MODELLING AND OPTIMIZATION OF CLOSED-LOOP SUPPLY CHAIN NETWORKS CONSIDERING PRODUCT RECOVERY

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Modelling and Optimization of Closed-Loop Supply Chain Networks Considering Product Recovery

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CERTIFICATE OF ORIGINALITY

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Abstract

Nowadays, environmental pollutions caused by improper abandoned end of life products are increasing dramatically. To improve the pollution situation caused by abandoned products, product recovery became popular in the research area of closed-loop supply chain recently. To accelerate the recovery of end of life products, so as to reduce the environmental pollution, the network of product recovery within closed-loop supply chain needs better planning. Since effective optimization design of product recovery network leads to efficiency and profitable business operation, thereby attracts more practitioners, it is significant to develop a closed-loop supply chain model considering product recovery. Correspondingly, the analysis of uncertainties became necessary. However, few of the work to date focused on the product recovery issues in closed-loop supply chain.

This research focuses on modeling and optimization of Closed-Loop Supply Chain (CLSC) network considering product recovery. Firstly, an integrated CLSC model considering product recovery is formulated. This model optimizes facility location and product delivery in CLSC network, considering product recovery simultaneously. Eight partners in CLSC are considered, including suppliers, manufacturers, warehouses, retailers, customer regions, collection points, recycling centers, and

waste disposal plant. In the literature, many closed-loop supply chain models were established and studied, but few of them analyzed the delivery activity for different kinds of recycled materials, and also only a few papers studied the situation that end of life products are classified according to their quality level. In this model, the delivery activities of different materials are considered and the end of life products are classified into good quality ones and poor quality ones. Producers will have different methods to process them.

To address the proposed closed-loop supply chain model considering product recovery, a modified two-stage Genetic Algorithm is proposed. The two-stage encoding algorithm in the proposed Genetic Algorithm reinforces the genetic searching ability in tackling this kind of problem. To demonstrate the ability of the developed Genetic Algorithm, Integer Programming is implemented to solve the testing instances and benchmarked with the proposed algorithm. The results show that this proposed Genetic Algorithm can obtain a more reliable and higher quality solution in a much shorter computational time.

To further inspect the process of product recovery in a CLSC, a multi-period decision model considering uncertainties is established. This model simulates the process of product refurbishment in a CLSC and discusses uncertainties in end of life products collection, including customer demand uncertainty, returned product quality uncertainty and returned product quantity uncertainty. In the literature, few research studies have focused on the process of returned products refurbishment in closed-loop supply chain networks. Considering the deepening crisis caused by abandoned end of life products, especially electronic waste, it is important to propose a model like this. This proposed model structures the end of life products refurbishment process and provides decision supports for end of life products collection, considering the uncertainties in both quantity and quality.

In this decision model, a two-layer fuzzy controller embedded with a quality indicator is developed. This proposed method effectively deals with the uncertainties of both supplies and demands in multi-period production planning of returned products refurbishment. A simulation system based on this model is implemented, which proves the effectiveness of the proposed fuzzy controller. It also proves the efficiency of the quality indicator dealing with the quality uncertainty. The developed simulation system provides decision support for end of life products collection for responsible manufacturers. Additionally, the increasing profits of end of life products refurbishment encourage product recovery to some extent.

The originality and significance of this research lies in the proposed models and algorithms. This research contributes to the body of knowledge by: (i) Establishing a closed-loop supply chain model with product recovery, which filling the gap of considering multiple materials with different quality in CLSC networks, (ii) developing a two-stage priority based encoding Genetic Algorithm to reinforce the genetic searching ability in tackling NP-hard problems in closed-loop supply chain, (iii) establishing a multi-period product refurbishment model in closed-loop supply chain, which fill the gap of describing product refurbishment process considering uncertainties, (iv) developing a two-layer fuzzy controller embedded with a quality indicator to deal with uncertainties effectively in product refurbishment, and (v) implementing a simulation system to simulate the process of product refurbishment, which providing decision supports for end of life product collection and in turn mitigate environmental problems. This research provides an important means to better understand the product recovery in closed-loop supply chain and contributes significantly to the further improvement of the performance of end of life product collection.

Publications Arising From the Thesis

International Journal Paper

Chen, Y.T., Chan, F.T.S. and Chung, S. H. (2015), An integrated closed-loop supply chain model with location allocation problem and product recycling decisions, International Journal of Production Research, Vol. 53, No. 10, pp. 3120-3140.

International Conference Papers

Chen, Y.T., Chan, F.T.S. and Chung, S. H. (2013), A Two-stage Priority based Genetic Algorithm for Closed-loop Supply Chain Network, The 2013 International Congress on Engineering and Information, (ICEAI), Bangkok, Thailand, 25-27 January, 2013, pp. 208-214.

Chen, Y.T., Chan, F.T.S., Chung, S. H. and Niu, B. (2013), Closed-loop supply chain network optimization for Hong Kong Cartridge recycling industry, The 2013 International Symposium on Marketing, Logistics, and Business (MLB), Graduate School of Information Science, Nagoya University International Academy Institute, Nagoya, Japan, 24-26 Sept 2013, pp. MLB107-MLB122.

Chen, Y.T., Chan, F.T.S. and Chung, S. H. (2015), Optimization of product refurbishment in closed-loop supply chain using multi-period model integrated with fuzzy controller under uncertainties, Flexible Automation and Intelligent Manufacturing (FAIM), University of Wolverhampton, UK, 23-26 June, 2015.

Chen, Y.T., Chan, F.T.S. and Chung, S. H. (2015), Optimization with fuzzy controller in closed-loop supply chain considering uncertainties, The International Research Conference on Engineering and Technology (IRCET), Bangkok, Thailand, 27-29 June, 2015.

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Chapter 1 Introduction

1.1 Problem Statement

The closed-loop supply chain has become more popular in recent years due to a number of reasons. One of the most prominent reasons is that environmental issues have gained increasing attention. European regulations have increased a producer's responsibility in several branches of industry, such as WEEE 2001 for consumer electronics (Wilkinson et al., 2001). Customers also expect to trade-in old products when buying new ones, making producers pay more attention to the reversion of used products or materials. Another crucial reason for operating in the CLSC is the cost. A well-designed CLSC network can provide significant cost savings in procurement, inventory, transportation and recovery processing. Hewlett-Packard estimated that the cost of returns was as much as 2% of their gross outbound sales (Guide and Van Wassenhove, 2006).

In the literature, it can be found that the research on CLSC covers many aspects. Product recovery issues in CLSC have gained increasing attention in many industries in the last decade due to a number of reasons driven by environmental, governmental and economic factors (Morana and Seuring, 2007). In recent years, economy with electronic products gains a prosperity development, and the life cycle of electronic devices turns out to be shorter and shorter, making electronic waste the fastest growing part of the garbage stream. Product recovery in a CLSC is commonly defined as the actions for the collection and recovery of returned products in supply chain management. The management of product recovery has increasingly received significant attention because of environmental concerns, legislative requirements, consumer interest in green products and the market image of manufacturers (Thomas and Griffin, 1996). Generally, there are more actors (e.g., remanufacturing and recycling companies, the customer in the role as a supplier for end-of-use or end-of-life equipment, etc.), more processes (e.g., collection, disassembly, remanufacturing of products, etc.) and more delays within these processes in a CLSC in comparison with the original supply chain (Chouinard et al., 2008).

Moreover, product return processes are also significantly affected by the high degree of uncertainty in terms of the quality, quantity and time of products being returned from the market (Vidal and Goetschalckx, 1997). The quantity of returned products is volatile and the time of returns is also unpredictable. Both of these factors will affect the operational planning of the recovery processes. As for the quality of returned products, the various abrasion may affect the working procedure in the product recovery process. Hence the research considering uncertainty in terms of quality and quantity of returned products in product recovery becomes significant.

While in the literature, few research inspected in this field of product recovery.

This research focused on the optimization of a CLSC network considering product recovery, and also examined the uncertainties in product recovery. In the process of product recovery, three sources of uncertainty are considered. One is demand uncertainty, which means the customer demand is volatile. One is the uncertainty of returned products quantity, which indicates the inaccurate forecasts of returned products quantity. The other one is the uncertainty of returned products quality, which describes the various abrasion of returned products.

The proposed CLSC network links the forward logistics and reverse logistics, in which the reverse part is connected by the action of customer recovery. The focused CLSC network problem covers both the product delivery and facility location problems at several stages. It optimizes the location and allocation problem of manufacturers, warehouses, retailers, collection centers, and recycling centers through a closed-loop supply chain network. At the same time, the product delivery route and delivery volume among the closed-loop supply chain network are also optimized. Additionally, the proposed CLSC model makes decisions regarding the recovery options for end of life products and components in recycling centers considering several materials and the quality of end of life products. To further research the process of product recovery in CLSC, a decision model was developed. This model describes product refurbishment in detail and investigates both quantity and quality uncertainties of end of life products. The beginning of products refurbishment is from end of life products collection. In the collection centre, companies have to make decisions whether or not to collect each returned end of life product. If customers trade-in their used products for brand-new ones, companies also have to decide the trade allowance. Hence a simulation system based on this decision model is implemented for further analysis.

In this academic area, most CLSC problems are formulated into linear or nonlinear problems (Akcali and Cetinkaya, 2011). Since the CLSP problem contains the capacitated *p*-median facility location problem, it is also NP-hard (Ko and Evans, 2007). To solve these kinds of NP-hard problems, exact algorithms can be an option, but for large-scale problems, the computational time is too long and not useful practically. Hence, heuristic algorithms such as the Genetic Algorithm (GA) have become an efficient method and have gained more popularity. Although GA can solve this kind of NP-hard problem more efficiently than exact algorithms, especially for large-scale ones, the genetic seeking ability has not been exploited sufficiently. In the literature, there are several kinds of adapted GA to solve the above mentioned problem, but all of the encoding processes are single-stage. The encoding of these adapted GAs is mainly classified into two categories. One with chromosomes only expresses the transportation route and facilities' operation state, and does not consider the product flows. These methods separate the problem and use GAs to solve part of it. The others, with chromosomes, express all the information, including transportation route, product flows and facilities' operation state. Since one chromosome in a single stage contains a vast amount of information, the genetic operations will become difficult due to a huge number of combinations. It will also dramatically decrease the genetic searching ability and increase the calculation time. Therefore, in our research area, a GA is specially designed to overcome the above mentioned problem.

In the process of product refurbishment, one of the important and complicated problems is the uncertainty of both the demand and supply. The supplies here mean the returned products. How is it possible to settle the uncertainty of both the input and output? One of the most difficult problems when dealing with the uncertainties of both supply and demand lies in the attributes of the returned products. The uncertainty in returned products is not only the quantity but also the quality, which makes the decision much more difficult. This research also finds answers to these research questions.

1.2 Aim and Objectives

The aim of this research is to improve closed-loop supply chain management considering environmental issues and recovery process. The main objective of this research is to optimize and analyze closed-loop supply chain network with recovery process of end of life returned products, especially for electronic wastes. To achieve this objective, several sub-objectives are implemented as follow:

1) Establish an integrated closed-loop supply chain model as the basic model.
2) Develop a heuristics algorithm which can design and optimize the closed-loop supply chain network more efficiently.
3) Evaluate the optimization reliability of the proposed algorithm. Benchmark the accuracy and efficiency of the proposed algorithm with other heuristic algorithms (such as spanning tree based genetic algorithm) and exact algorithms (such as mixed-integer linear programming).
4) Develop a decision model and research on the process of product recovery in closed-loop supply chain
5) Analyze the uncertainties of product recovery in closed-loop supply chain.
6) Develop a method to optimize the product recovery and deal with the above mentioned uncertainties. Implement a simulation model to demonstrate the effective and efficiency of the proposed method.

The research topics studied in the project is related to the network planning of closed-loop supply chain considering uncertainties in product refurbishment. The technology and process of remanufacturing and recycling (such as polishing, sand blasted, painted, etc.) is not involved, neither the reuse of products.

1.3 Significances and Contributions

Product recycling issues have gained increasing attention in many industries in the last decade due to a variety of reasons driven by environmental, governmental and economic factors. Producers are perceived to be responsible for the recycling of products that they have produced and sold. Due to the expensive cost of third-party recycling companies, many producers choose to establish their own recycling factories, and producers also have to design product recycling networks along with product delivery networks according to specific customer regions (Brissaud et al., 2006). This research on closed-loop supply chain can help producers optimize their closed-loop supply chain network integrating product recovery. It also provides decision supports for end of life products recovery while considering uncertainties. The significance of this research lies in both the literature and society. In the literature, it is important to formulate a mathematical model optimizing CLSC networks considering recycling activities. Additionally, the formulation of end of life product refurbishment and the analysis of the end of life product collection are also significant. For society, the simulation system based on the proposed decision model provides a helpful reference for end of life product recovery, especially with regard to electronic products, which benefits the environment in some ways.

Upon the completion of this research, some notable contributions to the field of product recovery in closed-loop supply chain can be highlighted as follows. The successful establishment of the integrated closed-loop supply chain model with product recycling decisions filled the gap of considering multiple materials with different quality in CLSC networks. The development of the two-stage priority based encoding Genetic Algorithm reinforced the genetic searching ability in tackling NP-hard problems in closed-loop supply chain. The establishment of the multi-period product refurbishment model in closed-loop supply chain filled the research gap of describing product refurbishment process considering uncertainties. The successful development of the two-layer fuzzy controller embedded with a quality indicator provided an effective approach dealing with uncertainties in product refurbishment. The implementation of the simulation system, which simulate the process of product refurbishment, provided helpful decision supports for end of life product collection and in turn mitigate environmental problems.

1.4 Thesis Organization

The thesis contains eight chapters. Chapter 1 introduces the research topics, objectives and contributions of this thesis. Chapter 2 describes the research background. Chapter 3 is the literature review, which provides the research foundation and explores the research gap. Chapter 4 to Chapter 7 present the research deliveries of PhD study in detail. Chapter 4 proposes a two-stage priority based Genetic Algorithm for minimizing the total operating cost for six-level closed-loop supply chain. Chapter 5 develops an integrated closed-loop supply chain model with location allocation problem and product recycling decisions. Chapter 6 establishes a decision model for multi-period product refurbishment under uncertainties using a fuzzy controller. Chapter 7 implements simulation of returned products collection and refurbishment under certainty integrated with a two-stage fuzzy controller. Chapter 8 summarizes the research work and indicates some future research directions.

Chapter 2 Background

2.1 Introduction

This chapter introduces the background of the research work. Firstly, the origin of closed-loop supply chain is introduced. It started from the integration of forward chain and reverse logistics. Secondly, green supply chain management is introduced as the background of the research of closed-loop supply chain management. Finally, the structure of a closed-loop supply chain and its components are described. In this description, the system of product recovery in a closed-loop supply chain is proposed, the current situation of WEEE recycling is introduced, and also the collection process of returned products in product recovery is described.

2.2 The Origin of Closed-Loop Supply Chain

This section inspects the origin of closed-loop supply chain management. The research of closed-loop supply chain starts from the integration of forward supply chain and reverse logistics. Some research also considered the "green" factors. In this section, the concept and problems of supply chain management are described firstly, and then, the research area of reverse logistics is inspected. Finally, green supply chain management is also introduced as the background of closed-loop supply chain generation.

2.2.1 Supply Chain Management (Forward Chain)

Closed-loop supply chain are extensions of supply chain. Since the research field of supply chain management covers a large scope, the literature review of supply chain management in this chapter cannot possibly cover all of the research aspects. The objective of the supply chain management review in this section is to examine the emergence of the closed-loop supply chain concept and reveal the necessary and significance of research in closed-loop supply chain.

In the year 1995, Cowdrick (1995) reviewed research papers in the 1990s and found that researchers focused on using computers to solve supply chain logistics problems in engineering at that time. In 1996, Gules and Burgess (1996) studied the supplier and buyer relationship in advanced manufacturing supply chain. They found the main factors affecting this relationship and demonstrated it using empirical data from a Turkish automotive company. In the same year, Thomas and Griffin (1996) studied the supply chain planning among three main levels: raw material procurement, production process and finished products distribution. They reviewed research papers in this area and found that information technology promoted planning in those days. In 1998, Beamon (1998) reviewed research articles on supply chain design and performance. They found the gap of multi-stage modelling in the research of supply chain management.

In the year 2005, Hugo and Pistikopoulos (2005) established a multi-objective model to optimize the strategic planning of supply chain networks considering environmental factors simultaneously. A Mixed Integer Programming model was formulated and solved to provide decision support for industries. In 2008, Amaro and Barbosa-Povoa (2008) developed a mathematical model considering supply chain planning and production scheduling simultaneously. This model structured the strategic planning and integrated tactical optimization whilst considering reverse flows in a real pharmaceutical case. In 2009, Melo et al. (2009) reviewed the facility location problem in supply chain management. They discussed the decision support for facility location problems together with other decisions in supply chain networks, such as product distribution and reverse logistics. At that time, research of reverse logistics together with forward supply chain became important.

In the year 2011, Bogataj et al. (2011) established a Mixed Integer Programming model to optimize the facility location in a global supply chain. This model decided facility locations using data information from processes of manufacturing, distribution, customer needs and reverse flow in the supply chain. This study indicated the necessity to consider reverse flow when optimizing the forward supply chain. In 2014, Farahani et al. (2014) reviewed supply chain network design over a comprehensive range. They basically classified the research papers in this area into three dimensions: strategic planning, tactical planning and operational optimization. They indicated that the research on green and sustainable supply chain would receive more attention. In the year 2015, Garcia and You (2015) reviewed research papers on supply chain design in recent years. Four challenges were found for future research in this field, one of which is sustainable supply chain design.

The literature review of supply chain management exposes that, in recent years, sustainable supply chain design integrated with reverse logistic became a popular and significant research topic in the research area of supply chain management.

2.2.2 Reverse Logistics Management (Reverse Chain)

2.2.2.1 Reverse Logistics Network

In the year 1997, Fleischmann et al. (1997) reviewed the quantitative models used in reverse logistics. At that time, the research of interest was to find the relationships between the forward chain and the reverse chain. In 2000, the research topic of reverse logistics was still new. Dowlatshahi (2000) reviewed the research articles and summarized the cases of reverse logistics implementation in reality. In 2007, reverse logistics implementation became a very important research topic. Alvarez-Gil et al. (2007) studied the reverse logistics systems implemented in companies. They found that the implementation of reverse logistics systems was impacted by several factors including customers and the government.

In the next year, Shankar et al. (2008) discussed the relationship among different variables in reverse logistics with system dynamics methods. Hsu et al. (2009) analyzed the information sharing among the central return centre in reverse logistics. They found that information flows play a significance role in reverse logistics. Lau and Wang (2009) used a case study in China to analyze the WEEE waste in reverse logistics. In 2010, Dowlatshahi (2010) used an exploratory case study approach to analyze the cost and benefits in reverse logistics. Several factors were found to improve the cost-benefit management in reverse logistics.

In the year 2011, Tuzkaya et al. (2011) established a multi-objective model for the network design of reverse logistics. They integrated FUZZY-TOPSIS and the Genetic Algorithm to solve this problem. Gobbi (2011) considered the residual value of returned products in reverse logistics and found two impact factors. Zhang et al. (2011) developed an inexact model to structure the solid waste system in reverse logistics. They raised the consideration of uncertainty in reverse logistics networks, and quantify it with interval parameters.

In 2012, Alumur et al. (2012) established a multi-period model to optimize profits in reverse logistics. They justified this formulation by using a case study in Germany. Kannan et al. (2012) developed a Mixed Integer Programming model to structure the environmentally friendly reverse logistics with carbon footprint. Further case studies showed the efficiency of this proposed model. In 2013, Bai and Sarkis (2013) proposed a conceptual network of reverse logistics with uncertainties. They considered the uncertainty factors and variables of performance measurement in reverse logistics.

2.2.2.2 Recycling Network Models

In the year 1996, BloemhofRuwaard et al. (1996) developed a linear programming model. Using this model, they structured different scenarios of product recycling network design. In 1999, Krikke et al. (1999a) studied the HV02-machine recycling network. A Mixed Integer Linear Programming model was established to optimize the operational costs in this recycling network. Krikke et al. (1999b) also proposed an optimization model to reduce the recycling cost of monitors for original equipment manufacturers. In 2001, Shih (2001) proposed a Mixed Integer Programming model to structure the end of life home appliances recycling network. This proposed model minimized the total costs in the recycling network.

In 2008, Gomes et al. (2008) analyzed two cases of product recycling in a decision support system called THOR. One is the recycling of plastic waste; the other is the recycling of construction waste. This paper proposed a data input approach considering preference in decision-making systems. Pati et al. (2008) developed a Mixed Integer Goal Programming model to optimize the paper recycling system in India. This proposed model considered three objectives simultaneously including recycling costs, environmental benefits and product quality improvement.

In 2010, Kannan et al. (2010) proposed a Mixed Integer Linear Programming model to structure the battery recycling network. A heuristic-based Genetic Algorithm was developed to solve this comprehensive model. Azadivar and Ordoobadi (2012) established quantitative decision rules to justify returned parts recycling. These rules were implemented in a simulation model to propose decision supports. Numerical examples demonstrated the efficiency of the proposed decision rules. Dat et al. (2012) developed a mathematical model to optimize the total costs of product recycling such as facility location cost and transportation cost. In 2013, Gołębiewski et al. (2013) proposed a mathematical model to minimize the total costs of an end of life vehicle recycling network. A Genetic Algorithm was used to solve this problem effectively. Schweiger and Sahamie (2013) established a mathematical model to optimize the paper recycling network, and a Tabu search method was implemented to improve the solutions.

2.2.2.3 Remanufacturing Network Models

Jayaraman et al. (1999) proposed a Mixed Integer Programming model to optimize the remanufacturing network in reverse logistics. This model solved the location and transportation problem in the remanufacturing network. Franke et al. (2006) introduced a mathematical model to analyze the facilities' capacity in mobile phone manufacturing. A simulation model was implemented to demonstrate the efficiency of the proposed formulation. Kim et al. (2006) established a mathematical model to plan the supplies in remanufacturing. Experimental data showed that the proposed model can minimize the total costs in the remanufacturing network.

Lu and Bostel (2007) developed a Mixed Integer Programming model to structure the facility location problem in remanufacturing networks. Mitra (2007) established a pricing model to manage the revenue of returned products, and numerical data showed the efficiency of the proposed model. Vlachos et al. (2007) developed a system dynamic model to optimize the facility's capacity in remanufacturing. The simulation results showed that the proposed model can provide great decision support for this problem.

In 2008, Chung et al. (2008) proposed an inventory model to demonstrate the efficiency of the integrated policy in closed-loop supply chain. Demirel and Gokcen (2008) developed a Mixed Integer Programming model to optimize the total cost in remanufacturing networks. Teunter et al. (2008) proposed a Mixed Integer Programming model to analyze the lot scheduling problem in multi-product remanufacturing. Li et al. (2009) established a stochastic dynamic programming to analyze the lot sizing problem in remanufacturing networks. In the year 2011, Wang et al. (2011) investigated a hybrid remanufacturing system to find the optimum value settings in remanufacturing processes. In 2012, Chen and Chang (2012) investigated the strategic decisions between original equipment manufacturers and the third-party companies in remanufacturing; several factors were found to affect the cooperation between these two partners.

2.2.3 Green Supply Chain Management

Since the beginning of the 21st century, developing low carbon economics has become a global goal under the threat of global warming. Broad-scale research of green logistics began in the 1990s. At that time, green logistics was regarded as the secondary aspect of logistics management. (Seuring and Müller, 2008)

In 1996, the Manufacturing Industries Research Association of Michigan State

University presented the concept of a green supply chain for the first time. Aiming at considering the development of manufacturing industry supply chain integration with an environmental effect and resources optimization (Angell and Klassen, 1999), Hoek (2002) in the management school of Cranfield provided a conceptual model of a green supply chain, as shown in Figure 2.1. Figure 2.1 shows that CLSC belongs to the operation layer of green supply chain and CLSC management is the operational aspect of green supply chain management.

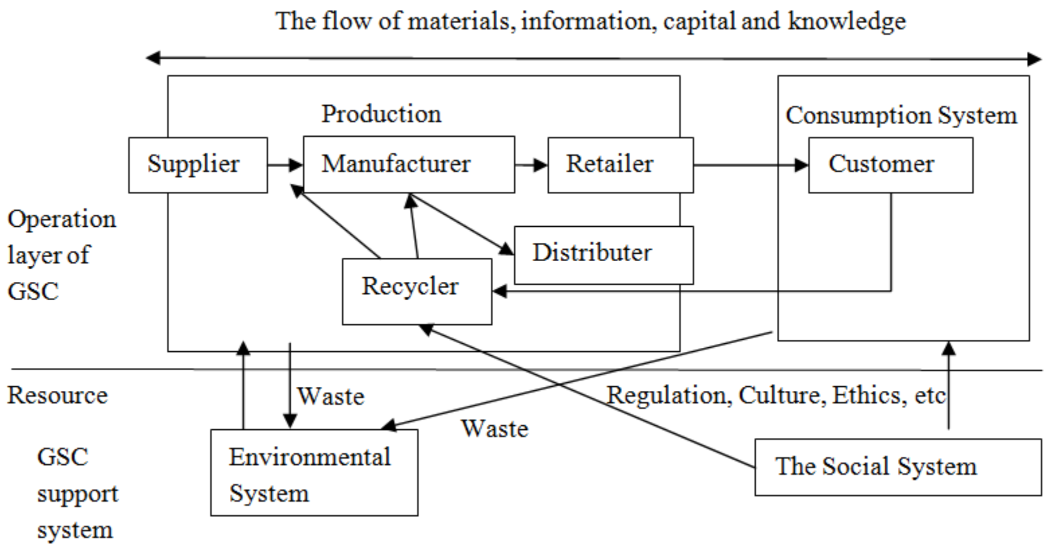

Figure 2.1The conceptual model of green supply chain

Min and Galle (1997) discussed how to make the decision of supplier selection under consideration of environmental protection. Walton et al. (1997) considered green supply chain management as joining the supplier in the enterprise's strategy of environmental protection, with the core target of applying integrated management ideas into green supply chain management. At the same time, Carter and Ellram (1998) defined green supply chain management as “the effort of purchasing department in activities such as waste reduction, recycle, reuse and materials substitution, etc.”.

In 1999, Saturn Corporation and its suppliers, together with the clean technology development centre of Tennessee University and Environment Protection Agency (EPA) became green supply chain management cooperative partners. Meanwhile, Beamon (1999) investigated the environmental factors contributing to extended environmental supply chain development, provided performance measures for the extended supply chain and also established a general procedure for achieving a green supply chain. The research is valuable but its quantitative evaluation of green and environmental issues in supply chain is of no concern.

Nagel and Ieee (2000) argued that green supply chain management involves the using, constitution and the whole productive process of commodities. He emphasized that technical support plays an important role in green supply chain operation. Zsidisin and Siferd (2001) stated that green supply chain management consists of the activities of design, purchasing, production, distribution, use and reuse for the sake of being environmentally friendly. It includes not only manufacture and transformation but also environmental design, and supplier operation process improvement and evaluation.

In the year 2003, the United Nations Environment Program (UNEP) provided the main factors of green supply chain management: (1) the support of environmental regulation from the top of an enterprise; (2) the horizontal cooperation among internal departments within an enterprise; (3) the effective process management toward suppliers concerning environmental problems (Toepfer, 2003). Sheu et al. (2005) established an optimization-based model to deal with integrated logistics operational problems of green supply chain management and meanwhile a linear multi-objective programming model was formulated. Hervani et al. (2005) provided an integrative framework for studying, designing and evaluating green supply chain management performance.

2.3 Closed-Loop Supply Chain Network

Closed-Loop Supply Chain Management (CLSCM) considers green issues in supply chain management. Guide and Wassenhove (2009) defined CLSCM as the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time. The management of CLSC describes the discipline of optimizing the delivery of goods, services and information from supplier to customer and simultaneously from customer recovery to supplier (Gen et al., 2006).

With the same principle as supply chain management, the goals of CLSCM typically include transportation network design, location of manufacture, distribution or dismantling centre, product recycling and other efforts to improve cost savings. CLSCM can be classified into three categories as strategic decisions, tactical decisions and operational decisions. Strategic decisions always have a long-term impact (years) on the firm's operations, such as network design, and facility location and allocation. Tactical decisions impact the firm's operations for weeks, such as inventory policies. Operational decisions are made daily and have only short-term impact, such as scheduling.

The planning of a CLSC network links the forward logistics and reverse logistics, in which the reverse part is connected by the action of customer recovery. It is focused on the design of transportation routes and the decision of facilities' operational state, instead of an investigation into the interactions between demands and returns, or uncertainties (Ozceylan and Paksoy, 2013; Sheu et al., 2005).

European regulations have increased a producer's responsibility in several branches of industry, such as WEEE 2001 for consumer electronics (Krikke et al., 2003). Customers also expect to trade-in old products when buying new ones, making producers pay more attention to the reversion of used products or materials. Another crucial reason for operating a CLSC is the cost. A well-designed CLSC network can provide significant cost savings in procurement, inventory, transportation and recovery processing. Hewlett-Packard estimated that the cost of returns was as much as 2% of their gross outbound sales (Guide and Wassenhove, 2006).

The practical applications of CLSC can be found in many fields. Krikke et al. (2003) developed a quantitative model which was applied to a Japanese company's refrigerator CLSC network design concerning its European strategies. Jayaraman (2006) proposed an analytical approach that consisted of remanufacturing aggregate production planning and a mathematical programming model to determine the number of core products being recycled and remanufactured during a given period of time. This approach was implemented in a mobile phone remanufacturing company in the USA where an optimal solution was obtained in the design of its expanded CLSC network. Bakar and Rahimifard (2007) investigated a real case of the WEEE recycling process, and indicated that systematic planning for an individual product's recycling process will improve the value of recovery significantly. Olugu and Wong (2012) implemented a CLSC performance evaluation system in a company in the automotive industry and reduced the cost of the whole CLSC network significantly.

2.3.1 Product Recovery

Product recovery is interpreted as a superior concept that involves concepts such as remanufacturing, refurbishment, reuse and material recycling (Brissaud et al., 2006). Remanufacturing is the process of rebuilding a product, during which the product is disassembled, defective components are replaced and the product is reassembled, tested and inspected to ensure it meets newly manufactured product standards (Seaver, 1994). Refurbishment is the process in which a product or component is cleaned and repaired in order to make a resell (Brissaud et al., 2006). Reuse is the additional use of a component, part or product after it has been removed from a clearly defined service cycle (Keoleian and Menerey, 1993). While material recycling is the process in which the structure of a product is destroyed in order to recapture its materials (Brissaud et al., 2006).

Among these processes, product refurbishment is one of the most profitable and environmentally beneficial processes, drawing more and more attention from both product producers and customers.

In Hong Kong, WEEE produced amounts to 70,000 tonnes per year, and the volume has been increasing at an annual rate of 2% in recent years (http://www. legco. gov. hk/yr11-12/english/panels/ea/papers/ea1128cb1-424-4-e.pdf). To deal with this growing noxious waste, product recycling is becoming popular. Every year, about 1.2 trillion inkjet cartridges are used globally, but less than 30% of them are recycled. This terrible situation lasted for many years until the mandatory legislation of Extended Producer Responsibility (EPR) gained more and more popularity around the world. Producers are perceived to be responsible for the recycling of products they have produced and sold.

Due to the abundant quantity of used products and the pressure of environmental concerns, producers have to optimize their forward and reverse networks to maximize the recycling rate and also maximize their profits. Many electronics producers have implemented product collection and refurbishment programs. Taking Apple for example, this company has taken the lead in introducing refurbished products into the market, called "apple certified refurbished products". These certified refurbished products, including many versions of IPad and MacBook, are available on the Apple website (http:// www.apple.com/ shop/ browse/ home/ specialdeals). Another example is one of the most popular electronic products companies in China, MEIZU. This company also has implemented a similar refurbishment plan, especially for mobile phone products. Due to strong quality guarantees and relatively low prices, the market for certified refurbished products is growing fast nowadays.

2.3.2 WEEE Recycling

The environmental and health risks of Waste Electric and Electronic Equipment (WEEE) are high, among which, used cartridges play an important role. Most of the used cartridges are improperly disposed of in landfills or by incineration. A toner cartridge tossed into a landfill will take 450 years or more to decompose and the toxic materials in it such as lead and mercury will leak out causing great damage to the Earth. Every year, about 1.2 trillion inkjet cartridges are used globally, but less than 30% of them are recycled. Although a recycled toner cartridge can save nearly 1 kg of raw materials like plastic and metal to reduce the environmental burden efficiently, it turns out that used cartridges at the end of their lifespan are still being disposed of improperly and their quantity has grown exponentially.

In July 2008, the Legislative Council enacted the Product Eco-responsibility Ordinance (Cap 603) to provide a legal framework for implementing mandatory producer responsibility schemes (http:// www. legislation. gov. hk/blis_pdf. nsf/ 6799165D2FEE3FA94825755E0033E532/42BBA0FC68F17FD1482575EF0021190 4/$FILE/CAP_603_e_b5.pdf). In his 2009-10 Policy Address, the Chief Executive of the Hong Kong SAR also identified this issue as the next target for a producer responsibility scheme. Although this scheme primarily focuses on bulky electrical and electronic equipment and computer products, producers in Hong Kong are perceived to be responsible for the recycling of products that they have produced and sold including printers and cartridges.

In Hong Kong, many companies started recycling ink cartridges and toner cartridges several years ago. For example, Epson HK set up some collection points and has collected used cartridges from 2007 (http:// www. epson. com. hk/ en/ exploreEpson/ environment. html) and Canon HK launched its ink cartridge recycling program from 2009 (http://www. canon. com. hk/en/corporate/main/csr. jspx). For these companies, they have to carry out efficient and profitable recycling of their products. Due to the expensive cost of third-party recycling centres, many cartridge producers choose to establish their own recycling factories. Hence the location and allocation of collection centres and recycling factories have to be optimized. In this sense, producers have to design product recycling networks along with product delivery networks according to specific customer regions. Each year, vast amounts of used cartridges are discarded, and the number is increasing. In the circumstances, a closed-loop supply chain network including cartridge recovery needs to be optimized to maximize the profits of producers and also protect the environment.

2.3.3 Returned Products Collection

In recent years, economy with electronic products gains a prosperity development, and the life cycle of electronic devices is becoming shorter and shorter, making electronic waste the fastest growing part of the garbage stream.

The beginning of product refurbishment is returned products collection. In the collection centre, companies have to make decisions whether or not to collect each returned product. Additionally, if customers trade-in their used products for brand-new ones, companies also have to decide the trade-in allowance. The simulation network in this research provides decision supports for these decisions, considering each returned product's quality and the inventory level. It helps companies minimize the total inventory costs and maximize customer profitability simultaneously.

In 2005, Nagurney and Toyasaki (2005) established a variation inequality formulation to describe the electronic waste recycling network. This model proposed effective decision supports for e-waste processors. Karaer and Lee (2007) introduced RFID into the reverse logistics. They used RFID to manage the information of customer demand and reduced the shortage cost. Lieckens and Vandaele (2007) established a Mixed Integer Linear Programming model to deal with the stochastic lead time in the reverse logistics.

Du and Evans (2008) developed a bi-objective model to solve the post-sale service problem in reverse logistics. Li and Olorunniwo (2008) studied the performance of reverse logistics systems implemented in three different companies. They provided efficient decision supports to related companies. In 2013, Feng et al. (2013) developed a mathematical model to analyze the product recovery system in remanufacturing networks. In 2015, Chen et al. (2015) proposed a two-stage stochastic model to provide decision supports for original equipment manufacturers with a remanufacturing and collection strategy.

2.4 Summary

This chapter described the background of the research. Firstly, the origin of closed-loop supply chain was inspected. Closed-loop supply chain management started from the integration of forward chain and reverse logistics. Factors in green supply chain management have also been considered. Secondly, the concept of closed-loop supply chain was summarized. Some nowadays popular and important problems in closed-loop supply chain were inspected. Such as product recovery problem, WEEE recycling problem and returned products collection problem in closed-loop supply chain. These background materials makes the foundation of this research more clear and substantial. In the following chapter, a review of related literature is presented.

Chapter 3 Literature Review

3.1 Introduction

In this chapter, research articles in the area of closed-loop supply chain management are reviewed. This review covers literature from 1995 to 2015, including the research history of closed-loop supply chain management, and tracks the latest advances in research in this area. This review is launched from four aspects: topics, problems, models and methods. Based on the literature review, the research objectives are decided according to the identified research gaps.

Section 3.2 reviews topics in the field of closed-loop supply chain management. These topics are enumerated according to the research history in the closed-loop supply chain management area. Firstly, the generation and network design of closed-loop supply chain is reviewed. Secondly, product recovery problem in closed-loop supply chain is reviewed. Thirdly, problems considering end of life products collection are inspected.

Section 3.3 reviews the optimization problems in closed-loop supply chain. These optimization problems are classified into strategic problems, tactical problems and operational problems. The typical problems include location and allocation problems, transportation routing problems, production planning, inventory management, and decision-making problems. Section 3.4 reviews the optimization methods in closed-loop supply chain. From the literature, genetic algorithms are found to be the most appropriate methods dealing with the focused topic in this research. The details are described in this Section. Section 3.5 reviews the uncertainty problems in closed-loop supply chain, including uncertainties in product recovery. Section 3.6 reviews the methods dealing with uncertainties in closed-loop supply chain, especially considering product recovery. From the review of the literature, fuzzy logic and simulation systems are chosen to deal with the considered uncertainty. The details are shown in the content of this section.

3.2 Closed-Loop Supply Chain Management

In this chapter, three main topics in the research field of closed-loop supply chain are reviewed. From this review, the main outline of the research history in the closed-loop supply chain area are traced as well as up-to-date research interests. This section shows the importance of closed-loop supply chain in the research area of supply chain management. From the literature review, the research topics of my study finally focused on the field of closed-loop supply chain. Section 3.2.1 reviews the research articles in the area of supply chain management. Section 3.2.2 reviews the research articles in the area of reverse logistics. And then, closed-loop supply chain are reviewed in Section 3.2.3.

