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Optimization of closed-loop food supply chain with returnable transport items

Yipei Zhang

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Optimisation de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables

Thèse de doctorat de l'Université Paris-Saclay et de Northwestern Polytechnical University, préparée à l'Université d'Evry-Val-d'Essonne

École doctorale n°580 Sciences et technologies de l'information et
de la communication (STIC)
Spécialité de doctorat: Informatique

Thèse présentée et soutenue à Xi'an, le 20 Décembre 2019, par

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Titre: Optimisation de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables

Mots clés: Chaîne logistique à boucle fermée ; nourriture périssable ; emballage réutilisable ; optimisation bi-critère ; émission carbone; heuristiques.

Résumé :

La chaîne logistique à boucle fermée, qui est une des branches importantes de la chaîne logistique, a reçu une attention particulière au cours des dernières décennies. Toutefois, on trouve peu de recherches dans la littérature sur la chaîne logistique agroalimentaire bien qu'elle soit largement pratiquée dans l'industrie. L'objectif de cette thèse est de proposer de nouveaux modèles et de nouvelles heuristiques pour l'optimisation de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables. A cette fin, trois nouveaux problèmes sont étudiés.

Nous étudions d'abord un problème de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables. Ce problème implique un seul fabricant et un seul détaillant. L'externalisation est autorisée. Et le budget d'achat d'emballages réutilisable est limité. L'objectif est de maximiser le profit global de la chaîne logistique. Le problème est formulé en programmation linéaire en nombres mixtes et est démontré NP-difficile. Pour sa résolution, une nouvelle « kernel search-based » heuristique est développée. Les expériences numériques sur un cas d'étude et sur un grand nombre d'instances générées aléatoirement montrent l'efficacité de la méthode proposée.

Ensuite, un problème bi-critère de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables est étudié. L'objectif est de maximiser le profit et de minimiser les émissions carbone, simultanément. Dans ce problème, plusieurs détaillants sont considérés. Ce problème est modélisé en programmation linéaire bi-objectif en nombres mixtes et résolu à l'aide d'une méthode de ε -contrainte. En particulier, une heuristique basée sur la « kernel search-based » est développée pour résoudre à chaque itération le problème transformé à un problème monocritère de la méthode de ε -contrainte. Les résultats numériques sur des instances générées aléatoirement indiquent que la performance de la méthode développée est comparable avec celle proposée par le solveur CPLEX.

Finalement, nous nous intéressons à un problème intégrant la gestion des stocks et la tournée de véhicules dans la chaîne logistique agroalimentaire à boucle

fermée avec emballages réutilisables. Dans ce problème, les emballages réutilisables avec différents niveaux de protection sont considérés. Le problème est formulé en programmation linéaire en nombres mixtes and est démontré NP-difficile. Le modèle proposé est validé via des expériences numériques.

Title: Optimization of closed-loop food supply chain with returnable transport items

Keywords: Closed-loop supply chain; perishable food; returnable transport item; bi-objective optimization; carbon emission; heuristic.

Abstract:

Closed-loop supply chain (CLSC), as an important branch of supply chain, has received increasing attention in recent decades. However, CLSC for perishable food products that is more complex than classic CLSC has been seldom studied in spite of its growing applications in practice. This thesis aims to develop new models and methods for optimizing closed-loop food supply chain with returnable transport items. To this end, three new problems are investigated.

Firstly, a closed-loop food supply chain with returnable transport items (CLFSC-RTI) is studied. This problem involves a single manufacturer and a single retailer. Outsourcing is permitted and RTI purchasing budget is limited. The objective is to maximize the total profit of the supply chain. The problem is formulated as a mixed integer linear program (MILP) and it is proved to be NP-hard. To solve the problem, an improved kernel search-based heuristic is designed. Computational experiments on a real case study and extensive random instances demonstrate the effectiveness and efficiency of the proposed model and heuristic.

Secondly, a bi-objective closed-loop food supply chain with returnable transport items (BCLFSC-RTI) is investigated. The two objectives are to maximize the total profit and to minimize carbon emissions, simultaneously. The studied problem considers multiple retailers. For this complex bi-objective problem, a bi-objective MILP is proposed for its modelling, and an iterative ε -constraint method is applied to solve it. Then, an improved kernel search-based heuristic is developed to solve the transformed single objective problem in each iteration of the ε -constraint method. Computational results based on various randomly generated instances show that the performance of the proposed method is comparable to that of a state-of-the-art commercial optimization solver CPLEX.

Finally, a closed-loop food inventory-routing problem with RTIs (CFIRP-RTI) is addressed. In this problem, a vehicle routing problem is integrated and returnable transport items with different protective levels are considered. An MILP is proposed to formulate the problem, and the problem is proved to be NP-hard. Numerical experiments are carried out to validate the proposed model.

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Chapter 1

Introduction

This thesis investigates a multi-period closed-loop supply chain (CLSC) optimization problem for fresh food industry involving returnable transport items (RTI). The research target is to provide optimal or near optimal planning by coordinating the forward product production-distribution and the RTI return flows to improve the global performance of the closed-loop food supply chain (CLFSC). In the chapter, the research background is first presented, and the contributions and content of the thesis are then highlighted.

1.1background

In this era, due to the growing environmental concerns, diminishing non-renewable resources, the increasing customer expectations and potential business opportunities, companies are seeking to improve sustainability performance of their supply chain (Glock et al. 2012, Santos et al. 2013). The government also enacts regulations that require the companies to properly treat the end-of-life or end-of-use products generated in their supply chain activities to reduce negative environmental impacts, such as carbon emissions and resource waste (Soysal 2016). One of the proper ways to address the above concerns is to introduce reverse logistics (RL) into the traditional forward supply chain (FSC) to form a closed-loop supply chain (CLSC) (Jindal and Sangwan 2014). CLSC contributes to realising sustainable development by reducing resource consumption and waste generation (Guide and van Wassenhove 2009). Thus, it has received more and more attentions from both academia and practice in recent decades (Glock 2017).

CLSC is an integration of the traditional FSC and RL by simultaneously considering the forward and reverse flows. The forward flow includes product production and its distribution from manufacturers to customers. The reverse flow refers to collecting the return items from customers to manufacturers for their reusing, recycling, remanufacturing and/or proper disposition. Broadly speaking, the return items in CLSCs include products, components, materials,

packaging, and so on (Jindal and Sangwan, 2014). Among them, the reusable packaging for shipping products, such as pallets, containers, boxes, trays, refillable bottles and so on, are called returnable transport items (RTIs) (Twede and Clarke 2004). Other expressions for them include Reusable Transport Items (IC-RTI, 2003), Returnable Transport Packaging (Sarkar et al. 2019) or Returnable/Reusable Logistical Packaging (Glock 2017). Note that term returnable transport item (RTI) will be used throughout the thesis for consistency. RTIs in the supply chain are defined by ISO (2007) as all means to assemble goods for transportation, storage, handling and product protection which are returned for further usage. As mentioned in the research of Glock (2017), RTIs represent an important corporate asset in many industries today.

Glock (2017) pointed out that using RTIs can reduce the material waste of one-way packaging, which helps relieve the saturation of landfill and the scarcity of resources. A recent survey revealed that using RTIs can significantly reduce the emission of CO₂ over their lifecycle compared to disposable ones, which will greatly lower negative impacts on the environment (Goellner and Sparrow 2014). More importantly, adopting RTIs can improve product protection during the process of handling, transport, and storage. It may also reduce final product cost if they are effectively managed (Mollenkopf et al. 2005). However, existing researches on CLSC predominantly focus only on the forward and reverse flows of finished products (Glock 2017), such as end-of-life vehicles (Schultmann et al. 2006), the spent lead-acid batteries (Kannan et al 2010), the recycling cartridge (Chen et al. 2014), etc. Fewer researches have been done on CLSC with packaging returns although its important role in improving supply chain performance and the increasing application in practice. Therefore, it is essential to further investigate this topic.

Due to the above mentioned RTIs' benefits over the one-way packaging, RTIs have been increasingly introduced into various industries (Hellström and Johansson 2010, Glock and Kim 2015). Among them, the fresh food industry has been showing great interests to use RTIs in its supply chain activities (Battini et al. 2016). Food industry with direct impacts on the daily life plays a vital role in the economy all over the world. Food supply chain management is more complicated because of food perishability, strict quality and safety requirements, high energy consumption and greenhouse emissions during production and distribution. Therefore, specific food characteristic, such as food quality level that represents

their deterioration degree is necessary to be considered for food CLSC performance evaluation. Moreover, food products, e.g. fruits and vegetables, are more vulnerable to various external elements during the process of storage, handling and transportation, such as vibrations, dropping and compression (Battini et al. 2016). These will lead to food damage and food wastes at different stages of the supply chain which directly affect the company revenue. The utilization of RTIs can improve food supply chain performance as they can provide better food protection, preserve food quality and reduce food damage.

Nevertheless, based on the survey of literature, we observed that the existing studies on food CLSC focus only on food product flow (Hasani et al. 2012, Mirakhorli 2014) or on RTIs flow separately (Humbert et al. 2009). Such separation may result in sub-optimal solutions and impact the global performance of CLSCs (Hasani et al. 2012, Pishvaei et al. 2010, Pålsson et al. 2012). Coordinating product and RTI flows in CLSCs has just received attentions in recent years and not been well studied (Özceylan and Paksoy 2013, Glock 2017). Food quality, as an important feature of perishable products, has been rarely integrally addressed. There is a gap between theory and practice for optimization of closed-loop food supply chain with RTIs (CLFSC-RTI).

The CLFSC-RTI is generally more complicated than classic CLSCs due to food characteristics, and the interdependencies between food products and RTIs. Therefore, new models and solution methods need to be developed to tackle it.

1.2 Content and contributions

This thesis is devoted to investigating three related multi-period planning optimization problems that coordinate the forward movement of perishable food products and the reverse flow of RTIs that used to ship them. Firstly, a closed-loop food supply chain with returnable transport items (CLFSC-RTI) is studied. This problem involves a single manufacturer and a single retailer. Outsourcing is permitted and RTI purchasing budget is limited. The objective is to maximize the total profit of the holistic supply chain. Then, a bi-objective CLFSC-RTI (BCLFSC-RTI) is investigated. The studied problem considers multiple retailers. The two objectives are to maximize the total profit and to minimize negative environmental impacts by reducing carbon emission, simultaneously. Finally, we focus on a closed-loop food inventory-routing problem with RTIs (CFIRP-RTI). In this problem, a vehicle routing problem is integrated and returnable transport items

with different protective levels are considered. Several important characteristics of the studied problems are presented in Table 1.1.

Table 1.1: Attributes of the studied problem

Problems	Objective	Retailer	RTI types	Environmental issues	Outsourcing	Routing
CLFSC-RTI	S	S	S		✓	
BCLFSC-RTI	M	M	S	✓		
CFIRP-RTI	M	M	M			✓

Note: S-single, M-multiple

The main contributions of the thesis are summarized as follows.

- 1) A CLFSC-RTI is investigated. For the problem, an appropriate mixed integer linear programming (MILP) model is formulated. The complexity of the problem is then proved. An improved kernel search-based heuristic is developed for its resolution. A case study derived from a food manufacturer in China illustrates the applicability of the proposed model and method. Computational experiments on randomly generated instances are conducted to further evaluate the performance of the proposed heuristic. The computation results show the heuristic to a great extent outperforms the state-of-the-art optimization solver CPLEX.
- 2) A BCLFSC-RTI with multiple retailers is studied. For the complex bi-objective problem, a bi-objective MILP is proposed for its modelling, and several inequalities are developed to narrow the solution space based on problem analysis. An iterative ε -constraint method is applied to solve it. In each iteration of the ε -constraint method, the improved kernel search-based heuristic is employed to solve the transformed single objective problems. A case study derived from a slaughterhouse illustrates the applicability of the proposed model and method. Computational results based on various randomly generated instances show the effectiveness and efficiency of the proposed model and method.
- 3) A CFIRP-RTI considering RTI product protective levels is addressed. A vehicle routing problem is integrated in it. For the complex problem, an appropriate MILP is proposed to formulate it, and the problem is proved to be NP-hard. Numerical experiments are carried out to validate the

proposed model.

The remainder of this thesis is organized as follows.

Chapter 2 presents a systematic literature review. We first reviewed existing studies on the CLSC involving RTIs. Then related research on closed-loop food supply chain with RTIs is presented. Finally, the mathematical programming - based heuristic, and the concept, solution methods and performance evaluation of multi-objective optimization are introduced.

Chapters 3, 4 and 5 studies the CLFSC-RTI, the BCLFSC-RTI, and CFIRP-RTI respectively.

Chapter 6 concludes this thesis and highlights the future research emphasis.

Chapter 2

Literature Review

In this chapter, we review the relevant state-of-the-arts to the considered problem. First, we present studies on the closed-loop supply chain problem in Section 2.1. Then, solution methods for supply chain problems are summarized in Section 2.2. Subsequently, in Section 2.3, multi-objective optimization principles, solution methods and performance evaluation are reviewed. Finally, Section 2.4 concludes the chapter.

2.1 Closed-loop supply chain problem

There are two kinds of supply chains: conventional/forward supply chain (FSC) and reverse supply chain (RSC). FSC focuses solely on the activities from the flow of raw materials to the distribution of finished products to end customers (Kazemi et al. 2019). In FSC, multiple supply chain operations like production, inventory and distribution are integrated planned to improve the supply chain performance (Thomas and Griffin 1996, Archetti et al. 2011). Up to now, a large number of studies has been carried out on FSC (Li et al. 2019a, Zhu et al. 2018). RSC is the reverse of FSC by collecting return items (used products, packaging materials, etc.) from customers for their proper dispositions e.g. reusing, repairing, re-manufacturing, or recycling (Guide and van Wassenhove 2009, Saman and Zhang 2013). As RSC is in accordance with sustainable development, it has been being widely studied since RL was introduced by Murphy and Poist. For more publications, please see Zhang et al. (2019), Li et al. (2019a), Zhang et al. (2016), Govindan et al. (2015), Lau and Wang (2009), etc.

Considering FSC and RSC simultaneously gives birth to a closed-loop supply chain (CLSC) that is more complex due to the coexistence of forward and reverse flows. In light of its key role in realizing sustainable development, CLSC has been a hot and research topic in recent decades. CLSC integrates FSC and RSC to avoid the sub-optimality caused by separately considering the forward and reverse flows (Devika et al. 2014). In the following, existing research for three main branches of CLSC: CLSC with product returns, CLSC involving RTIs, and the coordination of product and RTI flows are reviewed, respectively.

2.1.1 closed-loop supply chain with product returns

Most CLSC research is dedicated to product returns that focuses on managing the forward flow of material, intermediate, and final products, and the return of end-of-life or end-of-use product. As the thesis topic is related to food industry, we further distinguish existing works on industrial products and food flows.

A considerable amount of research pays attentions on the forward and reverse flows of industrial products. Schultmann et al. (2006) studied a CLSC for automotive industry considering the end-of-life vehicle treatment. Kannan et al. (2010) aimed to recover the secondary lead from the spent lead-acid batteries for producing new ones. Özceylan and Paksoy (2013) considered disassembling or refurbishing the returnable products and sending their usable components to plants for manufacturing new products. Chen et al. (2014) classified the recycling cartridge according to their qualities and then corresponding recovery options are applied. Garg et al. (2015) designed a CLSC network considering the use of usable product components and the dispose of the non-usable ones simultaneously. They developed a bi-objective integer nonlinear programming model to maximize the total profit and minimize the carbon emissions of the CLSC. For more state of the arts, please refer to a recent review paper by Govindan and Soleimani (2017).

As food industry directly impacts our daily life and plays a vital role in the economy all over the world, food supply chain has been studied by numerous researchers to improve its performance (e.g. Kaipia et al. 2012, Coelho and Laporte 2014, Kim 2014, Soysal et al. 2016, Li et al. 2016, Zhu et al. 2018, etc.). Different from industrial products, food products (such as fruits and vegetables) have special features, e.g. perishability and special conditions on their storage, processing, and distribution (Zhu et al. 2018). Thus, the management of food product flows is more complex than that of industrial product flows. Compared to a vast body of literature on CLSC with industrial products, little work on CLSC studies in food supply chains has been done (Banasik et al. 2017). Banasik et al. (2017) studied the consequences of closing loops in a mushroom supply chain. They proposed a multi-objective MILP model to show trade-offs between economic and environmental impacts. Sgarbossa and Russo (2017) studied a new sustainable CLSC problem for the meat industry in which the waste produced from the slaughtering process is recovered and returned to the forward supply chain as valuable resource inputs. Borrello et al. (2017) investigated the willingness of

consumers to convert the open-loop supply chains for the food sector to closed-loop ones to reduce food waste. Vljajic et al. (2018) conducted an empirical study of three fresh food CLSC networks considering food recovery issues. Note that nearly all the existing food CLSC publications concentrate only on recovering the residual value of food product itself with the aim to reduce food waste. Food packaging that can affect food quality and impact the performance of food supply chain, however, has not been widely studied (Manzini and Accorsi, 2013).

2.1.2 Closed-loop supply chain with RTI

RTIs and disposal/one-way packaging coexist in actual supply chains. A CLSC with RTIs is formally defined by Glock (2017) as a supply chain that uses returnable transport items to ship products along the different stages of the chain. Fig. 2.1 and Fig. 2.2 show a generic one-way packaging and an RTI supply chain configuration, respectively. As previously stated, using RTIs to ship finished products has many benefits compared to disposal packaging. Thus, they have been increasingly introduced into real-world practice and play an important role in improving supply chain performance. However, the management of CLSC involving RTIs has just begun to obtain academic attentions (Carrasco-Gallego et al. 2012). Fig. 2.3 proposed by Glock (2017) shows the number of articles related to CLSC with RTI published per year from 1981 to 2016 indicating that this research stream starts to prosper latterly since 2006. RTI flow has three main features that make it different from product flow: 1) RTIs can be re-introduced into the supply chain after simple treating, such as inspection, cleaning or occasionally repair; 2) new and reused RTIs have the similar function; and 3) RTIs are shared by different partners in different stages of CLSC (Carrasco-Gallego et al. 2012). According to Glock (2017), the existing RTI management studies can be mainly classified into two categories: the comparison of alternative one-way packaging and RTI systems (Capuz and Aucejo 2005, Mollenkopf et al. 2005, Ray et al. 2006, Grimes-Casey et al. 2007, Levi et al. 2011, Menesatti et al. 2012, Pålsson et al. 2012, Mazeika Bilbao et al. 2011, Zhang et al. 2015, Elia 2015, Carrano et al. 2015), and RTI management system (Tsiliyannis 2005, Thoroe et al. 2009, Kim and Glock 2014, Atamer et al. 2013, Goudenege et al. 2013, Bottani et al. 2015, Glock and Kim 2014, Kim et al. 2014, Glock and Kim 2016, Hariga et al. 2016, Ni et al. 2015, Elia and Gnoni 2015, Yusuf et al. 2017). The involved industry of RTI CLSC mainly include the grocery

sector, the automotive sector, the consumer goods sector, and the chemistry and floricultural sector (Glock 2017). In particular, Mollenkopf *et al.* (2005) addressed the viability of reusable packaging in a single-supplier and single-customer CLSC. Hellström and Johansson (2010) examined the impact of control strategies for RTI transfer and traceability. Levi *et al.* (2011) conducted comparison between RTIs and one-way packaging from life cycle perspective. Goudenege *et al.* (2013) proposed a generic model for RTI management by optimizing their storage and transportation. Bottani *et al.* (2015) studied pallet management for one provider, one manufacturer, and seven retailer system. Cobb (2016) proposed an inventory control model to determine the optimal cycle length for RTIs' inspection, repair, and purchase. For more insights on CLSC management with RTIs, please refer to the recent review paper (Glock 2017). To sum up, in the above publications, most packed products by RTIs are industrial products and only the return flow of RTIs is considered. The interdependencies between RTIs and finished products they carry in the forward flow are neglected.

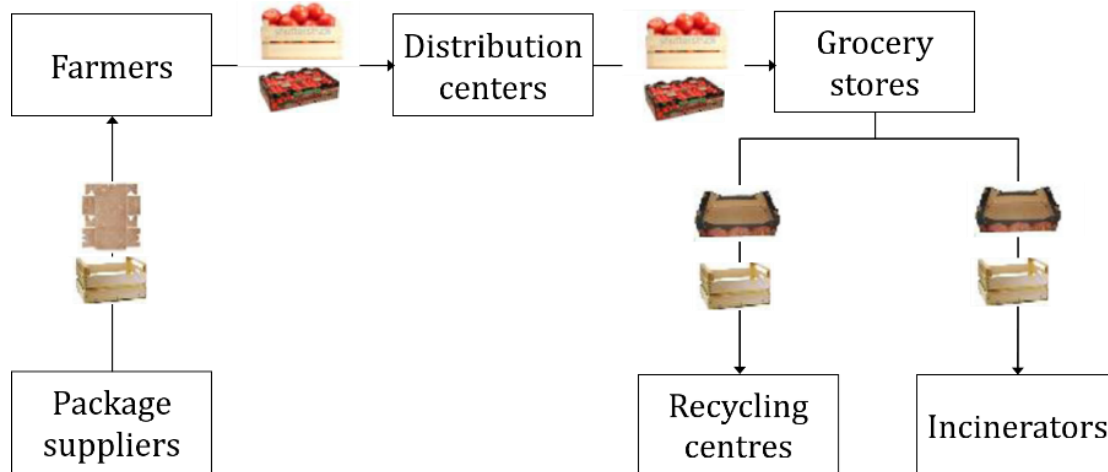


Fig. 2.1 A one-way packaging supply chain framework (Bortolini 2018)

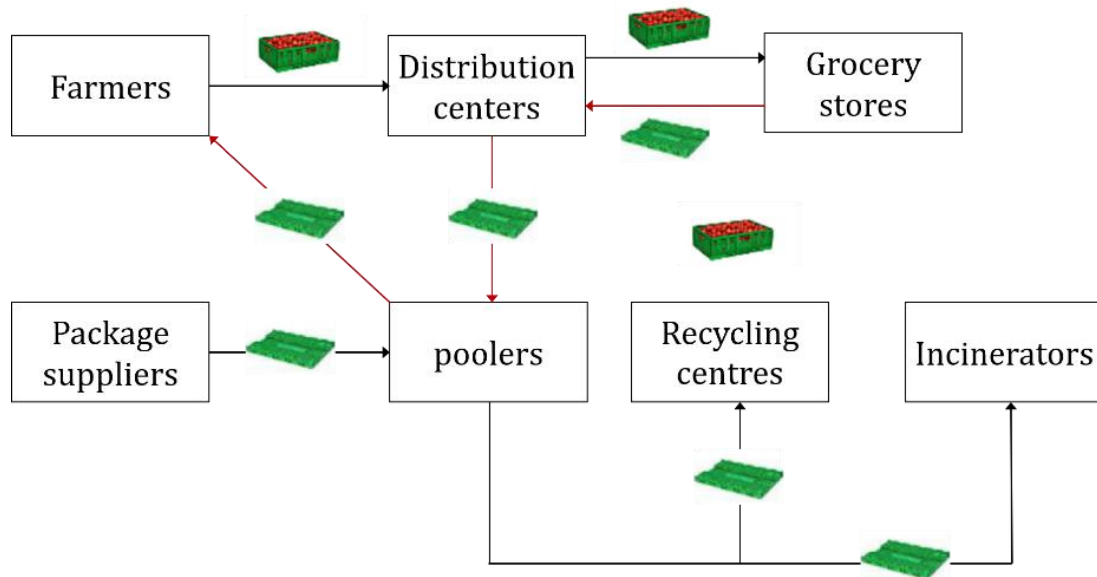


Fig. 2.2 An RTI supply chain framework (Bortolini 2018)

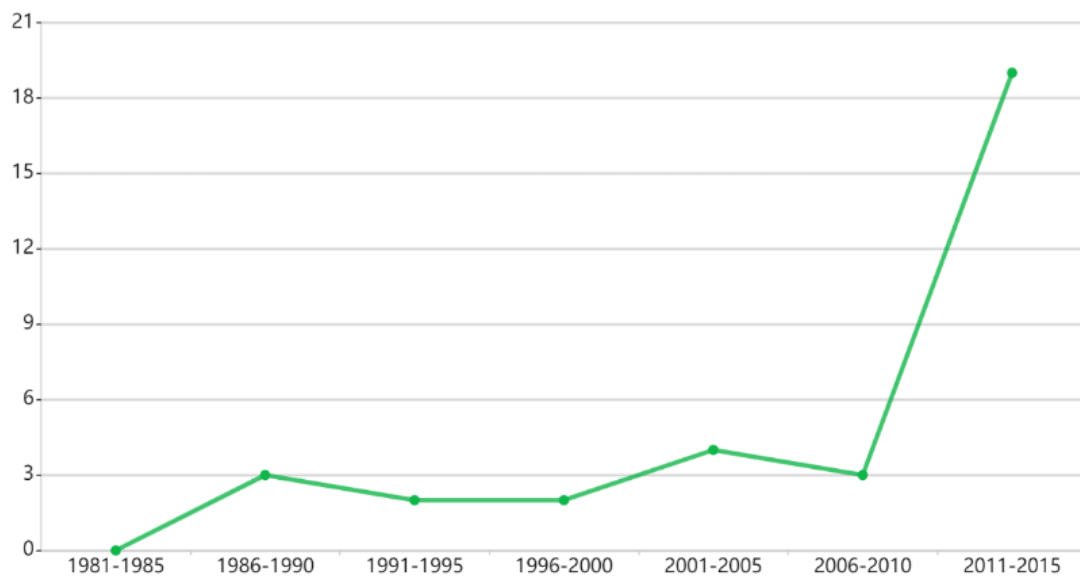


Fig. 2.3 The trend of RTI CLSC articles published per year (Glock 2017)

Due to that good packaging can protect food products, preserve their quality and prevent food waste (bruised, damaged, or spoiled throughout the food supply chain), RTIs have been increasingly applied in the fresh food industry (Battini 2016). It is observed that most existing studies on food packaging compare the economic and environmental impacts of RTIs and one-way packaging, and their protection for fresh food. For example, Singh et al. (2006), Levi et al. (2011) and Battini 2016 analyzed two packaging solutions for fresh food products from both

economic and environmental perspectives. Chonhenchob and Singh (2003), Singh et al. (2006) and Chonhenchob et al. (2008) conducted comparison analysis of single-use and reusable containers on the performance of protecting mangoes, fresh fruits and vegetables, and pineapples during the shipping and handling process. Although, it is recognized that RTIs can bring economic, environmental as well as social benefits, they have been rarely studied from CLSC optimization perspective (Bortolini et al. 2018).

2.1.3 Coordinating products and RTI flows in CLSC

Flow coordination of finished products and RTIs belongs to a challenging domain, and models and methods developed for the first two branches cannot be directly applied to it due to the interdependencies between the two flows. The existing literature in this stream of research mainly pays attention on coordinating RTIs and general product flows in CLSCs. Glock and Kim (2015) focused on optimizing the lot size for both finished products and RTIs in a single-supplier and single-buyer CLSC. A joint economic lot size model and a simulation method were developed to minimize the production and distribution costs. Glock and Kim (2014) investigated a CLSC that uses RTIs to ship finished products from a single supplier to multiple buyers. The objective is to minimize the total costs of the CLSC. They developed mathematical models for the problem and an exact method to determine cycle length, RTI quantity, shipment sequence. Glock and Kim (2016) proposed three safety measures, i.e., RTI safety return time, RTI safety stocks and the combination of both measures, to avoid RTI stock-out for a similar problem under the assumption that RTI return times are uncertain.

As to CLSC works on the coordination of food product and RTI flows. Kim et al. (2014) studied a CLSC where RTIs are used to ship perishable products from a supplier to a buyer. They developed a joint economic lot size model and conducted numerical simulation to analyze RTI's behavior. The results indicate that RTI return lot size can affect its stockout risk and the deterioration rate of finished products. Hariga et al. (2016) extended the model of Kim et al. (2014) by considering RTI renting. They proposed a mixed integer non-linear programming (MINLP) model and a search procedure for it. They found that renting RTIs is more profitable when shortage cost and the risk of late RTI returns is high.

It is noticeable that the above-mentioned works consider single-period

decision and assume customer demand to be constant while it can vary in practice. Moreover, the production, delivery and distribution planning decisions have not been considered integrally. And, product quality has not been taken into account except Kim et al. (2014) who assume that the products begin to deteriorate only when RTI stock-out occurs. Whereas in reality, the quality of food products continuously changes once they are produced (Akkerman 2010). These drawbacks motivate us to develop new models and methods for integrated planning of closed-loop food supply chain with RTIs (CLFSC-RTI) in Chapter 3 of this thesis.

It is observed that the previously reviewed researches for CLSC mostly involve only economic objective. Environmental issues have received very little attention compared to those for forward supply chain (Brandenburg et al., 2014). Bazan et al. (2015) indicated that it is very important to study greenhouse gas (GHG) emissions (mainly carbon emissions) in CLSC context. In Chapter 4 of the thesis, we study a bi-objective CLFSC-RTI (BCLFSC-RTI) that maximizes the total profit and minimize the negative environmental impacts simultaneously.

Moreover, we observe that most of the publications on CLSC is considered as direct-distribution problems. Vehicle routing practices can reduce transport cost and make better use of the vehicle capacity (Devika et al. 2014). By considering vehicle routing decisions in addition to those of inventory and distribution forms an inventory routing problem (IRP). The traditional IRP that only considers the forward or reverse flow operations has been extensively studied (e.g. Li et al. 2019a, Li et al. 2019b, Bertazzi et al., 2013, Mes et al., 2014, Soysal 2015, Elbek and Wohlk, 2016, Soysal et al., 2016, Zhang et al. 2016). As the importance of reverse supply chain activities increase, IRP with reverse flows that simultaneously address pickup and delivery starts to draw attentions (Parragh et al. 2008). However, up to now, research on closed-loop IRP (CIRP) is still very limited, especially in the context of RTIs (Soysal 2016) and food products. Soysal (2016) developed a probabilistic MILP model for RTI closed-loop inventory routing problem. Both forward and backward routing decisions, and inventory decisions are considered. Iassinovskaia et al. (2017) investigated a CLSC including a depot that distributes finished products packed by RTIs to customers and pick up empty RTIs from customers back to it. A delivery time window at customers has to be respected. Nevertheless, they only consider economic objective and RTIs are regarded as homogeneous. To the best of our knowledge, CIRP considering food quality and different RTI types simultaneously has not been investigated yet. In

Chapter 5 of this thesis, we address such a CFIRP-RTI.

2.2 Solution methods for the supply chain problem

In this section, we review the existing solution methods for the supply chain problem. Roughly speaking, these methods can be classified into three categories including exact methods, metaheuristics and constructive heuristics.

