The problem is to determine the routes and quantity of shipments in each period in such a way that the total cost comprising routing, inventory and waste costs is minimized. We developed a comprehensive chance-constrained programming model (M_{PF}) for the multi-period IRP that accounts for perishability, explicit fuel consumption and demand uncertainty. The proposed model manages relevant KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost simultaneously. To the best of our knowledge, the model was unique in using a comprehensive emission function and in modeling waste and service level constraints as a result of uncertain demand. To present the benefits of including perishability and explicit fuel consumption considerations in the model, we derived three additional models from the proposed model: model without perishability and explicit fuel consumption concerns (M), model with explicit fuel consumption concern (M_F) and model with perishability concern (M_P). Additionally, we proposed a simulation model to evaluate the solutions of these models and to check whether these solutions are feasible. A case study was provided to present an implementation of the proposed model, and its variations described above, on the fresh tomato distribution operations of a supermarket chain operating in Turkey.

Our analysis on different scenarios showed the consequences of perishability and/or explicit fuel consumption ignorance. The models M and M_F could not meet the desired service levels in all scenarios due to the perishability ignorance which resulted in relatively higher product wastes. On the contrary, accounting for the perishability allowed M_P and M_{PF} to satisfy the service levels in all scenarios. M_{PF} provided the least cost solutions in all scenarios. According to the optimization results, M_{PF} can achieve average savings in total cost by 24.3% compared to M, 20.5% compared to M_F and 0.9% compared to M_P. In the experiments, we successively changed the values of the following problem parameters: the demand means, coefficient of variations, fixed shelf lives, holding costs and service levels. It appeared that the added value of M_{PF} compared to the other model

variations in terms of total cost changes according to the parameter values. For instance, the total cost gap between M and M_{PF} solutions increased as C or α increases and decreased as m or h increases. Additionally, the use of a more environmentally-friendly objective function (in model M'_{PF}) showed that 2% decrease in total emissions can be obtained in return for a 25.2% significant total cost increase.

The results presented in this chapter supported the view that the improvement of the IRP model through perishability and explicit fuel consumption incorporation makes it more useful than a basic model that disregards both aspects for the decision makers in food logistics management. However, the problem deals with a single supplier (one-to-many distribution structure) and a single product which restricts the applicability of the developed model to the distribution networks where more than one supplier and product exist. This indicated improvement opportunity formed our main motivation to head towards another variant of the IRP that has a number of suppliers and products in Chapter 6. Another driver for the aforementioned variant was that dealing with the multiple supplier case would provide a chance to investigate the effects of horizontal collaboration besides vertical collaboration.

7.1.5 Environmentally friendly inventory routing for perishable products with horizontal collaboration and demand uncertainty

Chapter 6 addressed an IRP with many-to-many distribution structure that comprises a 3PL which serves as a rental vehicle company, and multiple suppliers and customers. This problem requires vertical collaboration among suppliers and customers, and horizontal collaboration among suppliers. The literature review on the problem pointed out that there was a need for decision support tools that incorporate perishability, explicit fuel consumption and demand uncertainty, and horizontal logistics collaboration in the IRP had not been explicitly addressed by researchers. Accordingly, we developed a comprehensive chance-constrained programming model with demand uncertainty for a generic IRP with multiple suppliers and customers that accounts for the KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost. The model provides routing and delivery plans by considering not only economic concerns, but also product wastes and emissions. Afterwards, the proposed model was used to analyze the benefits of horizontal collaboration in the IRP with respect to the aforementioned KPIs. We provided a case study on the distribution operations of two suppliers, where the first supplier produces figs and the second supplier produces cherries, to show the applicability of the model.

The results based on the case study data and a broad set of experiments illustrated the benefits of horizontal collaboration in terms of economic and environmental concerns. Horizontal collaboration among suppliers made it possible to reduce aggregated total cost by 17% and aggregated total emissions by 29% in the studied case. Extensive sensitivity analysis showed that the obtained gains were dependent on several modelling parameters. The following important conclusions were obtained through the results of the experimental analysis. The smaller supplier gained more total cost benefit from cooperation compared to the larger supplier. The logistics network structure has potential to change the gains obtained by cooperation. For instance, the change of the logistics network structure reduced the aggregated total cost gap to 6% and emission gap to 12%. The other factor affecting cooperation benefits is the number of common customers between suppliers. As the number of common customers decreased, the benefits obtained from working jointly to provide service to the customers decreased as well. For instance, the aggregated total cost and emission gaps fell to 4% and 8% respectively, when there was no common customer between the suppliers. All analyses showed that the aggregated total cost gap varies in a range of about 4-24% and the aggregated total emission gap varies in a range of about 8-33%. Lastly, the aggregated total cost and emission gains did not always go hand in hand in the investigated scenarios in such a way that when one increases, the other decreases. For instance, the decrease of routing cost reduced the cost gap from 17% to 15%, whereas it increased the emission gap from 29% to 32%. However, in another scenario, the decrease of vehicle speed increased the cost gap to 19%, whereas it reduced the emission gap to 25%.

7.2 Integrated findings

So far in this chapter, findings for each RO are presented separately. This section discusses the integrated findings in SFLM and decision support modelling using the research framework introduced in Figure 1.2 in Chapter 1.

7.2.1 Sustainable Food Logistics Management

Integrated findings from Chapters 2, 3, 4, 5 and 6 contribute to the SFLM literature by (i) reflecting the state of the art on the topic of quantitative logistic models which have sustainability considerations, (ii) providing decision support models which can be used by decision makers to improve the performance of the sustainable food logistics systems in terms of logistics cost, transportation energy use and carbon emissions, and/or

product waste, and (iii) presenting the applicability of the proposed models in different case studies based on mainly real data, multiple scenarios, and analysis. In the following, we first present the main research issues in SFLM. Secondly, the insights provided by the developed models to SFLM are discussed based on the results of the case study implementations. Lastly, we present the main benefits of explicit fuel consumption and perishability considerations in the models.

- *Main research issues in SFLM*

We presented thorough literature reviews on Operations Research (OR) models to understand the state of the art and modelling challenges in SFLM. In particular, Chapter 2 was devoted to the literature review of quantitative and qualitative studies in FLM. Additionally, Chapters 3, 4, 5 and 6 presented related literature reviews on OR models in the selected logistics problems to point out the gaps and justify the contributions of the studies. Note that these reviews are not restricted only to FSCs, but also cover studies on other supply chains.

Transition towards SFLM increased the importance of managing transportation energy use and emissions, and product waste in food logistics systems. However, the literature reviews show that traditional logistics decision support models often focus on logistics cost and disregard the aforementioned environmental and social concerns. The main drawbacks of the existing models can be summarized as follows. First, traditional logistics models often regard only traveled distance while calculating distribution cost between nodes in a supply chain. Other factors such as vehicle load, speed and type, however, affect fuel consumption and therefore distribution cost as well. Ignoring these factors while calculating fuel consumption amounts also leads to a misevaluation of related environmental impacts of transportation. Second, the traditional approach in logistics models is to assume an unlimited product shelf life, although most of the food products are subject to quality decay in practice. The non-perishability assumption restricts the usefulness of the proposed models in current food logistics systems. These two prominent drawbacks, which concern better management of transportation energy use and emissions, and product waste along with logistic cost, should be addressed by researchers to improve existing decision support models.

The traditional trend, which ignores environmental and social concerns, has been changing, especially in the last years, towards developing enhanced models that account for several logistics improvement opportunities regarding transportation energy use and emissions, and food waste. However, we have observed that these non-traditional attempts are still not sufficient in terms of adequately and also simultaneously addressing the aforementioned concerns. On one hand, some of these non-traditional attempts are regarded as

inadequate mainly due to the following reasons: (i) they estimate transportation energy use and emissions roughly without using comprehensive fuel estimation models that take multiple aspects (e.g., traveled distance, vehicle load and speed, etc.) into account, (ii) they consider product perishability, but do not allow product waste. On the other hand, some non-traditional models tackle the aforementioned issues properly, but fail to cover transportation energy use and emissions, and product waste concerns simultaneously. Note that all the analyses in Chapter 5 and 6 reveal that ignoring either transportation energy use (emissions) or product waste may have severe performance implications, and therefore both of these concerns should be incorporated into the decision making process in food logistics.

The use of comprehensive fuel estimation models and better control of product waste are clearly not the only logistics improvement opportunities for transportation energy use and emissions, and product waste. Therefore, the findings obtained from the literature reviews in Chapters 2, 3, 4, 5 and 6 lead us to conclude that there is still much room for further improvement of the existing logistics decision support models by means of incorporating the improvement opportunities introduced at Table 1.1 in Chapter 1 into the logistics models. As shown in Chapters 3, 4, 5 and 6, the potentially enhanced models can afterwards be used to meet the practical needs and to develop more sustainable logistics systems.

- *Insights provided by the developed models to SFLM*

We presented mathematical models in Chapters 3, 4, 5 and 6 for different logistics problems to provide decision support tools for sustainable food logistics systems. Table 7.1 presents the comparison of these models with respect to the elements of the research framework introduced in Figure 1.2 in Chapter 1. The elements are key decisions involved, perishability, fuel consumption and uncertainty considerations, main KPIs, inherently existing improvement opportunities and incorporated improvement opportunities. These models can be regarded as non-traditional in the sense that they involve several logistics improvement opportunities with the common aim to improve performance of SFLM. Case study implementations in the aforementioned chapters indicated that the proposed models provide opportunities to decision makers while further improving logistics performance. Examples from different chapters on the topic can be given as follows.

First, the MOLP model proposed in Chapter 3 can be used for logistics network problems for perishable products that have to be managed by a fleet composed of multiple vehicle types (see Table 7.1). The ability to manage an inhomogeneous fleet allowed the calculation of the trade-offs between logistics cost and transportation emissions in our case study, which involves old and new trucks with different renting costs and fuel efficiency

TABLE 7.1: Outline of the chapters including quantitative models

		Chapter 3 Network Problem	Chapter 4 2E-CVRP	Chapter 5 IRP (1-to-m)	Chapter 6 IRP (m-to-m)
Key decisions involved	Inventory quantity	✓	-	✓	✓
	Delivery quantity and schedule	✓	-	✓	✓
	Routes to deliver products	-	✓	✓	✓
Perishability	Shelf life	✓	-	✓	✓
	Product waste	-	-	✓	✓
Fuel or emissions considerations	Traveled distance	✓	✓	✓	✓
	Vehicle load	✓	✓	✓	✓
	Vehicle speed	-	✓	✓	✓
	Time-dependent speed	-	✓	-	-
Uncertainty	Demand	-	-	✓	✓
Main KPIs	Total fuel cost	✓	✓	✓	✓
	Total wage cost	-	✓	✓	✓
	Total inventory cost	✓	-	✓	✓
	Total waste cost	-	-	✓	✓
	Total energy use (emissions)	✓	✓	✓	✓
	Total driving time	-	✓	✓	✓
Intrinsic improvement opportunities	Better network management	✓	-	-	-
	Better route planning	-	✓	✓	✓
	Better vehicle sharing through — vertical collaboration	✓	-	✓	✓
	Better vehicle sharing through — horizontal collaboration	✓	-	-	✓
	Use of alternative distribution systems	-	✓	-	-
	Better inventory planning	✓	-	✓	✓
	More efficient information sharing (VMI)	-	-	✓	✓
Incorporated improvement opportunities	Use of fuel efficient fleet and multi-modality	✓	✓	-	-
	Use of comprehensive fuel estimation models	✓	✓	✓	✓
	Less exposure to traffic congestion	-	✓	-	-
	Tracking shelf life information	✓	-	✓	✓
	Controlling product waste	-	-	✓	✓

levels. For instance, results from the case study revealed that in approximate numbers an emission reduction of 8% comes at a cost increase of 3% and necessitates the use of 16% new trucks in the fleet (see Fig. 3.5a,b in Chapter 3).

Second, as shown in Table 7.1, the MILP model proposed in Chapter 4 takes traffic congestion (time-dependent speed) into account which becomes especially important for logistics problems in urban areas. Results from the case study showed that accounting for time-dependent speeds, rather than assuming that vehicles retain their speeds even in rush hours, led to significant savings in total cost (see Table 4.6 in Chapter 4).

