MODELING GREEN LOGISTICS ACTIVITIES FOR SUSTAINABLE DEVELOPMENT USING SWARM INTELLIGENCE

ZHANG SHUZHU

Ph.D

The Hong Kong Polytechnic University

2017

The Hong Kong Polytechnic University

Department of Industrial and Systems Engineering

Modeling Green Logistics Activities for Sustainable Development Using Swarm Intelligence

ZHANG Shuzhu

A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

May 2016

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

____________________________ (Signed)

_____Zhang Shuzhu__________ (Name of student)

Abstract

Global warming, environment deterioration and government regulation arouse the awareness of academic researchers and industrial practitioners to consider green strategies in logistics industry, which prompts the research of green logistics. Green logistics involves a number of activities which are operated for the purpose of sustainable development. The performance of green logistics cannot be measured simply in an economic way, but in a more comprehensive and sustainable way by taking account of environmental and social considerations as well. In order to facilitate the development of green logistics, the activities of green logistics shall be analyzed and modeled by incorporating the latest environmental and social requirements. Most of the activities in green logistics can be modelled as combinatorial optimization problems with single or multiple objectives, constraints and decision variables. Exact algorithms are less popular to solve these combinatorial optimization problems due to their high complexity and large scale. In this research, swarm intelligence is employed to solve the combinatorial optimization problems derived from green logistics. The integration of green logistics and swarm intelligence is pioneering, which helps to solve the green logistics problems efficiently and broaden the application scope of swarm intelligence simultaneously.

Two typical activities, i.e., vehicle scheduling and network design, are chosen to exemplify the modeling of green logistics activities and the application of swarm intelligence. The first activity is to propose an environmental vehicle routing model, which measures the carbon dioxide emission in addition to the economic cost along with the vehicle travelling. The second activity is to design a supply chain network with multiple distribution channels, which meets the development requirements of e-commerce. Swarm intelligence is employed to solve both problems by integrating with other programming skills. The results show that the modeling of green logistics activities are practicable and necessary, and swarm intelligence is capable and competitive to solve green logistics problems.

The contribution of this research is the modeling of green logistics activities by integrating the concept of sustainable development and the design of swarm intelligence into solving combinatorial optimization problems. Both the activity modeling and algorithm design can provide useful insights and guidance for the interdisciplinary research of green logistics and swarm intelligence. Moreover, a unified swarm intelligence algorithm framework is proposed in consideration of the common procedures and operators from different swarm intelligence algorithms and a number of strategies are provided as well for the implementation of this unified algorithm framework.

Publications Arising from the Thesis

Journal papers

1. S.Z. Zhang, C.K.M. Lee, K. Wu and K.L. Choy, (2016), *Multi-objective optimization for sustainable supply chain network design considering multiple distribution channels*, Vol. 65, PP. 87-99.
2. S.Z. Zhang, C.K.M. Lee, K.M. Yu and H. Lau (2015), *Design and development of a unified algorithm framework towards swarm intelligence*, Artificial Intelligence Review, PP. 1-25
3. L. Zhang, C.K.M. Lee and S.Z. Zhang (2016), *An Integrated Model for Strategic Supply Chain Design: Formulation and ABC-based Solution Approach*, Expert Systems With Applications, Vol. 52, PP. 39-49
4. S.Z. Zhang, C.K.M. Lee, H.K. Chan, K.L. Choy and Zhang Wu (2014), *Swarm intelligence applied in green logistics: A literature review*, Engineering Applications of Artificial Intelligence, Vol. 37, PP. 154-169
5. S.Z. Zhang, C.K.M. Lee, K.L. Choy, William Ho and W.H. Ip (2014), *Design and development of a hybrid artificial bee colony algorithm for the environmental vehicle routing problem*, Transportation Research Part D: Transport and Environment, Vol. 31, PP. 85-99

Conference papers

1. S.Z. Zhang and C.K.M. Lee, "*Flexible Vehicle Scheduling for Urban Last Mile Logistics: the Emerging Technology of Shared Reception Box*", 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM 2016), Bali, Indonesia
2. C.K.M. Lee* and S.Z. Zhang, "*Development of an Industrial Internet of Things Suite for Smart Factory towards Re-industrialization in Hong Kong*", 6th International Workshop of Advanced Manufacturing and Automation (IWAMA 2016), Manchester, UK
3. S.Z. Zhang and C.K.M. Lee, "*An Improved Artificial Bee Colony Algorithm for the Capacitated Vehicle Routing Problem*", IEEE International Conference on Systems, Man, and Cybernetics (SMC, 2015), Hong Kong, China
4. S.Z. Zhang and C.K.M. Lee, "*Optimization of facility location problem in reverse logistics network using Artificial Bee Colony algorithm*", IEEE International Conference on Industrial Engineering and Engineering Management (IEEM, 2013), Bangkok, Thailand

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Dr. Carman Lee, for her careful examination and valuable suggestions for this research. More importantly, Dr. Carman Lee's great patience and warm encouragement accompany me through the whole period of my study and research. I do appreciate the great opportunity to conduct my research under the supervision of Dr. Carman Lee.

I would like to thank my family. My parents' understanding and support help me to purchase my dream. My wife, Shirly, completes my life with her beautiful love. Special thanks go to my little girl, Effie, who came to the world in September, 2015. Her birth brings great happiness and vitality to our family.

The financial assistance provided by the Research Committee and the Department of Industrial and Systems Engineering of the Hong Kong Polytechnic University is greatly appreciated. Moreover, I would like to thank all my friends and colleges for our great friendship.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

3PL	Third Party Logistics
4PL	Fourth Party Logistics
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
B&B	Branch and Bound
COP	Combinatorial Optimization Problem
CSR	Corporate Social Responsibility
CVRP	Capacitated Vehicle Routing Problem
DC	Distribution Center
ECA	Evolutionary Computational Algorithm
EVRP	Environmental Vehicle Routing Problem
FLP	Facility Location Problem
GL	Green Logistics
GRASP	Greedy Randomized Adaptive Search Procedure
HABC	Hybrid Artificial Bee Colony
I&D	Intensification and Diversification
ILS	Iterative Local Search
LP	Linear Programming
MDCSCN	Multiple Distribution Channel Supply Chain Network
MILP	Mixed Integer Linear Programming

MOABC	Multi-Objective Artificial Bee Colony
MOGA	Multi-Objective Genetic Algorithm
PSO	Particle Swarm Optimization
RL	Reverse Logistics
SCN	Supply Chain Network
SD	Sustainable Development
SI	Swarm Intelligence
TS	Tabu Search
TSP	Travelling Salesman Problem
ULML	Urban Last Mile Logistics
VRP	Vehicle Routing Problem

Chapter 1 Introduction

In this chapter, the background of the research is introduced, and the challenges and importance of green logistics are illustrated. Green logistics is a relatively new and booming research direction, as an increasing number of people are now aware of green issues, such as environmental protection, resource and energy conservation and social responsibility, leading to new requirements of sustainable development. With respect to this developmental trend, new problems, such as the environmental vehicle scheduling and the remanufacturing problem, arise as well. Traditional approaches are less popular or inadequate in overcoming the new problems. Therefore, we need to re-analyze the problem context and propose new models, with new objectives, in view of the new emerging features. Correspondingly, new approaches, inspired from swarm intelligence, are designed and developed in order to solve the new problems. The effectiveness and efficiency of the swarm intelligence methodology is examined and evaluated in comparison with other methods. This research contributes to the theoretical development of green logistics and swarm intelligence, and pioneers the application of swarm intelligence to green logistics.

1.1 Research Background

Global warming, environment deterioration, government regulation and green consumption have aroused the awareness of academic researchers and industrial practitioners to consider the "green" strategies in the logistics industry, prompting research in Green Logistics (GL) (Murphy 2000). GL concerns not only the provision of green products or services to customers, but also the overall logistics flow of products and services from the cradle to grave. The implementation of green logistics requires not only efforts from individual logistics enterprises, but also the inter-organizational cooperation (Zhou, Cheng et al. 2000). GL involves a number of activities which can be operated for the "green" purpose, such as redesigning the supply chain network to optimize the location of warehouses and the allocation of customers to reduce the economic and environmental cost, and rescheduling the routes for transportation vehicles to reduce the energy resources and lower the carbon footprint of products. GL can be understood as the combination of traditional logistics and Reverse Logistics (RL). Traditional logistics comprises the flow from the raw materials to finished products, while RL is a rather new research field, which involves the concept of recycling used products in order to reduce waste and to increase industry's environmental performance and the resulting profits.

The performance of GL cannot be measured simply in an economic way, but in a sustainable way, taking account of environmental and social considerations as well, which are also the objectives of GL (Linton, Klassen et al. 2007). The economic measurement, environmental influence and social consideration are known as the triple bottom line for sustainable development (Carter and Rogers 2008). The economic measurement is commonly interpreted as either minimizing costs or maximizing profits. The environmental influence is measured in different ways. For example, data on the carbon footprint of a product can be collected from the perspective of product life cycle to illustrate how environmentally friendly this product is. The amount of energy consumption in an activity can represent its environmental efficiency. The collection of used products can help to reduce the environmental waste and utilize the remaining value of used products. Social consideration is another indispensable component for sustainable development, which involves customer satisfaction, corporate social responsibility and so on.

Most of the activities in GL can be treated as combinatorial optimization problems with single or multiple objectives, constraints and decision variables. Exact methods, such as Linear Programming (LP) and Branch-and-Bound (B&B), are not good at solving combinatorial optimization problems, as they are either unable to solve complicated combinatorial optimization problems with large number of variables or a long computational time is needed to find solutions for combinatorial optimization problems (Laporte 1992). In contrast, meta-heuristic approaches are becoming increasingly popular as these approaches are approximate approaches, which suggest that they aim to find satisfactory solutions within acceptable time instead of finding the optimal solution.

Intuitively speaking, meta-heuristic approaches can be classified into two categories: the single-solution based approach and the population based approach (Blum and Roli 2003). The single-solution based approach, also named the trajectory approach (Consoli and Darby 2007), such as Tabu Search (TS), Simulated Annealing (SA) and various local search methods, in which only one candidate solution exists during the whole search process. In contrast, the population based approach indicates that the search process starts with a population of candidate choices, and further evolves the whole population. The advantages and disadvantages of both single-solution based approach and population based approach can be found in the literature (Jones, Mirrazavi et al. 2002). Moreover, two important branches of the population based approach are Evolutionary Computational Algorithms (ECAs) and Swarm Intelligence (SI). The most typical example of ECAs is the Genetic Algorithm (GA), which was proposed by Holland (1975) and simulates the Darwin evolution concepts in which the populations with better fitness would survive. However, SI was initially inspired by the collective behavior of natural species, such as ants foraging, birds gathering, fish schooling and bees swarming (Beni and Wang 1993).

From the methodological perspective, SI is a relatively new branch of meta-heuristics, which uses approximate strategies to explore and exploit the search spaces of optimization problems effectively and efficiently, in order to find optimal or near-optimal solutions (Blum and Merkle 2008). SI has three fundamental and essential properties, namely decentralization, self-organization and collective behavior, which are necessary and sufficient to acquire SI behavior (Bonabeau, Dorigo et al. 1999). Decentralization means that no central control mechanism exists, and the behavior of individuals is self-determined. The self-organization of individuals relies upon four fundamental properties, i.e. positive feedback, negative feedback, fluctuations, and multiple interactions. The interaction between two individuals or the individual and the environment follows simple rules, and the result from an interaction would either impel or restrain the behavior of a certain individual as positive feedback or negative feedback respectively. The decision of a certain individual might be affected by random factors in addition to the result of interaction, which leads to fluctuations. Interaction occurs whenever a certain individual needs to make a decision. Collective behavior refers to a swarm, in which the individual behavior may be random. However the aggregation of individual behavior turns out to be globally intelligent.

In this research, SI is employed with the aim of to solving the combinatorial optimization problems derived from GL. The combination of GL and SI has promising research potential, which helps in solving the combinatorial optimization problems efficiently and broadens the application scope of SI simultaneously. The outcome of applying SI for GL varies case by case, as each

SI algorithm and GL problem has unique features. Therefore, modification is necessary for the successful application of SI in the green logistics domain, especially by exploiting the valuable information from the problem context.

1.2 Research Problem

Traditional logistics are facing new challenges due to global warming, environmental deterioration, energy and resouce consumption, among others. Governmental regulations and customer awareness have forced related enterprises to adopt environmental-friendly activities for the purpose of sustainable development. More importantly, enterprises would like to employ environmental-friendly activities, which can help to increase their competitive strength by maintaining a good public image and attracting more customers. The initial objectives of logistics are mainly derived from the economic considerations in terms of either cost minimization or profit maximization. However, sustainable development becomes the major concerns of most enteperises. A number of problems arise as well. For example, how do the enteriprises get the balance among economic, envionrmal and social objectives from the strategic level such as network design to operational level such as vehicle scheduling? In which context will the latest optimization techniques help to solve the optimization problem for green logistics? How do researchers design optimizaton techniques to fit the current logistics challenges faced by enterprises which intend to implement green logistics?

Green logistics is of great importance as it benefits both the enterprises and customers. The literature covers the management of green logistics, however, most of them are from the standpoint of strategic management, rather than the operational level applications. Given the fact that strategic management needs support from the operational level activities and the literature of operational level green logistics activities is either rare or individually independent, it is necessary to summarize the exisitng literature and synthesize the studies so as to conduct research in this area. Meanwhile, the incorporation of sustainable development into logistics is also at the pilot stage due to the fact that the definition and requirements of sustainability is not definite. The economic, environmental and social dimensions are acknlowdeged as the triple core components for sustainable development. However, their corresponding implementations vary case by case, especially environmental measurement and social consideration. Under these circumstances, it is also necessary to investigate the implementation of sustainable development in the existing literatures.

The models of green logistics activities turn out to be more complicated than ever before as new factors and/or objectives emerge, such as environmental constraints and social requirements, which requires more effective and efficient approaches. Swam intelligence, a new type of meta-heuristics, has become popular, attributed to its research potential of robust architecture and easy implementation. The application of swarm intelligence to numerical optimization problems has gain great success, however, its application to industrial problems is still at a preliminary stage. Therefore, an appropriate combination of swarm intelligence and green logistics can be a fruitful research area, involving the green logistics activities and expanding the application horizon of swarm intelligence.

The contents of this research comprise three major aspects, i.e., green logistics, sustainable development and swarm intelligence. The requirements of sustainable development drive the research and initiatives in logistics, in which the conventional activities are facing new challenges from environmental and social requirements in addition to the economic considerations. In other words, the transition from conventional logistics to green logistics is driven by the sustainable development. Swarm intelligence, as a new and promising branch of meta-heuristics, is employed to solve the combinatorial optimization problems derived from green logistics activities.

Therefore, this research is conducted by analyzing, modeling and solving green logistics activities. New models of green logistics activities are inspired by sustainable objectives and/or sustainable constraints. Moreover, in order to solve the green logistics problems, swarm intelligence is employed as the major approach. To be more specific, two typical activities of green logistics, i.e., environmental vehicle scheduling and supply chain network design with multiple distribution channels, are studied and solved using artificial bee colony algorithm.

1.3 Research Objective

Aiming at achieving the integration of green logistics and swarm intelligence, the following objectives need to be accomplished, in sequence.

The first objective is to investigate and analyze the current research status concerning green logistics, and further to propose the classification scheme of green logistics for better understanding the latest issues and contexts. Thereafter, the major green logistics activities can be identified.

The second objective is to investigate and analyze the application of swarm intelligence for solving logistics activities. Proper algorithm design is critical for specific problem considering the features derived from the problem context.

The third objective is to analyze and model the green logistics activities by taking into consideration the latest sustainable requirements. This objective covers the following sub-objectives.

(1) To identify and formulate the environmental and social factors

(2) To propose new models with sustainable objectives and constraints.

(3) To design proper swarm intelligence algorithms.

(4) To conduct experiments to examine and validate the effectiveness and efficiency of new models and algorithms.

1.4 Research Methodology

In this research swarm intelligence is employed as the major approach to solve the green logistics problems. Logistics activities are commonly modeled as combinatorial optimization problems. By incorporating environmental and social factors, the green logistics problems become even more complicated. Therefore, meta-heuristic algorithms are chosen instead of exact algorithms. Swarm intelligence is a relatively new branch of meta-heuristics in contrast to the ECAs, which becomes a popular approach due to its inherent features, such as decentralization and collective intelligence.

Swarm intelligence also covers a number of specific algorithms, such as ant colony optimization (ACO), particle swarm optimization (PSO), and artificial bee colony (ABC) algorithm. In this research, ABC algorithm is employed to solve the green logistics problems. In addition to the two inherent features of swarm intelligence, ABC algorithm possesses another unique feature, which is labor division. During the solving procedures, ABC algorithm is further revised and improved considering the problem features. The performance of ABC algorithm is further validated by comparing with ECAs, and the results show that the application of ABC algorithm is successful and ABC algorithm is a competitive choice.

1.5 Significance of the Research

Green logistics is becoming a popular topic because of environmental deterioration and energy consumption. More and more researchers and practitioners are devoting efforts in this research. However, our investigation suggests that most of the studies are from the strategic management perspective, by incorporating the concept of sustainable development as a new strategy. In the tactical and operational level, the implementation of green logistics involves the modeling and solving of operational level activities. However, such research is either rare or individually independent. Therefore, an extensive and comprehensive literature review concerning the fundamental research of green logistics is necessary in order to understand the current research status, and it is crucial to identify the research gaps, critical issues and research opportunities.

The employment of swarm intelligence for solving green logistics activities is a pilot study. Swarm intelligence is a relatively new type of meta-heuristics approach. Even though swarm intelligence has been successfully employed to solve numerical optimization problems with competitive performance, the theoretical model and application to practical industrial problems still needs further examination and validation. In this research, two examples of applying swarm intelligence to green logistics are introduced. These two examples illustrate the modeling of green logistics activities by considering sustainable development and the application of swarm intelligence to green logistics.