2.2.1 Exact method

Exact methods are capable of solving problems to optimality at the cost of large computation time and memory. This hinders it from providing solutions for realistic sized problems. Various exact methods have been used for solving supply chain problems, e.g. branch-and-bound (B&B) (Karimi and Davoudpour 2015, Zhou and Wang 2008, Amaro and Barbosa-Povoa, 2009) and branch-and-cut (B&C) (Masson et al. 2014, Cherkesly et al. 2016, Fang et al. 2017, Subramanian et al. 2011, Qiu et al. 2018b), etc. B&B is recognized as an effective algorithm for solving MILPs (Gupta and Ravindran 1985). Its basic idea is to relax systematically MILP to LP and to search continuous solutions, and then relaxed integer variables are successively forced to take integral values (Gupta and Ravindran 1985). The combination of B&B with cutting plane methods (B&C method) can improve the relaxation process to make closer approximation to the integer programming problem (Mitchell 2000). As claimed by Mitchell (2000), B&C can considerably accelerate the efficiency of B&B, making it one of the most commonly used exact methods. However, based on the literature survey, B&C is usually used to solve small-scale instances to test the validity of the proposed models for integrated NP-hard CLSC problems. To the best of our knowledge, only a handful of exact methods have been developed for the CLSC problem (Zhang et al. 2016). It is expected that the optimal solutions obtained by B&C can provide some insights to develop efficient heuristic for real-life applications (Iassinovskaia et al. 2017, Roshani 2017). And B&C are served as a reference to evaluate the heuristic performance. Further, we observe that the B&C algorithm is implemented in optimization solver such as CPLEX, LINDO, LINGO. IBM ILOG CPLEX is one of the best and classical commercial software for MIP problems (Angelelli et al. 2012). It uses B&C procedure, i.e., a combination of a cutting plane method and a branch-and-bound algorithm. In existing works in the literature, CPLEX has been intensively utilized

to solve MIPs of supply chain problems (e.g. Soysal 2016, Iassinovskaia et al. 2017, etc.) or is considered as a reference to evaluate the developed heuristics (e.g. Zhang et al. 2019, Li et al. 2019a,b, Soleimani and Kannan 2014, Soleimani et al. 2013, etc.).

2.2.2 Metaheuristic

Metaheuristic is generally a preferable choice to solve large real-sized combinatorial optimization problems that exact methods are powerless. It can exploit solution space efficiently by a guided search procedure and is able to avoid trapping into local optimum with accumulated search experience (Li et al. 2019a). The advantages of metaheuristic make it a popular and frequently used solution method for various supply chain problems. However, the solution quality of metaheuristics has usually to be assessed by other techniques and the metaheuristic performance is influenced greatly by its parameter setting.

There exists various metaheuristics such as genetic algorithm (GA), particle swarm optimization (PSO), etc. GA is originally introduced by Holland (1975) that based on the idea of the human body genetic procedure and the “survival of the fittest” in Darwin's theory (Soleimani et al. 2013). As GA's procedure can be found in many publications, we briefly explain GA framework here by Fig. 2.4 according to Dhanalakshmi et al. (2009). Similar to GA, PSO is also a population-based optimization method. One of the most important distinguished characteristics with GA is that PSO is able to memorize the best solution between populations and the best solution for each population.

GA is one of the most popular metaheuristic optimization techniques (Soleimani and Kannan 2014) and has been frequently used to solve CLSC problems. Sim et al. (2004) proposed a LP-based GA to solve a CLSC network design problem which is formulated as a MIP. The LP-based GA generates an initial population based on the LP-relaxed solution of the MIP by relaxing the binary variables. Computational results demonstrate that although the generated initial population in this way cannot ensure the optimality of the final solution, it is superior to the traditional GA in terms of solution quality. Kannan et al. (2010) proposed a GA to solve a CLSC model with battery recycling. The GA performance is evaluated by GAMS (General Algebraic Modeling System) software. Chen et al. (2014) developed a new modified two-stage GA for an integrated CLSC problem in

which the encoding process is decomposed into two stages. The first stage consists of route decision while the second stage includes freight volume decision. The searching ability of the proposed GA is reinforced. Soleimani and Kannan (2014) analyzed the strengths and weaknesses of GA and PSO and developed a hybrid GA-PSO algorithm for CLSC large-scale network design problem. The performance of GA-PSO is validated by comparing with CPLEX, GA and PSO. For more implementations of GA for solving CLSCs, we refer to the studies of Soleimani et al. (2013), Dhanalakshmi et al. (2009), and Sim et al. (2004). Moreover, a lot of other metaheuristics such as memetic algorithm (Pishvae et al. 2010), artificial bee colony algorithm (Cui et al. 2017) are also employed to solve CLSC network design problem.

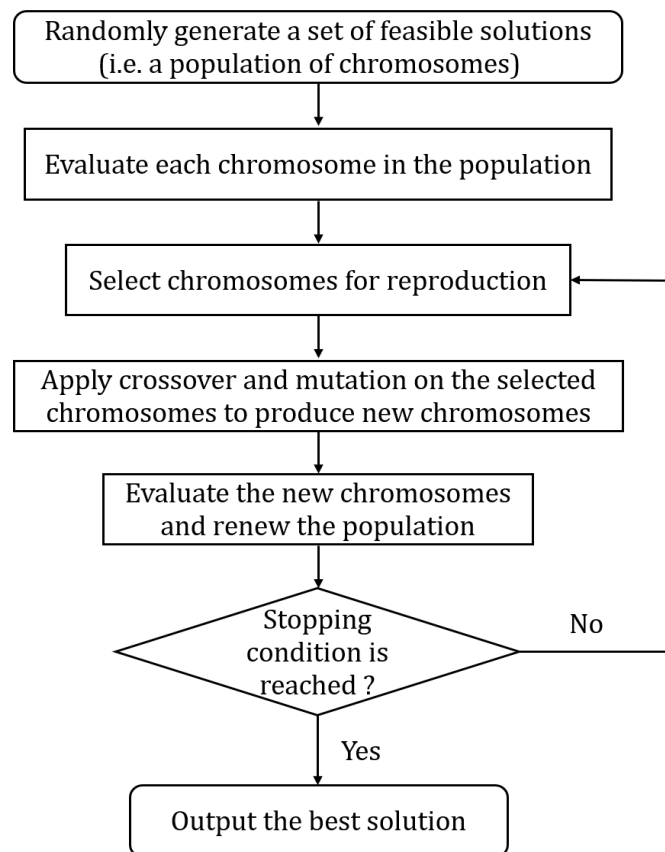


Fig. 2.4 The general procedure of GA

2.2.3 Heuristic

As integrated CLSC problems are usually combinatorial NP-hard problems whose

computational time increase exponentially with its size. Thus, obtaining optimal solutions by exact methods is extremely difficult and time-consuming for large scale problems (Soleimani and Kannan 2014, Sim et al. 2004). Researchers therefore seek to develop efficient heuristics based on problem specific characteristics to find quickly a near-optimal/optimal solution. In the following, two popular constructive heuristics used in the thesis namely kernel search-based heuristic and mathematical programming (MP)-based heuristic are presented.

2.2.3.1 Kernel-search based heuristic

Kernel Search (KS) is a two-phase heuristic recently introduced by Angelelli et al. (2007) to initially solve the portfolio optimization problem. Afterwards, it is deemed as a generic heuristic to solve problems that can be formulated as mixed integer programs (MILPs) (Guastaroba et al. 2017). Up to now, it has been successfully used to solve various combinatorial optimization problems such as multi-dimensional knapsack problem (Angelelli et al. 2010), facility location problem (Guastaroba and Speranza 2012a, Guastaroba and Speranza 2014), index tracking problem (Guastaroba and Speranza 2012b, Filippi et al. 2016), and intelligent transportation problem (Wu et al. 2016), etc.

Taking maximization problem as example, the principle of KS can be presented as follows. For a MILP, the first phase of Kernel Search is to determine an initial kernel K_0 and m buckets based on the solution of the relaxed MILP, denoted as LP. In the LP solution, binary variables having positive values are sorted in a list with non-increasing order of their values and followed by those having values 0 with non-decreasing order of their reduced costs. K_0 is composed by the first $|K_0|$ promising variables in the list, and the remaining variables are partitioned into m buckets, $\{B_i\}$, $i=1, \dots, m$. Thus, $m = \lceil (|N| - |K_0|)/L \rceil$ disjoint ordered buckets are formed, where $|N|$ is number of binary variables and L is the prespecified length of each bucket (the last one may be smaller than L). Then an initial restricted 0-1 MILP, named $RMILP(K_0)$ is formed with binary variables in K_0 while the values of the remaining variables are set to be zero, and $RMILP(K_0)$'s optimal solution provides a lower bound of the original problem, denoted as z_{LB} . Several points are worth to be pointed out in this phase that: 1) the promising binary variables means those likely take value 1 in the optimal solution of the original problem; 2) the constructed K_0 should be big enough to include more

promising variables such that it can provide high-quality solutions, and it should be small enough such that the formed RMILP can be efficiently solved.

The second phase of KS iteratively solves a sequence of m RMILPs. At the end of each iteration, the current kernel is updated. Specifically, at the i -th iteration, where $1 \leq i \leq m$, the i -th RMILP is formed by the variables in kernel K_i and bucket B_i , denoted as RMILP $(K_i \cup B_i)$. Then RMILP $(K_i \cup B_i)$ is optimally solved and its objective value z^* is obtained. After that, K_i is updated as K_{i+1} by the formula $K_{i+1} = K_i \cup (B_i \setminus B_i^-)$, where B_i^- is composed by all the variables taking values 0 in B_i . Subsequently, the variables in $K_{i+1} \cup B_{i+1}$ form the $(i+1)$ -th RMILP, i.e. RMILP $(K_{i+1} \cup B_{i+1})$. At the $(i+1)$ -th iteration, RMILP $(K_{i+1} \cup B_{i+1})$ is solved with two additional constraints. One is $z \geq z^*$; and the other is to guarantee that at least one binary variable in B_{i+1} takes value 1. Note that if variables in the kernel that have not been selected by the optimal solution of RMILP in the last p iteration(s) (p is a given parameter), they will be removed from the kernel. By doing this, the size of the kernel is controlled to guarantee the computation efficiency of solving RMILPs. After iteratively solving m restricted 0-1 MIPs, optimal or near-optimal solution and its corresponding objective value are outputted if exist. In view of the above discussions, the KS framework is presented in Fig. 2.5. The core of KS consists in determining the size of the initial kernel K_0 , the length of each bucket L , and the number of buckets m . These values depend highly on the characteristics of studied problems and can significantly impact KS's effectiveness and efficiency.

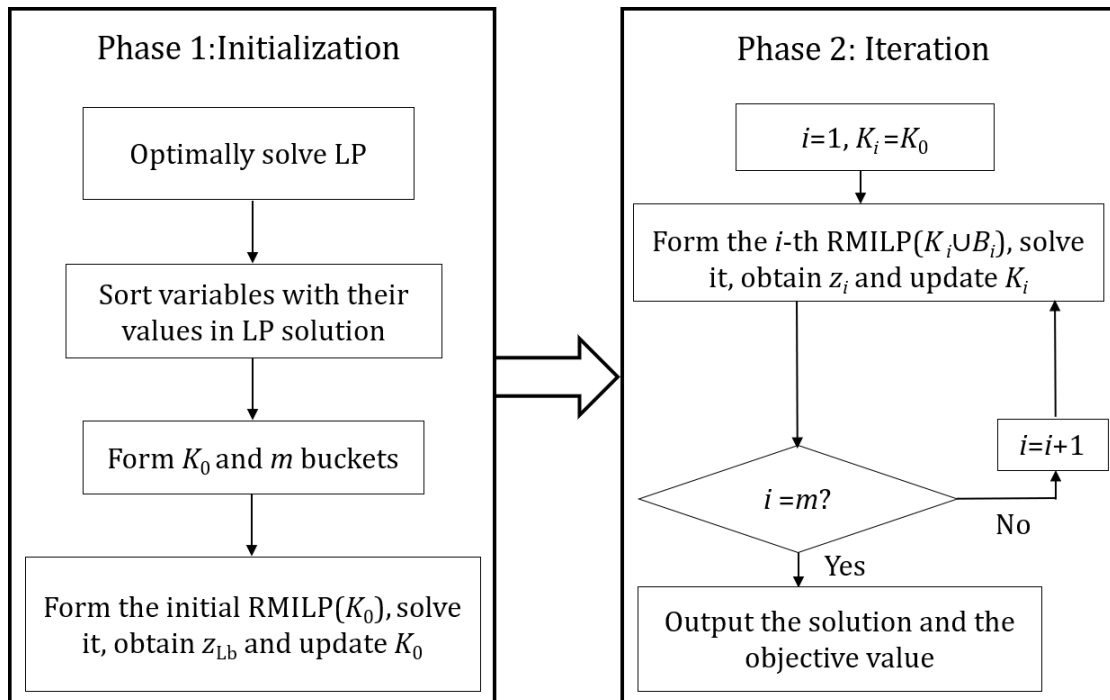


Fig. 2.5. Kernel search framework

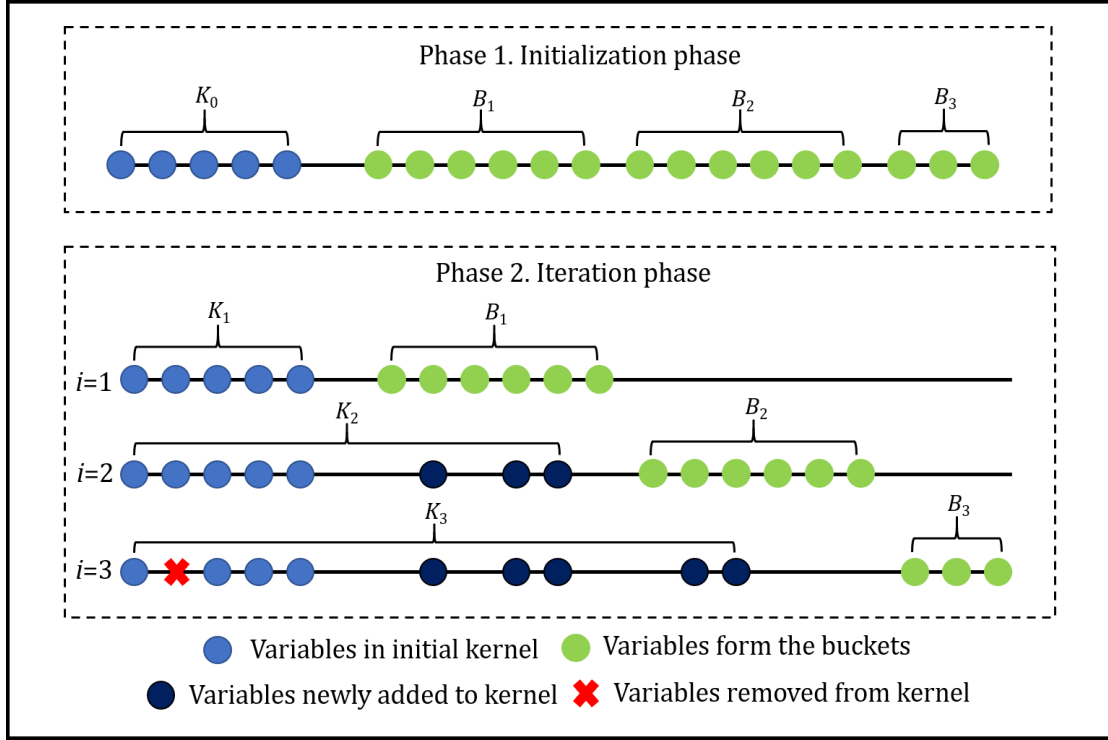


Fig. 2.6. A small illustrative example of kernel search heuristic

Fig. 2.6 illustrates KS by a small example for a maximization problem (P^{\max}) with binary variables x_n , $n \in N$ with parameters $|N|=20$, $|K_0|=5$, $L=6$, $m=\lceil(20-5)/6\rceil=3$, and $p=2$. In phase 1, K_0 and three buckets B_1 , B_2 , B_3 are determined, and RMILP (K_0) is then formed and solved to provide a lower bound z_{Lb^*} for P^{\max} if exist or else it will be set to be $-\infty$. After that we let $K_1=K_0$. In the 1-st iteration of phase 2, RMILP ($K_1 \cup B_1$) is formed with two additional constraints being $z \geq z_{\text{Lb}^*}$ and $\sum_{x_n \in B_1} x_n \geq 1$. After solving RMILP ($K_1 \cup B_1$), we obtain the objective value z_1 and form $K_2 = K_1 \cup (B_1 \setminus B_1^-)$. In the 2-nd iteration, RMILP($K_2 \cup B_2$) is formed by adding two similar constraints to RMILP ($K_1 \cup B_1$). After it is solved, we obtain z_2 . If variables in K_1 takes value 0 in both the 1-st and 2-nd iterations, they are removed from K_3 . Similarly, RMILP($K_3 \cup B_3$) is formed and solved in the 3-rd iteration. The obtained near-optimal/optimal solution and corresponding objective value z_3 are outputted if exists. In Chapter 3 of the thesis, an improved Kernel Search-based heuristic (IKSH) is designed to solve the CLFSC-RTI. Then the IKSH is called to solve the transformed single-objective problems in the BCLFSC-RTI of Chapter 4.

2.2.3.2 MP based heuristic

Mathematical programming (MP) based heuristics are directly built on the problem formulation (e.g. MIP, MILP, ILP) (Sahling et al. 2009). It is the combination of exact and heuristic methods and is rather flexible especially when the formulated models are altered or extended (Sahling et al. 2009). In general, MP-based heuristics decompose the original problem into small sub-problems that can often be efficiently solved by calling commercial MIP solvers, e.g. CPLEX, LINDO etc. Iassinovskaia et al. (2017) proposed a MIP-based approach to solve an inventory routing problem (IRP) in CLSC. The proposed approach combined the clustering heuristic and B&C algorithm. First, customers are partitioned into clusters and the number of the clusters corresponds to the vehicle fleet size. And then, all the sub-MILPs are solved by commercial solver CPLEX. In this way, the computation time of the B&C procedure is significantly reduced. Zhang et al. (2016) developed an iterative MILP-based heuristic to solve a multicommodity production routing problem (PRP) in supply chain. At each iteration, a restricted MILP model with a subset of candidate routes is solved by CPLEX. Then the restricted MILP is updated based on the solution and solved in the next iteration. Ouhimmou et al. (2008) split the planning horizon of a supply chain planning problem which is formulated as a MIP into small equal intervals. Then the smaller planning problems in these intervals are formulated as MIPs. After solving each MIP, binary variables that take value 1 are fixed and then are translated into constraints to form the next MIP. Computational results show that the proposed heuristic outperforms CPLEX. For more MP-based studies, please refer to Ball (2011), Toledo et al. (2013), Oliveira et al. (2014a), Toledo et al. (2016), Li et al. (2019b), Yang et al. (2019), etc.

Relax-and-fix (RF) (Dillenberger et al. 1994) is one of the most common MP-based heuristics which are often used to solve MILPs (Absi and van den Heuvel 2019). The main idea is to iteratively form and solve several sub-problems of the original problem in which only a subset of integer variables is maintained integrality. In the vast majority of papers, RFs decompose binary variables on the planning horizon $t \in T$ into three subsets, namely, the fixed binary variable subset (FVS), the binary variable subset (BVS) and the relaxed binary variable subset (RVS). In detail, the FVS includes binary variables that are fixed to 0 or 1. Binary variables whose integer constraints are retained consist of the BVS and the length

of BVS is set as a constant number α . The RVS is decomposed by binary variables that are relaxed to be continuous. After solving each sub-problem, the BVS moves forward by β ($\beta \leq \alpha$) periods and a certain number of variables in BVS are fixed until the original problem is solved. The number of iterations $iter$ can be computed by formula $iter = \lceil (|T| - \alpha) / \beta \rceil + 1$. The principle of RF heuristic is illustrated in Fig.2.7.

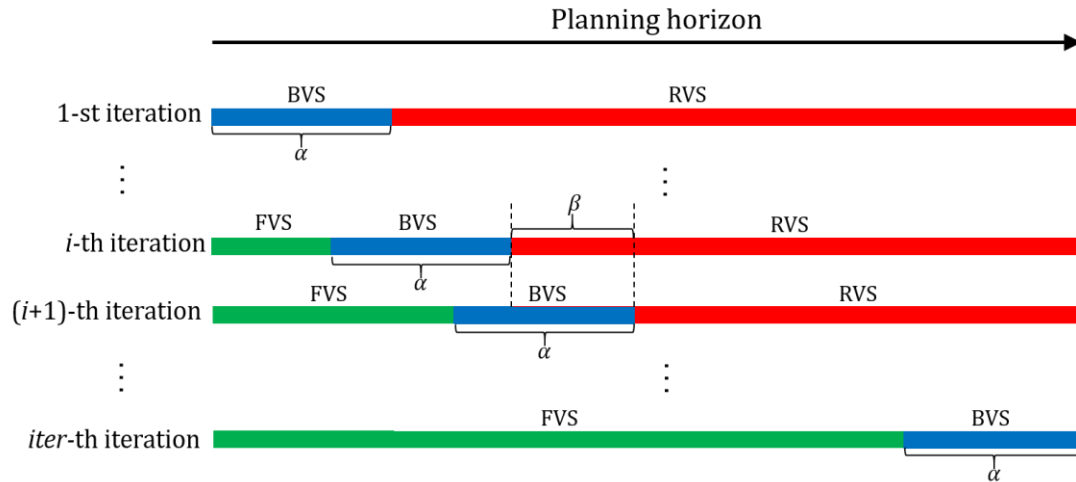


Fig. 2.7. General procedure of the RF heuristic

Fig. 2.7 presents the sub-problem structure in the 1-st, the last ($iter$ -th) and two successive (i - and $(i+1)$ -th) iterations. Specially, in the 1-st iteration, FVS is null. BVS and RVS form the 1-st sub-problem, denoted as $SUBP_1$. A certain number of variables in BVS is fixed after solving $SUBP_1$. In the i -th iteration, FVS shows up owing to the fixed operations in the previous iteration(s). Thus, $SUBP_i$ is composed by FVS, BVS and RVS. After $SUBP_i$ is solved, BVS moves forward by β periods and some ($\beta < \alpha$) or all ($\beta = \alpha$) variables in BVS are fixed. That means more variables are fixed and enter into FVS while the relaxed variables in RVS become less. Consequently, $SUBP_{i+1}$ whose structure resembles $SUBP_i$ is formed and solved. The procedure proceeds in the same manner until the $iter$ -th iteration in which RVS disappears and most of the variables are fixed except those in BVS. As soon as $SUBP_{iter}$ is solved, all the binary variables are fixed, and the obtained objective value and solution are the global objective value and solution of the original problem.

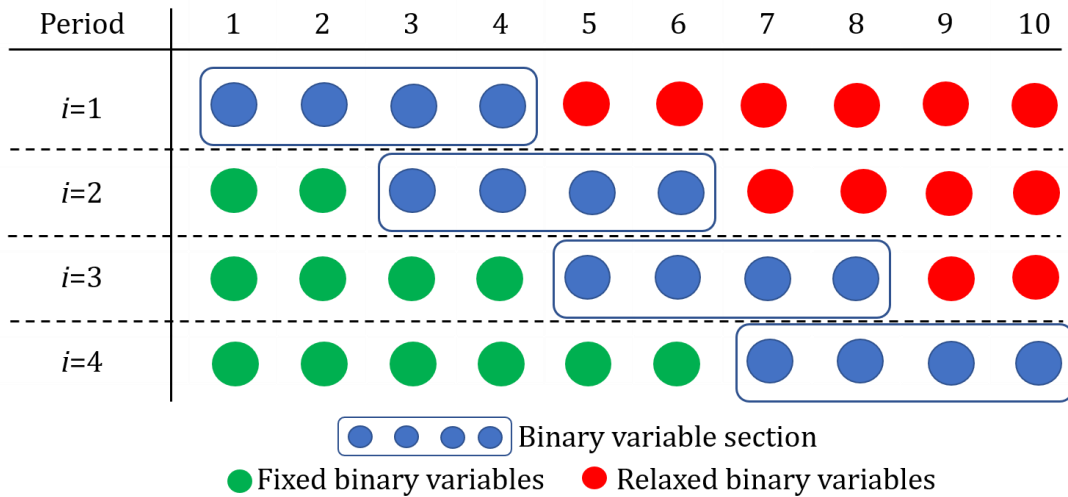


Fig. 2.8 An example of relax-and-fix heuristic

Fig. 2.8 demonstrates the RF procedure by an example with $|T|=10$, $\alpha=4$, $\beta=2$ and the consequent $iter = \lceil (10-4)/2 \rceil + 1 = 4$. As shown in Fig.2.8, when $i=1$, SUBP₁ is formed with binary variables in the first 4 periods being integer and the remaining being relaxed.

After solving SUBP₁, the BVS moves forward by 2 periods and variables in the first 2 periods are fixed to 0 or 1 based on the solution of SUBP₁. Thus, SUBP₂ is formed with the first 2 fixed binary variables, the BVS and the relaxed binary variables from periods 7 to 10. SUBP₃'s structure is similar to that of SUBP₂. In the 4-th iteration, binary variables in the BVS and those fixed in 1 to 3 iterations form SUBP₄. After solving SUBP₄, all the binary variables are fixed, and the objective value and optimal solution of the original problem are obtained.

Oliveira et al. (2014a) and Akartunalı and Miller (2009) indicated that RF is a promising method and is well-suited for combinatorial optimization problems such as lot sizing problems (LSPs) and production routing problems (PRPs). Note that LSP and PRP are both a partial of the integrated supply chain problem. Up to now, RF has been successfully applied in LSPs (e.g. Ferreira et al. 2010, Mohammadi et al. 2010, Wu et al. 2011, Toledo et al. 2013, Roshani et al. 2017, Wu et al. 2018, etc.), and most recently in PRPs (Miranda et al. 2018, Ribeiro et al. 2018, Friske and Buriol 2018, Qiu et al. 2018ab). Based on the survey of literature, all the LSPs using RF relax and fix the production set-up binary variables iteratively. PRPs solved by RF heuristic usually relax and fix production set-up variables as well as routing-related binary variables in each sub-problem. For more RF research, please see Noor-E-Alam and Doucette (2012) for the grid-based location problem,

Oliveira et al. (2014a) for the vehicle-reservation assignment problem, Oliveira et al. (2014b) for the traveling umpire problem, and Paquay et al. (2018) for the bin packing problem.

Based on the above statements, a RF based heuristic is developed in Chapter 3 of the thesis to solve the CLFSC-RTI.

2.3 Multi-objective optimization

The above reviewed CLSC studies mainly fall into the stream of mono objective optimization by minimizing the total cost or maximizing the total profit of the CLSC. Whereas, in actual supply chain practices, decision makers often desire to achieve also other goals such as minimizing negative environmental impacts (e.g. Wang et al. 2011, Pishvae and Razmi 2012, Chaabane et al. 2012, Accorsi et al. 2014, Chen et al. 2017, Garg et al. 2015, Nurjanni et al. 2017), or maximizing social benefits (e.g. Pishvae et al. 2010, Devika et al. 2014, Govindan et al. 2016, Nguyen et al. 2016, Kadambala et al. 2016, Soleimani et al. 2017). To help decision makers find a trade-off among several objectives, multi-objective optimization models and methods have to be introduced to model and solve the corresponding problems. In the following subsections, we recall the principles of multi-objective optimization, its solution methods and related performance indicators.

2.3.1 Principles

Notice that an objective function in maximization form can be transformed into a minimization one by adding a minus sign. Thus, without loss of generality, a multi-objective optimization problem (MOOP) can be expressed as follows (model P).

$$P: \text{Minimize } F(x) = \{f_1(x), f_2(x), \dots, f_n(x)\}$$

$$s.t. \quad x \in R$$

where x is decision variable vector and R represents feasible solution space; $f_1(x)$, $f_2(x)$, ..., $f_n(x)$ are the n objectives that need to be optimized, simultaneously.

Generally speaking, objectives in a MOOP are usually conflicting with each other, making it impossible to generate a single optimal solution that simultaneously optimizes all the objectives. Getting one objective improved usually cannot avoid deteriorating other ones, the decision makers (DMs) may therefore prefer to be provided with alternative solutions and select a most

preferred one. In the following, we present the definitions of multi objective optimization, which can be found in most MOOP references (e.g. Bérubé et al. 2009).

Definition 2.1: For any two solutions x_1 and $x_2 \in R$, x_1 is said to dominate x_2 , denoted as $x_1 \succ x_2$ such that $f_i(x_1) \leq f_i(x_2)$ for $i \in \{1, 2, \dots, n\}$ in which at least one strict inequality holds.

Definition 2.2: For a feasible solution $x^* \in R$, we say x^* is a non-dominant solution or Pareto optimal solution when no $x \in R$ exists such that $x \succ x^*$. Accordingly, $F(x^*)$ is called non-dominated point or Pareto point.

Definition 2.3: All non-dominated points constitute the MOOP's Pareto front.

For a bi-objective optimization problem (BOOP) which is a subclass of MOOP, two special points in the feasible objective space, namely Ideal point (f_1^I, f_2^I) and Nadir point (f_1^N, f_2^N) are often used to determine the range of a BOOP's Pareto front. They can be computed by exactly solving the following four single objective problems (e.g. Bérubé et al. 2009).

$$f_1^I = \min_{x \in R} f_1(x)$$

$$f_2^I = \min_{x \in R} f_2(x)$$

$$f_1^N = \min_{x \in R} f_1(x) \text{ subject to } f_2 = f_2^I$$

$$f_2^N = \min_{x \in R} f_2(x) \text{ subject to } f_1 = f_1^I$$

An example of the Pareto front, Ideal and Nadir points for a BOOP are depicted in Fig. 2.9. It is observed from Fig. 2.9 that the Pareto front is within a rectangle area (represented by dashed lines) bounded by (f_1^I, f_2^I) and (f_1^N, f_2^N) (Haimes et al. 1971). And (f_1^I, f_2^N) and (f_1^N, f_2^I) are two extreme Pareto points of the BOOP.

2.3.2 Solution methods

In general, weighting method and ε -constraint method are two of the most widely used methods in solving MOOPs. The weighting method converts a multi-objective problem into a single-objective one by assigning a weight to each objective. Through solving the MOOP by changing the weight of each objective function, a series of Pareto optimal solutions can be obtained. However, the weighting method has several drawbacks (Ripon et al. 2011): 1) it is difficult to determine

appropriately the weight for each objective function; 2) only one Pareto optimal solution generated in one run; 3) as all the objective functions are added up linearly, this method is difficult to find the Pareto optimal solutions that the

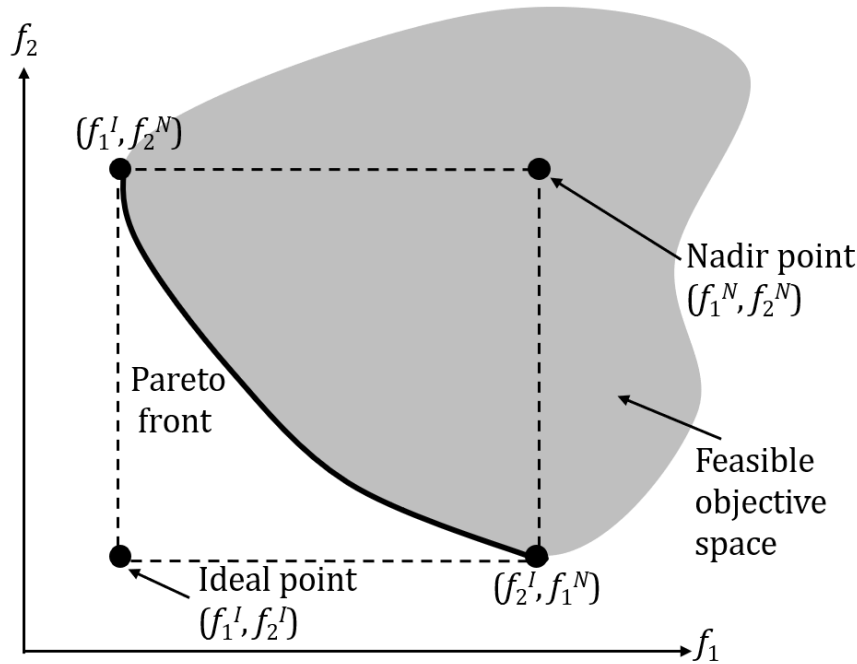


Fig. 2.9 Illustration of the Pareto front, Ideal and Nadir points of a BOOP

function objectives cannot be represented in linear form; 4) different combinations of weights may result in a same Pareto optimal solution.