3.2.1 Closed-Loop Supply Chain Network Design

In the literature, many CLSC models have been established and studied. The models and studies focus on different aspects and use many different methods. Fleischmann et al. (1997) and Wells and Seitz (2005) believe that the forward and reverse logistics chain should be combined in the operations and the flow of materials to establish a closed-loop supply chain.

Barros et al. (1998) proposed a two-level location model for a recycling problem and optimized its decision-making using heuristic procedures. Sheu et al. (2005) proposed a linear multi-objective programming model to solve an integrated CLSC problem. Yang et al. (2009) analyzed the equilibrium state of the CLSC using the theory of variation inequalities. Huang et al. (2009) discussed the robust operations in a class of dynamic CLSC models using control theories, and practical experiments in the Chinese steel industry were implemented. Paksoy et al. (2011) formulated a linear programming model to balance the equilibrium between various costs. Shi et al. (2011) developed a mathematical model to maximize the total profit of a CLSC by analyzing the pricing and production decisions simultaneously. Mitra (2012) proposed a stochastic and deterministic model for a two-level CLSC system, and the relationship between return rate and cost saving was discussed using numerical examples.

Among all the various research directions in closed-loop supply chain, the closed-loop network structure with product recovery has become one of the important directions. Most of the studies formulate this problem into linear or nonlinear programming models. Table 3.1(a) shows the major closed-loop supply chain networks from 2003 to 2010. Table 3.1(b) shows the major closed-loop supply chain networks from 2011 to 2014, which were formulated into linear or nonlinear programming models.

In Table 3.1(a) and Table 3.1(b), all of the models consider closed-loop networks with different focuses. Krikke et al. (2003) optimized both the structure of the logistics network and the structure of the products with a Mixed Integer Linear Programming model. Min et al. (2006a) focused on the initial collection points in reverse logistics networks. A Mixed Integer Nonlinear Programming model was proposed to solve the location problem of initial collection points and optimize the return products' holding time in them. Jayaraman (2006) developed a linear programming model for aggregate production planning and control in remanufacturing. In 2009, Kannan et al. (2009) designed a multi-echelon distribution inventory CLSC model for the built-to-order environment. Lee and Chan (2009) proposed a nonlinear programming model to determine the location of collection points so as to minimize the reverse logistics cost and to maximize the coverage of customers. RFID was also suggested to count the quantity of flow in collection points in their study. Kannan et al. (2010) developed a multi-echelon, multi-period, multi-product CLSC network model for product returns, considering transportation and recycling problems. Wang and Hsu (2010) established a generalized closed-loop model as an Integer Linear Programming model which integrated forward and reverse logistics. Zhang et al. (2011) formulated a remanufacturing model discussing the capacitated production plan problem. Amin and Zhang (2013) established a three-stage multi-objective Mixed Integer Linear Programming model designing the configuration and selection process of CLSC simultaneously. Lee and Lee (2012) developed an integrated CLSC model with an Integer Linear Programming model determining the optimal delivery route. Ozkir and Basligil (2012) proposed a Mixed Integer Linear Programming model to describe a CLSC network, in which three methods of recovery process were considered. In 2013, John and Sridharan (2013) established a closed-loop supply chain network and analyzed it under various situations. This network minimized the total costs and maximized the repaired and recycled products simultaneously. Ozceylan and Paksoy (2013) proposed a Mixed

Integer Programming Model to describe a multi-period multi-part CLSC network. This model optimized the flow of manufactured and disassembled products through determining the plants and retailers' locations. Soleimani et al. (2013) developed a comprehensive structure for a closed-loop supply chain network including all possible entities and considering minimum limitations on delivery routes. Demirel et al. (2014) proposed a Mixed Integer Programming model to analyze the situations of returned products and also proposed a fuzzy objective extension to solve the problem in the real world. Zeballos et al. (2014) developed a Mixed Integer Linear Programming to analyze the uncertain customer demands and raw material supplies in a closed-loop supply chain network.

Among the above literature, although many CLSC models have been studied, few of them analyzed the delivery activity for different kinds of materials extracted from used products, and also few papers studied the situation where collected used products are classified. In practice, products can be disassembled into many different parts and recycled into different materials, which have different delivery activities according to their attributes. So, it is important to consider different materials in the product recovery problem under closed-loop supply chain networks. Additionally, the quality of collected products is uncertain which contributes to the uncertain factors in closed-loop supply chain. It is important to consider it in network construction. In this model, the delivery activities of several kinds of materials are considered and the collected used products are classified into two categories: good quality ones and poor quality ones. Producers will have different methods to process them. This problem is also formulated into a Mixed Integer Linear Programming model.

Table 3.1(a) Closed-loop supply chain models (2003-2010)

References	**Model focus**	**Objective**	**Mathematical modeling**	**Method**
Krikke et al. (2003)	network structure and product structure	minimize the total costs	Mixed Integer Linear Programming	CPLEX
Min et al. (2006a)	initial collection points	minimize the total costs	Mixed Integer Nonlinear Programming	GA
Jayaraman (2006)	remanufacturing	minimize the total costs	linear programming	GAMS
Kannan et al. (2009)	the distribution and inventory problem	minimize the total costs	linear programming	GA, particle swarm optimization
Lee and Chan (2009)	location problem of collection points	maximize environmental profits	nonlinear programming	GA, RFID
Kannan et al. (2010)	transportation and recycling problem	minimize the total costs	Mixed Integer Linear Programming	GA
Wang and Hsu (2010)	transportation and location problem	minimize the total costs	Integer Linear Programming	GA

Table 3.1 (b) Closed-loop supply chain models (2011-2014)

References	**Model focus**	**Objective**	**Mathematical modeling**	**Method and Tools**
Zhang et al. (2011)	capacitated production plan problem	minimize the total costs	Integer Linear Programming	GA
Amin and Zhang (2013)	network structure	maximize the total profits	Multi-Objective Mixed-Integer Linear Programming	GAMS
Lee and Lee (2012)	determine the optimal delivery route	minimize the total costs	Integer Linear Programming	GA, Lingo
Ozkir and Basligil (2012)	three ways of recovery process	maximize the total profits	Mixed Integer Linear Programming	GAMS
John and Sridharan (2013)	determine the delivery flow and analysis the impact of parameters	minimize the total costs	Linear Programming	Lingo
Ozceylan and Paksoy (2013)	location problem of plants and retailers	minimize the total costs	Mixed Integer Programming Model	GAMS, CPLEX
Soleimani et al. (2013)	comprehensive network structure	maximize the total profits	Mixed Integer Linear Programming	GA, CPLEX
Demirel et al. (2014)	analysis product returns	maximize the total profits	Mixed Integer Programming	GAMS, CPLEX, GA
Zeballos et al. (2014)	analysis the uncertain supply and demand	minimize the total costs	Mixed Integer Linear Programming	GAMS, CPLEX

3.2.2 Product Recovery in Closed-Loop Supply Chain Models

Many research studies related to the recovery of products have been carried out in the area of supply chain, including both academic and industrial applications. To date, an accepted definition of product recovery indicates that, product recovery is a generalize description of recovery activities for products including product remanufacturing, product refurbishment, product reuse and material recycling, etc. (Daniel Brissaud, Serge Tichkiewitch and Peggy Zwolinski, Innovation in Life Cycle Engineering and Sustainable Development) Since environmental issues are becoming serious nowadays, and WEEE is one of the most poisonous varieties, many studies address the issue of WEEE recovery.

Jorjani et al. (2004) formulated a piece-wise linear concave program to find the optimal disassembly strategy for electronic equipment. Tsai and Hung (2009) focused on the treatment and recycling process of the system. They proposed a two-stage decision framework which includes treatment stage and recycling stage. Although supplier selection was added to this framework, it was not optimization of the whole closed-loop supply chain network. Veenstra et al. (2010) suggested a Markov chain model analyzing the flow of WEEE through the reverse chain. Gamberini et al. (2010) established a transportation network in Italy which contained vehicle routing problems. An integrated solution approach was used to solve it. Mar-Ortiz et al. (2011) optimized the design of a reverse chain for the collection of WEEE. In this network, a Mixed Integer Linear Programming model was formulated to address the facility location problem, a new Integer Programming model was established to solve the vehicle routing problem and a simulation study was implemented to assess the performance of the recovery system. Dwivedy and Mittal (2012) investigated the WEEE flows in India and used a Markov chain to model the business sector of WEEE trade, which includes the informal recycling of WEEE in developing countries. Alumur et al. (2012) proposed a multi-period reverse logistics network which was formulated into a Mixed Integer Linear Programming model. A real case of washing machines in Germany was implemented to justify this model. Olugu and Wong (2012) proposed a CLSC performance evaluation system to a company from the automotive industry which reduced the cost of the whole CLSC network prominently. Wang and Huang (2013) established a two-stage robust programming model to decide the recycling volume and time in a CLSC. From the literature, it can be found that the focus of research on WEEE is reverse network design and optimization, with a lack of research on integrating both forward and reverse networks.

Barros et al. (1998) proposed a two-level location model for a recycling problem and considered its optimization using heuristic procedures. Sheu et al. (2005) proposed a linear multi-objective programming model to solve an integrated CLSC problem. Paksoy et al. (2011) formulated a linear programming model to balance the equilibrium between various costs. Ozkir and Basligil (2012) proposed a Mixed

Integer Linear Programming model to describe a CLSC network, in which three methods of recovery process were considered. Amin and Zhang (2012) introduced a three-stage Multi-Objective Mixed Integer Linear Programming model to determine the uncertainty of the CLSC configuration and the selection process simultaneously. Hasani et al. (2015) proposed a comprehensive CLSC model to optimize the profits considering various factors in a global CLSC network. A mimetic algorithm was developed and numerical experiments were implemented to demonstrate the efficiency of the proposed algorithm.

Nie et al. (2013) developed three closed-loop supply chain models and conducted a comparison for three models in light of the retail price, demand, return rate, and the profits received by the supply chain members. In order to minimize the total disassembly cost, the sequencing of disassembly operations can be regarded as a Single-Period Partial Disassembly Optimization (SPPDO) problem. Tsai (2012) proposed a label correcting algorithm to find an optimal partial disassembly plan with the assumption that a definite reusable subpart can be obtained from the original return, and then used this algorithm in a heuristic procedure to solve the SPPDO problem. Loomba and Nakashima (2012) used a Markov decision process to examine the role of sorting used products before disassembly for parts' retrieval and remanufacturing under stochastic variability, based on customer demand. Lehr et al.

(2013) used system dynamics to capture the high complexity of reverse logistics processes and comprehensively analyzed the dynamic behavior of closed-loop supply chain. Kaya et al. (2014) also developed a large-scale mixed integer model to capture all the characteristics of the reverse supply chain system, and two-stage stochastic optimization and robust optimization approaches were used to analyze the system's behavior.

The literature review of product recovery activities shows that product refurbishment is an rising and important research area in product recovery, especially considering electrical and electronic products.

3.2.3 End of Life Products Collection in Closed-Loop Supply Chain

End of life products collection is one of the important links in the process of product recovery. Analyzing the collection of end of life products, the demands and supplies of refurbished products can be balanced. Additionally, the profits from both the economy and environment can be maximized.

Hanafi et al. (2008) established a collection network model to describe the collection process of end of life products. A forecasting method integrated with a fuzzy color

Petri net was implemented to solve this problem. Mansour and Zarei (2008) proposed a multi-period model to optimize the end of life product collection, considering both economic and environmental benefits. To solve this problem, a heuristics algorithm with a multiple start search was implemented. Cruz-Rivera and Ertel (2009) developed a closed-loop supply chain model to optimize the end of life vehicle collection in Mexico. Kim et al. (2009) proposed a vehicle routing approach to optimize the electronic waste collection in South Korea. Dat et al. (2012) established a mathematical reverse logistics model to optimize the collection of electronic waste. Numerical examples showed the effectiveness of this model. Gu and Tagaras (2014) applied a game theory to analyze the cooperation of collectors and remanufacturers. They optimize the collection quantity under uncertainties of demands and found that, collectors should deliver more valuable returned products than remanufacturers order quantity. Niknejad and Petrovic (2014) developed a production planning model considering returned product collection in reverse logistics. To find the solution to this problem, a two-stage fuzzy Mixed Integer Programming approach was implemented. Numerical experiments demonstrated the efficiency.

3.3 Optimization Models in Closed-Loop Supply Chain Network

In the literature, it can be seen that the research of CLSC covers many aspects. Optimization problems in closed-loop supply chain can be classified into three aspects: strategic planning problems, tactical planning problems and operational planning problems. The below sections review these aspects respectively.

3.3.1 Location Allocation and Delivery Problem in CLSC (Strategic Planning)

In this academic area, many researchers have studied various optimal CLSC networks. The facility location problem has received much attention since 1985, with the aim of deciding on the number of distribution centers and finding good locations to satisfy customer demand with minimum facility operation and delivery costs (Aikens, 1985). Owen and Daskin (1998) reviewed the facility location decisions and report the stochastic characteristics of facility location problems. Yang et al. (2009) optimized the equilibrium state of the CLSC network using the theory of variation inequalities. They optimized the location of suppliers, product manufacturers, sellers, customers and recycling centers in CLSC network.

Demirel and Gokcen (2008) proposed a Mixed Integer Programming model to optimize the location and transportation problem of remanufacturing in reverse logistics. Chouinard et al. (2008) established a stochastic programming model to optimize the location of returned products collection and service center in closed-loop supply chain. Ozceylan and Paksoy (2013) presented a multi-products multi-period Mixed Integer Programming model to decide the transportation flow in closed-loop supply chain network. Banaszewski et al. (2013) developed a model for the solution of transportation planning between decentralized entities. Based on a new multi-agent auction protocol, this developed model solved an actual case of a Brazilian oil supply chain problem. Zolfpour-Arokhlo et al. (2013) proposed a supply chain management model integrated with environmental conditions, and analyzed the effectiveness of this proposed model based on a multi-agent system for a road transportation network.

3.3.2 Production Planning and Inventory Management in CLSC (Tactical Planning)

With consideration of the optimization of manufacturing and remanufacturing sharing the same critical and limited resources, Chen and Abrishami (2014) developed a multi-integer linear programming model to solve production planning problems in hybrid manufacturing-remanufacturing systems, using a Lagrangian decomposition-based method. Cheng et al. (2013) described a job scheduling model of a refurbishing process. In the model, the refurbishing process is considered a two-stage flow shop including disassembled products and refurbished parts, and a heuristic approach, based on LP relaxation, was presented. Two heuristic algorithms, based on iterated local searching and ant colony optimization, were developed. Ramezani et al. (2013) established a multi-objective stochastic model to maximize the total profits in the closed-loop supply chain.

Li et al. (2009) proposed a stochastic programming model to optimize the inventory and production planning in remanufacturing system considering uncertainties. Yuan and Gao (2010) optimized the decision making of inventory management in a CLSC with elimination theory. The inspected CLSC integrated manufacturing process and remanufacturing process. Mitra (2012) established deterministic and stochastic models to analysis inventory management in CLSC network. They found that higher return rate and higher correlation can reduce the demand variability, but the decrease of demand variability may not bring to cost decrease. Kenne et al. (2012) developed a stochastic dynamic programming model to analyze the uncertainties in inventory management of remanufacturing system. Three types of inventory in the remanufacturing system are analyzed. A computational approach was implemented to solve this complicate problem. Nakandala et al. (2014) investigated the total cost of the inventory system, and found that the change in stochastic demand during the lead time is the major factor that affects the total inventory costs.

3.3.3 Decision Support System in CLSC (Operational Planning)

In order to evaluate the effects of randomness with respect to recovery, processing and demand volumes on the design decisions, a stochastic model was developed by Chouinard et al. (2008) for designing logistics networks with consideration of reverse logistics. In the year of 2010, Bakhrankova (2010) established a model-based decision support system (DSS) for a practical plant. This system minimized the energy cost and maximized the output simultaneously.

Shi et al. (2011) developed a mathematical model to maximize the total profit of the CLSC network by analyzing the pricing and production decisions simultaneously. Besiou et al. (2012) developed a simulation system to provide decision supports for long-term capacity planning. Mitra (2012) proposed a stochastic and deterministic model for a two-level CLSC system, and the relationship between return rate and cost saving was analyzed using numerical examples. Ogier et al. (2013) proposed a multi-agent system to model the decentralized decision-making behaviour in a supply chain. Lot-sizing models integrating quantity discounts were presented for the local planning problems. Experimental tests were implemented to determine the quantity discount parameters in achieving the best supply chain profit. Yuan et al. (2015) proposed a CLSC system with two types of partly centralized decision-making structures. The sensitivity analysis on return rate showed that the maximum system profit rises with the increase of the return rate for specified decision-making structures. Kristianto and Helo (2015) designed a decision support system to determine optimal product architecture modularity in closed-loop supply chain. The optimization model was tested under several scenarios and discussed in terms of their theoretical and managerial aspects.

3.4 Optimization Methods in Closed-Loop Supply Chain

Optimization methods of closed-loop supply chain network design can be classified into two main categories. One is using the exact mathematical algorithms leading to exact solutions, while the other entails heuristics methods, which can only give out approximate solutions. In this research, Genetic Algorithms in heuristics approach were the focus. This section firstly reviewed several frequently used heuristics methods and explained why Genetic Algorithm was chosen to deal with the focused problems. After that, academic articles applying Genetic Algorithms were inspected in sufficient details and research gap on methodology was found in this research field.

3.4.1 Heuristics Methods

Since the optimization problems in closed-loop supply chain are NP-hard, heuristics methods have become popular as efficient methods of solution. This section reviewed several common used heuristics methods, especially Simulated Annealing and Tabu Search, and then, compare Genetic Algorithm with these heuristics to explain why Genetic Algorithm is focused in this research.

Lee and Dong (2008) established a two-stage heuristic algorithm to analyze the product recovery network of end of life computers. Numerical experiments proved the efficiency of this method. Kannan et al. (2009) analyzed the structure of a closed-loop supply chain applying the particle swarm approach and Genetic Algorithm. Schulz (2011) proposed a sliver-meal-based heuristic approach to optimize the lot-sizing problem in a remanufacturing system. Piplani and Saraswat (2012) established a robust optimization method to optimize the service network in a closed-loop supply chain.

3.4.1.1 Simulated Annealing

Subramanian et al. (2013) proposed a priority based Simulated Annealing algorithm to optimize the network of a closed-loop supply chain. Numerical examples showed the effectiveness of this method. Lin et al. (2015) established a two-stage Simulated Annealing algorithm to improve the solution of a Many-to-Many Milk Run Routing problem. It demonstrated the effectiveness of Simulated Annealing dealing with vehicle routing problem. Yu et al. (2016) implemented a Simulated Annealing algorithm to solve an open vehicle routing problem. The results of benchmarking experiments showed that Simulated Annealing performances much better than CPLEX.

From the literature review, it can be observed that, Simulated Annealing were mostly used to deal with vehicle routing problems and network design in supply chain management. A large number of references showed the effective performance of Simulated Annealing dealing with vehicle routing problems. As for the network work design of closed-loop supply chain, few researchers choose it as an effective approach.

3.4.1.2 Tabu Search

Schultmann et al. (2006) implemented Tabu Search to optimize the vehicle routing part of in the problem of reverse logistic modeling. Easwaran and Uster (2009) implemented Tabu Search to explore the solution space in the problem of facility location in closed-loop supply chain. Computational results demonstrated the effeciency of the approach integrating Tabu Search with Benders Decomposition. Schweiger and Sahamie (2013) developed a hybrid Tabu Search algorithm structure for a product recovery network. A practical case of paper recycling was applied to demonstrate the effectiveness of this approach. Eskandarpour et al. (2014) proposed a new Tabu search-based heuristic method to optimize the location of collection and recycling centers in a reverse logistics network. Experimental results inspected that the proposed method performed better than the Simulated Annealing method.

3.4.1.3 The Reason Why Genetic Algorithm be Selected

Griffis et al. (2012) reviewed the heuristics applied in logistics and supply chain management. The appendix of this paper listed 128 research articles from 1991 to 2012, using heuristics in supply chain management. Among these 128 research articles, 56 research articles considering problems related to facility location and network design using heuristics were selected to further inspect. Among these 56 research articles, 25 articles implemented Genetic Algorithms, 18 articles implemented Tabu Search, 8 articles implemented Simulated Annealing and 5 articles used other heuristics. Figure 3.1 shows the percentage of various heuristics used in dealing with optimization problems related to facility location and network design in supply chain management.

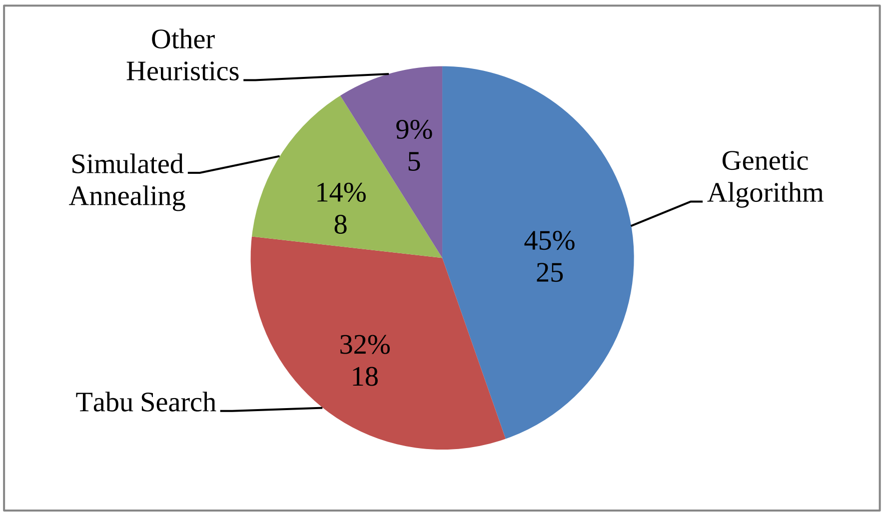

Figure 3.1 The percentage of various heuristics

From Figure 3.1, it can be seen that the commonly used heuristics in this research field is Genetic Algorithm, which occupies 45% percentage. Since the focused problem in my research using heuristics is related to facility location and network design in closed-loop supply chain management, Genetic Algorithm becomes a competitive method. Besides, a number of research articles in this area showed that Genetic Algorithm performed better than other heuristics such as Simulated Annealing and Tabu Search. The following paragraph illustrates some of these research articles.

Shukla et al. (2009) implemented artificial immune system to optimize a multi-stage supply chain, three benchmarking experiments demonstrated the effectiveness of the proposed method. Simultaneously, from the results of the benchmarking experiments, it can be inspected that Genetic Algorithm performed much better than Simulated Annealing. Jung and Lee (2010) compared five heuristics based on Genetic Algorithm and Simulated Annealing separately. These heuristics were used to optimize the production and transportation planning in supply chain network. Numerical examples demonstrated that heuristics algorithm based on Genetic Algorithm were best equipped to deal with the proposed problem and exhibited the most robustness of it. Similarly, Noroozi et al. (2013) investigated computational intelligence algorithms for scheduling problems in supply chain management. Numerical experiments demonstrated the advantage of hybrid Genetic Algorithm than hybrid Simulated Annealing. Castillo-Villar and Herbert-Acero (2014) developed two meta-heuristic algorithms dealing with supply chain network design problem. The results of computational experiments showed that the meta-heuristic algorithm based on Genetic Algorithm can find better quality solutions than the meta-heuristic algorithm based on Simulated Annealing.

Castillo-Villar (2014) analysed several meta-heuristic algorithms implemented in bioenergy supply chain. Genetic Algorithm was classified as one of population approaches, Tabu Search and Simulated Annealing were classified as trajectory approaches. Based on the literature review, Castillo-Villar found that, the integrated supply chain network design and planning problems were mainly solved by applying heuristics based on Genetic Algorithm. While the truck and task scheduling problems were primarily solved by implementing Simulated Annealing and Tabu Search.

From the literature review, Genetic Algorithm was demonstrated as the most commonly used and the best equipped approach to deal with the focused problem related to facility location and network design in closed-loop supply chain.

3.4.2 Genetic Algorithm

In the particular area of focused CLSC network optimization, GA is widely used in CLSC network optimization. Min et al. (2006b) proposed a Genetic Algorithm to solve a Nonlinear Mixed Integer Programming model designing the location problem of return centers. It proposed a binary chromosome with the forepart representing open or closed facilities, and the other part representing intervals for consolidation. The information in this chromosome was only about open or closed facilities. In research on the CLSC network, an open facility means that it is working, and a closed facility means that it has closed down. Gen et al. (2006) developed a priority-based encoding GA to solve a two-stage transportation problem. They proposed an integer chromosome representing the priority of use for each facility by the numbers. This kind of encoding only conveys information on the transportation route, and for the product flow, some flow allocation method had to be added after calculation of the GA. Similar to this case, Wang and Hsu (2010a) established a generalized closed-loop model as an Integer Linear Programming model which integrated forward and reverse logistics, and a revised spanning-tree-based GA was proposed. The encoding of its chromosome only contained information on the transportation route and it had to implement the spanning-tree method to allocate the product flow.

Kannan et al. (2009) designed a multi-echelon distribution inventory CLSC model for the built-to-order environment, and solved it with a Genetic Algorithm and particle swarm optimization. Lee and Chan (2009) proposed a Genetic Algorithm to determine the location of collection points so as to minimize the reverse logistics cost and to maximize the coverage of customers. RFID was also suggested to count the product flow at collection points, in their study. Kannan et al. (2010) developed a multi-echelon, multi-period, multi-product CLSC network model for product returns, where GA was applied as an efficient methodology.

Tuzkaya et al. (2011) used a GA to design a recovery network for the white goods industry in Turkey. The proposed chromosome also had binary strings, representing open or closed facilities and their collection periods. Capacity-based product flow allocation was also added. Zhang et al. (2011) formulated a remanufacturing model employing a CLSC strategy and proposed a Genetic Algorithm to solve this problem. The results of the computational experiments showed that the proposed approach can solve large remanufacturing problems efficiently. Lee and Lee (2012) developed an integrated CLSC model and designed an optimization approach with a hybrid Genetic Algorithm and a priority-based Genetic Algorithm using fuzzy logic control. The results of the experiments using real data demonstrated the efficiency of the hybrid Genetic Algorithm. Lim et al. (2013) established a multi-agent system consolidating process planning and production scheduling across different facilities. A Genetic Algorithm was implemented to tune the currency values for agent bidding. The effectiveness of the proposed multi-agent system was tested through the simulation of a case study. Demirel et al. (2014) developed a CLSC network with multi-period and multi-parts under secondary market pricing and incremental incentive policies. A Mixed Integer Programming model was proposed as the crisp formulation. In addition, a fuzzy multi-objective extension was applied to represent the vagueness in practical problems. To solve the developed model, a Genetic Algorithm approach was implemented.

Li et al. (2012) proposed a multi-objective reverse logistics network optimization model to improve the quality of post-sale repair services. To solve the established multi-objective optimization model, a Non-dominated Sorting Genetic Algorithm II was applied and its performance was evaluated by comparison with a Genetic Algorithm based on the weighted sum approach and Multi-Objective Simulated Annealing.

From the literature, it can be seen that in solving the CLSC problem with GAs, most of the encoding methods only include either delivery route information or freight volume information. While in the CLSC problem, the delivery route decision and freight volume decision are integrated. Hence a comprehensive GA solving both the transportation route design and product flow allocation may improve the performance of the GA in solving this kind of CLSC problem.

3.5 Uncertainty Problems in Closed-Loop Supply Chain

In the research area of closed-loop supply chain, problems with uncertainties are more complicated and have become popular. The uncertainties lie in many stages in closed-loop supply chain networks. This chapter outlines the uncertainty problems within closed-loop supply chain, especially in product recovery.

Vorst and Beulens (2002) defined supply chain uncertainty as "decision-making situations in the supply chain in which the decision maker does not know definitely what to decide as he (or she) is indistinct about the objectives; lack information about (or understanding of) the supply chain or its environment; lacks information processing capacities; is unable to accurately predict the impact of possible control actions on supply chain behavior; or, lacks effective control actions (non-controllability)."

Davis (1993) identified three sources of uncertainty in supply chain network, including demand, manufacturing process and supply uncertainty. Subsequently, Simangunsong et al. (2012) split demand uncertainty into customer demand, demand amplification and inaccurate forecasts. In 1998, Mason-Jones and Towill (1998) added control uncertainty as another uncertainty source in supply chain. These sources of uncertainty in supply chain network are mainly summarized in Figure 3.2 as bellow.

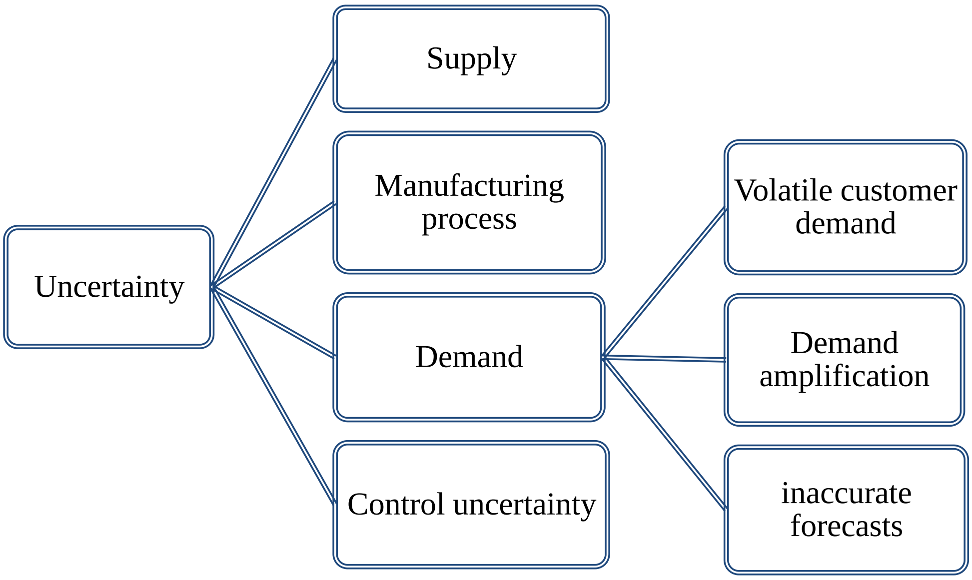

Figure 3.2 Sources of uncertainty in supply chain network

Uncertainty in supply is a result of the faults or delays in the suppliers deliveries. Uncertainty in the manufacturing process is caused by poorly reliable production process. As for the demand uncertainty, it is the most important among the three according to Davis (1993). Demand uncertainty is usually presented as a volatility demand or as inexact forecasting demands.

Many research articles analyze the uncertainties in closed-loop supply chain networks. Salema et al. (2007) developed a Mixed Integer Programming model to optimize a reverse logistics network with multi-products. This model considered the uncertainties in both demands and returns of used products. Zikopoulos and Tagaras (2007) proposed a single-period product refurbishment network, considering uncertainty in returned products' quality. Amaro and Barbosa-Povoa (2009) analyzed the effectiveness of uncertainties in closed-loop supply chain network planning using a linear programming model. Pishvaee and Torabi (2010) proposed a Mixed Integer Programming model integrated with a possibility approach to analyze the risk and uncertainties in closed-loop supply chain design. Giri and Bardhan (2015) developed a centralized and decentralized model to analyze the uncertainty between manufacturers and retailers in closed-loop supply chain.

In the product recovery system within closed-loop supply chain, all of these sources of uncertainties are exist and more complicated especially for the supply uncertainty, because of the difference between the supply in product manufacturing system and the supply in product recovery system. In product recovery system, the supply is from customers who prefer to return their used products to the collection centre. This supply is uncertain in each returned product quality, returned products quantity and also return lead time. So the analysis of uncertainty in product recovery system is more complicated than in product manufacturing system within closed-loop supply chain.

Zarei et al. (2010) presented a conceptual framework of a reverse logistics network to manage the whole recovery process efficiently. A mathematical model was developed with some specific assumptions and was solved by a Genetic Algorithm for simplicity. Because of the uncertainty of demand and of returned products, two types of risks of overstocking and understocking of multi-products should be considered in the forward supply chain. Zhou et al. (2014) developed a multi-product CLSC network equilibrium model in the context of oligopolistic firms that compete non-cooperatively in a Cournot-Nash framework under a stochastic environment. To tackle the uncertainty associated with the quantity of returned products, a stochastic programming model for waste stream acquisition systems was proposed by Behdad et al. (2012).

From the literature, it can be found that planning and modeling problems considering uncertainty became popular and it is significant to analyze uncertainty in the research of closed-loop supply chain, especially in the particular area of product recovery.

3.6 Methods Dealing with the Uncertainties in Closed-Loop Supply Chain

In the literature, a lot of methods are applied to solve the uncertainty problems in closed-loop supply chain. This chapter reviews the methods dealing with uncertainties and indicates the reason for choosing fuzzy logic and simulation as the main methods to deal with uncertainties in product recovery.

3.6.1 Methods Dealing with Uncertainties

Peidro et al. (2009) summarized four dimensions of modelling approach for dealing with uncertainties in supply chain management. The first one is analytical model which includes stochastic programming, games theory and linear programming etc. The second one is models based on artificial intelligence, including fuzzy goal programming, fuzzy numbers, evolutionary programming and genetic algorithm etc. The third dimension is simulation models which include discrete even simulation and system dynamics. The last one is hybrid models, including linear programming integrated with simulation, mixed integer linear programming integrated with discrete event simulation and genetic algorithm integrated with simulation and so on.

For the analytical models, Qiang et al. (2013) established a finite dimensional variation inequality formulation to discuss the delivery routes and competition within closed-loop supply chain. Simultaneously, the uncertainty of customer demands was also analyzed by discussing characteristics of the functions in variational inequality. Movahed and Zhang (2015) formulated a robust Mixed Integer Linear Programming model to inspect the inventory system in supply chain management. The robust techniques were used to deal with the uncertainties. Wang et al. (2015) inspected the impact of environmental uncertainties on supply chain management: 240 cases in Chinese companies were used. The results showed the direct and indirect effects of the environmental uncertainties.

For models based on artificial intelligence, Wang and Hsu (2010b) proposed a fuzzy linear programming model to solve the uncertainty problems in closed-loop supply chain network design. In this model, the uncertainty was expressed by fuzzy numbers. The solutions provided important information for risk analysis. Lieckens and Vandaele (2012) established a multi-stage reverse logistics network model combined with queuing relationships. This model structured the reverse logistics network considering uncertainties in supplies, processing time and quality. To solve this complicated model, a differential evolution approach was developed. A series of computational scenarios demonstrated the efficiency of this approach.

For the simulation models and hybrid models integrated programming methods with simulation systems, they are emerging and effective research approaches for the uncertainty analysis in product recovery system. Section 3.6.2 and Section 3.6.3 gives a review of these research approaches in product recovery in detail.

3.6.2 Simulation with Uncertainties

Implementing simulation systems is an effective way to analyze uncertainties in closed-loop supply chain networks. Franke et al. (2006) developed a discrete simulation model to simulate the process of mobile phone remanufacturing. This simulation system provided production planning for returned mobile phone remanufacturing considering uncertainties of both quality and quantity of returned mobile phones. Kara et al. (2007) proposed a practical simulation model to analyze the collection of the returned appliances in Sydney. The results showed that this model which minimized the collection costs provided an effective tool to analyze the collection system. Long et al. (2011) developed a multi-agent platform in a supply chain, and proposed a novel simulation modelling approach to simulate the operation in a three-echelon supply chain model. Azadivar and Ordoobadi (2012) developed a simulation model to provide decision supports for returned parts recycling. The returned parts were divided from returned products. The provided decision rules from the simulation model minimized the total costs in the returned products' recycling.

3.6.3 Fuzzy Logic and Fuzzy Controller

In general, a CLSC network comprises multiple customers, parts, products, suppliers, remanufacturing subcontractors and refurbishing sites. A three-stage model considering evaluation, network configuration, and selection and order allocation was developed by Amin and Zhang (2013). In the first stage, a new Quality Function Deployment model was proposed together with fuzzy set theory to assess the relationship between customer requirements, part requirements and process requirements. In the second stage, a stochastic Mixed Integer Non-linear Programming model was used to configure the closed-loop supply chain network. In the third stage, suppliers, remanufacturing subcontractors, and refurbishing sites were selected and order allocation determined. The strategic-level decisions concerned the amount of goods flowing in the forward and reverse chain, while the tactical-level decisions related to balancing the disassembly lines in the reverse chain.

Jindal and Sangwan (2014) established a fuzzy Mixed Integer Linear Programming model to optimize a multi-product, multi-facility capacitated CLSC uncertainty. Ozceylan and Paksoy (2014) investigated the strategic and tactical decisions in CLSC. A fuzzy multi-objective Mixed Integer Non-linear Programming model was established, and several fuzzy interactive programming approaches were applied to solve this model. The results of computational experiments showed that the proposed model and approaches can effectively be used in practical CLSC problems.

Pochampally and Gupta (2008) developed a three-stage fuzzy logic approach dealing with the uncertainties in reverse logistics. Illustrative examples have been implemented. Ganga and Carpinetti (2011) established a supply chain performance model based on fuzzy logic to predict supply chain performance. They found that the adoption of fuzzy logic in a prediction model contributes a lot to the decision-making in managing supply chain performance. Prakash and Deshmukh (2011) proposed a heuristic based on an artificial immune system, and a fuzzy logic controller was incorporated into it. A benchmarking experiment taken from the literature review showed the efficiency of the incorporated fuzzy controller. Kumar et al. (2013) established four multi-input single-output Mamdani fuzzy inference systems for supplier evaluation. This method, considering the extent of the production cost that involves raw material costs, can be very helpful to companies for making decisions about supplier evaluation. Nakandala et al. (2013) designed a fuzzy-based decision support model to deal with the uncertainty of delivery time. This model minimized the profit losses due to customer dissatisfaction and penalties.

Zarandi et al. (2013) proposed a flexible fuzzy reinforcement learning algorithm, in which the value function is approximated by a fuzzy rule-based system. The proposed algorithm has a separate module for tuning the structure of the fuzzy rules. Moreover, the parameters of the system are tuned during the learning phase, and the proposed algorithm is applied to the problem of inventory control in supply chains.