A unified SI algorithm framework is introduced through an in-depth analysis of typical examples of SI algorithms. The common procedures and operations of SI algorithms, such as the initialization mechanism, the neighborhood search, and the stopping criteria, are studied first. Then the common procedures and operations are reorganized and standardized to construct the base for the unified SI algorithm framework. The possible strategies acquired from the various procedures and operations are also explicitly enumerated and further analyzed. Such a unified SI algorithm framework not only can assist the understanding of the common features of SI, but also provides a straightforward support for the implementation and improvement of SI algorithms. Moreover, this unified SI algorithm framework can provide valuable research implications for algorithms related to SI.

1.6 Organization of the Research

After the introduction in Chapter 1, the rest of the thesis is organized as follows.

Chapter 2 gives a comprehensive and extensive literature review of the integration of green logistics and swarm intelligence from both the problem context and methodology perspective. The state-of-the-art applications of swarm intelligence approaches to the domain of green logistics are fully investigated and analyzed, helping scholars to obtain an intuitive and profound understanding of the latest research situations.

Chapter 3 presents the research framework and research methodology. The research framework summarizes the major contents explicitly, while the research methodology is explained and analyzed in depth. A unified swarm intelligence algorithm framework is proposed in this chapter, which helps the implementation and improvement of the swarm intelligence algorithms.

Chapter 4 is a pilot study for solving vehicle routing problems using hybrid artificial bee colony algorithm, considering the environmental influence of the logistics activity. Both economic performance and environmental performance measurement are used in the environmental vehicle routing problem and the transformation from the capacitated vehicle routing problem to the environmental vehicle routing problem can provide practical insights for logistics managers for decision making.

Chapter 5 pioneers the application of swarm intelligence to network design problems. A new strategic design of the supply chain network with multiple distribution channels is proposed. Economic cost, customer satisfaction and environmental influence are measured in this network simultaneously. A multi-objective artificial bee colony algorithm in designed for solving the model of the supply chain network with multi-distribution channels.

Chapter 6 discusses the potential issues when modeling the green logistics activities and the application of swarm intelligence. The algorithm balance is further discussed by taking account the intensification and diversification effect.

Chapter 7 concludes this thesis by recapitulating the major content and findings. The limitations are explained as well, and future work is suggested aiming to overcome the limitations and promote the further development of green logistics, sustainable development and swarm intelligence.

Chapter 2 Literature Review

In this chapter, an extensive literature review is conducted in accordance with this research. The problem context is the green logistics, which covers a variety of research topics from different perspectives. An increasing number of academic researchers and industrial practitioners become interested into the green logistics. The green logistics is gradually embodied towards sustainable development. The concept of sustainable development has been introduced years ago as well. However, the integration of sustainable development and green logistics is still at the pilot stage, which leads to a promising research area. Concerning the approach to tackle the new problems in this area, swarm intelligence is employed herein. In comparison with the evolutionary computational algorithms, Swarm intelligence is a relatively new branch of the meta-heuristic algorithms, which simulates the intelligent behavior of social animals or insects. The development and application of SI is becoming popular due to its unique features and research potential. The literature of green logistics, sustainable development and swarm intelligence are reviewed individually and cooperatively.

2.1 Introduction

The objective of literature review is to identify major works on interdisciplinary research in GL, SD and SI, and thereafter, to classify and integrate them so as to discover gaps, critical issues and opportunities for further study and research. The literature review is a valid approach and necessary step in exploring new research directions and forms an integral part of the related research, which also helps to scrutinize the conceptual aspects and guides the research toward new theoretical development (Meredith 1993; Seuring and Müller 2008). The literature review is conducted for content analysis, where quantitative and qualitative aspects are reviewed to assess the context as well as the content (Brewerton and Millward 2001). The process of this literature review follows a four-step process model proposed by Mayring (2004), i.e., material collection, descriptive analysis, category selection, and material evaluation, as described in Figure 2.1, and the review process is carried out accordingly. With the inherent nature of research related to GL, SD and SI, the targeted publications should mostly comprise operational activities, e.g. transportation problems, network design problems, production scheduling problem, etc. with the aim of improving the SD of GL through SI approaches.

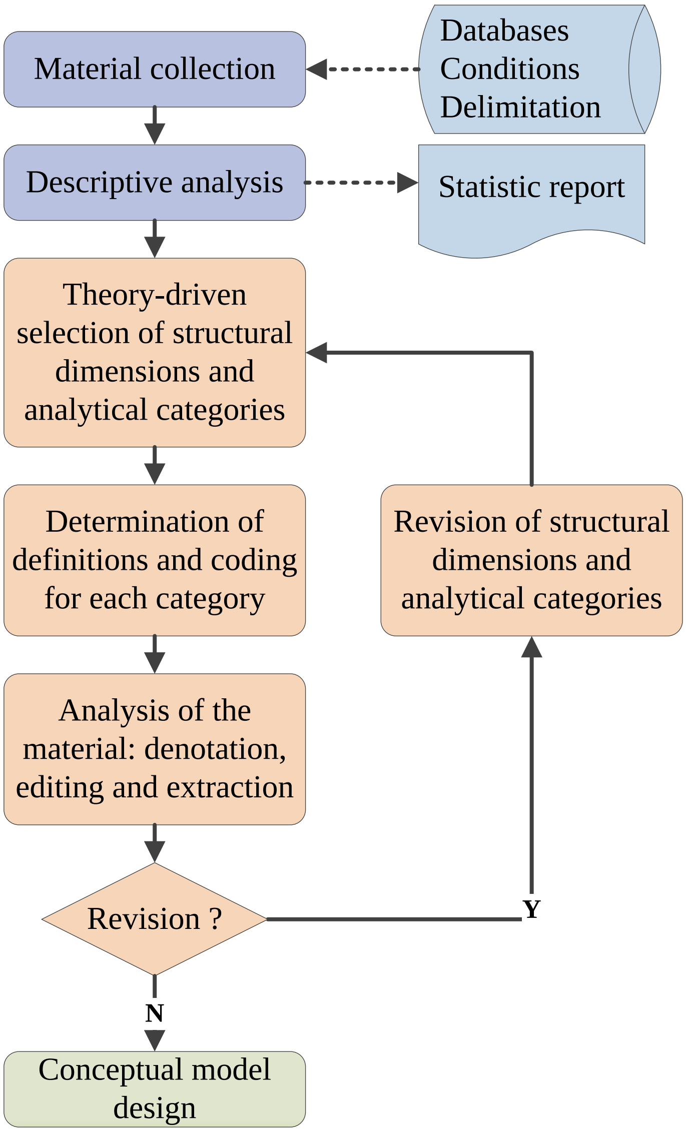


Figure 2.1 The flowchart of literature review

With this consideration, the following databases were selected for a comprehensive and extensive review of this interdisciplinary research: IEEE/IEE Electronic Library via IEEE Xplore, ScienceDirect by Elsevier, Scopus, and SpingerLink. In addition to those databases, Google Scholar was also used to complement the related publications search. The publications search was firstly conducted in terms of a structured combination of related keywords. Any “logistics” or “supply chain” related problems involving the concept of “green” or “environmental” or “sustainable” or “closed-loop” or “reverse”, and solved through the SI approaches were covered. After a first quick check, the qualified publications were acquired through cross-referencing. The delimitation of the publications is listed as follows.

(1) Only publications concerning specific logistics problems are considered.

(2) Only publications involving the adoption of SI approaches are included.

(3) Only peer-reviewed journal papers written in English are considered.

2.2 Green Logistics

The concept of GL was initially introduced to describe all the attempts to measure and minimize the ecological impact of logistics activities (Murphy, Poist et al. 1996), which can be well understood from different perspectives. For instance, from the logistics partionter point of view, GL involves all logistics parties including suppliers, manufacturers, distribution centers and customers. From the standpoint of logistics flows, GL can be viewed as the combination of forward logistics and reverse logistics. The activities and operations in GL associated with one or more members work collaboratively and cooperatively to construct an integrated model with one or more objectives to improve the performance of GL.

2.2.1 Parties in green logistics

All the logistics parties, e.g. supplier, manufacturers, distributors and customers, are involved in GL. The coordination of the GL members can be simply described as a closed loop, as illustrated in Figure 2.2, where the suppliers provide the raw materials to the manufacturers; the manufacturers produce the finished products and transport them to the distributors to distribute the finished products to customers; the customers consume the finished products; after consumption, the used products could be collected from customers and further processed to re-enter the cycle. Each member participates in the GL with its specific role and function.

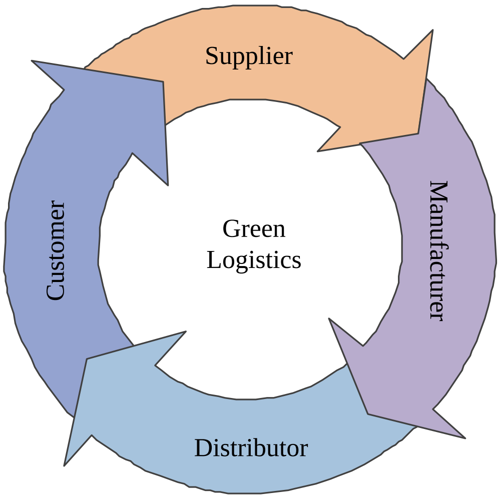


Figure 2.2 The closed loop of green logistics

In traditional logistics, suppliers, acting as the supply of raw materials, components or semi-products, are the very beginning of the logistics flows. However, in GL, in addition to the single purpose of supply, suppliers are expecting to accomplish more functions and undertake more responsibilities. Green supplier management can be roughly categorized as two streams in view of the interrelationship between suppliers and manufacturers. The first category is named as green supplier selection, which is suitable for the scenario of independent operation for suppliers and manufacturers (Humphreys, Wong et al. 2003; Che, Chiang et al. 2010). In this category, the major activities comprise supplier evaluation (Lin 2009), purchasing strategies (Min and Galle 1997), and so on. The second category is called green supplier integration, which differentiates the first category in the degree of cooperation and collaboration between suppliers and manufacturers (Das, Narasimhan et al. 2006; Giannakis

2008). In this category, manufacturers act as the focal company assisting the development of suppliers so as to build a more integrated alliance. Green knowledge transfer, investment transfer and resource transfer are some common practices employed in green supplier integration management (Bai and Sarkis 2010). More literatures regarding the green supplier selection and green supplier integration can be found in review papers (Wagner 2006; Ho, Xu et al. 2010; Genovese, Lenny et al. 2013).

Manufacturers are the core of the traditional logistics, which receive raw materials from upstream and provide finished products to downstream. Manufacturing activities, e.g. job-shop sequencing, flow-shop scheduling, etc. synthesize the operations of machines, resources and labors. Rusinko (2007) evaluated the relationships between specific environmentally sustainable manufacturing practices and specific competitive outcomes in industry. Prakash, Tiwari et al. (2008) resolved the traditional machine loading problem in flexible manufacturing systems in order to minimize the system unbalance and maximize the throughput. In addition to the manufacturing, remanufacturing has become a requisite aspect of manufacturers as well. Guide (2000) reported on managerial remanufacturing practices via a survey of production planning and control activities at remanufacturing firms. Guide and Van (2001) developed a framework for analyzing the profitability of reuse activities and influence from the management of product returns. Moreover, the integration of manufacturing and remanufacturing is also a promising research area (Kiesmüller 2003; Kenné

Dejax et al. 2012).

Inventory management and distribution management are the two main aspects of green activities and operations involved with distribution center. Inventory management covers not only the storage of products, but also the integration of inventory consideration with other activities, such as the inventory forecasting for multi-echelon supply chain (Noorul and Kannan 2006), inventory location problem (Gong, Li et al. 2007), inventory routing problem (Huang and Lin 2010), and inventory pricing problem (Ghasemy, Fatemi et al. 2014). By contrast to the inventory management, which concerns the storage of products, distribution management mainly involves the movement of products, either from the manufacturers to the distribution center or from the distribution center to the customers. Farahani and Elahipanah (2008) presented a bi-objective model to optimize the total cost and service level for just-in-time distribution in the context of supply chain management. Qu, Song et al. (2011) introduced a triangle distribution model based on third-party logistics alliance. The location of the distribution center is another critical issue when designing an efficient supply chain network. Amiri (2006) addressed a distribution network design problem in a supply chain system which involves locating production plants and distribution warehouses. Furthermore, urban last mile logistics is becoming an interesting topic in recent years due to the rapid development of e-commerce and technologies. For example, the emergence of reception box and delivery box alleviates the unattended problem significantly (Kämäräinen, Saranen et al. 2001;

Kamarainen and Punakivi 2004). Lee, Ho et al. (2011) discussed the application of radio frequency identification (RFID) technology in logistics workflows.

Activities involved customers is also one essential part towards the completeness of GL. Customer perception on products and services can influence the structure and operation of the whole supply chain. Boyer, Prud'homme et al. (2009) evaluated the effects of customer density and delivery time window on city logistics. Ehmke and Campbell (2014) introduced several customer acceptance mechanism for home deliveries in metropolitan areas. The studies and practices concerning customers can be more proactive instead of reactive analysis of existing data from customers. For instances, based on the cumulative data of customer purchases, massive and individual customer preferences can be determined. Therefore, more efficient product allocation and customization can be implemented accordingly (Büyüközkan and Çifçi 2013). The return of used products from customers can be motivated by some incentive policies as well (Agarwal, Barari et al. 2012).

2.2.2 Activities in green logistics

The implementation of GL consists of various green activities and operations. In this research, after a comprehensive and extensive literature review, we summarize the major green activities and operations as shown in Figure 2.3.

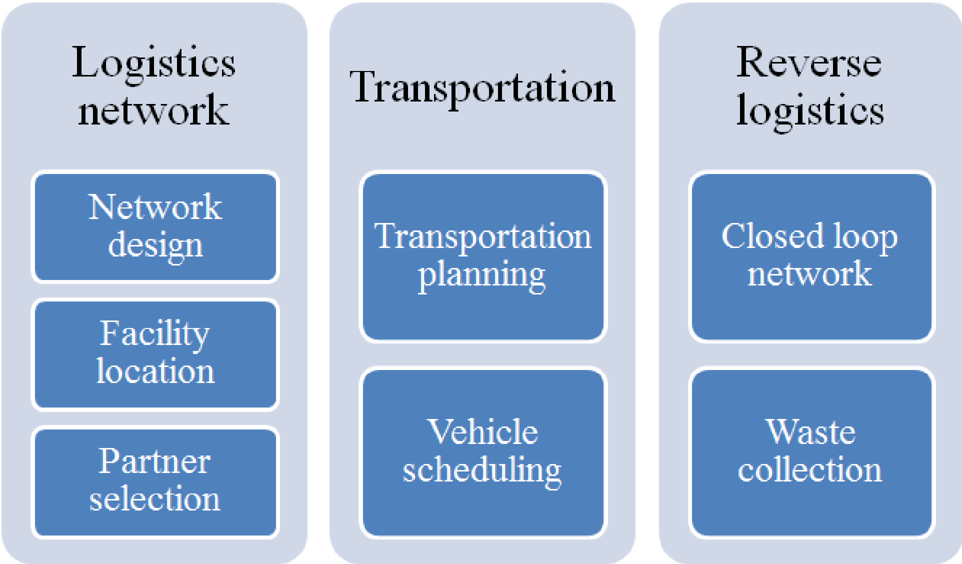


Figure 2.3 The activities of green logistics

Logistics network

The category of network design can be understood as either a singular problem of harmonizing all logistics entities simultaneously or a combination of a variety of sub-problems. The design of logistics networks are mostly processed as multi-echelon or multi-phase, differentiating the upstream, downstream and also reverse logistics, while models are normally proposed as multi-objective optimization problems. For example, Wang (2009) introduced a multi-echelon defective supply chain network design with a two-phase ant colony algorithm, and Pal, Chan et al. (2010) aggregated procurement, production and shipment planning for a three-echelon supply chain design. The performance analysis of existing logistics networks is the fundamental step for further improvement. Referring to the analysis of current logistics networks, the optimization operation can be influenced by numerous factors. Chen and Ju (2013) designed the supply chain network under various disruption scenarios. Che (2009) solved a balanced and defective supply chain problems considering WEEE/RoHS directives. Validi, Bhattacharya et al. (2013) even integrated a low-carbon distribution system into the design of product distribution logistics networks.

The Facility Location Problem (FLP) is another general dimension of the network design category, for either determining the location of new facilities or in selecting proper facilities from current extant (Guillermo, Enrique et al. 2012). Given that the relative location of manufacturers and customers are fixed, we need to select appropriate suppliers and distribution centers in order to meet the demand of production and consumption. Capacitated FLP is most practical category of FLP with regard to the capacity constraints of different facilities (Chen and Ting 2008). FLP is normally processed with another coverage problem, in which not only the open/close status of a facility is determined, but also its served targets.

Partner selection can also be regarded as a type of variants of FLP, in which supplier selection and 3PL service provider selection are two typical examples. In order to construct integrated Green Logistics, not only the core manufacturers need to “green” their process, but also the upstream sourcing, in which environmental factors influence both the supplier selection and procurement strategies (Che, Chiang et al. 2010). 3PL service providers, even the 4PL, play an important role in the sophisticated logistics systems (Efendigil, Önüt et al. 2008). 3PL is a relatively independent entity, which can provide professional service to both customers and vendors. The performance of 3PL also affects the efficiency of the whole logistics system; therefore, the selection of 3PL is crucial to the construction of logistics system (Qu, Song et al. 2011; Rajesh, Pugazhendhi et al. 2011).