The ε -constraint method was originally proposed by Haimes et al.(1971). Its basic idea is to retain only one primary (or the most preferred) objective function and transform the others into constraints, i.e. the so-called ε -constraints, to form a series of single objective ε -constraint problems. Exactly solving these ε -constraint problems allows to obtain the Pareto front of the BOOP. The method can overcome the drawbacks of the weighting method, thus receiving a large number of researchers' attentions, e.g. Bérubé et al., (2009), Mavrotas (2009), Mota et al. (2014), Wu et al. (2015), Cheng et al. (2016), Bagherinejad and Hassanpour 2016, Nguyen et al. 2016, Cheng et al. (2017), Tosarkani et al. (2018), Li et al. (2019a), etc.

With ε -constraint method framework, the model of a bi-objective P can be transformed into a series of ε -constraint problems, denoted as $P(\varepsilon)$ as follows if f_1 is selected as the primary objective:

$$\begin{aligned}
 P(\varepsilon): \quad & \text{Minimize } f_1(x) \\
 & \text{s.t.} \quad f_2(x) \leq \varepsilon
 \end{aligned}$$

$$x \in R$$

where ε is a parameter belonging to the interval $[f_2^l, f_2^N]$. A step size Δ is then necessary to be determined to progressively reduce the value of ε from f_2^N to f_2^l . Thus a sequence of single ε -constraint problems is formed. Exactly solving each ε -constraint problem allow to obtain all Pareto optimal solutions of P and the corresponding Pareto front.

Based on the manner to determine the value of Δ , the ε -constraint method falls into two categories: the equidistant ε -constraint method and the exact (or standard) ε -constraint method (Özlen and Azizoglu 2009, Wu et al. 2015, Cheng et al. 2016, Jindal and Sangwan 2016, Sáez-Aguado and Trandafir 2017).

The equidistant ε -constraint method divides the range of ε , i.e. $[f_2^l, f_2^N]$ into L equal sub-intervals, where L is a predetermined number. In this case, Δ can be computed by the formula $\Delta = (f_2^N - f_2^l) / L$ and the value of ε_l is set as the upper limit of each sub-interval that can be obtained by the following formula $\varepsilon_{l-1} - \Delta$, $l = 1, 2, \dots, L$, where $\varepsilon_0 = f_2^N$. Then $P(\varepsilon_l)$ is formed and solved at the l -th iteration of ε -constraint method. The advantage of the equidistant ε -constraint method lies in that it is able to control the number of iterations of the method and generate a limited number of Pareto optimal solutions. This method has been widely studied by many researchers (e.g. Jozefowicz et al. 2007, Tricoire et al. 2012, Zhou et al. 2013, etc.).

As to the exact ε -constraint method, the value of ε at the l -th iteration are computed by the formula $\varepsilon_l = f_2(x^{(l-1)*}) - \Delta$, $l = 1, 2, \dots, L$, where $x^{(l-1)*}$ represents optimal solution of $f_2(x)$ at the $(l-1)$ -th iteration, where $f_2(x^{0*}) = f_2^N$, and Δ is a predetermined step size. Exactly solving all $P(\varepsilon_l)$ allows to obtain the Pareto front. Existing works such as Bérubé et al. (2009) and Stidsen et al. (2014) set Δ as 1 for the problems with integer objectives. Wu et al. (2015) proposed a more general way to it, i.e. the minimum unit value of f_2 . Their method can be applied to integer programming or linear programming. The procedure of the exact ε -constraint method is outlined in algorithm 2.1.

Algorithm 2.1. Procedure of the exact ε -constraint method for BOOP

Compute the Idea and Nadir points, i.e. (f_1^l, f_2^l) , (f_1^N, f_2^N) of P .

Set $\Omega = \{(f_1^l, f_2^N), (f_1^N, f_2^l)\}$ and let $\varepsilon_l = f_2^N - \Delta$.

While $(\varepsilon_l > f_2^l)$, **do:**

Exactly solve $P(\varepsilon_l)$ to obtain an optimal solution x^*

Calculate the corresponding objective vector $(f_1^l(x^*), f_2^l(x^*))$

set $\Omega = \Omega \cup (f_1^l(x^*), f_2^l(x^*))$

Let $\varepsilon_{l+1} = f_2^l(\varepsilon_l) - \Delta$

$l = l+1$.

End while

Remove dominated points from Ω if exist and return Ω .

Note that the exact ε -constraint method can generate accurate Pareto front, thus it is very popular among researchers to solve BOOPs (Mavrotas 2009, Bérubé et al. 2009, Filippi and Stevanato 2013, Grandinetti et al. 2010, Wu et al. 2015, Cheng et al. 2016, Sáez-Aguado and Trandafir 2017). The disadvantages of the method are time-consuming, especially for large-sized NP-hard BOOP. One way to conquer the drawbacks is to employ heuristics/metaheuristics to efficiently generate an approximate Pareto front, denoted as AF , instead of the Pareto-optimal set (Filippi et al. 2016). Various algorithms exist in solving MOOPs, performance indicators are necessary to evaluate the quality of the obtained approximation Pareto front.

2.3.3 Performance evaluation

The solution quality of a single objective optimization problem can be evaluated by its lower or upper bounds. Whereas in BOOPs, the quality assessment of an approximate Pareto front is more complex to be assessed that need additional knowledge such as a reference set (RS) (Zitzler et al. 2008). A variety of performance indicators (PIs) has been proposed in the literature to evaluate algorithms for multi-objective optimization problems (Knowles and Corne 2002, Zitzler et al. 2003, and Okabe et al. 2003). In the following, we present several widely used ones including the cardinality, the hypervolume ratio, the spacing and the diversity. For the sake of simplicity and clarity, the following discussions in this subsection are based on BOOPs with two-dimensional objective space.

2.3.3.1 Cardinality

Let $|AF|$ and $|RS|$ represent the number of non-dominant points in AF and in a reference Pareto point set RS that can be an exact or approximate Pareto front,

respectively. If $|AF| > |RS|$, AF is then better than RS from the view of cardinality. To increase its assessment performance, many variants based on cardinality have been proposed. Divers cardinalities are proposed for performance evaluation of approximate Pareto front, such as Q_{AF} (Jaszkiewicz 2004, and Filippi et al. 2016), error ratio (Veldhuizen 1999, Veldhuizen and Lamont 1999) and ratio of the reference points found (Czyzzak and Jaszkiewicz 1998, Hansen and Jaszkiewicz 1998). Among others, Q_{AF} measures the approximated points in AF that are not dominated by any point in RS , which is computed as follows.

$$Q_{AF} = \frac{|\{(\omega, \varphi) \in AF: \nexists (\tau, \gamma) \in RS \text{ such that } (\tau, \gamma) \text{ dominates } (\omega, \varphi)\}|}{|AF|}$$

The larger is Q_{AF} , the better is the quality of AF . Cardinality are simple from the perspective of computation. The drawback of them lie in that they do not contain any information about the accuracy and distribution of these non-dominated points.

2.3.3.2 Hypervolume ratio

Hypervolume ratio (Zitzler and Thiele 1998a, b), denoted as HR , is a volume-based indicator that measures the accuracy of AF . Hypervolume H_{AF} means the area size of H_{AF} . As shown in Fig. 2.10, each point in AF forms a rectangular area with respect to a reference point (generally the Nadir point). H_{AF} represents the cumulative area of all these rectangles. The larger the value of the hypervolume, the better is the Pareto front. The hypervolume ratio HR between AF and RS can be calculated by $HR = H_{AF}/H_{RS}$. It is obvious that if $HR > 1$, the quality of AF is better than that of RS .

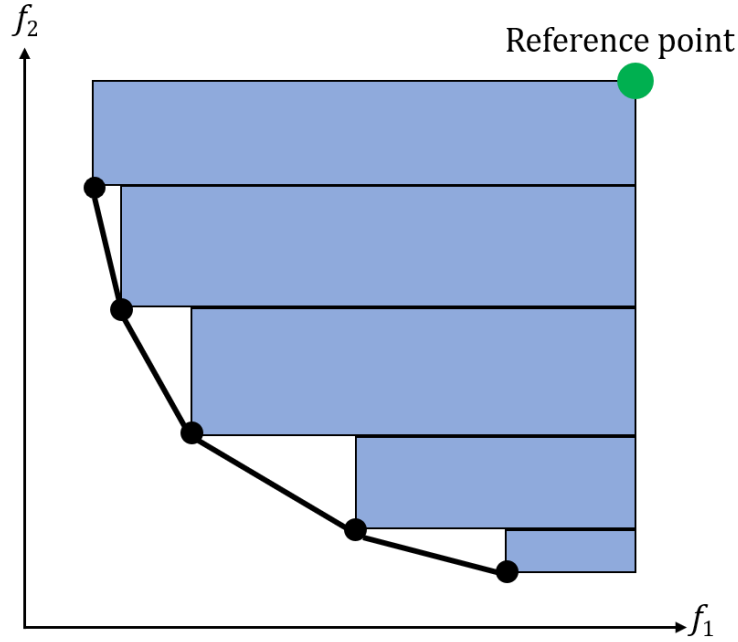


Fig. 2.10 Hypervolume indicator (Demir et al. 2013)

2.3.3.3 Spacing

Spacing metric (S), proposed by Schott (1995), aims to provide information about the distribution of the points in the obtained AF . It is defined as:

$$S = \sqrt{\frac{1}{|AF| - 1} \sum_{i=1}^{|AF|} (d_i - \bar{d})^2}$$

Where $d_i = \min_{x^i \in AF, x^i \neq x^j} \{|f_1(x^i) - f_1(x^j)| + |f_2(x^i) - f_2(x^j)|\}$, \bar{d} is the mean of all $d_i, i=1, 2, \dots, |AF|$, and x^i represents the i -th solution vector that corresponds to the objective vector in AF . This metric is able to well indicate how evenly the points are distributed on the obtained front (Tan et al. 2006, Raisanen and Whitaker 2005). Note that $S = 0$ implies all points on the Pareto front are equidistantly spaced in the solution space. However, the spacing only uses the non-sorted shortest distance from each point and it may be misleading in some cases. Please see the details in Okahe et al. (2003). Thus, Deb et al. (2000) proposed a more natural distributed-based metric S' . It is computed by:

$$S' = \sum_{i=1}^{|AF|-1} \frac{|d_i - \bar{d}|}{|AF| - 1}$$

Where d_i represents the Euclidean distance between consecutive solutions in AF . With a number of $|AF|$ points, there are $(|AF| - 1)$ consecutive distances. \bar{d} is an average of all $d_i, i= 1, 2, \dots, (|AF| - 1)$. According to Deb et al. (2000), S' is able to reflect the distribution of the points correctly. The drawback is it cannot be extended for MOOPs with more than two objectives due to the involved consecutive sorting.

2.3.3.4 Diversity

Later, Deb (2001) extended the distributed measure S' with spread information to form a diversity indicator denoted as Δ .

$$\Delta = \frac{d_m + d_n + \sum_{i=1}^{|AF|-1} |d_i - \bar{d}|}{d_m + d_n + (|AF| - 1)\bar{d}}$$

where d_m (resp. d_n) is the Euclidean distance between the upper (resp. lower) limit point of the obtained Pareto front and the upper (resp. lower) extreme point of a true Pareto front, respectively. The distances in the above equation are shown in Fig. 2.11. Note that a good distribution set would make all d_i equal to \bar{d} and would make $d_m = d_n = 0$ if extreme points in the nondominated set exist. In this case the value of Δ would be 0, which indicates a most widely and uniformly spread-out set of nondominated points. For any other cases, the value of Δ would be greater than 0.

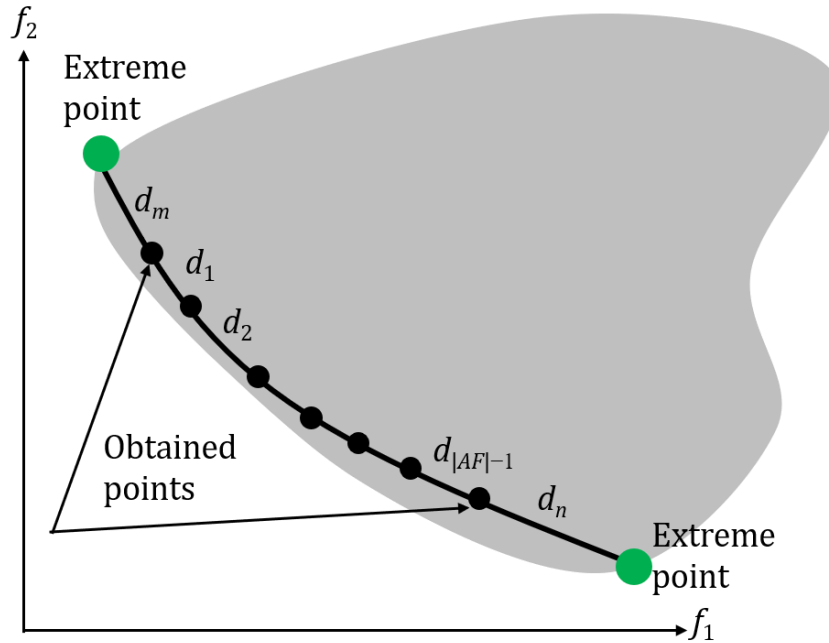


Fig. 2.11 Diversity indicator (Deb et al. 2002)

To sum up, each metric has its pros and cons and can only provide partial information of the solution quality. Thus, it is improper to evaluate the performance of a MOOP algorithm by solely one indicator. In chapter 4 of the thesis, ϵ -constraint method and some of these indicators are applied to assess the proposed method for the bi-objective CLFSC problems with RTIs.

2.4 Conclusion

In this chapter, we reviewed the closed-loop supply chain problems, the solution methods for the problem and multi-objective optimization problem, respectively. The studied problem is hard to solve due to the integrated production, inventory, distribution and routing decisions. Based on the literature review, it is found that 1) the majority of studies on CLSC focus on industrial product CLSC while food CLSC draws much less attention despite its widely application in practice; 2) CLSC with RTIs has just started to enjoy popularity in recent decades and RTI in food CLSC has been rarely studied, and 3) while environment issues are widely studied in FSC and RSC, they are not frequently investigated in the context of CLSC. In light of the above observations, this thesis tries to cope with the following three problems by proposing new models and effective solutions:

1) A single-objective multi-period closed-loop food supply chain with RTIs (CLFSC-RTI) that involves a single manufacturer and a single retailer. The CLFSC-RTI takes into consideration food quality level, dynamic customer demand and limited RTI purchasing budget.

2) A bi-objective CLFSC-RTI (BCLFSC-RTI) that includes a single manufacturer and multiple retailers. In the BCLFSC-RTI, economic and environmental objectives are simultaneously addressed.

3) A closed-loop inventory routing problem with RTIs (CFIRP-RTI) that integrated with vehicle routing decisions and considers heterogenous RTIs. RTIs of different types possess different production protective levels.

Chapter 3

Single-retailer Closed-loop Food Supply Chain with RTIs

3.1 Introduction

As stated in Chapter 2, food perishability greatly impacts the food supply chain performance. Moreover, aiming to reduce packaging waste and provide better protection for packed food, RTIs are increasingly adopted in closed-loop food supply chain (CLFSC). As RTIs are nowadays regarded as important assets by companies in many industries, providing a budget on purchasing RTIs is one of the conditions to ensure a rapid food distribution. Besides, due to limited production and transportation capacities and RTI's occasionally stock-out, outsourcing is an important way to guarantee customer satisfaction. Up to now, CLFSC problem with RTIs (CLFSC-RTI) is rarely studied and CLFSC-RTI with food quality, outsourcing and RTI purchasing budget consideration has not been investigated yet. As a beginning work, this chapter aims to investigate a multi-period single-objective CLFSC-RTI that focus on coordinating the flows of fresh food products and returnable containers (a kind of RTIs) including a single manufacturer and a single retailer. Based on the literature review, several existing researches are closely related to the studied CLFSC-RTI in this chapter. Table 3.1 differentiates the presented CLFSC-RTI from them in several important characteristics.

Table 3.1. Comparison of the CLFSC-RTI with relevant research

Article	Finished product type	Product quality consideration	Demand pattern	Outsourcing consideration	RTI purchase budget	Model type	Method
Glock and Kim (2014)	IP	No	C	No	No	Non-linear model	Exact algorithm
Kim et al. (2014)	FP	Yes	C	No	No	Non-linear model	Simulation
Glock and Kim (2015)	IP	No	C	No	No	Non-linear model	Simulation
Glock and Kim (2016)	IP	No	C	No	No	Non-linear model	LINGO
Hariga et al. (2016)	FP	No	C	No	No	MINLP model	Exact algorithm
Zhang et al. (2016)	FP	Yes	D	No	No	MILP model	CPLEX

This problem	FP	Yes	D	Yes	Yes	MILP model	Heuristic
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Note: IP is for industrial product, FP is for food product, C is for constant, D is for deterministic and dynamic

The considered problem integrates both forward supply chain of product production, distribution and transportation, and the reverse chain of containers return. Dynamic customer demand, food quality level, food outsourcing and RTI purchasing budget are considered. The objective is to propose an integrated planning for the CLFSC-RTI over a finite planning horizon to maximize the total profit of the holistic supply chain. The problem consists of determining for each period: (i) the production quantities and outsourcing quantities, (ii) the inventory quantities at the manufacturer and retailer, (iii) the delivery quantities from the manufacturer to the retailer, (iv) the amount of containers used, returned and purchased, and (v) the number of vehicles used. The problem is first formulated as a novel MILP and its complexity is proved as NP-hard. Then, an improved kernel search-based heuristic (IKSH) is developed to efficiently find its near-optimal/optimal solution. To evaluate the IKSH's performance, one of the promising MIP based heuristics being widely used in the literature namely relax-and-fix is adapted to solve the proposed model. A real case study deriving from a food manufacturer located in eastern China is conducted to illustrate the applicability of the proposed model and method. The simulation results show that the profit of the company could be increased by more than 10% with our method compared to its current practice. Furthermore, numerical results on 130 generated instances demonstrate that the proposed IKSH can provide high-quality solutions with an average gap of 0.20%. And the proposed IKSH only spends 13.36% and 22.16% average computation time of that spent by the state-of-the-art commercial solver CPLEX and that by the relax-and-fix (RF)-based heuristic, respectively.

The remainder of this chapter is organized as follows. Section 3.2 describes and formulates the studied CLFSC-RTI. Section 3.3 presents an IKSH for its resolution. In Section 3.4, computational results on a real case study and 130 randomly generated instances are reported. And sensitivity analysis is also performed. Section 3.5 concludes the chapter.

3.2 Problem description and formulation

3.2.1 Problem description

The proposed MILP model is based on a real case from a food manufacturer located in Zibo city, eastern China. To make it representative for different practical cases, we describe the problem in a generalized way hereafter. Fig. 3.1 presents the flowchart and main decision variables of the studied food CLSC. It includes a manufacturer and a retailer. A finite multi-period planning horizon is considered. Perishable foods are produced at the manufacturer, and identical returnable containers are used to pack them. New containers need to be purchased if current inventory is insufficient. The filled containers are shipped by a homogenous fleet vehicle to the retailer to satisfy customers. Note that quality levels of the perishable products decrease over periods if they are stored as inventory instead of being sold immediately. After foods are unloaded at the retailer, the emptied containers stay at least one period for being washed and repaired (if necessary). Meanwhile, the vacant vehicles ship back available emptied containers from the retailer to the manufacturer for reuse. If the current container inventory at the retailer exceeds the total capacity of available vehicles, the surplus containers continue remaining as inventory and wait to be returned in future periods.

Assumptions for model building are as follows:

- Without loss of generality, the initial container and product inventory at the manufacturer and the retailer are considered as 0.
- Term “age” is used to index the quality level of perishable products. It is assumed to belong to a discrete set $\{0, 1, 2, \dots, G\}$ where 0 represents newly produced products, and they are spoiled after their ages exceed $|G|$. The age increases by one unit along with products deteriorating over each period. Product of better quality (smaller age) has higher prices and that of less good quality (larger age) has lower prices. Note that if we set selling prices for products of several adjacent ages to be the same, it can be regarded as stepwise deterioration.
- Customers would accept products of different ages with different prices.
- The manufacturer has a limited production capacity whereas an unlimited inventory capacity. The retailer’s inventory capacity is limited.

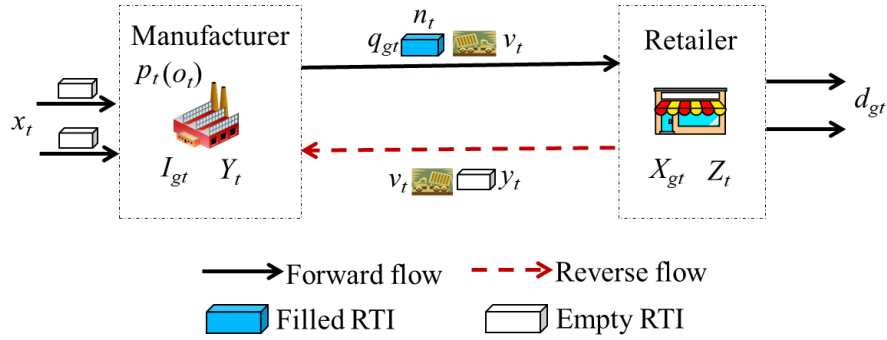


Fig. 3.1. Flowchart of the CLFSC-RTI

- Customer demand can be outsourced if the production capacity or available containers are insufficient.
- Backlogging and shortage are not allowed.
- Budget for container purchasing at the manufacturer is available.
- Fixed and variable costs related to production and transportation are considered.

Note that most of the above assumptions are in line with those in Li et al. (2016), Kim et al. (2014) and Coelho and Laporte (2014). The objective of the problem is to maximize the total profit of the CLFSC-RTI by optimally determining the quantity of food production and outsourcing, the quantity and quality level of products delivered, stored and satisfied the customers, the number of containers used, returned and purchased, and the number of vehicles used throughout the planning horizon.

3.2.2 Model formulation

We give the following notation before problem formulation:

Indices

T set of periods, indexed by $t, t=1, 2, \dots, |T|$

G set of product quality, indexed by $g, g=0, 1, 2, \dots, |G|$

Parameters

C_t production capacity in period t

Cap_1 product inventory capacity in terms of product at the retailer

Cap_2 container inventory capacity in terms of container at the retailer

C^C container capacity in terms of product

C^V vehicle capacity in terms of container

V	number of vehicles owned by the manufacturer
sc_t	production set-up cost in period t
c_t	unit production cost in period t
oc_t	unit product outsourcing cost in period t
h_1	unit product holding cost at the manufacturer
h_2	unit product holding cost at the retailer
h_3	unit container holding cost at the manufacturer
h_4	unit container holding cost at the retailer
c^p	unit purchasing cost for container
f	fixed transportation cost per vehicle
c^l	transportation cost per loaded container
c^e	transportation cost per empty container
d_t	demand at the retailer in period t
s_g	selling price of the product with quality $g \in G$ at the retailer
B	budget for purchasing containers
s	a number very close to 1 but not equal to 1

Decision variables

p_t	production quantity in period t
o_t	outsourcing quantity in period t
q_{gt}	quantity of products with quality g delivered to the retailer in period t
d_{gt}	quantity of products with quality g demanded at the retailer in period t
I_{gt}	inventory level of product with quality g at the manufacturer at the end of period t
X_{gt}	inventory level of product with quality g at the retailer at the end of period t
Y_t	container inventory level at the manufacturer at the end of period t
Z_t	container inventory level at the retailer at the end of period t
x_t	number of new containers purchased in period t
n_t	number of containers used for packing products to the retailer in period t
v_t	number of trucks used for shipping the products to the retailer in period t
y_t	number of containers returned in period t
w_t	$w_t = \begin{cases} 1, & \text{if production is needed in period } t \\ 0, & \text{otherwise} \end{cases}$

Model P:

Objective function

$$\begin{aligned}
\text{Maximize } z = & \sum_{g \in G} \sum_{t \in T} d_{gt} \cdot s_g - \sum_{t \in T} (sc_t \cdot w_t + p_t \cdot c_t + o_t \cdot oc_t) \\
& - \sum_{t \in T} x_t \cdot c^p - \sum_{g \in G} \sum_{t \in T} (h_1 \cdot I_{gt} + h_2 \cdot X_{gt}) - \sum_{t \in T} (h_3 \cdot Y_t + h_4 \cdot Z_t) \\
& - \sum_{t \in T} (f \cdot v_t + c^l \cdot n_t + c^e \cdot y_t)
\end{aligned} \tag{3.1}$$

subject to

$$p_t \leq C_t \cdot w_t, \forall t \in T \tag{3.2}$$

$$I_{0t} = p_t - q_{0t}, \forall t \in T \tag{3.3}$$

$$I_{gt} = I_{g-1,t-1} - q_{gt}, \forall t \in T, g \in G \setminus \{0\} \tag{3.4}$$

$$X_{0t} = q_{0t} - d_{0t}, \forall t \in T \tag{3.5}$$

$$X_{gt} = X_{g-1,t-1} + q_{gt} - d_{gt}, \forall t \in T, g \in G \setminus \{0\} \tag{3.6}$$

$$\sum_{g \in G} X_{gt} \leq Cap_1, \forall t \in T \tag{3.7}$$

$$\sum_{g \in G} d_{gt} + o_t = d_t, \forall t \in T \tag{3.8}$$

$$\sum_{g \in G} q_{gt} \leq C^C \cdot n_t, \forall t \in T \tag{3.9}$$

$$Y_t = Y_{t-1} + y_{t-1} - n_t + x_t, \forall t \in T \tag{3.10}$$

$$Z_t = Z_{t-1} + n_{t-1} - y_t, \forall t \in T \tag{3.11}$$

$$Z_t \leq Cap_2, \forall t \in T \tag{3.12}$$

$$\sum_{t \in T} x_t \cdot c^p \leq B \tag{3.13}$$

$$n_t \leq C^V \cdot v_t, \forall t \in T \tag{3.14}$$

$$n_t \geq C^V \cdot (v_t - s), \forall t \in T \tag{3.15}$$

$$y_t \leq C^V \cdot v_t, \forall t \in T \tag{3.16}$$

$$v_t \leq V, \forall t \in T \tag{3.17}$$

$$w_t \in \{0,1\}, \forall t \in T \tag{3.18}$$

$$I_{gt}, X_{gt}, p_t, o_t, d_{gt}, q_{gt} \geq 0, \forall t \in T, g \in G \quad (3.19)$$

$$x_t, n_t, y_t, Y_t, Z_t, v_t \geq 0 \text{ integer}, \forall t \in T \quad (3.20)$$

The objective is to maximize the total profit of the holistic food CLSC which is the total revenue minus the total costs. The total revenue is the multiplication of product quantity that satisfies the customer by production and the corresponding selling price. The total costs consist of product production and outsourcing costs, container purchasing cost, product and container transportation and inventory costs. Constraint (3.2) restricts that production in any period cannot exceed its capacity. It also implies that $p_t=0$ if $w_t=0$ for $\forall t \in T$. Constraints (3.3) and (3.4) represent the product inventory balance constraints and the aging of products at the manufacturer. Constraints (3.5) and (3.6) are the product inventory balance constraints and the aging of products at the retailer. Constraint (3.7) shows the inventory capacity at the retailer must be respected. Constraint (3.8) restricts that the demand of the customer is satisfied by the sum of the production and outsourcing amount. Constraint (3.9) requires that delivery quantity respects available container capacity in each period. Constraints (3.10) and (3.11) guarantee the container flow balance at the manufacturer and the retailer, respectively. Constraint (3.12) means that the container inventory capacity at the retailer must not be exceeded. Constraint (3.13) guarantees the container purchasing budget needs to be respected. Constraints (3.14) and (3.15) present the relationship between filled containers and vehicles used in the forward flow, where s is a small number that is very close to 1 but not equal to 1 to guarantee that no empty vehicles can go to the retailer side in the forward flow. Note that the quantity of containers that can be returned in each period is limited by the total capacity of the vehicles in the forward flow of that period. Constraint (3.16) shows the relationship between the number of returned containers and vehicles used in the reverse flow. Constraint (3.17) represents the vehicle capacity cannot be exceeded. Constraints (3.18) – (3.20) are binary, non-negativity and integrality constraints for the decision variables.

The complexity of the considered problem is proved as follows. If the transportation cost and container related costs are negligible, finished products do not deteriorate and outsourcing is not allowed, the proposed problem can be equivalent to the capacitated lot-sizing problem, which is known to be NP-hard (Florian et al. 1980). Therefore, the studied problem is also NP-hard. Due to the

NP-hardness of the problem, the existing optimization solver, e.g. CPLEX, is usually inefficient especially for medium- and large-size problems. More precisely, it often runs several days without finding a good/feasible solution or end with out of memory according to preliminary experiments. However, in practice, complex planning decisions may have to be made within a short amount of time, such as the first hour of the first shift on the day (Castillo and Cochran 1996). In addition, the planning of actual operations needs to be re-adjusted and updated according to different input parameters that largely affect the computation efficiency of our problem (see sensitivity analysis section). Therefore, efficient algorithm needs to be developed for the problem.

3.3 Improved kernel search heuristic

Due to that the considered CLFSC-RTI in the current chapter belongs to combinatorial optimization problem and we observe that the values of integer (non-binary) and real-valued variables in the proposed model are highly dependent on those of binary variables. Thus, an improved kernel-search based heuristic (IKSH) is developed as the resolution for the CLFSC-RTI. In this section, we introduce the developed IKSH.

In light of the basic idea of KS heuristic introduced in Chapter 2. The initial kernel size of K_0 is one of the key parameters that affect the performance of kernel search heuristic. In the existing studies, e.g. Angelelli et al. (2012), Wu et al. (2016), etc., K_0 is constructed by all the binary variables having value 1 in its LP solution, as these variables are more promising to take value 1 in the optimal solution of the original problem. But preliminary experiments show that few or even no binary variables take value 1 in the LP solution of our problem. Consequently, the extant method to form K_0 is not applicable. Thus, to form the initial RMILP₀ that can be solved efficiently and provide a good lower bound for the iteration phase, we propose in the following a new policy to form the initial kernel K_0 and buckets $\{B_i\}$, $i=1, \dots, m$, for our problem. The policy is based on a large amount of preliminary tuning experiments and the characteristics of the studied problem.

In the LP solution, binary variables having positive values are sorted in non-increasing order of their values and those having values 0 in non-decreasing order of their reduced costs. We denote $|K_0|$ as the number of variables in the initial kernel. It is chosen from range $(N/2-\eta, N/2)$ with equal probability, where N is

the number of relaxed binary variables, $0 \leq \eta < N/2$ is an appropriate value related to N . Then the first $|K_0|$ variables constitute the initial kernel K_0 . It is worth noting that the constructed K_0 should be big enough to include more promising variables such that it can provide high-quality solutions. Also, it should be small enough such that the formed RMILP can be efficiently solved. After determining the initial kernel, the remaining variables are divided into $m := \lceil (N - |K_0|)/L \rceil$ disjoint ordered buckets, where L is the length of each bucket (the last one may be smaller than L).