Third, the chance-constrained programming model proposed in Chapter 5 can be used for inventory routing problems for perishable products with demand uncertainty and environmental considerations (see Table 7.1). Analyses of the case study showed that the model could provide benefits in terms of cost and achieved service levels compared to its counterparts in the literature. For instance, as shown at Table 5.9 in Chapter 5, the model (M_{PF}) achieved total cost savings of 11.3% compared to another model (M) without perishability and explicit fuel consumption concerns. Additionally, simulation

results revealed that M could not meet the desired service levels, whereas M_{PF} satisfied the service level requirements.

Lastly, the chance-constrained programming model proposed in Chapter 6 can be used to evaluate the potential economic and environmental benefits of horizontal collaboration in inventory routing problems for perishable products with demand uncertainty and environmental considerations (see Table 7.1). According to the results of the case study, horizontal collaboration among the suppliers contributed to the decrease of aggregated total cost and emissions in the logistics system (see Fig. 6.C in Chapter 6).

In summary, the insights from the case study implementations discussed above support the view that the models developed in this PhD study give better aid to decision makers in SFLM compared to the existing attempts in the literature.

• *Main benefits of explicit fuel consumption and perishability considerations*

In this thesis, we are concerned with transportation energy use and carbon emissions, and product waste as environmental and social KPIs. These KPIs were measured and incorporated in the decision making process in logistics problems through the developed mathematical models. In particular, we employed comprehensive fuel estimation models to estimate transportation energy use and emissions more explicitly, and took perishability into account to control product waste. The results indicated that there is a twofold benefit from the incorporation of these aspects into the models: (i) opportunity to reduce relevant operational cost, (ii) opportunity to make logistics plans according to the environmental and social objectives. Therefore, the proposed models can be used to reveal the trade-off relationships among logistics cost, transportation energy use and emissions, and product waste.

The extension towards explicit fuel consumption helps to reduce cost, since the use of fuel estimation models based on not only travel distance but also other factors such as vehicle load, speed and type ensures more accurate calculation of the distribution costs (see Table 7.1). For instance, in Chapter 4, the comprehensive cost-minimizing objective comprising a detailed estimation of fuel consumption achieved significant savings in total cost compared to the traditional approaches based on only distance or time while estimating distribution cost. As presented at Table 4.6 in Chapter 4, respective saving is 12% compared to the distance-minimizing objective and 4% compared to the time minimizing-objective. The other extension towards perishability concern ensures feasible solutions that meet the desired service levels besides its cost reduction contribution. For instance, in Chapter 5, the model variations that ignore product perishability failed to meet the desired service levels, whereas the models with perishability concern were

successful in meeting those targets (see Table 5.6 in Chapter 5). Moreover, ignoring perishability in the models resulted in higher product wastes and therefore logistics cost (see Table 5.5 in Chapter 5).

Apart from these cost related benefits, the models with environmental and social concerns allow decision makers to bear in mind the state of the physical environment affected by the operations while making logistics plans. For instance, as presented in Chapter 3, a decision maker has the chance to select an optimal plan among a set of Pareto-optimal solutions according to his economic and environmental objectives. The other models also give users the opportunity to exploit the trade-offs among sustainability KPIs through using different objectives in Chapter 4, different model variations in Chapter 5 and cases with and without horizontal collaboration in Chapter 6. The results obtained from Chapters 3, 4, 5 and 6 show that the extension of the models towards explicit fuel consumption and perishability is important in terms of economic, environmental and social concerns. As a conclusion, the models provided in this PhD thesis give decision makers the opportunity to incorporate additional environmental and social concerns besides cost into the logistics decision making process. Therefore, the proposed models support the transition from traditional LM to FLM, and successively, to SFLM.

7.2.2 Decision support modelling

Moving towards SFLM requires new decision support models which can address recent sustainability concerns. In this PhD thesis, the following OR modelling approaches were employed to develop decision support models for SFLM: MOLP model in Chapter 3, MILP model in Chapter 4, and chance-constrained programming models in Chapter 5 and Chapter 6. The developed decision support models exploit several logistics improvement opportunities regarding transportation energy use and emissions, and/or product waste to better aid SFLM, as distinct from their counterparts in literature (see Table 7.1). In the following, we present common approaches used to incorporate transportation energy use and emissions, and product perishability into OR models. Afterwards, the topics of increasing modelling complexity and benefits of strengthening the developed models are discussed.

• *Common approaches used to incorporate transportation energy use and emissions, and product perishability into OR models*

Literature reviews conducted in Chapters 2, 3, 4, 5 and 6 enabled us to observe how transportation energy use and emissions, and product perishability have been tackled in OR models on the studied logistics problems.

Existing OR models in literature often estimate transportation emissions based on fuel consumption amounts by means of a fuel conversion factor (kg emissions per gallon). They incorporate special fuel consumption models, which are not necessarily developed in the decision science field, to estimate the fuel consumption amounts. These fuel consumption models differ from each other in terms of considered aspects such as traveled distance, vehicle load or type, etc. We incorporated the model of Defra (2005, 2011) into the MOLP model in Chapter 3, and the comprehensive emissions model of Barth et al. (2005) into the MILP model in Chapter 4, and chance-constrained programming models in Chapters 5 and 6. The use of aforementioned fuel consumption models provided the opportunity to estimate fuel consumption and transportation emissions more accurately, which increases the value of logistics plans proposed by the developed decision support models.

The common assumption in literature regarding product perishability is that products have fixed shelf lives and deteriorate linearly based on time. The existing models in literature, which account for perishability, do not always allow product wastes. Some of the models assume that products have to be used within limited time period and waste cannot occur. For others, it is not always possible to use products before they are spoilt and therefore product wastes occur. For instance, the case study results from Chapters 5 (Table 5.5) and 6 (Table 6.5) show that perishable product management without having waste is not always possible. In this PhD thesis, the MOLP model in Chapter 3 has constraints that restrict the maximum storage time of the product and therefore does not allow product waste. However, the chance-constrained programming models in Chapters 5 and 6 also take product waste into account, which is one of the challenges of logistics management of perishable products.

- *Increasing modelling complexity*

We provided different case studies in Chapters 3, 4, 5 and 6 to show the applicability of the proposed models to real-life situations. These experiences provided us with a better understanding of the increasing complexity, resulting in a considerable amount of computational times to find optimal solutions for the studied problems. The reason is that the challenged problems are already known as Non-deterministic Polynomial-time hard in OR literature and the extension of these problems towards making them more suitable for the sustainable food logistics adds to their complexity. For instance, according to the reported results on the computational time at Table 4.7 in Chapter 4, an optimal solution for the studied problem can be obtained far more quickly from a traditional distance-minimizing model than from the model that takes explicit energy consumption and time-dependent speed into account. However, note that the extended model outperformed the traditional one with a 12% difference in total cost. Therefore,

the cost performance improvement obtained from the additional logistical improvement opportunities comes with an increase in computational time.

The chance-constrained programming models in Chapters 5 and 6 take demand uncertainty into account. These models have stochastic constraints (5.6) and (6.6) which ensure the inventory level at the end of every period to be nonnegative with a probability of service level α. The models deal with perishable products which have fixed shelf lives as well. Therefore, if a product stays in inventory more than a given period, it becomes spoilt and cost of waste occurs. Solving the above chance-constrained models is complicated as the products have fixed expiration dates and the actual demand is not known in advance. In line with literature (e.g., Pauls-Worm et al. (2014) and Hendrix et al. (2012)), we therefore considered deterministic approximations of the models. The deterministic approximations of the chance-constrained programming models, however, still try to hedge the risk associated with uncertain demand to some extent by proposing to hold safety stock in each period. The amount of safety stock (inventory) changes according to the desired service level, as shown in the results of the sensitivity analysis presented in Table 5.8 in Chapter 5 and Table 6.C in Chapter 6. Note that as distinct from the deterministic models, the approximate models allow decision makers to manage demand uncertainty and are therefore useful to manage logistics problems in which demand is not known a priori.

- *Benefits of strengthening the developed models*

The ILOG-OPL development studio and CPLEX 12.2 optimization package has been used in this thesis to develop and solve the proposed formulations. It has been observed that it takes a significant computing time for the optimization software to calculate eventual proofs of optimality for the proposed models. Therefore, we decided to use valid inequalities to tighten the formulations, and accelerate the proof of optimality and the convergence to optimal solutions. We managed to reduce optimal solution times for the problems tackled in Chapter 4 and Chapter 6 by means of the employed valid inequalities. The results given at Tables 4.7 in Chapter 4 and 6.8 in Chapter 6 show the efficiency of the valid inequalities. For instance, after a three hours' time limit, the model without valid inequalities in Chapter 6 gave a feasible solution which was 0.02% above the optimal cost level with a 6.04% gap from the best bound. This means that it still needs some time to reach the optimal solution and afterwards to prove the solution's optimality. However, the model with valid cuts was solved to optimality by the solver within one and half hours, which shows that the valid cuts provided are useful.

7.3 Managerial insights

In practice, logistics decision makers are confronted with the recent challenges of reducing the amount of food waste and raising transportation energy efficiency to reduce greenhouse gas emissions. In order to have more sustainable logistics systems, the necessity for decision support models, which can address the aforementioned concerns besides logistics cost, has increased accordingly. This PhD thesis provided such enhanced decision support models, which are presented in Chapters 3, 4, 5 and 6. These models have been used in several case studies to get insight in how to improve the sustainability performance of food logistics systems.

The findings of the thesis demonstrate that perishability and explicit consideration of fuel consumption are important aspects in logistics problems. The resulting managerial insights regarding these additional aspects are that decision makers should not underestimate (i) the value of controlling product waste, and (ii) the effects of other parameters such as vehicle load, vehicle speed or traffic congestion besides traveled distance on fuel consumption. The results of the experimental analysis in Chapters 3, 4, 5 and 6 supported the view that decision support models, which account for one or both of these aspects, offer better support to decision makers who want to improve sustainability performance of logistics systems than the existing models.

All of the models proposed in this PhD thesis aim to minimize related logistics costs. As distinct from their counterparts in literature, these models also employ several logistics improvement opportunities to incorporate transportation energy use and emissions, and product waste concerns into the management of the addressed logistics problems. These features enable decision makers to evaluate not only the least cost solutions, but also the environmental and social externalities of the potential logistics plans. Therefore, the proposed models appear to be promising decision support tools providing decision makers in practice with much insight into the three fundamental sustainability dimensions (economic, environmental and social) of logistics operations.

The case study implementations demonstrate the applicability and the potential of the proposed models. The main managerial implications of the results obtained from each case study can be summarized as follows. The MOLP model presented in Chapter 3 provided compromise solutions between economic (cost) and environmental (transportation carbon emissions) performance for the studied network problem. This information is especially useful in practice when setting sustainability targets that need an evaluation of economic and environmental factors. The MILP model presented in Chapter 4 revealed the economic and environmental benefits of accommodating traffic congestion concern

in the routing problem. This model can aid decision making on planning routes in city centers which have traffic congestion that varies depending on the time of the day. The chance-constrained programming model presented in Chapter 5 allowed to have the least cost solutions for the studied IRP while satisfying the service level requirements of the customers. Analyses of the other variations of the model showed that ignoring perishability and explicit consideration of fuel consumption might lead to higher cost solutions which do not meet the desired service levels in practice. The chance-constrained programming model presented in Chapter 6 enabled us to evaluate the potential economic and environmental benefits of horizontal collaboration in the studied IRP. In summary, all of these analyses of different case studies show that the decision support models provided can be used in practice by decision makers to further improve sustainability performance of the food logistics systems.

The models have been developed for generic problems and, except for the one in Chapter 4, account for product perishability. They can be implemented in other cases from different industries, especially the supply chains where products are subject to quality decay, e.g., blood, and pharmaceuticals supply chains. The proposed models, therefore, can contribute to the sustainability performance improvement of not only food but also of other logistics systems.

7.4 Limitations of the study and future research directions

This PhD thesis demonstrated the potential of accounting for additional sustainability indicators (transportation energy use and emissions, and product waste) in logistics decision support models by means of the applications of the developed models in different case studies. Nevertheless, we acknowledge the limitations of the research.

Logistics improvement opportunities for transportation energy use and emissions, and product waste are presented in Table 1.1 in Chapter 1. Note that we did not test the performance implications of incorporating each of these improvement opportunities into the logistics decision support models. Therefore, it would be interesting to investigate potential benefits of other improvement opportunities such as "use of bio-fuels", "monitoring temperature history" or "enabling food redistribution to redirect edible food that would otherwise be discarded". We believe that the research on that topic would provide useful managerial insight into the development of sustainable logistics systems.