3.7 Summary

This chapter delivered a brief review of the literature in the research area of closed-loop supply chain. It firstly reviewed the focused research topics and problems in closed-loop supply chain. From the review, it can be found that, in the closed-loop supply chain network design, few research analyzed the delivery for different kinds of materials extracted from returned products. Correspondingly, the quality of returned products was rarely considered. Secondly, the main models and methods used to solve the focused problems are analyzed. This review explained why genetic algorithm was chosen to solve the proposed problem. Moreover, it found that a comprehensive genetic algorithm which can optimize both the delivery route and the facility allocation was needed. Finally, uncertainty problems in closed-loop supply chain are inspected. The review showed that it is an emerging field to research the uncertainties in product recovery. Both quality and quantity uncertainties of returned products affect the product recovery processes significantly. This review substantiate the basis of the research and identify the research gaps in this research field. This review also extends the current research work and detects research directions for future research works.

Chapter 4 An investigation on a six-level CLSC network using two-stage priority based encoding Genetic Algorithm approach

4.1 Introduction

Product recycling issues have gained increasing attention in many industries in the last decade due to a variety of reasons driven by environmental, governmental and economic factors. Closed-loop supply chain models integrate the forward and reverse flow of products, and since the optimization of these CLSC models is known to be NP-Hard, competition on optimization quality in terms of solution quality and computational time becomes one of the main focuses in the literature in this area. A typical six-level closed-loop supply chain network is examined in this chapter, which has great complexity due to the high level of echelons. The proposed solution uses a novel two-stage Genetic Algorithm, decomposing the problem into product flow and demand allocation process. To test and demonstrate the optimization quality of the proposed algorithm, three numerical experiments have been carried out based on a well-known benchmarking network. The results show that this two-stage genetic algorithm can obtain a more reliable and higher quality solution in a shorter computational time compared with Lingo and the spanning-tree based GA discussed in the literature.

4.2 Problem Description

Many mathematical models have been proposed to describe the CLSC problem. In this study, the model proposed by Wang and Hsu (2010a) is considered here. Six partners are included in this CLSC as shown in Figure 4.1.

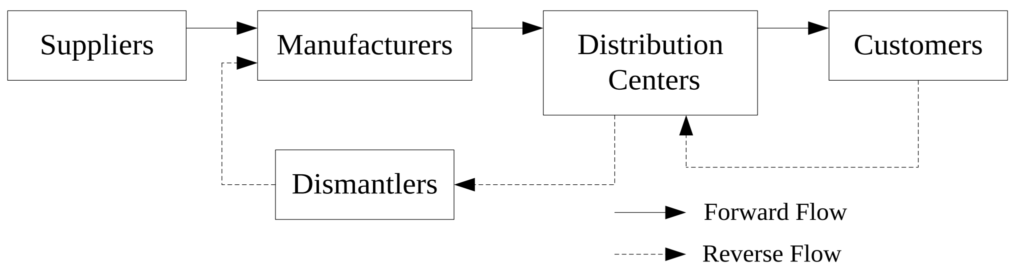

Figure 4.1 Concept model of the CLSC

In Figure 4.1, the three solid lines represent three levels of product flow in the forward chain, and the three dotted lines represent the three levels of product recycle flow in the reverse chain. In the forward chain, customer demands are given, and the distribution centers transport the finished products to customers to meet the demand. Manufacturers transport the corresponding finished products to the distribution centers. In order to produce sufficient products, manufacturers need sufficient raw materials. In this CLSC, both suppliers and dismantlers can provide raw materials to the manufacturers. The raw materials provided by dismantlers are from the recycling of used products collected by the distribution centers from customers. There are many different manufacturers, distribution centers and dismantlers located in different places. Each transportation route has its own unit shipping cost. The purpose of this model is to optimize the transportation network where the facilities are located. The notation and functions are defined as follow.

Indices

I	the number of suppliers with i=1,2,...,I
J	the number of manufacturers with j=1,2,...,J
K	the number of distribution centers with k=1,2,...,K
L	the number of customers with l=1,2,...,L
M	the number of dismantlers with m=1,2,...,M

Parameters

a_i	capacity of supplier i
b_j	capacity of manufacturer j
Sc_k	total capacity of forward and reverse logistics in the Distribution Center (DC) k
pd_k	the percentage of total capacity for reverse logistics in DC k
pc_l	recovery percentage of customer l
pl_m	the landfilling rate of dismantler m

d_l	demand of the customer l
e_m	capacity of dismantler m
s_{ij}	unit cost of production in manufacturer j using materials from supplier i
t_{jk}	unit cost of transportation from each manufacturer j to each DC k
u_{kl}	unit cost of transportation from DC k to customer l
v_{km}	unit cost of transportation from DC k to dismantler m
w_{mj}	unit cost of transportation from dismantler m to manufacturer j
Ru_{lk}	unit cost of recovery in DC k from customer l
f_j	fixed cost for operating manufacturer j
g_k	fixed cost for operating DC k
h_m	fixed cost for operating dismantler m
φ	fixed cost for landfilling per unit

Variables

x_{ij}	Quantity produced at manufacturer j using raw materials from supplier i
y_{jk}	Amount shipped from manufacturer j to DC k
z_{kl}	Amount shipped from DC k to customer l
o_{km}	Amount shipped from DC k to dismantler m
Rd_{mj}	Amount shipped from dismantler m to manufacturer j
Rz_{lk}	Quantity recovered at DC k from customer l

$$\alpha_j = \begin{cases} 1 & \text{if production takes place at manufacturer } j \\ 0 & \text{otherwise} \end{cases}$$

$$\beta_k = \begin{cases} 1 & \text{if DC } k \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_m = \begin{cases} 1 & \text{if dismantler } m \text{ is opened} \\ 0 & \text{otherwise} \end{cases}$$

Objective function:

$$\begin{aligned} \min \quad TC = & \sum_i \sum_j s_{ij} x_{ij} + \sum_j \sum_k t_{jk} y_{jk} + \sum_k \sum_l u_{kl} z_{kl} + \sum_k \sum_m v_{km} o_{km} + \sum_m \sum_j w_{mj} Rd_{mj} \\ & + \sum_l \sum_k Ru_{lk} Rz_{lk} + \sum_j f_j \alpha_j + \sum_k g_k \beta_k + \sum_m h_m \delta_m + \varphi \sum_m \left\lfloor pl_m \sum_k o_{km} \right\rfloor \end{aligned} \tag{4.1}$$

Subject to

$$\sum_j x_{ij} \leq a_i, \qquad \forall \mathrm{i} \tag{4.2}$$

$$\sum_k y_{jk} \leq b_j \alpha_j, \qquad \forall j \tag{4.3}$$

$$\sum_l z_{kl} + \sum_m o_{km} \leq Sc_k \beta_k, \qquad \forall k \tag{4.4}$$

$$\sum_m o_{km} \leq \lfloor pd_k Sc_k \beta_k \rfloor, \qquad \forall k \quad \lfloor \ \rfloor \text{: floor for Guass'symbol} \tag{4.5}$$

$$\sum_j Rd_{mj} + \left\lfloor pl_m \sum_k o_{km} \right\rfloor \leq \mathrm{e}_m \delta_m, \qquad \forall m \tag{4.6}$$

$$\sum_k Rz_{lk} \geq \left\lceil pc_l \sum_k z_{kl} \right\rceil, \qquad \forall l \quad \lceil \ \rceil \text{: ceiling for Gauss'symbol} \tag{4.7}$$

$$\sum_i x_{ij} + \sum_m Rd_{mj} = \sum_k y_{jk}, \qquad \forall j \tag{4.8}$$

$$\sum_j y_{jk} = \sum_l z_{kl}, \qquad \forall k \tag{4.9}$$

$$\sum_{l} Rz_{lk} = \sum_{m} o_{km}, \qquad \forall k \tag{4.10}$$

$$\sum_{k} o_{km} = \sum_{j} Rd_{mj} + \left\lfloor pl_m \sum_{k} o_{km} \right\rfloor, \qquad \forall m \tag{4.11}$$

$$\sum_{k} z_{kl} \geq d_l, \qquad \forall l \tag{4.12}$$

$$\alpha_j, \beta_k, \delta_m \in \{0,1\}, \qquad \forall j,k,m \tag{4.13}$$

$$x_{ij}, y_{jk}, z_{kl}, o_{km}, Rd_{mj}, Rz_{lk} \in N \cup \{0\} \qquad \forall i,j,k,l,m \tag{4.14}$$

The objective is to minimize the total cost which consists of transportation and operation costs, as represented by the objective function (4.1). In the objective function, the first item $\sum_{i}\sum_{j} s_{ij} x_{ij}$ means the cost of products produced in manufacturers using raw materials from suppliers. This cost includes both the raw material purchase cost and the products manufacture cost. The second to the fifth items $\sum_{j}\sum_{k} t_{jk} y_{jk} + \sum_{k}\sum_{l} u_{kl} z_{kl} + \sum_{k}\sum_{m} v_{km} o_{km} + \sum_{m}\sum_{j} w_{mj} Rd_{mj}$ contain transportation costs between each level in closed-loop supply chain, including transportation costs from manufacturers to DCs, DCs to customers, DCs to dismantlers and dismantlers to manufacturers. The sixth item $\sum_{l}\sum_{k} Ru_{lk} Rz_{lk}$ means the recovery cost of products in DCs. The seventh to the ninth items $\sum_{j} f_j \alpha_j + \sum_{k} g_k \beta_k + \sum_{m} h_m \delta_m$ means the facility location costs of manufacturers, DCs and dismantlers. The last item in the objective function $\varphi \sum_{m} \left\lfloor pl_m \sum_{k} o_{km} \right\rfloor$ is the landfilling cost. Constraints (4.2) and (4.3) formulate the capacity limitation of the suppliers and manufacturers. Constraint (4.4) shows that the total capacity of DC must be able to cover the gross flows, forwards and backwards. Constraints (4.5) and (4.6) show the capacity limitation in reverse logistics for the distribution centers and dismantlers. Constraint (4.7) explains the relationship between customer recovery and recovery rate. From each customer area, the quantity of returned products recovered to DCs are equal to or greater than the minimum recovery level according to the recovery rate. In Constraint (4.8), it can be seen that the in-flow of each manufacturer includes the brand new products from supplies in forward chain and the returned products recovered from dismantlers in reverse chain. Constraints (4.8), (4.9), (4.10) and (4.11) guarantee the in-flow equals the out-flow. Constraint (4.12) means that customer demand must be satisfied. Constraints (4.13) and (4.14) represent the binary and integer variables respectively.

4.3 Optimization Methodology: A Two-Stage Genetic Algorithm

4.3.1 A Genetic Algorithm with two-stage priority-based encoding

In this proposed CLSC problem, the objective is to find an appropriate delivery route and product flow to minimize the total cost of transportation and facility operation. So two problems have to be solved simultaneously, one is to decide the handling quantity of each active facility and the other is to decide the transportation route among the whole network. Additionally, these two problems are under a six-level CLSC which makes the problem more complicated.

By using the single-stage encoding GA, these two problems have to be expressed in a single chromosome, which means the chromosome must be able to convey the information on the route and volume and also the active state of the facilities. These vast amounts of information will make the genetic operation too complicated to handle because of too many possible combinations. In addition, this chromosome structure will obviously increase the calculation time. Since all the information is considered at the same time, the search is easy to get lost in the local optimum.

To solve the problems described above, a two-stage priority-based GA is developed in this study. This proposed GA decomposes the encoding process into two stages, which express the above mentioned two problems in the CLSC network respectively. Fig. 4.2 shows the flow diagram of this developed GA.

From Fig. 4.2, it can be observed that this GA has two stages in the encoding process which are: Stage 1 - "Route Decision" and Stage 2 - "Freight Volume Decision" respectively. Route Decision is applied to decide the delivery route between each level of the supply chain network. Freight Volume Decision is to decide the freight volume in each selected route according to the results of stage 1. These two stages are explained in detail in Section 4.4.2 and Section 4.4.3 respectively. The "Cost Rank" process before "Route Decision" is the preparation of the priority-based "Freight Volume Decision" which is explained in part 4.4.3.2. The right part of Fig. 4.2 describes the genetic operations. Section 4.4.4 gives details of genetic operations.

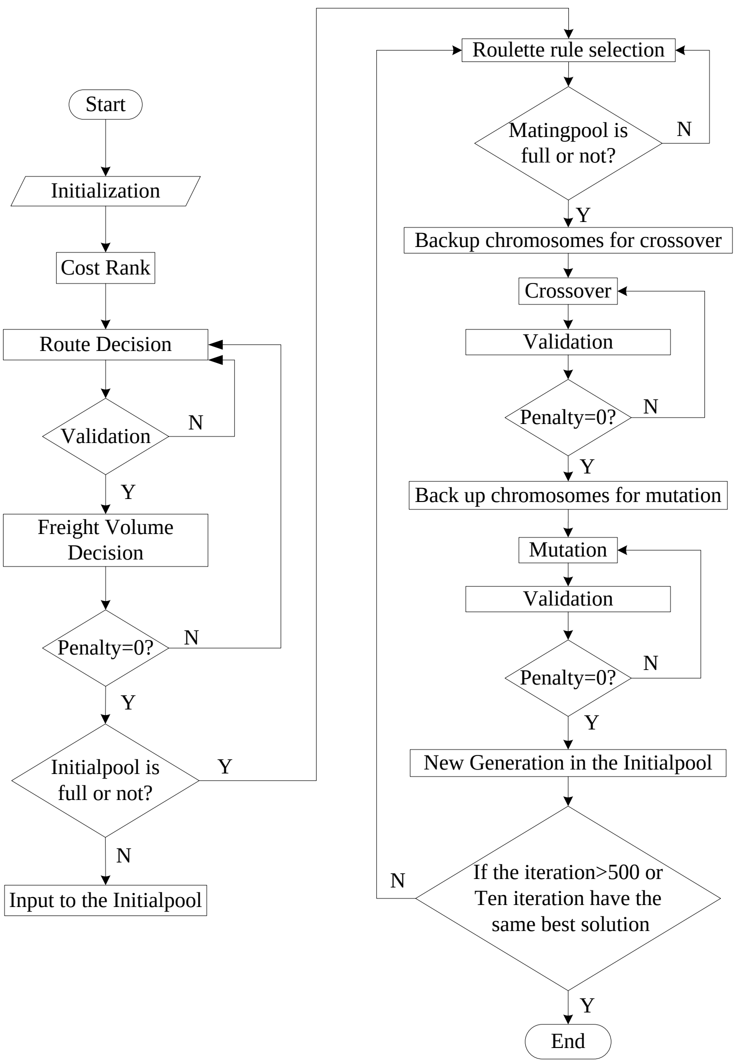

Figure 4.2 The flow diagram of two-stage priority based GA

4.3.2 Route Decision Stage

The first stage of encoding is to determine the appropriate delivery route. In this stage, the generated chromosome is composed of binary genes, which express information on the transportation route only. Since the chromosomes in stage 1 only deliver information on the transportation route, except for the quantity of product flow, it makes the genetic operations, especially the validation operation of chromosome, much more concise than the traditional GA.

Since this CLSC model has six levels, the chromosome has six sections to represent each level. In each section, the number of genes equals the product of the number of suppliers and the number of demanders. Totally, in a chromosome, the number of genes is $I \times J + J \times K + K \times L + L \times K + K \times M + M \times J$, where *I*, *J*, *K*, *L* and *M* are the number of suppliers, manufacturers, distribution centers, customers and dismantlers respectively.

To explain the proposed algorithm clearly, a numerical example is provided. In this example, I=3, J=5, K=2 which means that three suppliers provide materials to five manufacturers, and these five manufacturers provide finished products to two DCs. The chromosome at this stage in the example is shown in Figure 4.3, and the corresponding delivery route is shown in Figure 4.4(a).

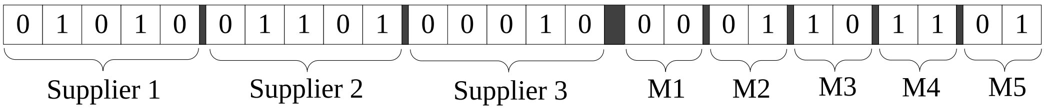

Figure 4.3 The first and second sections of chromosome in stage 1

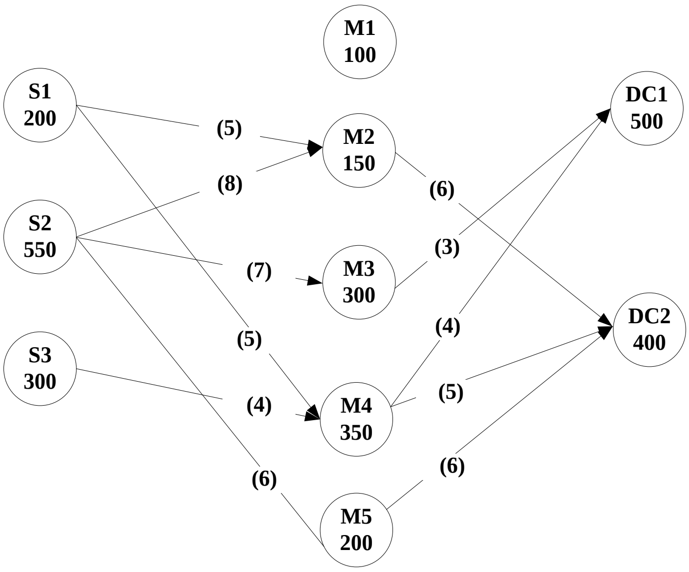

Figure 4.4 (a) Delivery route of the numerical example

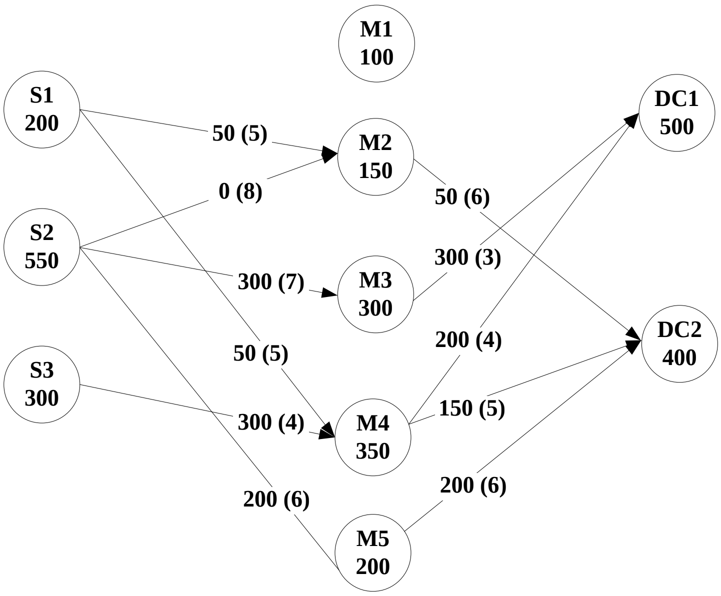

Figure 4.4 (b) Network of the numerical example

In Figure 4.3, each gene contains a binary number, where 1 means the delivery route is used and 0 means it is not. The first section of the chromosome has 3*5=15 genes: the first five genes represent the situation of supplier 1 providing materials to manufacturers 2 and 4 but not providing materials to manufacturers 1, 3 and 5. The second five genes represent supplier 2, and the third five genes represent supplier 3. The second section of the chromosome has 5*2=10 genes: The first two genes represent the situation of manufacturer 1 providing finished products to neither of the two DCs, and the second two genes represent manufacturer 2, and so on. Figure 4.4(a) illustrates the delivery route. The numbers in parentheses mean the unit transportation cost of each delivery route and the numbers in circles mean the capacity of each partners.

4.3.3 Freight Volume Decision Stage

After the first stage, a chromosome representing the delivery route is established, according to the route generated. The second stage is to decide the freight volume of materials or products which are called freight volume decision. Fig. 4.5 shows the chromosome after the second stage of encoding.

0	50	0	50	0	0	0	300	0	200	0	0	0	300	0	0	0	0	50	300	0	200	150	0	200
Supplier 1					Supplier 2					Supplier 3					M1		M2		M3		M4		M5	

Figure 4.5 The first and second sections of chromosome in stage 2

The structure of the chromosome remains the same as in stage one, except that the content of each gene has been changed. Among the first five genes, the first gene means supplier 1 won't deliver any raw materials to manufacturer 1, the second gene means that supplier 1 will deliver 50 units of raw materials to manufacturer 2. Other sections have similar principles. The last gene in Figure 4.5 means that manufacturer 5 will deliver 200 units of products to distribution center 2. The network, including delivery route and freight volume, is shown in Figure 4.4(b).

4.3.3.1 Process Outline

The process of the freight volume decision contains six steps. To explain the freight volume decision process in detail, the numerical example in Section 4.4.2 is used. In this three stage supply chain example, the step details are illustrated in Figure 4.4(a) and Figure 4.4(b) and described below. The numbers in parentheses mean the unit shipping cost of that delivery route. The demand of the distribution centers and the capacity of suppliers and manufacturers are represented by the numbers in the circles.

Step 1: Decide on the start level in the supply chain network. In this example, the terminal demand is at the distribution centers, so the freight volume decision process starts from the level of the manufacturer to the distribution center.

Step 2: Find the top priority delivery route with the lowest unit shipping cost in the current level. According to the result of "Cost Rank", the lowest unit shipping cost within the current level is 3, which is from manufacturer 3 to distribution center 1. Details of the "Cost Rank" are explained in Section 4.4.3.2.

Step 3: Check if there are other delivery routes with the same unit shipping cost and also the same demand as the one found in Step 2. In other words, check if the top priority delivery route is a multiple or not. If the result is yes, count out the number, mark as N and go to Step 4a, if not, go to Step 4b. Step 4a and Step 4b are parallel. In this example, the unit shipping cost 3 is unique at this level, so go to Step 4b.

Step 4a: The demand is divided into N parts randomly, and allocated to the N top priority delivery routes.

Step 4b: Compare the supply capacity and the demand, and allocate the transport flow with the smaller one. Since the supply capacity of manufacturer 3 is 300 units and the demand of distribution center 1 is 500 units, the freight volume between them is 300 units.

Step 5: Update the corresponding supply capacity and demand. The remaining supply capacity of manufacturer 3 is 300-300=0 and the updated demand of distribution center 1 is 500-300=200.

Step 6: Move to the next delivery route according to the results of "Cost Rank" and then repeat Step 2 to Step 6. When the whole level is finished, return to the next level. In this example, the delivery route between manufacturer 4 and distribution center 1 is found according to "Cost Rank" as the next operand.

Specifically, when the unit shipping cost of several different suppliers delivering to the same demander is the same, the delivery flow will be randomly generated. In this case, since the unit shipping cost of both manufacturer 2 and manufacturer 5 to distribution centers 2 are 6, the corresponding flows are randomly generated to be 50 and 200 respectively.

4.3.3.2 Cost Priority Rule

To decide the priority in Step 1 of the freight volume decision, the process "Cost Rank" is implemented at the beginning of encoding. The cost rank process includes six parts which represent the six levels of the supply chain. In each part, the unit cost of each delivery route is positive sequence ranked. The results of the rank are prepared for the freight volume decision process.

In this model, the demand of the entities at each level must be satisfied, so the process of the freight volume decision actually is the process of allocating the demand flow to different suppliers. In this problem, each delivery route has its own unit shipping cost. The route whose shipping cost is low has the priority to be firstly used for delivery, which is called cost priority rule.

This cost priority rule is more appropriate in this problem than other rules such as demand priority and equal distribution. With this rule, the freight volume decision process can reach the edge value of the transportation cost in the whole CLSC under the pre-decided delivery route. Since the demand must be satisfied, the flow allocation has to be started at the last stage of the supply chain. It means that the flow allocation will start at the level of the distribution centers delivery to customers in the forward chain, and then, move to the level of the manufacturers' delivery to the distribution centers. After that, rather than moving to the suppliers, it jumps to the reverse chain, which starts at the level of customers' recovery to the distribution centers, and then, to dismantlers and manufacturers. The flow allocation of suppliers delivering to manufacturers is implemented as the end procedure, because the manufacturing demand depends on both the demand of the distribution centers in the forward chain and the supply quantity of the dismantlers in the reverse chain.

This optimization problem considers the delivery route together with facility location.

Since the fixed cost of each facility is no small cost, in the optimization process, each capacity of facility has to be sufficiently used. Since the open facility is settled in the first stage of encoding, in the second stage of encoding, it is not a problem that choose the route with the minimum cost, but a problem allocate flow quantity to the settled route. The cost priority rule is not to compare the unit shipping cost within each facility, but to ranking unit shipping costs within each level. This priority rule can obtain the minimum total cost for each selected network. The formula derivation below can provide a simple proof.

The formula indicates each facility in the network, for easy to explain, Distribution Center 1 (DC1) is taken for example. Set d1 and d2 as two delivery routes through DC1. Set A1 as unit shipping cost of d1 from DC1 to customers, set A2 as unit shipping cost of d2 from DC1 to customers. Set B1 as unit shipping cost of d1 from manufacturers to DC1, set B2 as unit shipping cost of d2 from manufacturers to DC1. Set x1, x2 as flow quantities through DC1.

$$\begin{aligned} &\min \quad A_1x_1 + A_2x_2 + B_1x_1 + B_2x_2 \\ &where \qquad A_1 < A_2, B_1 > B_2 \end{aligned}$$

$$\begin{aligned} &\min \quad A_1x_1 + A_2x_2 + B_1x_1 + B_2x_2 = (A_1 + B_1)x_1 + (A_2 + B_2)x_2 \\ &if \quad A_1 + B_1 < A_2 + B_2 \quad then\ scenario1 \\ &if \quad A_1 + B_1 > A_2 + B_2 \quad then\ scenario2 \\ &if \quad A_1 + B_1 = A_2 + B_2 \quad then\ scenario3 \end{aligned}$$

From the formulas, it can be seen that, in Scenario1, the flow quantity through DC1 will be allocated in d1 as much as possible to obtain a minimum total cost. In Scenario2, the flow quantity through DC1 will be allocated in d2 as much as possible to obtain a minimum total cost. In Scenario3, the flow quantity can be allocated randomly. In the proposed genetic algorithm, the above three scenarios of each facility in the network can be easily obtained by using the proposed cost priority rule. Therefore, the development of the cost priority rule strengthens the searching ability of genetic algorithm, and at the same time, not missing the best solutions.

4.3.4 Genetic Operations

Genetic operations play an important role in Genetic Algorithms. Considering the properties of chromosomes in this problem, one-point crossover and one-point mutation is implemented because dramatic changes in the genetic structure can be avoided. This can prevent infeasible solutions.

4.3.4.1 Fitness Function

The fitness function is to calculate the fitness value of each chromosome which represents the viability of the chromosomes. In this model, the fitness is the reciprocal of the total cost. The lower the total cost is, the stronger is the chromosome viability.

$$Fitness = \frac{1}{Total\ Cost}$$

$$Total\cos t = Fix\cos t + Transportation\cos t$$

$$Fix\cos t = \sum_j f_j \alpha_j + \sum_k g_k \beta_k + \sum_m h_m \delta_m + \varphi \sum_m \left\lfloor pl_m \sum_k o_{km} \right\rfloor$$

$$\begin{aligned} Transportation\cos t = & \sum_i \sum_j s_{ij} x_{ij} + \sum_j \sum_k t_{jk} y_{jk} + \sum_k \sum_l u_{kl} z_{kl} \\ & + \sum_k \sum_m v_{km} o_{km} + \sum_m \sum_j w_{mj} Rd_{mj} + \sum_l \sum_k Ru_{lk} Rz_{lk} \end{aligned}$$

4.3.4.2 Selector Operator

In this GA, after generating the initial pool randomly, roulette wheel selection is implemented to generate the mating pool. In this roulette wheel selection, the fitness function is used to decide the probability of being selected for each chromosome. The roulette wheel function is

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j}$$

where P_i means the probability of being selected for chromosome i, f_i means the fitness of chromosome i, and N is the number of chromosomes in the initial pool.

4.3.4.3 Crossover Operator

In this algorithm, one-point crossover is applied. The characteristic of one-point crossover is that genes in the parent chromosomes will not be changed greatly after crossover, therefore, after several evolutions, weak genes will be easily identified

(Chan and Chung, 2004). In this CLSC problem, the chromosomes contain several sections, in which each section represents one stage in the supply chain network. A weak gene will cause a weak section, so the identification of weak genes is crucial in this problem. This process of crossover contains three steps as shown in Figure 4.6.

Step 1: Pick up two parents from the mating pool randomly.

Step 2: Randomly generate the cut point.

Step 3: Generate two offspring according to the cut point.

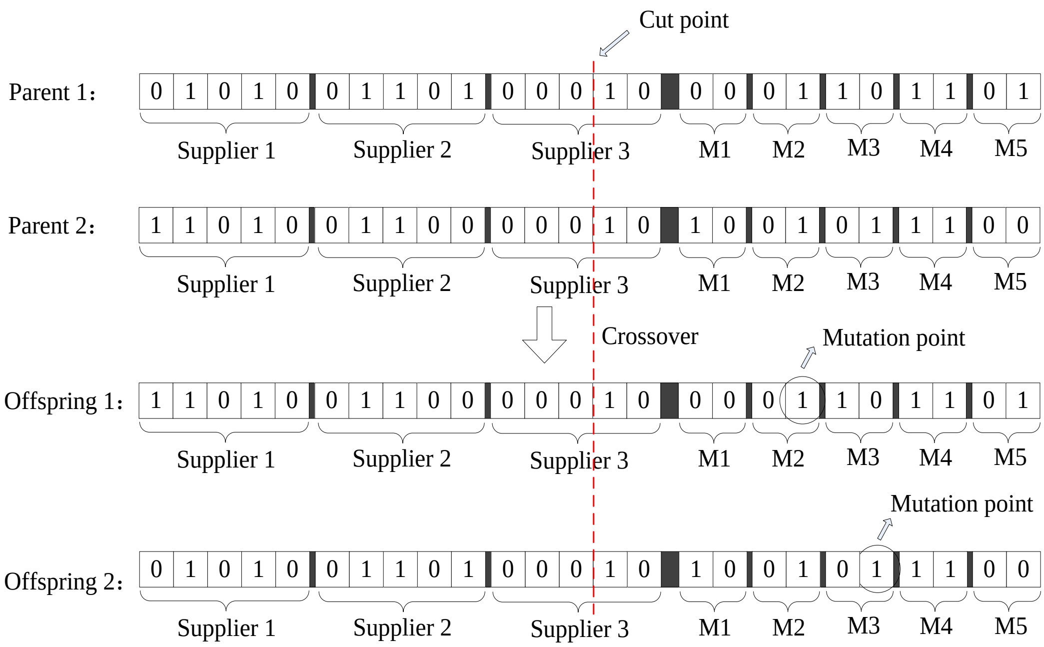

Figure 4.6 The process of crossover

4.3.4.4 Mutation Operator

Due to the special feature of this two-stage encoding, the search function of the proposed method is more easily trapped in a local optimum. The process of mutation here aims at preventing this situation. Therefore, in this algorithm, one-point mutation with 1 mutation rate is implemented. The process of mutation contains three steps as shown in Figure 4.7.

Step 1: Pick up one chromosome from the mating pool.

Step 2: Randomly generate a mutation point, and read the number of this gene as A.

Step 3: Calculate the result of 1 minus A, and load this result to the gene of the selected mutation point

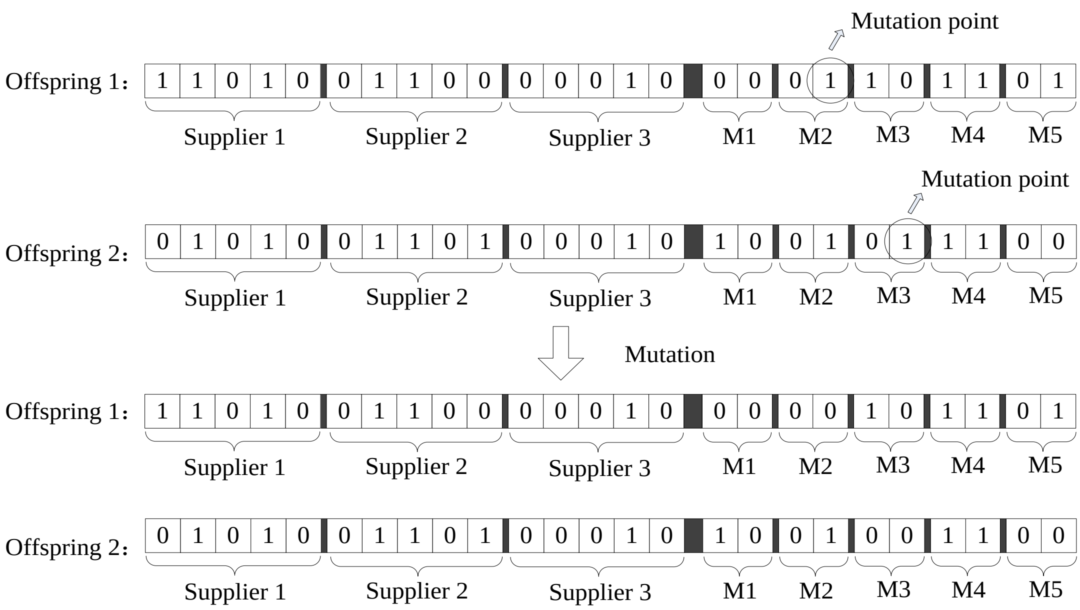

Figure 4.7 The process of mutation

4.3.4.5 Validation

In order to guarantee the feasibility after crossover and mutation, validation is implemented. Due to the characteristics of two-stage encoding, the validation contains two parts.

Part 1: Check capacity requirements

There are several situations for offspring invalidation after crossover and mutation. In Part 1, the procedure checks on the binary chromosome, which is the chromosome before the "freight volume decision". If one of the situations in Table 4.1 occurs, rollback of the crossover and mutation processes will be implemented.

Table 4.1 Capacity requirements

Validation requirements
1. The total capacity of the active distribution centers must be able to satisfy the total demand of customers.
2. The total capacity of active manufacturers must be able to satisfy the total demand of customers.
3. The genes of each customer cannot be zero simultaneously which means that each customer must return used products to at least one distribution centers.
4. Since the demand of customers must be satisfied, each customer must have at least one distribution center to supply the needed products.

In Figure 4.6, the active manufacturers in offspring 1 are M3, M4, and M5. The total capacity cannot satisfy the total demand of customers and causes invalidation, so the whole process of crossover will be rollbacked. The selected parents will be assigned in the pool after crossover as the offspring.

Part 2: Check penalty

If the offspring get through the capacity check in Part 1, the penalty check in Part 2 will be implemented. In Part 2, this validation procedure acts on the integer chromosome, which is the chromosome after the "freight volume decision ". In this step, the penalty for the transformed chromosome is examined. If the penalty is not equal to zero as before, the procedure will undo the whole process of respective crossover and mutation.

In Figure 4.7, offspring 2 after mutation, shows the invalidation of the penalty in Part 2. To show the detail and explain the calculation process of the penalty, the network of offspring 2 is drawn in Figure 4.8.

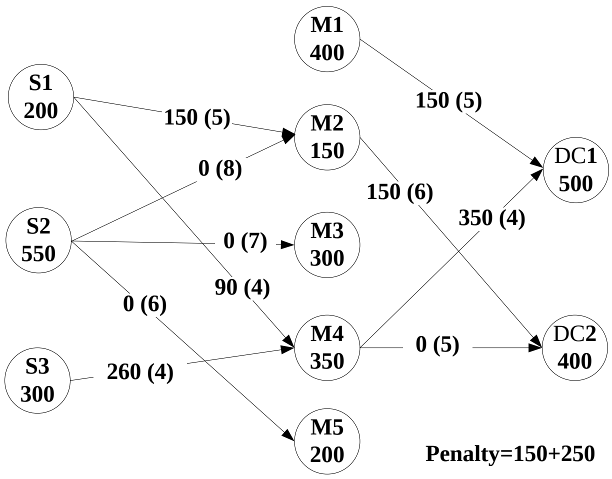

Figure 4.8 The network of offspring

For each entity in this closed-loop supply chain network, take M2 in Figure 4.8 for example, the input flow quantity should equal to the output flow quantity. When the value of input and output are unequal, penalty occurs. The penalty here is the total number of the difference value between the input flow quantity and the output flow quantity. To explain it more clearly, let's take Figure 4.8 as an illustration. In Figure 4.8, it can be seen that, the input and output flow quantity of M1 are unequal, with the difference value of 150 (150-0=150). Simultaneously, the input and output flow quantity of DC2 are also unequal, with the difference value of 250 (400-150=250). So in this calculation, the penalty is the sum of 150 and 250, equals to 400.

4.3.4.6 Stopping Condition

The proposed GA will improve the initial pool iteratively until one of the stopping conditions below is met: a preset maximum number of generations is reached, or a feasible solution is generated in twenty successive generations.

4.4 Computational experiments

In this section, three computational experiments are implemented to demonstrate the efficiency and stability of the proposed GA. For the convenience of comparison, the same dataset as in Wang and Hsu's paper (2010) is used for Experiment 1. In this referenced paper, a revised spanning-tree based GA was proposed to optimize the

CLSC model.

The great difference between the fixed costs of the entities in Experiment 1 shows that it is an extreme case in this computational experiment. Hence, Experiment 2 and Experiment 3 are needed to illustrate more usual cases. In Experiment 2, the fixed cost and corresponding capacity of the distribution centers are close, which make the optimal search become difficult. In Experiment 3, the entities within the same level have similar fixed cost and corresponding capacity, which makes the optimal search even more difficult. All of the three experiments include five sub-problems with a scale from basic to large. Table 4.2 shows the five scales.

Table 4.2 Scale of computational experiments

	Suppliers	manufacturers	DCs	Customers	Dismantlers
Basic Scale	3	5	3	4	2
Second Scale	6	10	6	8	4
Third Scale	12	20	12	16	8
Fourth Scale	24	40	24	32	16
Fifth Scale	48	80	48	64	32

4.4.1 Experiment 1 of Two-Stage GA

In this experiment, the dataset in Wang and Hsu's paper (2010) has been used. With the same input data, the comparison between the single-stage encoding spanning tree based GA and the proposed GA is convincing. Table 4.3 shows the capacity, fixed cost and demand in Experiment 1. Table 4.4 shows the unit shipping cost for each stage in this experiment.