Transportation

The category of transportation covers a wide range of activities, which involve the construction of transportation network, transportation planning, the consideration of vehicles and customers, and so on. The construction of transportation network varies in different environments. For example, the utilization of cross-docking facility can facilitate the transportation of products significantly as products are no longer needed to be stored in warehouses or distribution centers. Musa, Arnaout et al. (2010) addressed a cross docking transportation network problem where the products are transferred from suppliers to retailers through the cross docking facilities using ant colony optimization algorithm. Shahin, Fatemi et al. (2014) managed the vehicle routing and scheduling in a network consisting of suppliers, customers and a cross dock. Mohtashami, Tavana et al. (2015) proposed a multi-objective mathematical model to minimize the make-span, transportation cost and the number of truck trips in a supply chain with cross-dock facility. In addition to the facilities in the transportation network, there are some other problems when planning the transportation. For example, Sprenger and Mönch (2012) introduced a large-scale cooperative transportation planning problem, which involves several complementary manufacturers for same customers. Meiyi, Xiang et al. (2015) presented a mathematical model considering the transportation of hazardous materials. Lin, Contreras et al. (2016)

The Vehicle Routing Problem (VRP), derived from the Travelling Salesman Problem (TSP), is the core of modern logistics practices, due to the fact that transportation accounts for the largest proportion of logistics operations. Indeed, the number of VRP publications almost accounts for 50% of the category of network design based on the reviewed literature, which indicates the importance of this category for research and application. The importance of VRP can be categorized as one independent research area. Since the introduction of VRP, numerous VRP variants have been proposed considering the different conditions, application scenarios and practical needs. The top two variants are Capacitated VRP (Mazzeo and Loiseau 2004) and VRP with time windows (Favaretto, Moretti et al. 2007) taking into account the capacity of vehicle and customer requirements. In reverse logistics, VRP with backhauls is an interesting research direction of great importance, which synthesizes the operations of delivery and pickup of used products simultaneously (Gajpal and Abad 2009). Goksal, Karaoglan et al. (2013) further introduces a VRP with simultaneous pickup and delivery. A number of researchers are conducting research in this area, a more comprehensive and extensive reviews of VRP can be found in literature (Bochtis and Sørensen 2010; Lin, Choy et al. 2013).

VRP has acquired great attention ever since its introduction due to its significance and importance. Numerous academic researchers attempted to solve VRP using different approaches. Lenstra and Kan (1981) firstly identified VRP as NP-hard problem and claimed that exact approach was only feasible for small instances. Toth and Vigo (2002) further identified that the instance with 50 nodes was still possible to be solve by exact solutions, whereas larger instances could be solved using approximate approaches. With this consideration, Bullnheimer, Hartl et al. (1999) employed ACO algorithm to solve VRP, while Baker and Ayechew (2003) adapted GA for solving VRP. More approximate heuristic approaches can be found in the literature (Nag, Golden et al. 1988; Fisher 1995; Toth and Vigo 2002; Blum and Roli 2003).

Reverse Logistics

The introduction of RL complements the integrity of GL (Lee and Lam 2012). The collection, recycling and disposal of the used products are the typical activities of reverse logistics as shown in Figure 2.4. Depending on the results of inspection, the returned products could be directly reused by customers, repaired in distribution center, remanufactured by manufacturer or recycled by suppliers to fully utilize their remaining values (Fleischmann, Bloemhof et al. 1997; Rogers and Ronald 2001).

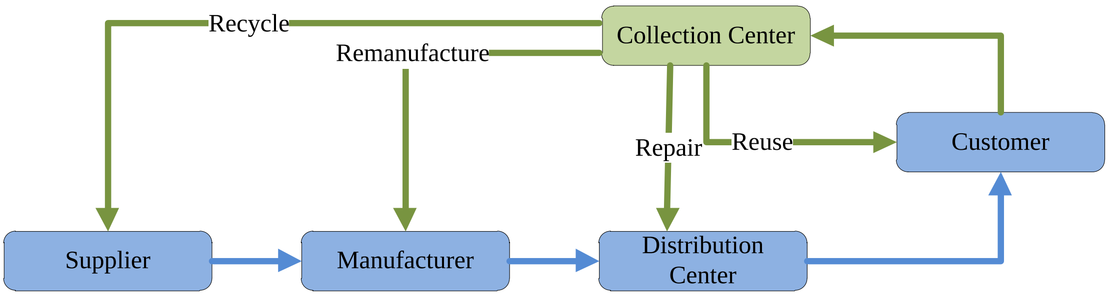


Figure 2.4 The activities of reverse logistics

Comparatively, reverse logistics is one of the important aspect of contemporary logistics , which concerns the flow of products from the point of consumption to the point of origin (Zhang and Guo 2014). The moves of reverse logistics normally consist of collection, inspection, separation, pre-processing and final disposal of used products, while the main operations of used products can be direct reuse; repair; refurbish; recycle or landfill. Due to the unique features of reverse logistics, the comparison between reverse logistics and forward logistics, together with identifying the differences and similarities, always attract researchers' attention (Marsillac 2008). Reverse logistics could be either an independent research field or a complemented research aspect to forward logistics contributing to the construction of an integrated logistics network (Marsillac 2008). For instance, Ko and Evans (2007) introduced a dynamic integrated forward/reverse logistics network model considering 3PLs. Easwaran and Üster (2010) proposed a closed loop supply chain network design model with an integrated forward and reverse channel decisions. Pishvaee, Farahani et al. (2010) also raised a bi-objective integrated forward/reverse logistics network design model. Apparently, the integration of reverse logistics with forward logistics is more popular than studying reverse logistics alone.

Apart from the process of used products in reverse logistics, waste management is another important aspect. Waste management is a key process to protect the environment and to conserve resources. The increasingly sophisticated reverse logistics networks also guarantee the efficient waste avoidance and waste reduction. Bautista and Pereira (2006) modeled the location problems of collection areas for urban waste management. Karadimas, Doukas et al. (2008) tried to optimize the routing for urban solid waste transportation. Ye, Ye et al. (2011) proposed a location set covering model for waste resources recycling centers in Taiwan.

2.3 Sustainable Development

Different members in GL have their own roles and objectives. GL is concerned with producing, distributing and consuming goods in a sustainable way, taking account of environmental and social factors. Thus the objectives are not only concerned with the economic impact of logistics activities and operations, but also the wide effects on environment and society, such as the environmental pollution measurement, waste treatment and customer satisfaction analysis (Sbihi and Eglese 2007). Different objectives associated with different problems and models can be adopted as the criteria to measure the performance of GL. The objectives of GL models cover three aspects: economic, environmental and societal objective, which are also known as triple bottom line of sustainable development (Elkington 1998; Dyllick and Hockerts 2002) as described in Figure 2.5.

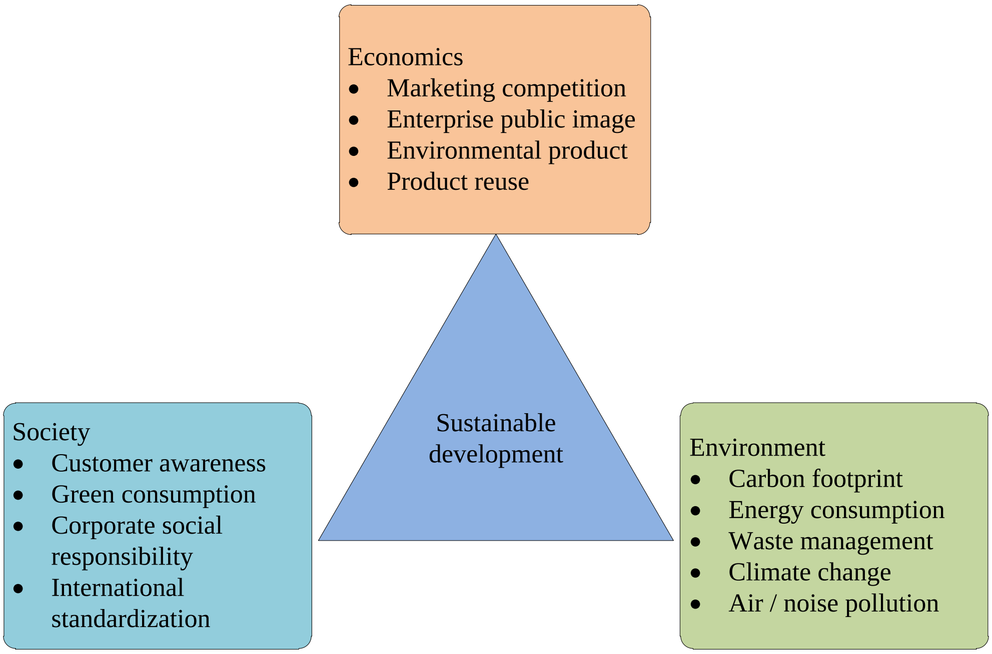


Figure 2.5 The dimensions of sustainable development

The initial design and implementation of logistics activities and operations always start from the economic perspective in terms of either minimizing cost or maximizing profit. The objective when modeling the corresponding activity or operation complies with the above perspective. A number of literatures exist concerning the economic measurement of logistics activity. For example, Farahani and Elahipanah (2008) developed a Just-In-Time (JIT) distribution model in the context of supply chain with two objectives, minimizing costs and minimizing the sum of backorders and surpluses of products. Rajabalipour, Desa et al. (2013) configured a supply chain network in order to minimize response time to consumers, transportation cost and facility cost. Gong and Huang (2012) proposed a multi-echelon inventory model for closed-loop supply chain under uncertainty, whose target function is to maximize the joint profit of supply chain members. Chen and Ju (2013) formulated the supply chain network design problem under disruption scenarios as a mixed integer nonlinear problem which maximizes the total profit for the whole system.

In addition to the traditional economic objectives, the environmental objectives gradually attract attentions from academic researchers and industrial practitioners. The environment management was originally introduced as a strategic component of supply chain management. Different attitudes towards the environmental management in supply chains, e.g., progressive, moderate or conservative, lead to different managerial policies (Murphy, Poist et al. 1996). The interaction between supply chain and environment is analyzed as well (Rondinelli and Berry 2000). In contrast to the strategic consideration of environmental management, nowadays, the environmental influence is measured in operational level along with the development of advanced technologies. Carbon footprint is an environmental factor which is commonly adopted as a criterion to measure the environmental performance (Sundarakani, Desouza et al. 2010). Numerous activities are reformulated incorporating the environmental measurement, such as network design (Elhedhli and Merrick 2012) and vehicle routing problem (Zhang, Lee et al. 2014). Waste management is another important factor which can improve the environment performance. The determination of the collection centers for waste management is the first issue need to be solved (Bautista and Pereira 2006). Meanwhile, the efficient routing to collect waste also needs to be rescheduled (Kim, Kim et al. 2006).

Social objectives can be understood from two perspectives. The first one is the customer awareness of the supply chain performance. Customer satisfaction and loyalty is the key to the success of enterprises or supply chain (Rust and Zahorik 1993; Mittal and Kamakura 2001). Customer satisfaction level can be reflected in other factors, such as the product quality, the lead time, and the flexibility of distribution. Taleizadeh, Niaki et al. (2010) solved a constraint joint single buyer single vendor inventory problem with changeable lead time and inventory policy. Ehmke and Campbell (2014) summarized the customer acceptance mechanism for home deliveries in metropolitan areas.

Corporate Social Responsibility (CSR) is another consideration for the sustainable development of enterprises. CSR is defined as "business firms contributing in a positive way to society by going beyond a narrow focus on profit maximization (McWilliams 2000)". Amaeshi, Osuji et al. (2008) describes the possible practices of CSR in supply chains of global brands and their possible implications. Comparing with other objectives, the CSR is still at the pilot stage as it lacks efficient quantification measurement and standardization (Castka and Balzarova 2008). One attempt to handle this issue is from the International Organization for Standardization (ISO), which has initiated the

ISO 9000 (Quality management systems), ISO14000 (Environmental management systems standard) and ISO26000 (Guidance on social responsibility).

2.4 Swarm Intelligence

The concept of SI was originally introduced by Beni and Wang (1993) in the context of cellular robotic systems, while Bonabeau, Dorigo et al. (1999) redefined it as "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies". Most of the SI approaches are inspired by the collective behavior of natural species, such as ants foraging, birds flocking and bees gathering honey. Nevertheless, the term swarm could be extended to any constrained collection of interacting agents or individuals. Some examples of SI are summarized in Table 2.1.

With different inspirations, various different SI algorithms have been proposed, among which the most popular and successful exemplars are the ACO, PSO and ABC as surveyed in recent literature (Blum and Li 2008). A number of literatures concerning the application of ACO, PSO and ABC algorithms have been conducted due to their simple yet robust architectures and easy implementation, which facilitates their development towards theory integrity. The popularity of ant, particle and bee related SI algorithms can be reflected from survey papers (Karaboga and Akay 2009; Kennedy 2010; Chandra and Baskaran 2012). Thus, in this research, we take these three typical exemplars of SI as initiative objects to conduct the literature review.

Table 2.1 The examples of swarm intelligence

Entities	Swarming behavior	SI algorithms
Ants	Foraging	Ant Colony Optimization (Colorni, Dorigo et al. 1991), Termite Algorithm (Roth 2005), Ant System (Dorigo, Maniezzo et al. 1996), Ant Colony System (Dorigo and Gambardella 1997), MAX-MIN Ant System (Stützle and Hoos 2000)
Particles	Aggregating	Particle Swarm Optimization (Kennedy and Eberhart 1995)
Bees	Foraging	Bee Algorithm (Pham, Ghanbarzadeh et al. 2006), Artificial Bee Colony Algorithm (Karaboga 2005), Bee Colony Algorithm (Lucic and Teodorovic 2002), Marriage in Honey Bees Optimization Algorithm (Abbass 2001), Wasp Swarm Algorithm (Pinto, Runkler et al. 2007), Bee Collecting Pollen Algorithm (Lu and Zhou 2008)
Masses	Gathering	Gravitational Search Algorithm (Esmat, Hossein et al. 2009)
Wolves	Preying	Grey Wolf Optimizer (Mirjalili, Mirjalili et al. 2014)
Bats	Echolocation	Bat Algorithm (Yang 2010)
Bacteria	Growth	Bacteria Foraging Optimization (Passino 2010)
Fishes	Aggregating	Artificial Fish School Algorithm (Li, Lu et al. 2004)
Birds	Mating	Bird Mating Optimizer (Askarzadeh and Rezazadeh 2013)
Dolphins	Clustering	Dolphin Partner Optimization (Shiqin, Jianjun et al. 2009)
Monkeys	Climbing	Monkey Search (Mucherino and Seref 2007)
Flies	Foraging	Fruit fly Optimization Algorithm (Pan 2012)
Fireflies	Gathering	Firefly Algorithm (Yang 2008)
Glowworm	Gathering	Glowworm Swarm Optimization (Krishnanand and Ghose 2005)
Cockroaches	Foraging	Roach Infestation Optimization (Havens, Spain et al. 2008)
Cuckoos	Brooding	Cuckoo Search Algorithm (Yang and Deb 2009)
Krill	Herding	Krill Herd Algorithm (Gandomi and Alavi 2012)
Frogs	Jumping	Jumping Frogs Optimization (Garcia and Perez 2008)

2.4.1 Ant Colony Optimization

ACO algorithm mimics the collective behavior of ant foraging, which was firstly introduced by Colorni, Dorigo et al. (1991). During the searching process of food source, ants behave intelligently to find the optimal path to food source, which is practically achieved by the utilization of pheromone. The existence of pheromone shows the trace of an ant, and provides heuristic information for other ants, which decide to follow this pheromone trace or not. If the new ant chooses to follow this pheromone trace, it would reinforce the density of pheromone. Otherwise the pheromone would be gradually evaporated and finally exhausted. The above decision strategies can be regarded as positive feedback and negative feedback respectively. Higher pheromone density indicates higher chosen probability. Therefore, more and more ants choose to follow the trace with high pheromone density and construct the optimal path to food source. Since the introduction of ACO algorithm, it has gained much popularity and diverse variants of ACO have also been proposed for adapting various optimization problems, such as Ant System (Dorigo, Maniezzo et al. 1996), Ant Colony System (Dorigo and Gambardella 1997) and MAX-MIN Ant System (Stützle and Hoos 2000). More comprehensive description of ant related algorithms can be found in literature (Cordon, Herrera et al. 2002).