The cases studied in Chapters 3, 4, 5 and 6 can be regarded as small or medium size. Larger case studies, which are more usual in practice, will require long computational

times, which might reduce the practical applicability of the proposed models. Solution approaches, therefore, have to be developed for handling such large case studies. This area of study has much potential for future research to be able to manage larger problems with the defined key sustainability concerns. We would like to note that the models proposed in this PhD thesis can be used to validate and verify the potential of such solution approaches.

Restricting the analysis to transportation energy use and emissions, and product waste, which are of most interest to the public and practitioners in food chains, allowed us to address these issues in a quantitative manner. It is obvious that sustainability of food logistics comprises other aspects such as traffic accidents, land usage, water consumption, etc. In future research it would be interesting to address other environmental or social concerns in quantitative models to satisfy the emerging needs of companies that change from economically driven to sustainability driven entities.

The models in Chapters 5 and 6 do not rely on a completely deterministic environment and take demand uncertainty into account. The other parameters such as supply, quality decay or travel times required in the proposed models can be subject to uncertainties in practice as well. Therefore, it would be interesting to investigate parameters which are not always predictable in practice and incorporate the identified uncertainties to the models. This way of improvement, however, can come at a cost of increased computational times, which might increase the necessity of using solution approaches.

The models in Chapters 3, 5 and 6 assume that products have fixed shelf lives and deteriorate based on time. However, several other factors also exist depending on the product type that affect product quality degradation in food chains (e.g., such as temperature, pH, oxygen or ascorbic acid). Therefore, as shown also in Table 1.1 in Chapter 1, there is ample opportunity for further improving the logistics decision support models developed by using specific quality decay approaches that consider not only time but also other factors while estimating product shelf life or quality.

The focus in this thesis is on transportation and inventory management activities. Accordingly, a network problem, a routing problem and two different inventory routing problems have been addressed which mainly tackle logistics decisions related with transportation and inventory management activities. However, logistics management also comprises other logistics activities such as facility location, production planning etc. These activities are also crucial for the success of SFLM. Therefore, the last future direction worth mentioning here is to investigate the potential of accounting for key sustainability indicators in other logistics problems.

Summary

For the last two decades, food logistics systems have seen the transition from traditional Logistics Management (LM) to Food Logistics Management (FLM), and successively, to Sustainable Food Logistics Management (SFLM). Accordingly, food industry has been subject to the recent challenges of reducing the amount of food waste and raising energy efficiency to reduce greenhouse gas emissions. These additional challenges add to the complexity of logistics operations and require advanced decision support models which can be used by decision makers to develop more sustainable food logistics systems in practice. Hence, the overall objective of this thesis was to obtain insight in how to improve the sustainability performance of food logistics systems by developing decision support models that can address the concerns for transportation energy use and consequently carbon emissions, and/or product waste, while also adhering to competitiveness. In line with this overall objective, we have defined five research objectives.

The first research objective (RO), which is to identify key logistical aims, analyse available quantitative models and point out modelling challenges in SFLM, is investigated in Chapter 2. In this chapter, key logistical aims in LM, FLM and SFLM phases are identified, and available quantitative models are analysed to point out modelling challenges in SFLM. A literature review on quantitative studies is conducted and also qualitative studies are consulted to better understand the key logistical aims and to identify the relevant system scope issues. The main findings of the literature review indicate that (i) most studies rely on a completely deterministic environment, (ii) the food waste challenge in logistics has not received sufficient attention, (iii) traveled distance is often used as a single indicator to estimate related transportation cost and emissions, and (iv) most studies propose single objective models for the food logistics problems. This chapter concludes that new and advanced quantitative models are needed that take specific SFLM requirements from practice into consideration to support business decisions and capture food supply chain dynamics. These findings motivated us to work on the following research objectives RO2, RO3, RO4 and RO5.

RO2, which is to analyse the relationship between economic (cost) and environmental (transportation carbon emissions) performance in a network problem of a perishable product, is investigated in Chapter 3. This chapter presents a multi-objective linear programming (MOLP) model for a generic beef logistics network problem. The objectives of the model are (i) minimizing total logistics cost and (ii) minimizing total amount of greenhouse gas emissions from transportation operations. The model is solved using the ϵ - constraint method. This study breaks away from the literature on logistics network models by simultaneously considering transportation emissions (affected by road structure,

vehicle and fuel types, weight loads of vehicles, traveled distances), return hauls and product perishability in a MOLP model. We present computational results and analyses based on the application of the model to a real-life international beef logistics chain operating in Nova Andradina, Mato Grosso do Sul, Brazil, and exporting beef to the European Union. Trade-off relationships between multiple objectives are observed by the derived Pareto frontier that presents the cost of being sustainable from the point of reducing transportation emissions. The results indicate the importance of distances between actors in terms of environmental impact. Moreover, sensitivity analysis on important practical parameters show that export ports' capacities put pressure on the logistics system; decreasing fuel efficiency due to the bad infrastructure has negative effects on cost and emissions; and green tax incentives result in economic and environmental improvement.

RO3, which is to investigate the performance implications of accommodating explicit transportation energy use and traffic congestion concerns in a two-echelon capacitated vehicle routing problem (2E-CVRP), is investigated in Chapter 4. The multi-echelon distribution strategy in which freight is delivered to customers via intermediate depots rather than using direct shipments is an increasingly popular strategy in urban logistics. Its popularity is primarily due to the fact that it alleviates the environmental (e.g., energy usage and congestion) and social (e.g., traffic-related air pollution, accidents and noise) consequences of logistics operations. This chapter presents a comprehensive mixed integer linear programming formulation for a time-dependent 2E-CVRP that accounts for vehicle type, traveled distance, vehicle speed, load, multiple time zones and emissions. A case study in a supermarket chain operating in the Netherlands shows the applicability of the model to a real-life problem. Several versions of the model, each differing with respect to the objective function, are tested to produce a number of selected Key Performance Indicators (KPIs) relevant to distance, time, fuel consumption and cost. This chapter offers insight in the economies of environmentally-friendly vehicle routing in two-echelon distribution systems. The results suggest that an environmentally-friendly solution is obtained from the use of a two-echelon distribution system, whereas a single-echelon distribution system provides the least-cost solution.

RO4, which is to investigate the performance implications of accommodating explicit transportation energy use, product waste and demand uncertainty concerns in an inventory routing problem (IRP), is investigated in Chapter 5. Traditional assumptions of constant distribution costs between nodes, unlimited product shelf life and deterministic demand used in the IRP literature restrict the usefulness of the proposed models in current food logistics systems. From this point of view, our interest in this chapter is to enhance the traditional models for the IRP to make them more useful for decision makers in food logistics management. Therefore, we present a multi-period IRP model

that includes truck load dependent (and thus route dependent) distribution costs for a comprehensive evaluation of CO_2 emission and fuel consumption, perishability, and a service level constraint for meeting uncertain demand. A case study on the fresh tomato distribution operations of a supermarket chain shows the applicability of the model to a real-life problem. Several variations of the model, each differing with respect to the considered aspects, are employed to present the benefits of including perishability and explicit fuel consumption concerns in the model. The results suggest that the proposed integrated model can achieve significant savings in total cost while satisfying the service level requirements, and thus offers better support to decision makers.

RO5, which is to analyse the benefits of horizontal collaboration in a green IRP for perishable products with demand uncertainty, is investigated in Chapter 6. This chapter presents a decision support model, which includes a comprehensive evaluation of CO_2 emission and fuel consumption, perishability, and a service level constraint for meeting uncertain demand, for the IRP with multiple suppliers and customers. The model allows to analyse the benefits of horizontal collaboration in the IRP with respect to several KPIs, i.e., total emissions, total driving time, total routing cost comprised of fuel and wage cost, total inventory cost, total waste cost, and total cost. A case study on the distribution operations of two suppliers, where the first supplier produces figs and the second supplier produces cherries, shows the applicability of the model to a real-life problem. The results show that horizontal collaboration among the suppliers contributes to the decrease of aggregated total cost and emissions in the logistics system, whereas the obtained gains are sensitive to the changes in parameters such as supplier size or maximum product shelf life. According to the experiments, the aggregated total cost benefit from cooperation varies in a range of about 4-24% and the aggregated total emission benefit varies in a range of about 8-33%.

Integrated findings from Chapters 2, 3, 4, 5 and 6 contribute to the SFLM literature by (i) reflecting the state of the art on the topic of quantitative logistic models which have sustainability considerations, (ii) providing decision support models which can be used by decision makers to improve the performance of the sustainable food logistics systems in terms of logistics cost, transportation energy use and carbon emissions, and/or product waste, and (iii) presenting the applicability of the proposed models in different case studies based on mainly real data, multiple scenarios, and analysis. The developed decision support models exploit several logistics improvement opportunities regarding transportation energy use and emissions, and/or product waste to better aid SFLM, as distinct from their counterparts in literature. To conclude, the case study implementations in this thesis demonstrate that (i) perishability and explicit consideration of fuel consumption are important aspects in logistics problems, and (ii) the provided decision support models

can be used in practice by decision makers to further improve sustainability performance of the food logistics systems.

Samenvatting

In de afgelopen twee decennia heeft logistiek management in voedselketens een ontwikkeling doorgemaakt waarbij steeds meer prestatie indicatoren moeten worden meegenomen. In de traditionele benadering van logistiek management (LM) ligt de nadruk op de afweging tussen logistieke kosten en service. Specifiek in voedselketens moeten additionele indicatoren worden meegenomen gerelateerd aan de specifieke eigenschappen van deze ketens, zoals variabiliteit in productkwaliteit en de bederfelijkheid van producten. In het Engels spreken we dan over Food Logistics Management, afgekort FLM. Tot slot is er de laatste jaren veel aandacht gekomen voor duurzaamheid. Zo wordt de voedingsindustrie uitgedaagd om voedselverspilling tegen te gaan en de uitstoot van broeikasgassen te verminderen door efficiënter met energie om te gaan. In het Engels spreken we dan van Sustainable Food Logistics Management, afgekort SFLM.

Deze ontwikkelingen zorgen voor een toename in de complexiteit van besluitvorming omtrent het ontwikkelen van duurzamere logistieke systemen voor voedselketens. Om ondersteuning te geven aan besluitvormers zijn daarom geavanceerde beslissingsondersteunende modellen nodig. Daarin zijn energieverbruik en de daaraan gekoppelde uitstoot tijdens transport en/of productverlies van belang, mits competitief aantrekkelijke oplossingen worden gevonden. Het doel van dit onderzoek is inzicht te krijgen in de mogelijkheden om duurzamere logistieke systemen voor voedselketens te ontwikkelen met behulp van zulke modellen. Voor dit doel zijn vijf onderzoeksdoelstellingen opgesteld.

De eerste onderzoeksdoelstelling (RO1) is het analyseren van beschikbare kwantitatieve logistieke modellen voor verschillende logistieke doelstellingen en het identificeren van de uitdagingen bij het modelleren van SFLM. Deze RO wordt uitgewerkt in hoofdstuk 2. In dit hoofdstuk worden de belangrijkste logistieke doelstellingen in de opeenvolgende fasen van LM, FLM en SFLM geïdentificeerd. Geraadpleegde kwalitatieve onderzoeken worden samen met een literatuurstudie van kwantitatieve studies gebruikt om de belangrijkste logistieke doelstellingen beter te begrijpen en de relevante problemen in het toepassingsgebied te identificeren. De belangrijkste uitkomsten van de literatuurstudie zijn als volgt: (i) de meeste studies gaan uit van een volledig deterministisch systeem en besteden geen aandacht aan onzekerheid; (ii) de uitdaging om productverlies in de voedsellogistiek te beperken heeft onvoldoende aandacht gekregen; (iii) de enige indicator om transportkosten en emissies te schatten is vaak de afgelegde afstand; (iv) de meeste modellen hebben een enkelvoudige doelstelling om het logistieke probleem aan te pakken (meestal kostenminimalisatie). Dit hoofdstuk concludeert dat nieuwe, geavanceerde kwantitatieve modellen nodig zijn om besluitvorming in de praktijk van SFLM te ondersteunen. Deze modellen dienen rekening te houden met de specifieke dynamiek

van voedselketens. Deze bevindingen vormen de basis voor het werk aan de onderzoeks-
doelstellingen RO2, RO3, RO4 en RO5.