Based on the above policy to determine initial kernel and buckets. The IKSH of our problem is described as follows: let $LP(P)$ be a linear relaxation of model P in section 3.2.2 via relaxing the production setup binary variables $w_t, t \in T$. In the first phase, $LP(P)$ is optimally solved, and the variables w_t having positive values in LP solution are sorted in non-increasing order of their values and those having values 0 in non-decreasing order of their reduced costs. Then the first $|K_0|$ variables constitute the initial kernel K_0 . Here, $|K_0|$ is generated from range $(\lfloor |T|/2 - \eta, \lfloor |T|/2 \rfloor)$ with equal probability, where $0 \leq \eta < |T|/2$, $|T|$ is the number of periods. And m disjoint ordered buckets are formed by $m = \lceil (|T| - |K_0|)/L \rceil$. In the first phase of IKSH, the initial restricted problem, denoted by $RMILP_0$, is formulated with K_0 as follows:

$$\begin{aligned} \text{RMILP}_0: \quad & \text{Maximize } z_0 \\ \text{s.t.} \quad & \text{Constraints (3.2) - (3.20)} \\ & w_t = 0, \forall w_t \notin K_0 \end{aligned} \tag{3.21}$$

where constraint (3.21) restrains binary variables of $RMILP_0$ to K_0 by fixing $w_t=0$ for all $w_t \notin K_0$. Let z_0^* be the objective function value of $RMILP_0$. The values of the variables in K_0 are fixed to their optimal values of after solving the $RMILP_0$.

In the second phrase, m RMILPs are iteratively formed and solved. More specifically, at the i -th iteration, $i=1, \dots, m$, the problem $RMILP_i$ restricted with variables in subset $K_i \cup B_i$, denoted as $RMILP_i$ is formed as follows:

$$\begin{aligned} \text{RMILP}_i: \quad & \text{Maximize } z_i \\ \text{s.t.} \quad & \text{Constraints (3.2) - (3.20)} \\ & w_t = 0, \forall w_t \notin K_i \cup B_i \end{aligned} \tag{3.22}$$

$$\sum_{w_t \in B_i} w_t \geq 1 \tag{3.23}$$

$$z_i \geq z_{i-1}^* \tag{3.24}$$

where constraint (3.22) restricts the binary variables of $RMILP_i$ to $K_i \cup B_i$. Constraints (3.23) and (3.24) are added to reduce computation time. Specifically,

constraint (3.23) assures that at least one new period is selected as production period in B_i . Constraint (3.24) sets the lower bound for RMILP_i as a cut-off value. By the addition of (3.23) and (3.24), if the consequent RMILP_i is feasible, the current objective value z_i^* will be improved and the actual kernel K_i will be updated by introducing into at least one new set-up period.

For K_i updating, we have the following formula:

$$K_i = K_{i-1} \cup (B_{i-1} \setminus B_{i-1}^-) \text{ for } i=2, \dots, m+1, \quad (3.25)$$

Where B_{i-1}^- is composed by all the w_t equals to 0 in B_{i-1} in the solution of RMILP_{i-1} . Then the values of variables that newly added to kernel K_{i-1} , i.e. variables in $B_{i-1} \setminus B_{i-1}^-$ are fixed to 1.

The improved KS heuristic (IKSH) can be summarized in Algorithm 3.1.

Algorithm 3.1 The proposed IKSH

The first phase: Initialization phase

Step 1: Optimally solve LP of the original problem by relaxing $w_t, t \in T$.

Step 2: Sort w_t with predefined sorting criterion.

Step 3: Form K_0 by the first $|K_0|$ variables and $m = \lceil (|T| - |K_0|) / L \rceil$ disjoint ordered buckets.

Step 4: Solve RMILP_0 , output the objective function z_0^* if feasible and then fix the variables in K_0 to their solution values.

The second phase: Iteration phase

Step 5: Set $i := 1$;

while $i \leq m$, **do**:

Step 5.1: Solve RMILP_i with w_t in subset $K_i \cup B_i$ and if feasible, update z_i^* ;

Step 5.2: Update K_i according to (3.25);

Step 5.3: Fix the variables in $B_{i-1} \setminus B_{i-1}^-$ to 1.

$i := i+1$.

End while

Step 6: Output z_m^* and the solution of RMILP_m .

3.4 Computational results

In this section, the real case derived from a food manufacturer is presented to illustrate the applicability of the proposed model and method. 130 instances are randomly generated and solved to evaluate the proposed IKSH by comparing with and relax-and-fix (RF) algorithm and CPLEX solver. Sensitivity analysis is also

conducted to better understand the impact of parameters on the performance of the proposed model and algorithm. The proposed model and algorithm are implemented in C++ code on a HP PC with 2GHz CPU and 12GB RAM. The LP and RMILPs in Algorithm 3.1 and the subproblems in RF method are solved by ILOG CPLEX (version 12.6.0).

IBM ILOG CPLEX is one of the best commercial software for MILP problems (Angelelli et al. 2012). It uses branch-and-cut procedure, i.e., a combination of a cutting plane method and a branch-and-bound algorithm. A mass of literature has employed it to solve MILP problems and the computation results are used to compare with those obtained by the developed algorithm (see e.g. Angelelli et al. 2012 and Wu et al. 2016). Thus, CPLEX is chosen as a reference to evaluate the performance of the developed algorithm.

Note that via preliminary experiments, the parameter MIPEmphasis of CPLEX is set to “BESTBOUND” when it is used to solve the instances. The MIPEmphasis parameter is used to control trade-offs between speed, feasibility, optimality, and moving bounds in MIP. The corresponding values to the available setting options, i.e. Balance optimality and feasibility (default), Emphasize feasibility over optimality, Emphasize optimality over feasibility, Emphasize moving best bound, Emphasize finding hidden feasible solutions, are 0, 1, 2, 3, 4, respectively. To observe the performance of the solver under different MIPEmphasis parameter settings, we have conducted experiments for each setting. The results are shown in Tables 3.2–3.4. Note that figures in the brackets indicate the number of instances in each problem set that cannot be solved to optimality within 3600s. Regarding the results, we find the best setting for our problem, i.e. moving best bound. The advantage is most obvious for the medium-scale instances where the computational time is reduced by 33.7%, followed by a 9.2% reduction for the large-scale instances. And, it is observed that the objective function of only 16 out of 130 instances obtained with Emphasis 3 have minor deteriorations of solution quality compared with the default setting. That means moving the best bound can eventually discover the optimal feasible solution faster for the studied problem.

Table 3.2. Computational results for small-scale instances under different MIPEmphasize settings

Set	T	G	0	1	2	3	4
1	10	3	0.198	0.216	0.172	0.175	0.172
2	20	3	0.484	0.319	0.438	0.893	0.541
3	30	3	0.847	364.292	0.878	1.928	0.891
4	40	3	1.276	733.744(1)	1.509	3.162	2.140
5	50	3	4.298	1444.05(2)	6.705	3.464	5.089
6	10	5	0.194	0.187	0.188	0.216	0.181
7	20	5	0.432	0.347	0.375	0.588	0.616
8	30	5	1.409	743.299(1)	1.924	2.013	1.515
9	40	5	1.957	1445.18(2)	2.483	3.329	2.91
10	50	5	1.624	10.334	2.012	2.252	2.052
Average			1.272	474.197	1.668	1.802	1.611

Table 3.3. Computational results for medium-scale instances under different MIPEmphasize settings

Set	T	G	0	1	2	3	4
11	60	5	3.488	1475.95(2)	3.278	5.532	4.1462
12	80	5	7.513	2885.88(4)	12.338	14.228	8.417
13	100	5	780.555(1)	3607.04(5)	760.123(1)	103.865	754.775(1)
14	120	5	746.714(1)	2164.92(3)	737.011(1)	785.964(1)	745.024(1)
15	140	5	828.495(1)	3607.24(5)	757.478(1)	747.804(1)	774.678(1)
16	60	10	7.286	2375.03(3)	6.943	14.392	8.9848
17	80	10	49.479	2887.53(4)	35.031	32.736	32.3894
18	100	10	877.725(1)		754.008(1)	76.895	775.034(1)
19	120	10	913.169(1)	3609.54(5)	953.581(1)	747.789(1)	1450.61(2)
20	140	10	748.412(1)	3607.66(5)	741.965(1)	763.346(1)	759.278(1)
Average			496.284	2982.852	476.176	329.255	531.334

Table 3.4. Computational results for large-scale instances under different MIPEmphasize settings

Set	T	G	0	1	2	3	4
21	150	10	1594.151(2)	3606.41(5)	1605.96(2)	1595.94(2)	1774.42(2)
22	200	10	2223.905(3)	3609.32(5)	2250.61(3)	2200.57(3)	2250.07(3)
23	250	10	2251.219(3)	3609.75(5)	1611.97(2)	1780.43(2)	2013.49(2)
24	150	15	2235.130(3)	3609.66(5)	2239.2(3)	2193.04(3)	2209.65(3)
25	200	15	2238.314(3)	3608.95(5)	2246.91(3)	1532.9(2)	2223.17(3)
26	250	15	2894.424(4)	3608.69(5)	2895.12(4)	2895.519(4)	2899.26(4)
Average			2239.524	3608.796	2141.628	2033.067	2228.343

3.4.1 Case study

In this subsection, we examine how the proposed model and heuristic perform on a real food CLSC. The company produces meat-like perishable food, such as beef jerky, meatball, sausage and so on. It uses a smooth productivity policy and a constant production is launched every day. Finished products can be stored at the company or sent to its retailers by owned homogeneous trucks every day. Currently, disposable boxes (DB) are used to pack finished products. Motivated by environment protection, local regulations and potential profit, the company seeks at present to optimize their productivity and delivery process and investigate the economic potential of replacing DB with returnable boxes (RB). Additionally, it should be noted that among all kinds of products produced by the company, beef jerky accounts for more than 70% of the total sales volume. Moreover, among all its retailers, a big supermarket owned by the company itself located in the city center accounts for 60% of the demands. Therefore, we focus on only beef jerky and consider the company as well as its biggest retailer integrally in this case study. The company sets different selling prices for the products according to their quality level. Periodic demand of customer must be fully satisfied, and no backorders and outsourcing are allowed. The budget for purchasing packaging boxes is not critical.

The studied horizon for this case spans 15 days (periods). The beef jerky's selling price is 60 CNY in the first 12 days after being produced and 50 CNY in the remaining 3 days. And the products are destroyed after 15 days according to food regulations. The customer demand d_t , set-up cost s_t , production capacity C_t and unit production cost c_t in each period are presented in Table 3.5. Other related parameters are given in Table 3.6. Note that higher product inventory cost at the retailer side is due to more expensive rent; higher RB inventory cost at the retailer side is due to the inclusion of cleaning or possibly repair cost; returnable box (RB) can carry more products than disposal box (DB) in the same size because of its higher quality.

To better illustrate the benefits of using RB for the company, we compute the total profit under 3 scenarios: 1) using the current production-delivery strategy with DB; 2) using the proposed method with DB; and 3) using the proposed method with RB. Note that the latter two scenarios are computed by CPLEX directly as the studied horizon is small. Table 3.7 presents the total profit, total

revenue and total cost under the 3 scenarios, where the total profit equals to the total revenue minus the total cost. Table 3.8 shows the variable values related to production and delivery quantities. Columns 2, 4 and 6 of Table 3.8 give the quantity of production. Columns 3, 5 and 7 of Table 3.8 present the quantity and quality level of products delivered.

It is observed from Table 3.7 that the total revenues are the same for the three scenarios, which means that all the beef jerky is sold in the first 12 periods before the price goes down. However, the total profit can be increased by 11.18% = $(613716.0 - 552002.0) / 552002.0$ from scenario 1 to 2. It shows that the company can earn more profit with the proposed model and optimized method, although using DB. The main reason is that production is launched in every period and the production quantity is constant under scenario 1, which induces high production and inventory costs as the customer demand is dynamic. That can also explain why the ages of delivered products range from 0 to 5 in Column 3 of Table 3.8.

Moreover, the profit can be improved by 12.22% = $(619459.5 - 552002.0) / 552002.0$ from scenario 1 to 3, and 0.94% = $(619459.5 - 613716.0) / 613716.0$ from scenario 2 to 3. It implies that replacing DB with RB is more profitable for the company. Columns 4–7 show the optimal quantities of production and delivery for scenarios 2 and 3, respectively. It can be observed that compared with scenario 1, the company does not need to set up production for all the periods. Specifically, for both scenarios 2 and 3, there are 5 periods (periods 3,5,7,10,13) having no set-ups, which reduces production set-up costs. The same set-up scheme for scenarios 2 and 3 implies that using RB to replace DB does not impact the set-up decision. Besides, the product ages under scenarios 2 and 3 are only up to 2 after optimizing the production and delivery process. It in turn reduces product inventory costs. However, due to the different storage costs at the company and its retailer, and different amounts of available containers that can be used to ship products under scenarios 2 and 3, the production and delivery quantities and product ages between them are different. Table 3.9 presents the number of containers purchased in each period under scenarios 2 and 3, respectively. We can observe that unlike scenario 2, the company do not need to purchase containers from time to time under scenario 3 thanks to the return of RB. Seven hundred and twenty-three units of DB are needed under scenario 2 while only 93 units of RB is sufficient, which helps to reduce the one-way packaging waste.

Based on the above observations, we can conclude that the proposed model

can optimize the production-delivery process and increase profit for the studied company. And although RB costs much more (4 times) than DB, needs to be stored at a higher cost and shipped back, the reusability of RB can make up for those disadvantages, thus making it more economical even within a small horizon. It is rational to infer that the advantages of using RB would be more obvious in a long run. Therefore, replacing DB with RB can not only achieve economic potential, but also contribute to resource conservation and environment protection. The conclusion may provide a good justification for the decision makers who intend to improve the production-delivery process and introduce RTIs in their supply chain.

Table 3.5 Customer demand d_t , set-up cost s_t , production capacity C_t and unit production cost c_t in each period

t	1	2	3	4	5	6	7	8
d_t	833	1110	1102	1384	1232	1159	1367	1049
s_t	2824	2242	2138	1728	2496	1863	2296	1773
C_t	3302	3142	1716	2619	2357	3288	3972	2619
c_t	25	24	29	21	26	22	28	20
t	9	10	11	12	13	14	15	
d_t	1287	1188	1198	869	1455	1177	1590	
s_t	2681	1427	1679	1038	2609	1506	2558	
C_t	1498	3099	2619	1906	3753	2546	1702	
c_t	22	27	25	27	30	21	22	

Table 3.6. Other related parameters for the case study

Parameter	Value
Purchasing price of unit DB/ RB	10/ 40 CNY
Capacity of unit DB/ RB in terms of beef jerky	25/ 30
Capacity of truck in terms of DB/ RB	20/ 20
Vehicle fixed cost	300 CNY
Variable costs of unit empty/ filled DB or RB	0.5/ 2 CNY
Unit product inventory cost at the manufacturer/ retailer	2/ 3 CNY
Unit DB inventory cost at the manufacturer/ retailer	1/ 0 CNY
Unit RB inventory cost at the manufacturer/ retailer	1.5/ 2 CNY
The number of trucks owned by the company	5
Inventory capacity at the retailer for products/ containers	1660/ 830

Table 3.7. Computing results for the case study under 3 scenarios

	Total profit	Total revenue	Total cost
Scenario1	552002.0	1080000.0	527998.0
Scenario2	613716.0	1080000.0	466284.0
Scenario3	619459.5	1080000.0	460540.5

Table 3.8. Production and delivery quantities and ages for the 3 scenarios

t	Scenario 1		Scenario 2		Scenario 3	
	p_t	q_{gt}	p_t	q_{gt}	p_t	q_{gt}
1	1200	833(0)	833	833(0)	833	833(0)
2	1200	743(0), 367(1)	2212	1212(0)	2212	1110(0)
3	1200	645(0), 457(1)	0	1000(1)	0	1102(0)
4	1200	1200(0), 184(1)	2616	1391(0)	2616	1416(0)
5	1200	861(0), 371(1)	0	1225(1)	0	1200(0)
6	1200	820(0), 339(1)	2526	1159(0)	2526	1176(0)
7	1200	987(0), 380(1)	0	1367(1)	0	1350(0)
8	1200	836(0), 213(1)	2524	1049(0)	2037.35	1136(0)
9	1200	923(0), 364(1)	1000	1475(1)	1498.65	298.65(0), 01.35(1)
10	1200	1188(0)	0	1000(1)	0	1200(1)
11	1200	1186(0), 12(1)	2619	1198(0)	2619	1200(0)
12	1200	869(0)	903	874(0)	891	869(0), 241(1)
13	1200	1200(0), 255(1)	0	29(1), 1421(2)	0	22(1), 1178(2)
14	1200	900(0), 277(5)	1267	1267(0)	1177	1177(0)
15	1200	1200(0), 300(1), 76(3), 14(4)	1500	1500(0)	1590	1590(0)

Note: Figs in the parentheses indicate the age of the delivered products

Table 3.9. Optimal purchasing quantities of DB under scenario 2 and RB under scenario 3

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Scenario2	34	49	40	56	49	47	55	42	59	40	48	35	58	51	60
Scenario3	28	37	9	11	3	0	5	0	0	0	0	0	0	0	0

Table 3.10. Results for the case study under scenario3

Solution method	Objective value (CNY)	CPU time (s)
CPLEX	619459.5	0.33
IKSH	619431.5	0.56

Meanwhile, to observe the performance of the proposed IKSH on the practical problem, we also use it to solve scenario 3. The computational results are given in Table 3.10. Here, the $|K_0|$ is set to be 7 and L is equal to $|K_0|$. From Table 3.10, we notice that the proposed IKSH can solve the real case efficiently while achieving a

solution value nearly as good as CPLEX. Similar results are obtained when solving the random instances in Section 3.4.2.

3.4.2 Randomly generated instances

To gain additional insights into the performance of the proposed model and algorithm, we test 26 randomly generated problem sets with 5 instances for each set, i.e., 130 instances in total. These instance sets are solved by the proposed IKSH, the RF heuristic, and the direct use of commercial solver CPLEX (version 12.6.0). Meanwhile, to validate the effectiveness of the proposed policy to determine two key parameters of KS, i.e. the initial kernel size and the length of each bucket. The standard KS heuristic (SKSH) framework outlined in Chapter 2 is also applied to solve the CLFSC-RTI after the initialization phase.

The ranges used to generate randomized parameters are based on the real-life case study presented in Section 5.1, as shown in Table 3.11. Note that, we refer to the way in Coelho and Laporte (2014) to generate selling prices for products in each age.

The performance of the proposed IKSH is compared with the SKSH, the RF heuristic, and the direct use of CPLEX solver in terms of computation time (in CPU seconds) and solution quality (in gap). In this study, the results of gap in column “Gap1%” are computed by $(z^{C^*} - z^{S^*}) / z^{S^*}$, where z^{C^*} and z^{S^*} represent the objective values obtained by CPLEX and SKSH, respectively. “Gap2%” are computed by $(z^{C^*} - z^{I^*}) / z^{I^*}$, where z^{C^*} and z^{I^*} represent the objective values obtained by CPLEX and IKSH, respectively. “Gap3%” are computed by $(z^{C^*} - z^{RF^*}) / z^{RF^*}$, where z^{C^*} and z^{RF^*} represent the objective values obtained by CPLEX and RF, respectively. 3600s is set as the time limit of CPLEX, which is commonly used in the literature (Filippi et al. 2016, Roshani et al. 2017, Iassinovskaia et al. 2017, etc.) to stop the searching and output the best solution found so far. Experiments show that CPLEX solver cannot optimally solve all the instances within the time limit. In this case, z^{C^*} is the best objective value found by CPLEX when reaching the time limit. Columns “ T_CPLEX ”, “ T_SKSH ”, “ T_IKSH ” and “ T_RF ” report the computation time by CPLEX, SKSH, IKSH, and RF respectively. Bracketed text in column “ T_CPLEX ” indicates the number of instances in each set that cannot be solved to optimality within 3600s.

As described in Section 4, we use range $(|T|/2 - \eta, |T|/2)$ to generate the size of the initial kernel size $|K_0|$ with equal probability for IKSH and SKSH. Here, we

set $\eta=1$ for $|T|=10, 20, 30, 40$, $\eta=5$ for $|T|=50, 60, 80$, $\eta=10$ for $|T|=100, 120, 140, 150$, and $\eta=40$ for $|T|=200, 250$.

For RF heuristic and according to the introduction of RF framework, we set $\theta = |T|/2$ and $\gamma = 2, 2, 5, 5, 6$ for $|T|=10-50$, $\gamma = 6, 8, 8, 9, 10$ for $|T|=60-140$, and $\gamma = 25, 20, 25$ for $|T|=150-250$, where θ is the length of BVS and after each iteration the BVS window moves forward by γ periods.

Table 3.11. The way to generate parameters based on the real-life case

Notation	Description	Notation	Description
d_t	$\sim U(800, 1600)$	h_1	$\sim U(1, 3)$
C_t	$\sim U(1600, 2000)$	h_2	$1.5 * h_1$
Cap_1	$\sim U(2000, 3000)$	h_3	$0.5 * h_1$
Cap_2	$\sim U(800, 1000)$	h_4	$1.5 * h_3$
C^c	$\sim U(20, 50)$	f	$\sim U(200, 400)$
V	$\sim U(4, 8)$	c^d	$4 * c^e$
C^v	$\sim U(10, 30)$	c^e	$\sim U(1, 2)$
s_t	$\sim U(1500, 5000)$	s_g	$c - (c-d)g/ G $, where c is generated by $U(60, 70)$ and d by $U(50, 55)$
c_t	$\sim U(20, 30)$	c^o_t	$\sim U(c_t, d)$
c^p	$\sim U(30, 50)$		

The average values of $|K_0|$ for all sets are presented in column “ $|K_0|$ ”. The length of bucket L is set equal to $|K_0|$. And we set $B=2000$ for $|T|=10-100$, $B=2500$ for $|T|=120-200$ and $B=3000$ for $|T|=250$. Note that the considered period is up to 250 which is approximate to the total workdays of one year. As claimed by Alumur et al. (2012), future adjustment in the optimal solution is possible for all the multi-period models. They indicated that when some previous parameter settings become unrealistic at one period, redesigning the optimal plan for the remaining planning horizon is very easy by fixing the previously made and already implemented decisions. Another reason of a one-year planning horizon is to reflect the seasonality aspect of production and demand. Ouhimmou et al. (2008) claimed that these processes are all seasonal and their cycles typically span a year.

Tables 3.12–3.14 report the computational results for small-, medium- and large-scale instances solved by the proposed IKSH, the RF method, the SKSH and the direct use of CPLEX, respectively. Note that we test 5 instances for each set and present the average value.

Table 3.12 shows the computational results for small instances where $|G|=3, 5$ and $|T|$ increasing from 10 to 50. The results show that CPLEX, IKSH, KS and SKSH can all efficiently solve small-scale instances within an average time of 5

seconds. In terms of solution quality, IKSH can achieve solutions of high quality with very small gaps from 0.00% to 0.13% (0.03% on average) when compared with the best solution obtained by CPLEX. In fact, IKSH can obtain optimal solutions for 7 out of 10 sets. It is worth noting that the proposed IKSH is more efficient than the direct use of CPLEX in solving the small-scale problems. While SKSH can achieve all optimal solutions with a relatively longer computation time. However, RF has relatively bigger gaps (ranging from 0.00% to 9.98%) and longer computation time compared to CPLEX. So, we can say that the proposed IKSH is both more efficient and more effectiveness than the RF method in solving small-scale problems. The small gaps obtained by the IKSH and SKSH also indicates that the proposed policy for determining K_0 allows IKSH and SKSH to iteratively solve sub-problems very efficiently while maintaining high-quality/optimal solutions.

Table 3.12. Computational results for small instances with $|G|=3, 5$, and $|T|=10-50$

Set	$ T $	$ G $	$ K_0 $	T_CPLEX	T_SKSH	Gap1(%)	T_IKSH	Gap2(%)	T_RF	Gap3(%)
1	10	3	4.8	0.18	0.57	0.00	0.58	0.00	1.06	0.64
2	20	3	10	0.89	0.81	0.00	0.67	0.00	2.17	0.76
3	30	3	15	1.93	1.53	0.00	1.32	0.00	2.7	2.08
4	40	3	20	3.16	2.71	0.00	1.53	0.13	3.59	0.31
5	50	3	23	3.46	4.20	0.00	2.59	0.00	12.18	0.18
6	10	5	5	0.22	0.59	0.00	0.51	0.00	0.93	0.00
7	20	5	10	0.59	0.92	0.00	0.72	0.00	1.82	0.78
8	30	5	14.8	2.01	2.29	0.00	1.30	0.08	3.07	0.17
9	40	5	20	3.33	4.18	0.00	3.22	0.13	7.42	0.20
10	50	5	24.4	2.25	2.69	0.00	1.35	0.00	4.07	9.98
Avg.				1.80	2.05	0.00	1.38	0.03	3.90	1.51

Table 3.13 presents the computational results of medium-scale instances with $|T|$ ranging from 60 to 140 and $|G|=5$ and 10, respectively. From Table 3.13, we can observe that for medium-scale instances, the computation time generally increases with the values of $|T|$ and the average computation time is 329.26s by CPLEX. For sets 14, 15 and 19, 20, there is 1 out of 5 instances that cannot be solved optimally within 3600s by CPLEX. However, the proposed IKSH can achieve near-optimal solutions in an average computation time of 25.89s, which is only 7.86% of the direct use of CPLEX. Besides, the obtained solutions by IKSH are of high quality with gaps ranging from 0.00% to 0.94% (0.17% on average). For SKSH, its computation time is also smaller than CPLEX but much larger than IKSH. However, the solution quality of SKSH is very competitive with an average gap of 0.005%.

For RF algorithm, its computation time is also smaller than CPLEX but much larger than IKSH. Furthermore, the average gap 0.42% is also larger than that of IKSH with the worst one being 1.49%. It demonstrates that the proposed IKSH outperforms CPLEX and RF in terms of both computation time and solution quality for the medium-scale instances.

Table 3.13. Computational results for instances with $|G|=5,10$ and $|T|=60-140$

Set	$ T $	$ G $	$ K_0 $	T_{CPLEX}	T_{SKSH}	Gap1(%)	T_{IKSH}	Gap2(%)	T_{RF}	Gap3(%)
11	60	5	29	5.53	5.83	0.00	2.59	0.00	8.55	0.07
12	80	5	34	14.23	18.66	0.03	15.01	0.19	36.86	1.49
13	100	5	42	103.87	46.62	0.02	26.37	0.30	172.20	0.51
14	120	5	58	785.96(1)	30.44	0.00	13.23	0.02	170.46	0.23
15	140	5	62	747.80(1)	133.22	0.00	28.04	0.00	606.79	0.23
16	60	10	28	14.39	19.89	0.00	12.86	0.06	24.37	0.16
17	80	10	38	32.74	36.06	0.00	9.39	0.09	28.28	0.21
18	100	10	50	76.90	769.85	0.00	31.79	0.94	653.96	1.15
19	120	10	58	747.79(1)	1266.66	0.00	75.39	0.02	145.00	0.04
20	140	10	66	763.35(1)	565.56	0.00	44.20	0.04	120.30	0.08
Avg.				329.26	289.28	0.005	25.89	0.17	196.68	0.42

Note: Figures in the parentheses indicate the number of instances for each set that cannot be solved within 3600s.

Table 3.14 shows the computational results of large-scale instances with $|T|$ increasing from 150 to 250 and $|G|=10$ and 15, respectively. We can see from the results that CPLEX is of poor performance in solving large-scale instances. Specifically, 16 out of 30 instances cannot be solved to optimality within 3600s by CPLEX. Nevertheless, the proposed IKSH can obtain near optimal solutions with gaps ranging from 0.26% to 0.78% (0.53% on average) in 13.45% computation time of that spent by CPLEX. However, for sets 23 and 26 where $|T|$ increases up to 250, an obvious increment in the computation time is observed. On the other hand, the SKSH can achieve high-quality solutions with an average gap of 0.01% with the computation time being 61.13% and 454.68% than that spent by CPLEX and the IKSH, respectively. RF algorithm is also efficient than CPLEX but 77.67% slower than the IKSH with 4 out of 30 instances exceeding the time limit. Based on the discussions, the proposed IKSH is still preferable for solving large-scale instances.

Table 3.14. Computational results for instances with $|G|=10,15$ and $|T|=150-250$

Set	$ T $	$ G $	$ K_0 $	T_{CPLEX}	T_{SKSH}	Gap2(%)	T_{IKSH}	Gap2(%)	T_{RF}	Gap3(%)
21	150	10	75	1595.94(2)	702.67	0.00	62.41	0.71	737.55	0.27

22	200	10	95	2200.57(3)	1240.63	0.02	114.05	0.77	561.41	0.27
23	250	10	96	1780.43(2)	1716.09	0.01	789.20	0.29	1541.79(2)	0.09
24	150	15	71	2193.04(3)	1128.33	0.00	76.35	0.34	1068.31(1)	0.38
25	200	15	97	1532.9(2)	914.12	0.00	59.56	0.78	824.48	1.00
26	250	15	83	2895.52(4)	1755.38	0.03	697.90	0.26	2611.46(1)	0.18
Avg.				2033.07	1242.87	0.01	273.35	0.53	1224.17	0.37

Note: Figures in the parentheses indicate the number of instances for each set that cannot be solved within 3600s

According to the results of the random instances, we conclude that the proposed IKSH are very competitive compared with CPLEX, SKSH and RF heuristic. More specifically, when the planning horizon is small (within 80 periods), the proposed IKSH and other three methods are all very efficient to optimize the studied problem and obtain optimal or high-quality solutions except the RF that yields relatively large gaps. However, solving by SKSH, CPLEX and RF need heavy computation burden when the planning horizon increases up to 100 or longer. In such cases, the proposed IKSH is a desirable alternative to provide the decision makers with high-quality solutions very efficiently. The efficient heuristic ensures DMs to shorten response time in volatile management practice, i.e. the planning re-adjusted according to different input parameters.

3.4.3 Sensitivity analysis

In this subsection, we perform sensitivity analysis on several key parameters of the model and the optimization method.

For the model, we conduct the sensitivity analysis for three main parameters based on preliminary experiments, i.e. production set-up cost (sc_t), the budget of purchasing container (B) and the selling price of products in different ages (s_g). Take instance $|G|=5$, $|T|= 80$ (i.e. 5–80) as an example. We first observe the performance of the model when sc_t changes and the results are presented in Fig. 3.2. Note that S in Fig. 3.2 indicates basic set of sc_t , and $1.5S$ means 1.5 times of the basic set, and so on. From Fig. 3.2, we can see that when sc_t increase, the computation time increases and the total profit decreases. It means that the model is sensitive to sc_t . When it is small, most periods need to set up production in the optimal solution. Consequently, more products will be sold at their fresher state with higher prices. Therefore, the profit is higher. In this case, the problem can be solved relatively efficiently as the delivery amount, the age the products and inventory issues are not critical. Conversely, when sc_t is larger, less periods will be

chosen to set up production to reduce set-up costs. Regarding the same demand amount, production quantity in set-up periods is larger and product inventory increases in turn. As the product quality drops over periods, the profit declines generally. In this situation, other parameters (such as production and delivery quantities and inventory costs) need better trade-offs to achieve an optimal solution, which increases the computation burden. It suggests that decision makers should reduce production set-up costs by introducing new technology or energy-saving machines to gain greater economic benefit.