The applications of ACO in green logistics are of great quantity as the intrinsic features of ACO algorithm, finding the shortest route by ants, and promoting its popular application in vehicle routing problems. For example, Dorigo and Gambardella (1997) firstly applied ant colonies to solve the standard Travelling Salesman Problem (TSP), while Bell and McMullen (2004) further adapted ACO techniques to handle the VRP. The whole procedure of ACO algorithm could be illustrated in Figure 2.6. Initially, ants are placed on the nodes of the graph randomly. Then each ant decides a connected and unvisited node as its next movement probabilistically. The probability is influenced two factors, the distance from current node to next node and the pheromone on associated edge. This movement is executed iteratively until all ants have traversed all the nodes on the graph, which is called one cycle. After each cycle, the pheromone deployment of the whole graph is updated. The principle is that whenever an ant moves through an edge, the pheromone on that edge is reinforced. Otherwise, it would be evaporated and exhausted. After a certain number of cycles, the path with highest pheromone density is found, which represents the optimal solution.

```
While termination conditions not met
    Place ants on the graph randomly
    Add current node to the visited list
    For all ants
        While the visited list is not full
            Determine next node for visiting
            Move to next node
            Add the current node to the visited list
        End while
    End for
    Update the pheromone deployment
End while
```

Figure 2.6 The process of the ACO algorithm for routing problems

The ACO algorithm was initially designed to solve discrete optimization problems, especially routing related problems, such as the TSP and the Vehicle Routing Problem (VRP). However, the application of the ACO could be generalized to common optimization problems in addition to the related routing problems. Figure 2.7 illustrates a possible approach for the generalization purpose of the ACO. Each ant represents a candidate solution, which possesses two properties, i.e., pheromone density and fitness. At the beginning, all ants are randomly deployed, which means the initial solutions are also randomly generated. After the initialization phase, each ant moves one step, referring to other ants. The criterion herein of finding referable ants for the current ant is that the referable ants have higher pheromone density than the current ant. The fitness difference between the referable ants and the current ant is treated as the neighborhood of the current ant. The current ant then chooses its reference among the referable ants probabilistically, and such a probability is determined by the pheromone density of the referable ants and the fitness difference between the referable ants and the current ant. After the one-step movement of all ants, the individual pheromone density and fitness of ants are updated. Ants keep moving until the optimal solution is found or the stopping criteria are met.

```
Initialize ants in the search space randomly
Evaluate the ants
While termination conditions not met
    For all ants
        Determine next position
        Move to next position
        Update the pheromone density
    End for
    Find the best ant
End while
```

Figure 2.7 The process of modified ACO algorithm for general problems

Apart from the general adoption of ACO, researchers are also trying to improve the effectiveness and efficiency of ACO through various attempts. Chen and Ting (2006) proposed an Improved Ant Colony System (IACS) algorithm, possessing a new state transition rule, a new pheromone update rule and diverse local search approaches, to solve VRP. Agrawal and Tiwari (2007) introduced a

Collaborative Ant Colony Optimization (CACO) to resolve stochastic mixed-model U-shaped disassembly line balancing and sequencing problem. The distinguishing feature of this proposed CACO was that it maintained bilateral colonies of ants which independently identified the two disassembly sequences, but using the information obtained by their collaboration to guide the future path. Gajpal and Abad (2009) presented a Multi-Ant Colony System (MACS) using a new construction rule as well as two multi-route local search schemes for VRP with backhauls. Yu, Yang et al. (2009) brought forward an Improved Ant Colony Optimization (IACO) including a new pheromone updating strategy, called ant-weight strategy, and a mutation operation. Çatay (2010) come up a saving-based ant algorithm by employing a new saving-based visibility function and pheromone updating procedure. Liu, Peng et al. (2012) improved the max-min ant system based on the strategy of sorting elite ants to tackle the disassembly sequence planning.

Another direction for the improvement of ACO algorithm is the hybridization with other techniques. Other techniques could either provide good initial solutions as the input for ACO at the beginning, or perform the function of improving middle candidate solutions. For instance, Chen and Ting (2008) combined Lagrangian Heuristic and Ant Colony System are used to create a new hybrid algorithm, named LH-ACS, to handle the single source capacitated FLP. Lee, Lee et al. (2010) proposed an enhanced ant colony optimization (EACO), in which the Simulated Annealing (SA) provided initial solutions for ACO. Zhu and

Zhang (2010) presented an Ant Colony Optimization with Elitist Ant (ACOEA) algorithm. Both Tabu Search (TS) and elitist strategy were adopted in this ACOEA to improve the performance of candidate solutions. Balseiro, Loiseau et al. (2011) hybridized ACO with an aggressive insertion heuristic to overcome the shortcoming of ACO in case of infeasible solutions in VRP. Wang (2013) presented an Adaptive Ant Colony Algorithm (AACA), coupled with a Pareto local search algorithm, to conquer the premature convergence problem when applying ACO into VRP.

2.4.2 Particle Swarm Optimization

PSO algorithm simulates the movement of a set of particles in search space under predetermined rules in order to find the optimal position. PSO was originally proposed by Eberhart and Kennedy (1995), which was inspired from bird flocking, fish schooling, and even human social behavior. Reynolds (1987) had been proposed a birdoid model to simulate the behavior of bird flocking. Therein each individual followed three simple rules: collision avoidance, velocity matching, and flock centering. Derived from the birdoid model, in PSO, individuals representing solutions herein are treated as particles, and each particle is characterized by its associated fitness value, position vector and velocity vector. Apart from the three inner attributes, each particle also memorizes its historical best position (local best position) and global best position of the swarm, and refers to those two positions whenever it moves to next position. During the iterative process of movement, all particles gradually converge at the global optimal position.

The procedure of PSO algorithm can be described in Figure 2.8. At the beginning, a number of particles are randomly placed in the search space. Each particle holds its position and velocity information in a vector format. Whenever movement, the particle needs to update its velocity information firstly, referring to three factors: its current velocity, the local best position and the global best position. Different weightings of different factors indicate different optimization strategies. Subsequently, the particle updates its position information following the updated velocity vector. The positions of each particle correspond to candidate solutions. The local and global best positions are updated after each movement provided that the particle arrives at a better position. This procedure is conducted iteratively until the stopping criteria are met. The global best position is the optimal solution which can be found so far.

```
Initialize particles in the search space randomly
Evaluate the particles
While the termination conditions not met
    For all particles
        Update the velocity of particles
        Update the position of particles
        Evaluate particles
        Update the local best positions
        Update the global best position
    End for
    Find the best particle
End while
```

Figure 2.8 The process of the PSO algorithm

Wang and Liu (2010) proposed a Chaotic Particle Swarm Optimization (CPSO) approach to handle the assembly line balancing problem, in which the chaos method was utilized to improve the solution quality and to increase the convergence rate. Kanthavel, Prasad et al. (2012) developed a nested particle swarm optimization, as the integration of two other mechanism, Master Particle Swarm Optimization (MPSO) and Slave Particle Swarm Optimization (SPSO), to tackle the VRP with simultaneously delivery and pickup. Shankar, Basavarajappa et al. (2012)introduced a hybrid multi-objective particle swarm optimization (MOPSO) algorithm to solve the bi-objective distribution scheduling, while Venkatesan and Kumanan (2012) employed another Multi-Objective Discrete Particle Swarm Algorithm (MODPSA), containing two different global guide selection techniques, for supply chain network design.

Qi (2011) proposed an improved Discrete Particle Swarm Optimization (DPSO), in which an Iterated Local Search (ILS) method was adopted to ensure the avoidance of local minimum. Latha, Basavarajappa et al. (2013) integrated a Non-Dominated Sorting (NDS) procedure in Multi-Objective Hybrid Particle Swarm Optimization algorithm (MOHPSO) to achieve bi-objective optimization of two conflicting objectives. Validi, Bhattacharya et al. (2013) presented a Design of Experiment (DoE) guided Multiple-Objective Particle Swarm Optimization (MOPSO) optimizer, in which DoE was utilized to eliminate the un-realistic set of feasible and optimal solution sets, while another popular multi-attribute decision-making approach, TOPSIS, were employed to evaluate the solutions through exhaustive analysis, e.g. prioritization, ranking and scenario analysis.

2.4.3 Artificial Bee Colony

Artificial Bee Colony (ABC) algorithm was introduced by Karaboga (2005), which imitates the collective and collaborative forging behavior of bee colony. When forging, different bees work collaboratively to explore and exploit the food sources with rich nectar. Artificial bee colony consists of three types of bees, scout bees, employed bees and onlooker bees, which play different roles in the exploration and exploitation of food sources. Food sources are regarded as the solutions of specific problem, among which the ones with more nectar correspond to better solutions.

The whole procedure of ABC algorithm could be described in Figure 2.9. Scout bees are assigned to find the initial food sources by carrying a random search in the search space. After that, employed bees are sent out to exploit the discovered food sources, and each employed bee matches one food source. During the exploitation procedure, each employed bee also carries out a neighborhood search and tries to find a better food source nearby. If a better food source is found, the employed bee would abandon the previous food source and exploit the better one. After the completion of all employed bees, they return to the hive and share their information of food sources with onlooker bees waiting in the hive through a waggle dance. The onlooker bees would choose to follow certain employed bees and exploit corresponding food sources probabilistically. This probability is computed by the richness of corresponding food sources. Once a looker bee chooses to follow an employed bee, it becomes an employed bee and repeats the procedure of employed bees. After certain number of iteration of the exploration and exploitation procedure, a food source may be exhausted and abandoned. In that case, the corresponding employed bee becomes a scout bee and randomly finds a new food source to replace the abandoned one. The whole procedure of ABC algorithm is described with four periods confirmed in above description, (1) initialization phase, (2) employed bee phase, (3) onlooker bee phase and (4) scout bee phase.

```
Initialize food sources by scout bees
Evaluate the food sources
While termination conditions not met
    For all employed bees
        Conduct neighborhood search
    End for
    For all onlooker bees
        Determine to exploit the food sources preferably
        Become employed bees
        Conduct neighborhood search
    End for
    If a food source is exhausted
        Find a new food source by scout bee
    End if
    Find the best food source
End while
```

Figure 2.9 The process of the ABC algorithm

To improve the performance of ABC algorithm, various improvement and enhancement techniques are considered. Shi, Meng et al. (2012) tried to improve the global search capacity with tournament selection strategy when solving VRP with time windows. Zhang and Guo (2014) adopted a greedy adjustment strategy in their proposed discrete artificial bee colony algorithm. Yao, Hu et al. (2013) attempted to incorporate multi-dimensional heuristic information and a local optimization based on scanning strategy into ABC. Zhang, Song et al. (2013) devised a tree search algorithm, through analyzing the neighborhood property, to enhance the exploitation capability of ABC. Pandey and Kumar (2013) incorporated different types of real-coded crossover operators into ABC in order to improve its exploration property. Kumar, Liou et al. (2013) proposed a Chaos-based Interactive Artificial Bee Colony (CI-ABC) algorithm to resolve the remanufacturing operation scheduling.

Guillermo, Enrique et al. (2012) proposed a hybrid approach, combining ABC and mixed integer programming, for large-scale capacitated FLP. They mentioned the hybrid implementation could help to bypass certain inherited weaknesses of each algorithm and was capable of finding an optimal solution in an acceptable computational time. Li and Yin (2012) introduced a discrete artificial bee colony algorithm with composite mutation strategies, which comprises Nawaz-Enscore-Ham (NEH) heuristic for initialization, composite mutation strategies for population improvement and fast local search property for enhancing the best individual. Liu and Liu (2013) presented a Hybrid Discrete Artificial Bee Colony (HDABC) algorithm, in which the initial population were generated from Greedy Randomized Adaptive Search Procedure (GRASP) based on NEH heuristic and were further improved through discrete operators and algorithms.

2.5 Application of Swarm Intelligence to Green Logistics

With the given GL classification scheme and the SI classification scheme, the publications reviewed in this research are presented in Table 2.2. Given the previous determined literature review process and method, there are 105 publications fulfilling our selection criteria and among the publications from

2004 to 2016. Two publications (Kumar, Tiwari et al. 2009; Pal, Chan et al. 2010) are used more than once, as more than one SI approach are adopted in their solutions.

From the result, it could be noticed that two categories, i.e., network design and vehicle routing, take a large proportion, which are 24.76% and 39.05% respectively. Indeed, the design of closed loop network can also be treated as a variant of network design. Such a result could indicate their relative weighting of each category in the associated domain. Among the three exemplars of swarm intelligence, the applications of ACO algorithm and PSO algorithm are much more than the application of ABC algorithm, which partially due to the fact that the ABC algorithm is a new swarm intelligence algorithm in contrast to the ACO algorithm and PSO algorithm. Furthermore, among the applications of the ACO algorithm, routing related problems account for 61.4%, which attributes to the inherent features of the ACO algorithm. The applications of the PSO algorithm are relatively even and more applications of the ABC algorithm can be expected.

Table 2.2 The publication distribution

GL and SI		Ant	PSO	Bee	Total
Logistics network	Network design	(Poorzahedy and Rouhani 2007; Silva, Sousa et al. 2009; Wang 2009; Asef, Kazemi et al. 2010; Moncayo Martínez and Zhang 2011)	(Kumanan, Prasanna Venkatesan et al. 2007; Che 2009; Kumar, Tiwari et al. 2009; Pal, Chan et al. 2010; Che 2012; Kadadevaramath, Chen et al. 2012; Venkatesan and Kumanan 2012; Latha, Basavarajappa et al. 2013; Qian, Zhexue et al. 2013; Validi, Bhattacharya et al. 2013; Cárdenas and Treviño 2014; Govindan, Jafarian et al. 2015; He, Huang et al. 2015; Khalifehzadeh, Seifbarghy et al. 2015; Yamada and Febri 2015)	(Kumar, Tiwari et al. 2009; Pal, Chan et al. 2010; Chen and Ju 2013; Mastrocinque, Yuce et al. 2013; Miandoabchi, Daneshzand et al. 2013; Nikolić and Teodorović 2013; Yuce, Mastrocinque et al. 2014; Zhang, Lee et al. 2016)	26
	Facility location	(Chen and Ting 2008; Wang and Lee 2015)	(Yapicioglu, Smith et al. 2007; Shankar, Basavarajappa et al. 2012; Gang, Tu et al. 2015)	(Guillermo, Enrique et al. 2012)	6
	Partner selection	(Tsai, Yang et al. 2010)	(Che, Chiang et al. 2010; Kuo, Hong et al. 2010; Huang, Tong et al. 2011; Xiao, Chen et al. 2012; Su, Huang et		6

			al. 2015)		
Transportation	Transportation planning	(Musa, Arnaout et al. 2010; Sprenger and Mönch 2012; Shahin, Fatemi et al. 2014; Veluscek, Kalganova et al. 2015; Lin, Contreras et al. 2016)	(El-Sherbiny and Alhamali 2013; Govindan, Jafarian et al. 2014; Meiyi, Xiang et al. 2015; Mohtashami, Tavana et al. 2015; Pramanik, Jana et al. 2015; Poole and Kotsialos 2016)		11
	Vehicle routing	(Bell and McMullen 2004; Mazzeo and Loiseau 2004; Montemanni, Gambardella et al. 2005; Chen and Ting 2006; Favaretto, Moretti et al. 2007; Rizzoli, Montemanni et al. 2007; Yi and Kumar 2007; Donati, Montemanni et al. 2008; Zhang, Tian et al. 2008; Fuellerer, Doerner et al. 2009; Gajpal and Abad 2009; Gajpal and Abad 2009; Yu, Yang et al. 2009; Bell and Griffis 2010; Çatay 2010; Hu and Cheng 2010; Lee, Lee et al. 2010; Pradhananga, Taniguchi et al. 2010; Santos, Coutinho et al. 2010; Balseiro, Loiseau et al.	(Qi 2011; Gong, Zhang et al. 2012; Kanthavel, Prasad et al. 2012; Moghaddam, Ruiz et al. 2012; Goksal, Karaoglan et al. 2013; Tlili, Faiz et al. 2014; Kumar, Kondapaneni et al. 2015)	(Marinakis, Marinaki et al. 2010; Szeto, Wu et al. 2011; Shi, Meng et al. 2012; Ruan, Zhang et al. 2013; Yao, Hu et al. 2013; Zhang, Lee et al. 2014)	41

		2011; Yu and Yang 2011; Adiba, Elhassania et al. 2013; Tang, Ma et al. 2013; Wang 2013; Gómez S, Cruz et al. 2014; Reed, Yiannakou et al. 2014; Sicilia, Royo et al. 2014; Jabir, Panicker et al. 2015)			
Reverse logistics	Closed loop network		(Kannan, Noorul et al. 2009; Che, Chiang et al. 2012; Gong and Huang 2012; Subramanian, Ramkumar et al. 2012; Zhou, Zhao et al. 2012; Asl, Zahiri et al. 2015; Chen, Wang et al. 2015; Soleimani and Kannan 2015)	(Šelmić, Teodorović et al. 2010; Zhang and Guo 2014)	10
	Waste collection	(Karadimas, Papatzelou et al. 2007; Bautista, Fernández et al. 2008; Karadimas, Doukas et al. 2008; Mostafavi and Afshar 2011)	(Lin and Chen 2013)		5
Total		45	45	17	

2.6 Research Gap

During the literature review process, it is noticed that most of the literatures regarding modeling of logistics activities are conducted with the economic objectives, which are represented in terms of either minimizing cost or maximizing profit. Environmental consideration is seldom mentioned or used, so as the social consideration. Moreover, most of the literatures concerning sustainable development are conducted from the perspective of strategic management, instead of practical and operational level implementations. In contrast to other meta-heuristic approaches, the development of swarm intelligence is still at the initial stage in terms of both application scope and theory development.

Therefore, in this research, modeling green logistics activities is conducted by taking sustainable development into consideration to meet the requirements of environment and society, and swarm intelligence is selected as the major approach to solve the green logistics problems, aiming to both enlarge the application scope and facilitate the theory development of swarm intelligence.

2.7 Summary

Because of the deterioration of environment and the consumption of the finite and diminishing energy sources, green logistics is gaining increasing attention substantially. Economic performance is no longer the only objective in logistics; two other aspects, environmental and societal performance, are becoming more important than ever before for the purpose of sustainable development. The operational level activities in logistics are the fundamental for any upper level management strategies, thus the modeling and implementing of green activities are of great importance. In this research, the green activities are classified into different dimensions and categories considering their inherent features and swarm intelligence is chosen as the major approach to solve the complex optimization problems.

The requirements of sustainable development challenge the modeling of logistics activities. Indeed, the requirements of sustainable development not only constrain the modeling of logistics activities, but also they become the objectives of the new models. However, the research of modeling of sustainable development in logistics is still at pilot stage. Moreover, considering the fact that swarm intelligence is relatively a new branch of meta-heuristic approaches, both the theory and the application are at developing phase. This research can contribute to both the individual development of each discipline and their integration.