Het tweede onderzoeksdoel (RO2) is het analyseren van de relatie tussen economis-
che prestaties (kosten) en milieu prestaties (broeikasgasemissies door transport) in een
netwerk van een bederfelijk product. Deze RO wordt uitgewerkt in hoofdstuk 3. Een
lineair programmeringsmodel met meerdere doelstellingen (in het Engels multi-objective
linear programming, afgekort MOLP) wordt gepresenteerd voor een generiek logistiek
netwerkprobleem voor een rundvleesketen. De doelstellingen van het model zijn: (i) het
minimaliseren van de totale logistieke kosten, en (ii) het minimaliseren van de totale
broeikasgasemissie door transportactiviteiten. Het model wordt opgelost met behulp van
de ϵ-constraint methode. Dit onderzoek onderscheidt zich van de huidige literatuur over
logistieke netwerkmodellen door tegelijkertijd emissies door transport (o.a. beïnvloed door
de kwaliteit van wegen, het type voertuig en brandstof, de voertuig belading en gereden
afstand), de terugreis na aflevering van de lading en bederfelijkheid van de producten, op
te nemen in een MOLP model. Het model wordt gebruikt in een casus van een bestaande
internationale logistieke keten voor rundvlees, waarin het vlees naar de Europese Unie
wordt geëxporteerd vanuit Nova Andradina, Mato Grosso do Sul, Brazilië. De analyse en
resultaten van de gemaakte berekeningen worden gepresenteerd. De afwegingen tussen
de verschillende doelstellingen worden zichtbaar gemaakt met een Pareto-curve. Hierin is
te zien wat de kosten zijn van verduurzaming door middel van reductie van emissies door
transport. De resultaten wijzen op het belang van de afstand tussen de actoren voor de
totale milieu-impact van de keten. Bovendien laat gevoeligheidsanalyse van belangrijke
parameters zien dat: (i) de (beperkte) capaciteit van exporthavens druk uitoefent op het
logistieke systeem; (ii) slechte infrastructuur zorgt voor afnemende brandstofefficiëntie
en dus een negatieve invloed heeft op de kosten en emissies; (iii) groene fiscale prikkels
leiden tot economische en milieu-gerelateerde verbeteringen.

Voor het derde onderzoeksdoel (RO3) onderzoeken we de invloed van het expliciet meen-
emen van verkeersopstoppingen en energieverbruik tijdens transport op prestaties in een
routeringsprobleem met twee niveaus of echelons, rekening houdend met het laadver-
mogen van voertuigen (in het Engels two-echelon capacitated vehicle routing problem,
afgekort 2E-CVRP). Dit wordt uitgewerkt in hoofdstuk 4. De multi-echelon distributies-
trategie waarin een vracht wordt geleverd aan klanten via tussenliggende depots in plaats
van in rechtstreekse zendingen, is een steeds populairdere strategie in stedelijke logistiek.
Deze populariteit is vooral te danken aan het feit dat deze strategie de milieueffecten
(zoals energieverbruik en verkeersopstoppingen) en sociale effecten (zoals verkeersgere-
lateerde luchtvervuiling, ongevallen en lawaai) van logistieke handelingen verbetert. Dit

hoofdstuk presenteert de formulering van een uitgebreid gemengd integer lineair programmeringsmodel voor een tijdsafhankelijk 2E-CVRP. Hierin wordt rekening gehouden met het type voertuig, de afgelegde afstand, de snelheid en belasting van het voertuig, verschil in verkeersdrukte gedurende de dag en emissies. Een case studie voor een Nederlandse supermarktketen toont de toepasbaarheid van het model aan op een reëel probleem. Verschillende varianten van het model, elk met een andere doelfunctie, worden getest om een aantal belangrijke prestatie indicatoren (in het Engels Key Performance Indicator, afgekort KPI) te genereren. Deze zijn gerelateerd aan afstand, tijd, brandstofverbruik en kosten. Dit hoofdstuk biedt inzicht in de economische analyse van milieuvriendelijke routering van voertuigen in distributiesystemen met twee echelons. De resultaten wijzen erop dat een milieuvriendelijke oplossing wordt verkregen met het gebruik van een distributiesysteem met twee echelons, terwijl een distributiesysteem met één echelon de oplossing biedt met de laagste totale kosten.

Voor het vierde onderzoeksdoel (RO4) onderzoeken we de implicaties van het expliciet meenemen van energieverbruik tijdens transport, productverlies en onzekere vraag op de prestatie van een voorraad- en routeringsprobleem (in het Engels inventory routing problem, afgekort IRP). RO4 wordt uitgewerkt in hoofdstuk 5. Gebruikelijke veronderstellingen die in de IRP literatuur worden gebruikt, zoals constante distributiekosten tussen knooppunten, onbegrensde houdbaarheid van het product en een deterministische vraag, beperken het nut van de voorgestelde modellen voor besluitvorming in de huidige logistieke systemen voor voedselketens. Daarom is dit hoofdstuk erop gericht de traditionele IRP modellen te verbeteren, om ze bruikbaarder te maken voor besluitvormers in het logistiek management van voedselketens. Een IRP model voor meerdere tijdsperioden wordt gepresenteerd, waarin vrachtwagenafhankelijke (en dus routeafhankelijke) distributiekosten en een minimaal service niveau worden meegenomen in de evaluatie van de CO_2-emissie, het brandstofverbruik en het bederf in de voedselketen. Een casestudie naar de distributieactiviteiten van een supermarktketen voor verse tomaten toont de toepasbaarheid van het model op een reëel probleem. Variaties van het model worden gebruikt om de voordelen van het opnemen van houdbaarheid en brandstofverbruik in het model zichtbaar te maken. De resultaten suggereren dat met het voorgestelde geïntegreerde model aanzienlijke besparingen op de totale kosten kunnen worden bereikt, terwijl voldaan wordt aan de vereisten voor het service niveau. Daarmee biedt het model dus een betere ondersteuning aan besluitvormers dan de traditionele IRP modellen.

Het vijfde onderzoeksdoel (RO5) betreft het analyseren van de voordelen van horizontale samenwerking in een groen IRP voor bederfelijke producten met onzekere vraag. Dit wordt uitgewerkt in hoofdstuk 6. Een beslissingsondersteunend model wordt gepresenteerd. Dit model voor een IRP met meerdere leveranciers en klanten bevat een

uitgebreide evaluatie van de CO_2-emissie, het brandstofverbruik en bederf, en een vereist service niveau om aan de onzekere vraag te voldoen. Het model maakt het mogelijk om de voordelen van horizontale samenwerking in de IRP te analyseren met betrekking tot een aantal KPI's, in dit geval de totale uitstoot, totale rijtijd en de totale kosten bestaande uit de voorraadkosten, afvalkosten en de routekosten (brandstof- en loonkosten). Een case studie naar de distributieactiviteiten van twee leveranciers, een vijgenproducent en een kersenproducent, toont de toepasbaarheid van het model op een reëel probleem. De resultaten tonen aan dat de horizontale samenwerking tussen de leveranciers bijdraagt aan de afname van de gezamenlijke totale kosten en emissies in het logistieke systeem, maar dat de verkregen voordelen afhangen van veranderingen in parameters zoals de grootte van een leverancier of de maximale houdbaarheid van een product. Volgens de experimenten varieert het gezamenlijke kostenvoordeel van samenwerking van 4 tot 24% en de gezamenlijke reductie van totale emissies varieert tussen de 8 en 33% ten opzichte van de variant waarin niet wordt samengewerkt.

De bevindingen uit de hoofdstukken 2, 3, 4, 5 en 6 dragen bij aan de SFLM literatuur door: (i) het weergeven van de stand van zaken van kwantitatieve logistieke modellen waarin (aspecten van) duurzaamheid worden meegenomen; (ii) het verstrekken van beslissingsondersteunende modellen die door beleidsmakers kunnen worden gebruikt om de duurzaamheidsprestaties van logistieke systemen voor voedselsketens te verbeteren op het gebied van logistieke kosten, energieverbruik en uitstoot tijdens transport, en product verlies; (iii) het aantonen van de toepasbaarheid van de voorgestelde modellen in verschillende case studies met meerdere scenario's, gebaseerd op data uit de praktijk. In tegenstelling tot al bestaande modellen benutten de ontwikkelde beslissingsondersteunende modellen diverse logistieke verbeteringsmogelijkheden met betrekking tot energieverbruik en emissies door transport en / of de reductie van voedselverliezen. De case studies in dit proefschrift laten tot slot zien dat (i) bederfelijkheid en het expliciet meenemen van brandstofverbruik belangrijke aspecten zijn in logistieke problemen, en (ii) de beschreven beslissingsondersteunende modellen door beleidsmakers in de praktijk gebruikt kunnen worden om de duurzaamheid van logistieke systemen voor voedselketens verder te verbeteren.

Bibliography

Abdallah, T., Farhat, A., Diabat, A., Kennedy, S., 2012. Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment. Applied Mathematical Modelling 36, 4271–4285.

Abdul Rahim, M.K.I., Zhong, Y., Aghezzaf, E.H., Aouam, T., 2014. Modelling and solving the multiperiod inventory-routing problem with stochastic stationary demand rates. International Journal of Production Research , 1–13.

Abiec, 2012a. Brazilian Beef Exports. Technical Report. Brazilian Beef Exporters Association. http://www.abiec.com.br/download/Relatorio%20exportacao%202010.pdf,Onlineaccessed:September2012.

Abiec, 2012b. Structure of Brazilian Beef Chain-2010. Technical Report. Brazilian Beef Exporters Association. http://www.abiec.com.br/download/Brazilian%20Beef%20Chain.pdf,Onlineaccessed:September2012.

Abiec, 2012c. Export numbers for ports in Brazil-2010. Technical Report. Brazilian Beef Exporters Association. http://abiec.com.br/download/stat_portos.pdf,Onlineaccessed:September2012.

Abiec, 2012d. Global Beef Exports. Technical Report. Brazilian Beef Exporters Association. http://www.abiec.com.br/download/stat_mercadomundial.pdf,Onlineaccessed:September2012.

Adachi, Y., Nose, T., Kuriyama, S., 1999. Optimal inventory control policy subject to different selling prices of perishable commodities. International Journal of Production Economics 60-61, 389–394.

Aghezzaf, E.H., Raa, B., Van Landeghem, H., 2006. Modeling inventory routing problems in supply chains of high consumption products. European Journal of Operational Research 169, 1048–1063.

Aguayo, E., Escalona, V., Artés, F., 2004. Quality of fresh-cut tomato as affected by type of cut, packaging, temperature and storage time. European Food Research and Technology 219, 492–499.

Ahn, B., Watanabe, N., Hiraki, S., 1994. A mathematical model to minimize the inventory and transportation costs in the logistics systems. Computers & Industrial Engineering 27, 229–232.

Ahuja, R.K., 2007. A heuristic approach to the multi-period single-sourcing problem with production and inventory capacities and perishability constraints. Informs Journal on Competing 19, 14–26.

Ahumada, O., Villalobos, J.R., 2009a. Application of planning models in the agri-food supply chain: A review. European Journal of Operational Research 196, 1–20.

Ahumada, O., Villalobos, J.R., 2009b. A tactical model for planning the production and distribution of fresh produce. Annals of Operations Research 190, 339–358.

Ahumada, O., Villalobos, J.R., 2011. Operational model for planning the harvest and distribution of perishable agricultural products. International Journal of Production Economics 133, 677–687.

Aiking, H., Boer, J., 2004. Food sustainability diverging interpretations. British Food Journal 106, 359–365.

Akkerman, R., Farahani, P., Grunow, M., 2010. Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. OR Spectrum 32, 863–904.

Akkerman, R., Yang, W., Grunow, M., 2009. MILP approaches to sustainable production and distribution of meal elements, in: International Conference on Computers & Industrial Engineering, 2009. CIE 2009. International Conference on, IEEE. pp. 973–978.

Al-Khayyal, F., Hwang, S.J., 2007. Inventory constrained maritime routing and scheduling for multi-commodity liquid bulk, Part I: Applications and model. European Journal of Operational Research 176, 106–130.

Al Shamsi, A., Al Raisi, A., Aftab, M., 2014. Pollution-inventory routing problem with perishable goods, in: Golinska, P. (Ed.), Logistics Operations, Supply Chain Management and Sustainability. Springer International Publishing. EcoProduction, pp. 585–596.