Table 4.3 Capacity, fixed cost (US$) and demand in Experiment 1

Supplier	Manufacturer		DC		Customer	Dismantler	
Capacity	Capacity	Fixed cost	Capacity	Fixed cost	Demand	Capacity	Fixed cost
500	400	1800	870	1000	500	540	900
650	550	900	890	900	300	380	800
390	490	2100	600	1600	400		
	300	1100			300		
	500	900					

Table 4.4 Unit shipping cost for each stage (US$) in Experiment 1

	Manufacturer				
Supplier	1	2	3	4	5
1	5	6	4	7	5
2	6	5	6	6	8
3	7	6	3	9	6

	Customer			
DC	1	2	3	4
1	7	4	5	6
2	5	4	6	7
3	7	5	3	6

	DC		
Manufacturer	1	2	3
1	5	8	5
2	8	7	8
3	4	7	4
4	3	5	3
5	5	6	6

	DC		
Customer	1	2	3
1	3	7	4
2	8	5	5
3	4	3	4
4	3	2	5

	Manufacturer				
Dismantler	1	2	3	4	5
1	2	3	4	2	5
2	3	4	6	3	4

	Dismantler	
DC	1	2
1	3	2
2	2	5
3	3	3

After the computation using the proposed GA, the result of the basic scale problem turns out to be the same as the original paper, which is to say, the total cost of the basic scale problem is the same, while the flow delivered at each stage is slightly different. Since this model is a NP-hard problem, it is good news to find another optimal solution. This result can be verified by drawing the closed-loop supply chain. The verification of the result is shown in Figure 4.9, the numbers in the squares are the differences to the original result.

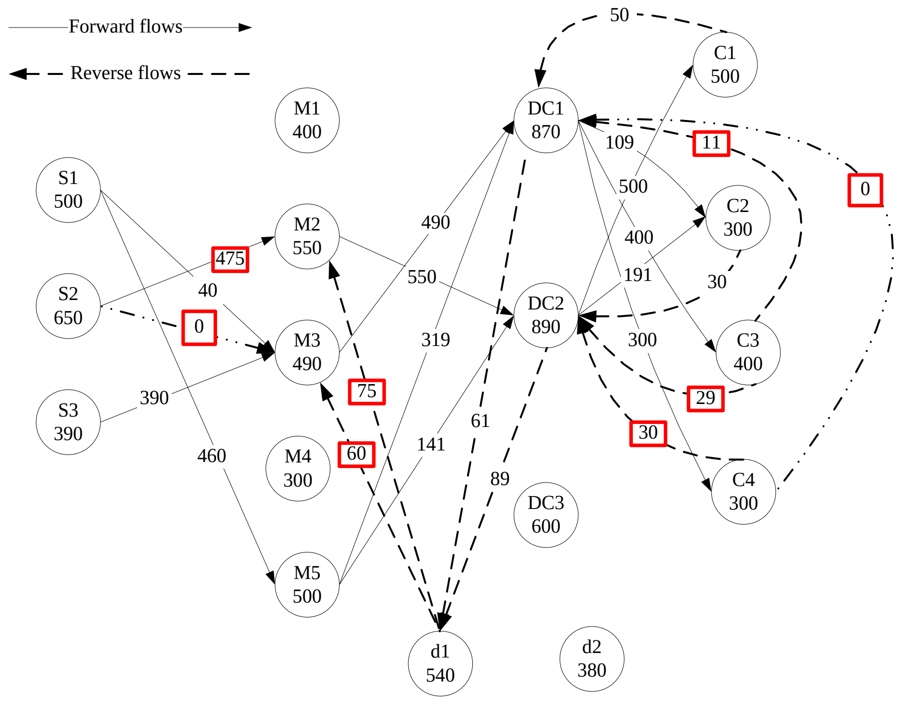

Figure 4.9 Result of basic scale problem in Experiment 1

To further test the proposed GA, four larger scale problems have been computed. The dataset is also the same as the original paper. Table 4.5 shows the comparison between the proposed GA and the revised spanning tree based GA (Revised ST-GA) in Wang and Hsu's paper (2010). Table 4.6 shows the comparison between the proposed GA and Lingo. The results of Lingo and the provided GA are worked out using a PC with Intel(R) Core(TM) i7-2600 CPU @ 3.4GHz, 8.0G RAM. The results in the original paper used a PC with Intel® Pentium® M processor 1.86GHz, 1.0G

RAM.

Table 4.5 Comparison between the GA and the spanning tree based GA

30 Times each problems	Scale	Numerical examples 1	2	3	4	5
Revised ST-GA (population size=100) in original paper	Min-cost(US$)	29848	58368	115866	235309	469089
	Ave-cost(US$)	29966	58999	117524	237820	470310
	Ave-time(s)	2.04	6.35	22.49	72.74	356.28
Two stage priority based GA (population size=100)	Min-cost(US$)	29848	58325	115246	232983	463117
	Ave-cost(US$)	29931	58867	116865	234478	464445
	Ave-time(s)	0.09	1.21	9.25	40.25	230.80
Results comparison	Absolute difference	0	43	620	2326	5972
	Percentage difference	0	0.07%	0.54%	0.99%	1.27%
Average time comparison	Absolute difference	1.95	5.14	13.24	32.49	125.48
	Percentage difference	95.6%	80.9%	58.9%	44.7%	35.2%

In Table 4.5, the results of revised ST-GA are from the original paper. Suite reference again, from the optimal value comparison and the average time comparison, it is obvious that the proposed GA can obtain a better solution within a shorter computing time. Take Scale 2 for example, in the optimal value comparison, the percentage difference is 0.07%, which means the result of the proposed GA is 0.07% better than the spanning tree GA. Furthermore, in the average time comparison, the percentage difference is 80.9%, which means the running time of the proposed GA is 80.9% faster than the spanning tree GA. When the scale of the problem increases, the accuracy of the proposed GA improves and the running time is always shorter. In Scale 3, the result of the proposed GA is 0.54% better than the spanning tree GA, and the average running time is 58.9% better. In Scale 4, the result of the proposed GA increases to 0.99% better, with 44.7% of the running time, which is twice as fast as the speed of the spanning tree GA. Furthermore, in Scale 5, when the number of variables is almost 19000, the quality result is 1.27% better than the spanning tree GA with about one third of the running time 35.2%.

Table 4.6 shows the comparison between Lingo 11.0 and the proposed GA with five scales. The row of "absolute difference" expresses the value of the Lingo values minus the results of the proposed GA. The minus sign means disparity. Take Scale 2 for example, the value of the absolute difference is -19, and the percentage difference is -0.03%, which means the result of proposed GA is 0.03% disadvantageous compared with that of Lingo. However, the average time of the proposed GA is 1.21 s, which is only 10.1% of the time for Lingo.

When the scale of the problem grows larger, the speed advantage of the proposed GA is more obvious. In Scale 3, the result of the proposed GA is 0.38% disadvantageous compared with that of Lingo, and the running time is less than 0.93% of that of

Lingo. In Scale 4, the result is 2.14% disadvantageous compared to that of Lingo, while the running time is less than 1.49%. In Scale 5, although the quality of proposed GA is 1.77% behind Lingo, the time is faster than Lingo by almost 40 times. Furthermore, if the scale of the problem keeps growing, Lingo cannot even produce an optimal result within an acceptable time. However, the proposed GA can solve it effectively.

Table 4.6 Comparison between the proposed GA and Lingo

30 Times each problems	Scale	Numerical examples 1	2	3	4	5
Lingo 11.0	Optimal(US$)	29848	58306	114805	228092	455041
	Time(s)	1	12	>1000	>2700	>9000
Two stage priority based GA (population size=100)	Min-cost(US$)	29848	58325	115246	232983	463117
	Absolute difference	0	-19	-447	-4891	-8076
	Percentage difference	0	-0.03%	-0.38%	-2.14%	-1.77%
	Average-cost (US$)	29931	58867	116865	234478	464445
	Average-time (s)	0.09	1.21	9.25	40.25	230.80
	Percentage of time	9%	10.1%	<0.93%	<1.49%	<2.56%

4.4.2 Experiment 2 of Two-Stage GA

From Figure 4.9, it can be seen that manufacturer 1, manufacturer 4 and distribution center 3 are not used due to their high fixed cost and low capacity. To make the model more complex, the fixed cost of manufacture and distribution are changed, and some of the unit shipping costs are also changed to allow more entities to be used. After the data change, the fixed cost and corresponding capacity of all the distribution centers are close to each other, which make the optimal solution tighter and the optimal search more difficult. Table 4.7 shows the capacity and fixed cost. Table 4.8 shows the changed unit shipping cost for each stage.

Table 4.7 Capacity, fixed cost (US$) and demand in Experiment 2

Supplier	Manufacturer		DC		Customer	Dismantler	
Capacity	Capacity	Fixed cost	Capacity	Fixed cost	Demand	Capacity	Fixed cost
500	400	1100	870	1000	500	540	900
650	550	900	890	900	300	380	800
390	490	2100	600	800	400		
	300	800			300		
	500	900					

Since the dataset is different to that in the original paper (Wang and Hsu, 2010a), the comparison is only between the proposed GA and Lingo. For simplicity, only the dataset of the basic scale is shown. Other scales are doubled and redoubled to the basic one, which was the same data building method as that in the original paper (Wang and Hsu, 2010). The optimal solution is shown in Table 4.9. Table 4.10 is the comparison with Lingo.

Table 4.8 Unit shipping cost for each stage (US$) in Experiment 2

	DC				DC		
Manufacturer	1	2	3	Customer	1	2	3
1	5	8	5	1	3	7	4
2	8	6	8	2	8	5	5
3	5	7	4	3	4	4	4
4	3	5	3	4	3	3	5
5	5	6	6				

Table 4.9 The optimal solution of Experiment 2

Objective Value						29099
x_{ij}	$x_{13}=100$	$x_{15}=365$	$x_{22}=510$	$x_{33}=390$		
y_{jk}	$y_{22}=510$	$y_{33}=490$	$y_{51}=500$			
z_{kl}	$z_{12}=290$	$z_{14}=210$	$z_{21}=500$	$z_{22}=10$	$z_{33}=400$	$z_{34}=90$
o_{km}	$o_{12}=87$	$o_{22}=3$	$o_{32}=60$			
Rd_{mj}	$Rd_{25}=135$					
Rz_{lk}	$Rz_{11}=50$	$Rz_{22}=3$	$Rz_{23}=27$	$Rz_{31}=7$	$Rz_{33}=33$	$Rz_{41}=30$
α_j	$\alpha_2=1$	$\alpha_3=1$	$\alpha_5=1$			
β_k	$\beta_1=1$	$\beta_2=1$	$\beta_3=1$			
δ_m	$\delta_2=1$					

Since Lingo is an exact algorithm and GA is a heuristic algorithm, Lingo can usually get better results when the calculation scale is relatively small. But when the calculation scale gets large, Lingo cannot produce an acceptable result within an acceptable period of time. That's where heuristic algorithm works.

Table 4.10 Comparison with Lingo in Experiment 2

30 Times each problems		Numerical examples				
	Scale	1	2	3	4	5
Lingo 11.0	Optimal(US$)	29099	55817	110137	218677	436697
	Time(s)	1	4	>1000	>2700	>9000
Two stage priority based GA (population size=100)	Min-cost(US$)	29099	55936	111172	226053	447644
	Absolute difference	0	-119	-1035	-7376	-10947
	Percentage difference	0	-0.21%	-0.94%	-3.37%	-2.50%
	Average cost(US$)	29173	56385	112258	228165	449377
	Average time(s)	0.15	1.12	9.37	73.33	258.40
	Percentage of time	15%	28%	<0.94%	<2.72%	<2.87%

From Table 4.10, it can be seen that although the quality of the results is reduced, the calculation speed is far faster than Lingo. In Scale 1, the proposed GA can find the same optimal solution as Lingo within a shorter time, and is only 15% of the Lingo running time. In Scale 2, the quality result is 0.21% disadvantageous compared to Lingo, however, the running time is only 28%. When the scale grows to Scale 3, the result is 0.94% poorer than Lingo, but the running time is shorter to less than 0.94%. In Scale 4, the result is 3.37% disadvantageous compared to that of Lingo, but the running time shortens to 2.72%. In Scale 5, the result becomes 2.5% disadvantageous to that of Lingo, but the running time is less than 2.87%. It is observed from the "Percentage difference" row that all the reduced quality of results are below 3.5%, while the running times in the row of "Percentage of time" are 100 times faster than Lingo.

4.4.3 Experiment 3 of Two-Stage GA

The fixed cost of entities and the unit shipping cost are further changed in Experiment 3 in order to make almost all of the entities in the same level have close fixed cost and corresponding capacities to each other. This makes the solution of the whole network tighter, and the search for the optimal solution is more difficult. From the optimal solution of the basic scale in Experiment 3 shown in Table 4.13, it can be seen that four manufacturers and three distribution centers are being used.

For clarity, only the changed part of the unit shipping cost is shown, the other part is the same as that in Experiment 2. Table 4.11 shows the capacity and fixed cost. Table 4.12 shows the unit shipping cost for each stage. The optimal solution is shown in Table 4.13. Table 4.14 is the comparison with Lingo.

Table 4.11 Capacity, fixed cost (US$) and demand in Experiment 3

Supplier	Manufacturer		DC		Customer	Dismantler	
Capacity	Capacity	Fixed cost	Capacity	Fixed cost	Demand	Capacity	Fixed cost
500	450	400	870	1000	500	540	900
650	350	740	890	900	300	380	800
390	400	1900	600	800	400		
	300	600			300		
	600	600					

Table 4.12 Unit shipping cost for each stage (US$) in Experiment 3

	Manufacturer						DC		
Supplier	1	2	3	4	5	Manufacturer	1	2	3
1	5	6	4	7	5	1	6	8	5
2	6	5	6	6	4	2	4	3	5
3	7	6	3	5	6	3	5	7	4
						4	3	5	3
						5	5	6	6

Table 4.14 shows the results and comparison with Lingo. In Scale 1, the proposed GA can get the optimal solution within only 12% of the time of Lingo. In Scale 2, the result is a 0.44% disparity with Lingo, but the running time is 15.6%. When the problem scale grows to Scale 3, the result is a 1.73% disadvantage compared to that of Lingo, but the time is less than 0.9%. In Scale 4, although the quality result is 4.7% disadvantageous compared to Lingo, the running time is less than 1.83%. In Scale 5, the result is 3.86% poorer than Lingo, but the running time is less than 2.97%. Although the optimal search in Experiment 3 becomes more difficult, it can be observed from the "Percentage difference" row that the error rate is still below 5%. From the row of "Percentage of time", the advantage of the running time is obvious.

From the results of Experiment 3, it can be further demonstrated that when the scale of the problem grows, the proposed GA can still give a near optimal solution with a fast calculation time.

Table 4.13 The optimal solution of Experiment 3

Objective Value						26771
x_{ij}	x_{11}=400	x_{22}=200	x_{25}=450	x_{32}=150	x_{32}=150	x_{34}=165
y_{jk}	y_{13}=400	y_{22}=350	y_{41}=300	y_{51}=300	y_{52}=150	
z_{kl}	z_{12}=300	z_{14}=300	z_{21}=500	z_{33}=400		
o_{km}	o_{11}=61	o_{21}=89				
Rd_{mj}	Rd_{14}=135					
Rz_{lk}	Rz_{11}=50	Rz_{22}=30	Rz_{32}=40	Rz_{41}=11	Rz_{42}=19	
α_j	$\alpha_1=1$	$\alpha_2=1$	$\alpha_4=1$	$\alpha_5=1$		
β_k	$\beta_1=1$	$\beta_2=1$	$\beta_3=1$			
δ_m	$\delta_1=1$					

Table 4.14 Comparison with Lingo in Experiment 3

30 Times each problems	Scale	Numerical examples 1	2	3	4	5
Lingo 11.0	Optimal(US$)	26771	51667	101947	202097	403570
	Time(s)	1	8	>1000	>2700	>9000
Two stage priority based GA (population size=100)	Min-cost(US$)	26771	51892	103714	211602	419135
	Absolute difference	0	-225	-1767	-9505	-15565
	Percentage difference	0	-0.44%	-1.73%	-4.70%	-3.86%
	Average cost (US$)	26772	52528	104793	213463	421102
	Average time (s)	0.12	1.25	9.21	49.52	267.34
	Percentage of time	12%	15.60%	<0.90%	<1.83%	<2.97%

4.5 Summary

Due to the growing environmental issues nowadays, product recycling problems within closed-loop supply chain are drawing more attention. To solve these problems, many CLSC models have been established in this research area. This chapter describes a six-level CLSC model which can be incorporated into an Integer Linear Programming model. In light of the small scale of this model, it can be solved by Lingo. However, when the complexity of this model grows with increase of scale, to a larger one, Lingo cannot solve it within an acceptable period of time. A new GA has been developed to improve the solution of this kind of CLSC model. It helps in the research for implementing GA more efficiently for CLSC problems.

Three computational experiments have been implemented. Experiment 1 had the same dataset as Wang and Hsu's experiments, and the results show that this newly developed algorithm can achieve reliable and higher-quality solutions with shorter computing time. Since Experiment 1 were an extreme case with several entities idling, Experiment 2 and Experiment 3 are implemented to demonstrate the performance of the proposed GA in usual cases. In Experiment 2, all of the distribution centres were close in fixed cost and capacity which made the optimal search more difficult. The results of Experiment 2 demonstrate that the proposed GA can generate high-quality results within shorter running times. In Experiment 3, all of the entities within the same level were close in fixed cost and corresponding capacity, which made the optimal search even more difficult. The results of Experiment 3 show that the proposed GA can still provide an acceptable solution. Throughout these three computational experiments, the efficiency and stability of the proposed algorithm were proven.

Chapter 5 An integrated closed-loop supply chain model with location allocation problem and product recycling decisions

5.1 Introduction

Environmental pollutions caused by improper abandoned cartridges increase dramatically nowadays. In Hong Kong, due to abundant quantity of cartridges being used, producers have to optimize their forward and reverse networks to maximize the recycling rate and their profits. In this research, an eight-level CLSC model is established. This model contains eight partners in CLSC and describes the electronic wastes recycling situation, especially the cartridge recycling. In the literatures, many CLSC models were established and studied, but few of them analyzed the delivery activity for different kinds of materials extracted from the used products, and also few papers studied the situation that used products are classified into good and poor quality. In this model, delivery activities of different materials are considered and the used cartridges are classified into good quality ones and poor quality ones. Producers will have different methods to process them. This problem is formulated into an Integer Programming model. Since both delivery routes and delivery quantities problems are known to be NP-hard, a modified two-stage GA is developed. The two-stage encoding algorithm in the proposed GA reinforces the genetic searching ability in tackling this kind of problem. As the model is new in literature, Integer Programming is implemented to solve the testing instances and benchmark with the proposed algorithm. The results show that a near optimal solution can be obtained by the proposed GA in a much shorter computational time.

5.2 Problem Definition

In this model, the demands of customers are preset. In order to fulfill the demand, manufacturers have two choices, one is to produce brand new products using components, and the other one is to remanufacture the collected used products with good condition/quality. As for the components, manufacturers have two acquisition channels: one is from suppliers and the other is from recycling centers. In the proposed model, it considers that manufacturers purchase several kinds of components from suppliers and recycling centers to produce brand new products, which means multi-products is considered.

In this model, it is assumed that manufactures can make sure that remanufactured products have the same quality as brand new products, and also sale prices in the market are same. After producing new products and remanufacturing used products as brand new ones, manufacturers deliver the products oversea to their warehouses in

Hong Kong. Then, from warehouses, products are transported to retailers, and, finally, the retailers sell them to customers. Since retailers not belong to manufacturers, this part of revenue and cost is excluded from consideration in the CLSC network optimization. Therefore, the demand of each retailer also has to be preset, and the sum of all the retailers demand must be equal to the sum of all the customer demand.

Customers always discard the used ink and toner cartridge at the end of their lifecycle in the corner. In HK situation, collection points will pick used products up from patron. In each customer area, managers of the cartridge company have to consider the vehicle routing problem of one or more collection points, which will make the CLSC network too complex to solve as whole. For simplicity, it is assumed that collection points will have a round trip in each customer areas to fetch used products. The transportation cost for a round trip is proportional to the quantity of used products collected in this round trip. The unit transportation cost for each used products are preset as a parameter.

No matter which method is used to collect, collection points will pay customers the used products. In this model, it is assumed that the price collection points paid for either good quality used products or poor quality used products are the same. After collection, collection points deliver all the used products to recycling centers.

In the recycling center, all the used products will be cleaned and classified according to two categories: good quality used products and poor quality used products. The good quality ones will be packaged and transported to manufacturers. For the poor quality ones, recycling center will disassemble and smash them and extract raw materials through further process. During the whole process, most of the substance can be recycled as raw materials. The remaining parts need to be disposed by the waste disposal plant using method of burn or landfill. The maximal disposal rate is preset in this model. The recycled raw material will finally be delivered to manufacturers for producing new products.

This study will solve three sub-problems at the same time, in the proposed CLSC problem, as follows: (1) to judge whether each potential facility is active or not, and determine the handling quantity of each active facility according to this set of demand. (2) to select the transportation route and decide the volume among the whole network. (3) to set the recycling options for rebounded products and components in the recycling centers.

5.3 Model Formulation

Figure 5.1 displays the whole CLSC network of this proposed model. The proposed model contains eight partners in the CLSC network: suppliers (S), manufacturers (M), warehouses (W), retailers (R), customers (Cu), collection points (Co), recycling centers (RC) and waste disposal plant (WDP).

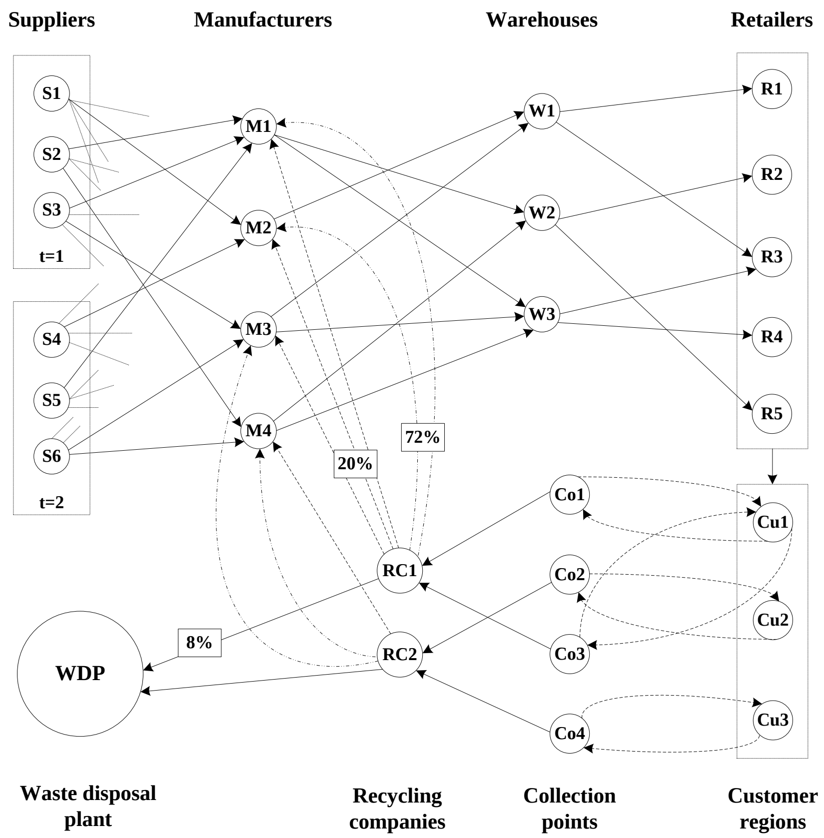

Figure 5.1 The CLSC network in the proposed model

The indices, parameters and decision variables are shown as below.

Indices

I_t the number of suppliers supplying material t with i =1,2,...,I

J the number of manufacturers with j =1,2,...,J

K the number of warehouses with k =1,2,...,K

L the number of retailers with l =1,2,...,L

V the number of customers with v =1,2,...,V

M the number of collection points with m =1,2,...,M

N the number of recycling centers with n =1,2,…,N

T the number of components with t =1,2,…,T

Parameters

c_i^s capacity of supplier i

c_j^m capacity of manufacturer j

c_k^w capacity of warehouse k

d_l demand of retailer l

d_v demand of customers in area v

c_m^{co} capacity of collection point m

s_{ijt} unit cost of transportation of component t from supplier i to manufacturer j

m_{jk} unit cost of transportation from manufacturer j to warehouse k

w_{kl} unit cost of transportation from warehouse *k* to retailer *l*

cu_{vm} unit cost of round trip transportation for collection point *m* taking back used products from customers in area *v*

co_{mn} unit cost of transportation from collection point *m* to recycling center *n*

r_{njt} unit cost of transportation of component *t* from recycling center *n* to manufacturer *j*

r_{nj}^{0} unit cost of transportation of used product with good quality from recycling center *n* to manufacturer *j*

f_j^m fixed cost for operating manufacturer *j*

f_k^w fixed cost for operating warehouse *k*

f_m^{co} fixed cost for operating collection point *m*

f_n^r fixed cost for operating recycling center *n*

s unit sorting cost for the used product

x_0 unit producing cost of new products using components including component purchase cost

x_1 unit profit for the returned product with good quality of ETN

x_2 unit disassembly cost for the used product with poor quality

x_3 unit dispose cost for the material which cannot be recycled

p_1 the price of new products

p_2 unit cost that collection point pay to customers for the used product

λ the percentage of good quality used products in all the recycling products

η_t the weight of required quantity of component *t* to produce one new product

δ_t the recycled percentage for ETN of component *t* in one used product

μ_v the recycling rate of customer area *v*

φ the maximal disposal rate

ε unit weight per used product

y_t^{etn} The profit of ETN for component t in unit returned product

y_t^r The profit of recycling as raw materials for component t in unit returned product

Decisions Variables

q_{ijt}^s Amount of component *t* shipped from supplier *i* to manufacturer *j*

q_{jk}^m Amount shipped from manufacturer *j* to warehouse *k*

q_{kl}^w Amount shipped from warehouse *k* to retailer *l*

q_{vm}^{cu} Amount shipped from customers in area *v* to collection point *m*

q_{mn}^{co} Amount shipped from collection point *m* to recycling center *n*

q_{njt}^{etn} Amount of component *t* shipped from recycling center *n* to manufacturer *j*

q_{nj}^0 Amount of used product with good quality shipped from recycling center n to manufacturer j

q_{nt}^{z} Amount of disposed t materials from recycling center n

q_{j}^{new} Amount of new produced products in manufacturer j

$$\alpha_j = \begin{cases} 1 & \text{if production takes place at manufacturer } j \\ 0 & \text{otherwise} \end{cases}$$

$$\beta_k = \begin{cases} 1 & \text{if warehouse } k \text{ is open} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_m = \begin{cases} 1 & \text{if collection point } m \text{ is open} \\ 0 & \text{otherwise} \end{cases}$$

$$\gamma_n = \begin{cases} 1 & \text{if recycling company } n \text{ is open} \\ 0 & \text{otherwise} \end{cases}$$

Objective function:

$$\max \quad TP = TR - TC \tag{5.1}$$

$$TR = p_1 \sum_l d_l \tag{5.2}$$

$$TC = TC_1 + TC_2 + TC_3 \tag{5.3}$$

$$\begin{aligned} TC_1 = & \sum_t \sum_i \sum_j s_{ijt} q_{ijt}^{s} + \sum_j \sum_k m_{jk} q_{jk}^{m} + \sum_k \sum_l w_{kl} q_{kl}^{w} + \sum_v \sum_m cu_{vm} q_{vm}^{cu} \\ & + \sum_m \sum_n co_{mn} q_{mn}^{co} + \sum_t \sum_n \sum_j r_{njt} q_{njt}^{etn} + \sum_n \sum_j r_{nj0} q_{nj}^{0} \end{aligned} \tag{5.4}$$

$$TC_2 = \sum_j f_j^m \alpha_j + \sum_k f_k^w \beta_k + \sum_m f_m^{co} \delta_m + \sum_n f_n^r \gamma_n \tag{5.5}$$

$$\begin{aligned} TC_3 = & \; p_2 \cdot Q + s \cdot Q + x_2 (Q - \sum_n \sum_j q_{nj}^{0}) + x_3 \sum_t \eta_t \sum_n q_{nt}^{z} + x_0 \sum_j q_j^{new} \\ & - \sum_t (y_t^{etn} \sum_n \sum_j q_{njt}^{etn}) - \sum_t (y_t^{r} \sum_n q_{nt}^{r}) - x_1 \sum_n \sum_j q_{nj}^{0} \end{aligned} \tag{5.6}$$

The objective is to maximize the total profit which is the value of total revenue minus total cost as showed in the objective function (5.1). The total revenue is the revenue of sale the new product which is displayed in function (5.2). The total cost consists of the total transportation cost, total facility fixed cost and total processing cost as represented by function (5.3). Equation (5.4) shows the total transportation cost in the CLSC network, which consists of seven section costs in different stages shown as follow: component transportation cost from suppliers to manufacturers, new product transportation cost from manufacturers to warehouses, the cost of new products delivered from warehouses to retailers, and the round trip cost of collection points to fetch the used products from customers, also the delivery cost for collected used products from collection points to recycling centers, the recycled component transportation cost from recycling centers to manufacturers and the delivery cost of collected good quality used products from recycling centers to manufacturers. Equation (5.5) shows the total fixed costs of the manufacturers, warehouses, collection points and recycling centers. Equation (5.6) displays the sum of used products obtained costs paid by collection points to customers, used products sorting costs in recycling centers, good quality used products processing costs in manufacturers, and poor quality used products processing costs in recycling centers, disposed costs and the costs of newly produced products using components in manufacturers.

Subject to

$$\sum_j q_{ij}^s \le c_i^s \qquad \forall i \tag{5.7}$$

$$\sum_k q_{jk}^m \le c_j^m \alpha_j \qquad \forall j \tag{5.8}$$

$$\sum_l q_{kl}^w \le c_k^w \beta_k \qquad \forall k \tag{5.9}$$

$$\sum_n q_{mn}^{co} \le c_m^{co} \delta_m \qquad \forall m \tag{5.10}$$

$$\sum_m q_{mn}^{co} \le c_n^r \gamma_n \qquad \forall n \tag{5.11}$$

$$\sum_k q_{kl}^w \ge d_l \qquad \forall l \tag{5.12}$$

$$d_v \mu_v = \sum_m q_{vm}^{cu} \qquad \forall v \tag{5.13}$$

$$\sum_j q_{jk}^m = \sum_l q_{kl}^w \qquad \forall k \tag{5.14}$$

$$\sum_v q_{vm}^{cu} = \sum_n q_{mn}^{co} \qquad \forall m \tag{5.15}$$

$$\sum_j q_{njt}^{etn} \le \delta_t \left(\sum_m q_{mn}^{co} - \sum_j q_{nj}^0\right) \qquad \forall n, \forall t \tag{5.16}$$

$$\sum_n q_{njt}^{etn} + \sum_i q_{ijt}^s = q_j^{new} \qquad \forall j, \forall t \tag{5.17}$$

$$\sum_n q_{nj}^0 + q_j^{new} = \sum_k q_{jk}^m \qquad \forall j \tag{5.18}$$

$$\sum_j q_{nj}^0 \le \lambda \sum_m q_{mn}^{co} \qquad \forall n \tag{5.19}$$

$$\sum_m q_{mn}^{co} = \sum_j q_{nj}^0 + \sum_j q_{njt}^{etn} + q_{nt}^r + q_{nt}^z \qquad \forall n \tag{5.20}$$

$$q_{nt}^z \le \varphi \cdot \sum_m q_{mn}^{co} \qquad \forall n, \forall t \tag{5.21}$$

$$Q = \sum_v d_v \mu_v \tag{5.22}$$

$$\alpha_j, \beta_k, \delta_m, \gamma_n \in \{0,1\} \qquad \forall j, k, m, n \tag{5.23}$$

$$q_{ijt}^s, q_{jk}^m, q_{kl}^w, q_{vm}^{cu}, q_{mn}^{co}, q_{njt}^{etn}, q_{nj}^0, q_{nt}^z, q_j^{new} \in N \cup \{0\} \qquad \forall i, j, k, l, m, n, v \tag{5.24}$$

Constraints (5.7) and (5.8) formulate the capacity limitation of suppliers and manufacturers. Constraint (5.9) represents the capacity limitation of DCs. Constraints (5.10) and (5.11) show the capacity limitation in reverse logistics for collection points and recycling centers. Constraint (5.12) restrains that the retailers' demand must be satisfied, which also means the customer demand must be satisfied. Constraint (5.13) explains the relationship between customer recovery and recovery rate. Constraints (5.14) and (5.15) guarantee the in-flow equal to out-flow in each warehouse and each collection point respectively. Constraint (5.16) guarantees the output recycled materials will not exceed the maximum value that each recycling center can extract from used products. Constraint (5.17) shows that for each material in each manufacturer, the sum of the component from both suppliers and recycling centers can meet the demand for producing and remanufacturing needed new products. Constraint (5.18) restricts that for each manufacturer, the quantity of the provided products are the sum of the newly produced ones and the remanufactured ones. Constraint (5.19) restricts that the percentage of good quality used products in each recycling center cannot exceed the maximum value preset. Constraint (5.20) represents that the disposed materials are remaining materials after all of the recycling processes. Constraint (5.21) restricts that in each recycling center, the total quantity of disposed materials must under the acceptable value, the right item of this inequality displays the transformation from the quantity of returned poor quality products to the weight of the material needs to be disposed of. Constraint (5.22) explains Q as the total amount of returned used products from all customer areas. Constraint (5.23) represents the binary variables. Constraint (5.24) represents the integer variables.

5.4 A Genetic Algorithm with two-stage priority-based encoding

In the proposed model, to deal with three sub-problems described in the part of problem definition, the standard encoding GA has to be expressed in a single chromosome. Hence, the chromosome should cover the information of transportation route and amount, the active state of facilities, and also the recycling options. These vast quantities of information in a chromosome tend to make the genetic operation hard and time-consuming to handle. When all these information are considered simultaneously, the search will easily trapped in the local optimum. To solve these problems, a two-stage priority-based GA is developed in this study. This proposed GA decomposes the encoding process into two stages. Figure 5.2 shows the flow diagram of this developed GA.

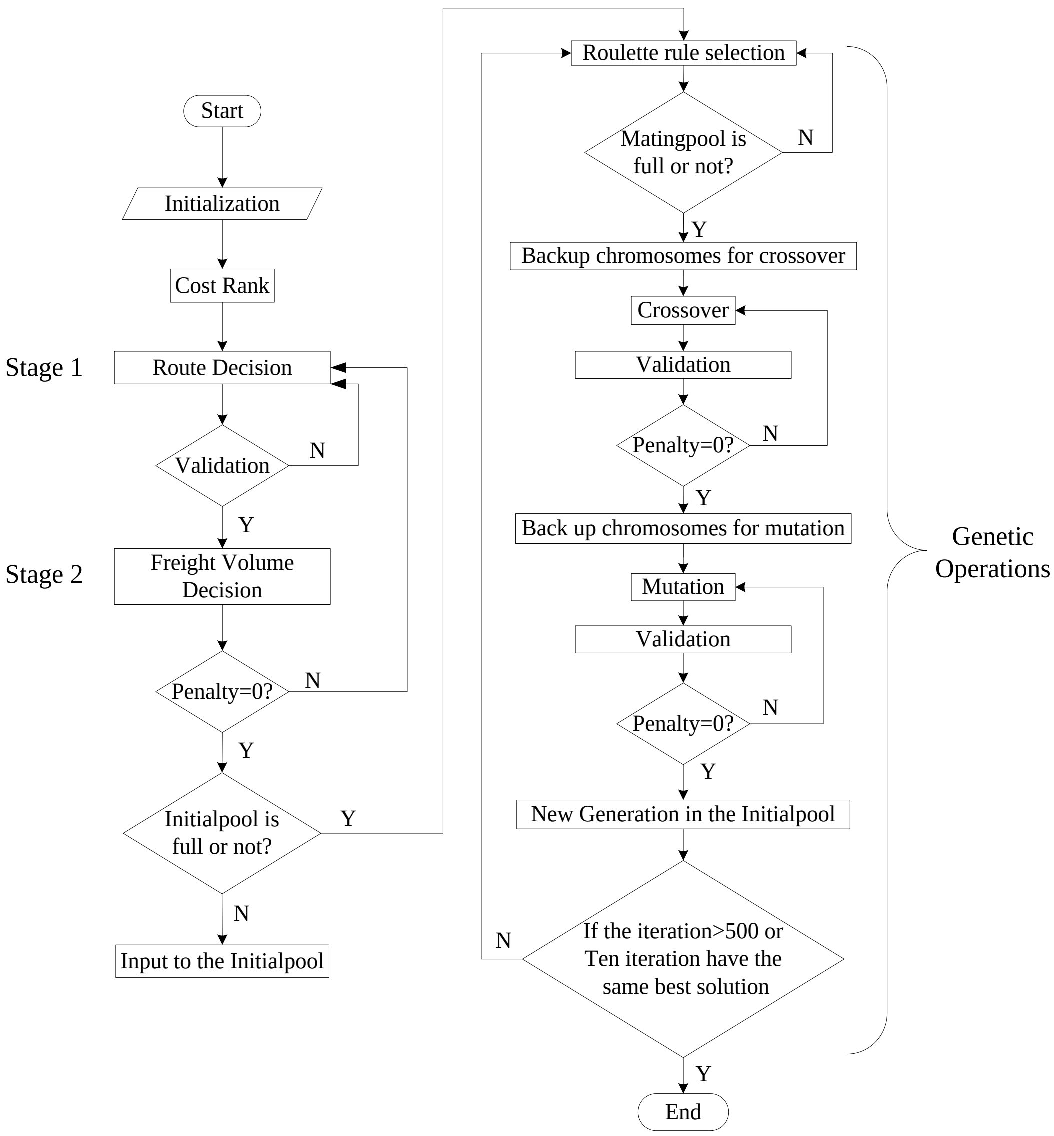

Figure 5.2 The flow diagram of two-stage priority based GA

Figure 5.2 shows that this GA has two stages in the encoding process: Route Decision and Freight Volume Decision. The Route Decision stage can decide the delivery route between each level of the supply chain network. Then the freight volume in each selected delivery route is determined in the Freight Volume Decision stage. These two stages are explained in detail in Section 5.4.1 and Section 5.4.2, respectively. The right part of Figure 5.2 states the genetic operations. Section 5.4.3 gives details of them.