Chapter 3 Research Framework

In this chapter, the research framework is introduced, which integrates the green logistics, sustainable development and swarm intelligence. Among the numerous activities in green logistics, two sub-categories are studied in detail, i.e., vehicle routing and network design. New features arise in these two categories along with the sustainable requirements from enterprises, customers and governments. Economic performance is no longer the only measurement for enterprises, but also the environmental influence and social consideration in their operations are important. Sustainability becomes the objective for modeling the activities and operations of enterprises. Swarm intelligence is employed to solve the optimization models derived from green activities. Swarm intelligence comprises a number of algorithms, which possess different features. In the same manner, different optimization problems possess different characteristics, which require some adjustments of the chosen algorithm specific to the unique features of the optimization problem. In order to find an appropriate SI algorithm for a specific optimization problem, the intrinsic features of SI algorithms have to be well understood and analyzed. However, with the increasing number of SI algorithms, it becomes a difficult issue in regard to the selection, implementation and improvement of a particular SI algorithm. Therefore, a unified framework is essential for the comprehension and implementation of SI algorithms.

3.1 Introduction

Referring to the results of the literature review, green logistics activities cover a wide range of studies, in which two main categories, i.e., vehicle scheduling and network design, are of great popularity. Therefore, these two categories are chosen as two cases for green logistics modeling. Regarding the requirement of sustainable development, not only the objectives, but also various constraints need to be redesigned. The concept of sustainable development can be realized differently for different activities. For example, the emission of carbon dioxide associated with the transportation of products can be measured as a criterion of environmental performance for vehicle scheduling. In network design, the environmental performance can also be measured using the emission of carbon dioxide, however, the emission of carbon dioxide is caused by both manufacturing process and transportation. Each activity needs to be modeled individually, considering their different features and emphases.

The application of Swarm Intelligence (SI) has now become increasingly popular in various disciplines, such as computer science, engineering, and operation research. For instance, the Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) have been employed by researchers in various areas and have achieved considerable success (Blum and Li 2008). From the methodological perspective, SI is a relatively new branch of meta-heuristics, which uses approximate strategies to explore and exploit the search spaces of optimization problems effectively and efficiently in order to find optimal or near-optimal solutions (Blum and Merkle 2008). Inheriting the features of meta-heuristic algorithms, the original SI algorithms also have no direct and explicit relation to any specific types of optimization problems, which indicates the possibility of any combination of optimization problems and SI algorithms.

On one hand, different SI algorithms possess different features, which lead to different performance even in solving the same optimization problems. On the other hand, different optimization problems possess different characteristics, which require some adjustments of the chosen algorithm specific to the unique features of the optimization problem. In order to find a proper SI algorithm for a specific optimization problem, the intrinsic features of SI algorithms have to be well understood and analyzed. However, with the increasing number of SI algorithms, the selection, implementation and improvement of a certain SI algorithm becomes an unresolved issue. Therefore, a unified framework is essential for the comprehension and implementation of SI algorithms. Fledelius and Mayoh (2008) attempted to develop a unified framework for swarm based image analysis. However, it is limited to the application of image analysis, which is difficult for more general application purposes. The objective of this research is to propose a unified framework, integrating the common features of SI and providing general principles for the implementation and improvement of SI algorithms, so as to cover the research gap as mentioned above.

3.2 Research Framework

The research framework consists of three components, i.e., performance measurement, application implementation and swarm intelligence as methodology, as illustrated in Figure 3.1. As mentioned earlier, the sustainable development is measured in three dimensions, i.e., economic, environmental and social dimension. The realization of each dimension in different activities is different. Two major activities, i.e., vehicle scheduling and network design, are studied in detail.

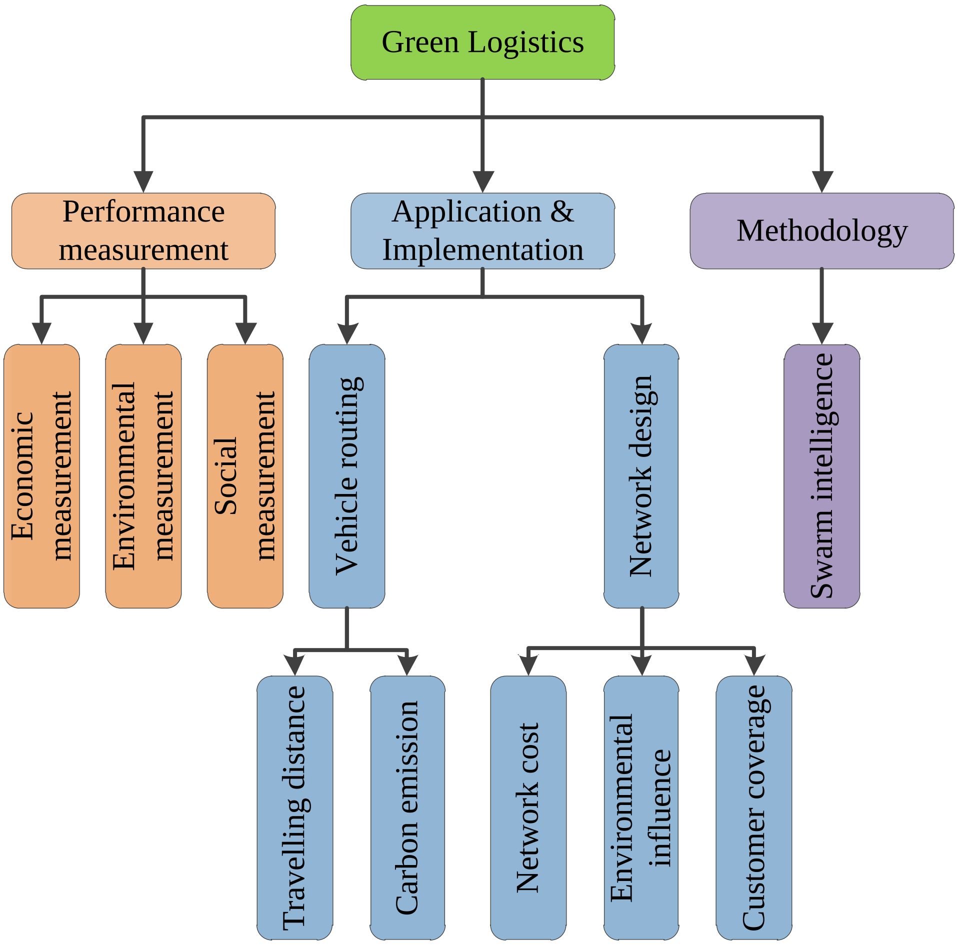


Figure 3.1 The research framework

The performance measurement criteria are designed towards sustainable development. As mentioned in Chapter 2, sustainable development comprises three dimensions, containing their own sub-indices. More importantly, different indices can be employed when decisions are made from different management levels. In this research, the economic measurement is realized in terms of cost, the environmental measurement is implemented by considering the emission of carbon dioxide, and the social measurement is achieved by maximizing the customer coverage so as to increase customer satisfaction.

Vehicle scheduling is to determine the optimal schedule for each vehicle, which comprises the route, the load, the time periods, etc. The optimal schedule is mainly determined by the vehicle information and customer requirements, and the target is to fulfill customer requirements. For example, the cumulative customer demands in one route decide the load of a vehicle. The time window requirements of customers influence the departure time and the service time of a vehicle. Since the vehicle scheduling mainly involves the transportation of products, one possible way to measure the environmental influence is to measure the emission of carbon dioxide.

Network design is the initiative and fundamental activity for logistics management. An efficient network is comprised of a number of facilities in proper locations, with proper capacities. The facility location and partner selection problems are two modes of the network design problem. The facility location problem applies to the scenario in which no available facilities exist and the enterprise intends to build its own facility, while the partner selection problem occurs when cooperation and/or collaboration among different enterprises is needed. Concerning the objectives for designing an effective and efficient network, customer satisfaction level and carbon footprint of products are two indicators of the social measurement and environmental measurement respectively.

Regarding the application and implementation, Figure 3.2 illustrates the process of activity implementation, which fits both vehicle scheduling and network design. First of all, we need to understand the background of the problem and find the new changes which are frequently driven by customer latest requirements, technology development, market demand and so on. Then we need to analyze these new changes and convert them into different objective functions so as to construct the new model. As such, new changes also cause new constraints. After the model formulation, we need to find the appropriate approach to solve the new model. The match of algorithm and problem is a complicated issue. Generally speaking, hybrid approaches are commonly employed which integrate one meta-heuristic approach with some other programming skills or techniques. The final step for implementation is the experiment design, which aims for at least two targets, to demonstrate the advantages of the new model and illustrate the efficiency of the proposed approach.

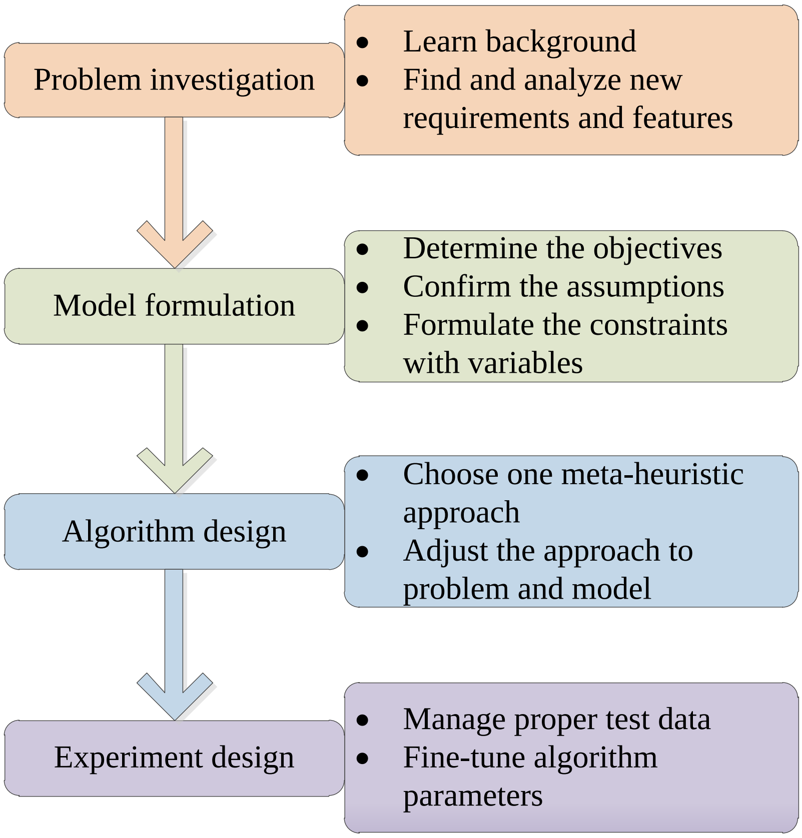


Figure 3.2 The process of activity implementation

3.3 Research Methodology

Through a comprehensive and thorough analysis, the common phases shared among the SI algorithms, namely initialization, individual update, population update and stopping criteria, are used to construct the fundamentals of the unified framework towards SI as shown in Figure 3.3. The initialization and stopping criteria can be interpreted literally. The individual update indicates the transformation from the current individual solution to its corresponding counterpart in the next population, while the population update means the additional update strategy from the current population to the next population. The features of SI, i.e. decentralization, self-organization and collaborative behavior, are reflected in the individual update phase and population update phase.

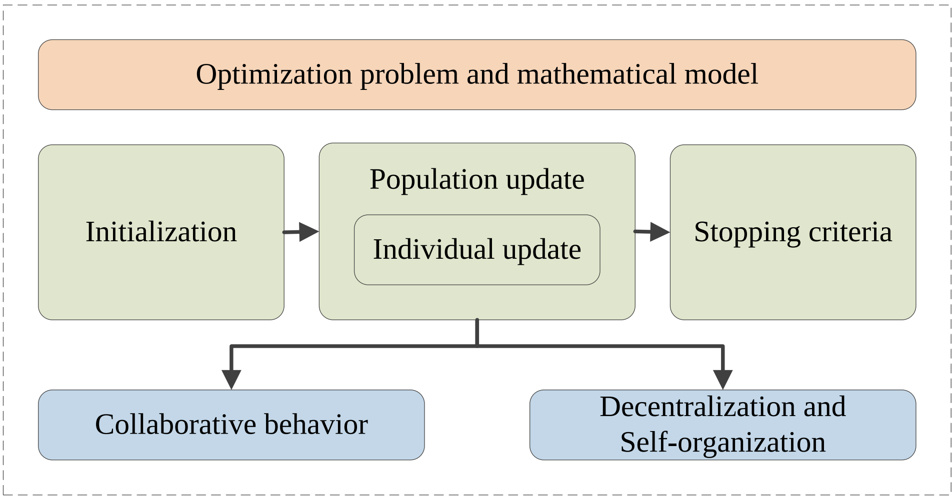


Figure 3.3 The unified algorithm framework towards swarm intelligence

The operational procedures of this framework are represented in Figure 3.4, in which a population is constituted by a number of individual solutions. The individual update is implemented through a neighborhood search for each individual, while the population update is realized through the incremental and cumulative individual updates. When the stopping criterion is met, the best individual from the population is regarded as the optimal solution.

$P = \{s_1, s_2, \cdots, s_n\} \leftarrow$ GenerateInitialPopulation

Evaluate(P)

While termination conditions not met **do**

    For all $s \in P$ **do**

        $s' \leftarrow \mathcal{N}(s)$ // find proper reference

        $s'' = s \otimes s'$ // interact with the chosen reference

        $s \leftarrow s$ or s'' // determine the new individual

        Update individual

    End for

    Update population

    Find the best $s \in P$

End while

Figure 3.4 The unified algorithm process towards swarm intelligence

For a better understanding, Table 3.1 lists a distinct comparison between the framework from Fledelius and Mayoh (2008), noted as the reference framework, and our propose framework. In general, these two frameworks share similar components and processes. However, the major differences exist in several aspects. First of all, even though the reference framework is claimed to be a unified framework derived from the ACO algorithm and the PSO algorithm, it still uses the concepts from the PSO algorithm, such as position, direction and speed, which limits the generalizability of the unified framework. Secondly, the arbiter concept in the reference framework conflicts with the feature of SI, i.e., decentralization. More importantly, the reference framework is limited to the application of image analysis, where the concept of digital habitat is employed and the cumulative footprints of agents constitute the final image. In comparison with the reference framework, our proposed framework is abstract to a higher level and applicable to a wider range.

Table 3.1 The component comparison between two frameworks

	Reference framework	**Proposed framework**
Problem-specific components	Digital habitat	Search space
	Parallel habitat	Segment of search space
	Action radius	Neighborhood
Algorithm-specific components	Agent	Individual
	Rule-set	Strategy-base
	Initial rules	Initialization strategies
	Internal rules/state rules/ motion rules	Individual update strategies
	Habitat rules	Population update strategies
	Arbiter	N/A

The unified framework is simple, yet powerful, in representing the inherent features of SI algorithms. Following the phases of the unified algorithm flowchart, Table 3.2 summarizes the most frequently used strategies in SI algorithms. Before the execution of a certain SI algorithm, the representation scheme of the candidate solutions and the initial settings of the parameters should be confirmed first. Different representation schemes of the candidate solutions could result into different algorithm performances. For example, the binary string format and real string format diverge significantly when the precision of the decision variables is high. Meanwhile, the solution format also influences the execution of the solution initialization, as a number of solutions need to be generated using swarm intelligence. For the parameter settings, two requisite parameters are the size of population and the number of iterations. Apart from these, there are some other algorithm-specific or problem-specific parameters, such as the *limit* setting in the ABC algorithm, the coefficient setting in the PSO algorithm and the penalty setting due to various constraints in specific mathematical models. Another aspect that needs to be mentioned is that the setting of the parameters is not once and for all. In most cases, the parameters have to be modified iteratively in order to find the best combination. Some parameters are even adaptive, which means they can self-change along with the algorithm process.

Table 3.2 The unified algorithm process and strategies

<table>
<tr><th>Algorithm process</th><th colspan="2">Strategies</th></tr>
<tr><td rowspan="2">Solution representation</td><td colspan="2">Solution format</td></tr>
<tr><td colspan="2">Optimal solution</td></tr>
<tr><td rowspan="3">Parameters</td><td colspan="2">Size of population</td></tr>
<tr><td colspan="2">Number of iterations</td></tr>
<tr><td colspan="2">Other algorithm-specific or problem-specific parameters</td></tr>
<tr><td rowspan="2">Initialization</td><td colspan="2">Encode mechanism (real-encoding, 0-1 encoding, etc.)</td></tr>
<tr><td colspan="2">Initialization mechanism (random initialization considering initial range, etc.)</td></tr>
<tr><td rowspan="4">Population update</td><td colspan="2">P-A: Update population after all individuals have been updated</td></tr>
<tr><td colspan="2">P-B: Update population after one individual has been updated.</td></tr>
<tr><td colspan="2">P-C: Update current population based on fitness ranking</td></tr>
<tr><td colspan="2">P-D: Update other configuration of population-related factors</td></tr>
<tr><td rowspan="10">Individual update</td><td rowspan="4">Step 1: Find proper reference(s)</td><td>I-A: Find another individual randomly</td></tr>
<tr><td>I-B: Find another individual preferably</td></tr>
<tr><td>I-C: Find another positive individual preferably</td></tr>
<tr><td>I-D: Find the local- and global-best individuals</td></tr>
<tr><td rowspan="2">Step 2: Interact with the chosen reference(s)</td><td>I-E: One dimension interaction</td></tr>
<tr><td>I-F: Multiple dimensions interaction</td></tr>
<tr><td rowspan="2">Step 3: Determine the new individual</td><td>I-G: Non-greedy selection</td></tr>
<tr><td>I-H: Greedy selection</td></tr>
<tr><td rowspan="2">Step 4: Other changes</td><td>I-I: Mutation operation</td></tr>
<tr><td>I-J: Abandonment and regeneration</td></tr>
<tr><td rowspan="4">Stopping criteria</td><td colspan="2">S-A: Number of iterations</td></tr>
<tr><td colspan="2">S-B: Computational time</td></tr>
<tr><td colspan="2">S-C: Solution convergence</td></tr>
<tr><td colspan="2">S-D: Solution quality</td></tr>
</table>

In the initialization phase, with the given solution format, the initial solutions are generated following particular strategies. The most frequently employed strategy is random generation considering the range of decision variables. The decisional variables are commonly encoded using the same or a different mechanism in considering their own features. One decision variable is treated as one segment of the integrated solution. In addition to the decision variables, the number of solutions and the features of the search space are two other considerations in the initialization phase, as a large number of solutions for a small search space may be a waste of resources and a small number of solutions for a big search space may lead to a premature situation or being trapped in a local optima.