Alkawaleet, N., Hsieh, Y.F., Wang, Y., 2014. Inventory routing problem with CO_2 emissions consideration, in: Golinska, P. (Ed.), Logistics Operations, Supply Chain

Management and Sustainability. Springer International Publishing. EcoProduction, pp. 611–619.

Alvarez, S.A., Barney, J.B., 2001. How entrepreneurial firms can benefit from alliances with large partners. Academy of management perspectives 15, 139–148.

Amorim, P., Meyr, H., Almeder, C., Almada-Lobo, B., 2013. Managing perishability in production-distribution planning: a discussion and review. Flexible Services and Manufacturing Journal 25, 389–413.

Andersson, H., Hoff, A., Christiansen, M., Hasle, G., Løkketangen, A., 2010. Industrial aspects and literature survey: Combined inventory management and routing. Computers & Operations Research 37, 1515–1536.

Andersson, J., 2000. A survey of multiobjective optimization in engineering design. Technical Report. Department of Mechanical Engineering Linktjping University, Linköping, Sweden.

Andiç, E., Yurt, O., Baltacıoğlu, T., 2012. Green supply chains: Efforts and potential applications for the turkish market. Resources, Conservation and Recycling 58, 50–68.

Ankersmit, S., Rezaei, J., Tavasszy, L., 2014. The potential of horizontal collaboration in airport ground freight services. Journal of Air Transport Management 40, 169–181.

Apaiah, R.K., Hendrix, E.M.T., 2005. Design of a supply chain network for pea-based novel protein foods. Journal of Food Engineering 70, 383–391.

Apaydin, O., Gonullu, M.T., 2008. Emission control with route optimization in solid waste collection process: A case study. Sadhana 33, 71–82.

Ashby, A., Leat, M., Hudson-Smith, M., 2012. Making connections: a review of supply chain management and sustainability literature. Supply Chain Management: An International Journal 17, 497–516.

Aung, M.M., Chang, Y.S., 2014. Traceability in a food supply chain: Safety and quality perspectives. Food Control 39, 172–184.

Azaron, A., Brown, K.N., Tarim, S.A., Modarres, M., 2008. A multi-objective stochastic programming approach for supply chain design considering risk. International Journal of Production Economics 116, 129–138.

Bakker, M., Riezebos, J., Teunter, R.H., 2012. Review of inventory systems with deterioration since 2001. European Journal of Operational Research 221, 275–284.

Baldacci, R., Mingozzi, A., Roberti, R., Calvo, R.W., 2013. An exact algorithm for the two-echelon capacitated vehicle routing problem. Operations Research 61, 298–314.

Bard, J.F., Huang, L., Jaillet, P., Dror, M., 1998. A decomposition approach to the inventory routing problem with satellite facilities. Transportation Science 32, 189–203.

Bard, J.F., Nananukul, N., 2009. Heuristics for a multiperiod inventory routing problem with production decisions. Computers & Industrial Engineering 57, 713–723.

Barth, M., Boriboonsomsin, K., 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transportation Research Part D: Transport and Environment 14, 400–410.

Barth, M., Younglove, T., Scora, G., 2005. Development of a Heavy-Duty Diesel Modal Emissions and Fuel Consumption Model. Technical Report. California Path Program Institute of Transportation Studies, University of California, Berkeley.

Bauer, J., Bektaş, T., Crainic, T.C., 2010. Minimizing greenhouse gas emissions in intermodal freight transport: an application to rail service design. Journal of the Operational Research Society 61, 530–542.

Beamon, B.M., 1998. Supply chain design and analysis: Models and methods. International Journal of Production Economics 55, 281–294.

Bektaş, T., Laporte, G., 2011. The Pollution-Routing problem. Transportation Research Part B: Methodological 45, 1232–1250.

Benoist, T., Gardi, F., Jeanjean, A., Estellon, B., 2011. Randomized local search for real-life inventory routing. Transportation Science 45, 381–398.

Bertazzi, L., Bosco, A., Guerriero, F., Lagana, D., 2013. A stochastic inventory routing problem with stock-out. Transportation Research Part C: Emerging Technologies 27, 89–107.

Bertazzi, L., Savelsbergh, M., Speranza, M.G., 2008. Inventory routing, in: The vehicle routing problem: latest advances and new challenges. Springer, pp. 49–72.

Beske, P., Land, A., Seuring, S., 2014. Sustainable supply chain management practices and dynamic capabilities in the food industry: A critical analysis of the literature. International Journal of Production Economics 152, 131–143.

Bettley, A., Burnley, S., 2008. Towards sustainable operations management integrating sustainability management into operations management strategies and practices, in: Misra, K.B. (Ed.), Handbook of Performability Engineering. Springer-Verlag London, pp. 875–904.

Bilgen, B., Gunther, H.O., 2010. Integrated production and distribution planning in the fast moving consumer goods industry: a block planning application. Or Spectrum 32, 927–955.

Bilgen, B., Ozkarahan, I., 2007. A mixed-integer linear programming model for bulk grain blending and shipping. International Journal of Production Economics 107, 555–571.

Bing, X., Bloemhof-Ruwaard, J.M., Van der Vorst, J.G.A.J., 2012. Sustainable reverse logistics network design for household plastic waste. Flexible Servies and Manufacturing Journal 26, 119–142.

Blackburn, J., Scudder, G., 2009. Supply chain strategies for perishable products: The case of fresh produce. Production and Operations Management 18, 129–137.

Bloemhof, J.M., 2005. Sustainable supply chains for the future. Medium Econometrische Toepassingen 13, 12–15.

Bookbinder, J.H., Tan, J.Y., 1988. Strategies for the probabilistic lot-sizing problem with service-level constraints. Management Science 34, 1096–1108.

Bosona, T.G., Gebresenbet, G., 2011. Cluster building and logistics network integration of local food supply chain. Biosystems Engineering 108, 293–302.

Bourlakis, M., Maglaras, G., Aktas, E., Gallear, D., Fotopoulos, C., 2014. Firm size and sustainable performance in food supply chains: Insights from Greek SMEs. International Journal of Production Economics 152, 112–130.

Brandenburg, M., Govindan, K., Sarkis, J., Seuring, S., 2014. Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research 233, 299–312.

Brown, G., Keegan, J., Vigus, B., Wood, K., 2001. The Kellogg company optimizes production, inventory, and distribution. Interfaces 31, 1–15.

Brundtlandt, G.H., 1987. Our common future. Oxford-New York: World Commission on Environment and Development.

Cachon, G.P., Fisher, M., 2000. Supply chain inventory management and the value of shared information. Management Science 46, 1032–1048.

Campbell, A., Clarke, L., Kleywegt, A., Savelsbergh, M., 1998. The inventory routing problem, in: Fleet management and logistics, pp. 95–113.

Campbell, A.M., Savelsbergh, M.W.P., 2004. A decomposition approach for the inventory-routing problem. Transportation Science 38, 488–502.

Caputo, M., Mininno, V., 1996. Internal, vertical and horizontal logistics integration in italian grocery distribution. International Journal of Physical Distribution & Logistics Management 26, 64–90.

Carter, C.R., Rogers, D.S., 2008. A framework of sustainable supply chain management: moving toward new theory. International Journal of Physical Distribution & Logistics Management 38, 360–387.

Cederberg, C., Meyer, D., Flysjö, A., 2009. Life cycle inventory of greenhouse gas emissions and use of land and energy in Brazilian beef production. Technical Report. The Swedish Institute for Food and Biotechnology.

Chaabane, A., Ramudhin, A., Paquet, M., 2011. Designing supply chains with sustainability considerations. Production Planning & Control 22, 727–741.

Chaabane, A., Ramudhin, A., Paquet, M., 2012. Design of sustainable supply chains under the emission trading scheme. International Journal of Production Economics 135, 37–49.

Chaabane, A., Ramudhin, A., Paquet, M., Benkaddour, M.A., 2008. An integrated logistics model for environmental conscious supply chain network design, in: Americas Conference on Information Systems (AMCIS), Toronto, ON, Canada. pp. 1–12.

Chabada, L., Dreyer, H.C., Romsdal, A., Powell, D.J., 2013. Sustainable food supply chains: Towards a framework for waste identification, in: Advances in Production Management Systems. Competitive Manufacturing for Innovative Products and Services, pp. 208–215.

Chang, R., 1981. Physical Chemistry with Applications to Biological Systems. Macmillan Publishing Corperation, New York.

Charnes, A., Cooper, W.W., 1959. Chance-constrained programming. Management science 6, 73–79.

Chen, H.K., Hsueh, C.F., Chang, M.S., 2009. Production scheduling and vehicle routing with time windows for perishable food products. Computers & Operations Research 36, 2311–2319.

Chopra, S., 2003. Designing the distribution network in a supply chain. Transportation Research Part E-Logistics and Transportation Review 39, 123–140.

Chopra, S., Meindl, P., 2010. Supply Chain Management: Strategy, Planning and Operation. Pearson Education, New Jersey.

Christopher, M., Juttner, U., 2000. Developing strategic partnerships in the supply chain:a practitioner perspective. European Journal of Purchasing & Supply Management 6, 117–127.

Coelho, L.C., Cordeau, J.F., Laporte, G., 2012a. The inventory-routing problem with transshipment. Computers & Operations Research 39, 2537–2548.

Coelho, L.C., Cordeau, J.F., Laporte, G., 2012b. Thirty years of inventory-routing. Technical Report. CIRRELT-2012-52, CIRRELT, Montreal, Canada.

Coelho, L.C., Laporte, G., 2013. The exact solution of several classes of inventory-routing problems. Computers & Operations Research 40, 558–565.

Coelho, L.C., Laporte, G., 2014. Optimal joint replenishment, delivery and inventory management policies for perishable products. Computers & Operations Research 47, 42–52.

Coley, D., Howard, M., Winter, M., 2009. Local food, food miles and carbon emissions: A comparison of farm shop and mass distribution approaches. Food Policy 34, 150–155.

Cordeau, J.F., Pasin, F., Solomon, M.M., 2006. An integrated model for logistics network design. Annals of Operations Research 144, 59–82.

Crainic, T.G., Mancini, S., Perboli, G., Tadei, R., 2008. Clustering-based heuristics for the Two-echelon Vehicle Routing Problem. Technical Report. CIRRELT-2008-46, CIRRELT, Montreal, Canada.

Crainic, T.G., Mancini, S., Perboli, G., Tadei, R., 2011. Multi-start heuristics for the two-echelon vehicle routing problem, in: Merz, P., Hao, J.K. (Eds.), Evolutionary Computation in Combinatorial Optimization. Springer Berlin Heidelberg. volume 6622 of *Lecture Notes in Computer Science*, pp. 179–190.

Crainic, T.G., Mancini, S., Perboli, G., Tadei, R., 2012. Impact of generalized travel costs on satellite location in the two-echelon vehicle routing problem. Procedia - Social and Behavioral Sciences 39, 195–204.

Crainic, T.G., Ricciardi, N., Storchi, G., 2004. Advanced freight transportation systems for congested urban areas. Transportation Research Part C: Emerging Technologies 12, 119–137.

Crainic, T.G., Ricciardi, N., Storchi, G., 2009. Models for evaluating and planning city logistics systems. Technical Report. CIRRELT-2009-11, CIRRELT, Montreal, Canada.

Crainic, T.G., Sgalambro, A., 2014. Service network design models for two-tier city logistics. Optimization Letters 8, 1375–1387.

Cruijssen, F., Cools, M., Dullaert, W., 2007. Horizontal cooperation in logistics: Opportunities and impediments. Transportation Research Part E: Logistics and Transportation Review 43, 129–142.

Dabbene, F., Gay, P., Sacco, N., 2008. Optimisation of fresh-food supply chains in uncertain environments, Part I: Background and methodology. Biosystems Engineering 99, 348–359.

Defra, 2005. Guidelines for company reporting on greenhouse gas emissions. Technical Report. Department for Environment, Food and Rural Affairs.

Defra, 2006. Food Industry Sustainability Strategy. Technical Report. Department for Environment, Food and Rural Affairs.

Defra, 2007. Guidelines to Defra's GHG conversion factors for company reporting - Annexes updated June 2007. Technical Report. Department for Environment, Food and Rural Affairs.

Defra, 2011. 2011 guidelines to Defra/DECC's GHG conversion factors for company reporting: methodology paper for emisssion factors. Technical Report. Department for Environment, Food and Rural Affairs.

Dekker, R., Bloemhof, J.M., Mallidis, I., 2012. Operations research for green logistics – an overview of aspects, issues, contributions and challenges. European Journal of Operational Research 219, 671–679.