5.4.1 Stage 1-Route Decision

In the first stage of encoding, the chromosome has nine sections to represent each level of CLSC respectively. In each section, the number of genes equals to the product of the number of suppliers and the number of demanders. Totally in a chromosome, the number of genes is

$I \times J \times T + J \times K + K \times L + \mathrm{V} \times M + M \times N + N \times J \times (T+1)$.

The first stage of encoding is to determine the appropriate delivery route. In this stage, the generated chromosome composed with binary genes, which express the information of transportation route only. Each binary genes in the chromosome is generated randomly. After generation, the chromosome will be validated in the process of validation. This validation process is explained in detail in Section 5.4.3.5 Part 1. Figure 5.3 shows an example of the complete chromosome in this stage.

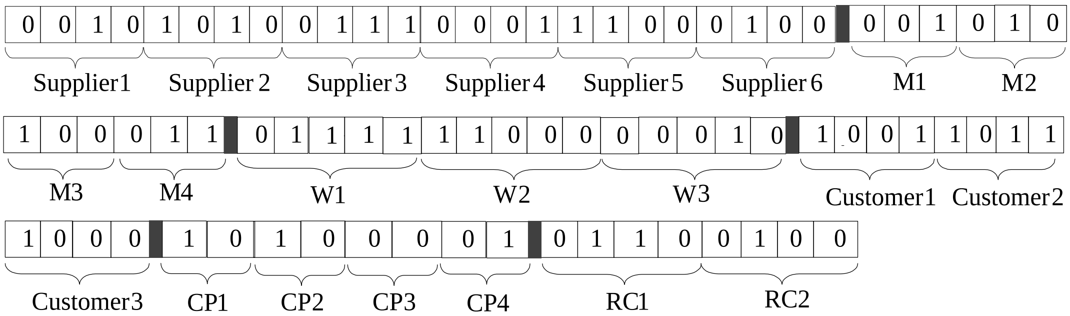

Figure 5.3 The complete chromosome in Stage 1

Part of the complete chromosome are chosen as an numerical example. In this numerical example, T=2, I_1=3, I_2=2, J=4, K=2. Two kinds of materials are considered. I_1=3 means the number of suppliers supplying material one is three, I_2=2 means the number of suppliers supplying material two is two. Suppliers provide materials to four manufacturers, and these four manufacturers will deliver finished products to two warehouses.

Each gene contains a binary number, 1 means the delivery route is used and 0 means not. The chromosome at this stage is shown in Figure 5.4. Apparently, the first section of the chromosome has 3*4=12 genes, it represents the delivery route of material one: the first four genes represent the situation of supplier one providing material one to manufacturers two and four but not providing materials to manufacturers one and three. The second four genes represent supplier two with material one, and the third four genes represent supplier three with material one. The second section of the chromosome has also 2*4=8 genes, which represents the delivery route of material two. The principle is the same as the first section. The third section of the chromosome has 4*2=8 genes: The first two genes represent the situation of manufacturer one providing finished products to neither of the two warehouses, the second two genes represent manufacturer two, and so on.

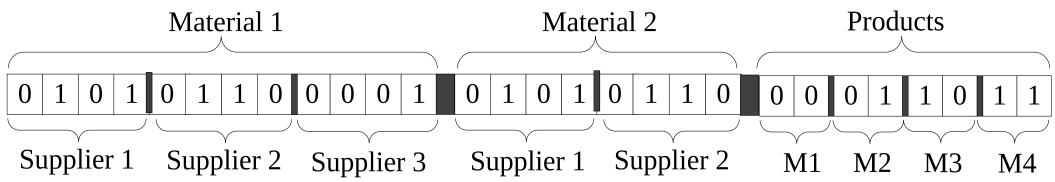

Figure 5.4 The first three sections of chromosome in Stage 1

5.4.2 Stage 2-Freight Volume Decision

After the first stage, a chromosome representing the delivery route has been established. The second stage is to decide the freight volume of materials or products according to the generated route. It is called freight volume decision. Figure 5.5 shows the chromosome after the second stage of encoding.

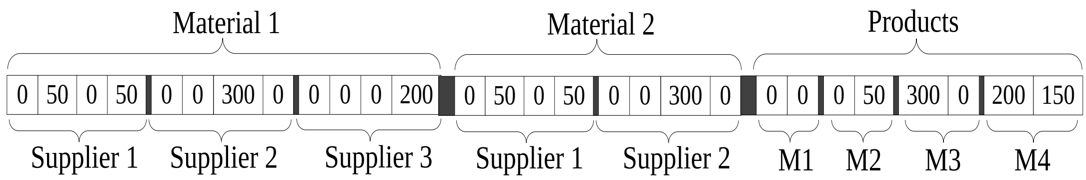

Figure 5.5 The first three sections of chromosome in Stage 2

The structure of the chromosome remains the same as in Stage 1, but the content has been changed. Among the first four genes, the first gene means Supplier One won't delivery any raw material one to Manufacture One, the second gene represents that Supplier One will deliver 50 units of raw material one to Manufacture Two. Other sections have the close principle. The last gene in Figure 5.5 represents that Manufacture Four will deliver 150 units of products to Warehouse Two.

5.4.2.1 Process outline of freight volume decision

It contains six steps in the freight volume decision. To explain this decision process clearly, the numerical example in Section 5.4.1 is used. Figure 5.6 shows the step details. The numbers in parentheses mean the unit shipping cost of that delivery route. The demand of warehouses and the capacity of suppliers and manufacturers are represented by the numbers in the circles.

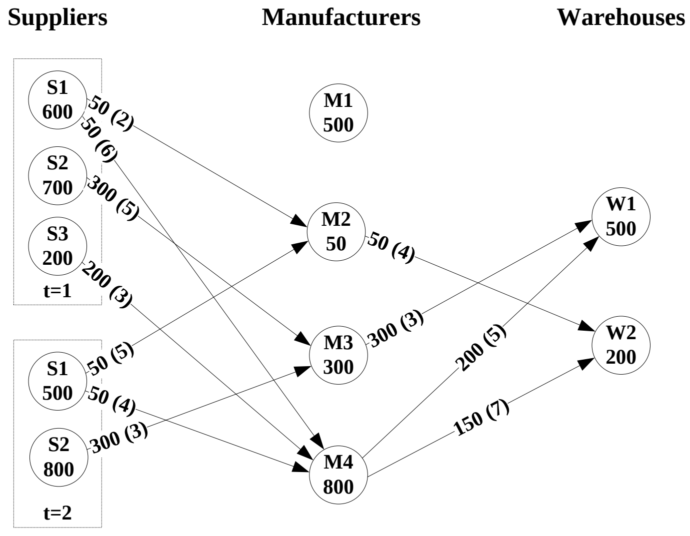

Figure 5.6 An instance for freight volume decision

Step 1: Decide the beginning level. In this example, the terminal demand is the warehouses', so the freight volume decision process starts from the level of manufacturer delivering finished products to warehouse.

Step 2: Find out the lowest unit shipping cost among the current level. The delivering route with the lowest unit shipping cost has the highest priority to be used. According to the result of "Cost Rank", delivering route from Manufacturer 3 to Warehouse 1 own the lowest cost.

Step 3: Check if the top priority delivery route is multiple or not among current level. If yes, count out the number, mark as N and go to Step 4a, if not, go to Step 4b. Step 4a and Step 4b are parallel. Here, the lowest unit shipping cost 3 is unique at current level, so go to Step 4b.

Step 4a: The demand is randomly divided into N parts, allocated to the N top priority delivery routes.

Step 4b: Compare the supply capacity and the demand, allocate the transport flow with the smaller one. Since the supply capacity of Manufacturer 3 is 300 units and the demand of Warehouse 1 is 500 units, the freight volume between them comes out to 300 units.

Step 5: Update the corresponding supply capacity and demand. The remaining supply capacity of Manufacturer 3 is 300-300=0 and the updated demand of Warehouse 1 is 500-300=200.

Step 6: Move on to the next delivery route according to the results of "Cost Rank" and then repeat Step 2 to Step 6. When the whole level is finished, return to the next level.

Exceptionally, when the unit shipping cost of several different suppliers delivering to the same demander is identical, the delivery volume will be randomly generated.

5.4.2.2 Cost Rank

In Step 1 of freight volume decision, the process "Cost Rank" is used to decide the priority. It is implemented at the beginning of encoding. This cost rank process contains eight parts representing eight levels in the CLSC. In each part, the unit shipping cost of each delivery route is positive sequence ranked. The results of the rank are prepared for the freight volume decision process.

5.4.3 Genetic operations

Considering the characteristics of chromosomes in this problem, one-point crossover and one-point mutation is implemented to avoid dramatic changes in the genetic structure and prevent random genetic searches.

5.4.3.1 Fitness function

In this problem, the fitness is the reciprocal of the total cost. The lower the total cost is, the stronger the chromosome viability will be.

5.4.3.2 Selector operator

In the proposed GA, the roulette wheel selection is implemented to generate the mating pool. The roulette wheel function is

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j}$$

Where P_i represents the probability of being selected for chromosome i, f_i represents the fitness of chromosome i, N is the number of chromosomes in the initial pool.

5.4.3.3 Crossover

In this algorithm, one-point crossover is implemented. In one-point crossover, genes in the parent chromosomes will not be changed greatly, therefore, after several evolution, weak genes will be easily identified (Chan and Chung, 2004). In this particular problem, the chromosomes includes several sections representing several levels in CLSC. A weak gene will cause a weak section, hence identification of weak genes in this problem is crucial. Figure 5.7 shows an example of crossover process.

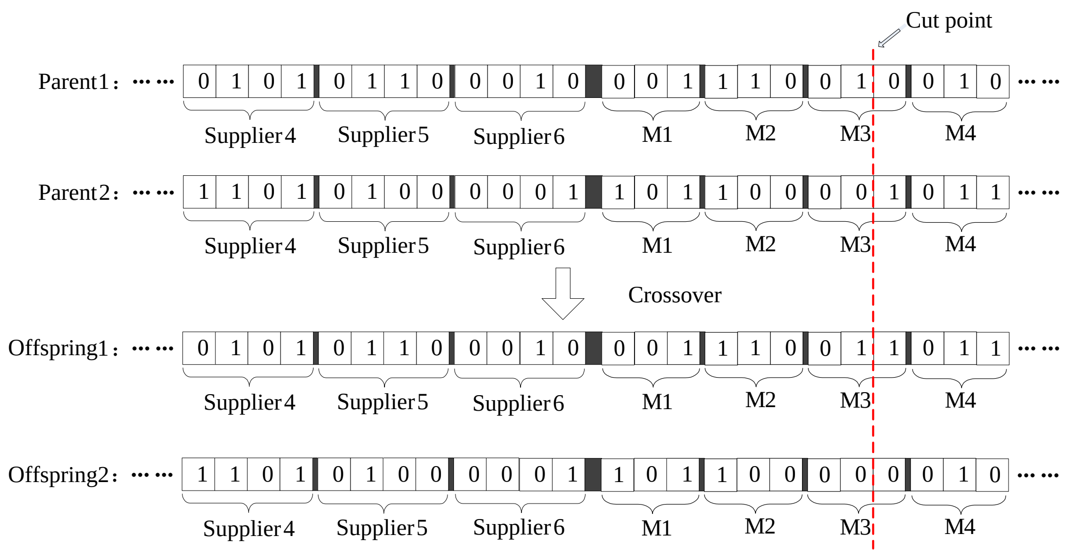

Figure 5.7 Crossover process

5.4.3.4 Mutation

The process of mutation here aims at preventing the search trapped in a local optimum. One-point mutation with 1 mutation rate is implemented. Figure 5.8 shows an example of mutation process.

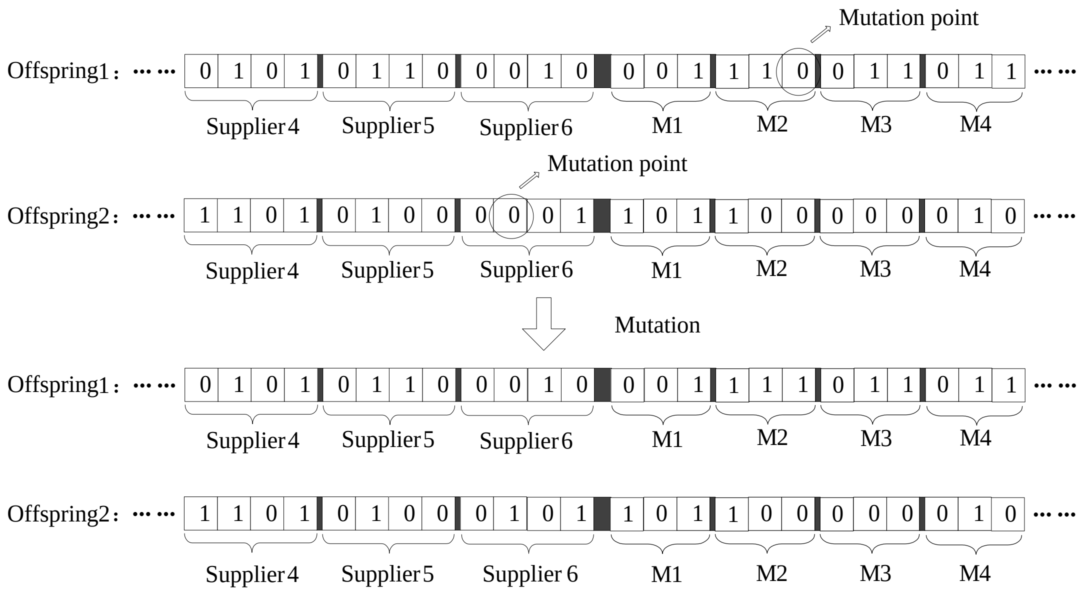

Figure 5.8 Mutation process

5.4.3.5 Validation

In the Genetic Algorithms, validation is applied to guarantee the feasibility. In this proposed algorithm, validation is divided into two parts.

Part 1: Capacity check

Part 1 is to check the binary chromosome after the first stage of encoding. If one of the validation requirements are not achieved, crossover and mutation processes will be rollback and done again. The validation requirements are shown as below.

i. The total capacity of active distribution centers must be able to satisfy the total demand of customers.

ii. The total capacity of active manufacturers must be able to satisfy the total demand of customers.

iii. The genes of each customer cannot be zero simultaneously which means that each customer must return used products to at least one distribution centers.

iv. Since the demand of customers must be satisfied, each customer must have at least one distribution center to supply the needed products.

For example, in Figure 5.8, the active manufacturers in offspring 2 is M1, M2, and M4. The total capacity cannot satisfy the total demand of customers causing the invalidation, therefore, the whole process of crossover will be rollbacked. The selected parents will be assigned in the pool after crossover as the offspring.

Part 2: Penalty check

After the capacity check, penalty check will be implemented on the offspring. In this part, it applied on the integer chromosome after the second stage of encoding. In this part, the penalty of the transformed chromosome will be examined. If the penalty is not equal to zero as before, the whole process of respective crossover and mutation will be rollback and done again.

5.5 Computational experiments

Three sets of experiments are conducted to prove the stability and efficiency of the proposed GA. Experiment 1 shows that this computational experiment in an extreme case with large difference between the fixed costs of the entities. Hence, Experiment 2 and Experiment 3 exhibit normal cases. In Experiment 2, the fixed cost and corresponding capacity of the distribution centers are close. In Experiment 3, the fixed cost and corresponding capacity of the entities within the same level are also close. All three experiments contain seven sub-problems with seven scales from small to large, as shown in Table 5.1.

Table 5.1 Scale of computational experiments

Scales	Suppliers (t=1)	Suppliers (t=2)	Manufacturers	Warehouses	Retailers
No. 1	3	3	4	3	5
No. 2	6	6	8	6	10
No. 3	12	12	16	12	20
No. 4	24	24	32	24	40
No. 5	48	48	64	48	80
No. 6	72	72	96	72	120
No. 7	96	96	128	96	160

Scales	Customers	Collection Points	Recycling Centers
No. 1	3	4	2
No. 2	6	8	4
No. 3	12	16	8
No. 4	24	32	16
No. 5	48	64	32
No. 6	72	96	48
No. 7	96	128	64

5.5.1 Experiment 1 with Eight-Stage CLSC Model

In Experiment 1, Lingo is used to compute the same problem for benchmark. Table 5.2 shows the capacity and fixed cost in the small scale of Experiment 1. Table 5.3 shows the unit shipping cost in the small scale of Experiment 1.

Table 5.2 The capacity and fixed cost in the basic scale of Experiment 1

Suppliers		Manufacturers		Collection points	
Capacity		Capacity	Fixed cost	Capacity	Fixed cost
t=1	t=2	500	1300	100	95
600	500	600	1400	150	110
700	800	700	1500	180	140
800	850	800	1800	200	180

Recycling centers		Warehouses	
Capacity	Fixed cost	Capacity	Fixed cost
180	300	800	500
260	450	900	650
		1000	900

Table 5.3 The unit shipping cost in the basic scale of Experiment 1

Costs	M			
S	1.5	2.5	2	3
	3	1.5	2.5	4
	2	2.5	2.5	2
	4.5	6	7.5	6.5
	7	6	5.5	6.5
	5	6	6.5	6.5

	W		
M	10	12	15
	15	13	14
	9	10	14
	10	11	12

	R				
W	5	4	8	7	4
	8	6	5	3	5
	9	4	5	6	7

	Co			
Cu	9	8	12	8
	7	9	11	12
	9	10	13	10

	RC	
Co	10	10
	12	12
	15	14
	10	15

		M			
RC	t=0	9	8	7	9
		8	6	10	8
	t=1	5	6	7	4
		6	7	4	4
	t=2	10	13	12	15
		12	14	13	10

S: Supplier, M: manufacturer, W: warehouse, R: retailer,

Cu: customer, Co: collection points, RC: recycling center

A sample solution for illustrating the detail is shown in Figure 5.9 for instance No. 1. To further test the proposed two stage priority-based GA, six larger scale problems are calculated with the same dataset. Table 5.4 shows the results of the comparison between the proposed GA and Lingo using a PC with Intel(R) Core(TM) i7-2600 CPU @ 3.4GHz, 8.0G RAM. The results in the original paper used a PC with Intel® Pentium® M processor 1.86GHz, 1.0G RAM.

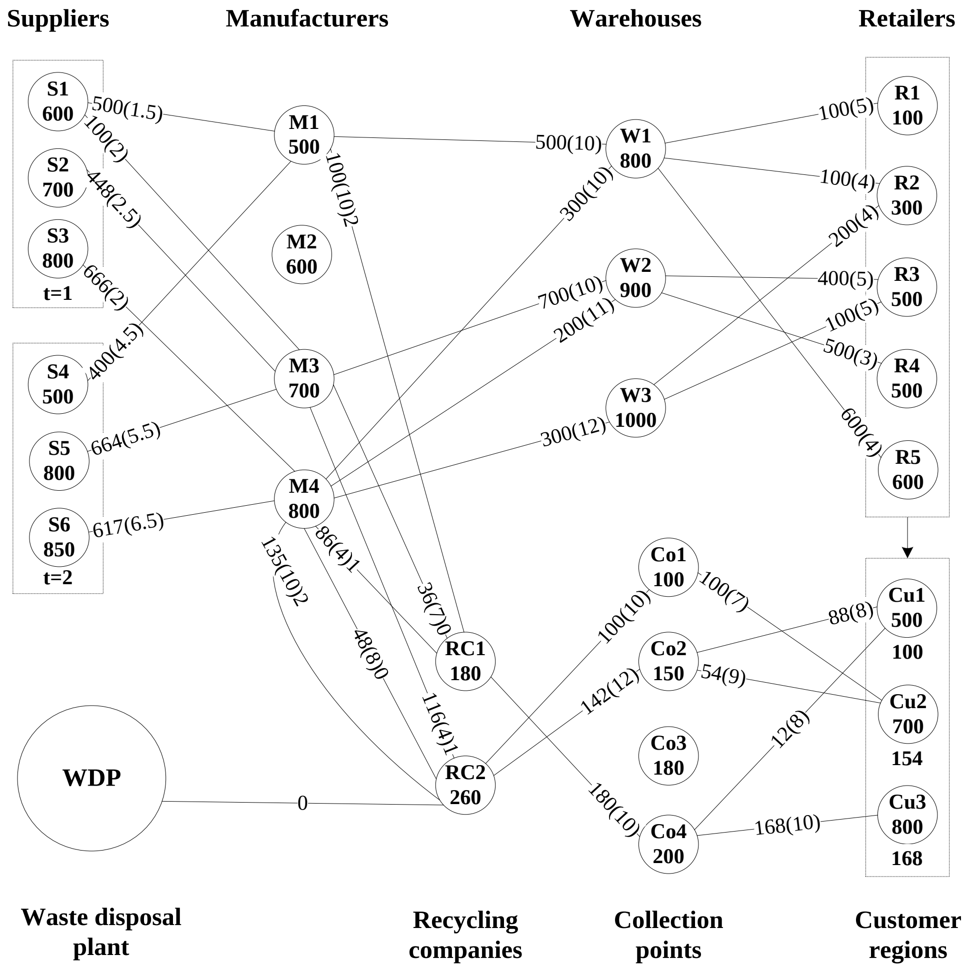

Figure 5.9 Result of basic scale problem in Experiment 1

Table 5.4 Results comparison between the proposed GA and Lingo

30 Times each problems	Scale	Numerical examples 1	2	3	4	5	6	7
Lingo 11.0	Solutions (US$)	61513.5*	122124*	243419	497629	974069	1459770	1962190
	Time(s)	1s	110s	>30mins	>30mins	>50mins	>60mins	>90mins
Two stage priority based GA (population size=100)	Solutions (US$)	61513.5	122841	249790	501275	1000663	1504369	2010220
	Absolute difference	0	-717	-6371	-3646	-26594	-44599	-48030
	Percentage difference	0	-0.59%	-2.62%	-0.73%	-2.73%	-3.06%	-2.45%
	Average cost (US$)	61812	123389	250051	502136	1001252	1510245	2020254
	Average time (s)	1s	72s	160s	306s	987s	2018s	3812s
	Percentage of time	100%	65.5%	<8.89%	<17%	<32.9%	<56.06%	<70.6%

Solutions by Lingo 11.0, with * are optimal, others are feasibility solutions obtained.

Table 5.4 shows the results of the comparison between Lingo 11.0 and the proposed GA with seven scales. The row of "absolute difference" donates the results of the Lingo minus the results of the proposed GA and the minus sign means disparity. Take Scale 2 for example, the value of the absolute difference is -717, and value of the percentage difference is -0.59%, which means that the result of proposed GA is 0.59% disadvantageous compared with that of Lingo. However, the average time of the proposed GA is only 72 s, which is only 65.5% of the time for Lingo. In Scale 3, the result of the proposed GA is 2.62% disadvantageous compared with that of Lingo, and the running time is less than 8.89% of that of Lingo. In Scale 4, the result is 0.73% disadvantageous than that of Lingo, while the running time is less than 17% of that of Lingo. In Scale 5, although the quality of proposed GA is 2.73% behind Lingo, the time is faster than Lingo by almost three times. Therefore, it can be seen that the proposed GA is more effective than Lingo in solving the problems, but the solution obtained with at most only 3.06% different.

5.5.2 Experiment 2 with Eight-Stage CLSC Model

In the Experiment 1, Figure 5.9 shows that Manufacturer 2 and Collection point 2 are not used because they are of high fixed cost and low capacity. To simulate the normal situation as in Experiment 2, the fixed cost of manufacture and distribution are changed, while some of the unit shipping costs are changed to allow more entities to be used. As a result, the fixed cost and corresponding capacity of all the collection points are close to each other, which make the optimal solution tighter and the optimal search more difficult.

The comparison is developed between the proposed GA and Lingo. Due to the doubled and redoubled relationship between the small scale and the other scales, only the dataset of the small scale is shown for simplicity. Table 5.5 shows the capacity, fixed cost and demand in Experiment 2. Table 5.6 shows the changed unit shipping cost for each stage in Experiment 2. Table 5.7 shows the results of the comparison between the proposed GA and Lingo. Figure 5.10 shows the verification of the basic scale.

Table 5.5 Capacity, fixed cost (US$) and demand in Experiment 2

Manufacturers		Warehouses		Collection points		Recycling centers		Suppliers	
Capacity	Fixed cost	Capacity	Fixed cost	Capacity	Fixed cost	Capacity	Fixed cost	Capacity	
500	1300	800	500	80	65	180	300	t=1	t=2
600	1400	900	650	100	90	260	450	600	500
700	1500	1000	900	120	100			700	800
800	1800			150	140			800	850

Table 5.6 Unit shipping cost for each stage (US$) in Experiment 2

<table>
<tr><td>Costs</td><td colspan="4">M</td><td></td><td colspan="3">W</td><td></td><td colspan="5">R</td></tr>
<tr><td rowspan="6">S</td><td>1.5</td><td>2.5</td><td>2</td><td>3</td><td rowspan="4">M</td><td>10</td><td>12</td><td>15</td><td rowspan="3">W</td><td>5</td><td>6</td><td>8</td><td>7</td><td>4</td></tr>
<tr><td>3</td><td>1.5</td><td>2.5</td><td>4</td><td>15</td><td>13</td><td>14</td><td>8</td><td>6</td><td>5</td><td>3</td><td>5</td></tr>
<tr><td>1.5</td><td>2.5</td><td>2.5</td><td>2</td><td>9</td><td>10</td><td>14</td><td>9</td><td>4</td><td>5</td><td>6</td><td>7</td></tr>
<tr><td>4.5</td><td>6</td><td>7.5</td><td>6.5</td><td>10</td><td>11</td><td>12</td><td colspan="6"></td></tr>
<tr><td>7</td><td>6</td><td>5.5</td><td>6.5</td><td colspan="4" rowspan="2"></td><td></td><td colspan="5">M</td></tr>
<tr><td>5</td><td>6</td><td>6.5</td><td>6.5</td><td rowspan="6">RC</td><td rowspan="2">t=0</td><td>9</td><td>8</td><td>7</td><td>9</td></tr>
<tr><td></td><td colspan="4">Co</td><td></td><td colspan="3">RC</td><td>8</td><td>6</td><td>10</td><td>8</td></tr>
<tr><td rowspan="3">Cu</td><td>9</td><td>10</td><td>10</td><td>8</td><td rowspan="4">Co</td><td>10</td><td colspan="2">13</td><td rowspan="2">t=1</td><td>5</td><td>6</td><td>7</td><td>4</td></tr>
<tr><td>7</td><td>9</td><td>7</td><td>12</td><td>12</td><td colspan="2">12</td><td>6</td><td>7</td><td>4</td><td>4</td></tr>
<tr><td>9</td><td>10</td><td>12</td><td>10</td><td>13</td><td colspan="2">14</td><td rowspan="2">t=2</td><td>10</td><td>13</td><td>12</td><td>15</td></tr>
<tr><td colspan="5"></td><td>10</td><td colspan="2">15</td><td>12</td><td>14</td><td>13</td><td>10</td></tr>
</table>

S: Supplier, M: manufacturer, W: warehouse, R: retailer,

Cu: customer, Co: collection points, RC: recycling center

Table 5.7 Comparison with Lingo in Experiment 2

30 Times each problems	Scale	1	2	3	4	5	6	7
		Numerical examples						
Lingo 11.0	Solutions (US$)	61964.5*	123027	244615	490442	974016	1476620	1945480
	Time(s)	1s	>20mins	>30mins	>30mins	>50mins	>100mins	>170mins
Two stage priority based GA (population size=100)	Solutions (US$)	61964.5	124708	250011	501383	1004215	1513106	2020155
	Absolute difference	0	-1681	-5396	-10941	-30199	-36486	-74675
	Percentage difference	0	-1.37%	-2.21%	-2.23%	-3.1%	-2.47%	-3.84%
	Average cost (US$)	62102	125012	250126	502549	1005638	1522145	2025413
	Average time (s)	1s	16s	25s	124s	524s	1026s	2653s
	Percentage of time	100%	<1.33%	<1.39%	<6.89%	<17.47%	<17.1%	<26%

Solutions with * are optimal solutions, others are near optimum solutions.

As can be seen in Table 5.7, the compute speed of the proposed GA is far faster than that of Lingo, although the quality of results is reduced slightly. In Scale 2, the quality result of the proposed GA is 1.37% disadvantageous than that of Lingo, but the running time of the proposed GA is only 1.33% of Lingo. When comes to Scale 3, the result of the proposed GA is 2.21% poor than that of Lingo, but the running time of the proposed GA is only 1.39% of it. In Scale 4, the result of the proposed GA is 2.23% disadvantageous of that of Lingo, but the running time required only 6.89% of it. In Scale 5, the result becomes 3.1% disadvantageous of that of Lingo, but the running time is only 17.47% of it. The "Percentage difference" row states that all the reduced quality of results are below 3.9%, while the running time of proposed GA in the row of "Percentage of time" are 10 times faster than that of Lingo.

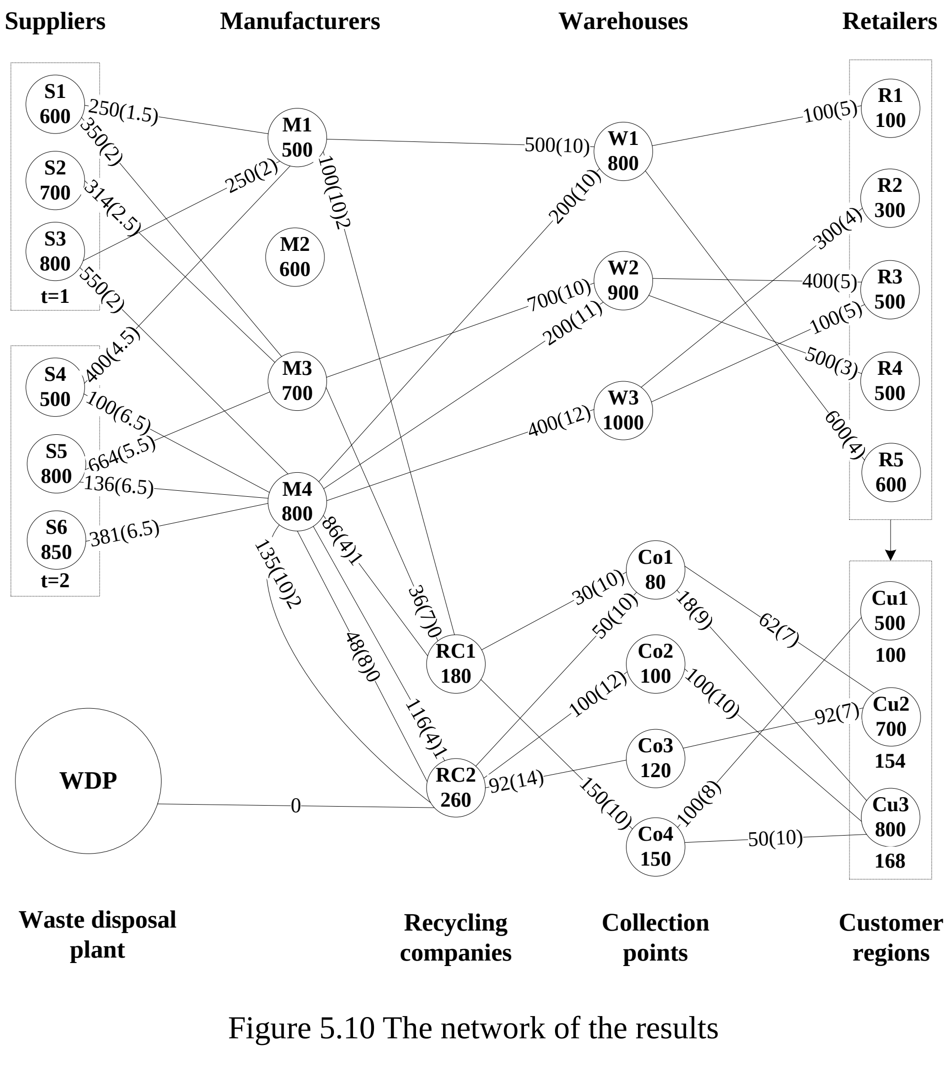

Figure 5.10 The network of the results

5.5.3 Experiment 3 with Eight-Stage CLSC Model

Similar to Experiment 2, the fixed cost of entities and the unit shipping cost are further varied in Experiment 3, causing almost all of the entities within the same level are of close fixed cost and corresponding capacities. This makes the solution of the whole network tighter, and the search for the optimal solution is more difficult. Table 5.8 shows the capacity and fixed cost in the basic scale of Experiment 3. Table 5.9 shows the unit shipping cost for each stage in Experiment 3. Table 5.10(a) and Table 5.10(b) show the results of the comparison between the proposed GA and Lingo in Experiment 3. Table 5.10(a) shows the optimal solution of Scale 1 to Scale 4, and Table 5.10(b) shows the optimal solution of Scale 5 to Scale 7. It can be seen that five manufacturers and four collection points are being used.

Table 5.8 The capacity and fixed cost in the basic scale of Experiment 3

Manufacturers		Warehouses		Collection points		Recycling centers		Suppliers	
Capacity	Fixed cost	Capacity	Fixed cost	Capacity	Fixed cost	Capacity	Fixed cost	Capacity	
500	1100	800	500	80	65	180	300	t=1	t=2
600	1400	900	650	100	90	260	450	600	500
600	1500	1000	900	120	100			700	800
800	1800			150	140			800	850

Table 5.9 The unit shipping cost in the basic scale of Experiment 3

Costs	M			
S	1.5	2.5	2	3
	3	1.5	2.5	4
	2	2.5	2.5	2
	4.5	6	7.5	6.5
	7	6	5.5	6.5
	5	6	6.5	6.5

	W		
M	10	12	15
	15	13	14
	9	10	14
	10	11	12

	R				
W	5	6	8	7	4
	8	6	5	3	5
	9	4	5	6	7

	Co			
Cu	9	8	10	8
	7	9	10	12
	9	10	12	10

	RC	
Co	10	13
	12	12
	13	14
	10	15

		M			
RC	t=0	9	8	7	9
		8	6	10	8
	t=1	5	6	7	4
		6	7	4	4
	t=2	10	13	12	15
		12	14	13	10

S: Supplier, M: manufacturer, W: warehouse, R: retailer,

Cu: customer, Co: collection points, RC: recycling center

Table 5.10 (a) Comparison with Lingo in Experiment 3 (Scale 1-4)

30 Times each problems	Scale	Numerical examples 1	2	3	4
Lingo 11.0	Solutions (US$)	63709.5*	125118	249030	496338
	Time(s)	2s	>30mins	>30mins	>40mins
Two stage priority based GA (population size=100)	Solutions (US$)	63767	126281	250389	503841
	Absolute difference	-57.5	-1163	-1359	-7503
	Percentage difference	-0.09%	-0.93%	-0.55%	-1.51%
	Average cost (US$)	63767	126389	260054	505956
	Average time (s)	1s	18s	56s	189s
	Percentage of time	50%	<1%	<3.1%	<7.88%

Solutions with * are optimal solutions, others are near optimum solutions.

Table 5.10 (b) Comparison with Lingo in Experiment 3 (Scale 5-7)

30 Times each problems	Scale	Numerical examples		
		5	6	7
Lingo 11.0	Solutions (US$)	988044	1512670	2324090
	Time(s)	>60mins	>120mins	>120mins
Two stage priority based GA (population size=100)	Solutions (US$)	1015874	1527508	2307488
	Absolute difference	-27830	-14838	16602
	Percentage difference	-2.82%	-0.98%	0.71%
	Average cost (US$)	1020251	1538960	2329846
	Average time (s)	784s	2520s	4850s
	Percentage of time	<21.78%	<35%	<67.4%

Solutions with * are optimal solutions, others are near optimum solutions.

Table 5.10 shows the results of the comparison between the proposed GA and Lingo. In Scale 1, the time of the proposed GA, used to get the optimal solution, is only 50% of that of Lingo. In Scale 2, the result of the proposed GA is 0.93% disparity to that of Lingo, but the running time of the proposed GA is only 1% of it. When grows to Scale 3, the result of the proposed GA is a 0.55% disadvantage to that of Lingo, but the time is only 3.1% of it. In Scale 4, although the quality result is 1.51% disadvantageous to Lingo, the running time is only 7.88% of it. In Scale 5, the result is 2.82% poor than Lingo, but the running time is only 21.78% of it. Although the optimal search in Experiment 3 is very difficult, it can be observed from the "Percentage difference" row that the error rate is still below 2.9%. From the row of

"Percentage of time", the advantage of the running time is obvious. The Lingo calculation time in this table is the time when Lingo first came out the feasible solution. In this experiment, each scale of Lingo have been run for 24 hours, but even after 24 hours, the solution of Lingo cannot have much improvement.

5.6 Summary

With the booming development of the electronics industry, the exponential growth of waste cartridges has polluted the environment seriously. Producers are perceived to be responsible for the recycling of the products they have produced. However, few manufacturers have adopted proper measures to deal with this because of expensive costs. To solve this problem, a CLSC model of cartridge recycling was established in this chapter. This model, based on the situation of cartridge recycling, integrates both forward and reverse flows of products and contains eight partners in the CLSC. In this research area, although many researchers discuss CLSC models, few of the models analyze the delivery activity for different kinds of materials extracted from used products, and also few studies classify the collected used products according to their quality. The model proposed in this chapter can address these issues. Moreover, this problem was incorporated into an Integer Programming Model and solved with a modified two-stage priority-based encoding GA which enhances the genetic searching ability. The adopted algorithm optimizes the CLSC network and the results show a near optimal solution, which can provide producers reliable decision support.