Then we discuss the effect of container purchasing budget B . Take instances 5–80 and 5–100 as examples. The results of the sensitivity analysis are shown in Fig. 3.3. It can be observed from Fig. 3.3 that with the increment of B , the computation time has a general decrease trend. The reason is that when the budget is relatively small, the manufacturer will not be able to buy containers all the time to satisfy the demand. In this case, outsourcing is necessary as backorder is not allowed. But when to buy containers and how to outsource the order need to be optimized considering related costs, which enlarges the search space of the optimal solution. On the contrary, when the budget is large enough, containers can be purchased at any time without complicated decision-making. Thus, it can be concluded that the computation time is sensitive to B . The decision maker should appropriately set this value.

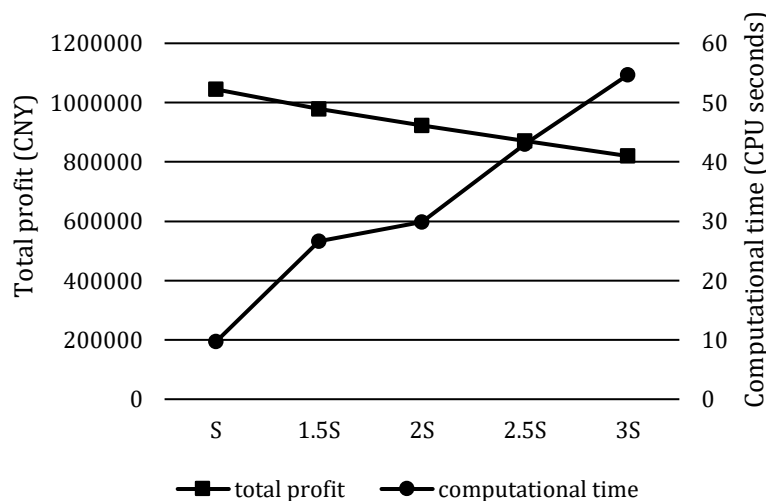


Fig. 3.2. Sensitivity analysis of production set up cost (sc_t)

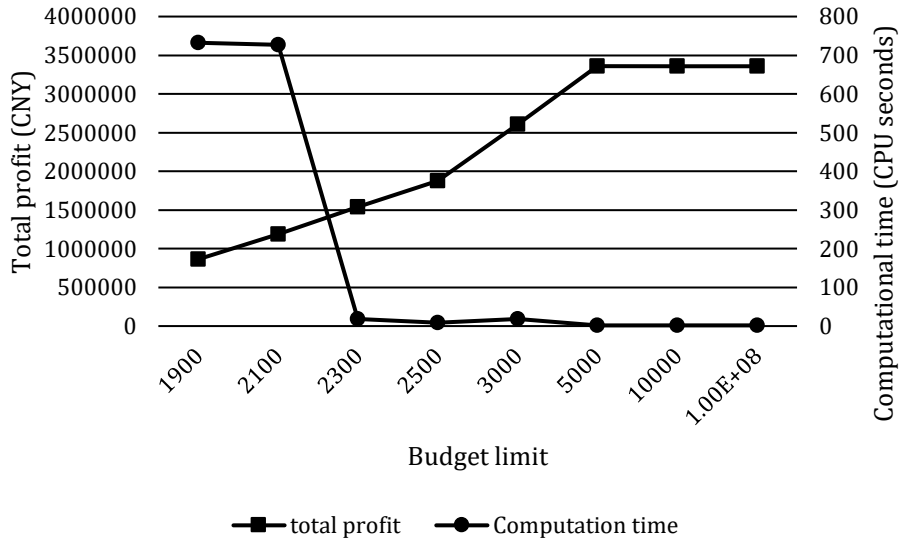


Fig. 3.3. Sensitivity analysis of budget (B)

As mentioned above, s_g is generated by $c - (c-d)g/|G|$, where c and d are randomly generated by uniform distribution. In order to observe the model performance with different changes in s_g , we fix the range as $[60, 70]$ to generate c . The range of d is set as $[40, 45]$, $[50, 55]$ and $[55, 60]$, respectively. When d is smaller, the selling price of the product is more sensitive to its quality (age). The obtained results are shown in Table 3.15 and Fig. 3.4. We can see from Table 3.15 that with the increment of the range of d , the average computation time decreases from 599.215 to 478.554 while the average total profit increases from 1257309.531 to 1985010.218. The trend is illustrated in Fig. 3.4. The smaller is the range of d , the more obvious of the changed trend. It is because when d is smaller, the selling price declines quickly as its quality decreases, making the gap of selling price between products of different quality bigger. Thus, more periods will be chosen to set up production to provide the customer with better-quality products for a higher profit. Consequently, the decision process becomes complex as production set-up variable is highly associated with other variables. That is why the computation time is longer. Meanwhile, more production set-up periods induce larger cost. Combined with lower selling prices, the total profit is lower. Therefore, decision makers should pay attention to product preservation to keep high quality, thus narrowing the price difference.

For IKSH, apart from the size of the initial kernel $|K_0|$ discussed in the previous section, the length of the bucket L is also a key parameter that can affect its performance. When L is smaller and the consequent bucket number m is bigger, the efficiency of the algorithm increases while the solution quality decreases. It is

because CPLEX is efficient to solve small sub-problems although it needs to iterative more times. However, smaller sub-problems lead to poorer interdependencies among variables and therefore lower the solution quality. On the contrary, bigger L and smaller m result in larger sub-problems. Variables in these sub-problems have better interdependencies to provide solutions with smaller gaps at the cost of longer computation time. To observe the impact of L on the proposed IKSH, we conduct the experiments with $L= 0.8|K_0|$, $|K_0|$ and $1.2|K_0|$ for instances 5–80 and 5–100. The obtained results are presented in Table 3.16. It is observed from Table 3.16 that the setting of L has a big impact on the computation time but is not sensitive to the solution quality. It means that the proposed IKSH is relatively stable in terms of solution quality.

Table 3.15. Sensitivity analysis on selling price of product with different quality (s_g)

d	$ T $	$ G $	CPU time (s)	Total profit (CNY)
[40, 45]	60	5	2.2296	1254946.768
[40, 45]	80	5	11.016	1170067.656
[40, 45]	100	5	1447.66	46034.63
[40, 45]	120	5	738.31	2413351.486
[40, 45]	140	5	796.861	1402147.116
Avg.			599.215	1257309.531
[50, 55]	60	5	3.0168	1276055.624
[50, 55]	80	5	6.3142	1198769.172
[50, 55]	100	5	876.085	94047.442
[50, 55]	120	5	744.411	3729235.084
[50, 55]	140	5	794.263	3456846.668
Avg.			484.81	1950990.798
[55, 60]	60	5	3.5852	1292674.082
[55, 60]	80	5	13.2172	1219836.744
[55, 60]	100	5	70.8294	158725.524
[55, 60]	120	5	32.7664	3755054.382
[55, 60]	140	5	2272.37	3498760.358
Avg.			478.554	1985010.218

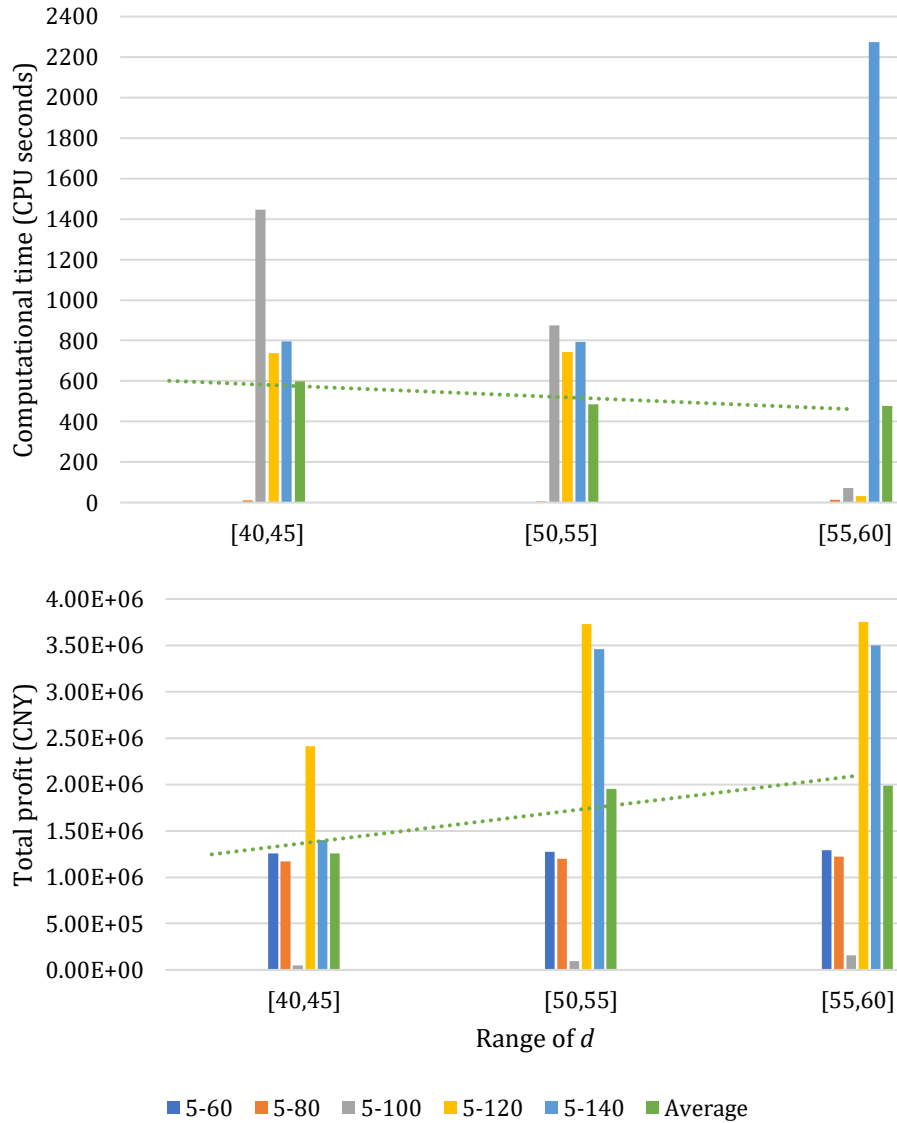


Fig. 3.4. Sensitivity analysis of selling price (s_g)

Table 3.16. Sensitivity analysis results for parameter L of the proposed IKSH

Set	$L=\lceil 0.8 K_0 \rceil$		$L= K_0 $		$L=\lceil 1.2 K_0 \rceil$	
	Gap%	T_{IKSH}	Gap%	T_{IKSH}	Gap%	T_{IKSH}
5-80	0.20	9.321	0.19	15.014	0.21	101.247
5-100	0.31	29.243	0.30	26.374	0.30	451.587

3.5. Conclusions

This chapter studies a multi-period closed-loop food supply chain with RTIs considering food quality level and dynamic customer demand. We first formulated the problem into a MILP model, which is subsequently proved to be NP-hard. Then, we developed an improved kernel search-based heuristic (IKSH) to solve it. Finally,

a case study and 130 randomly generated instances are conducted to demonstrate the performance of the proposed model and method. Sensitivity analysis is also conducted to better understand the parameters' impact on the proposed model and heuristic. Results of the real case show that the profit of a food manufacturer is improved by more than 10% with our method. Results of the random instances demonstrate that the proposed IKSH is significantly efficient compared with the direct use of CPLEX and RF algorithm while yielding high-quality solutions. More importantly, this study can give insights to the decision makers of various companies who intend to build CLSC for perishable products and introduce RTIs. It helps to increase the profits and check the economical potentials by replacing disposal packages with environmental-friendly RTIs according to the proposed model and method. The efficiency and effectiveness of the proposed IKSH provides basis for developing efficient heuristics for similar problems.

The corresponding work has been published in the following papers.

Y. Zhang, F. Chu, A. Che, Y. Yu and X. Feng. Novel model and kernel search heuristic for multi-period closed-loop food supply chain planning with returnable transport items. *International Journal of Production Research*, 2019. DOI: 10.1080/00207543.2019.1615650

Y. Zhang, F. Chu, A. Che. A mixed integer linear programming approach for closed-loop food Supply chain with returnable transport items. *the 46-th International Conference on Computers and Industrial Engineering (CIE46)*, 2016.

Chapter 4

Bi-objective Multi-retailer Closed-loop Food Supply Chain with RTIs

4.1 Introduction

In Chapter 3, the studied closed-loop food supply chain with RTIs (CLFSC-RTI) involves one manufacturer and one retailer. However, supply chains configured by multiple retailers are more common in practice. And this will no doubt increase problem complexity. Moreover, selling price of the same products may be different at different retailers due to, e.g. the district or scale of them. On the other hand, the objective function in Chapter 3 is to maximize the total profit of the CLSC. As reviewed in Chapter 2, due to the severe environmental concerns faced by the contemporary generation, considering environmental issues in companies' activities is mandatory. Barros et al. (2019) indicated that environmental objective such as the minimization of greenhouse gases (GHG) emission has been extensively studied in recent decades.

Therefore, this Chapter naturally extends the work of Chapter 3 to consider a bi-objective CLFSC-RTI (BCLFSC-RTI). The BCLFSC-RTI includes a single manufacturer and multiple retailers. The aim is to optimally decide for each period the quantity of food production, the quantity and quality of product delivery and inventory, the amount of RTIs purchased, used, and returned, and the number of vehicles used for transportation throughout the planning finite horizon. The two conflicting objectives are to maximize the total profit and to minimize CO₂ emissions of the holistic CLSC. In so doing, we intend to help decision makers gain insights into the tradeoffs between the economic and environmental impacts of the companies under stringent environmental policies.

The remainder of this chapter is organized as follows. Section 4.2 describes and formulates the studied BFCLSCP-RTI. Section 4.3 presents a kernel search heuristic based ε -constraint method for the resolution. In Section 4.4, computational experiments on a real case study of a fresh meat supplier and various randomly generated instances are conducted to evaluate the performance of the proposed model and algorithm. Section 4.5 concludes the chapter.

4.2 Problem description and formulation

4.2.1 Problem description

The studied BCLFSC-RTI includes a single manufacturer and multiple retailers. The maximization of total profit and the minimization of the carbon emissions are the two conflicting objectives. The framework of the BCLFSC-RTI and all the decision variables are presented in Fig. 4.1. The planning horizon are finite and divided into discrete period $t \in T = \{1, 2, \dots, |T|\}$. The customer demand of retailer $r \in R = \{1, 2, \dots, |R|\}$ in period t is known a priori as D_{rt} . The manufacturer produces perishable food with production capacity C_t , periodic production set-up cost S_t and unit production cost c_t . Similar to Chapter 3, the quality of the finished products deteriorates over time. Term “age” is used as Li et al. (2016) and Coelho and Laporte (2014) to index food quality. The age of food is assumed to belong to a discrete set $g \in G = \{0, 1, 2, \dots, |G|\}$ where 0 represents newly produced products and the products are spoiled and cannot be sold anymore after their age exceeds $|G|$. The product selling price of age g at retailer r is s_{gr} . Note here that the selling price of product of the same age at different retailer may be different due to the district and scale of the retailer.

The manufacturer uses same-sized RTIs to pack finished products and each of them with a capacity C^C in term of products. The filled RTIs are then shipped to retailers by a homogenous fleet vehicle, each with a capacity of C^V RTIs, a fixed transportation cost f and a variable transportation cost β related to the payload and drive distance. All the vehicles are possessed by the manufacturer. Distance between the manufacturer and retailer r is dis_r . After the vehicles reach at each retailer, the filled RTIs are emptied and become the retailer’s inventory. At the same time, the vacant vehicles ship back “ready-to-be-returned” RTIs to the manufacturer for reuse. When RTIs are out of stock, the manufacturer needs to purchase new ones from external suppliers. The replenishment is instantaneous and the lead-time to the manufacturer is neglected. The operation sequence per period at the supplier and retailers that impacts the model formulation is illustrated in Figure 4.2, respectively. Such sequence that impacts the problem modelling will be detailed in subsection 4.2.2.

The manufacturer has limited inventory capacity for product and RTIs, denoted as C^P and C^{RTI} , respectively. Each retailer’s inventory capacity is limited,

C_r^P for product and C_r^{RTI} for RTIs. The unit product and RTI holding costs are h and a for the manufacturer. The unit product and RTI holding costs at retailer r are h_r and a_r . All the above-mentioned notations are summarized in Table 4.1.

Additional assumptions for formulating the problem:

1. Without loss of generality, the initial container and product inventory at both the manufacturer and the retailers are zero.
2. The age of the product increases by one unit along with products deteriorating in each period, and the corresponding selling price decreases.
3. Customers would accept products of different ages with different costs.
4. Selling prices of products are distinguished according to the region of the retailer.
5. The locations of the manufacturer and retailers are known a priori.
6. Vehicles used to ship loaded RTIs are assumed unlimited. The reason lies in that the manufacturer will choose to hire vehicles to fulfill the transportation task instead of not satisfying customers' demand.
7. The empty RTIs can be folded to half size such that vehicle's capacity for empty RTIs is two times than that for filled ones.

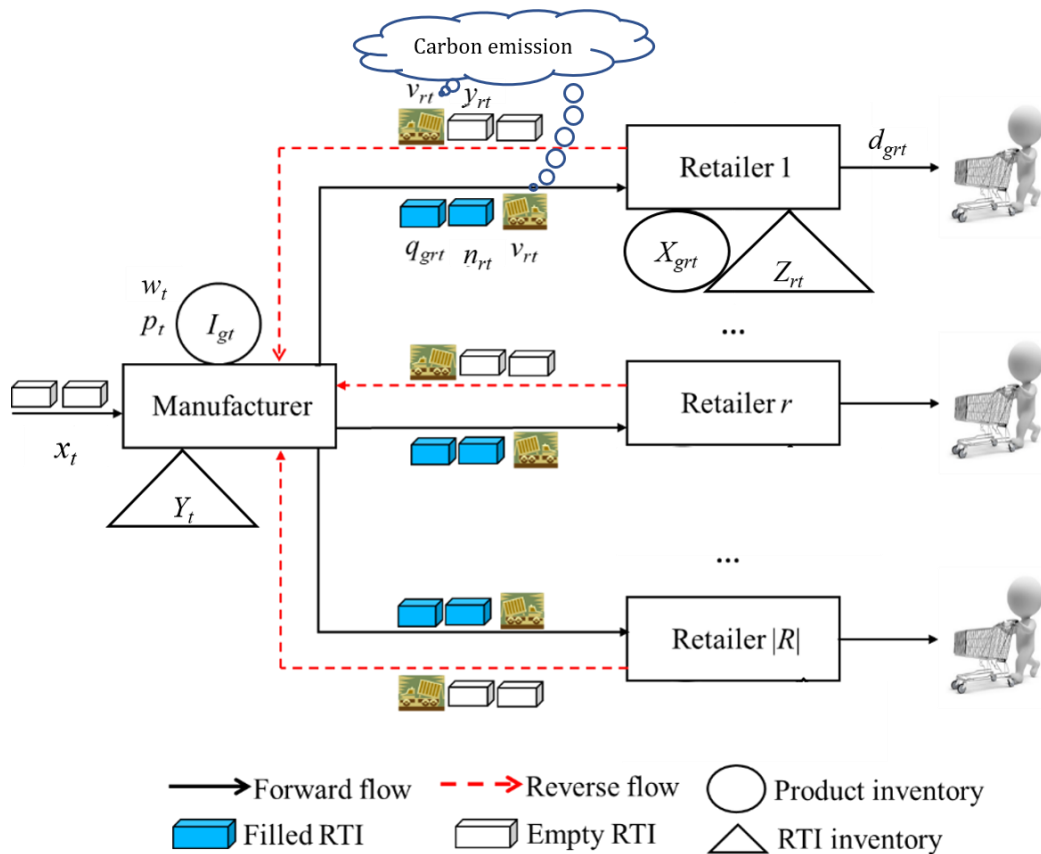
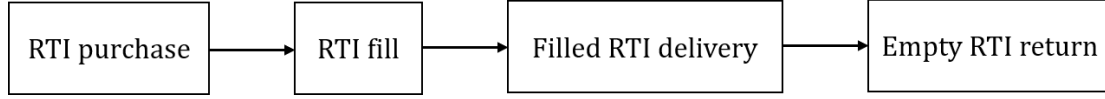
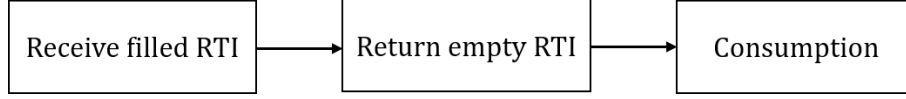


Fig. 4.1. Framework of the CLSC under investigation



(a) Operation sequence at supplier



(b) Operation sequence at each retailer

Fig. 4.2 Operation sequence

4.2.2 Problem formulation

Table 4.1 summarizes the notations used for problem formulation.

Table 4.1. Sets, parameters and decision variables

Notation	Description
Sets	
T	Set of periods, $t \in T = \{1, 2, \dots, T \}$
G	set of product quality, $g \in G = \{0, 1, 2, \dots, G \}$, $ G \leq T $
R	set of retailers, $r \in R = \{1, 2, \dots, R \}$
Parameters	
D_{rt}	Demand at retailer r in period t
s_{gr}	Selling price of the product with quality $g \in G$ at retailer r
C_t	Production capacity in period t
C^P	Product inventory capacity in terms of products at the supplier in period t
C^{RTI}	RTI inventory capacity in terms of RTIs at the supplier in period t
C_r^P	Product inventory capacity in terms of products at retailer r in period t
C_r^{RTI}	RTI inventory capacity in terms of RTIs at retailer r in period t
C^C	RTI capacity in terms of products
C^V	Vehicle capacity in terms of RTIs
S_t	Production set-up cost in period t
c_t	Unit production cost in period t
h	Unit product holding cost at the supplier
a	Unit RTI holding cost at the supplier
h_r	Unit product holding cost at retailer r
a_r	Unit RTI holding cost at retailer r
c^P	Unit RTI purchasing cost
m	Net weight of unit RTI
f	Fixed transportation cost per vehicle
β	Variable transportation cost per kg per km
dis_r	Distance between manufacturer and retailer r (km)
Decision variables	
p_t	Production quantity in period t
w_t	= 1 if $p_t > 0$; otherwise 0

q_{grt}	Quantity of products with quality g delivered to retailer r in period t
d_{grt}	Quantity of products with quality g satisfy customers at retailer r in period t
x_t	Amount of RTIs purchased by manufacturer in period t
n_{rt}	Amount of RTIs used to ship products to retailer r in period t
y_{rt}	Returned amount of RTI from retailer r in period t
v_{rt}	Number of vehicles used to ship RTIs to retailer r in period t
I_{gt}	Inventory of products with quality g at the manufacturer at the end of period t
X_{grt}	Inventory of products with quality g at retailer r at the end of period t
Y_t	Inventory of RTIs at manufacturer at the end of period t
Z_{rt}	Inventory of RTIs at retailer r at the end of period t

Model P_0 :

Objective function

$$\begin{aligned}
\max f_1 = & \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} s_{gr} d_{grt} - \left\{ \sum_{t \in T} (S_t w_t + c_t p_t) \right. \\
& + \sum_{g \in G} \sum_{t \in T} (h l_{gt} + \sum_{r \in R} h_r X_{grt}) + \sum_{t \in T} (a Y_t + \sum_{r \in R} a_r Z_{rt}) \\
& \left. + \sum_{t \in T} \sum_{r \in R} f v_{rt} + \sum_{t \in T} \sum_{g \in G} \sum_{r \in R} dis_r \beta (q_{grt} + m(n_{rt} + y_{rt})) + \sum_{t \in T} c^p x_t \right\}
\end{aligned} \tag{4.1}$$

$$\min f_2 = \sum_{r \in R} \sum_{t \in T} v_{rt} \tag{4.2}$$

subject to:

$$p_t \leq C_t w_t, \forall t \in T \tag{4.3}$$

$$I_{0t} = p_t - \sum_{r \in R} q_{0rt}, \forall t \in T \tag{4.4}$$

$$I_{gt} = I_{(g-1)(t-1)} - \sum_{r \in R} q_{grt}, \forall t \in T, g \in G \setminus \{0\} \tag{4.5}$$

$$X_{0rt} = q_{0rt} - d_{0rt}, \forall t \in T, r \in R \tag{4.6}$$

$$X_{grt} = X_{(g-1)r(t-1)} + q_{grt} - d_{grt}, \forall t \in T, r \in R, g \in G \setminus \{0\} \tag{4.7}$$

$$\sum_{g \in G} I_{gt} \leq C^p, \forall t \in T \tag{4.8}$$

$$\sum_{g \in G} X_{grt} \leq C^p_r, \forall t \in T, r \in R \tag{4.9}$$

$$\sum_{g \in G} d_{grt} = D_{rt}, \forall t \in T, r \in R \tag{4.10}$$

$$\sum_{g \in G} q_{grt} \leq C^c n_{rt}, \forall t \in T, r \in R \tag{4.11}$$

$$Y_t = Y_{t-1} - \sum_{r \in R} n_{rt} + \sum_{r \in R} y_{rt} + x_t, \forall t \in T \tag{4.12}$$

$$\sum_{r \in R} n_{rt} \leq Y_{t-1} + x_t, \forall t \in T \tag{4.13}$$

$$Z_{rt} = Z_{r(t-1)} + n_{rt} - y_{rt}, \forall t \in T, r \in R \quad (4.14)$$

$$y_{rt} \leq Z_{r(t-1)}, \forall t \in T \quad (4.15)$$

$$Y_t \leq C^{RTI}, \forall t \in T \quad (4.16)$$

$$Z_{rt} \leq C^{RTI}_r, \forall t \in T, r \in R \quad (4.17)$$

$$n_{rt} \leq C^v v_{rt}, \forall t \in T, r \in R \quad (4.18)$$

$$y_{rt} \leq 2C^v v_{rt}, \forall t \in T \quad (4.19)$$

$$w_t \in \{0,1\}, \forall t \in T \quad (4.20)$$

$$I_{gt}, X_{grt}, p_t, d_{grt}, q_{grt} \geq 0, \forall t \in T, g \in G, r \in R \quad (4.21)$$

$$x_t, n_{rt}, y_{rt}, v_{rt}, Y_t, Z_{rt} \geq 0 \text{ integer}, \forall t \in T, r \in R \quad (4.22)$$

The objective is to maximize the total profit and to minimize the total transport emissions of the holistic CLSC, simultaneously. The total profit equals to the total revenue minus the total costs. The total revenue is the sum of product quantity of each age that satisfies customers multiplied by the corresponding selling price at each retailer (the first part of (4.1)). The total costs represented by the remaining parts of (4.1) consist of product production cost, product and RTI inventory costs, product and RTI transportation costs, and RTI purchasing cost. As mentioned above, the other objective of this study is to minimize the negative impacts of the CLSC. Being aware of that transportation activities contributes to most of the carbon emissions, we minimize the total vehicle transportation trips to achieve this goal, which is inspired by Garg et al. (2015). The formulation is shown in (4.2). Constraint (4.3) restricts production in any period cannot exceed its capacity. Constraints (4.4) and (4.5) represent the product inventory conservation and the aging of products at the manufacturer. Constraints (4.6) and (4.7) are the product inventory balance constraints and the aging of products at each retailer. Constraints (4.8) and (4.9) guarantee product inventory capacity must be respected at the manufacturer and each retailer, respectively. Constraint (4.10) shows that demand at the retailers must be satisfied. Constraint (4.11) requires that delivery quantity to each retailer respects available RTI capacity in each period. Constraints (4.12) and (4.14) guarantee the RTI flow balance at the manufacturer and the retailer, respectively. Constraints (4.13) and (4.15) restrict

the amount of RTI used and returned according to the operation sequence shown in Fig. 4.2(a) and (b), respectively. Specifically, Fig. 4.2(a) shows that RTIs are filled with products first at the supplier. Then these loaded RTIs are delivered to retailers and empty RTIs are picked up at the same time. Finally, empty RTIs are carried back to the supplier. Thus, in constraint (4.12) the quantity of returned empty RTIs in period t , i.e. $\sum_{r \in R} y_{rt}$ cannot be used to pack products. Consequently, constraint (4.13) restrict that empty RTIs used to fill products at period t would be no more than those from the inventory of period $t-1$ plus those being purchased at period t . From Fig. 4.2(b), we can see that retailers receive filled RTIs first and the vehicle returns to the supplier with available empty ones. Then customer consumption begins and filled RTIs are emptied. For this reason, empty RTIs after consumption at period t , i.e. n_{rt} in constraint (4.14) would not be returned. Therefore, constraint (4.15) restricts that empty RTI returned at period t would be no more than its inventory from period $t-1$. Constraints (4.16) and (4.17) mean that RTI inventory capacity at the manufacturer and each retailer must not be exceeded, respectively. Constraints (4.18) and (4.19) present the relation of RTIs and vehicles used to ship them in the forward and reverse flows. Note that the quantity of RTI returned in each period is limited by the total capacity of the vehicles in the forward flow of that period. Constraints (4.20)–(4.22) are binary, non-negativity and integrality constraints for the decision variables.

4.2.3 Further strengthen of the model

In this section, in order to narrow the solution search space and thereby reducing the computational burden, we come up with the following constraints to improve model P_0 based on the feature analysis of it.

Notice that in constraint (4.3), if period t needs to set up production, then the production quantity p_t must be less than or equal to the production capacity C_t , which is less tight along with period increasement. To make it tighter, constraint (4.3) can be rewritten as follows:

$$p_t \leq C_t w_t, \text{ if } C_t \leq \sum_{r \in R} \sum_{t'=t}^T D_{t'r}, \quad \forall t \in T, \quad (4.23)$$

$$p_t \leq \sum_{r \in R} \sum_{t'=t}^T D_{t'r} w_t, \text{ if } C_t > \sum_{r \in R} \sum_{t'=t}^T D_{t'r}, \quad \forall t \in T, \quad (4.24)$$

Equation (4.23) means that if in period t , the production capacity is less than or equal to the sum of the demand at all retailers from period t to the last period T , then constraint (4.3) will be replaced by formula (4.23), otherwise, by formula (4.24).

In addition, for the current model, the number of production set-up times ranges from 1 to $|T|$, which is not tight. Instead, we can compute its lower bound, i.e. the required smallest number of production set-up times, denoted as NS . Due to the deteriorating feature of the products, the production needs to be set up at least $NS_1 = \lceil |T|/|G| \rceil$ times. For example, if the horizon spans 30 periods and the age of the product is 5, then production need to be set up at least 6 times as the products can be stored at most 5 periods. Besides, it also relates to the total demand. Let SUM represent the sum of all the demands, i.e. $SUM = \sum_{r \in R} \sum_{t \in T} D_{rt}$, let NS_2 be the smallest set up times in this case. Then we rank all the production capacity in non-increasing order denoted as A'_t , we thus have

$$NS_2 = \begin{cases} t' + 1, & \text{if } \sum_{t=1}^{t'} A'_t < SUM, \text{ and } \sum_{t=1}^{t'+1} A'_t \geq SUM, \forall t \in T, 1 \leq t' \leq T-1, \\ |T|, & \text{otherwise} \end{cases} \quad (4.25)$$

Formula (4.25) means that if there exists t' , $1 \leq t' \leq T-1$ such that the sum of production capacities from period 1 to t' is smaller than the total demands SUM , and that of the production capacity from period 1 to $t'+1$ is greater than or equal to SUM , then at least $t'+1$ periods need to set up production, i.e. $NS_2 = t'+1$. Otherwise, we set $NS_2 = |T|$. Finally, the smallest number of production set-up times would be the larger one between NS_1 and NS_2 , we thus have $NS = \max \{NS_1, NS_2\}$. We then add constraint (4.26) to the model. And it is obvious that period 1 is mandatory to set up production, or else customer demands cannot be satisfied. This is represented by constraint (4.27).

$$\sum_{t \in T} x_t \geq NS \quad (4.26)$$

$$w_1 = 1 \quad (4.27)$$

Besides, we notice that the lower bound of vehicle transportation trips can be determined by (4.28).

$$\sum_{r \in R} \sum_{t \in T} v_{rt} \geq \sum_{r \in R} \left[\frac{\sum_{t \in T} D_{rt}}{C^C} \right] \frac{1}{C^V}, \quad (4.28)$$

Moreover, we have the following constraints.

$$\sum_{g=t}^{|G|-1} q_{grt} = 0, \forall r \in R \quad (4.29)$$

$$\sum_{g=t}^{|G|-1} d_{grt} = 0, \forall r \in R \quad (4.30)$$

$$\sum_{r \in R} d_{0rt} \leq C_t p_t, \forall t \in T \quad (4.31)$$

Constraint (4.29) means that in period t where $(1 \leq t \leq |G| - 1)$, there is no products with age $g=t$ that are delivered to each retailer to satisfy customers. Consequently, customers cannot obtain products with corresponding ages which is represented by constraint (4.30). Constraint (4.31) implies that if production is not set up in period t , there would be no products with age $g=0$ delivered to all the retailers. Accordingly, customers cannot be provided with the freshest products. According to the above analysis, a tighter MILP model P is formed as follows.