Delgado, C., Rosegrant, M., Steinfeld, H., Ehui, S., Courbois, C., 1999. Live stock to 2020 The Next Food Revolution. Technical Report. International Food Policy Research Institute, Food and Agriculture Organization of the United Nations, International Livestock Research Institute.

Delmore, R.J., 2009. Beef shelf life. Technical Report. Cattlemen's Beef Board and National Cattlemen's Beef Association.

Demir, E., Bektaş, T., Laporte, G., 2011. A comparative analysis of several vehicle emission models for road freight transportation. Transportation Research Part D: Transport and Environment 16, 347–357.

Demir, E., Bektaş, T., Laporte, G., 2012. An adaptive large neighborhood search heuristic for the Pollution-Routing problem. European Journal of Operational Research 223, 346–359.

Demir, E., Bektaş, T., Laporte, G., 2014a. The bi-objective Pollution-Routing Problem. European Journal of Operational Research 232, 464–478.

Demir, E., Bektaş, T., Laporte, G., 2014b. A review of recent research on green road freight transportation. European Journal of Operational Research 237, 775–793.

DHL, 2010. Delivering tomorrow: Towards Sustainable Logistics. Technical Report. Deutsche Post AG.

Eguia, I., Racero, J., Molina, J.C., Guerrero, F., 2013. Environmental Issues in Vehicle Routing Problems, in: Erechtchoukova, M.G., Khaiter, P.A., Golinska, P. (Eds.), Sustainability Appraisal: Quantitative Methods and Mathematical Techniques for Environmental Performance Evaluation. Springer Berlin Heidelberg. EcoProduction, pp. 215–241.

Eksioglu, S.D., 2002. Optimizing integrated production, inventory and distribution problems in supply chains. Ph.D. thesis. University of Florida.

Eksioglu, S.D., Jin, M., 2006. Cross-facility production and transportation planning problem with perishable inventory. Computational Science and Its Applications 3982, 708–717.

Elhedhli, S., Merrick, R., 2012. Green supply chain network design to reduce carbon emissions. Transportation Research Part D: Transport and Environment 17, 370–379.

Erdogan, S., Miller-Hooks, E., 2012. A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review 48, 100–114.

Euclides Filho, K., 2004. Supply chain approach to sustainable beef production from a brazilian perspective. Livestock Production Science 90, 53–61.

EuropeanCommission, 2011. Bio-waste prevention guidelines. Technical Report. European Commission: A project under the Framework contract ENV.G.4/FRA/2008/0112.

Federgruen, A., Prastacos, G., Zipkin, P.H., 1986. An allocation and distribution model for perishable products. Operations Research 34, 75–82.

Feliu, J.G., Perboli, G., Tadei, R., Vigo, D., 2007. The two-echelon capacitated vehicle routing problem. Technical Report. DEIS OR.INGCE 2007/2(R), Department of Electronics, Computer Science, and Systems, University of Bologna, Bologna, Italy.

Figliozzi, M., 2010. Vehicle routing problem for emissions minimization. Transportation Research Record: Journal of the Transportation Research Board 2197, 1–7.

Figliozzi, M.A., 2011. The impacts of congestion on time-definitive urban freight distribution networks CO_2 emission levels: Results from a case study in portland, oregon. Transportation Research Part C: Emerging Technologies 19, 766–778.

Fisher, M.L., 1997. What is the right supply chain for your product? Harward Business Review March-April, 1–16.

Franceschetti, A., Honhon, D., Van Woensel, T., Bektaş, T., Laporte, G., 2013. The time-dependent Pollution-Routing problem. Transportation Research Part B Methodological 56, 265–293.

Fritz, M., Schiefer, G., 2008. Food chain management for sustainable food system development: a european research agenda. Agribusiness 24, 440–452.

Fritz, M., Schiefer, G., 2009. Tracking, tracing, and business process interests in food commodities: A multi-level decision complexity. International Journal of Production Economics 117, 317–329.

Frota Neto, J.Q., Bloemhof-Ruwaard, J.M., Van Nunen, J.A.E.E., Van Heck, E., 2008. Designing and evaluating sustainable logistics networks. International Journal of Production Economics 111, 195–208.

Frota Neto, J.Q., Walther, G., Bloemhof, J.M., Van Nunen, J.A.E.E., Spengler, T., 2009. A methodology for assessing eco-efficiency in logistics networks. European Journal of Operational Research 193, 670–682.

Gajanand, M.S., Narendran, T.T., 2013. Green route planning to reduce the environmental impact of distribution. International Journal of Logistics Research and Applications 16, 410–432.

Garnett, T., 2011. Where are the best opportunities for reducing greenhouse gas emissions in the food system (including the food chain)? Food Policy 36, Supplement 1, S23–S32.

Gebresenbet, G., Ljungberg, D., 2001. Coordination and route optimization of agricultural goods transport to attenuate environmental impact. Journal of Agricultural Engineering Research 80, 329–342.

Gelders, L.F., Pintelon, L.M., Vanwassenhove, L.N., 1987. A location allocation problem in a large belgian brewery. European Journal of Operational Research 28, 196–206.

Govindan, K., Jafarian, A., Khodaverdi, R., Devika, K., 2014. Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. International Journal of Production Economics 152, 9–28.

Gunasekaran, A., Lai, K.H., Cheng, T.C.E., 2008. Responsive supply chain: A competitive strategy in a networked economy. Omega 36, 549–564.

Hafliason, T., Olafsdottir, G., Bogason, S., Stefansson, G., 2012. Criteria for temperature alerts in cold supply chains. International Journal of Physical Distribution & Logistics Management 42, 355–371.

Haijema, R., 2013. A new class of stock-level dependent ordering policies for perishables with a short maximum shelf life. International Journal of Production Economics 143, 434–439.

Harris, I., Naim, M., Palmer, A., Potter, A., Mumford, C., 2011. Assessing the impact of cost optimization based on infrastructure modelling on CO_2 emissions. International Journal of Production Economics 131, 313–321.

Hassini, E., Surti, C., Searcy, C., 2012. A literature review and a case study of sustainable supply chains with a focus on metrics. International Journal of Production Economics 140, 69–82. Sustainable Development of Manufacturing and Services.

Helms, M., 2004. Food sustainability, food security and the environment. British Food Journal 106, 380–387.

Hemmelmayr, V., Doerner, K.F., Hartl, R.F., Savelsbergh, M.W., 2010. Vendor managed inventory for environments with stochastic product usage. European Journal of Operational Research 202, 686–695.

Hemmelmayr, V.C., Cordeau, J.F., Crainic, T.G., 2012. An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics. Computers & Operations Research 39, 3215–3228.

Hendrix, E.M.T., Haijema, R., Rossi, R., Pauls-Worm, K.G.J., 2012. On solving a stochastic programming model for perishable inventory control, in: Murgante, B., Gervasi, O., Misra, S., Nedjah, N., Rocha, A.A.C., Taniar, D., Apduhan, B.O. (Eds.), Computational Science and Its Applications – ICCSA 2012. Springer Berlin Heidelberg. volume 7335 of *Lecture Notes in Computer Science*, pp. 45–56.

Higgins, A., Beashel, G., Harrison, A., 2006. Scheduling of brand production and shipping within a sugar supply chain. Journal of the Operational Research Society 57, 490–498.

Hoen, K.M.R., Tan, T., Fransoo, J.C., Van Houtum, G.J., 2010. Effect of carbon emission regulations on transport mode selection in supply chains. Technical Report. Eindhoven University of Technology, School of Industrial Engineering.

Hsu, C.I., Hung, S.F., Li, H.C., 2007. Vehicle routing problem with time-windows for perishable food delivery. Journal of Food Engineering 80, 465–475.

Huang, S.H., Lin, P.C., 2010. A modified ant colony optimization algorithm for multi-item inventory routing problems with demand uncertainty. Transportation Research Part E: Logistics and Transportation Review 46, 598–611.

Hvattum, L.M., Løkketangen, A., 2009. Using scenario trees and progressive hedging for stochastic inventory routing problems. Journal of Heuristics 15, 527–557.

Ibge, 2012. Mato Grosso do Sul, cattle - effective herd. Technical Report. Brazilian Institute of Geography and Statistics. `http://www.ibge.gov.br/cidadesat/comparamun/compara.php?codmun=500020&coduf=50&tema=prodpec2010&codv=v01&lang=_EN,Onlineaccessed:September2012`.

Ioannou, G., 2005. Streamlining the supply chain of the hellenic sugar industry. Journal of Food Engineering 70, 323–332.

Jabali, O., Van Woensel, T., de Kok, A.G., 2012. Analysis of travel times and CO_2 emissions in time-dependent vehicle routing. Production and Operations Management 21, 1060–1074.

James, S.J., James, C., Evans, J.A., 2006. Modelling of food transportation systems - a review. International Journal of Refrigeration 29, 947–957.

Janic, M., 2006. Sustainable transport in the European Union: A review of the past research and future ideas. Transport Reviews 26, 81–104.

Jansen, D.R., Van Weert, A., Beulens, A.J.M., Huirne, R.B.M., 2001. Simulation model of multi-compartment distribution in the catering supply chain. European Journal of Operational Research 133, 210–224.

Jedermann, R., Nicometo, M., Uysal, I., Lang, W., 2014. Reducing food losses by intelligent food logistics. Philosophical Transactions of the Royal Society A 372, 1–20.

Jemai, J., Zekri, M., Mellouli, K., 2012. An NSGA-II algorithm for the green vehicle routing problem, in: Hao, J.K., Middendorf, M. (Eds.), Evolutionary Computation in Combinatorial Optimization. Springer Berlin Heidelberg. volume 7245 of *Lecture Notes in Computer Science*, pp. 37–48.

Jemai, Z., Rekik, Y., Kalai, R., 2013. Inventory routing problems in a context of vendor-managed inventory system with consignment stock and transshipment. Production Planning & Control 24, 671–683.

Jenny, G., Christel, C., Ulf, S., Robert, V.O., Alexandre, M., 2011. Global food losses and food waste: Extent, causes and prevention. Technical Report. Food and Agriculture Organization of the United Nations (FAO) and Rural Infrastructure and Agro-Industries Division (AGS).

Jepsen, M., Spoorendonk, S., Ropke, S., 2013. A branch-and-cut algorithm for the symmetric two-echelon capacitated vehicle routing problem. Transportation Science 47, 23–37.

Jia, T., Li, X., Wang, N., Li, R., 2014. Integrated inventory routing problem with quality time windows and loading cost for deteriorating items under discrete time. Mathematical Problems in Engineering , 1–14.

Jonsson, P., 2008. Logistics and Supply Chain Management. McGraw-Hill Education, New York.

Juan, A.A., Faulin, J., Perez-Bernabeu, E., Jozefowiez, N., 2014. Horizontal cooperation in vehicle routing problems with backhauling and environmental criteria. Procedia - Social and behavioral sciences 111, 1133–1141.

Kaipia, R., Dukovska-Popovska, I., Loikkanen, L., 2013. Creating sustainable fresh food supply chains through waste reduction. International Journal of Physical Distribution & Logistics Management 43, 262–276.

Kamakaté, F., Schipper, L., 2009. Trends in truck freight energy use and carbon emissions in selected OECD countries from 1973 to 2005. Energy Policy 37, 3743–3751.

Kara, I., Kara, B.Y., Yetis, M.K., 2007. Energy minimizing vehicle routing problem, in: Dress, A., Xu, Y., Zhu, B. (Eds.), Combinatorial Optimization and Applications. Springer Berlin Heidelberg. volume 4616 of *Lecture Notes in Computer Science*, pp. 62–71.

Karaesmen, I.Z., Scheller–Wolf, A., Deniz, B., 2011. Managing perishable and aging inventories: Review and future research directions, in: Kempf, K.G., Keskinocak, P., Uzsoy, R. (Eds.), Planning Production and Inventories in the Extended Enterprise. Springer US. volume 151 of *International Series in Operations Research & Management Science*, pp. 393–436.

Klassen, R.D., Whybark, D.C., 1999. The impact of environmental technologies on manufacturing performance. The Academy of Management Journal 42, 599–615.

Kolb, A., Wacker, M., 1995. Calculation of energy consumption and pollutant emissions on freight transport routes. Science of The Total Environment 169, 283–288.