Chapter 6 A Decision model for multi-period product refurbishment under uncertainties using fuzzy controller

6.1 Introduction

The purpose of research in this chapter is to find an effective method to deal with the uncertainties of both supplies and demands in returned products refurbishment and provide decision supports to companies which implement returned products trade in and recycling programs. A fuzzy controller embedded with a quality indicator is developed in this chapter. This proposed method effectively deals with the uncertainties of both supplies and demands in multi-period production planning of returned products refurbishment. Numerical experiments prove the effectiveness of the proposed fuzzy controller, dealing with the uncertainties of supply and demand in an efficient way. Additionally, the quality indicator is proven to enhance the ability of dealing with the quality uncertainty of a fuzzy controller. This study structures and optimizes the process of product refurbishment, considering inventories and uncertainties with multi-period. In the literature, few research studies have focused on the process of returned products refurbishment in CLSC, especially the electronic wastes. The proposed simulation system provides the returned products collection planning for companies to decide how to collect returned products.

6.2 Problem Description

In this research, the focus is the refurbishment process of returned products in a closed-loop supply chain. Companies have to make decisions on each returned products to reduce the inventory costs and improve the total profits including long-term profits.

In the process of product collection, customers are classified according to customer profitability. Customers who trade in their used products for brand new ones are more profitable than those who simply return their used products, because they will probably consume company's applications and services continuously. Furthermore, customers repurchasing and hanging around with brand and company will persist, if usage experience is positive with first time. Considering customer profitability, the simulation in this research includes two kinds of customers as returned products providers. For customers who simply return used products, collection center has to decide whether to collect those returned products or not, according to the quality and inventory level. While for customers who trade in used products for brand new ones, collection center will decide the trade in allowance according to the quality and inventory level. The simulation model in this research provides a decision support for this problem.

In the process of product refurbishment, returned products will be disassembled into returned components. These returned components will be tested and classified as relatively good quality and relatively poor quality. The relatively poor quality returned components will go through further processing, while relatively good quality components will be refurbished and assembled into refurbished products. Figure 6.1 shows the structure of product refurbishment in CLSC. In Figure 6.1, Inv1 means returned products inventory, Inv2 means refurbished products inventory, CompInv1 means the brand new components inventory, CompInv2 means the returned components inventory.

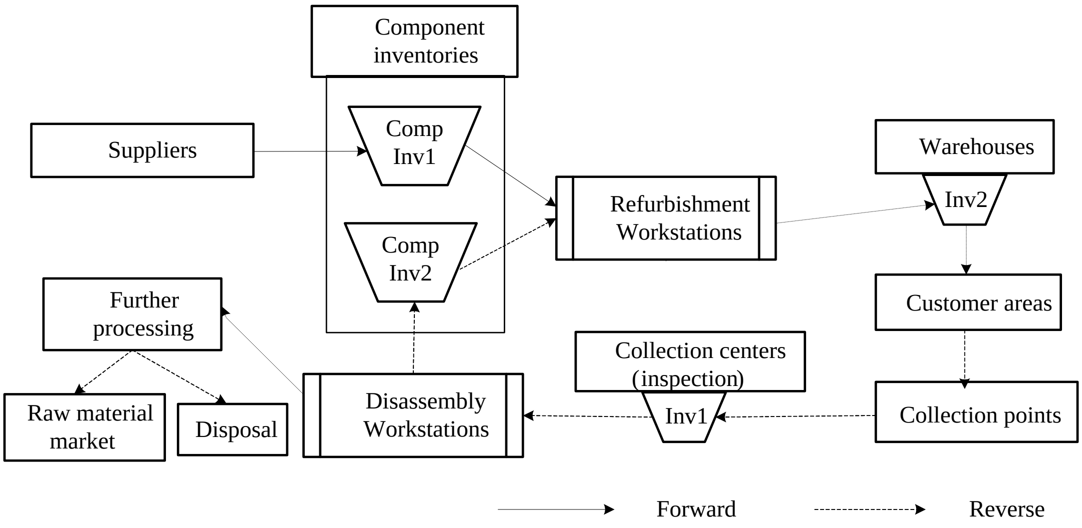

Figure 6.1 Products refurbishment in CLSC

In the simulation system, the input is the collected returned products at the collection center, called supplies. The output is the finished-refurbishing products to fulfill the demands of the customers. In this problem, the demands of the customers mean the demand for refurbished products only. The demands for brand new products are not considered. The input and output are shown as the beginning and termination of this system, in Figure 6.2.

In a refurbishment factory, there are two kinds of workstations, the disassembly workstation and the refurbishment workstation. These two kinds of workstations operate in parallel. In the disassembly workstation, poor quality returned products, which cannot be refurbished directly, are disassembled into components. Some of these components are still in good condition, and can be reused in the process of refurbishment. In the refurbishment workstation, returned components are refurbished and assembled, and sold as certified refurbished products. In Figure 6.2, the rectangle shows the workstations, the trapezoid shows the inventories, and the arrows shows the process flow.

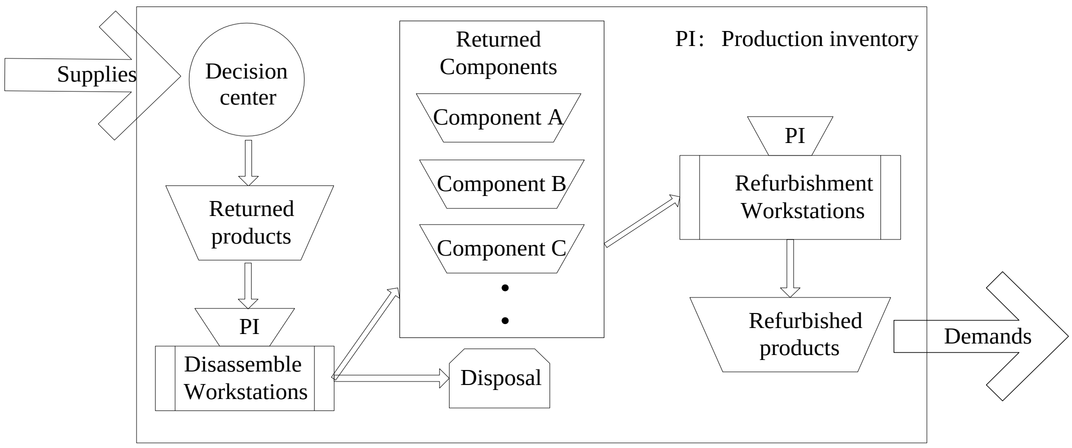

Figure 6.2 The structure and flows in the considered system

Two steps are considered during the process of refurbishment. Multi periods are considered in this problem. Take period *t* for example. In period *t*, Step One is implemented in the decision center. If customers simply return used products, then decide collect or not. If customers trade in used products for brand new ones, then decide the trade in allowance. In period *t+1*, disassemble workstations disassemble collected returned products from period *t* into returned components. Meanwhile, refurbishment workstations produce the refurbished products using returned components from period *t*. After refurbishing and quality tests, the finished products, called certificated refurbished products, are sold to fulfill the demands of customers.

In this system, the objective is to minimize the total cost in multi-period and improve customer profitability simultaneously. The total costs include the disassembly costs in the disassembly workstations, the refurbishment costs in the refurbishment workstations, the inventory costs of the returned products, the renewable products, the returned components and finished products, the shortage costs of returned components in the process of refurbishment, and the shortage costs of the finished products. In this network, returned products, as supplies, are uncertain in both quantity and quality, making this problem complicated. To deal with it, a fuzzy controller embedded with a quality indicator is developed. Numerical experiments show that this proposed method can deal with the uncertainty of demand, returned quantity and returned quality in an effective way.

6.3 Model Formulation

The decision model in this research includes two parts. Part I descript the decisions on collect or not in the collection center. Part II descript the decisions to improve customer profitability.

6.3.1 Decision Model of Part I

The objective in this part is to minimize the total cost in multi-period recovery processes. The indices, parameters and decision variables are shown as follows.

Indices

i returned product i

j returned product j

t time period t

Parameters

rc_i unit refurbishing cost of returned product *i*

dc unit disassembly cost of each returned product

n the quantity of returned products in consideration batch

R_i quality vector of returned product *i*

vc_j	unit inventory cost of returned component *j* for each period
vq_j^t	inventory quantity of component *j* in period *t*
Q_t	returned quantity of returned products in period *t*
D_t	customer demands of finished products in period *t*
rvc	unit inventory cost of each returned product for each period
rvq_t	inventory quantity of returned products in period *t*
fvc	unit inventory cost of each finished product for each period
fvq_t	inventory quantity of finished products in period *t*
rsc_j	unit shortage cost of component *j*
fsc	unit shortage cost of finished product
rsq_j^t	shortage quantity of component *j* in period *t*
fsq_t	shortage quantity of finished products in period *t*
rq_t	the quantity of refurbished products in period *t*
dq_t	the quantity of disassemble products in period *t*
$reduq_j^t$	the quantity of component *j* reduced in period *t*
$incrq_j^t$	the quantity of component *j* increased in period *t*

Decisions Variables

$$x_i^t = \begin{cases} 1 & if\ \ returned\ \ product\ \ i\ \ is\ \ refurbished\ \ in\ \ period\ \ t \\ 0 & otherwise \end{cases}$$

Objective function:

$$\min \quad TC = PC + IC + SC \tag{6.1}$$

$$PC = \sum_{i=1}^{n} dc \cdot (1 - x_i^t) + \sum_{i=1}^{n} x_i \cdot R_i \qquad \forall t \tag{6.2}$$

$$IC = \sum_t \sum_j vq_j^t vc_j + \sum_t rvc \cdot rcq_t + \sum_t fvc \cdot fcq_t \tag{6.3}$$

$$SC = \sum_t \sum_j rsc_j \cdot rsq_j^t + \sum_t fsc \cdot fsq_t \tag{6.4}$$

The objective is to minimize the total cost (TC) which includes the processing cost (PC) in both the disassembly workstation and refurbishing workstation, the inventory cost (IC) of returned components, renewable products and finished products, and also the shortage cost (SC) of returned component and finished products in the objective function (6.1) to (6.4). The total cost (TC) in function (6.1) includes the processing cost in both the disassembly workstation and the refurbishing workstation, the inventory cost of returned components, renewable products and finished products, and also the shortage cost of returned components and finished products. The processing costs (PC) are shown in Equation (6.2). Equation (6.3) displays the inventory costs (IC) and Equation (6.4) indicates the shortage costs (SC).

Subject to

$$Q_t = rq_t + dq_t \qquad \forall t \tag{6.5}$$

$$\sum_i x_i^t = rq_t \qquad \forall i, t \tag{6.6}$$

$$\sum_i (1 - x_i^t) = \mathrm{dq}_t \qquad \forall i, t \tag{6.7}$$

$$vq_j^{t+1} = vq_j^t - reduq_j^t + incrq_j^t \qquad \forall j, t \tag{6.8}$$

$$fvq_{t+1} = fvq_t + rq_t - D_t \qquad \forall t \tag{6.9}$$

Constraint (6.5) indicates that all the returned products are processed either to be refurbished or disassembled in each period. Constraints (6.6) and (6.7) show the equations of the binary decision variable. Constraint (6.8) restrains the inventory of each component in each period. Constraint (6.9) indicates the inventory of finished products.

6.3.2 Decision Model of Part II

The objective in this part is to maximize customer profitability in the process of returned products collection.

According to Tukel and Dixit (2013), the profit of customer *i* is calculated as:

$$CP_i = PPC_i + LI_i \cdot FPC_i \tag{6.10}$$

where:

PPC_i is the past profit contribution of customer *i*.

LI_i is the loyalty index of customer *i*.

FPC_i is the future profit contribution of customer *i*.

Customer profits considered here includes customer profits in the past and customer profits in future. For customers who returned used products, customer profits in the past are set to be the same. In this research problem, we focus on the group of customer who returned used products to the company, that are providers of returned products. These customers can be classified into two categories. One category includes customers who trade new product for old. The other one includes customers who simply return used product without buying new product. Customer profits of these two categories are discrepant.

6.4 Methodology of Fuzzy Controller

The model of the inspected system is a Nonlinear Multi-period Integer Programming, it cannot be solved by mathematical algorithm. Since the decision variable in this system is to decide refurbish or not for each collected used product, called returned product, simulation system is implemented to simulate the operation of the system and provide decision support to companies. In the simulation, three uncertainties have to be considered. Among returned products, the returned quantity is uncertainty, and the quality of each returned product is also uncertainty. Additionally, customer demand is uncertain simultaneously. To deal with this complicated problem, including uncertainty in quantity and quality of returned products and customer demands, a fuzzy controller is implemented. This methodology contains two parts. Section 6.4.1

explains the proposed fuzzy controller. Section 6.4.2 decrypts the indicator within the proposed fuzzy controller, in detail.

6.4.1 Proposed Fuzzy Controller

To implement a fuzzy controller, three main processes are followed: fuzzification, inference engine, and defuzzification. Figure 6.3 shows the main parts of a fuzzy controller. The inputs are the quantity and demand of the returned products in each period. The output is the change of the indicator. Section 6.4.1.1 explains the fuzzification in this problem, Section 6.4.1.2 displays the fuzzy rules, and Section 6.4.1.3 describes the defuzzification.

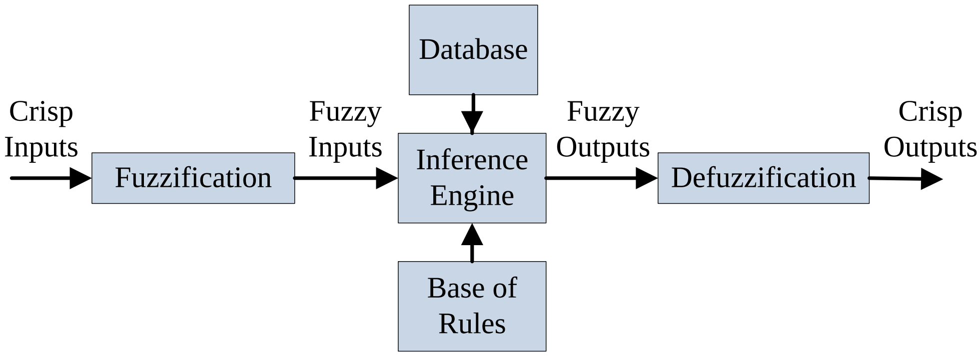

Figure 6.3 Main parts of a fuzzy controller

6.4.1.1 Fuzzification

The proposed fuzzy controller developed here deals with the problem of the supply and demand uncertainty. The supply in this system is the quantity of returned products. The member function of the returned products' quantity and demand are shown in Figure 6.4 and Figure 6.5. Figure 6.6 shows the membership function of the change of indicator. Figure 6.4, Figure 6.5 and Figure 6.6 are the fuzzy inputs. Figure 6.7 is the fuzzy output.

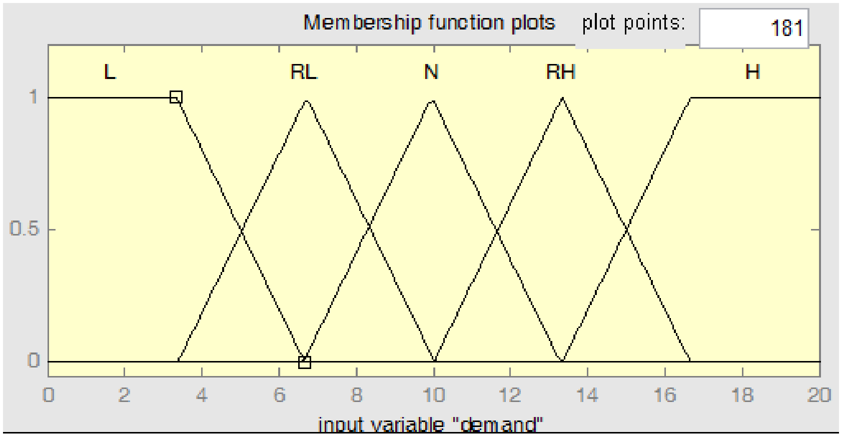

Figure 6.4 Membership function of demands

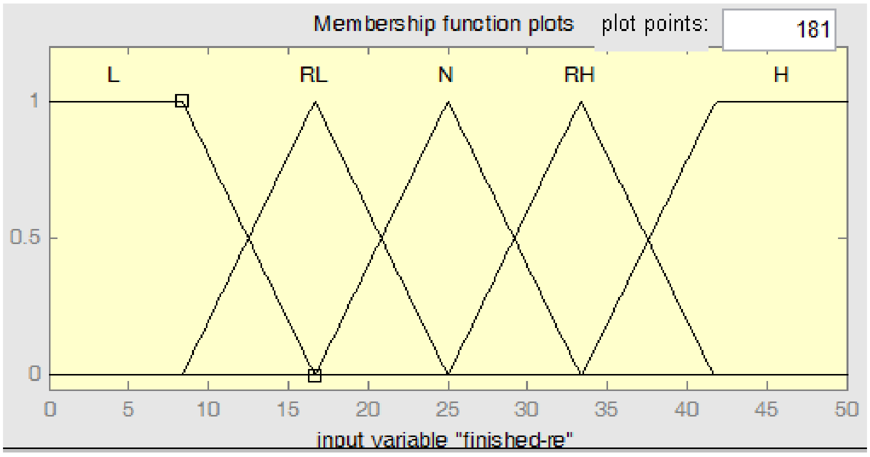

Figure 6.5 Membership function of refurbished products inventory

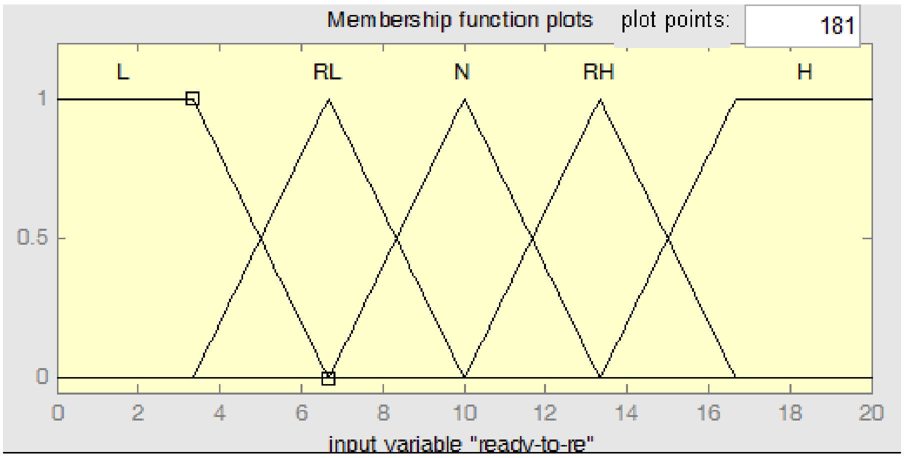

Figure 6.6 Membership function of returned products inventory

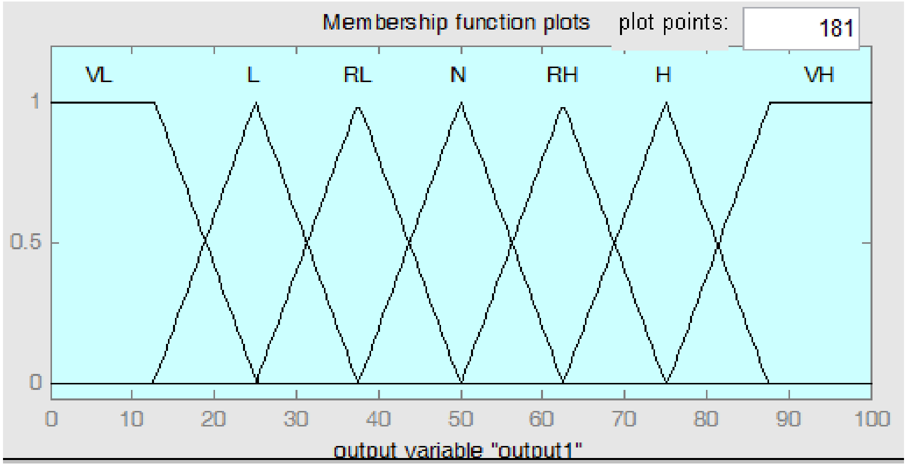

Figure 6.7 Membership function of the fuzzy controller output

6.4.1.2 Fuzzy Rules

In this inference engine, fuzzy rules are the basis of inference. Table 6.1 shows the fuzzy rules implemented in this problem. The focus is on the uncertainty of the returned products and demand. In this part, a finished refurbished returned product is assembled from the returned components. The optimization is for multi-period model. In this step, the optimization is in the decision center. Since the quality of the returned products is irregular, the decision center has to decide which returned product to collect. Meanwhile, to deal with the uncertainty of supply and demand, a fuzzy controller is implemented for the solution.

Table 6.1 shows the rules table to control the uncertainty of the quantity of returned products. It also consider the uncertainty of demands.

D: the total demand of the finished refurbished products. (L, RL, N, RH, H)

FRE: the inventory level of finished refurbished products. (L, RL, N, RH, H)

RRE: the inventory level of returned products. (L, RL, N, RH, H)

Here, L means low, RL means relatively low, N means normal, RH means relatively high, H means high.

IND: the index of the fuzzy controller pointer. (VL, L, RL, N, RH, H, VH)

Here, VL means very Low, L means low, RL means relatively low, N means normal, RH means relatively high, H means high, VH means very high.

Table 6.1 Rules of the fuzzy controller

If D is H, FRE is H and RRE is H	Then IND is VL
If D is H, FRE is H and RRE is RH	Then IND is L
If D is H, FRE is H and RRE is N	Then IND is RL
If D is H, FRE is H and RRE is RL	Then IND is N

If D is H, FRE is H and RRE is L	Then IND is N
If D is H, FRE is RH and RRE is H	Then IND is L
If D is H, FRE is RH and RRE is RH	Then IND is RL
If D is H, FRE is RH and RRE is N	Then IND is N
If D is H, FRE is RH and RRE is RL	Then IND is RH
If D is H, FRE is RH and RRE is L	Then IND is RH
If D is H, FRE is N and RRE is H	Then IND is RL
If D is H, FRE is N and RRE is RH	Then IND is N
If D is H, FRE is N and RRE is N	Then IND is RH
If D is H, FRE is N and RRE is RL	Then IND is H
If D is H, FRE is N and RRE is L	Then IND is H
If D is H, FRE is RL and RRE is H	Then IND is N
If D is H, FRE is RL and RRE is RH	Then IND is RH
If D is H, FRE is RL and RRE is N	Then IND is H
If D is H, FRE is RL and RRE is RL	Then IND is VH
If D is H, FRE is RL and RRE is L	Then IND is VH
If D is H, FRE is L and RRE is H	Then IND is RH
If D is H, FRE is L and RRE is RH	Then IND is H
If D is H, FRE is L and RRE is N	Then IND is H
If D is H, FRE is L and RRE is RL	Then IND is VH
If D is H, FRE is L and RRE is L	Then IND is VH
If D is RH, FRE is H and RRE is H	Then IND is VL
If D is RH, FRE is H and RRE is RH	Then IND is L
If D is RH, FRE is H and RRE is N	Then IND is RL
If D is RH, FRE is H and RRE is RL	Then IND is N
If D is RH, FRE is H and RRE is L	Then IND is N
If D is RH, FRE is RH and RRE is H	Then IND is L
If D is RH, FRE is RH and RRE is RH	Then IND is RL
If D is RH, FRE is RH and RRE is N	Then IND is N
If D is RH, FRE is RH and RRE is RL	Then IND is RH
If D is RH, FRE is RH and RRE is L	Then IND is RH
If D is RH, FRE is N and RRE is H	Then IND is RL
If D is RH, FRE is N and RRE is RH	Then IND is N
If D is RH, FRE is N and RRE is N	Then IND is RH

If D is RH, FRE is N and RRE is RL	Then IND is H
If D is RH, FRE is N and RRE is L	Then IND is VH
If D is RH, FRE is RL and RRE is H	Then IND is RH
If D is RH, FRE is RL and RRE is RH	Then IND is H
If D is RH, FRE is RL and RRE is N	Then IND is H
If D is RH, FRE is RL and RRE is RL	Then IND is VH
If D is RH, FRE is RL and RRE is L	Then IND is VH
If D is RH, FRE is L and RRE is H	Then IND is RH
If D is RH, FRE is L and RRE is RH	Then IND is H
If D is RH, FRE is L and RRE is N	Then IND is H
If D is RH, FRE is L and RRE is RL	Then IND is VH
If D is RH, FRE is L and RRE is L	Then IND is VH
If D is N, FRE is H and RRE is H	Then IND is VL
If D is N, FRE is H and RRE is RH	Then IND is RL
If D is N, FRE is H and RRE is N	Then IND is L
If D is N, FRE is H and RRE is RL	Then IND is L
If D is N, FRE is H and RRE is L	Then IND is L
If D is N, FRE is RH and RRE is H	Then IND is L
If D is N, FRE is RH and RRE is RH	Then IND is RL
If D is N, FRE is RH and RRE is N	Then IND is RL
If D is N, FRE is RH and RRE is RL	Then IND is RL
If D is N, FRE is RH and RRE is L	Then IND is RL
If D is N, FRE is N and RRE is H	Then IND is RL
If D is N, FRE is N and RRE is RH	Then IND is N
If D is N, FRE is N and RRE is N	Then IND is N
If D is N, FRE is N and RRE is RL	Then IND is RH
If D is N, FRE is N and RRE is L	Then IND is RH
If D is N, FRE is RL and RRE is H	Then IND is RH
If D is N, FRE is RL and RRE is RH	Then IND is H
If D is N, FRE is RL and RRE is N	Then IND is H
If D is N, FRE is RL and RRE is RL	Then IND is VH
If D is N, FRE is RL and RRE is L	Then IND is VH
If D is N, FRE is L and RRE is H	Then IND is VH
If D is N, FRE is L and RRE is RH	Then IND is VH

If D is N, FRE is L and RRE is N	Then IND is VH
If D is N, FRE is L and RRE is RL	Then IND is VH
If D is N, FRE is L and RRE is L	Then IND is VH
If D is RL, FRE is H and RRE is H	Then IND is VL
If D is RL, FRE is H and RRE is RH	Then IND is VL
If D is RL, FRE is H and RRE is N	Then IND is VL
If D is RL, FRE is H and RRE is RL	Then IND is L
If D is RL, FRE is H and RRE is L	Then IND is L
If D is RL, FRE is RH and RRE is H	Then IND is L
If D is RL, FRE is RH and RRE is RH	Then IND is RL
If D is RL, FRE is RH and RRE is N	Then IND is RL
If D is RL, FRE is RH and RRE is RL	Then IND is N
If D is RL, FRE is RH and RRE is L	Then IND is N
If D is RL, FRE is N and RRE is H	Then IND is RL
If D is RL, FRE is N and RRE is RH	Then IND is RL
If D is RL, FRE is N and RRE is N	Then IND is N
If D is RL, FRE is N and RRE is RL	Then IND is N
If D is RL, FRE is N and RRE is L	Then IND is N
If D is RL, FRE is RL and RRE is H	Then IND is N
If D is RL, FRE is RL and RRE is RH	Then IND is N
If D is RL, FRE is RL and RRE is N	Then IND is N
If D is RL, FRE is RL and RRE is RL	Then IND is RH
If D is RL, FRE is RL and RRE is L	Then IND is RH
If D is RL, FRE is L and RRE is H	Then IND is H
If D is RL, FRE is L and RRE is RH	Then IND is H
If D is RL, FRE is L and RRE is N	Then IND is VH
If D is RL, FRE is L and RRE is RL	Then IND is VH
If D is RL, FRE is L and RRE is L	Then IND is VH
If D is L, FRE is H and RRE is H	Then IND is VL
If D is L, FRE is H and RRE is RH	Then IND is VL
If D is L, FRE is H and RRE is N	Then IND is VL
If D is L, FRE is H and RRE is RL	Then IND is VL
If D is L, FRE is H and RRE is L	Then IND is VL
If D is L, FRE is RH and RRE is H	Then IND is VL

If D is L, FRE is RH and RRE is RH	Then IND is VL
If D is L, FRE is RH and RRE is N	Then IND is L
If D is L, FRE is RH and RRE is RL	Then IND is L
If D is L, FRE is RH and RRE is L	Then IND is L
If D is L, FRE is N and RRE is H	Then IND is L
If D is L, FRE is N and RRE is RH	Then IND is L
If D is L, FRE is N and RRE is N	Then IND is RL
If D is L, FRE is N and RRE is RL	Then IND is RL
If D is L, FRE is N and RRE is L	Then IND is RL
If D is L, FRE is RL and RRE is H	Then IND is RL
If D is L, FRE is RL and RRE is RH	Then IND is RL
If D is L, FRE is RL and RRE is N	Then IND is L
If D is L, FRE is RL and RRE is RL	Then IND is L
If D is L, FRE is RL and RRE is L	Then IND is N
If D is L, FRE is L and RRE is H	Then IND is N
If D is L, FRE is L and RRE is RH	Then IND is N
If D is L, FRE is L and RRE is N	Then IND is RH
If D is L, FRE is L and RRE is RL	Then IND is RH
If D is L, FRE is L and RRE is L	Then IND is H

6.4.1.3 Defuzzification

In the defuzzification of this problem, the center of area method is selected. The center of area method is the most widely used defuzzification technique. It determines the center of area of membership function, and can work efficiently with three inputs fuzzy controller in this simulation. The general equation is

$$Y = \frac{\sum_{j=1}^{N} w_j \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} \tag{6.10}$$

where w, C and A denote the weight, center of gravity and area respectively, for each individual implication result.

6.4.2 Proposed Score System and Indicator

The objective of the fuzzy controller is to solve the problem of the uncertainty of the returned products quantity and quality, which means the supplies uncertainty has two aspects, for minimizing the total manufacturing costs. In the decision center, it is necessary to decide on the process for each returned product. Since the quality of each product is different, each product is scored according to its quality. The focus of the decision center is to decide on the indicator score to classify the returned products properly. The fuzzy controller here is to control the indicator according to the uncertainty of the returned products quantity. Figure 6.8 shows the concept of the fuzzy controller. In Figure 6.8, the ceiling boundary is the refurnish line, and the bottom boundary is the disassembly line.

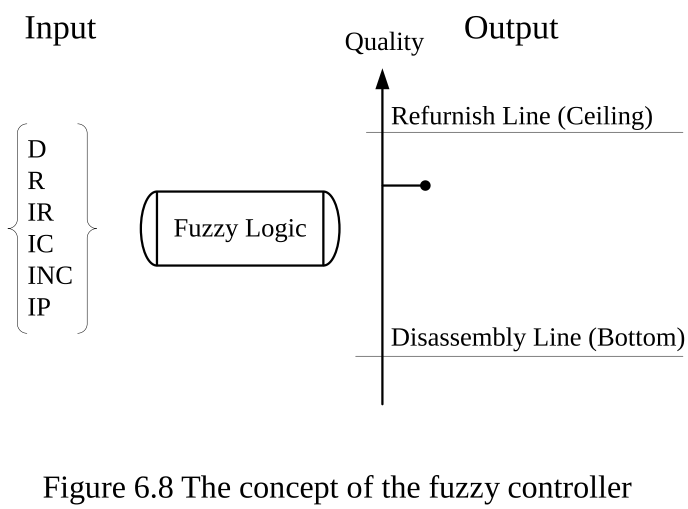

Figure 6.8 The concept of the fuzzy controller

For each used component, the practical value is the present value after depreciation, the original value is the value when it is new. The score is in direct proportion to the practical value of a returned product. The coefficient indicates the quality level of returned components. The practical value equals the original value times the coefficient. The score of one component equals 100 times the percentage of this component practical value in the practical of this returned product. Table 6.2 shows an example of the score of a returned product.

Table 6.2 The score of components

components	1	2	3	4	5	6	7	8	9	10	Total
original value	20	49	15	56	80	4	8	98	30	50	---
coefficient	0.5	1.0	0.7	0.3	0.4	0.2	0.9	0.3	0.6	0.8	---
practical value	10	49	10.5	16.8	32	0.8	7.2	29.4	18	40	213.7
scores	4.7	22.9	4.9	7.86	15.0	0.4	3.4	13.8	8.4	18.7	100

6.5 Numerical Experiments

To demonstrate the effectiveness of the fuzzy controller, and inspect into the refurbish process of returned products, simulation is implemented in this part. Section 6.5.1 shows the simulation process in MATLAB. Section 6.5.2 shows the initial data generation. Section 6.5.3 shows the calculation and the results.

The assumptions are as follows.

(1) The trade in allowance of one returned product is only related to the quality of that returned product.
(2) The quality and quantity of returned products in each period is uncertain, which means that both the uncertainties of the quality and quantity are considered in this scenario.
(3) The demand for refurbished products is uncertain in each period, which means the uncertainty of the demands is considered.
(4) The capacity for disassembly and refurbishment is not considered.

6.5.1 Simulation process

To simulate the process of returned products collected, refurbished and sold, a simulation system of this problem is established using Simulink in MATLAB. Since MATLAB has a toolbox of fuzzy logic, it is convenient to integrate the fuzzy controller with the simulation system. Figure 6.9 shows the simulation system Part I established in MATLAB, Figure 6.10 shows the simulation system Part II.

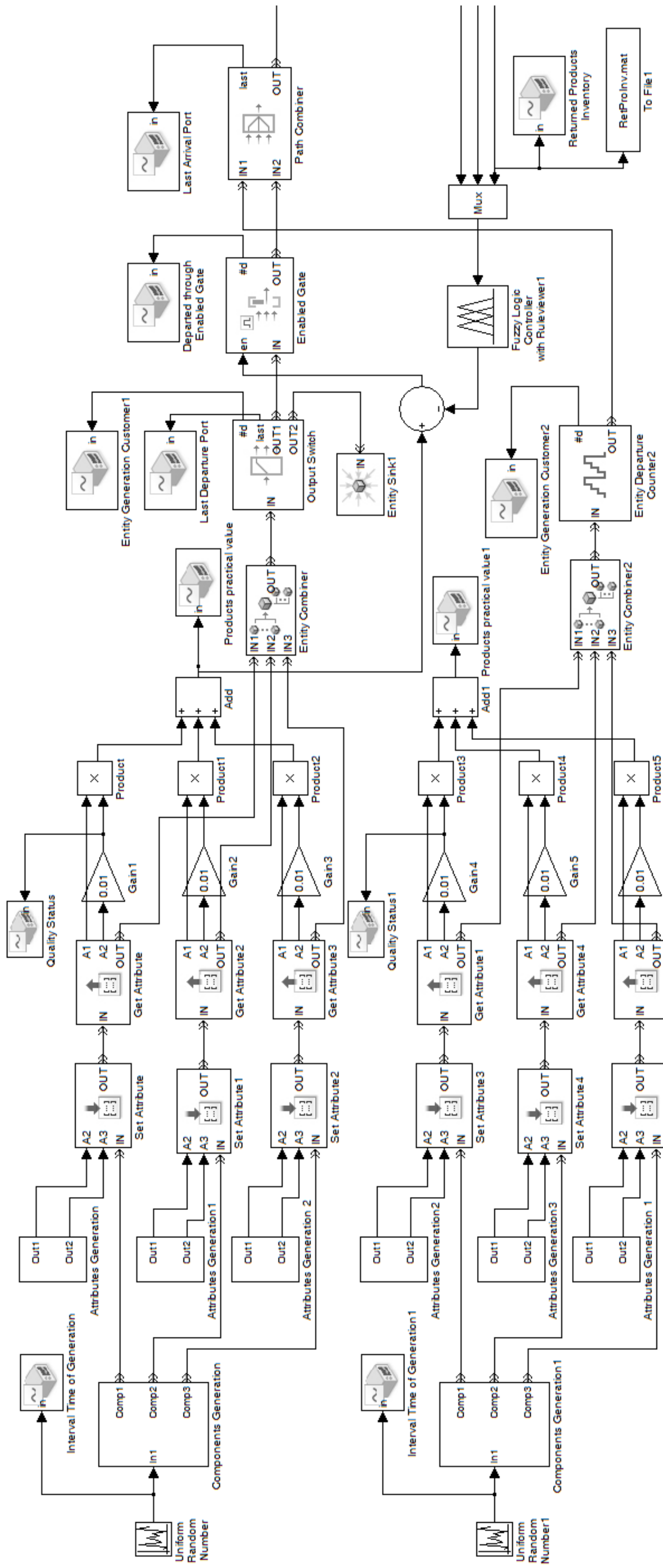

Figure 6.9 Simulation system in MATLAB-Part I

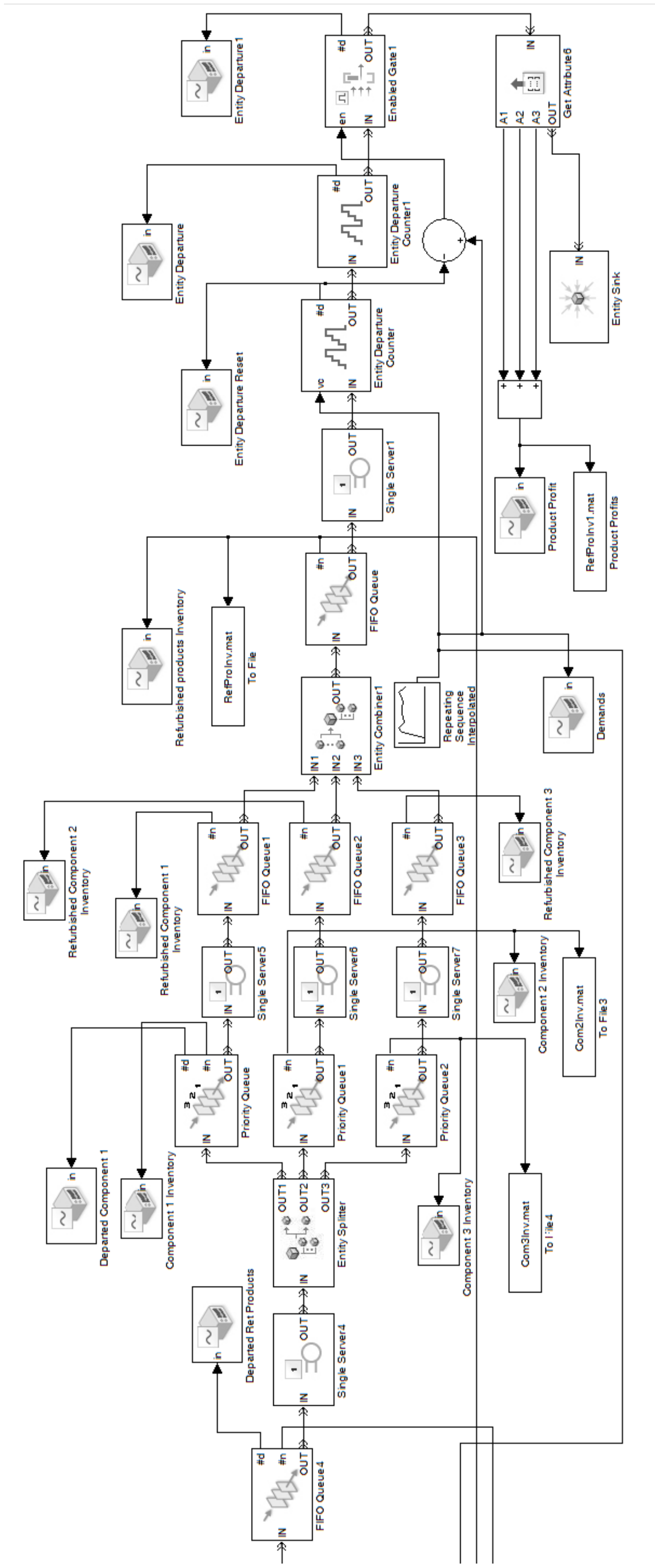

Figure 6.10 Simulation system in MATLAB-Part II

6.5.2 Initial Data Generation

Since the proposed problem is the optimization of daily production planning in the refurbishing process, the period here is set to 10 days. In the simulation runs, 110 seconds means 10 days. The total running time is 330 seconds, which means the inspection time in this simulation is 3 periods. Figure 6.11 shows the demands of the refurbished products. The selling price of each refurbished product is about 75% of that of a brand new product.