Model P:

Objective function

$$\begin{aligned} \max f_1 = & \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} s_{gr} d_{grt} - \left(\sum_{t \in T} (\delta_t w_t + c_t p_t) + \sum_{g \in G} \sum_{t \in T} (h I_{gt} + \sum_{r \in R} b_r X_{grt}) \right) \\ & + \sum_{t \in T} (a Y_t + \sum_{r \in R} e_r Z_{rt}) + \sum_{t \in T} \sum_{r \in R} f v_{rt} + \sum_{t \in T} \sum_{g \in G} \sum_{r \in R} dis_r \beta (q_{grt} + m(n_{rt} + y_{rt})) + \sum_{t \in T} c^p x_t \\ \min f_2 = & \sum_{r \in R} \sum_{t \in T} v_{rt} \end{aligned}$$

subject to:

Constraints (4.4) – (4.24) and (4.26) – (4.31).

4.3 Solution method

In this section, we design a modified ε -constraint method embedded by an improved kernel search heuristic (IKSH) to solve the proposed bi-objective MILP model. Hereafter, the method is named EIKSH. Our aim is to find an approximate

Pareto set for the studied problem. As reviewed in Chapter 2, ε -constraint method is one of the most commonly used method to solve multi-objective optimization problems, especially bi-objective problems. Its main idea is to retain one primary objective function and convert the others into constraints. In so doing, the multi-objective problem is transformed into a sequence of mono-objective ones, called ε -constraint problems.

Now we explain how the proposed EIKSH solves the BCLFSC-RTI. For the sake of brevity, the studied problem can be rewritten as follows.

$$\text{Maximize } f_1$$

$$\text{Minimize } f_2$$

s.t. Constraints (4.4) – (4.24) and (4.26) – (4.31).

The two objectives of our problem are the maximization of the total profit (f_1) and the minimization of the vehicle transportation trips (f_2) of the holistic supply chain, respectively. As decision makers care more about the profit of the supply chain, we consider f_1 as the primary objective function and change f_2 into constraints. The consequent single-objective ε -constraint problem, denoted as $P(\varepsilon)$ is formulated as:

$$P(\varepsilon): \quad \text{Maximize } f_1$$

$$\text{s.t. } f_2 \leq \varepsilon \quad (4.32)$$

and Constraints (4.4) – (4.24) and (4.26) – (4.31).

By varying the value of ε , a series of mono-objective problems are generated, and the Pareto front is obtained by solving them. The range of ε is determined by the so-called idea and Nadir points (f_1^I, f_2^I) , (f_1^N, f_2^N) . The idea and Nadir points (f_1^I, f_2^I) , (f_1^N, f_2^N) determine the search area in the two-dimensional objective space. As demonstrated by Bérubé et al. (2009), (f_1^N, f_2^I) and (f_1^I, f_2^N) are two Pareto optimal points of problem P . All the other efficient points will fall into the rectangle area with the lower left corner and upper right corner being (f_1^N, f_2^I) and (f_1^I, f_2^N) , respectively (Filippi et al. 2016). These efficient points form the Pareto front of P , denoted as Ω .

In the exact ε -constraint method, the mentioned idea and Nadir points (f_1^I, f_2^I) , (f_1^N, f_2^N) are computed by optimally solving the following single objective subproblems of P :

$$\begin{aligned}
P_1: & \quad f_1^l = \text{Maximize } f_1 \\
& \text{s.t. Constraints (4.4) – (4.24) and (4.26) – (4.31) .} \\
P_2: & \quad f_2^l = \text{Minimize } f_2 \\
& \text{s.t. Constraints (4.4) – (4.24) and (4.26) – (4.31) .} \\
P_3: & \quad f_1^N = \text{Maximize } f_1 \\
& \text{s.t. } f_2 = f_2^l \tag{4.33} \\
& \text{and Constraints (4.4) – (4.24) and (4.26) – (4.31) .}
\end{aligned}$$

$$\begin{aligned}
P_4: & \quad f_2^N = \text{Minimize } f_2 \\
& \text{s.t. } f_1 = f_1^l \tag{4.34} \\
& \text{and Constraints (4.4) – (4.24) and (4.26) – (4.31).}
\end{aligned}$$

The EIKSH approximates the idea and Nadir points (f_1^l, f_2^l) , (f_1^N, f_2^N) by heuristically solving the above four mono-objective problems P_1 to P_4 using the improved kernel search-based algorithm developed in Chapter 3. We denote the approximate points as (f_1^{Al}, f_2^{Al}) and (f_1^{AN}, f_2^{AN}) , respectively. Then the range of ε , i.e. the upper and lower bounds of f_2 is approximated as $[f_2^{Al}, f_2^{AN}]$. A sequence of ε -constraint problems will be generated by decreasing the value of ε within this interval. Here, we divide the interval $[f_2^{Al}, f_2^{AN}]$ by K points. Then step size Δ that to reduce ε at each iteration can be computed by formula $(f_2^{AN} - f_2^{Al}) / (K + 1)$. The IKSH is employed to solve the consequent mono-objective problem. When the iteration ends, we obtain the approximated Pareto front of the problem, denoted as Ω^A . The framework of the EIKSH is outlined in Algorithm 4.1.

Algorithm 4.1. Procedure of the EIKSH

1. Compute the approximated idea and Nadir points (f_1^{Al}, f_2^{Al}) , (f_1^{AN}, f_2^{AN}) of P using the improved kernel search heuristic developed in Chapter 3, i.e. Algorithm 3.1.
 2. Determine the step size $\Delta = (f_2^{AN} - f_2^{Al}) / (K + 1)$.
 3. Set $\Omega^A = \{(f_1^{AN}, f_2^{Al}), (f_1^{Al}, f_2^{AN})\}$ and let $\varepsilon_j = f_2^{AN} - \Delta, j = 2$.
 - 4. While ($\varepsilon_j > f_2^{Al}$), do:**
 - 4.1. Solve $P(\varepsilon_j)$ with Algorithm 3.1 and add the obtained objective vector $(f_1^{Al}(\varepsilon_j), f_2^{Al}(\varepsilon_j))$ to Ω^A .
-

4.2. Let $\varepsilon_{j+1} = \varepsilon_j - \Delta$ and $j = j+1$.

5. End while

6. Return Ω^A .

4.4 Computational experiments

In this section, a real case study derived from a fresh chilled pork meat supplier is used to validate the application of the proposed models. And various random instances are generated and solved to evaluate the performance of the proposed EIKSH. All the experiments are implemented in C++ code on a HP PC with 2GHz CPU and 12GB RAM. The mono-objective LP and RMILPs in Algorithm 4.1 are solved by commercial optimization software ILOG CPLEX (version 12.6.0).

To validate the performance of the improved model P , we implement algorithm 4.1 where CPLEX is used to solve the transformed single-objective problems by model P_0 and P , respectively. For each model, we compute the same solution points to observe the computation time and solution quality. Note that the computational time for the transformed single-objective problems is limited within 900s to stop the searching and output the best solution found so far. Let T_P , T_{P_0} and T_{EIKSH} denote the CPU seconds consumed by the proposed models and method. N_1 and N_2 denote the number of Pareto solutions obtained by the models and the algorithm, respectively.

4.4.1 Application of the model to a case study

4.4.1.1 Case background and description

The case study is derived from a medium-scale slaughterhouse located in Luohe city, China that produces fresh chilled pork meat. Fresh chilled pork meat refers to the meat whose temperature is dropped sharply to 0~4 degrees after slaughtered under -20 degree. After that it needs strict temperature conditions in the whole process of production, transportation and marketing to preserve quality and safety, and reduce product waste. And special food RTIs are mandatory to pack the meat. Figure 4.3 shows one of the workshops of the company. Fresh chilled meat can be stored for 3 to 7 days at 0~4 degrees. It has better taste, higher nutritional value

and is much safer than traditional fresh meat. However, due mostly to its higher cost and the consequent higher selling price, fresh chilled meat's market share is less than 30% while that in the developed countries is more than 90%. Therefore, it is very meaningful to investigate and optimize the fresh chilled meat supply chain to improve its performance and thus reducing product cost to stimulate consumption. In this section, we aim to utilize the proposed model to optimize the fresh chilled meat supply chain of the studied company to provide insights to decision makers.

The studied slaughterhouse produces fresh chilled pork meat and delivers them to its chain specialty stores in Zhengzhou city, China, with homogeneous refrigerated vans. The company has 91 chain specialty stores in Zhengzhou city which spread over 6 districts. Note that we consider customer demand of each district rather than each chain store in the case. Thus, products are transported to the distribution center of each district and the "last-mile" transportation is neglected.

Currently, the company produces and delivers products every day according to the demand amount. Therefore, no product inventory exists at the supplier and each retailer. Decision makers now would like to resort to the mathematical models to make plans week by week (7 days) to sell their meat products with different quality to the customers. The age of the meat product ranges from 0 to 6. The company notes that meat products with different quality level only impact the appearance and flavor but not the safety. Meanwhile, the tightened laws and regulations prompt the company to pay attention on the environmental impacts of their supply chain. Compared to regular trucks, refrigerated vans generate more carbon emissions. Therefore, minimizing the number of vans' transportation trips helps to reduce carbon emissions of the supply chain. The company's decision makers are interested in the trade off between the profit and the carbon emissions of their supply chain activities.

By interviewing with a relevant manager in the company, we obtain the input data for the case study, some of which is approximate for confidentiality reasons. The data is shown in Tables 4.1-4.5. Note that product (resp. RTI) storage capacity at the company (resp. each store) is not critical. Thus, constraints (4.10) –(4.11) and (4.18) –(4.19) in model P are removed when solving the model.



Fig. 4.3. A workshop of the company in the case study

Table 4.1 Demand of each district per period (in kg)

Days	District					
	Erqi	Zhongyuan	Jinshui	Huiji	Guancheng	Shangjie
1	4165	4748	6497	1250	2000	670
2	5525	5083	6431	1550	2850	916
3	5550	6012	7775	1687	2900	900
4	5800	6612	8548	1740	3150	928
5	6350	7261	8374	1995	3600	1064
6	6350	7261	8374	1995	3600	1064
7	4165	4748	6497	1250	1950	670

Table 4.2 Selling price of the product with different ages per district (in CNY)

Product Age	District					
	Erqi	Zhongyuan	Jinshui	Huiji	Guancheng	Shangjie
0	70	68	78	68	70	60
1	68.5	66.5	73.5	66.5	67.5	58.5
2	66	64	68	64	66	55
3	63.5	59.5	63.5	59.5	63.5	52.5
4	55	54	55	54	55	48
5	50	49.5	50	49.5	50	40
6	40	45	35	40	40	30

Table 4.3 Distance between the cold fresh meat supplier and the customer district (in km)

From	To District					
	Erqi	Zhongyuan	Jinshui	Huiji	Guancheng	Shangjie
The supplier	157	159	159	179	152	195

Table 4.4 Production capacity, production set-up cost and unit production cost per period

Parameters	Days						
	1	2	3	4	5	6	7
Production capacity (kg)	25000	27500	30000	35000	40000	40000	25000
Production set-up cost (CNY)	30000	32000	34000	40000	45000	45000	30000
Unit production cost (CNY)	35	34	33	30	28	28	35

Table 4.5. Remaining data for the case study

Parameter	Values
RTI capacity in terms of product	15kg
Vehicle capacity in terms of RTI	175RTI
Unit product holding cost at the supplier	0.05CNY
Unit RTI holding cost at the supplier	0.005CNY
Unit product holding cost at retailer r	0.05CNY
Unit RTI holding cost at retailer r	0.005CNY
Unit purchasing cost for RTI	30CNY
Net weight of unit RTI	2kg
Fixed transportation cost per vehicle	300CNY
Variable transportation cost per kg per km	0.01CNY

4.4.1.2 Results and managerial implications

Based on the above data, we first compute the company's solution the next week using the current production-delivery strategy, denoted as scenario S_0 . The total profit and vehicle transportation trips of S_0 are 6102984.4 and 87, respectively. The point is represented by a red rectangular in Figure 4.3(a). Then we employ the proposed models and method to obtain the Pareto front of the case study, denoted as the base case B. In the base case, the company uses RTIs with the capacity of 15kg in terms of products and vans with the capacity of 3t that can carry 175 loaded RTIs as shown in Table 4.5. Being aware that in fresh chilled meat industry, RTIs with capacity of 20kg (130 RTIs for a van with capacity of 3t) and vans with capacity of 5t, i.e. 290 in terms of RTIs are also frequently used. Thus, we observe the impacts on the company profit when changing the capacity of RTIs and vans, denoted as scenario S_1 and S_2 , respectively. Note that when the capacity of RTIs or vans changed, some relevant parameters such as the net weight of RTIs will also change. Thus, we summarize the changed data for scenarios S_1 and S_2 in Table 4.6. Moreover, to observe the impact of the selling price for products with different quality compared to the base case B, we conduct scenario S_3 that reduces the gap between the selling prices for products with different quality. The changed selling prices are presented in Table 4.7.

Table 4.6 Data for scenario S_1 and S_2

Parameters	Scenario S_1	Scenario S_2
RTI capacity (kg)	20	–
Vehicle capacity (RTI)	130	290
Unit RTI purchasing cost (CNY)	40	–
Net weight of unit RTI (kg)	2.6	–
Fixed vehicle transportation cost (CNY)	–	450
Variable transportation cost (kg)	–	0.02

Note: “–” means the data is the same as the base case B in Table 4.5.

Table 4.7 Product selling price for scenario S_3

Product Age	District					
	Erqi	Zhongyuan	Jinshui	Huiji	Guancheng	Shangjie
0	70	68	78	68	70	60
1	69.5	67	76.5	66.5	69.5	58.5
2	68	66.5	74	64	66	56
3	65.5	63	73.5	63	64.5	54.5
4	60	60	70	60	62	52
5	55	58	66	59.5	59.5	49.5
6	50	52.5	60	57	55	46

With models P_0 and P and by employing the solution method in Section 4.3, we solve the base case B and scenarios S_1 , S_2 and S_3 . The computation time is shown in Table 4.8. It can be found that the improved model (P) is much more efficient than the initial one (P_0) owing to the narrowed solution space. In detail, it only spent 4.4%, 2.1%, 61.7% and 17.8% of CPU time by P of that spent by P_0 , respectively. Note that there is 1 out of 18 single-objective problems is not solved to optima under scenario S_1 and a feasible solution is returned with a gap of 4.7% to the optimum when solving P_0 . It means the computation time is in fact much longer than 919.4s to obtain the optimal solution. Whereas model P is able to obtain all the optimal solutions in much shorter computation time.

Moreover, in order to observe the optimal profit of each scenario, we present the profit and cost breakdown in Table 4.9. From the first two rows of Table 4.9, we can see that the company’s profit of the next planning week improves 1.2% from 6102984.5 CNY to 6175274.1 CNY with the proposed optimized method. By analogy, the company can earn more profit in the long run. It can be seen from the second and third row that, when the capacity of RTIs increase from 15kg to 20kg, the profit has a slight increase of 1449.9 CNY. Thus, the decision makers of the

studied company may consider using RTIs with larger capacity although they are costlier. Regarding the use of vehicles with larger capacity, we observe from the fourth row of Table 4.9 that an obvious reduction in the profit occurs. It is because although larger vehicle can carry more RTIs to reduce transportation trips, they have higher fixed and variable costs. And as products' perishability, the production quantity is limited making larger vehicle not be better used of. The total profit of scenario S_3 in the last row has a big increase when narrow the gap of selling price between products with different quality. It is mainly due to the increase in the total revenue. This encourages decision makers of the company to strictly control all the stages of the meat supply chain to better preserve the quality.

Fig. 4.6 shows the obtained accurate Pareto front that contains all the efficient points of base case B and scenarios S_1 , S_2 and S_3 through solving model P by CPLEX. The two points (f_1^I, f_2^N) and (f_1^N, f_2^I) marked in red represent the extreme cases where each of the two objectives is individually optimized. In the following, we take Fig.4.6(a) as an example to analyze the trade-off between the efficient points. The optimal profit of the company f_1^I is 6175274.1 CNY with the corresponding vehicle transportation trips f_2^N being 86. When solely optimizing the second objective, we obtain $f_2^I = 67$ as the optimum value and the economic objective f_1^N is 6099703.3 CNY. The profit has a reduction of 12.2% while the vehicle transportation trips decrease by 22.1%. It can be observed from the Fig. 4.6(a) that each of the values between 67 and 86 with its corresponding value of the profit form a non-dominated point in the objective space. The profit increases at the expense of more vehicle transportation trips and the consequent more carbon emissions. The reason lies in that more frequent transportation means more fresher products are delivered to the retailer and less product inventory is induced. Similarly, if the company decision makers desire to improve the green image of the company by reducing the negative impact on the environment, a substantial decrease in the obtained profit is inevitable. This reveals the conflict nature of the considered two objectives. Decision makers could choose a desirable trade-off solution between the total profit and the carbon emissions from the alternative Pareto solutions which are shown in Table 4.10.

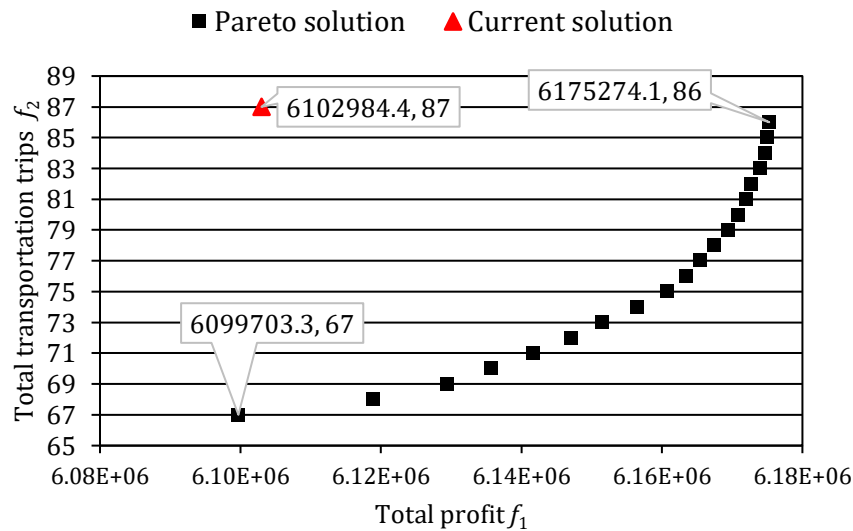
Table 4.8 Computation time for the base case B and three scenarios by models P_0 and P

	T_{P_0}	T_P	T_P / T_{P_0} (%)	N_1
B	459.5s	20.4s	4.4	20
S_1	919.4s(1)	19.5s	2.1	18
S_2	34.2s	21.1s	61.7	18
S_3	104.3s	18.6s	17.8	20

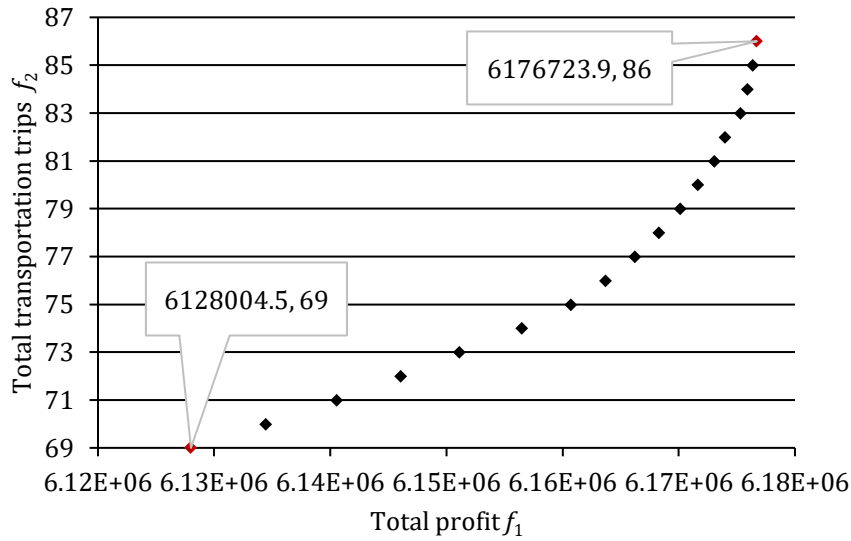
Note: Figures in the parentheses indicate the number of single-objective problems that cannot be solved within 900s

Table 4.9 Results of the scenarios when only f_1 is considered

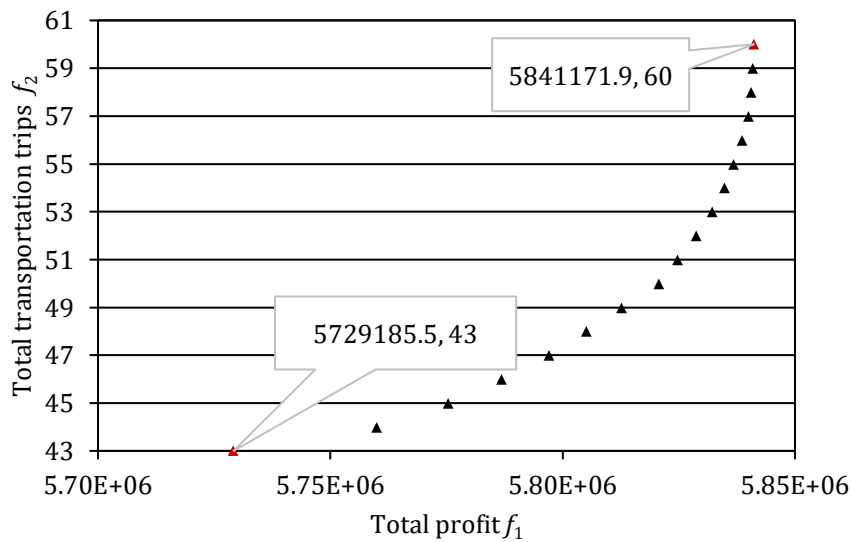
CNY	Total profit	Total revenue	Production cost	Product inventory cost	RTI inventory cost	Transportation cost	RTI purchasing cost
S_0	6102984.4	12141314	5594016	0	110.2	329783.4	114420
B	6175274	12079044.5	5429061	1360.4	110.7	358608.4	114630
S_1	6176723.9	12079010	5429131	1362.1	83.0	357110	114600
S_2	5841171.9	12079031	5429069	1360.8	110.7	692568.6	114750
S_3	6213157.5	12116895	5429082	1361.4	110.6	358583.5	114600



(a) Solution of S_0 and Pareto front of base case B



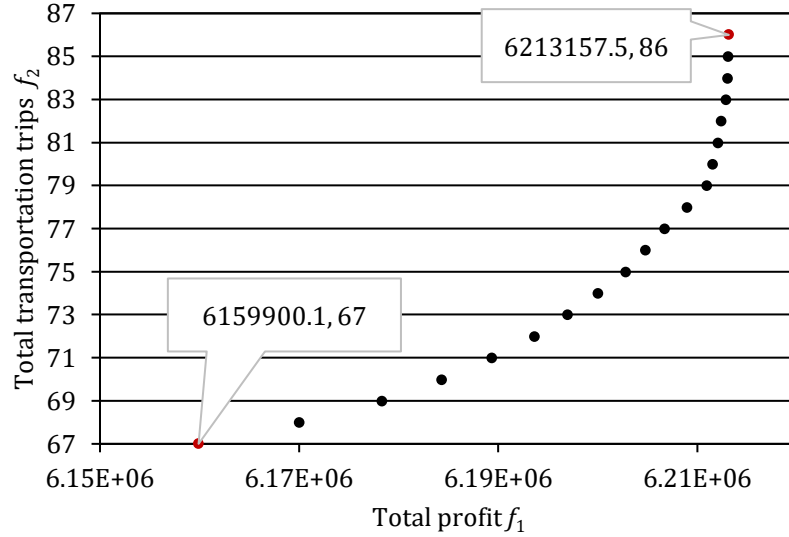
(b) Pareto front of scenario S_1



(c) Pareto front of scenario S_2

4.4.2. Random test instances

To gain additional insights into the performance of the proposed models and method, we test 15 randomly generated problem sets with 5 instances for each set, i.e., 75 instances in total. These instance sets are solved by CPLEX solver with model P_0 , model P and the EIKSH with model P , respectively. Table 4.11 presents



(d) Pareto front of scenario S_3

Fig. 4.4 Pareto front of each scenario

Table 4.10 All the non-dominated points for the base case

No.	(f_1, f_2)	No.	(f_1, f_2)	No.	(f_1, f_2)	No.	(f_1, f_2)
1	(6175274.1,86)	6	(6171956.4,81)	11	(6163427.7,76)	16	(6141629.3,71)
2	(6175036.2,85)	7	(6170819.6,80)	12	(6160733.4,75)	17	(6135791.1,70)
3	(6174643.3,84)	8	(6169448.1,79)	13	(6156537.8,74)	18	(6129467.6,69)
4	(6173978.7,83)	9	(6167434,78)	14	(6151528.9,73)	19	(6118919.9,68)
5	(6172763.1,82)	10	(6165496.7,77)	15	(6147185.5,72)	20	(6099703.3,67)

the way to generate parameters for the random instances which is based on the data of the case study in the previous section. $U(a, b)$ is a uniform distribution function between parameters a and b . The computational results are reported in Table 4.12, in which columns “Set”, “ $|G|$ ”, “ $|T|$ ” and “ $|R|$ ” represent the set number, the number of product ages, planning periods, and retailers, respectively. The number of product ages changes from 3 to 5, the number of planning period ranges from 5 to 7 and the number of retailers varies from 5 to 15. Note that the results in columns “ T_{P_0} ”, “ T_{P_0} ”, “ T_{EIKSH} ”, “ N_1 ” and “ N_2 ” are the mean value of the five instances in the same set. Setting the solution sets obtained by the improved model P as the reference set (RS), we use three metrics, i.e. the number of solutions NS_2 , Q_{AF} that measures the approximated points in the obtained Pareto set that are not dominated by any point in RS , and the hypervolume ratio HF to evaluate the EIKSH’s performance.

It can be observed from Table 4.12 that computational time increases explicitly with the number of planning periods and the retailers. The improved

model P is more efficient than the initial one P_0 . Specifically, the average computation time by model P_0 is 1932.6s with 138 in total transformed mono-objective problems being not solved within the time limit, whereas the average computation time spent by model P is 953.7s which is 49.3% of the former.

Table 4.11. Parameter generation scheme for the random instances

Notation	Description	Notation	Description
D_{rt}	$U(1000, 8000)$	c_t	$U(25, 40)$
s_{gr}	$c - (c-d) \cdot g / G $, where c is generated by $U(80, 100)$ and d by $U(60, 80)$	h	$U(0.3, 1)$
C_t	$U(1.5, 5) \sum_{r \in R} D_{rt}$	a	$U(1, 1.5)h$
A	$\max\{C_t\}$	b_r	$U(0.001, 0.005)$
B	$[0.2 A]$	e_r	$U(0.005, 0.01)$
E_r	$\max\{D_{rt}\}$	c^p	$U(20, 100)$
H_r	$U(0.2, 0.5)E_r$	m	$U(0.5, 2.5)$
C^C	$U(10, 30)$	f	$U(200, 400)$
C^v	$U(50, 200)$	β	$U(0.01, 0.1)$
δ_t	$U(5000, 15000)$	dis_r	$U(20, 200)$

Table 4.12. Results of the random instances

Set	$ G $	$ T $	$ R $	T_{P_0}	T_P	N_1	T_{EIKSH}	N_2	Q_{AF}	HF
1	3	5	5	552.1	3.2	8	12.9	8	0.75	0.95
2	3	5	10	1081.1	22.4	20.4	88.5	20	0.75	0.99
3	3	5	15	1046.5	276.4	26.6	300.9	26	0.86	0.95
4	3	6	5	692.2	7.3	11.8	7.6	11.8	0.73	0.99
5	3	6	10	1313.4	599.1	22.2	437.3	21.8	0.89	0.99
6	3	6	15	3331.8	2394.6	31.8	1563.8	31.2	0.86	0.97
7	3	7	5	742.4	11.2	13.6	36.6	13.6	0.83	0.99
8	3	7	10	2693.3	2163.0	21.2	1522.9	21.2	0.97	0.97
9	3	7	15	8083.1	6844.3	31.8	4645.2	31.2	0.78	0.93
10	4	5	5	188.5	4.3	9	6.9	9	0.76	0.95
11	4	5	10	885.2	122.3	14.2	244.1	14.2	0.95	0.95
12	4	5	15	2596.3	527.4	26.2	311.7	26	0.89	0.95
13	5	5	5	329.4	4.2	9.4	7.1	9.4	0.8	0.95
14	5	5	10	1215.3	52.5	15.4	281.9	15.4	0.94	0.97
15	5	5	15	4237.8	1274.3	22	603	22	0.83	0.95
Ave.				1932.6	953.7	18.9	671	18.7	0.84	0.96

This demonstrate that the improved model outperforms the initial one in terms of solution efficiency.

The proposed EIKSH is more efficient than the two models in terms of computation time. N_2 , Q_{AF} and HF are used to evaluate the solution quality by the

EIKSH. And the set obtained by the improved model P is used as the reference set. We can see from table 4.12 that the average number of solutions obtained by the EIKSH is 18.7 which is nearly equal to 18.9 that by the models. It means the proposed method can yield comparable number of approximated solutions. The average value of Q_{AF} is 0.84, which implies that on average 84% solutions obtained by the proposed method is not dominated by any points in the Pareto optimal set obtained by model P . The average value of HF 0.96 that is approximate to 1 also demonstrates solution obtained by the proposed EIKSH is of good quality. It can be concluded that the proposed EIKSH is slightly more efficient than model P while maintaining good solution quality.

4.5 Conclusions

This chapter investigates a bi-objective closed-loop food supply chain with RTIs. The two conflict objectives are the maximization of the total profit and the minimization of the total negative environmental impacts throughout the planning horizon. The problem is first formulated as a bi-objective MILP, and several inequalities are then developed to narrow the solution space based on problem property. For the resolution, an iterative ε -constraint method is applied to solve it. In each iteration of the ε -constraint method, the improved kernel search-based heuristic is employed to solve the transformed single-objective problems. The effectiveness and efficiency of the proposed model and method are assessed by a real case study derived from a slaughterhouse and various randomly generated instances. Computational results demonstrate that the improve model is much more efficient than the initial one and that the proposed method outperforms the direct use of the commercial optimization solver CPLEX.