As for the strategies of the population update, *P-A* (update the population after all individuals have been updated) and *P-B* (update the population after each individual has been updated) are alternative options. The strategy *P-A* is the theoretical choice, which helps to methodize and standardize an algorithm. Comparatively, the strategy *P-B* might be slightly informal, which blurs the interval between any two populations. However, the adoption of the strategy *P-B* can achieve outstanding performance in certain situations when combined with other strategies, as the strategy *P-B* can facilitate a more diversified search to a greater extent. The strategy *P-C* (update the current population based on the fitness ranking) is another frequently employed strategy. The operation of roulette wheel selection, for example, can be treated as a variant of the strategy

P-C. The strategy *P-D* is listed here as an update of some population based configurations, and also leaves the possibility for further extension.

The individual update strategies are of the most importance. In order to generate the next corresponding solution from the current individual, four steps are recommended, among which the first three steps are requisites, and the last one is an optional choice. Step 1 is to find the proper reference(s) for the current individual, which contains at least four strategies derived from the SI algorithms, namely *I-A* (find another individual randomly), *I-B* (find another individual preferably), *I-C* (find another positive individual preferably) and *I-D* (find the local and global best individuals) respectively.. The strategy of *I-A* indicates that the reference is searched for randomly in the current population. The strategy of *I-B* means that the individuals within the current population are sorted first according to their fitness, and then the reference is chosen probabilistically from the sorted list. The strategy of *I-C* is a further process based on the strategy of *I-B,* in which the term positive means the fitness of the chose reference has to surpass the current individual. The strategy of *I-D* is derived from the PSO algorithm, which means the current individual would interact with two references, i.e. the local optimal individual and the global optimal individual in the current population. Step 2 in the individual update phase is the interaction mechanism between the current individual and the reference(s). Most optimization problems involve multiple decision variables, which are normally represented through a long string of binary numbers or real numbers in solution format, containing an encoded sub-string for each decision variable. Thus the interaction between two individuals may be limited to one certain decision variable (*I-E*) or based on multiple decision variables (*I-F*). In step 3, the *I-G* (non-greedy selection) means that the current solution is replaced by its next generation immediately, regardless of its fitness value, while *I-H* (greedy selection) suggests that the current solution is replaced by its next generation only if its next generation is better than the current one, otherwise the current solution is retained. Step 4 in this phase contains some further modifications after the generation of a new solution, such as the mutation operation, local search and replacement operation.

As for the stopping criteria in the unified framework, four possible strategies are *S-A* (number of iterations), *S-B* (computational time), *S-C* (solution convergence) and *S-D* (solution quality). Each criterion has its applicable scenarios, as needed. Among them, *S-A* is the most commonly used strategy, especially for the purpose of performance comparison of different algorithms. The efficiency of one SI algorithm can be reflected by its result after a number of iterations. *S-B* is a natural consideration when comparing the performance of two algorithms. However, the option of *S-B* gradually becomes obsolete due to the differences in hardware and programming skills when comparing two algorithms. In other words, *S-B* is applicable only if the algorithms are implemented with the same externalities, such as hardware and programming skill. *S-C* might be used to determine whether an algorithm could converge on a satisfactory point or not, while *S-D* might be employed when a solution with designated precision is needed.

The performance of an algorithm is determined by its framework and associated combination of strategies. Different strategies have different effects on the algorithm performance. Even the same strategy may perform differently in different algorithms as the effects of a certain strategy might be strengthened or weakened by other strategies in the same combination. Therefore, it is critical to analyze and estimate the possible effects of the strategies before application so as to estimate and measure the algorithm performance.

3.4 Summary

The research framework explicitly describes the major content conducted in this research. Two typical activities, i.e., vehicle scheduling and network design, are studied in detail in Chapter 4 as two successful application cases of modeling green logistics activities. The modeling of these two activities involves the requirements and measurement of sustainable development. Swarm intelligence is employed as the major approach to tackle the combinatorial optimization models derived from the two activities. The detailed methodology is described in the following two chapters.

Derived from the essential behavior of the SI algorithms, a unified framework integrating the common procedures and operations from SI is proposed. Various SI algorithms can be regarded as different application instances of this unified framework with different foci. Such a unified framework can provide not only straightforward understanding of the various SI algorithms, but also practical guidance for the implementation and improvement of SI algorithms step by step. Moreover, the proposed unified framework can provide useful and valuable insights for the SI algorithm innovation.

Chapter 4 Vehicle Scheduling

The Vehicle Routing Problem (VRP) is a critical and vital problem in logistics for the design of an effective and efficient distribution network, within which the Capacitated Vehicle Routing Problem (CVRP) has been widely studied for several decades due to the practical relevance of logistics operation. However, CVRP with the objectives of minimizing the overall travelling distance or the travelling time cannot meet the latest requirements of green logistics, which concern more about the influence on the environment. This chapter studies the CVRP from an environmental perspective and introduces a new model called Environmental Vehicle Routing Problem (EVRP) with the aim of reducing the adverse effect on the environment caused by the routing of vehicles. In this chapter, the environmental influence is measured through the amount of the emission carbon dioxide, which is a widely acknowledged criteria and accounts for the major influence on environment. A hybrid Artificial Bee Colony (ABC) algorithm is designed to solve the EVRP model, and the performance of the hybrid algorithm is examined and evaluated through a number of well-known CVRP instances.

4.1 Introduction

Due to increasingly serious environmental deterioration, green logistics is becoming a vital issue facing by various enterprises. Both environmental regulations and customer expectations have driven enterprises to employ more environment-friendly operations (Dobers, Röhrig et al. 2013). Environmental issues can affect various logistics decisions, such as warehouse location, material sourcing, modal selection, transportation management and so on (Wu and Dunn 1995; Suzuki 2011; Tancrez, Lange et al. 2012). Transportation is the largest source of pollution in logistics. For example, in Canada, transportation accounted for 27% of greenhouse gas (GHG) emission in 2007 (Environment Canada, 2009), and in the United States, the transportation sector contributed 28% of national GHG emission (US EPA, 2009). Amongst various transportation modes, medium to heavy-duty diesel vehicles account for around one-third of GHG emissions from transportation (Elhedhli and Merrick 2012). Therefore, more effort should be devoted to handle transportation management in logistics with the objective of minimizing the environmental impact (Salimifard, Shahbandarzadeh et al. 2012).

The VRP has been extensively studied ever since its introduction. The initial idea of the VRP is to deliver a certain amount of goods to a set of customers with known demands through a number of vehicles to achieve the objective of minimizing cost. VRP plays a pivotal role in the design of distribution networks

(Bochtis and Sørensen 2010). The VRP has been extended to different specific problems, such as CVRP concerning the limited capacity of vehicles, VRP with time windows (VRPTW) considering the delivering goods within a time window, multi-depot VRP (m-VRP), VRP with simultaneous pick-up and delivery (VRPSPD) and so on. Each of these has different objectives, constraints and application backgrounds. Surveys and reviews of classical and derived VRP model can be found by Toth and Vigo (2002), Golden, Raghavan et al. (2008), and Hoff, Andersson et al. (2010). Among the various types of VRPs, the CVRP is the most well-known and practical one and has been extensively studied by academic researchers. Traditional VRP is designed with the economic objective of minimizing the cost while designing the route and scheduling vehicles. The cost is normally represented in the form of travelling distance or time. However, in recent years, the objective in solving VRP does not exclusively consider the economic needs.

In green logistics, the VRP involving environmental issue has been studied from different perspectives by academic researchers (Lin, Choy et al. 2013). For example, Kara, Kara et al. (2007) firstly proposed an Energy Minimizing Vehicle Routing Problem (EMVRP), considering a new cost function based on distance and the vehicle load, in which the cost function was derived more from physical and mechanical analyses. Xiao, Zhao et al. (2012) extended the idea of EMVRP and proposed a fuel consumption optimization model for CVRP. In their research, they formulated a linear expression between fuel consumption rate and the weight of vehicles based on the analysis of past statistical data. Nevertheless, in their research, the load of each vehicle was not explicitly represented with the combination of the route traversed. In addition, in their numerical experiments, they assumed the full-load and empty-load fuel consumption rates as 2 and 1 for simplicity, which is not reasonable for practical situations. In numerical experiments, we find that the settings of these two parameters can largely affect the construction of the final solution. Thus, in this research, we set the parameters in accordance with a practical case study by Ubeda, Arcelus et al. (2011), the CO_2 emission rate per liter of fuel is 2.61 kg/l in case of the diesel oil and the empty-load and full-load fuel consumption rates are as 0.296 and 0.390 respectively.

In this research, the emission of CO_2 is employed as a measurement to formulate an environmental vehicle routing problem (EVRP) model. In contrast to the CVRP, the objective of the EVRP is to find the optimal solution with minimum environmental impact in terms of minimizing CO_2 emissions. For the purpose of generalization, the emission of CO_2 is determined by the fuel consumption directly. The fuel consumption of one vehicle is subjected to three major factors, the travelling distance, the truckload and the travelling speed (Elhedhli and Merrick 2012). Modeling the fuel consumption function depends on the transportation strategy. In the CVRP, we adopt a linear function relating fuel consumption and the load of vehicles (Xiao, Zhao et al. 2012) , wherein the speed is assumed to be constant. Apart from the three factors mentioned earlier, other factors like road conditions, traffic jams and weather may also affect the fuel consumption. Nevertheless, these factors are relatively insignificant, and occur in special cases; hence they are not included herein.

VRPs can be modeled as combinatorial optimization problems (COPs) with a number of objectives, constraints and decision variables. Exact methods, such as Linear Programming (LP) and Branch-and-Bound (B&B), are becoming less popular for solving COPs, as they are either unable to solve complicated COPs with large numbers of variables or consume nearly unaffordable time to find the solution for COPs (Laporte 1992). By contrast, meta-heuristic approaches are becoming increasingly popular as these approximate approaches, which suggest that they could find satisfactory solutions within an acceptable time instead of finding the optimal solution. Swarm intelligence, which was originally inspired by the collective behavior of natural insect colonies and animal societies, is a new branch of meta-heuristics, comparing with the evolutionary computations (Bonabeau, Dorigo et al. 1999). Swarm intelligent algorithms use approximate and non-deterministic strategies to effectively and efficiently explore and exploit the search space in order to find near-optimal solutions (Blum and Li 2008; Blum and Merkle 2008). One of the typical example of swarm intelligence is the behavior of bee colonies, which derives the introduction of the ABC algorithm by Karaboga (2005). The ABC algorithm exemplifies the classical features of swarm intelligence, which are decentralization, self-organization and collective intelligence. In addition, the labor division is another feature of the ABC algorithm, which indicates that different tasks are performed simultaneously by specialized individuals, and is believed to be more efficient than the sequence task performance by unspecialized individuals (Jeanne 1986). The framework of ABC algorithm balances the effect of diversification and intensification effectively when searching the whole search space, which means the exploration of the whole search space and the exploitation of the promising area in the search space are well organized. Since the introduction of ABC algorithm, it has gained much popularity because of its robust mechanism and easy implementation (Akay and Karaboga 2012; Karaboga, Ozturk et al. 2012). However, until now there are few studies of applying ABC algorithm into green logistics. Therefore, this research is a pioneering attempt for the integration of swarm intelligence and green logistics. Differing from the original ABC algorithm, we introduce a hybrid ABC algorithm by incorporating the evolutionary concept of genetic algorithm (GA) and the local search algorithm for EVRP. The computational performance of the proposed hybrid ABC algorithm is measured in numerical experiments, and compared with GA.

The contribution of this chapter is two-fold. First, we introduced a new vehicle routing model taking account of the environmental influence. The environmental influence in EVRP is identified and quantified in terms of the emission of CO_2, which is well acknowledged. And the CO_2 emission is further computed by the fuel consumption, which is determined by various possible factors in transportation. In contrast with the CVRP, the proposed EVRP model is rather straight-forward and well perceived, without excessive assumptions or constraints and can directly inspire practitioners in realizing the importance of green transportation management. Second, the proposed hybrid ABC algorithm, which is proven to be effective and efficient in solving EVRP, is a pilot attempt of applying swarm intelligence into green logistics, which could facilitate the integrated study of green logistics and swarm intelligence. Apart from the above two aspects, the comparative studies in numerical experiments indicates the transformation of the optimal solutions from the situation of shortest travelling distance to the situation of minimum environmental influence, and provides practical managerial implications for decision-making in green logistics.

4.2 Problem Formulation

4.2.1 Vehicle Routing Model

VRP is normally modeled on a graph, which comprises a set of nodes and the associative edges. The set of nodes represent the depot(s) and customers, while the edges represent the routes among them. A number of vehicles depart from the depot(s), visit customers and return to the depot(s). The number of vehicles, the allocation of customers for vehicles and the optimal routes for vehicles are three intrinsic aspects of VRP. The objective of the VRP is to find the optimal routs with minimum travelling cost and number of vehicles, while serving all the customers. Figure 4.1 illustrates the fundamental concept of the VRP.

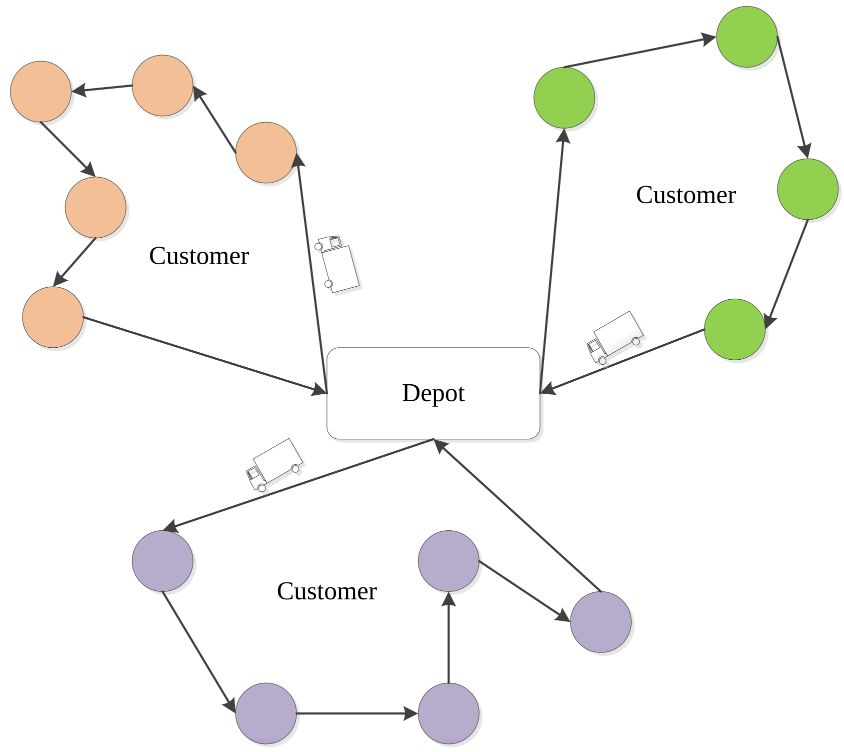


Figure 4.1 The illustration of the VRP

The settings and notations of VRP are described in Table 4.1. In this research, the scenario of single depot and symmetric network is adopted, which means all the vehicles depart from and return to the same depot and the route between two nodes contains no directional information. In detail, node $i = 0$ is the depot, and the other nodes $i = 1,2,\cdots,n$ represent customers. The distance between node i and node j is represented as d_{ij} $(i,j \in V, i \neq j)$, and the symmetric network indicates that $d_{ij} = d_{ji}$ $(i,j \in V, i \neq j)$. Customer demand is represented as r_i $(i = 1,2,\cdots,n)$, which is predetermined in this research. m vehicles with same load capacity Q are available. The travelling cost between customer i and j is illustrated as c_{ij}, and treated from a distance perspective as $c_{ij} = \alpha * d_{ij}$, in which α is the correlative coefficient depicting the proportion between economic cost and travelling distance. The above assumptions and notations are sufficient to construct a vehicle routing model with the objective of finding the shortest travelling distance. In practical situations, there might be some other constraints for the entities (i.e. depot, customers and vehicles), such as multiple depots, uncertain demand and time window for customers, and maximum allowed travelling distance for vehicles.

Table 4.1 The notations and settings of the VRP

Parameters	**Notations**	**Meanings**
Graph related parameters	$G = (V,\ A)$	The graph
	$V = \{0,1,2,\cdots,n\}$	The set of nodes in the graph
	$A = \{(i,j)\|i,j \in V, i \neq j\}$	The set of edges in the graph
	$d_{ij} = d_{ji}\ (i,j \in V, i \neq j)$	The distance between i and j
	$c_{ij} = \alpha * d_{ij}$	The travelling cost on edge (i,j)
Customer-related parameter	$r_i\ (i = 1,2,\cdots,n)$	The customer demand
Vehicle-related parameter	Q	The vehicle capacity
	m	The maximum number of vehicles

4.2.2 Environmental Influence

As we mentioned above, the environmental influence is externalized in terms of the CO_2 emission. Therefore, the critical issue is to measure the amount of CO_2 emission. In this research, we use e_{ij} to denote the amount of CO_2 emission when a vehicle travels from customer i to customer j, and try to find the optimal routes with the least CO_2 emission considering the balance between c_{ij} and e_{ij}. The added settings and notations for environmental measurement are provided in Table 4.2.