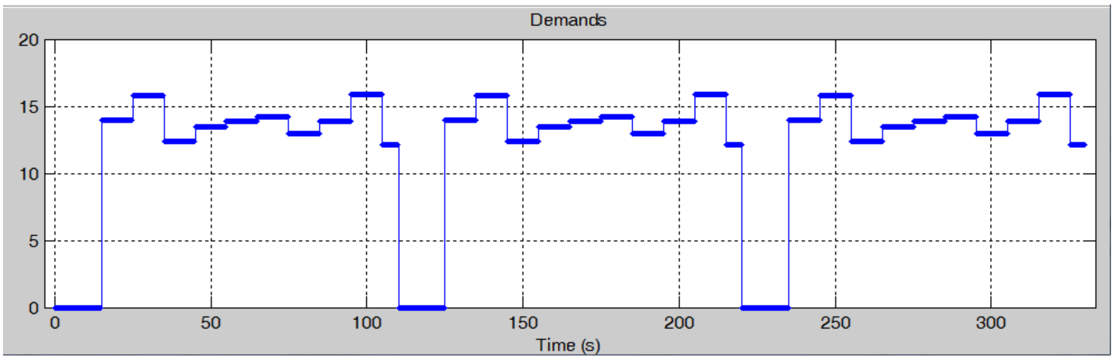

Figure 6.11 The demands of the refurbished products

Since the quality of each returned product is different, all of them in each period have to be generated and displayed. To obtain information on the components, Apple iPad 4 LTE A1459 is used as an practical example. An ipad is mainly divided into the following 3 group of parts. Group 1 includes parts with low damage rate, such as memory and processor etc. Group 2 includes parts with middle damage rate, like display and touch screen. Group 3 includes parts with high damage rate, such as user interface sensors, mechanical parts, etc. Table 6.3 shows the components information. All company names, product names, and service names mentioned are used for identification only and academic analysis. The value analyses presented in this case study are estimated from generally available data. Therefore the actual values may be different from these estimates. The quality status of returned components are set according to Table 6.3. Figure 6.12 displays the quality status of returned components in the simulation.

Table 6.3 Components information

No.	Name	Estimated value (US$)	Percent	Damage rate
1	Memory and Processor etc.	143.53	44.81%	22%
2	Display and Touch screen	100.44	31.36%	54%
3	Mechanical/Electro-Mechanical/Others	76.27	23.83%	81%
	Total	320.24	100%	

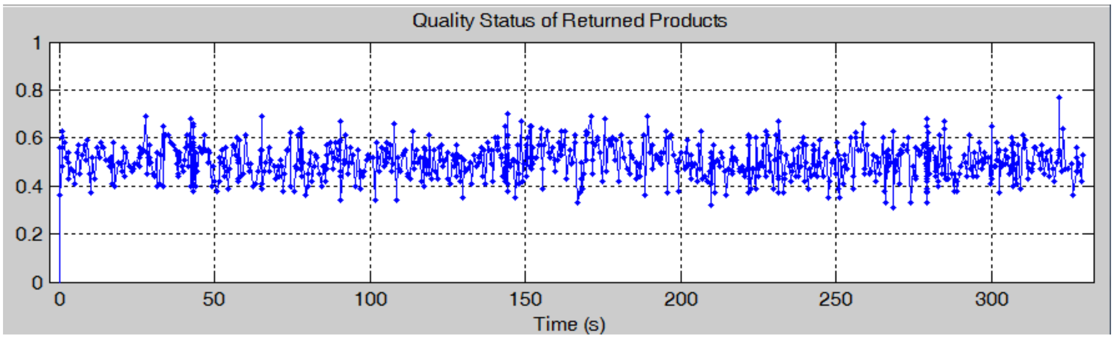

Figure 6.12 The quality status of the returned products

6.5.3 Calculation and Results

The simulation is run for 330 seconds, which represents 30 days in practical. In the fuzzy controller, Mamdani-Type fuzzy inference was used. Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in more intuitive, more human-like manner. Hence it is widely used in particular for decision support application (Kaur and Kaur, 2012). To demonstrate the effectiveness and efficiency of the proposed fuzzy controller, benchmarking experiment is implemented. In this simulation system, total profits are apportioned into each sold refurbished products. Further numerical experiment with considering customer profitability is implemented in Section 6.5.4.

6.5.3.1 Numerical Experiment

The objective of this simulation experiment is to demonstrate the effectiveness of the proposed fuzzy controller. Using the input data in Section 6.5.2, the results of indicators are shown in Figure 6.13, which is the fuzzy controller output. Figure 6.14 shows the inventory level of refurbished products. The profits of each sold refurbished products are shown in Figure 6.15.

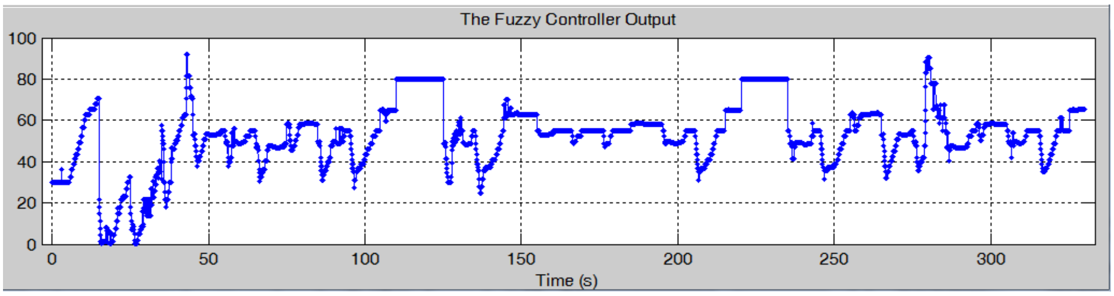

Figure 6.13 The fuzzy controller output

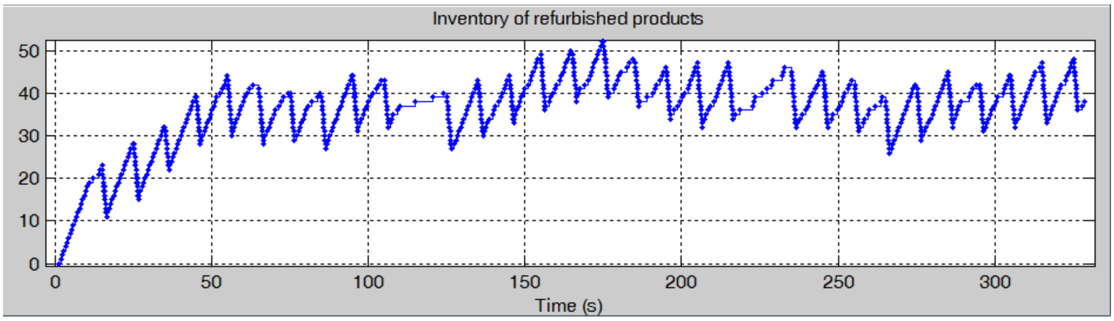

Figure 6.14 Inventory of refurbished products

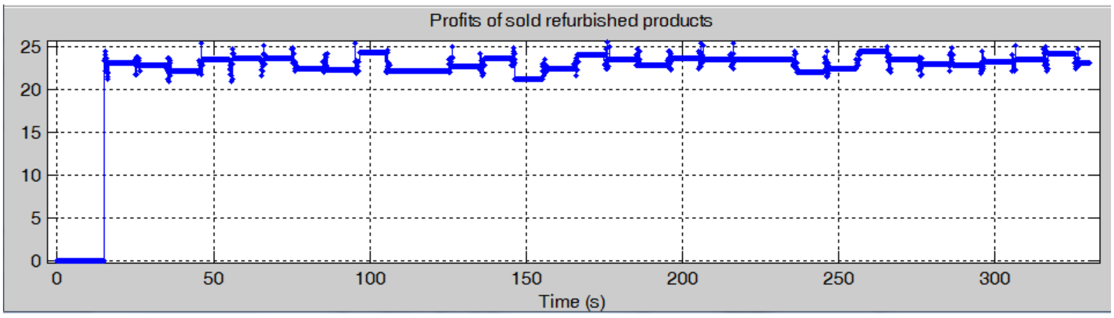

Figure 6.15 The profits of each sold refurbished products

From Figure 6.11, it can be seen that the demands in the first ten seconds keeps zero. Since this period of time is for inventory accumulation, the inventory of refurbished products and returned products increase rapidly. From Figure 6.13 and Figure 6.14, it can be seen that in the first 110 seconds, named the first period is the warm up period. After the first 110 seconds, which means at the beginning of the second period, the fuzzy controller starts a nearly regular change. The inventory level of refurbished products reached a nearly stable level. Figure 6.16 shows the data after the warm up period, called stable periods.

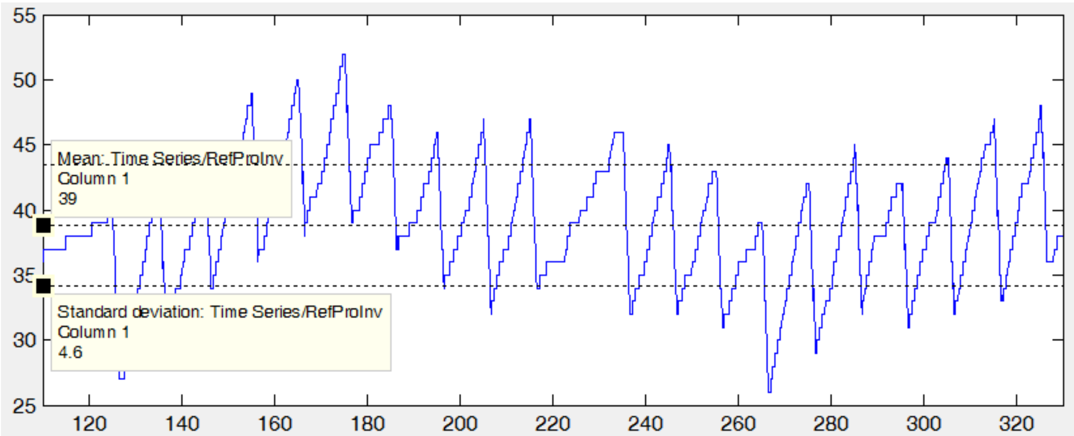

Figure 6.16 The refurbished products inventory of stable periods

From Figure 6.16, it can be seen that the mean of refurbished products inventory is 39, the standard deviation is 4.6, which means the proposed fuzzy controller effectively controlled the inventory level around 39 and the volatility is 4.6.

6.5.3.2 Benchmarking Experiment

In this benchmarking experiment, all of the input data and parameters are the same with that in Section 6.5.3.1. The only difference of this benchmarking experiment is not using the fuzzy controller, which means the output of the fuzzy controller here is set to zero. Figure 6.17 shows the inventory level of refurbished products in this benchmarking experiment.

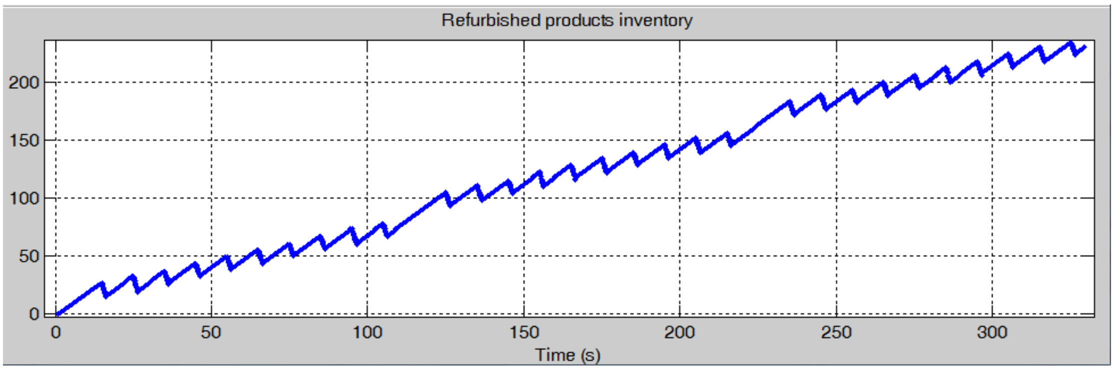

Figure 6.17 The inventory of refurbished products

To compare Figure 6.14, Figure 6.16 and Figure 6.17, it can be seen that the refurbished products inventory can be controlled at a stable level with fuzzy controller. While without fuzzy controller, the inventory level rises straightly.

6.5.4 Further Experiment Considering Customer Profitability

Since customer profitability contributes a lot in companies profits, it has been considered in this additional experiment. In this simulation system, total profits are apportioned into each sold refurbished products, including customer profitability. In this section, the input parameters of demands and returned products are the same with that in Section 6.5.2. But in this experiment, customer profitability has been considered in decision making process. Figure 6.18 shows the fuzzy controller output, Figure 6.19 shows the inventory level of refurbished products. Figure 6.20 shows the inventory of refurbished products in stable periods. Figure 6.21 shows the profits of each sold refurbished products. Figure 6.22 shows the sold refurbished product profits in stable periods. For comparison, the sold refurbished product profits without considering customer profitability are shown in Figure 6.23.

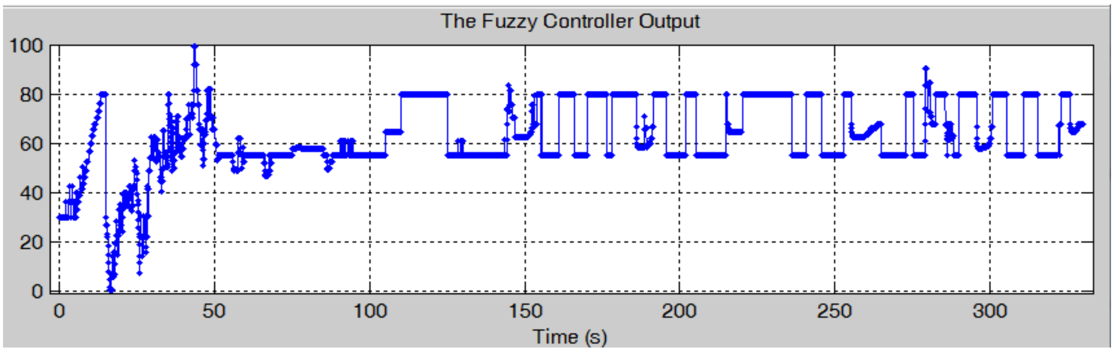

Figure 6.18 The fuzzy controller output

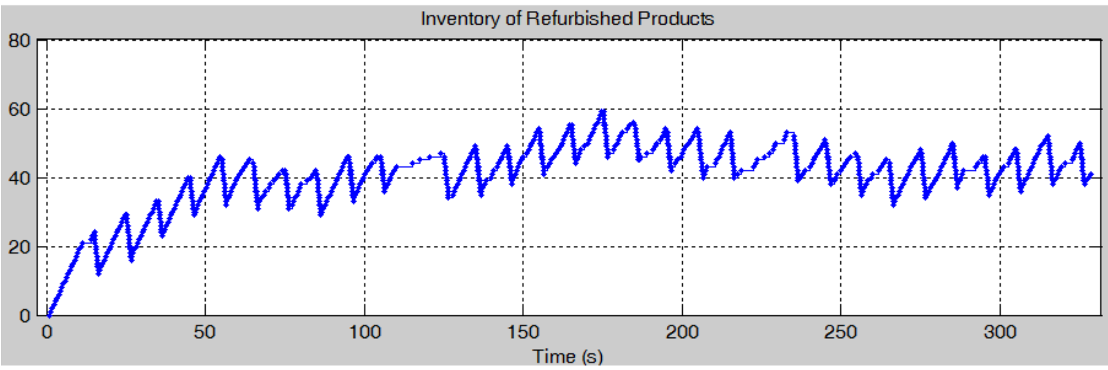

Figure 6.19 Inventory of refurbished products

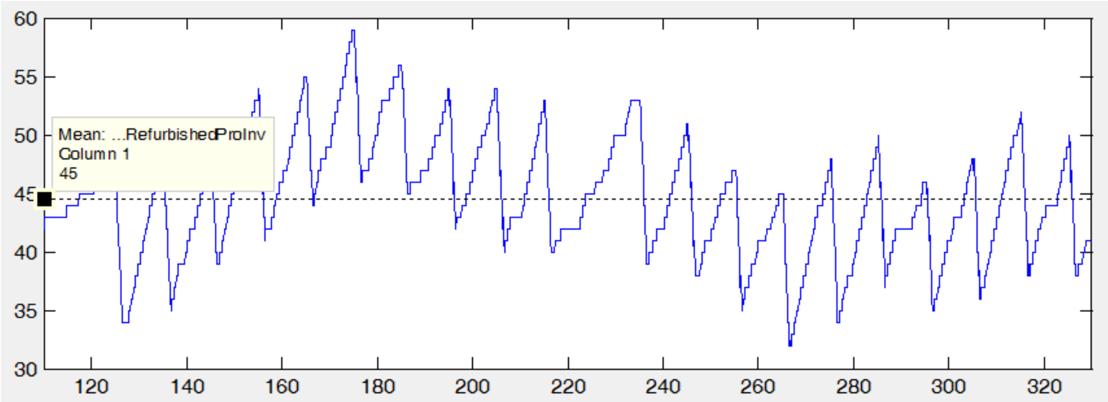

Figure 6.20 The inventory level of refurbished products in stable periods

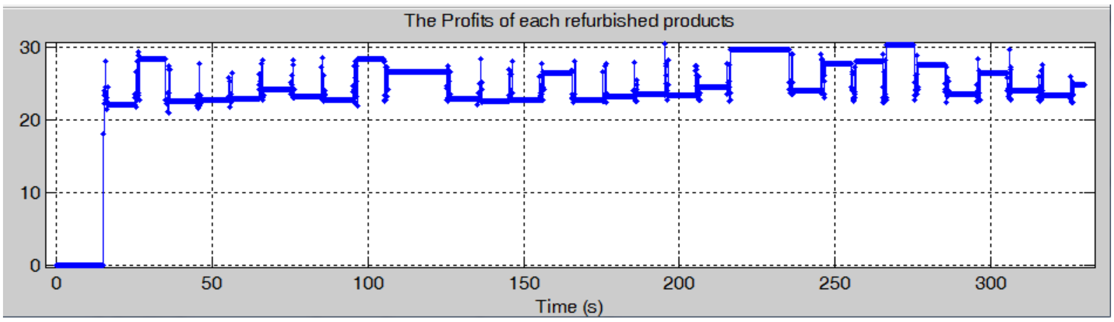

Figure 6.21 The profits of each sold refurbished products

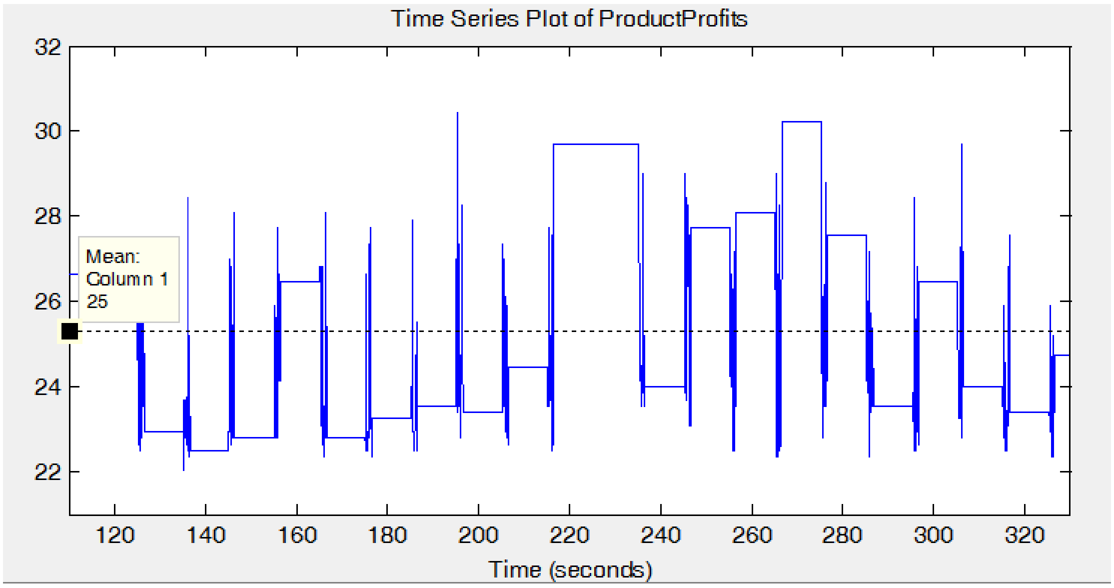

Figure 6.22 The sold refurbished product profits in stable periods

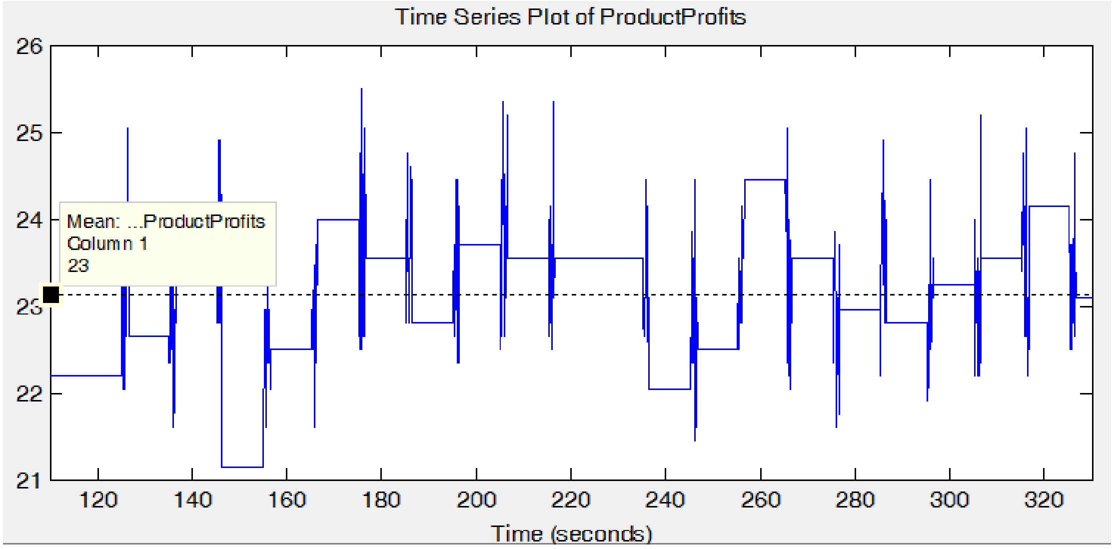

Figure 6.23 The sold refurbished product profits without customer profitability

From Figure 6.16, it can be seen that the mean of refurbished products inventory without considering customer profitability is 39. From Figure 6.20, the mean of refurbished products inventory considering customer profitability is 45. To compare Figure 6.16 and Figure 6.20, it can be seen that the refurbished products inventory level is slightly lower without considering customer trade in. However, the comparison of Figure 6.22 and Figure 6.23 shows that the average profits of each sold refurbished products decreased from 25 to 23, which means the total profits decreased without considering customer trade in. In summary, although collection of trade in products leads to a slightly higher inventory level, the long-time profits from the trade in customers increase even more higher. In this scene, companies should encourage customers trade in behavior, even provide some trade in allowance, it's still profitable.

6.6 Summary

Due to environmental issues, product refurbishment is becoming more and more important nowadays. Optimization of products refurbishing process in closed-loop supply chain needs to be studied. However, in the literature, few papers focus on this problem. In the process of returned products' refurbishment, the uncertainty of the quantity and quality of the returned products makes the problem much more complicated. This research fills the research gap in this area. The contributions of this chapter are stated as follows.

Academically, a mathematical model describing the process of returned products' refurbishment was established. This model structures and optimizes the process of product refurbishment, considering inventories and uncertainties with multi-period. Additionally, a novel fuzzy controller with a value indicator was proposed to solve the uncertainty of the returned products' quantity considering the various qualities. The simulation results of numerical experiments prove that the proposed fuzzy controller can solve this multi-period uncertainty problem in an effective way, especially with the quality indicator, which enhances the ability of the proposed fuzzy controller to deal with uncertainties regarding both quantity and quality.

For companies and society, this research provides decision support to implement used products' trade-in and recycling programs. The proposed simulation system in this research provides returned products' collection planning to decide how to collect returned products. This chapter also established a method dealing with uncertainties in the process of returned products' refurbishment, which can decrease the cost and increase the profits, encouraging companies to recycle end of life products, and in turn mitigate environmental problems.

Chapter 7 Simulation of returned products' collection and refurbishment under uncertainty integrated with a two-layer fuzzy controller

7.1 Introduction

Due to environmental issues, optimization of closed-loop supply chain has become popular nowadays. Among several research fields of CLSC, returned products' refurbishment is drawing more and more attention due to its profit in economics and environmental benefits. The difficulties in production planning of returned products' refurbishment is the uncertainties in both supply and demand. To deal with these uncertainties, a two-layer fuzzy controller embedded with a quality indicator was developed. This proposed two-layer fuzzy controller analyzes the returned products' quality in the component level, which make the decision more accurate. In Level 1, fuzzy controller estimates the returned products' quality in the component level and provides data for the collection decision in Level 2. In this research, simulation was implemented using MATLAB. The results prove the effectiveness of the proposed two-layer fuzzy controller to deal with uncertainties in demand and supply, considering quality.

7.2 Problem Description

Product recovery is one of the most popular research fields in closed-loop supply chain. The processes of product recovery include product recycling, remanufacturing, refurbishment, reuse, resell, etc. Among these processes, product refurbishment is one of the most profitable and environmentally beneficial processes, drawing more and more attention from both product manufacturers and customers. In fact, many electronic products manufacturers have implemented product collection and refurbishment programms. In the literature, few research studies have focused on the process of returned products refurbishment in CLSC.

This chapter describes the structuring and optimization of the process of product refurbishment, considering inventories and uncertainties. A multi-period model was established. The difficulties in optimizing CLSC with product refurbishment is derived from the uncertainties of both supply and demand. Here, supplies in product refurbishment are returned products with uncertainties in regard to both quantity and quality. Hence uncertainties become an obstacle in the optimization of product refurbishment. To deal with these uncertainties, a modified two-stage fuzzy controller embedded with a quality indicator is proposed, integrated with the established multi-period model. The quality indicator is employed to enhance the ability to deal with the quality uncertainty of the fuzzy controller.

In this system, the input is the collected returned products in the collection centre, which are called supplies. The output is the finished refurbished products to fulfill the demands of customers. Multi-period are considered in this problem. The objective is to minimize the total cost in multi-period including the disassembly costs in disassembly workstations, the refurbishment costs in refurbishment workstations, the inventory costs of returned products, renewable products, returned components, and finished products, as well as the shortage costs of returned components in the process of refurbishment; and the shortage costs of finished products.

In the collection points, the company collects returned products from customers. They will pay customers for the returned products, which is called the returned price. This is the focus of decision-making in this system. In the collection centres, returned products are inspected and cleaned and then, sent to disassembly. All the returned products will be disassembled into components. Some of them of good quality will be refurbished, while others will be repaired. After refurbishment or repair, these components can be used again in the assembly of refurbished products, which are called returned components. In the refurbishment centre, returned components are assembled into refurbished products. The finished refurbished products are sent to the warehouse to satisfy customer demands. Fig. 7.1 shows the concept of the proposed control system.

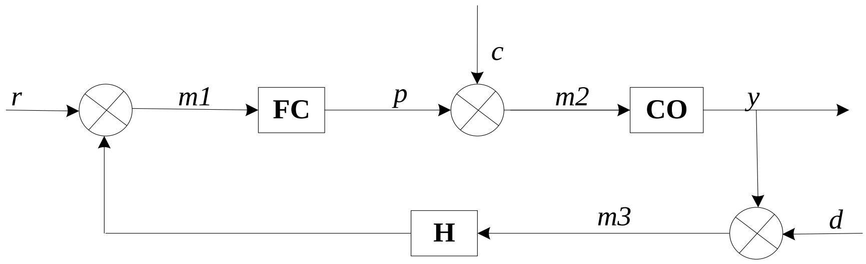

Figure 7.1 The concept of proposed control system

In this control system, the control object CO is the unit cost. The objective is to control the inventory cost and collection cost at a low level while satisfying the demand. $CO = \dfrac{inventory\ \cos t + collection\ \cos t}{demands}$

where r is the standard, m1 is the input of the fuzzy controller, p is the output of the fuzzy controller called price, c is the customer's response to the price, m2 is the returned products. y is the results, the total cost and the satisfied demand, d is the change of demand, and m3 is the feedback information. When one control cycle ends and a new cycle begins.

In the traditional control method, the mathematical formulation of the control objective has to be analyzed. In this problem, the control objective is the whole system, but the analysis for this system using a mathematical method is too difficult, so fuzzy logic is used. To control the uncertainties regarding both quantity and quality, a two-stage fuzzy controller is proposed in this chapter. This two-stage fuzzy controller can control both of the uncertainties simultaneously instead of a single stage fuzzy controller. Fig. 7.2 shows the concept of the proposed fuzzy controller.

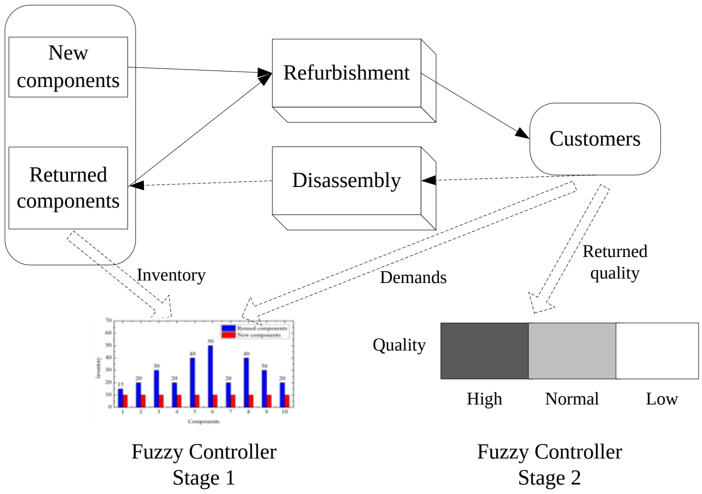

Figure 7.2 The concept of proposed fuzzy controller

7.3 Methodology of Two-layer Fuzzy Controller

In this research, a two-stage fuzzy controller was established to deal with the uncertainty of both the quality and quantity of returned products.

7.3.1 Fuzzy Controller Layer 1

Fuzzy controllers in the first stage decide the desirable level of each component in returned products. The input of these fuzzy controllers are refurbished components' inventory level and returned components' quality. The output is a desirable coefficient. Fuzzy controller 1 indicates the real demand for each returned component. It depends on the demand for refurbished products and the inventory level of returned components. Q: quality, INV: the inventory level of a refurbished component, which has finished undergoing the refurbishing process. DE: the desirable coefficient, which means the indicator of how much they need the component. The desirable coefficient from Stage 1 is used to calculate the adjusted value of each returned product, as shown in Fig. 7.3. Table 7.1 shows the fuzzy rules of Stage 1. Fig. 7.4 is the membership function of refurbished components' inventory level, Fig. 7.5 shows the membership function of quality, Fig. 7.6 is the membership function of the output and Fig. 7.7 is the Surface of the fuzzy rules in Stage 1.

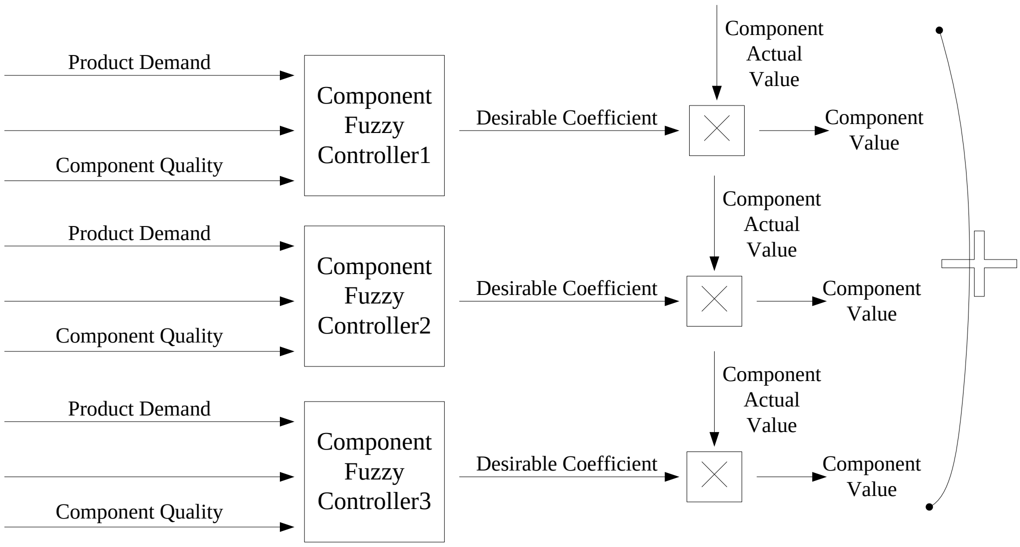

Figure 7.3 The concept of fuzzy controller Stage 1

Table 7.1 Rules table of Fuzzy Controller Stage 1

Inputs:	
INV: (VL, L, N, H, VH) Q: (VP, P, N, G, VG)	
Outputs:	
DE: (VL, L, RL, N, RH, H, VH)	
If INV is VL, Q is VP	Then DE is VL
If INV is L, Q is VP	Then DE is VL
If INV is N, Q is VP	Then DE is VL
If INV is H, Q is VP	Then DE is VL
If INV is VH, Q is VP	Then DE is VL
If INV is VL, Q is P	Then DE is RH
If INV is L, Q is P	Then DE is N
If INV is N, Q is P	Then DE is RL
If INV is H, Q is P	Then DE is L
If INV is VH, Q is P	Then DE is VL
If INV is VL, Q is N	Then DE is H
If INV is L, Q is N	Then DE is RH
If INV is N, Q is N	Then DE is N
If INV is H, Q is N	Then DE is RL
If INV is VH, Q is N	Then DE is L
If INV is VL, Q is G	Then DE is VH
If INV is L, Q is G	Then DE is H
If INV is N, Q is G	Then DE is RH
If INV is H, Q is G	Then DE is N
If INV is VH, Q is G	Then DE is RL
If INV is VL, Q is VG	Then DE is VH
If INV is L, Q is VG	Then DE is H
If INV is N, Q is VG	Then DE is RH
If INV is H, Q is VG	Then DE is N
If INV is VH, Q is VG	Then DE is RL

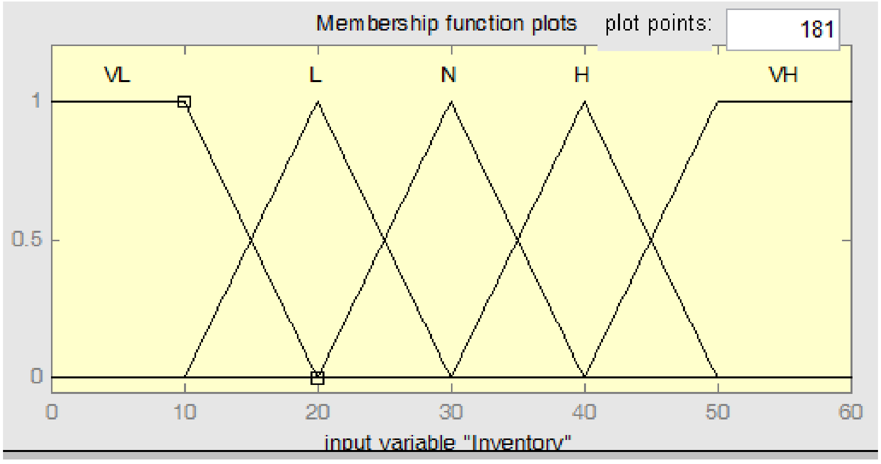

Figure 7.4 Membership function of refurbished components inventory level

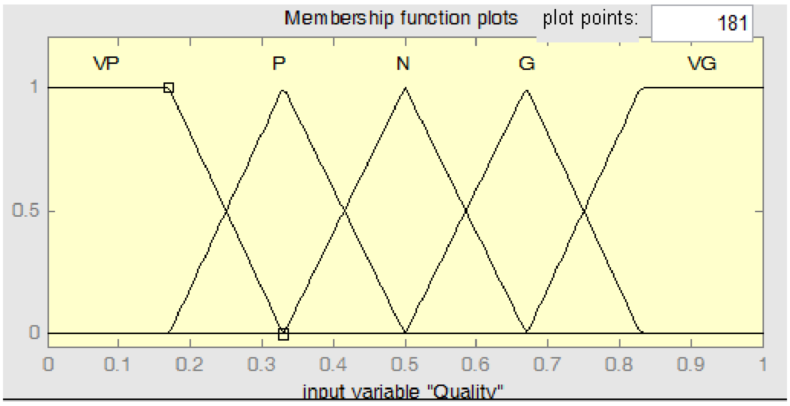

Figure 7.5 Membership function of quality

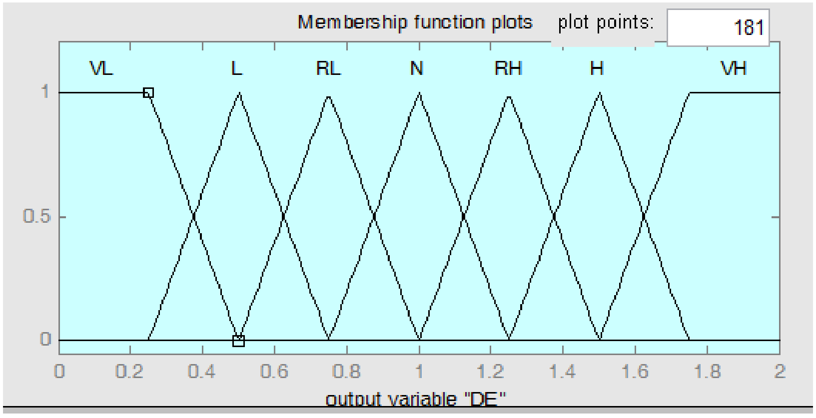

Figure 7.6 Membership function of desirable coefficient

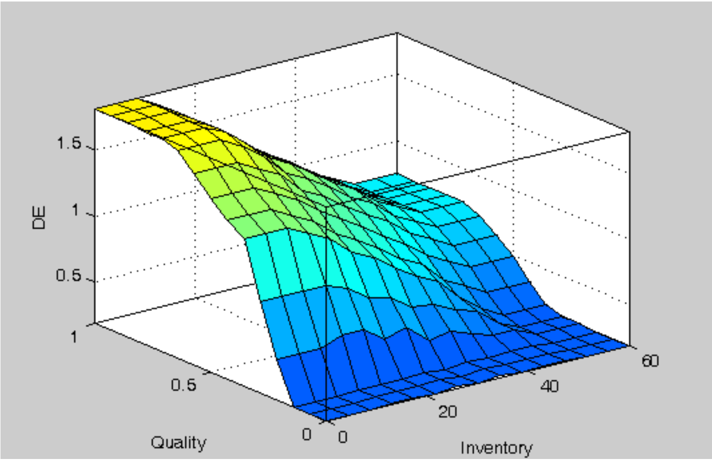

Figure 7.7 The surface of the rules

7.3.2 Fuzzy Controller Layer 2

The fuzzy controller in Stage 2 decides whether to collect the returned products or not. It considers refurbished product demand and the inventory. The two inputs of this fuzzy controller are refurbished product demand and refurbished product inventory. The output is the value pointer. If the adjusted value of returned products is higher than the value pointer, then they are collected. Otherwise, they are not collected. Fig. 7.8 shows the concept of fuzzy controller Stage 2.