Part of the work has been published in the following paper.

Y. Zhang, F. Chu, A. Che. Bi-objective optimization for closed-loop food supply chain involving returnable transport items. The 8th International Conference on Industrial Engineering and Systems Management (IESM 2019), 25-27 September in Shanghai 2019.

Chapter 5

Closed-loop Food Inventory Routing Problem with Multi-type RTIs

5.1 Introduction

In a supply chain that characterized by multiple retailers, vehicle routing problem (VRP) is always considered to reduce distribution cost/distance, lower harmful gas emissions during transportation activities, and improve resource (e.g. vehicle capacity) utilization. As stated in Chapter 2, VRP has been widely studied in both forward and reverse supply chain. Whereas, it is rarely considered in the context of CLSCs. This Chapter naturally extends the closed-loop food supply chain problem with RTIs (CLFSC-RTI) of Chapters 3 and 4 by considering vehicle routing decisions. Combined with the included inventory decisions in Chapters 3 and 4, a multi-period closed-loop food inventory routing problem with RTIs (CFIRP-RTI) has to be addressed in this chapter. In the CFIRP-RTI, filled RTIs are delivered to each retailer and meanwhile empty RTIs at the retailer are picked up and are finally carried back to the supplier for reuse. Up to now, only a handful of literature has focused on this kind of supply chain.

On the other hand, fresh food products such as fruits and vegetables, are with limited shelf life and are vulnerable to dropping and vibrations. Thus, they require good temperature control and protection during the storage, transportation and handling to ensure the quality. RTIs play a crucial role in this regard. However, as reviewed in Chapter 2, most RTI-related studies from the perspective of supply chain consider only one kind of RTI as in Chapters 3 and 4 of the thesis. Whereas in the real-world food sector, there exist many kinds of RTIs. They may be in different materials or have diverse structures resulting in different performance, i.e. the impacts on food itself and the external environment. For example, some RTIs are made up of environmentally friendly material (e.g. organic plastic) while some are in general or inferior material (e.g. recycling material rather new material). RTIs with holes can ensure ventilation but cannot keep inside temperature. More protective RTIs such as those with covers and/or cushions can reduce bruise damage of products like strawberry and mango but are costlier

(Chonhenchob et al. 2008, Stock et al. 2001). In view of their complementary attributes, considering mixed use of different types of RTIs and then selecting the most suitable combination for food supply chains are necessary. As package types have significant effects on food quality (such as taste and appearance) and the resultant selling price and customer satisfactory, it is essential to consider the RTIs' protective performance for the food they carry. To the best of our knowledge, such considerations in the CFIRP-RTI has not been investigated yet.

This chapter aims to narrow the above-mentioned research gap by investigating a CFIRP-RTI where RTIs are in different types. Note that the problem is also called CFIRP-RTI for short hereafter. The CFIRP-RTI is first formulated as an integer linear program (ILP). Then computational experiments on a fresh cherry distribution case study and randomly generated instances are conducted to validate the proposed model. Finally, the CFIRP-RTI is extended to a bi-objective case (BCFIRP-RTI) with additional objective function and parameters. A bi-objective ILP is formulated, and the case study is used to validate it.

The remainder of this chapter is organized as follows. Section 5.2 describes and formulates the CFIRP-RTI. In Section 5.3, computational results on a numerical instance and 140 randomly generated instances are reported. Section 5.4 studies the BCFIRP-RTI. Section 5.5 concludes this chapter.

5.2 Problem description and formulation

5.2.1 Problem description

The studied CFIRP-RTI can be defined on a directed graph $G = (N, A)$ with $N = \{0, \dots, |N|\}$ as the node set and $A = \{(i, j): i, j \in N, i \neq j\}$ being the set of arcs. Vertex 0 represents the supplier and $N_0 = N \setminus \{0\}$ represents $(|N| - 1)$ retailers. The considered planning horizon is finite and is divided into discrete periods $t \in T = \{1, 2, \dots, |T|\}$. The supplier with limited capacity produces or receives perishable food products and packs them into various kinds of RTIs indexed by $k \in K = \{1, 2, \dots, |K|\}$. Note that these RTIs are assumed to be sorted in an increasing order of their quality for the convenience of modeling. The filled RTIs are then delivered to each retailer with limited inventory capacities by capacitated homogeneous vehicles $l \in L = \{1, 2, \dots, |L|\}$ at the supplier. After the vehicles reach each retailer, a certain amount of filled RTIs are unloaded and at the same time "ready-to-be-returned"

RTIs are picked up. These RTIs are finally taken back to the supplier for refilling. Figure 5.1 presents the general framework of the studied problem. The operation sequence per period at the supplier and retailers that impacts the model formulation is in accordance with that illustrated in Figure 4.2 of Chapter 4. And in line with most IRP literature, we assume that each retailer can be visited at most once and each vehicle can only perform one route starting from the supplier to a subset of retailers and ending at the supplier per period.

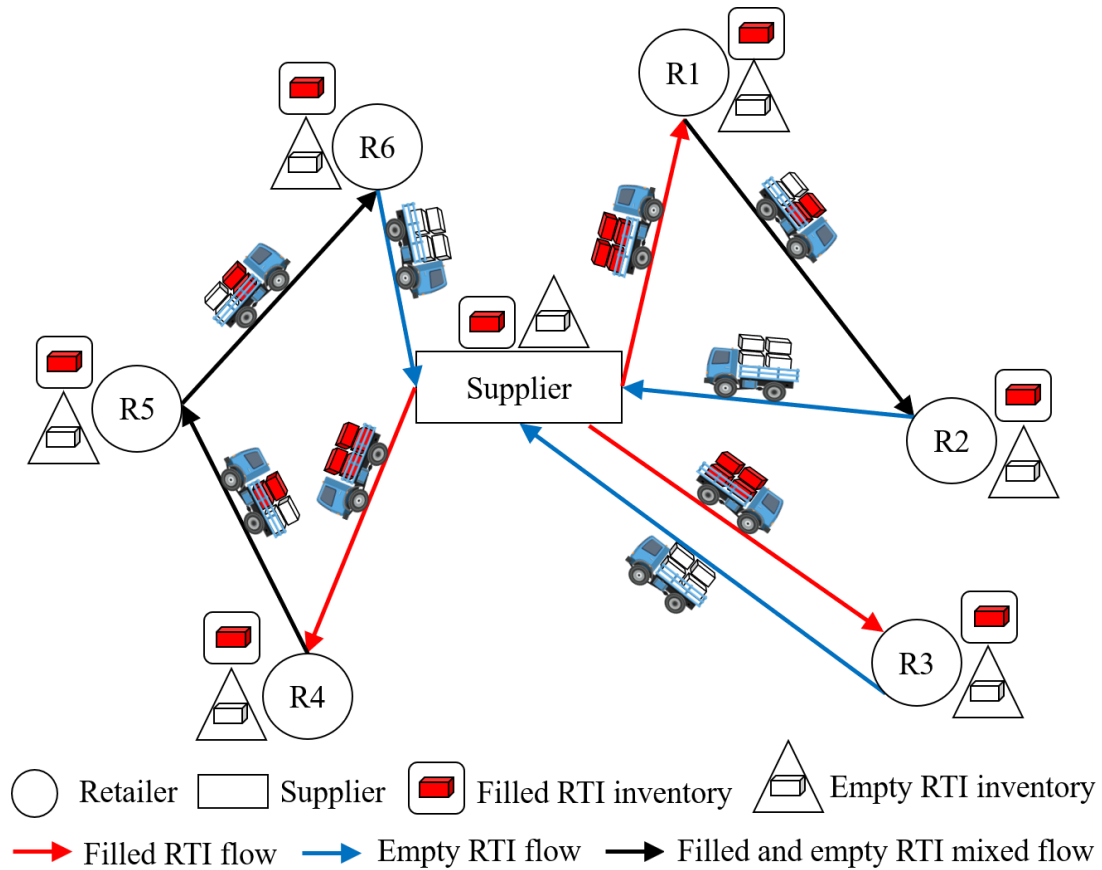


Fig. 5.1. Framework of CIRP with RTIs

We have the following additional assumptions for model formulation:

- 1) The supplier has sufficient inventory and capacity to tackle all the deliveries and pickups during the planning horizon such that all the demands are satisfied.
- 2) Without loss of generality, the initial filled and empty RTIs at each node are zero.
- 3) Different kinds of RTIs have the same size but different purchase costs, different net weight and different product protection abilities, which impact the final selling price of the product. It is rational to assume that

better-material RTIs have larger purchasing cost, smaller net weight and bigger product protective ability.

- 4) Products packed with RTIs possessing better protective performance have higher average selling prices which are distinguished according to the region of the retailer.
- 5) Storage cost for filled RTIs are higher than empty RTIs as products need special storage conditions. And it cost less to store RTIs at the supplier than at retailers due to economies of scale.
- 6) RTI replenishment happens at the beginning of the period if necessary and is instantaneous.
- 7) The returned empty RTIs are regarded as the same with the newly purchased ones.
- 8) Variable transportation cost is related to truck payload and drive distance.

Note that most of the above assumptions are in line with the literature, e.g. Iassinovskaia et al. (2017). The aim of the problem is to optimally determine for each period (i) the routes and quantities of filled/empty RTI delivery/pick up to/from the retailers, (ii) the filled and empty RTI inventory levels at each node, (iii) how many and in which kind of RTIs purchased and filled, (iv) the amount and in which kind of filled RTIs are used to satisfy demand at each retailer to maximize the total profit of the supply chain.

5.2.2 Problem formulation

Table 5.1 shows the notations used for problem formulation.

Table 5.1. Sets, parameters and decision variables

Notation	Description
Sets	
N	Set of nodes including the supplier, $N = \{0, \dots, N \}$
N_0	Set of retailers, $N_0 = N \setminus \{0\}$
T	Set of periods, $t \in T = \{1, 2, \dots, T \}$
A	Set of arcs, $A = \{(i, j): i, j \in N, i \neq j\}$
K	Set of RTI types, $k \in K = \{1, 2, \dots, K \}$
L	Set of vehicles, $l \in L = \{1, 2, \dots, L \}$
Parameters	
a_i	Storage capacity for filled RTI at node $i \in N$ (RTI)
b_i	Storage capacity for empty RTI at node $i \in N$ (RTI)
v	Vehicle capacity (RTI)
h_{ik}	Storage cost for filled RTI k at node $i \in N$ (CNY/RTI)

n_{ik}	Storage cost for empty RTI k at node $i \in N$ (CNY/RTI)
δ_{ij}	Distance between nodes $i \in N$ and $j \in N$ (km)
α	Fixed transportation cost of vehicle (CNY/km)
β	Variable transportation cost of vehicle (CNY/kg·km)
θ_k	Purchase cost for RTI k (CNY/RTI), $\theta_1 < \theta_2 < \dots < \theta_{ K }$
f	RTI capacity (kg/RTI)
w_k	Weight of empty RTI k (kg/RTI), $w_1 > w_2 > \dots > w_{ K }$
d_{it}	Demand at node $i \in N_0$ in period t (RTI)
c	Unit product cost (CNY/kg)
r_{ik}	Average selling price of unit product in RTI k at node $i \in N_0$ (CNY/kg), $r_{i1} < r_{i2} < \dots < r_{i K }$

Decision variables

I_{ikt}	Inventory level of filled RTI k at node $i \in N$ at the end of period t (RTI)
X_{ikt}	Inventory level of empty RTI k at node $i \in N$ at the end of period t (RTI)
Y_{ikt}	Quantity of filled RTI k delivered to node $i \in N_0$ in period t (RTI)
Z_{ikt}	Quantity of empty RTI k returned from node $i \in N_0$ in period t (RTI)
D_{ikt}	Quantity of filled RTI k used to satisfy customer at node $i \in N_0$ in period t (RTI)
x_{ijkt}	Quantity of filled RTI k transported from node $i \in N$ to node $j \in N$ in period t (RTI)
y_{ijkt}	Quantity of empty RTI k transported from node $i \in N$ to node $j \in N$ in period t (RTI)
Z_{kt}	Quantity of new RTI k purchased by the supplier in period t (RTI)
m_{kt}	Quantity of RTI k filled by the supplier in period t (RTI)
u_{ijlt}	= 1 if arc (i, j) is traversed by vehicle l in period t ; otherwise 0

The proposed integer linear programming model are as follows.

Model P:

$$\begin{aligned} \max f_1 = & \sum_{i \in N_0} \sum_{k \in K} \sum_{t \in T} fr_{ik} D_{ikt} - \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} (h_{ik} I_{ikt} + n_{ik} X_{ikt}) - \sum_{k \in K} c f m_{kt} \\ & - \sum_{i \in N} \sum_{j \in N} \sum_{t \in T} \delta_{ij} (\alpha \sum_{l \in L} u_{ijlt} + \beta (\sum_{k \in K} ((f + w_k) x_{ijkt} + w_k y_{ijkt}))) - \sum_{k \in K} \sum_{t \in T} \theta_k z_{kt} \end{aligned} \quad (5.1)$$

subject to

$$I_{ik0} = 0, \forall i \in N, k \in K \quad (5.2)$$

$$X_{ik0} = 0, \forall i \in N, k \in K \quad (5.3)$$

$$I_{0kt} = I_{0k(t-1)} + m_{kt} - \sum_{i \in N_0} Y_{ikt}, \forall t \in T, k \in K \quad (5.4)$$

$$I_{ikt} = I_{ik(t-1)} + Y_{ikt} - D_{ikt}, \forall i \in N_0, k \in K, t \in T \quad (5.5)$$

$$X_{0kt} = X_{0k(t-1)} + z_{kt} - m_{kt} + \sum_{i \in N_0} Z_{ikt}, \forall t \in T, k \in K \quad (5.6)$$

$$X_{ikt} = X_{ik(t-1)} - Z_{ikt} + D_{ikt}, \forall i \in N_0, k \in K, t \in T \quad (5.7)$$

$$m_{kt} \leq X_{0k(t-1)} + z_{kt}, k \in K, \forall t \in T \quad (5.8)$$

$$Z_{ikt} \leq X_{ik(t-1)}, \forall i \in N_0, k \in K, t \in T \quad (5.9)$$

$$\sum_{k \in K} I_{ikt} \leq a_i, i \in N, t \in T \quad (5.10)$$

$$\sum_{k \in K} X_{ikt} \leq b_i, \forall i \in N, t \in T \quad (5.11)$$

$$\sum_{k \in K} D_{ikt} = d_{it}, \forall i \in N_0, t \in T \quad (5.12)$$

$$\sum_{i \in N, j \neq i} x_{ijkt} - \sum_{i \in N, i \neq j} x_{jikt} = Y_{jkt}, \forall j \in N_0, k \in K, t \in T \quad (5.13)$$

$$\sum_{i \in N, i \neq j} y_{jikt} - \sum_{i \in N, j \neq i} y_{ijkt} = Z_{jkt}, \forall j \in N_0, k \in K, t \in T \quad (5.14)$$

$$\sum_{k \in K} (x_{ijkt} + y_{ijkt}) \leq v \sum_{l \in L} u_{ijlt}, \forall (i, j) \in A, t \in T \quad (5.15)$$

$$\sum_{i \in N, j \neq i} u_{ijlt} = \sum_{i \in N, i \neq j} u_{jilt}, \forall j \in N, l \in L, t \in T \quad (5.16)$$

$$\sum_{j \in N_0} u_{0jlt} \leq 1, \forall l \in L, t \in T \quad (5.17)$$

$$\sum_{i \in N} \sum_{l \in L} u_{ijlt} \leq 1, \forall j \in N_0, t \in T \quad (5.18)$$

$$\sum_{i \in S} \sum_{j \in S} u_{ijlt} \leq |S| - 1, \forall S \subseteq N_0, |S| \geq 2, l \in L, t \in T \quad (5.19)$$

$$u_{ijlt} \in \{0, 1\}, \forall (i, j) \in A, l \in L, t \in T \quad (5.20)$$

$$I_{ikt}, X_{ikt}, x_{ijkt}, y_{ijkt}, z_{kt}, m_{kt} \in \mathbb{Z}^+, \forall i, j \in N, k \in K, t \in T \quad (5.21)$$

$$Y_{ikt}, Z_{ikt}, D_{ikt} \in \mathbb{Z}^+, \forall i \in N_0, k \in K, t \in T \quad (5.22)$$

The objective function (5.1) is to maximize the total profit which equals to the total revenue minus the total costs. The total revenue is the summation of the multiplication of three items, i.e. the unit selling price of product packed by RTI k at retailer i , the capacity of RTI and the amount of filled RTI k delivered to retailer i in period t . The total costs consist of filled and empty RTI storage costs, product cost, transportation cost, and new RTI purchasing cost. Constraints (5.2) and (5.3) initialize the inventory level for filled and empty RTIs at the beginning of the horizon to be zero, respectively. Constraints (5.4) and (5.5) represent the filled RTI inventory conservation at the supplier and retailers, respectively. Constraints (5.6) and (5.7) express the empty RTI inventory balance constraints at the supplier and retailers, respectively. Constraint (5.8) and (5.9) restrict the quantity of filled (resp. empty) RTIs delivered (resp. returned) to (resp. from) each retailer according to the operation sequence shown in Fig. 4.2(a) and (b) of Chapter 4, respectively. Specifically, Fig. 4.2(a) shows that RTIs are filled with products first at the supplier.

Then these loaded RTIs are delivered to retailers and empty RTIs are picked up at the same time. Finally, empty RTIs are carried back to the supplier. Thus, in constraint (5.6) the quantity of returned empty RTIs in period t , i.e. $\sum_{i \in N_0} Z_{ikt}$ cannot be used to pack products. Consequently, constraint (5.8) restrict that empty RTIs used to fill products at period t would be no more than those from the inventory of period $t-1$ plus those being purchased at period t . From Fig. 4.2(b), we can see that retailers receive filled RTIs first and at the same time return the empty ones. Then customer consumption begins and filled RTIs are consequently emptied. For this reason, empty RTIs after consumption at period t , i.e. D_{ikt} in constraint (5.7) would not be returned. Therefore, constraint (5.9) restricts that empty RTI returned at period t would be no more than its inventory from period $t-1$. Constraints (5.10) and (5.11) guarantee that inventory capacity for filled and empty RTIs at each node must be respected, respectively. Constraint (5.12) shows that demands at the retailers must be satisfied. Constraints (5.13) and (5.14) indicate the quantity of filled RTIs delivered and empty RTIs returned to and from retailers, respectively. Constraint (5.15) restricts vehicle capacity on each arc cannot be exceeded. Constraint (5.16) represents vehicle flow balance at each node per period. Constraints (5.17) restricts that each vehicle can perform at most one route per period. Constraint (5.18) ensures each retailer can be visited by at most one vehicle per period. Constraint (5.19) guarantees no subtours are allowed. Constraints (5.20) and (5.22) impose nonnegativity and integrality on decision variables. The CFIRP-RTI possesses NP-hard feature as it contains a conventional vehicle routing problem which has been proved to be NP-hard (Lenstra and Rinnooy Kan, 1981).

5.3 Computational experiments

To validate the proposed model, we test it on a numerical instance and 140 randomly generated instances. The model is implemented in C++ code on a HP PC with 2GHz CPU and 12GB RAM and is solved by ILOG CPLEX (version 12.6.0). We set 3600s as the time limit of CPLEX to stop the searching and output the best solution found so far. Note that as the number of subtour elimination constraint (5.19) increases exponentially with the number of nodes and thus greatly increasing computational burden, it is added only when violated as most literature does (e.g. Archetti et al. 2011). More specifically, the original model P of the CFIRP-

RTI is solved with constraint with (5.19) being relaxed. If subtours occur in the obtained solution, (5.19) is added iteratively and the model is re-solved to eliminate them. The iteration ends until no subtours exist and the current solution is output as the optimal solution. If the time limit is reached while subtours are still not eliminated, then CPLEX is deemed infeasible to provide any solution.

5.3.1 A numerical instance

The numerical instance is generated based on a real case for fresh cherry distribution derived from Soysal et al. (2016). Note that some of the data is adapted and added for the consistency of the studied problem. The case is characterized by 6 nodes including 1 supplier and 5 wholesale markets, i.e. $i, j \in N = \{0, 1, \dots, 5\}$, a planning horizon of 6 weeks, i.e. $t \in T = \{1, 2, \dots, 6\}$, 2 types of RTIs, i.e. $k \in K = \{1, 2\}$ and 2 homogeneous vehicles, i.e. $l \in L = \{1, 2\}$. The capacity of vehicles $v=500$ in term of RTIs. The fixed and variable transportation costs α and β are 0.8 CNY/km and 0.002 CNY/kg·km, respectively. The cherry cost is 20 CNY/kg. The demand of each retailer per week is shown in Table 5.2. The storage cost for filled RTI at each retailer is $h_{i1}=13$ CNY/RTI-week and $h_{i2}=10$ CNY/RTI-week. The storage cost for empty RTI at each retailer is $n_{i1}=3$ CNY/RTI-week and $n_{i2}=1.5$ CNY/RTI-week. The storage capacity for filled and empty RTIs at the nodes and the average unit selling price of cherry packed in RTI k at each retailer are shown in Table 5.3. Distance matrix between nodes are shown in Table 5.4. Parameters related to RTI feature are shown in Table 5.5.

Table 5.2. Customer demand

d_{it} (RTI)	1	2	3	4	5	6
1	100	74	100	174	20	27
2	94	107	140	14	7	80
3	80	187	20	47	87	120
4	94	94	194	24	10	87
5	54	100	74	40	84	77

Table 5.3 Values of parameters a_i , b_i , and r_{ik}

Parameter	0	1	2	3	4	5
a_i (RTI)	700	350	280	360	350	200
b_i (RTI)	700	350	280	360	350	200
r_{i1} (CNY/kg)	—	50	40	45	48	42
r_{i2} (CNY/kg)	—	52	43	46	50	45

Table 5.4. Distance matrix

δ_{ij} (km)	0	1	2	3	4	5
0	0	179	228	161	179	92.2
1	177	0	175	287	339	214
2	228	173	0	285	385	310
3	163	288	282	0	169	166
4	178	339	383	170	0	112
5	91.5	215	312	170	114	0

Table 5.5. Values of parameters f , θ_k , and w_k

Parameter	$k=1$	$k=2$
f (kg/RTI)	15	15
θ (CNY/RTI)	10	50
w (kg/RTI)	2	1

The case study is solved to optimality quickly in 6.85s and the optimum profit is 906850.8 CNY. The results of decision variables through the planning 6 weeks are presented in Figure 5.2 and Tables 5.6 and 5.7. Note that figures in the brackets indicate the types of RTI. Figure 5.2 shows the locations of the supplier and 5 wholesalers and the results of routing-related variables, i.e. the routing per period and the filled (in black font) and empty (in red font) RTIs transported between nodes. The quantity of RTI purchased and filled per period is shown in Table 5.6. Other results are presented in Table 5.7. In detail, we can see from Figure 5.2 that not any empty RTIs are returned in the first week. The reason is twofold: 1) the initial inventory of empty RTIs at each retailer is set as zero, and 2) consumption has not begun such that RTIs are all still occupied according to the operation sequence illustrated in Chapter 4. Then empty RTIs' return occurs when it is cost-effective. However, 1 empty RTI is returned from node 5 at the end of the planning horizon although it is not economical as the inventory capacity of empty RTIs at the node is exceeded. It can be observed from Table 5.6 that a number of 352 RTIs in type 1 is purchased while that number is 738 for RTIs in type 2. And the number of RTIs that is chosen to pack cherries is 352 in type 1 and 2058 in type 2. It implies that RTIs in type 1 are used to ship cherries only once while RTIs in type 2 are used multiple times after purchased. It is because although RTIs in type 2 are more expensive than those in type 1, they incur less storage and transportation cost and can provide better protection for cherries they carry which leads to a higher selling price. The results in Table 5.7 are in accordance with the above analysis.

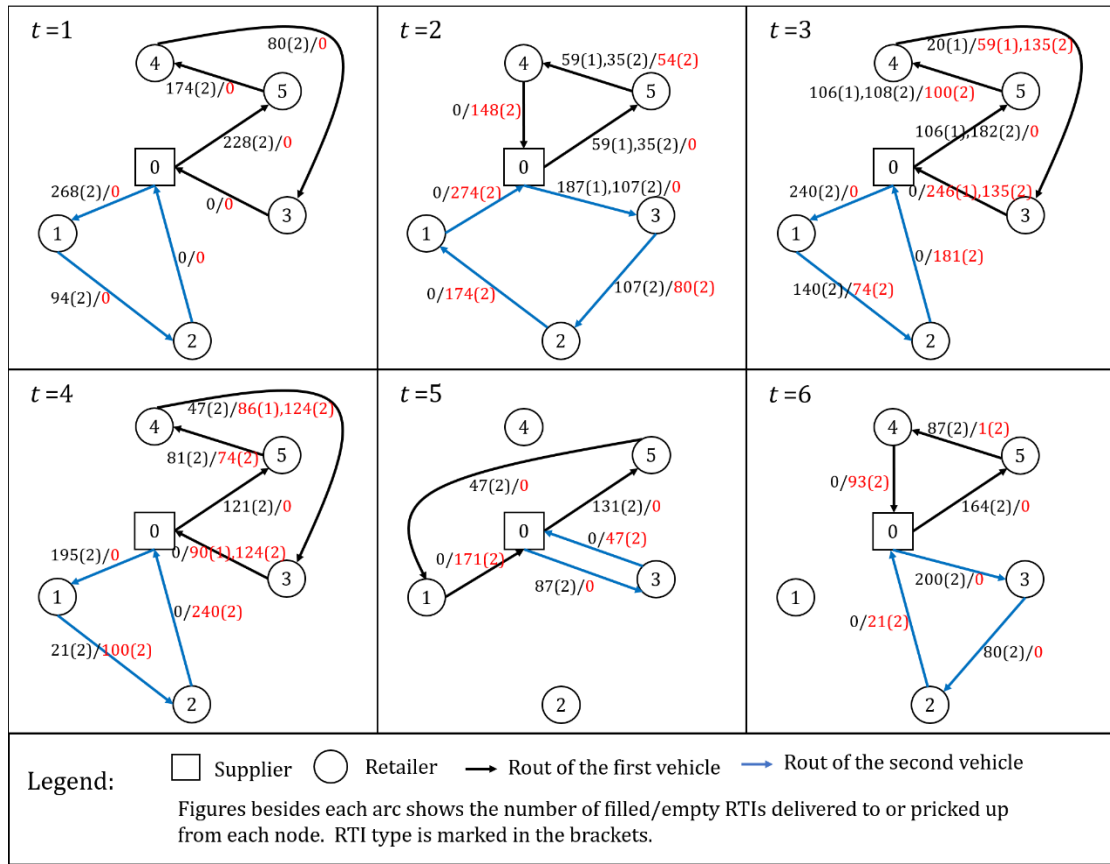


Fig. 5.2 Results of the routing-related variables per week

Table 5.6 Results of RTI purchased/filled per period, in RTI

	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
z_{kt}	496(2)	246(1), 242(2)	106(1)	0	0	0
m_{kt}	496(2)	246(1), 242(2)	106(1), 422(2)	316(2)	218(2)	364(2)

Table 5.7 Filled/ empty RTI delivery/ return, inventory, customer demand satisfied quantities during the planning weeks, in RTI

Node	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
1	174(2)		100(2)	174(2)	47(2)	
2	94(2)	107(2)	140(2)	21(2)		80(2)
Y_{ikt} 3	80(2)	187(1)	20(1)	47(2)	87(2)	120(2)
4	94(2)	59(1), 35(2)	86(1), 108(2)	34(2)		87(2)
5	54(2)	100(2)	74(2)	40(2)	84(2)	77(2)
0						
1	74(2)					
2						
I_{ikt} 3						

	4		7(2)		10(2)		
	5	27(2)					
	0		422(2)	246(1), 316(2)	336(1), 364(2)	336(1), 364(2)	336(1), 114(2)
	1	100(2)	74(2)	100(2)	174(2)	23(2)	50(2)
	2	94(2)	107(2)	140(2)	14(2)	21(2)	80(2)
X_{ikt}	3	80(2)	187(1)	20(1)	16(1), 47(2)	16(1), 87(2)	16(1), 207(2)
	4	94(2)	59(1), 35(2)	86(1), 108(2)	82(2)	92(2)	87(2)
	5	54(2)	100(2)	74(2)	40(2)	124(2)	200(2)
	1	100(2)	74(2)	100(2)	174(2)	20(2)	27(2)
	2	94(2)	107(2)	140(2)	14(2)	7(2)	80(2)
D_{ikt}	3	80(2)	187(1)	20(1)	47(2)	87(2)	120(2)
	4	94(2)	59(1), 35(2)	86(1), 108(2)	24(2)	10(2)	87(2)
	5	54(2)	100(2)	74(2)	40(2)	84(2)	77(2)
	1		100(2)	74(2)	100(2)	171(2)	
	2		94(2)	107(2)	140(2)		21(2)
Z_{ikt}	3		80(2)	187(1)	4(1)	47(2)	
	4		94(2)	59(1), 35(2)	86(1), 50(2)		92(2)
	5		54(2)	100(2)	74(2)		1(2)

5.3.2 Random instances

To gain further insights into the model performance, we test 28 randomly generated problem sets with 5 instances for each set, i.e., 140 instances in total. For these instances, the number of retailers $|N_0|=5-11$ for $|T|=5$, the number of planning periods $|T|=6-10, 15, 20$ for $N_0=5$, the number of RTI types $|K|$ is set to 2 and 3, and the number of vehicles $|L|=2$ for $|N_0|=5, 6, 7$, $|L|=3$ for $|N_0|=8, 9, 10$, and $|L|=4$ for $|N_0|=11$. Other parameters are generated by the way described in Table 5.8. Computational results are reported in Tables 5.9–5.10 and Figures 5.3–5.4, respectively. Column “ CT ” represents the computational time. Each value is the average of 5 instances in the same problem set.

Table 5.8. Parameter generation scheme for the random instances

Notation	Description
d_{it}	$\sim U(10, 50)$
a_0	$=\eta (\max \{\sum_{i \in N} d_{it}\})$, where $\eta \sim U(1, 1.5)$, $t \in T$
a_i	$=\eta (\max \{\sum_{t \in T} d_{it}\})$, where $\eta \sim U(2,3)$, $i \in N_0$

b_0	$=\eta (\max \{\sum_{i \in N} d_{it}\})$, where $\eta \sim U(1, 2)$, $t \in T$
b_i	$=\eta (\max \{\sum_{t \in T} d_{it}\})$, where $\eta \sim U(1, 2)$, $i \in N_0$
v	$=\eta(\max \{\sum_{i \in N} d_{it}\} / L)$, where $\eta \sim U(1.5, 2)$, $t \in T$
h_{ik}	$\sim U(0.01, 0.04)$ for $i=0$; $\sim U(0.05, 1.0)$ for $i \in N_0$, where $k \in K$
n_{ik}	$=0.5 h_{0k}$ for $i=0$; $=0.5 h_{ik}$ for $i \in N_0$, where $k \in K$
θ_k	$\sim U(10, 30)$ for $k=1$; $= 2\theta_{k-1}$ for $1 \leq k \leq K $
δ_{ij}	$=\lceil \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} + 0.5 \rceil$, where $x_i, x_j \sim U(10, 100)$, $i, j \in N_0$
α	$\sim U(0.8, 3)$
β	$\sim U(0.01, 0.05)$
f	$\sim U(10, 25)$
w_k	$\sim U(2, 3)$ for $k=1$; $= 0.5\theta_{k-1}$ for $1 \leq k \leq K $
c	$\sim U(20, 50)$
r_{ik}	$=\eta p$, where $\eta \sim U(1.5, 3)$ for $k=1, i \in N_0$; $= 1.02r_{i(k-1)}$ for $1 \leq k \leq K , i \in N_0$

Table 5.9. Results of random instances when $|T|=5$, and $|N_0|=5-11$

Set	$ N_0 $	$ T $	$ K $	$ L $	CT	Set	$ N_0 $	$ T $	$ K $	$ L $	CT
1	5	5	2	2	9.83	8	5	5	3	2	8.72
2	6	5	2	2	12.01	9	6	5	3	2	24.15
3	7	5	2	2	37.86	10	7	5	3	2	252.67
4	8	5	2	3	59.79	11	8	5	3	3	838.23(1)
5	9	5	2	3	102.22	12	9	5	3	3	930.35(1)
6	10	5	2	3	1053.52(1)	13	10	5	3	3	1881.19(2)
7	11	5	2	4	3600(5)	14	11	5	3	4	1198.61(1)
Ave.					682.66	Ave.					733.42

Note: Figures in the parentheses indicate the number of instances for each set that cannot be solved to optimality within 3600s.