Table 4.2 The notations and settings for environmental measurement

Parameters	**Notations**	**Description**
CO_2 emission	CER	The CO_2 emission rate
	FCR	The fuel consumption rate
	$e_{ij} = CER * FCR * d_{ij}$	The amount of CO_2 emission
Fuel consumption	ρ_0	The empty-load FCR
	ρ^*	The full-load FCR
	ρ	The FCR provided that load is q
Vehicle load	q	The real-time load of vehicle
	q_{ijk}	The load of vehicle k on edge $(i,\ j), i, j \in V, i \neq j$
	q_{0jk}	The initial load of vehicle k
	q_{i0k}	The final load of vehicle k

The mechanism of environmental measurement is described in the following. The emission of CO_2 is caused directly by the consumption of certain type of fuel for vehicles. The CO_2 emission rate (*CER*) is relative fixed provided that the type of fuel is known, e.g. 2.61 kg/liter in case of the diesel oil. The fuel consumption is determined by the travelling distance and the load of vehicles. In order to calculate the fuel consumption, we adapt a linear expression between the fuel consumption rate (*FCR*) and the weight of vehicle, and integrate it into our model. The empty-load and full-load fuel consumption rate of vehicles are denoted as ρ_0 and ρ^* respectively. The fuel consumption rate ρ under the load q is expressed as equation (4.1).

$$\rho(q) = \rho_0 + \frac{\rho^* - \rho_0}{Q} q \tag{4.1}$$

When vehicle k is travelling from customer i to customer j, the travelling distance and the load of vehicle k are represented as d_{ij} and q_{ijk} respectively, thus the CO_2 emission for vehicle k should be represented as equation (4.2).

$$e_{ijk} = CER * \left(\rho_0 + \frac{\rho^* - \rho_0}{Q} q_{ijk}\right) * d_{ij} \tag{4.2}$$

4.2.3 Environmental Vehicle Routing Model

Based on the fundamental vehicle routing model and the new environmental consideration described in the above sections, we can provide the complete formulation of the EVRP. Decision variables involved in the EVRP are defined as Table 4.3.

Table 4.3 The decision variables for the EVRP

Decision variables	**Description**
x_{ijk}	Binary variable, $x_{ijk} = 1$ if node j is followed by node i in sequence by vehicle k, otherwise $x_{ijk} = 0$.
y_{ik}	Binary variable, $y_{ik} = 1$ if node i is visited by vehicle k, otherwise $y_{ik} = 0$.

Two objectives are designed for the EVRP. Objective (4.3) is designed to calculate the overall cost aiming to find the optimal routes with minimum economic cost in terms of shortest distance, while objective (4.4) is to find the optimal routes with minimum environmental cost in terms of the CO_2 emission.

$$\min f_1 = \sum_i \sum_j \sum_k \alpha * d_{ij} * x_{ijk} \tag{4.3}$$

$$\min f_2 = \sum_i \sum_j \sum_k CER * \left(\rho_0 + \frac{\rho^* - \rho_0}{Q} q_{ijk}\right) * d_{ij} * x_{ijk} \tag{4.4}$$

The associated constraints of the EVRP are summarized as follows.

$$\sum_{i=1}^{n} r_i y_{ik} \leq Q, \forall k \tag{4.5}$$

$$\sum_{k=1}^{m} x_{ijk} \leq m, i = 0, \forall j \tag{4.6}$$

$$\sum_{k=1}^{m} y_{ik} = 1, \forall i \tag{4.7}$$

$$\sum_{i=0}^{n} x_{ijk} = y_{jk}, \forall j, , i \neq j, \forall k \tag{4.8}$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik}, \forall i, i \neq j, \forall k \tag{4.9}$$

$$q_{0jk} = \sum_{i=1}^{n} r_i y_{ik}, \forall k, j \tag{4.10}$$

$$q_{i0k} = 0, \forall k, i \tag{4.11}$$

$$q_{ijk} = q_{uik} - r_i, (u \rightarrow i \rightarrow j), \forall k \tag{4.12}$$

$$\mathrm{X} = \left(x_{ijk}\right) \in S, (S \subset V \backslash \{0\}) \tag{4.13}$$

$$\sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1 \ (|S| \geq 2; i \neq j; \forall k) \tag{4.14}$$

$$\begin{gathered} x_{ijk} = 0 \ or \ 1, \forall i, j, k \\ y_{ik} = 0 \ or \ 1, \forall i, j, k \end{gathered} \tag{4.15}$$

Constraint (4.5) indicates that the cumulative customer requirement in one route cannot exceed the maximum capacity of the vehicle. Constraint (4.6) means the number of vehicles used should be less than the predetermined setting m, because some vehicles may be arranged for backup or emergency use. Each customer can only be visited and served by one vehicle under constraint (4.7). Constraints (4.8) and (4.9) guarantee the connectivity of each sub-route, which means the visiting vehicle; the departing vehicle and the serving vehicle for one customer can only be the same one. Constraint (4.10) and (4.11) describe the initial load and the final load of vehicle k respectively, in which the initial load should equal the cumulative demand of customers associated with this vehicle and the final load should be 0. While en route, the real-time load of vehicle k can be calculated through the deduction of the demand of its preceding visited customer from its former load, which is expressed in constraint (4.12) provided that vehicle k visits customers u, i and j sequentially. Constraint (4.13) and (4.14) are designated to avoid sub-tours, while the constraint (4.15) is the binary constraint for the decision variables.

4.3 Algorithm Design

The ABC algorithm belongs to the category of swarm intelligence, which mimics the intelligent behavior of various species, such as ants, birds, bees. Two common distinguishing features of swarm intelligence are self-adjusting and rapid-responsiveness. The ABC algorithm imitates the behaviors of honeybees, which are divided into three types, scout bees, employed bees and onlooker bees. Different types of bees play different roles in the procedure of exploration and exploitation of food sources. Food sources are regarded as the solutions to specific problems, while the ones with more nectar correspond to better solutions.

The whole procedure of the ABC algorithm can be described as follows. Scout bees are designated to find the initial food sources by carrying out a random search in the search space. Subsequently, employed bees are sent out to exploit the found food sources, and each employed bee matches one food source. During the procedure of exploitation, each employed bee also carries out a neighborhood search and tries to find a better food source nearby. If a better food source is found, the employed bee would abandon the previous food source and exploit the better one. After the completion of the work of all employed bees, they return to the hive and share their information of their associated food sources with onlooker bees waiting in the hive through a waggle dance. The onlooker bees choose to follow certain employed bees and exploit the corresponding food sources probabilistically. This probability is affected mainly by the richness of the corresponding food sources. Once an onlooker bee chooses to follow an employed bee, it becomes an employed bee and repeats the procedure of the employed bees. After certain number of iterations of the procedure of exploitation and exploration, one food source may be exhausted. In that case, the associated employed bee becomes a scout bee and repeating the procedure of scout bees, randomly finding a new food source to replace the abandoned one. The flow chart of ABC algorithm is described in Figure 4.2 with four periods confirmed in the above description, (1) initialization phase, (2) employed bee phase, (3) onlooker bee phase and (4) scout bee phase.

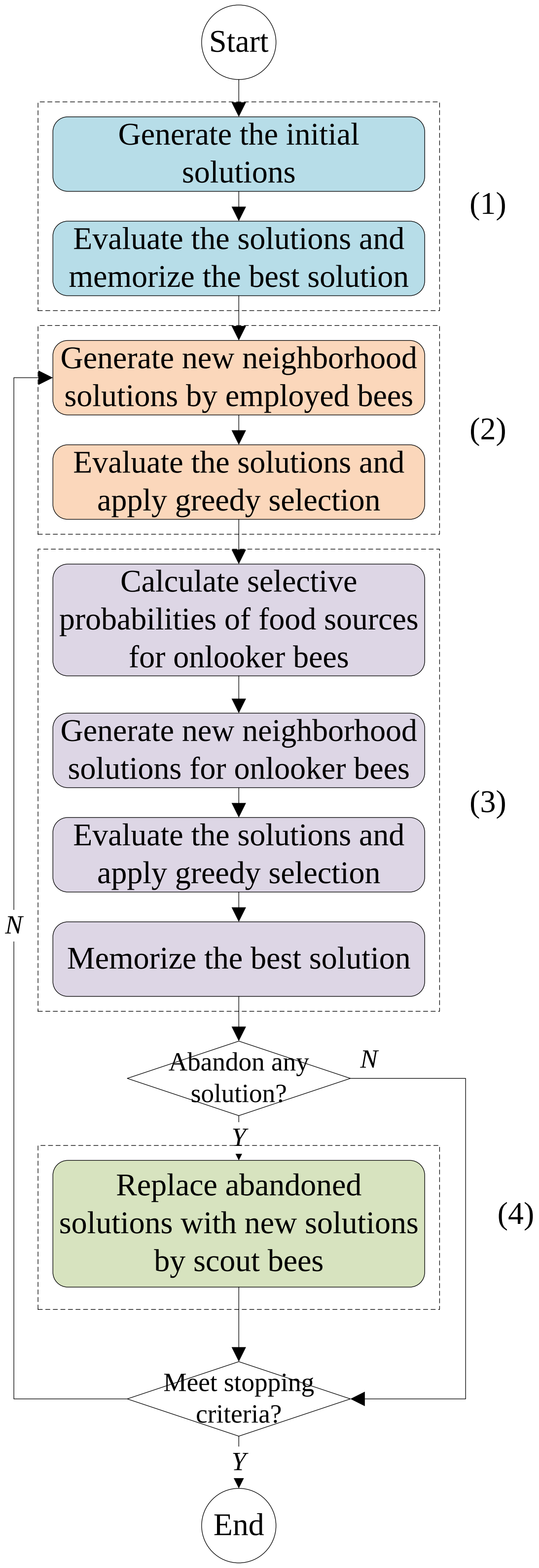


Figure 4.2 The flow chart of the ABC algorithm

Based on the procedures mentioned above, we provide the pseudo code of ABC algorithm in Table 4.4 and Figure 4.3, which also contains the explanation of the notations used. The ABC algorithm was initially proposed to solve continuous numerical problems without constraints; the generation of initial solutions is determined by the intrinsic range of each dimensional variable referring to equation (1). The neighbor solution is computed through the intersection of the two existing solutions in equation (3); the current solution and another randomly chosen solution. Greedy selection is applied in each neighborhood search which can facilitate the capability of the intensive search, while the abandonment function enhances the capability of the diversified search. However, the original ABC algorithm is not appropriate for the EVRP model due to the different problem contexts, the discrete variable structures and the irregular search space. Apart from that, the required constraints in the proposed model also force the changes of original ABC algorithm. Therefore, based on the original ABC algorithm, we propose a hybrid ABC algorithm for the EVRP model described in the following subsections.

Table 4.4 The notations of the ABC algorithm

Notations	**Description**
SN	The number of solutions
$limit$	The criterion of abandoning a solution
MNI	The predetermined maximum number of iteration
$x_i, i = 1,2,\cdots,SN$	The index of individual solution
D	The dimension of individual solution
$x_{ij}, j \leq D$	The j^{th} dimension of solution x_i
x_{ub}^{j}, x_{lb}^{j}	The upper bound and lower bound of x_{ij}
f_i	The function value of solution x_i
fit_i	The fitness value of solution x_i
p_i	The probability of selecting solution x_i
v_i	The neighbor solution of solution x_i
$trial(x_i)$	The number of iterations in which solution x_i cannot be improved.
ω, φ	Random number, $0 \leq \omega \leq 1$ and $-1 \leq \varphi \leq 1$

Initialization

(1) Generate the initial solutions $x_i, i = 1,2,\cdots,SN$ randomly

$$x_{ij} = x_{lb}^{j} + \omega\left(x_{ub}^{j} - x_{lb}^{j}\right), \forall j$$

(2) Calculate the fitness of initial solutions $fit_i, \forall i$

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, & if\ f_i \geq 0 \\ 1 + abs(f_i), & if\ f_i < 0 \end{cases}, \forall i$$

Set $iteration = 1$

Repeat

For each employed bee

(1) Conduct neighborhood search for $x_i, \forall i$

$$v_{ij} = x_{ij} + \varphi\left(x_{ij} - x_{kj}\right), \forall i, i \neq k$$

(2) Calculate the fitness of neighbor solution v_i

(3) Apply greedy selection between x_i and v_i

For each onlooker bee

(1) Calculate the selective probability for each solution $x_i, \forall i$

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i}, \forall i$$

(2) Select solution x_i referring to the correlative p_i

(3) Repeat the employed bee operation

If any abandoned solution exist $trial(x_i) > limit$

Then replace it with a new random solution

Find and memorize the best solution found so far

$iteration = iteration + 1$

Until $iteration = MNI$

Figure 4.3 The pseudo code of the ABC algorithm

4.3.1 Solution Scheme

Since the ABC algorithm is initially designed for continuous numerical problems, the initial solutions are generated by taking into account the lower and upper bounds of the dimensional variables of a specific problem. However, in CVRP, all dimensions of each solution are related, which means the dimensional variables cannot be generated separately. Therefore, we have to consider all dimensional variables simultaneously in constituting the solution. After an extensive review of the relevant literature, we find two popular representation schemes which are frequently used. The first one is expressed as $X = \{X_v, X_r\}$. X_v and X_r are the vehicle information and route information associated with each customer respectively. $1 \leq x_{vi} \leq K$ (K is the number of vehicles, x_{vi} is the vehicle information of customer i). $1 \leq x_{ri} \leq N$ (N is the number of customers, x_{ri} is the route information of customer i). The dimension of solution X is $2N$ (two times of the number of customers). For example, $X_v = \{1,2,2,2,2,3,3\}$ and $X_r = \{5,4,3,2,7,1,5\}$. Due to the random generation of X_r, it may have to be re-sorted per vehicle as $X_r^* = \{1,3,4,1,2,1,2\}$. In this case, the solution contains three sub-routes, $\{0,1,0\}$, $\{0,4,5,2,3,0\}$ and $\{0,6,7,0\}$.

The second one is stated as a random permutation of customers with multiple delimiters, such as 0. Each sub-sequence between two close delimiters is treated as a route. The dimension of this scheme is $N + K + 1$. For example, $\mathrm{X} = \{0,1,0,4,5,2,3,0,6,7,0\}$ indicates exactly the same result as the one in first representation scheme. Table 4.5 illustrates the comparison of the above two representation schemes with a simple example of 7 customers. Compared with the first scheme, the second one is more intuitive and succinct. Not only because of the smaller dimensional scale, the inner generation mechanism of the second scheme can significantly decrease the computational complexity. Thus the second scheme is chosen. The advantage of the first scheme is that it has the potential to handle VRPs with different types of vehicles because the labeled vehicles can be identified.

Table 4.5 The comparison of two solution schemes

<table>
<tr><th colspan="3">Customer indices</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th><th>7</th><th>Solution</th></tr>
<tr><td rowspan="3">Scheme 1</td><td>Vehicle</td><td>X_v</td><td>1</td><td>2</td><td>2</td><td>2</td><td>2</td><td>3</td><td>3</td><td rowspan="4">Route 1:
{0,1,0}
Route 2:
{0,4,5,2,3,0}
Route 3:
{0,6,7,0}</td></tr>
<tr><td>Route</td><td>X_r</td><td>5</td><td>4</td><td>3</td><td>2</td><td>7</td><td>1</td><td>5</td></tr>
<tr><td>Updated route</td><td>X_r^*</td><td>1</td><td>3</td><td>4</td><td>1</td><td>2</td><td>1</td><td>2</td></tr>
<tr><td>Scheme 2</td><td></td><td colspan="8">$X = \{0,1,0,4,5,2,3,0,6,7,0\}$</td></tr>
</table>

In order to facilitate the process of exploration and exploitation, the search space is not restricted into the feasible region only, which means infeasible solutions are acceptable in the interim states. The infeasible solutions can be used as intermediate solutions to assist the generation of better feasible solutions at next state. In ABC algorithm, given the existing solution, when an employed bee carries out a neighborhood search in the neighborhood area, it may find one solution from the infeasible region. In classical CVRP, when a solution violates the maximum capacity constraint, this solution has to be labeled as an infeasible solution. However, in this research, we use the evaluation mechanism to handle the tolerance of infeasible solutions. For each solution, $x \in X$, let $p(x)$ denote the total violation of capacity constraints (Alvarado, Garcia et al. 2013). Referring to the previous notation, the capacity violation $p(x)$ can be expressed as equation (4.16). As a result, each solution can be evaluated through the evaluation function as equation (4.17). The parameter δ is self-adjusted, which is gradually enlarged with the increase number of iterations. This allows the existence of infeasible solutions during the searching process but exclude them at the end. The permission and propagation of infeasible solutions during the searching process can substantially raise the exploration and exploitation of the search space.

$$p(x) = \sum_{k=1}^{m} max\left\{\sum_{i=1}^{n} r_i y_{ik} - Q, 0\right\} \tag{4.16}$$

$$f(x) = c(x) + \delta * p(x) \tag{4.17}$$

4.3.2 Initialization Phase

In the original ABC algorithm, the initial solutions are randomly generated by considering the range of dimensional variables. However, this approach can only be used for continuous numerical problems, where the dimensional variables are all real numbers and have a certain range. In this research, a simple and efficient mechanism to generate initial solutions is introduced by using the representation scheme mentioned above. First, we generate a random permutation with a set of customers only, and then split this random permutation of customers into various routes, taking account of the capacity of the vehicles as described in Figure 4.4. Empty routes are also added if necessary to meet the dimensional requirement. Following this mechanism, all the initial solutions can be easily generated and guaranteed to be feasible. It can speed up the convergence of the solutions to a large extent. The guarantee of feasible solutions in the initialization phase does not conflict with the permission and propagation of infeasible solutions in the next states. Another improvement in our designed hybrid ABC algorithm is that we can run the program multiple times in order to evaluate the average performance. However, the initial solutions are only generated once in the first iteration. Apart from that, the output of last iteration is used as the input of next execution, so the solutions can be continuously improved, which also accelerates the speed of convergence.