Krajewska, M.A., Kopfer, H., Laporte, G., Ropke, S., Zaccour, G., 2008. Horizontal cooperation among freight carriers: request allocation and profit sharing. Journal of the Operational Research Society 59, 1483–1491.

Kritikos, M.N., Ioannou, G., 2013. The heterogeneous fleet vehicle routing problem with overloads and time windows. International Journal of Production Economics 144, 68–75.

Kuo, Y., 2010. Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem. Computers & Industrial Engineering 59, 157–165.

Kuo, Y., Wang, C.C., 2011. Optimizing the VRP by minimizing fuel consumption. Management of Environmental Quality: An International Journal 22, 440–450.

Kwon, Y.J., Choi, Y.J., Lee, D.H., 2013. Heterogeneous fixed fleet vehicle routing considering carbon emission. Transportation Research Part D: Transport and Environment 23, 81–89.

Lambert, D.M., Cooper, M.C., 2000. Issues in supply chain management. Industrial Marketing Management 29, 65–83.

Le, T., Diabat, A., Richard, J.P., Yih, Y., 2013. A column generation-based heuristic algorithm for an inventory routing problem with perishable goods. Optimization Letters 7, 1481–1502.

Leitner, R., Meizer, M., Prochazka, M., Sihn, W., 2011. Structural concepts for horizontal cooperation to increase efficiency in logistics. CIRP Journal of Manufacturing Science and Technology 4, 332–337.

van Lier, T., Caris, A., Macharis, C., 2014. Sustainability si: Bundling of outbound freight flows: Analyzing the potential of internal horizontal collaboration to improve sustainability. Networks and Spatial Economics , 1–26.

Ligterink, N.E., Tavasszy, L.A., Lange, R., 2012. A velocity and payload dependent emission model for heavy-duty road freight transportation. Transportation Research Part D: Transport and Environment 17, 487–491.

Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H., Lam, H.Y., 2014. Survey of Green Vehicle Routing Problem: Past and future trends. Expert Systems with Applications 41, 1118–1138.

Linton, J.D., Klassen, R., Jayaraman, V., 2007. Sustainable supply chains: An introduction. Journal of Operations Management 25, 1075–1082.

Lipinski, B., Hanson, C., Lomax, J., Kitinoja, L., Waite, R., Searchinger, T., 2013. Reducing Food Loss and Waste. Technical Report. Washington, DC: World Resources Institute.

Léonardi, J., Baumgartner, M., 2004. CO_2 efficiency in road freight transportation: Status quo, measures and potential. Transportation Research Part D: Transport and Environment 9, 451–464.

Lutke Entrup, M., Gunther, H.O., Van Beek, P., Grunow, M., Seiler, T., 2005. Mixed-integer linear programming approaches to shelf-life-integrated planning and scheduling in yoghurt production. International Journal of Production Research 43, 5071–5100.

Maden, W., Eglese, R., Black, D., 2010. Vehicle routing and scheduling with time-varying data: A case study. Journal of the Operational Research Society 61, 515–522.

Mallidis, I., Dekker, R., Vlachos, D., 2012. The impact of greening on supply chain design and cost: a case for a developing region. Journal of Transport Geography 22, 118–128.

McKinnon, A., Allen, J., Woodburn, A., 2012. Development of greener vehicles, aircraft and ships, in: McKinnon, A., Browne, M., Whiteing, A. (Eds.), Green Logistics: Improving the Environmental Sustainability of Logistics. Kogan Page Publisher, Great Britain and United States, 2 edition. pp. 145–171.

McKinnon, A.C., 2011. Developing a decarbonisation strategy for logistics, in: Waterson, B. (Ed.), Proceedings 16th Annual Logistics Research Network Conference, Smarter Logistics: Innovation for Efficiency, Performance and Austerity, held 7-9 September 2011 at the University of Southampton, pp. 1–10.

McKinnon, A.C., Edwards, J.B., 2010. Opportunities for improving vehicle utilisation, in: McKinnon, A.C., Cullinane, S.L., Browne, M., Whiteing, A. (Eds.), Green Logistics: Improving the Environmental Sustainability of Logistics. Kogan Page, London. chapter 9, pp. 195–213.

Meneghetti, A., Monti, L., 2014. Greening the food supply chain: an optimisation model for sustainable design of refrigerated automated warehouses. International Journal of Production Research 0, 1–21. Doi:10.1080/00207543.2014.985449.

Mihyeon Jeon, C., Amekudzi, A., 2005. Addressing sustainability in transportation systems: Definitions, indicators, and metrics. Journal of Infrastructure Systems 11, 31–50.

Minner, S., Transchel, S., 2010. Periodic review inventory-control for perishable products under service-level constraints. OR spectrum 32, 979–996.

Mirzapour Al-ehashem, S.M.J., Rekik, Y., 2013. Multi-product multi-period inventory routing problem with a transshipment option: A green approach. International Journal of Production Economics , –Doi:10.1016/j.ijpe.2013.09.005.

Mogensen, L., Hermansen, J.E., Halberg, N., Dalgaard, R., Vis, J.C., Smith, B.G., 2009. Life cycle assessment across the food supply chain, in: Baldwin, C.J. (Ed.), Sustainability in the Food Industry. A John Wiley & Sons, Ltd., New Delhi, India, pp. 115–144.

Moin, N.H., Salhi, S., 2007. Inventory routing problems: A logistical overview. The Journal of the Operational Research Society 58, 1185–1194.

Mula, J., Peidro, D., Diaz-Madronero, M., Vicens, E., 2010. Mathematical programming models for supply chain production and transport planning. European Journal of Operational Research 204, 377–390.

Nahmias, S., 1982. Perishable inventory theory: A review. Operations Research 30, 680–708.

Natarajarathinam, M., Stacey, J., Sox, C., 2012. Near optimal heuristics and managerial insights for the storage constrained, inbound inventory routing problem. International Journal of Physical Distribution & Logistics Management 42, 152–173.

Nepstad, D.C., Stickler, C.M., Almeida, O.T., 2006. Globalization of the amazon soy and beef industries: Opportunities for conservation. Conservation Biology 20, 1595–1603.

Nikbakhsh, E., Eskandarpour, M., Zegordi, S.H., 2013. Designing a robust post-sales reverse logistics network, in: Ao, S.I., Gelman, L. (Eds.), Electrical Engineering and Intelligent Systems. Springer New York. volume 130 of *Lecture Notes in Electrical Engineering*, pp. 313–325.

Nzte, 2010. Beef market in Brazil, Market profile. Technical Report. New Zealand Trade and Enterprise. http://www.gd218.org.cn/2012ggxxfwz/scbg/12Beef%20Market%20Profile%20Brazil%20Ocotber%202010.pdf,Onlineaccessed:September2012.

Oglethorpe, D., 2010. Optimising economic, environmental, and social objectives: a goal-programming approach in the food sector. Environment and Planning A 42, 1239–1254.

Osvald, A., Stirn, L.Z., 2008. A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. Journal of Food Engineering 85, 285–295.

Paksoy, T., Bektaş, T., Ozceylan, E., 2011a. Operational and environmental performance measures in a multi-product closed-loop supply chain. Transportation Research Part E: Logistics and Transportation Review 47, 532–546.

Paksoy, T., Ozceylan, E., Weber, G.W., 2011b. A multi objective model for optimization of a green supply chain network. Transaction on Evolutionary Algorithm and Continuous Optimization 2, 84–96.

Parfitt, J., Barthel, M., Macnaughton, S., 2010. Food waste within food supply chains: quantification and potential for change to 2050. Philosophical Transactions of the Royal Society B: Biological Sciences 365, 3065–3081.

Pauls-Worm, K.G.J., Hendrix, E.M.T., Haijema, R., van der Vorst, J.G.A.J., 2014. An MILP approximation for ordering perishable products with non-stationary demand and service level constraints. International Journal of Production Economics 157, 133–146.

Perboli, G., Tadei, R., Tadei, R., 2010. New families of valid inequalities for the two-echelon vehicle routing problem. Electronic Notes in Discrete Mathematics 36, 639–646.

Perboli, G., Tadei, R., Vigo, D., 2011. The two-echelon capacitated vehicle routing problem: Models and math-based heuristics. Transportation Science 45, 364–380.

Persson, J.A., Gothe-Lundgren, M., 2005. Shipment planning at oil refineries using column generation and valid inequalities. European Journal of Operational Research 163, 631–652.

Piecyk, M.I., McKinnon, A.C., 2010. Forecasting the carbon footprint of road freight transport in 2020. International Journal of Production Economics 128, 31–42.

Pieters, R., Glockner, H.H., Omta, S.W.F., Weijers, S., 2012. Dutch logistics service providers and sustainable physical distribution: Searching for focus. International Food and Agribusiness Management Review 15, 107–126.

Pradenas, L., Oportus, B., Parada, V., 2013. Mitigation of greenhouse gas emissions in vehicle routing problems with backhauling. Expert Systems with Applications 40, 2985–2991.

Qin, L., Miao, L., Ruan, Q., Zhang, Y., 2014. A local search method for periodic inventory routing problem. Expert Systems with Applications 41, 765–778.

Qu, Y., Bektaş, T., Bennell, J.A., 2014. Multimode multicommodity network design model for intermodal freight transportation with transfer and emission costs. Networks and Spatial Economics .

Raa, B., Aghezzaf, E.H., 2009. A practical solution approach for the cyclic inventory routing problem. European Journal of Operational Research 192, 429–441.

Ramkumar, N., Subramanian, P., Narendran, T.T., Ganesh, K., 2012. Mixed integer linear programming model for multi-commodity multi-depot inventory routing problem. OPSEARCH 49, 413–429.

Ramos, T.R.P., Gomes, M.I., Barbosa-Póvoa, A.P., 2014. Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. Omega 48, 60–74.

Rijpkema, W., Rossi, R., Van der Vorst, J.G.A.J., 2014. Effective sourcing strategies for perishable product supply chains. International Journal of Physical Distribution & Logistics Management 44, 494–510.

Rix, G., Rousseau, L.M., Pesant, G., 2014. A transportation-driven approach to annual harvest planning. Technical Report. CIRRELT-2014-24, CIRRELT, Montreal, Canada.

Robinson, T., Thornton, P., Franceschini, G., Kruska, R., Chiozza, F., Notenbaert, A., Cecchi, G., Herrero, M., Epprecht, M., Fritz, S., You, L., Conchedda, G., See, L., 2011. Global livestock production systems. Technical Report. Food and Agriculture Organization of the United Nations (FAO) and International Livestock Research Institute (ILRI).

Ronen, D., 2002. Marine inventory routing: Shipments planning. The Journal of the Operational Research Society 53, 108–114.

Rong, A., Akkerman, R., Grunow, M., 2011. An optimization approach for managing fresh food quality throughout the supply chain. International Journal of Production Economics 131, 421–429.

Rong, A., Grunow, M., 2010. A methodology for controlling dispersion in food production and distribution. Or Spectrum 32, 957–978.

Rossi, R., Tarim, S.A., Hnich, B., Prestwich, S., 2008. A global chance-constraint for stochastic inventory systems under service level constraints. Constraints 13, 490–517.

Rossi, R., Tarim, S.A., Hnich, B., Prestwich, S.D., 2010. Computing replenishment cycle policy parameters for a perishable item. Proceedings of the 24th MEC-EurOPT-2010, Izmir, Turkey , 241–247.

RTA, 2007. Operating Conditions: Specific permits for oversize and overmass vehicles and loads. Technical Report. NSW Roads and Traffic Authority, RTA Special Permits Unit, Glen Innes, Australia. `www.rta.nsw.gov.au/heavyvehicles/oversizeovermass, Onlineaccessed:September2013`.

Santos, F.A., da Cunha, A.S., Mateus, G.R., 2013. Branch-and-price algorithms for the two-echelon capacitated vehicle routing problem. Optimization Letters 7, 1537–1547.

Savelsbergh, M., Song, J.H., 2007. Inventory routing with continuous moves. Computers & Operations Research 34, 1744–1763.

Savelsbergh, M., Song, J.H., 2008. An optimization algorithm for the inventory routing problem with continuous moves. Computers & Operations Research 35, 2266–2282.

Sazvar, Z., Mirzapour Al-ehashem, S.M.J., Baboli, A., Akbari Jokar, M.R., 2014. A bi-objective stochastic programming model for a centralized green supply chain with deteriorating products. International Journal of Production Economics 150, 140–154.

Schulz, S.F., Blecken, A., 2010. Horizontal cooperation in disaster relief logistics: benefits and impediments. International Journal of Physical Distribution & Logistics Management 40, 636–656.