From Table 5.9, we can observe that for $|T|=5$ and $|K|=2$, CT tends to increase with $|N_0|$. And when $|N_0|$ is from 10 to 11, the increasement is quite sharp. To be specific, when $|N_0|$ increases from 5 to 11, CT increases from 9.83s to 3600s. For $|T|=5$ and $|K|=3$, CT has an increase trend with $|N_0|$ ranging from 5 to 10. However, when $|N_0|=11$, CT reduces a bit. It implies that other parameters impact the computational results. They will be studied in the sensitivity analysis in Section 5.3.3. The comparison results for $|K|$ are shown in Figure 5.3 which indicates that CT increases in general from $|K|=2$ to $|K|=3$. It is rational that the model becomes hard to solve when $|K|$ increases as more trade-offs need to be made when choosing appropriate RTIs.

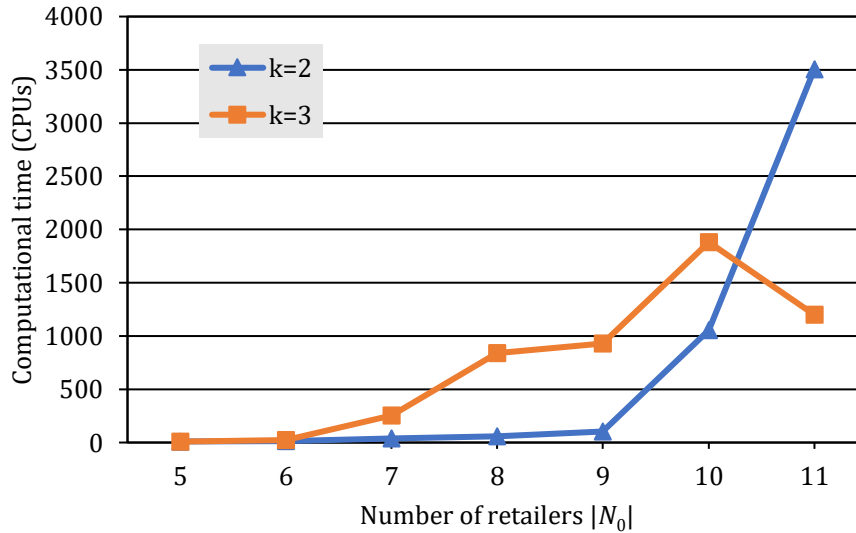


Fig. 5.3. Comparison results of k when $|T|=5$

Table 5.10. Results of random instances when $|T|=6-10,15,20$, and $|N_0|=5$

Set	$ N_0 $	$ T $	$ K $	$ L $	CT	Set	$ N_0 $	$ T $	$ K $	$ L $	CT
15	5	6	2	2	11.26	22	5	6	3	2	31.72
16	5	7	2	2	20.34	23	5	7	3	2	730.53
17	5	8	2	2	34.32	24	5	8	3	2	56.87
18	5	9	2	2	57.97	25	5	9	3	2	80.39
19	5	10	2	2	1657.82(1)	26	5	10	3	2	156.87
20	5	15	2	2	3047.17(4)	27	5	15	3	2	3280.41(4)
21	5	20	2	2	3600(5)	28	5	20	3	2	3600(5)
Ave.					1204.13	Ave.					1133.83

Note: Figures in the parentheses indicate the number of instances for each set that cannot be solved to optimality within 3600s.

It can be observed from Table 5.10 that when $|N_0|=5$ and $|K|=2$, CT increases with $|T|=6-10, 15$ and 20 . For $|N_0|=5$ and $|K|=3$, CT generally enjoys an increase trend with an exception of set 23. Comparison results between the case of $|K|=2$ with those of $|K|=3$ under the same setting of $|N_0|$ and $|T|$ are illustrated in Figure 5.4. From Figure 5.4, we learn that the latter case is not always more difficult to solve than the former one. This is caused by the similar reason mentioned above when analyzing the results of Table 5.9.

Moreover, we can see that when $|N_0|$, $|T|$ and $|K|$ increase, the number of instances that cannot be solved to optimality within 3600s become more. In detail, 1 out of set 6, 11, 12, 14, 19 and 42, 2 out of set 13, 4 out of set 20, 27, and 5 out of set 7, 21 and 28 instances cannot be solved to optimality when the time limit is reached. It is because the NP-hard complexity of the problem. Thus, efficient

algorithm needs to be developed for the problem in the future work.

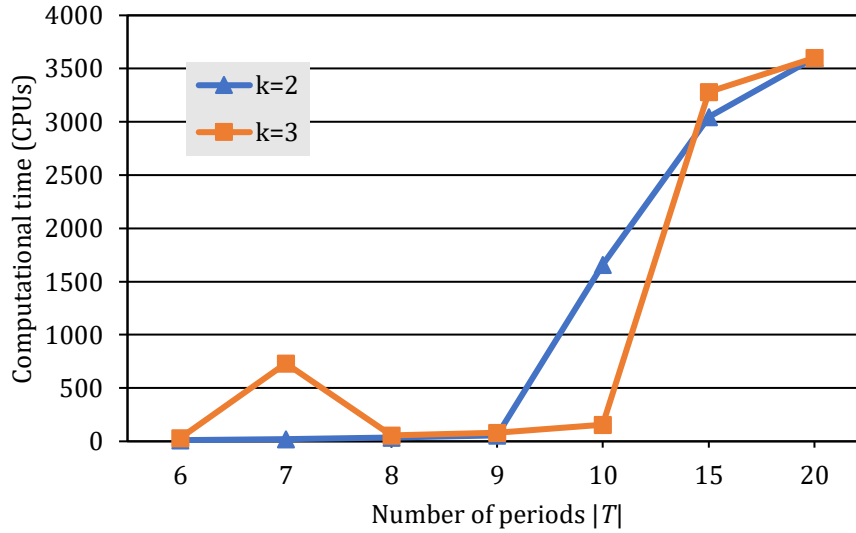


Fig. 5.4. Comparison results of k when $|N_0|=5$

5.3.3 Sensitivity analysis

In this subsection, we conduct sensitivity analysis for the model on the changes in vehicle capacity (v), distance between nodes (δ_{ij}), variable transportation cost (β), and average selling price of product packed by different types of RTIs (r_{ik}). The results are reported in Table 5.11 of which column 1 lists the name of the parameters, column 2 presents how the parameters change, columns 3–8 reports the total revenue, total costs and the resultant total profit and the last column gives the computation time. Note that the results of set 9 in Table 5.9 is used as the base case and are in bold. All the values are the average of 5 instances in the set. It can be observed from Table 5.11 that in all the cases, the optimal solution has the characteristic that the total product cost is constant. It is equal to unit product cost multiplied by the total customer demand throughout the planning horizon. In what follows, we analysis the impact of parameter changes in detail.

For the sensitivity analysis of vehicle capacity v , we only observe the model performance when it is larger (1.5 times of the value in the base case) as a smaller value may lead to infeasibility. From Table 5.11, we can see that the total profit has a slight increase with the increase of v . It is because that a bigger vehicle capacity enables the vehicle to load more RTIs when performing each delivery task. In this case, the fixed transportation cost is allotted to more products. Thus, the total transportation cost decreases at the expense of a higher inventory cost. As the

inventory cost increases more slowly than the transportation cost, the profit is slightly bigger than the base case. This inspires decision makers to choose a vehicle with bigger capacity in the studied case.

For variable transportation cost β , the cases of $1/2\beta$, 2β and 4β are investigated. It can be observed from Table 5.11 that when β increases, the total revenue and each of the total cost increase while the total profit decreases. The reason lies in that when the variable transportation cost becomes larger, fewer empty RTIs will be returned as it is more economic to buy new ones. Thus, the total RTI purchasing cost and inventory cost become larger. It is preferable for decision makers to choose RTIs that are made of lighter material and that can be well folded and stacked to reduce the variable transportation cost.

With respect to the distance between nodes δ_{ij} , three cases of $1/2\delta_{ij}$, $2\delta_{ij}$, and $4\delta_{ij}$ are studied. Table 5.11 shows that the impact of δ_{ij} is similar to that of β . This implies that longer travel distance between the supplier and its retailers increases the cost of transportation and empty RTI returns. This indicates that supply chains that use RTIs to ship products and simultaneously pick up empty RTIs are more effective and applicable when the distance between nodes is relatively short.

Lastly, we aim to obtain insights into the changes in the selling price for product packed by different kinds of RTIs. In the base case, selling price for unit product packed by better-quality RTIs is 2% more than that by less better-quality RTIs. When the percentage increases up to 5%, we can see from Table 5.11 that the total revenue and the total RTI purchasing cost increase significantly. As the total revenue increases much faster than the total RTI purchasing cost, the total profit also enjoys a great increasement. This is rational that more better-quality RTIs will be purchased and used to pack products as the gap between the selling price of product packed by better-quality and less better-quality RTIs is bigger. When the percentage continues to increase, the increasement is not obvious as almost all the packages are chosen to use better-quality RTIs. So, there is little space to increase the resultant profit. Based on the above arguments, choosing better-quality RTIs to protect the product they carry at the expense of higher purchasing cost is economical when the gap between the unit selling price of products packed by different kinds of RTIs.

Table 5.11 Results of sensitivity analysis

Par. Scenarios	Total revenue	Total inventory	Total trans. cost	Total RTI purchasing	Total product	Total profit	Comput. time
----------------	---------------	-----------------	-------------------	----------------------	---------------	--------------	--------------

		cost	cost	cost	cost	cost	cost	cost
β	$1/2\beta$	1553877.5	57.0	30075.0	33630	675403.6	814711.9	30.0
	β	1554278.4	57.5	55826.1	34432	675403.6	788559.2	24.2
	2β	1554924.3	58.1	107094.6	35458	675403.6	736865.0	20.9
	4β	1555009.9	63.6	207217.0	38056	675403.6	634269.7	31.3
δ_{ij}	$1/2\delta_{ij}$	1553749.7	57.6	28224.0	33422.8	675403.6	816641.7	18.4
	δ_{ij}	1554278.4	57.5	55826.1	34432	675403.6	788559.2	24.2
	$2\delta_{ij}$	1554925.4	57.5	111091.6	35446.8	675403.6	732920.2	28.5
	$4\delta_{ij}$	1555186.6	65.7	217922.4	39076.8	675403.6	622718.1	63.0
r_{ik}	$1.02r_{i(k-1)}$	1554278.4	57.5	55826.1	34432	675403.6	788559.2	24.2
	$1.05r_{i(k-1)}$	2040386.0	53.8	55402.9	39225.6	675403.6	1270300.1	16.3
	$1.1r_{i(k-1)}$	2128368.6	53.8	55387.4	39505.6	675403.6	1358018.1	13.5
v	v	1554278.4	57.5	55826.1	34432	675403.6	788559.2	24.2
	$1.5v$	1554267.4	61	55695.3	34432	675403.6	788675.5	23.0

5.4 An extension to bi-objective case

The model P in section 5.2.1 aims to maximize the total profit of the holistic CLSC. In the single-objective CFIRP-RTI, different kind of RTIs with different features (e.g. product protective performance, cost, net weight) are available to pack products at the supplier. The RTI protective performance in the model P is reflected indirectly by the final selling price of products. In this subsection, we are interested in studying the RTI protective performance as an independent objective function to observe the tradeoff between it and the total profit. Thus, we extend the CFIRP-RTI to a bi-objective case (BCFIRP-RTI) by introducing a second objective function that maximizes the total RTI protective performance. To this aim, a new parameter is defined, i.e. P_k which represents the product quality protection level of RTI type k and obviously we have $P_1 < P_2 \dots < P_{|K|}$. Higher protection level for the food product means higher customer satisfactory as she/he will receive better-quality products. As this parameter is qualitative, decision makers may quantize it with the help of decision-making techniques such as analytic hierarchy process (Amin and Zhang 2013). And the value of the parameter is between 0 and 1. By introducing the additional parameter, the second objective function can be written as:

$$\max f_2 = \sum_{k \in K} \sum_{t \in T} P_k m_{kt} \quad (5.23)$$

With (5.23), the BCFIRP-RTI is formulated into model BP as follows.

Model BP:

$$\max f_1 = \sum_{i \in N_0} \sum_{k \in K} \sum_{t \in T} f r_{ik} D_{ikt} - \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} (h_{ik} I_{ikt} + n_{ik} X_{ikt}) - \sum_{k \in K} c f m_{kt}$$

$$-\sum_{i \in N} \sum_{j \in N} \sum_{t \in T} \delta_{ij} (\alpha \sum_{l \in L} u_{ijlt} + \beta (\sum_{k \in K} ((f + w_k)x_{ijkt} + w_k y_{ijkt})) - \sum_{k \in K} \sum_{t \in T} \theta_k z_{kt} \quad (5.1)$$

$$\max f_2 = \sum_{k \in K} \sum_{t \in T} P_k m_{kt} \quad (5.23)$$

subject to:

Constraints (5.2) – (5.22).

As introduced in Chapter 2, ε -constraint method is one of the most widely used methods to address bi-objective optimization problems (BOOP). This motivates us to employ it as the resolution for the BCFIRP-RTI in this chapter. The basic idea of ε -constraint method is to retain one primary objective function and transform the others into constraints to form a series of single objective ε -constraint problems. Exactly solving these ε -constraint problems allows to obtain the Pareto front of the BOOP. For details, please recall the introduction for the ε -constraint method in Chapter 2.

Since the thesis focuses on the total profit of the CLSC, we select f_1 as the primary objective and transform f_2 into a constraint. In so doing, the bi-objective model BP is converted to a single objective, denoted by $BP(\varepsilon)$ as follows.

Model $BP(\varepsilon)$:

$$\begin{aligned} \max f_1 = & \sum_{i \in N_0} \sum_{k \in K} \sum_{t \in T} fr_{ik} D_{ikt} - \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} (h_{ik} I_{ikt} + n_{ik} X_{ikt}) - \sum_{k \in K} cfm_{kt} \\ & - \sum_{i \in N} \sum_{j \in N} \sum_{t \in T} \delta_{ij} (\alpha \sum_{l \in L} u_{ijlt} + \beta (\sum_{k \in K} ((f + w_k)x_{ijkt} + w_k y_{ijkt})) - \sum_{k \in K} \sum_{t \in T} \theta_k z_{kt} \end{aligned} \quad (5.1)$$

subject to:

$$\sum_{k \in K} \sum_{t \in T} P_k m_{kt} \geq \varepsilon, \text{ and constraints (5.2) – (5.22).}$$

where ε is a parameter determined by the so-called Idea point (f_1^I, f_2^I) and Nadir point (f_1^N, f_2^N) . They can be computed by exactly solving the following four single objective problems (Bérubé et al. 2009).

$$BP(\varepsilon)1: \quad f_1^I = \max f_1(x) \quad \text{subject to constraints (5.2) – (5.22).}$$

$$BP(\varepsilon)2: \quad f_2^I = \max f_2(x) \quad \text{subject to constraints (5.2) – (5.22).}$$

$$BP(\varepsilon)3: \quad f_1^N = \max f_1(x) \quad \text{subject to } f_2 = f_2^I \text{ and constraints (5.2) – (5.22).}$$

$$BP(\varepsilon)4: \quad f_2^N = \max f_2(x) \quad \text{subject to } f_1 = f_1^I \text{ and constraints (5.2) – (5.22).}$$

The Pareto front is within a rectangle area bounded by (f_1^I, f_2^I) and (f_1^N, f_2^N) (Haimes et al. 1971) as illustrated by Figure 2.9 in Chapter 2. As reviewed in Chapter 2, ε -constraint method can be roughly divided into the so-called exact ε -

constraint method and equidistant ε -constraint method. The exact ε -constraint method is able to obtain the complete Pareto front of the studied BCFIRP-RTI. However, based on the preliminary experiments, an overwhelming number of solutions is provided with the exact ε -constraint method for the studied problem, which is not necessary for decision makers. Thus, we choose the equidistant ε -constraint method to achieve a desirable number of efficient points in order to improve the efficiency of decision-making.

In light of the above discussions, f_2 is bounded by $[f_2^N, f_2^I]$. Preliminary experiments show that f_2^N and f_2^I are very time-consuming to compute for our problem. However, based on analysis of the two competing objectives, it is found that we can obtain the values of f_2^I and f_2^N without solving problems $BP(\varepsilon)_2$ and $BP(\varepsilon)_4$ as the conventional ε -constraint method does. Instead, they can be simply computed by the formula $\sum_{k \in K} \sum_{t \in T} P_k m_{kt}^*$ and $P_{|K|} \sum_{k \in K} \sum_{t \in T} m_{kt}^*$, respectively, where m_{kt}^* represents the optimal solution of m_{kt} after solving problem $BP(\varepsilon)_1$.

With the interval of f_2 , i.e. $[f_2^N, f_2^I]$ and the introduction of the equidistant ε -constraint method in Chapter 2, the method is adapted to solve the BCFIRP-RTI as illustrated in algorithm 5.1. After implementing algorithm 5.1, a number of $K+1$ non-dominated points is obtained.

To validate the bi-objective model and gain insights into the tradeoff between f_1 and f_2 , we solve the bi-objective version of the numerical instance in Section 5.3.1 with additional objective function f_2 and parameters $P_1=0.5$ and $P_2=0.9$. The value of K in Algorithm 5.1 is set to be 10 to obtain 11 Pareto optimal solutions. It takes 59.88s to solve the BCFIRP-RTI. The obtained 11 non-dominated points in the objective space are shown in Figure 5.5. The extreme points (906851, 2028.2) and

Algorithm 5.1. Procedure of the equidistant ε -constraint method for BCFIRP-RTI

Compute the Idea and Nadir points, i.e. (f_1^I, f_2^I) , (f_1^N, f_2^N) of BP .

Initialize set $\Omega = \{(f_1^I, f_2^N), (f_1^N, f_2^I)\}$, $l=0$, $\varepsilon_l = f_2^N$, $range = f_2^I - f_2^N$ and the number of iteration number K

While ($l < K$), **do**:

Form problem $BP(\varepsilon_l)$ where $\varepsilon_l = f_2^N + \frac{range}{K} * l$

Exactly solve $BP(\varepsilon_l)$ to obtain an optimal solution x^*

Calculate the corresponding objective vector $(f_1^l(x^*), f_2^l(x^*))$

Let $\Omega = \Omega \cup (f_1^l(x^*), f_2^l(x^*))$

$l = l+1.$

End while

Return $\Omega.$

(902447, 2169) marked in the figure indicate that the values of the total profit f_1 decreases from 906851 CNY to 902447 CNY while those of the total protective performance f_2 increases from 2028.2 to 2169. Decision makers can choose a solution from them according to their preference. Specifically, when the decision maker is profit oriented, she/he may choose a solution where f_1 is with a larger value. Whereas, if the decision maker cares more about the quality of cherries that customers receive and accordingly their satisfactory, a solution with larger f_2 is preferred.

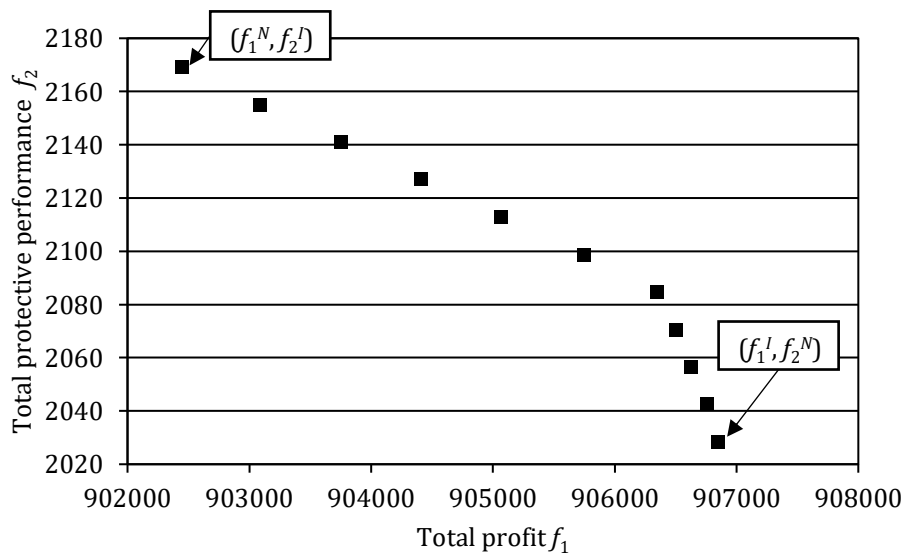


Fig. 5.5. Pareto front of the numerical instance

5.5 Conclusion

This chapter investigates a single-objective as well as a bi-objective food CLSC with routing decisions and different RTI types consideration. Accordingly, a single-objective ILP and a bi-objective ILP are developed. Computational experiments on a cherry distribution case study and 140 randomly generated instances

demonstrate the effectiveness and correctness of the models. As an ongoing work, the problems are only solved by CPLEX for small-scale instances. Despite that, we can obtain some insights for developing efficient heuristic for larger-sized problems in the future work.

Chapter 6

Conclusions and perspectives

This thesis investigates a multi-period closed-loop food supply chain (CLFSC) optimization problem involving returnable transport items (RTI). The research target is to provide optimal or near optimal planning by coordinating the forward product production-inventory-distribution and the RTI return flows to improve the global performance of the studied food supply chain. To this end, three novel closed-loop supply chain problems for perishable food products with RTIs are studied: 1) A single-objective closed-loop food supply chain with RTIs (CLFSC-RTI) that involves a single manufacturer and a single retailer; 2) A bi-objective CLFSC-RTI (BCLFSC-RTI) that includes a single manufacturer and multiple retailers; and 3) A closed-loop inventory routing problem with RTIs (CFIRP-RTI) that integrated with vehicle routing decisions and considers heterogenous RTIs. In the following, we first conclude the work done in the thesis and then highlight the future research directions.

First, we study a CLFSC-RTI that coordinates the flows of fresh food products and returnable containers. The CLFSC-RTI takes into consideration food quality level, dynamic customer demand and limited RTI purchasing budget. It integrates both forward supply chain planning of product production, delivery and distribution, and the reverse chain of RTIs return. For the problem, a novel MILP model is formulated and is proved to be NP-hard. Then an improved kernel search-based heuristic is developed for its resolution. A real case study derived from a food manufacturer verifies the applicability of the proposed model and method. The results indicate that the manufacturer's profit can be improved by more than 10% with our method. Numerical experiments on extensive randomly generated instances are conducted to further demonstrate that the proposed heuristic can yield high-quality solutions with much less computation time compared to the state-of-the-art commercial optimization solver CPLEX and one of the promising heuristics in the literature.

Then a bi-objective CLFSC-RTI that simultaneously maximizes the total profit and minimizes the total negative environmental impacts of the supply chain is addressed. The problem is first formulated as an original bi-objective MILP model. The model is then strengthened based on the analysis of problem property. An

improved kernel-search heuristic based ε -constraint method is designed to solve it. A real case study of a slaughterhouse is derived to evaluate the applicability of the proposed model. For the case study, we first observe the model performance when only economic objective is involved. Computational results show that the slaughterhouse's total profit can be improved by 1.2% in a one-week planning, and that it is more profitable to use RTIs with larger capacities. Then the proposed bi-objective model is solved to reveal the trade-off between the economic and environment objectives of the company. The performance of the proposed models and method are further examined by randomly generated instances. Results demonstrate that the improved model is much more efficient than the initial one and that the proposed heuristic is comparable to the direct use of the commercial solver CPLEX.

Finally, we investigate a closed-loop inventory routing problem with RTIs (CFIRP-RTI) that integrated with vehicle routing decisions and considers heterogeneous RTIs. RTIs are assumed to be made of heterogeneous materials that possess different protective performance. For the problem, a new MILP model is developed, and its complexity is proved. A numerical instance whose data is based on a cherry distribution case as well as random instances are used to evaluate the model. Then the model is extended to bi-objective case that simultaneously maximizing the total profit and food protection level. A bi-objective MILP is formulated for it and the case study is adapted to validate the model. This ongoing work is directly solved by CPLEX solver for small scale problems.

The closed-loop supply chain with RTIs (CLSC-RTI) has been attracting increasingly attention from both academia and practice. The dissertation is only one of the first attempts to study it in the context of perishable food products. There are still a lot of works need to be done in the future research, which are summarized as follows.

- 1) Extending the problem. This includes (a) The studied supply chain problems in the thesis involve only two stage, i.e. the manufacturer and the retailer. It is meaningful to insert other echelons, such as RTI pooler, RTI supplier, the third-party logistics (3PL), the collection center and the disposition center, etc; (b) The presented work only related to one kind of products. In practice, most companies or plants produce multiple types of products. For instance, a slaughter always not only provides fresh chilled meat but also frozen meat; (c) The thesis focuses on the economic and

environmental objectives of the studied closed-loop food supply with RTIs. However, social dimension is also an indispensable part for sustainable development. It is meaningful to consider the packaging choice on the quality and ergonomics of the labor, e.g. folding, stacking, sorting and washing of RTIs; and (d) Retailers in practice are not always available to the delivery service. Instead, a certain time interval is imposed by them to receive products. Thus, it is important to respect the time window set by retailers when delivering products. This is especially crucial in the context of food supply chain as the perishable characteristics of the products.

- 2) Addressing uncertainties. As losses or irreparable damage of RTIs frequently occurs in practical CLSC with RTIs, the quantity and quality of returned RTIs are uncertain. Moreover, customer demand is also a source of uncertainty. It is hard to know the demand information in all the periods beforehand. Therefore, these uncertainties should be considered, and the corresponding stochastic models and their solution method need to be developed.
- 3) Developing efficient algorithms. As an ongoing work, the studied BCLFSC-RTI in Chapter 5 is only solved by the commercial optimization solver for small scale problems. Efficient algorithm needs to be designed for large practical problems. Moreover, the proposed method for the problem in Chapter 4 is not efficient enough to solve larger sized problems. It needs to be improved in the coming future work.

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Y. Zhang, F. Chu, A. Che, Y. Yu and X. Feng. Novel model and kernel search heuristic for multi-period closed-loop food supply chain planning with returnable transport items. *International Journal of Production Research* 2019.

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Titre : Optimisation de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables

Mots clés : Chaîne logistique à boucle fermée ; nourriture périssable ; emballage réutilisable ; optimisation bi-critère ; émission carbone; heuristiques.

Résumé : La chaîne logistique à boucle fermée, qui est une des branches importantes de la chaîne logistique, a reçu une attention particulière au cours des dernières décennies. Toutefois, on trouve peu de recherches dans la littérature sur la chaîne logistique agroalimentaire bien qu'elle soit largement pratiquée dans l'industrie. L'objectif de cette thèse est de proposer de nouveaux modèles et de nouvelles heuristiques pour l'optimisation de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables. A cette fin, trois nouveaux problèmes sont étudiés.

Nous étudions d'abord un problème de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables. Ce problème implique un seul fabricant et un seul détaillant. L'externalisation est autorisée. Et le budget d'achat d'emballages réutilisable est limité. L'objectif est de maximiser le profit global de la chaîne logistique. Le problème est formulé en programmation linéaire en nombres mixtes et est démontré NP-difficile. Pour sa résolution, une nouvelle « kernel search-based » heuristique est développée. Les expériences numériques sur un cas d'étude et sur un grand nombre d'instances générées aléatoirement montrent l'efficacité de la méthode proposée.

Ensuite, un problème bi-critère de la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables est étudié. L'objectif est de maximiser le profit et de minimiser les émissions carbone, simultanément. Dans ce problème, plusieurs détaillants sont considérés. Ce problème est modélisé en programmation linéaire bi-objectif en nombres mixtes et résolu à l'aide d'une méthode de ε -contrainte. En particulier, une heuristique basée sur la « kernel search-based » est développée pour résoudre à chaque itération le problème transformé à un problème monocritère de la méthode de ε -contrainte. Les résultats numériques sur des instances générées aléatoirement indiquent que la performance de la méthode développée est comparable avec celle proposée par le solveur CPLEX.

Finalement, nous nous intéressons à un problème intégrant la gestion des stocks et la tournée de véhicules dans la chaîne logistique agroalimentaire à boucle fermée avec emballages réutilisables. Dans ce problème, les emballages réutilisables avec différents niveaux de protection sont considérés. Le problème est formulé en programmation linéaire en nombres mixtes and est démontré NP-difficile. Le modèle proposé est validé via des expériences numériques.

Title : Optimization of closed-loop food supply chain with returnable transport items

Keywords : Closed-loop supply chain; perishable food; returnable transport item; bi-objective optimization; carbon emission; heuristics.

Abstract : Closed-loop supply chain (CLSC), as an important branch of supply chain, has received increasing attention in recent decades. However, CLSC for perishable food products that is more complex than classic CLSC has been seldom studied in spite of its growing applications in practice. This thesis aims to develop new models and methods for optimizing closed-loop food supply chain with returnable transport items. To this end, three new problems are investigated.

Firstly, a closed-loop food supply chain with returnable transport items (CLFSC-RTI) is studied. This problem involves a single manufacturer and a single retailer. Outsourcing is permitted and RTI purchasing budget is limited. The objective is to maximize the total profit of the supply chain. The problem is formulated as a mixed integer linear program (MILP) and it is proved to be NP hard. To solve the problem, an improved kernel search-based heuristic is designed. Computational experiments on a real case study and extensive random instances demonstrate the effectiveness and efficiency of the proposed model and heuristic.

Secondly, a bi-objective closed-loop food supply chain with returnable transport items (BCLFSC-RTI) is investigated. The two objectives are to maximize the total profit and to minimize carbon emissions, simultaneously. The studied problem considers multiple retailers. For this complex bi objective problem, a bi-objective MILP is proposed for its modelling, and an iterative ϵ -constraint method is applied to solve it. Then, an improved kernel search-based heuristic is developed to solve the transformed single objective problem in each iteration of the ϵ -constraint method. Computational results based on various randomly generated instances show that the performance of the proposed method is comparable to that of a state-of-the-art commercial optimization solver CPLEX.

Finally, a closed-loop food inventory-routing problem with RTIs (CFIRP-RTI) is addressed. In this problem, a vehicle routing problem is integrated and returnable transport items with different protective levels are considered. An appropriate MILP is proposed to formulate the problem, and the problem is proved to be NP-hard. Numerical experiments are carried out to validate the proposed model.