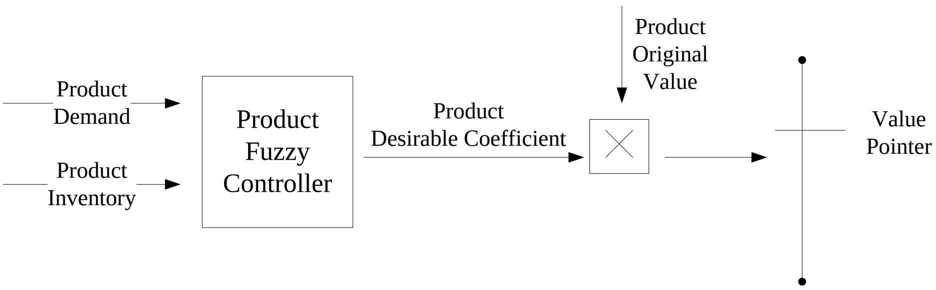

Figure 7.8 The concept of fuzzy controller Stage 2

FRE means the inventory level of finished refurbished products, D is the demand and IND is the value pointer. Table 7.2 shows the fuzzy rules of Stage 2. Fig. 7.9 shows the membership function of inventory, Fig. 7.10 shows the membership function of demand, Fig. 7.11 is the membership function of the output and Fig. 7.12 shows the Surface of fuzzy rules in Stage 2.

Inputs: FRE: (VL, L, N, H, VH), D: (VL, L, N, H, VH).

Outputs: IND: (VL, L, RL, N, RH, H, VH).

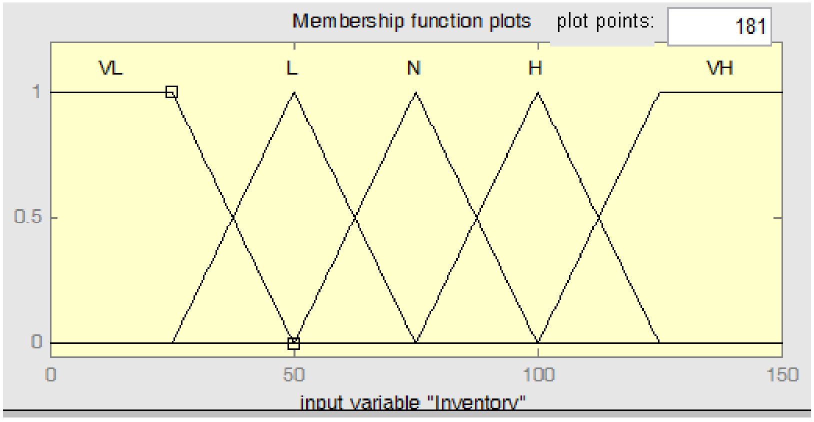

Figure 7.9 Membership function of inventory

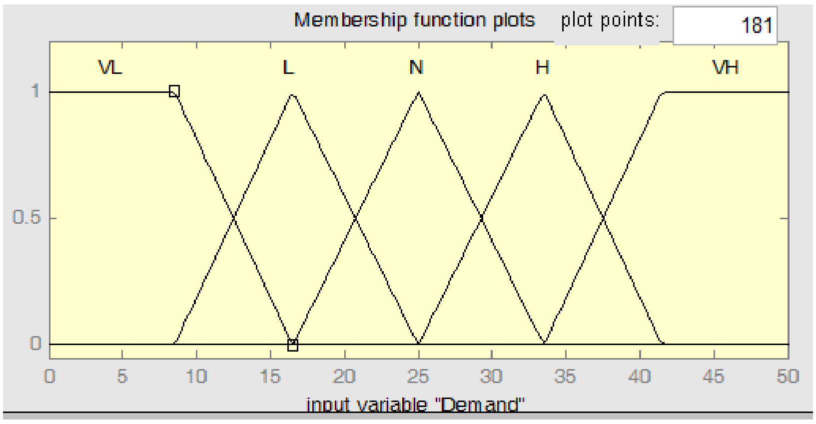

Figure 7.10 Membership function of demands

Table 7.2 Rules table of fuzzy controller Stage 2

If FRE is VL, D is VL	Then IND is L
If FRE is VL, D is L	Then IND is RL
If FRE is VL, D is N	Then IND is L
If FRE is VL, D is H	Then IND is VL
If FRE is VL, D is VH	Then IND is VL
If FRE is L, D is VL	Then IND is RH
If FRE is L, D is L	Then IND is N
If FRE is L, D is N	Then IND is RL
If FRE is L, D is H	Then IND is L
If FRE is L, D is VH	Then IND is VL
If FRE is N, D is VL	Then IND is H
If FRE is N, D is L	Then IND is RH
If FRE is N, D is N	Then IND is N
If FRE is N, D is H	Then IND is RL
If FRE is N, D is VH	Then IND is L
If FRE is H, D is VL	Then IND is VH
If FRE is H, D is L	Then IND is H
If FRE is H, D is N	Then IND is RH
If FRE is H, D is H	Then IND is N
If FRE is H, D is VH	Then IND is RL
If FRE is VH, D is VL	Then IND is VH
If FRE is VH, D is L	Then IND is VH
If FRE is VH, D is N	Then IND is H
If FRE is VH, D is H	Then IND is RH
If FRE is VH, D is VH	Then IND is N

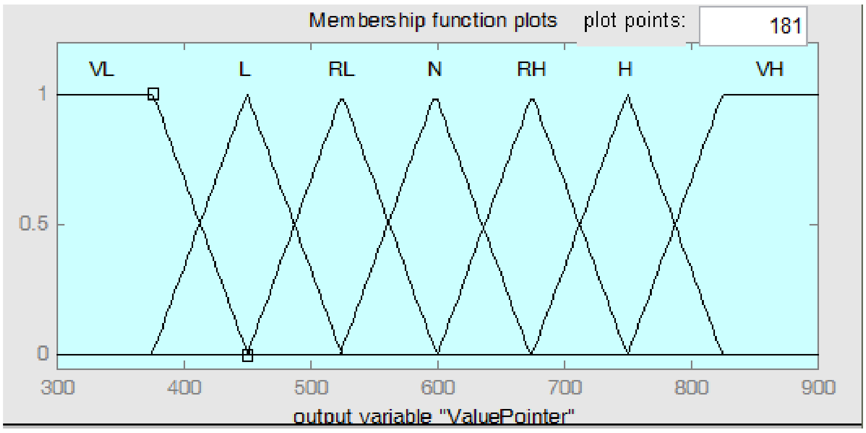

Figure 7.11 Membership function of the value pointer

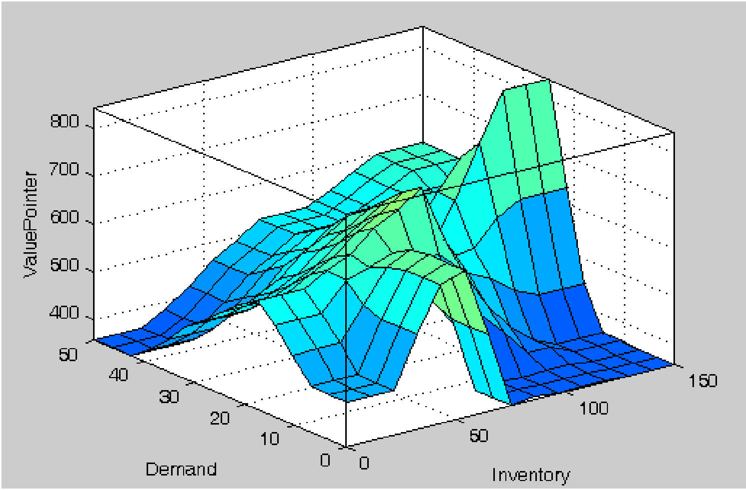

Figure 7.12 The surface of fuzzy rules

7.4 Simulation Integrated with Fuzzy Controller

To integrate fuzzy controllers into the simulation, the Simulink toolbox of MATLAB was selected to implement the simulation. Figure 7.13 shows the simulation system in Layer 1. Figure 7.14 shows the simulation system in Layer 2.

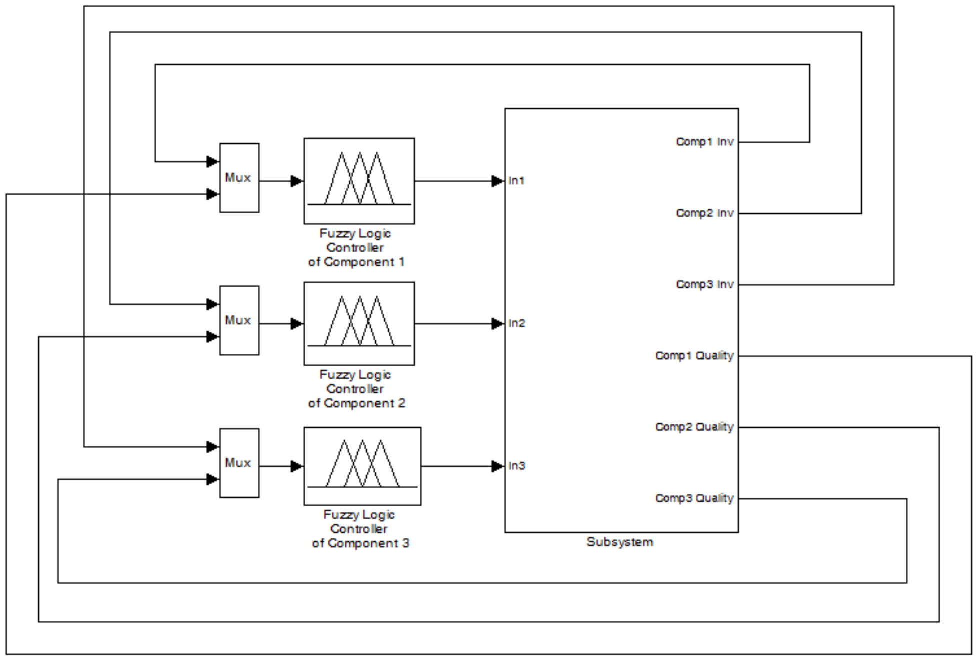

Figure 7.13 The simulation system in MATLAB Layer 1

Figure 7.13 shows the first layer in the simulation system. In this layer, three fuzzy controllers control the quality and quantity of three components separately. The output of these three fuzzy controllers is sent as the inputs to the second layer. For each fuzzy controller, the inputs are extracted from the second layer.

Figure 7.14 shows the refurbishment process of returned products, which includes products' collection, quality testing, classification, cleaning, decomposition, recycling and refurbishment.

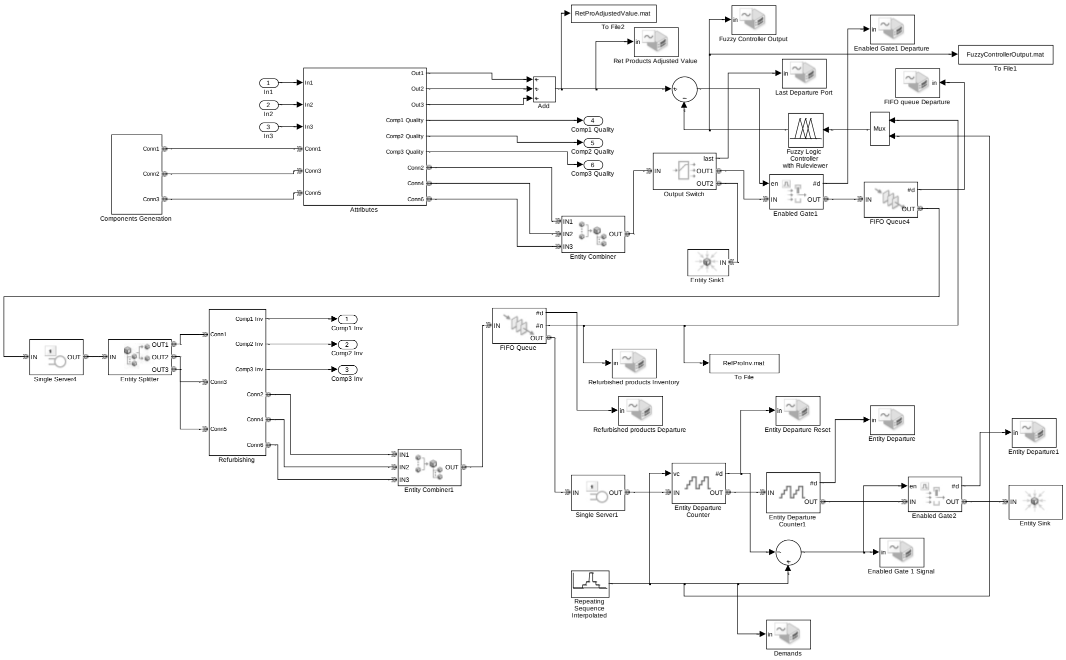

Figure 7.14 The simulation system in MATLAB Layer 2

7.5 Results and Analysis

This section will present and analyze the simulation results to test the proposed fuzzy controller and the simulation system. In the simulation experiments, three demand patterns have been implemented. In the literature of product recovery, computational experiments with different demand patterns were always been implemented to test the effective of the proposed method. Baki et al. (2014) used stationary pattern of demand, positive trend and negative trend of demand in the computational study to test the effective of the proposed approach. Ignaciuk (2015) implemented demand patterns following normal distribution, Poisson and negative binomial to demonstrate the performance of the proposed method. In this section, three demand pattern including uniform demands, increasing demands and decreasing demands have been implemented in the simulation experiments to test the effective and efficiency of the proposed fuzzy controller. The results and analysis have been explained the following sub-sections.

7.5.1 Simulation Experiment with Uniform Demands

In this experiment, the demands were set to uniformity variations, which can be seen in Figure 7.15. The range of demand lies from 0 to 40. After simulation, the outputs are shown in Figure 7.16 and Figure 7.17. Figure 7.16 shows the indicators from the fuzzy controller. Figure 7.17 shows the refurbished products' inventory.

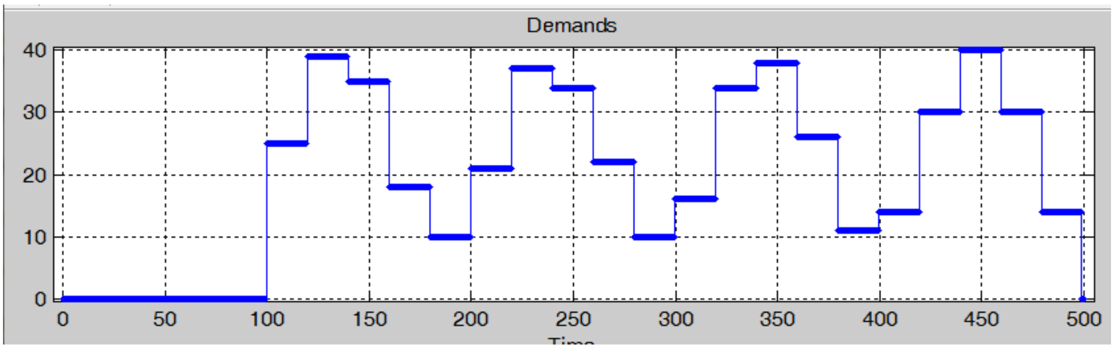

Figure 7.15 Demands in Experiment 1

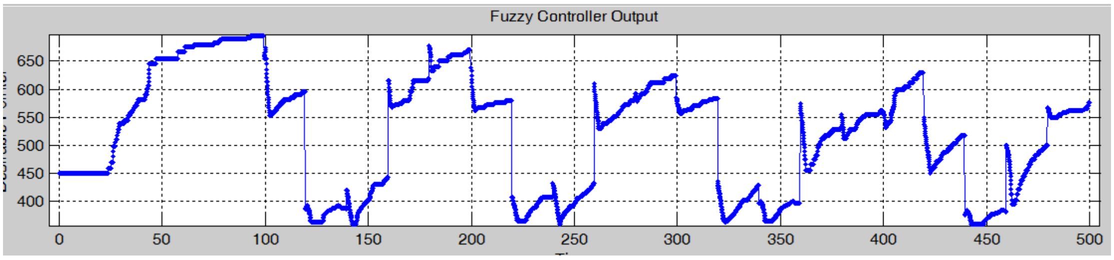

Figure 7.16 Fuzzy controller output in Experiment 1

From Figure 7.16, it can be seen that the fuzzy controller output is uniformity variations, similar to the demand. It ranges from 350 to 700. When the demand is low, the indicator is high, and when the demand increases, the indicator decreases correspondingly. This result pattern is quite reasonable. The indicator changes along with the demand to keep the inventory at a proper level.

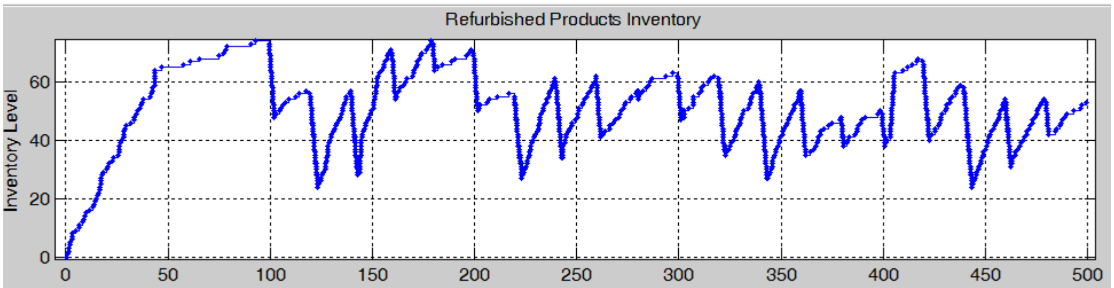

Figure 7.17 Refurbished products inventory in Experiment 1

From Figure 7.17, it can be observed that the inventory of refurbished products is maintained at a proper level between 24 and 68. The average number is 42. The results show that this controller can keep the inventory at a stable level and reduce the costs of returned products' refurbishment.

7.5.2 Simulation Experiment with Increasing Demands

In this experiment, the demands were set to increase in uniformity variations, which can be seen in Figure 7.18. The range of demand lies from 0 to 40. After simulation, the outputs are shown in Figure 7.19 and Figure 7.20. Figure 7.19 shows the indicators from the fuzzy controller. Figure 7.20 shows the refurbished products' inventory.

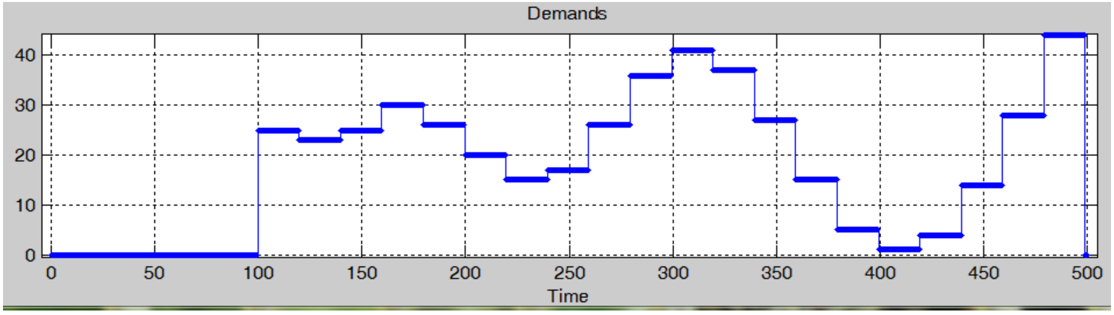

Figure 7.18 Demands in Experiment 2

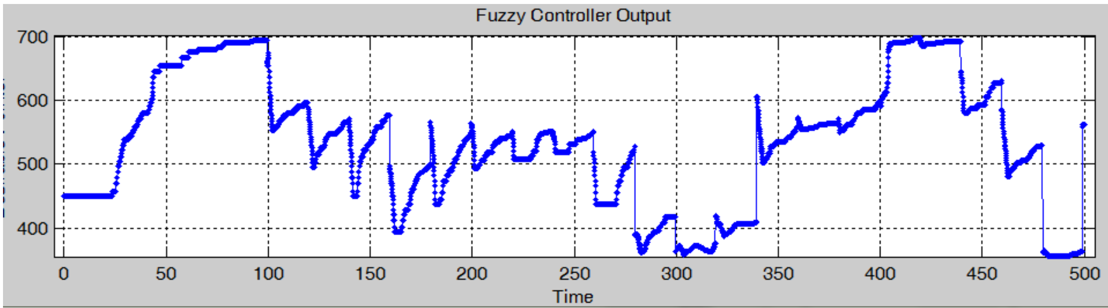

Figure 7.19 Fuzzy controller output in Experiment 2

From Figure 7.19, it can be seen that the fuzzy controller output is increased uniformity variations, similar to the demand. It ranges from 360 to 700. When the demand is low, the indicator is high, and when the demand increases, the indicator decreases correspondingly. This result pattern is quite reasonable. The indicator changes along with the demand to keep the inventory at a proper level. If the simulation time grows, the pattern of indicators' distribution can be seen clearly.

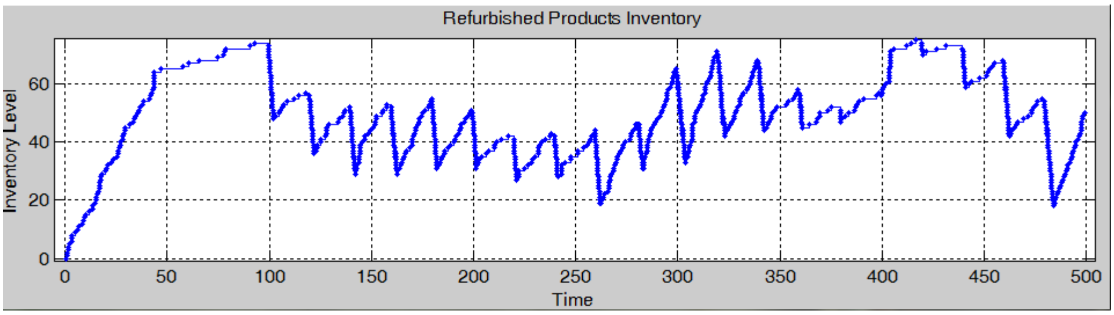

Figure 7.20 Refurbished products inventory in Experiment 2

From Figure 7.20, it can be observed that the inventory of refurbished products is still maintained at a proper level. This time, it lies from 19 to 69. The average number is 45. The results show that this controller can still keep the inventory at a stable level even when demand changes non-uniformly.

7.5.3 Simulation Experiment with Decreasing Demands

In this experiment, the demands were set to decrease in uniformity variations, which can be seen in Figure 7.21. The range of demand lies from 0 to 40. After simulation, the outputs are shown in Figure 7.22 and Figure 7.23. Figure 7.22 shows the indicators from the fuzzy controller. Figure 7.23 shows the refurbished products' inventory.

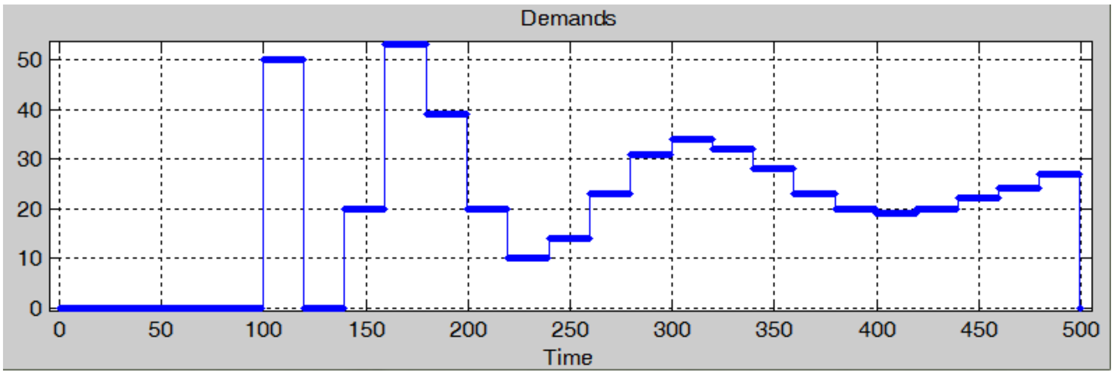

Figure 7.21 Demands in Experiment 3

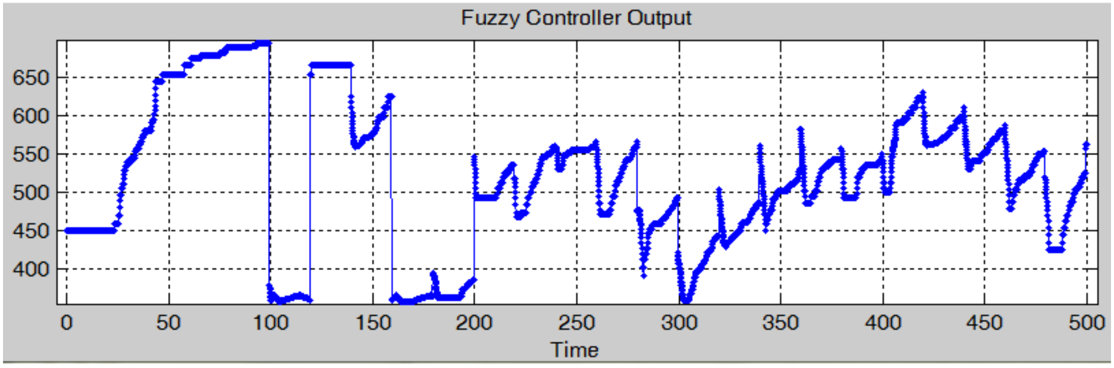

Figure 7.22 Fuzzy controller output in Experiment 3

From Figure 7.22, it can be seen that the fuzzy controller output is decreased uniformity variations, similar to the demand. This time, it ranges from 350 to 700. When the demand is low, the indicator is high, and when the demand increases, the indicator decreases correspondingly. This result pattern is quite reasonable. The indicator changes along with the demand to keep the inventory at a proper level. This time, the indicator changes frequently.

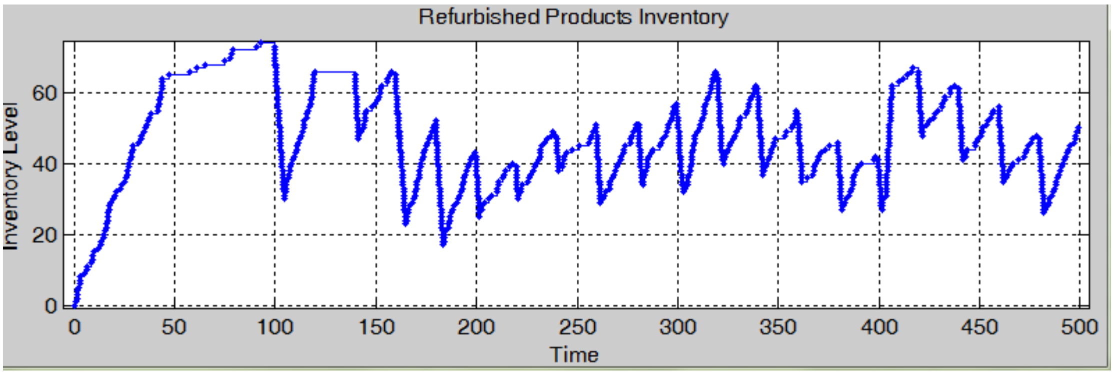

Figure 7.23 Refurbished products inventory in Experiment 3

From Figure 7.23, it can be analyzed that the inventory of refurbished products is still maintained at a proper level. This time, it lies from 18 to 68. The average number is 44. The results show that this controller can still keep the inventory at a stable level even when demand changes non-uniformly. Because the demand changes frequently and the indicator also changes frequently to keep the inventory in a stable state, the proper and stable level of inventory leads to a substantial reduction of inventory costs.

7.6 Summary

Due to environmental issues, product recovery became an emerging research point in closed-loop supply chain. In the practice, more and more companies pay attention to this issue, and tend to seek effective decision support system to management the process of product recovery efficiently. Uncertainties in the process of product recovery, especially the process of returned products collection, became a difficult and unavoidable problem.

This chapter focused on the uncertainties in the process of product recovery. In this research, three sources of uncertainty are considered. One is the uncertainty in the demand of end customers. One is the uncertainty in the quantity of returned products. And the other is the uncertainty of the returned products quality. To deal with these uncertainties simultaneously, a two-layer value indicated fuzzy controller has been established. This proposed method further enhance the ability of fuzzy controller dealing with both quality uncertainty and quantity uncertainty at the same time.

To test the effective of the proposed fuzzy controller, a simulation system was developed and implemented. The results demonstrate the efficiency of the developed two-layer fuzzy controller in dealing with more complicate uncertainty problems. This developed simulation system also provides decision supports for the collection planning of end of life products, which make the activity of returned products recovery more profitable.

Chapter 8 Conclusions and Suggestions for Future Research

8.1. Overall Conclusions

Product recovery in closed-loop supply chain becomes more and more significant due to growing environmental issues nowadays. In the literature, many researchers focus on this area. This research studies product recovery within CLSC in two main aspects. One is the CLSC network optimization considering product recovery. The other one is decision-making in product refurbishment process within CLSC network.

For the aspect of CLSC network optimization, this research firstly described a six-level CLSC model. For the small scale of this model, it can be solved by Lingo. However, when the complexity of this model grows with increase of scale, to a larger one, Lingo cannot solve it within an acceptable period of time. A two-stage GA was developed to improve the solution of this kind of CLSC model. It helps in the research for implementing GA more efficiently on the optimization of CLSC problem. Three computational experiments were implemented to prove the effectiveness of the proposed two-stage GA.

Secondly, although many researchers discuss CLSC models in this research area, few of the models analyze the delivery activity for different kinds of materials textracted from end of life products, and also few studies classify the collected end of life products according to the quality. In this research, an eight stage CLSC model was developed to classify the collected end of life products according to their quality, and analyze the delivery activity for different materials. Moreover, a modified two-stage priority-based encoding GA was proposed to optimize the eight stage CLSC network. Computational experiments proved the reliable performance of the proposed method.

For the aspect of decision-making in product refurbishment process, although it is an important topic in CLSC, few research focus on this problem in the literature, and few papers deal with the uncertainties in product recovery. This research fills the research gap in this field. Academically, this research developed a mathematical model describing the process of returned products' refurbishment in multi-period. It also considered the uncertainties in both quality and quantity. As for the methodology, this research developed a fuzzy controller integrating with a value indicator, this proposed value indicated fuzzy controller can solve the multi-period uncertainty problem in an effective way. The value indicator enhanced the ability of fuzzy controller to deal with uncertainties regarding both quantity and quality. To prove the effectiveness of the proposed value indicated fuzzy controller, a simulation system was implemented.

Since the quality uncertainty of end of life products lies in the uncertainty of each components quality, to make a more accurate decision support for end of life products' collection, a two-layer fuzzy controller was established. This two-layer fuzzy controller analyzed the quality uncertainty in the component level and deal with the quantity uncertainty in the product level. This proposed two-layer fuzzy controller enhanced the ability to deal with uncertainties on both quality and quantity simultaneously. Several simulation scenarios were implemented to prove the efficiency of the proposed method.

Upon the completion of this research, the major findings and their impacts in the theoretical and experimental study can be summarized as follows. In this research, an eight-level closed-loop supply chain model has been established, which fill the research gap in closed-loop supply chain models considering various quality of returned products, especially for electronic products. A two-stage encoding Genetic Algorithm was developed to solve the NP-hard problem in the proposed model. This two-stage encoding approach reinforced the genetic searching ability to tackle NP-hard problems in closed-loop supply chain. To further inspect in product recovery problems within closed-loop supply chain, a decision model structuring and optimizing the process of product refurbishment, while considering inventories and uncertainties with multi-period was established. This model filled the research gap in the research field of product recovery, considering uncertainties of demand, returned products quality and returned products quantity simultaneously. To analyze the considered uncertainties, a fuzzy controller embedded with a quality indicator was developed. The quality indicator enhanced the ability of the proposed fuzzy controller to deal with uncertainties regarding both quantity and quality. To further improve the effectiveness of the proposed fuzzy controller, a two-layer fuzzy controller was developed. The implemented simulation system proved the efficiency of the proposed two-layer fuzzy controller.

Academically, this research established a model focused on product recovery in closed-loop supply chain, providing the foundation of academic research in product recovery process. The developed two-stage encoding Genetic Algorithm and two-layer fuzzy controller also proved as effective approaches in solving corresponding problems within closed-loop supply chain. Practically, the proposed model and simulation system in this research provided useful decision supports and profitable analysis to related companies.

8.2 Limitations and Suggestions for Future Work

In the current eight stage CLSC model, only one type of returned products were considered, and the return rate was settled. In real situations, the product flow in a CLSC network contains different kinds of products and the return rate is uncertain. Hence for future research of the eight stage CLSC model, three main further research directions need to be studied. Firstly, multi-products can be considered. Secondly, the return rate in the eight stage CLSC model can be set as variable, which means that the interaction between demand and return, and the uncertainty of returns can be considered. Additionally, during different product life cycles, the relationship between customer demand and returned products is diverse, so several scenarios of different life cycles also need to be considered.

For the decision making model of product recovery in CLSC, it currently focused on the process of returned products refurbishment. In the process of returned products collection, the trade-in price was preset. In the process of returned products refurbishment, the inventory capacity were set to be infinity. And the recovered product may affect the brand new product's market and the manufacturer's profit in practical. In future research, four aspects need to be improved. Firstly, the market relationship between the recovered product and the brand new product should be considered, and the impact on the manufacturer's profit of the recovered product should be analyzed. Secondly, the model should consider other product recovery process besides product refurbishment, such as returned product repair, returned product resell and returned product recycling. Thirdly, the inventory capacity should be considered in the process of returned product refurbishment. Finally, in the process of returned product collection, the relationship between trade-in price and the demand of returned products should be analyzed. The analysis of this relationship will provide valuable information for the market of returned product collection.

To implement this research model of product recovery in the practical, one of the most important additional resources is the data collection and record system for returned products. In the proposed research model of product recovery, one of the significant processes is to classify the returned products according to their quality. And the quality status of each component within returned products should be recorded for the purpose of calculation and decision making in later. Hence an information system for data collection and record is needed in practical implementation, in which, technology based on RFID may play an important role on this issue. Therefore, it's an interesting research direction for the practical research in future.

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