Seuring, S., Muller, M., 2008. From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production 16, 1699–1710.

Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E., 2009. Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies. McGraw-Hill/Irwin, New York.

Soysal, M., Bloemhof, J.M., Meuwissen, M.P.M., Van der Vorst, J.G.A.J., 2012. A review on quantitative models for sustainable food logistics management. International Journal on Food System Dynamics 3, 136–155.

Soysal, M., Bloemhof, J.M., Van der Vorst, J.G.A.J., 2014. Modeling food logistics networks with emission considerations: The case of an international beef supply chain. International Journal of Production Economics 152, 57–70.

Soysal, M., Bloemhof-Ruwaard, J.M., Bektaş, T., 2015a. The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations. International Journal of Production Economics 164, 366–378.

Soysal, M., Bloemhof-Ruwaard, J.M., Haijema, R., Van der Vorst, J.G.A.J., 2015b. Modeling an inventory routing problem for perishable products with environmental considerations and demand uncertainty. International Journal of Production Economics 164, 118–133.

Suzuki, Y., 2011. A new truck-routing approach for reducing fuel consumption and pollutants emission. Transportation Research Part D: Transport and Environment 16, 73–77.

Tarantilis, C.D., Kiranoudis, C.T., 2001. A meta-heuristic algorithm for the efficient distribution of perishable foods. Journal of Food Engineering 50, 1–9.

Tarantilis, C.D., Kiranoudis, C.T., 2002. Distribution of fresh meat. Journal of Food Engineering 51, 85–91.

Tavares, G., Zsigraiova, Z., Semiao, V., da Graça Carvalho, M., 2008. A case study of fuel savings through optimisation of msw transportation routes. Management of Environmental Quality: An International Journal 19, 444–454.

Tavares, G., Zsigraiova, Z., Semiao, V., Graça Carvalho, M., 2009. Optimisation of MSW collection routes for minimum fuel consumption using 3D GIS modelling. Waste Management 29, 1176–1185.

Treitl, S., Nolz, P.C., Jammernegg, W., 2014. Incorporating environmental aspects in an inventory routing problem. A case study from the petrochemical industry. Flexible Services and Manufacturing Journal 26, 143–169.

Trienekens, J., Zuurbier, P., 2008. Quality and safety standards in the food industry, developments and challenges. International Journal of Production Economics 113, 107–122.

Ubeda, S., Arcelus, F.J., Faulin, J., 2011. Green logistics at Eroski: A case study. International Journal of Production Economics 131, 44–51.

UPS, 2013. Corporate Sustainability Report. Technical Report. UPS.

Validi, S., Bhattacharya, A., Byrne, P.J., 2014. A case analysis of a sustainable food supply chain distribution system—a multi-objective approach. International Journal of Production Economics 152, 71–87.

Van Donk, D.P., 2001. Make to stock or make to order: The decoupling point in the food processing industries. International Journal of Production Economics 69, 297–306.

Van Donselaar, K., Van Woensel, T., Broekmeulen, R., Fransoo, J., 2006. Inventory control of perishables in supermarkets. International Journal of Production Economics 104, 462–472.

Van Elzakker, M.A.H., Zondervan, E., Raikar, N.B., Hoogland, H., Grossmann, I.E., 2014. Optimizing the tactical planning in the fast moving consumer goods industry considering shelf-life restrictions. Computers & Chemical Engineering 66, 98–109.

Vanovermeire, C., Sörensen, K., Breedam, A.V., Vannieuwenhuyse, B. amd Verstrepen, S., 2013. Horizontal logistics collaboration: decreasing costs through flexibility and

an adequate cost allocation strategy. International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management 17, 339–355.

Verderame, P.M., Floudas, C.A., 2009. Operational planning framework for multisite production and distribution networks. Computers and Chemical Engineering 33, 1036–1050.

Vidović, M., Popović, D., Ratković, B., 2014. Mixed integer and heuristics model for the inventory routing problem in fuel delivery. International Journal of Production Economics 147, 593–604.

Van der Vorst, J.G.A.J., Beulens, A.J.M., 2002. Identifying sources of uncertainty to generate supply chain redesign strategies. International Journal of Physical Distribution & Logistics 32, 409–430.

Van der Vorst, J.G.A.J., Beulens, A.J.M., Van Beek, P., 2000. Modelling and simulating multi-echelon food systems. European Journal of Operational Research 122, 354–366.

Van der Vorst, J.G.A.J., Beulens, A.J.M., Van Beek, P., 2005. Innovations in logistics and ict in food supply chain networks, in: Jongen, W., Meulenberg, M. (Eds.), Innovation in Agri-Food Systems. Wageningen Academic Publishers, Wageningen, pp. 245–292.

Van der Vorst, J.G.A.J., Beulens, A.J.M., de Wit, W., Van Beek, P., 1998. Supply chain management in food chains: Improving performance by reducing uncertainty. International Transactions in Operational Research 5, 487–499.

Van der Vorst, J.G.A.J., Tromp, S.O., Van der Zee, D.J., 2009. Simulation modelling for food supply chain redesign; integrated decision making on product quality, sustainability and logistics. International Journal of Production Research 47, 6611–6631.

Van der Vorst, J.G.A.J., Van Kooten, O., Luning, P., 2011. Towards a diagnostic instrument to identify improvement opportunities for quality controlled logistics in agrifood supply chain networks. International Journal on Food System Dynamics 2, 94–105.

Van der Vorst, J.G.A.J., Van Kooten, O., Marcelis, W., Luning, P., Beulens, A.J.M., 2007. Quality controlled logistics in food supply chain networks: integrated decision-making on quality and logistics to meet advanced customer demands, in: Proceedings of the Euroma 2007 conference, Ankara, Turkey, pp. 18–20.

Wakeland, W., Cholette, S., Venkat, K., 2012. Food transportation issues and reducing carbon footprint, in: Boye, J.I., Arcand, Y. (Eds.), Green Technologies in Food Production and Processing. Springer Science+Business Media, LLC. Food Engineering Series, pp. 211–236.

Wang, F., Lai, X.F., Shi, N., 2011. A multi-objective optimization for green supply chain network design. Decision Support Systems 51, 262–269.

Wang, X., Li, D., O'brien, C., Li, Y., 2010. A production planning model to reduce risk and improve operations management. International Journal of Production Economics 124, 463–474.

WEF, 2009. Supply Chain Decarbonization, The Role of Logistics and Transport in Reducing Supply Chain Carbon Emissions. Technical Report. World Economic Forum. Geneva.

Whitelegg, J., 2005. London Sustainable Food Hub Opportunities for a sustainable food logistics centre in London. Technical Report. Sustain: the alliance for better food and farming.

Wognum, P.M., Bremmers, H., Trienekens, J.H., Van der Vorst, J.G.A.J., Bloemhof, J.M., 2011. Systems for sustainability and transparency of food supply chains – current status and challenges. Advanced Engineering Informatics 25, 65–76.

World-Bank, 2010. How to Decrease Freight Logistics Costs in Brazil. Technical Report. Sustainable Development Department Brazil Country Management Unit Latin America and the Caribbean Regional Office World Bank.

World-Bank, 2012. Brazil Green Freight Transport Report -Mainstreaming Green Trucks in Brazil. Technical Report. World Bank. http://siteresources.worldbank.org/BRAZILINPOREXTN/Resources/3817166-1323121030855/Green_Freight.pdf?resourceurlname=Green_Freight.pdf,Onlineaccessed:September2012.

Wouda, F.H.E., Van Beek, P., Van der Vorst, J.G.A.J., Tacke, H., 2002. An application of mixed-integer linear programming models on the redesign of the supply network of nutricia dairy & drinks group in hungary. Or Spectrum 24, 449–465.

Xiao, Y., Zhao, Q., Kaku, I., Xu, Y., 2012. Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computers & Operations Research 39, 1419–1431.

Yan, C., Banerjee, A., Yang, L., 2011. An integrated production-distribution model for a deteriorating inventory item. International Journal of Production Economics 133, 228–232.

You, F., Tao, L., Graziano, D.J., Snyder, S.W., 2012. Optimal design of sustainable cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle assessment and input–output analysis. American Institute of Chemical Engineers (AIChE) Journal 58, 1157–1180.

Yu, Y., Chen, H., Chu, F., 2008. A new model and hybrid approach for large scale inventory routing problems. European Journal of Operational Research 189, 1022–1040.

Yu, Y., Chu, C., Chen, H., Chu, F., 2012. Large scale stochastic inventory routing problems with split delivery and service level constraints. Annals of Operations Research 197, 135–158.

Zanoni, S., Zavanella, L., 2007. Single-vendor single-buyer with integrated tran sport-inventory system: Models and heuristics in the case of perishable goods. Computers & Industrial Engineering 52, 107–123.

Zanoni, S., Zavanella, L., 2012. Chilled or frozen? Decision strategies for sustainable food supply chains. International Journal of Production Economics 140, 731–736.

Zhang, X., Huang, G.H., Chan, C.W., Liu, Z., Lin, Q., 2010. A fuzzy-robust stochastic multiobjective programming approach for petroleum waste management planning. Applied Mathematical Modelling 34, 2778 – 2788.

Zucchi, J.D., Zeng, A. Z., Z., Caixeta-Filho, J.V., 2011. Optimum location for export-oriented slaughterhouses in Mato Grosso, Brazil: a dynamic mathematical model. International Journal of Logistics Research and Applications 14, 135–148.

Zuo, M., Kuo, W., Mcroberts, K.L., 1991. Application of mathematical-programming to a large-scale agricultural production and distribution-system. Journal of the Operational Research Society 42, 639–648.

About the Author

Mehmet Soysal was born on 11 March 1984, in Turkey. He has a B.Sc. degree in Management and an M.Sc. degree in Operations Research from Hacettepe University, in Turkey. His master's research on supply chain inventory policies was supported by The Scientific and Technological Research Council (TUBITAK) of Turkey. He was also awarded a scholarship from TUBITAK to pursue his Ph.D. degree.

He conducted his Ph.D. research regarding decision support modeling for Sustainable Food Logistics Management in the Operations Research and Logistics Group at Wageningen University, The Netherlands, between 2011 and 2015. Here, he participated in two projects as a researcher. The first project named "Knowledge-based sustainable value-added food chains: innovative tools for monitoring ethical, environmental and socio-economical impacts and implementing EU-Latin America shared strategies" is a collaborative project funded by the European Commission under the 7th Framework Program theme: Knowledge-Based Bio-Economy. The second project named "Step change in agri-food logistics ecosystems" is a collaborative project partly funded by INTER-REG IVB North-West Europe, which is a financial instrument of the European Union's Cohesion Policy.

His primary research interests are Operations Research, Supply Chain Management, Logistics Management and Sustainability. His research is published in international peer reviewed journals and at international conferences.

Mehmet Soysal

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Sustainable Enterprise & Emerging Theory and Practice	WASS	2011	0.5
Heuristic Methods in Operations Research	LNMB	2011	6
Courses (PhD) from Prior Education i. Inventory Control ii. Supply Chain Management iii. Mathematical Programming iv. Production Planning: Model Building v. Operations Research: Advanced Topics	Hacettepe University/ Turkey	2010 - 2011	8
B) General research related competences			
Introduction course	WASS	2011	1
Scientific Writing	WGS	2012	1.8
Techniques for Writing and Presenting a Scientific Paper	WGS	2012	1.2
Courses (PhD) from Prior Education i. Research Methods-I ii. Research Methods-II	Hacettepe University/ Turkey	2010 - 2011	4
C) Career related competences/personal development			
Writing Research Proposal	WASS	2011	6
'A review of quantitative models for sustainable food logistics management challenges and issues'	IGLS international conference, Innsbruck	2011	1
'An integrated model for sustainable food logistics management'	EURO international conference, Vilnius	2012	1
'Time dependent capacitated vehicle routing problem with emission consideration'	EURO international conference, Rome	2013	1
'Modelling a stochastic inventory routing problem for perishable products with environmental considerations'	WASS PhD day	2014	1
'The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations'	EURO international conference, Barcelona	2014	1
Supervising BSc, MSc students	WUR, ORL	2014	2
Contribution to SALSA workshops		2014	2
Assistant in the courses: Decision Science, Supply Chain Management and Sustainability in Food Chains	WUR, ORL	2014	2
Total			**39.5**

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* One ECTS represents a study-load of 28 hours.