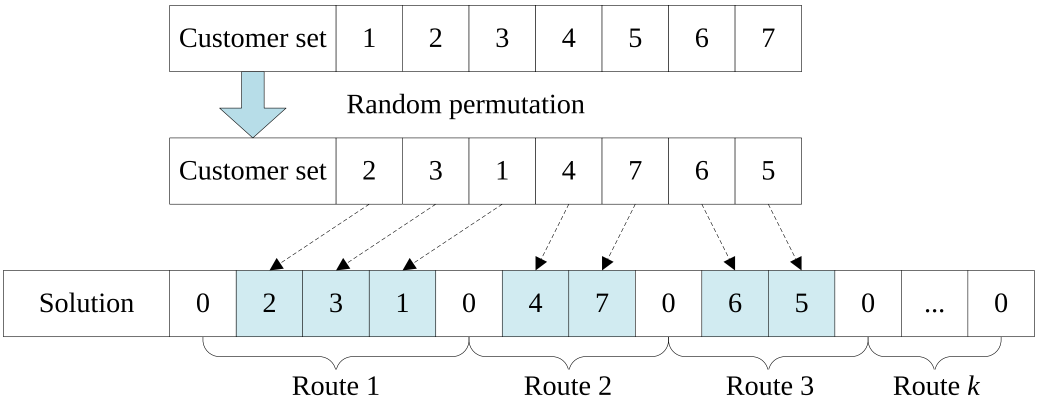


Figure 4.4 The generation of initial solutions

4.3.3 Employed Bee Phase

The initial solutions are generated repetitively following the approach introduced above. Subsequently, employed bees are assigned to exploit the found food sources. One employed bee is assigned to exactly one food source, which means the number of employed bees is the same as the number of food sources. Given the known food source, the corresponding employed bee also tries to search its neighborhood for potential better food sources. In the original ABC algorithm, the candidate solution is generated through the modification of the current solution by referring to another randomly selected solution. However, when the ABC algorithm is applied into CVRP, this mechanism does not work efficiently. Many researchers have tried to adapt various operators in this procedure to improve the probability of finding better solutions, such as the swap operator, the reverse operator, and the insert operator and so on (Szeto, Wu et al. 2011; Xiao, Zhao et al. 2012; Alvarado, Garcia et al. 2013) as described in Figure 4.5.

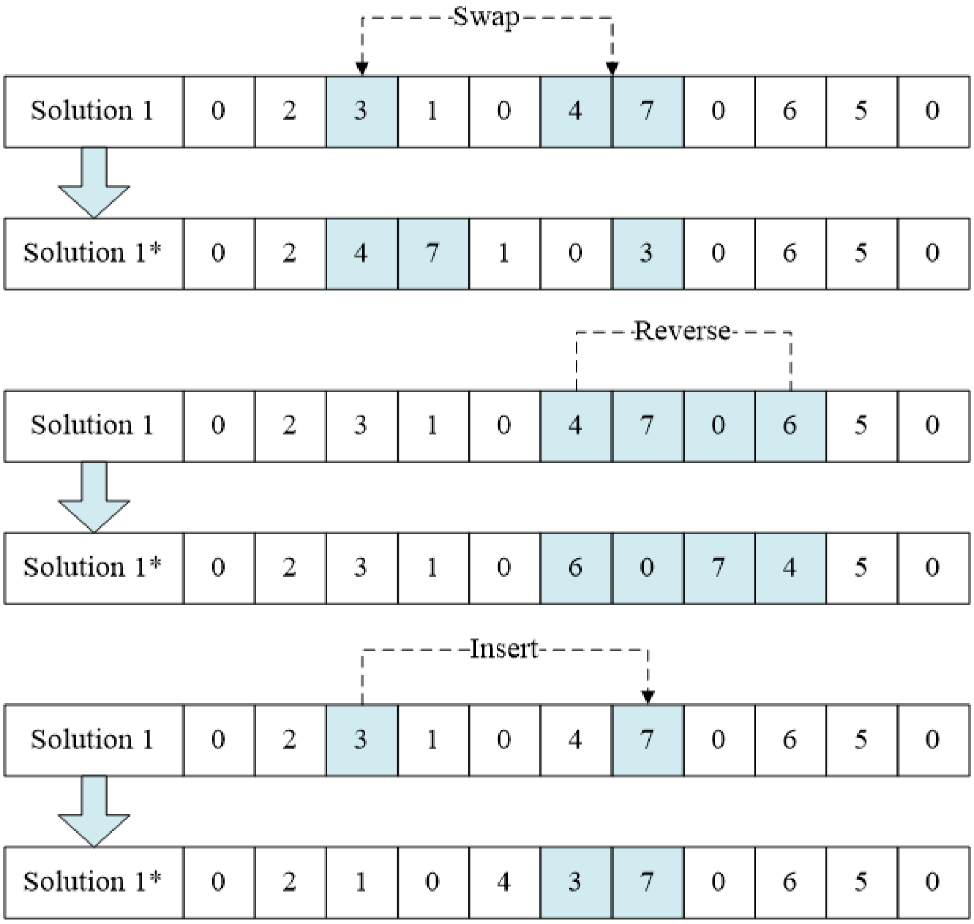


Figure 4.5 The design of operators

The numerical analysis of the efficiency of swap, reverse and insert operators indicates that all of them can assist the evolution of solutions to a certain extent. However, these operators all behave using random searching, which cannot fully utilize the existing information of the current solution. The well-performed sub-routes in the current solution could be easily destroyed by these operators unintentionally. Therefore, in this research, we incorporate the crossover concept from the Genetic Algorithm (GA) (Prins 2004) into our ABC algorithm . To better utilize the existing information, we choose to use the rule of maximum retention exchange, which is illustrated in Figure 4.6. The well-performed sub-route from parent solution 1 is selected and reserved in the new solution, while the other parts of this new solution are complemented by parent solution 2, following the rule of maximum retention exchange. Likewise, the well-performed sub-route from parent solution 2 can also be saved and inherited by its child solution. By incorporating this crossover operator, the evolution of solutions can be guided in a good direction and the convergence of solutions can also be increased.

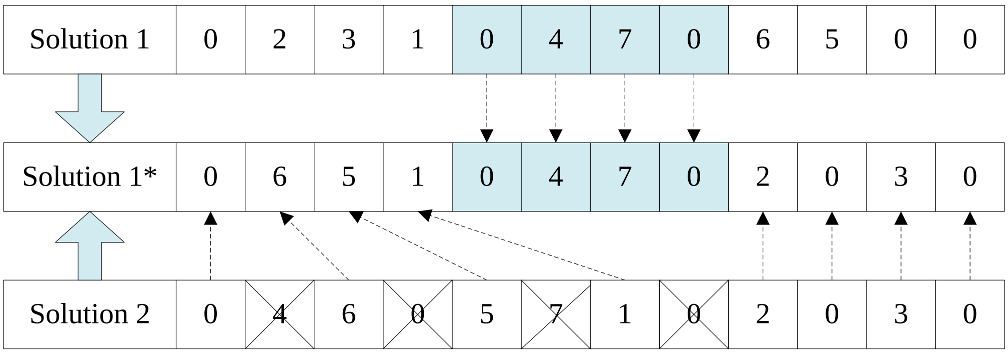


Figure 4.6 The crossover operator

Another improvement is the adoption of the local search mechanism to each sub-route within the new generated solutions. The approaches of 2-optimization and 3-optimization, which optimize the provided solution through the exchange of two or three elements, are both considered in our research depending on the length of corresponding sub-route. Once a new solution is generated, we apply the local search operator to all valid sub-routes contained in this solution. Essentially, the above swap, reverse, insert and crossover operators are all designed to be applied to the solution level, while the local search operator is adapted in the sub-route level. This means the local search operator can complement the flaws in the randomness of swap, reverse, insert and crossover operators and enhance the efficiency of the intensive search around the optimal solution. The efficiency of the local search operator is evaluated and analyzed in our numerical experiments.

4.3.4 Onlooker Bee Phase

After the completion of the employed bee phase, the employed bees return to the hive and share their food information with onlooker bees. The onlooker bees choose to follow certain employed bees and exploit their corresponding food sources randomly. In the ABC algorithm, the number of onlooker bees is set to be equal to the number of employed bees, and the selective probability is computed through the roulette wheel mechanism. Therefore, the food sources with large amounts of nectar may be selected multiple times, which could promote the propagation of good solutions, and intensify the local search and increase the speed of convergence. For solution x_i, let f_i, fit_i and p_i denote the total cost, fitness function value and selective probability of this solution respectively. The calculation of fit_i and p_i can be found in Figure 4.3. With the known probability, an onlooker bee chooses to exploit a specific food source, and repeats the same procedure as the employed bee phase.

4.3.5 Scout Bee Phase

Due to iterative exploitation, the nectar in some food sources is gradually consumed and may finally be exhausted. The exhausted food source would be abandoned by its corresponding employed bee. In this case, the associated employed bee becomes a scout bee, and finds a new food source randomly to replace the abandoned one. In the ABC algorithm, each solution is labeled with one trial number. If one solution cannot be improved after a certain number of trials, it would be abandoned. The procedure is: when a neighborhood search of the current solution is conducted and no better solutions are found, the trial number of the current solution is increased by 1. However, if a new solution with better fitness is found, it directly replaces the current solution and resets the trial number as 0. After each onlooker bee phase, the trial numbers of all the solutions will be checked. If the trial number of one solution exceeds a predetermined parameter, this solution would be replaced by a new generated solution in the scout bee phase. As a result of this supplemental scout bee phase, the diversified search ability of the ABC algorithm is strengthened, which facilitates the convergence of the solutions to a global optimal one.

4.4 Experiment and Analysis

In the numerical experiment, fifteen benchmark distance-constrained VRP instances from Augerat, Belenguer et al. (1995) and four instances from Christofides and Eilon (1969) are adopted. The names of instances indicate the category of the associated files, the number of nodes on the graph, and the number of vehicles acquired in the optimal solutions. For example, instance "A-n32-k5" indicates that this instance is in category A with 32 nodes, and 5 vehicles are used in the optimal solution. The locations of customers and the depot are provided in a coordinated form. The demand of customers and the capacity of vehicles are predetermined in each instance as well.

The ABC algorithm provides a rather simple swarm-based optimization technique, in which only two parameters need to be tuned. The first one is the size of the bee colony (*CS*), which is two times of the number of solutions (*SN*). The number of employed bees and onlooker bees, which equals the number of food sources, is set to be half of the bee colony size. The second parameter is the criterion of the abandonment of certain solutions (*limit*). The detailed analysis of parameter *SN* and *limit* is provided in the following subsection. As for the parameter δ employed in the evaluation function as $f(x) = c(x) + \delta * p(x), x \in X$, since the variance of δ is consistent with the increase of the number of iterations, we calculate δ by multiplying another positive coefficient τ and the current index of iterations. In this case, we set τ to be 0.1 referring to the setting of the maximum number of iterations. The complete parameter settings are provided in Table 4.6. The hybrid ABC algorithm is coded in Java with Eclipse IDE, and all tests are performed on a PC with a 2.5GHz processor. Each combination of parameters and operators is executed 10 times repetitively, and the average value is used to illustrate the computational performance in order to provide convincing results.

Table 4.6 The parameter settings for numerical experiment

Settings	**Explanation**
Instance	The number of customers is provided in each instance. The locations of customers and the depot are provided in coordinate format in each instance. The customer demands are provided in each instance. The vehicle capacity is provided in each instance. The full connectivity among all the nodes on the graph is assumed. The distance between two nodes, $i(x_i, y_i)$ and $j(x_j, y_j)$, is calculated as $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
Model	$\alpha = 1$ for the calculation of economic cost in terms of distance $CER = 2.61$ The CO_2 emission rate in terms of the diesel oil $\rho_0 = 0.296$ The empty-load *FCR* $\rho^* = 0.390$ The full-load *FCR* $m = 2k$ The maximum number of vehicle available $\delta = \tau * the\ index\ of\ current\ iteration$ The penalty coefficient $\tau = 0.1$
Algorithm	CS The size of be colony $limit$ The criterion of abandonment of solutions

4.4.1 Parameter Analysis

As we mentioned, the ABC algorithm provides a relatively simple mechanism, in which only two parameters need to be tuned, *SN* and *limit*. In general, larger size of bee colony can initiate more parallel searches simultaneously and facilitate the diversified exploration. However, the computational time increases substantially because of the size of bee colony, especially when the number of iterations is also large. The *limit* is normally set to be the product of the number of solutions (*SN*) and the number of dimensions (D) as $limit = SN * D$. However, in this case, D is replaced with the number of vehicles (K) in one solution as $limit = SN * K$, because the latter one can promote the diversified exploration of the search space better.

The analysis of parameters is conducted with the instance E-n51-k5 first so as to find the best combination, which is displayed in Figure 4.7. The results show that the setting of colony size (*CS*) as 10 is not sufficient to acquire a good performance. By contrast, the *CS* setting as 20 is already adequate for an acceptable result; meanwhile it costs less time than the *CS* setting as 40 and 80. Once the *CS* as 20 is determined, we test the performance of the hybrid ABC algorithm with different settings of the *limit*. From the Figure 4.7 it is found that the smaller of the limit, the more diversified of the evolution. In this case, we set the *limit* as *SN**K* in order to balance the effect of diversification and intensification of the evolution procedure. Thus the combination of *CS* as 20 and *limit* as *SN*K* is eventually employed solving all the instances.

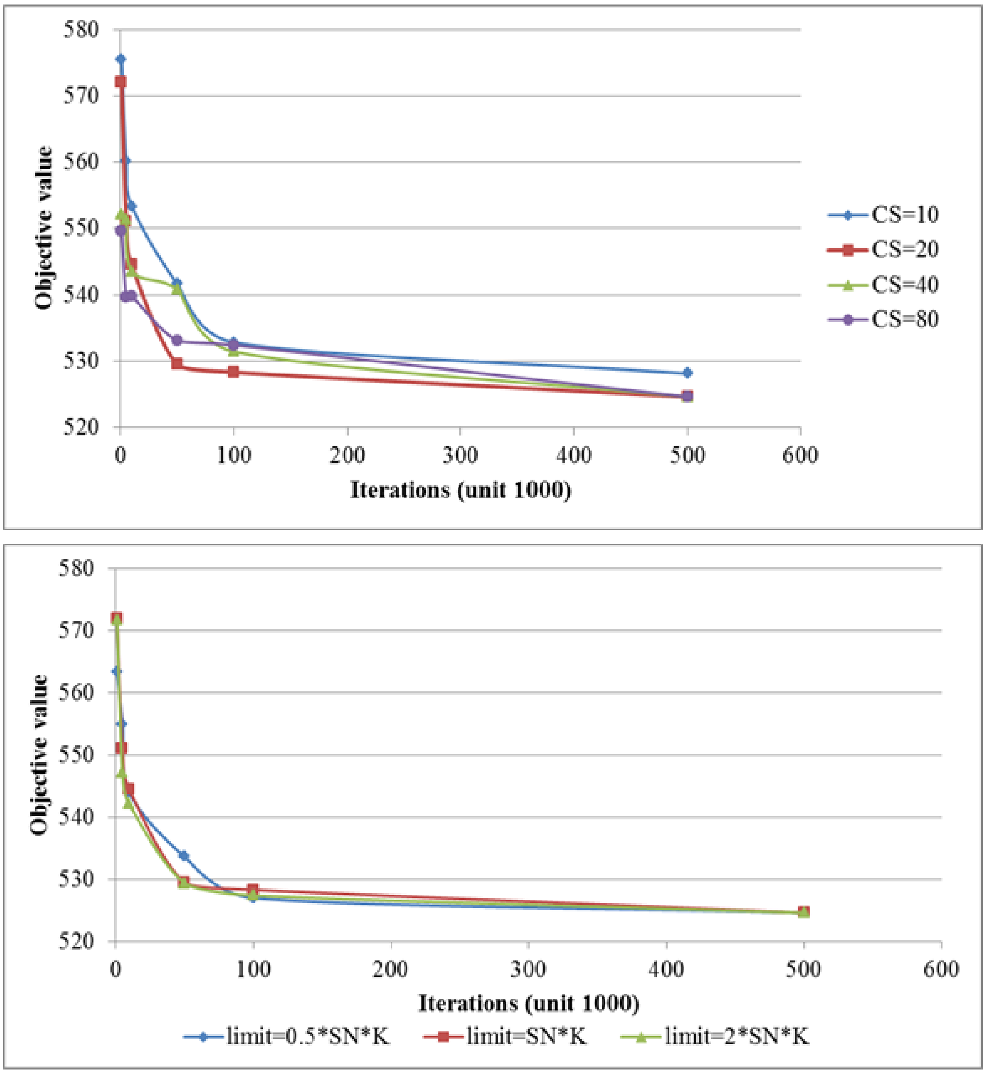


Figure 4.7 The settings of colony size and limit

4.4.2 Operator Analysis

In the proposed hybrid ABC algorithm, five operators (i.e. swap operator, reverse operator, insert operator, crossover operator and local search operator) are adopted. Among them, the swap, reverse and insert operators are frequently used in many research studies (Szeto, Wu et al. 2011). However, there are no distinguishing strengths and weaknesses among them. Different research provides different efficiency analysis of these three operators, and most of them are based on specific problems. In this case, the above mentioned benchmark instance (i.e. E-n51-k5) is adopted to compare the performance of the three operators. We then incorporate the crossover operator and local search operator into the procedure of neighborhood search, and constitute a hybrid operator by combining all the mentioned operators. The operational performances of swap, reverse, insert and hybrid operators are illustrated in Figure 4.8.

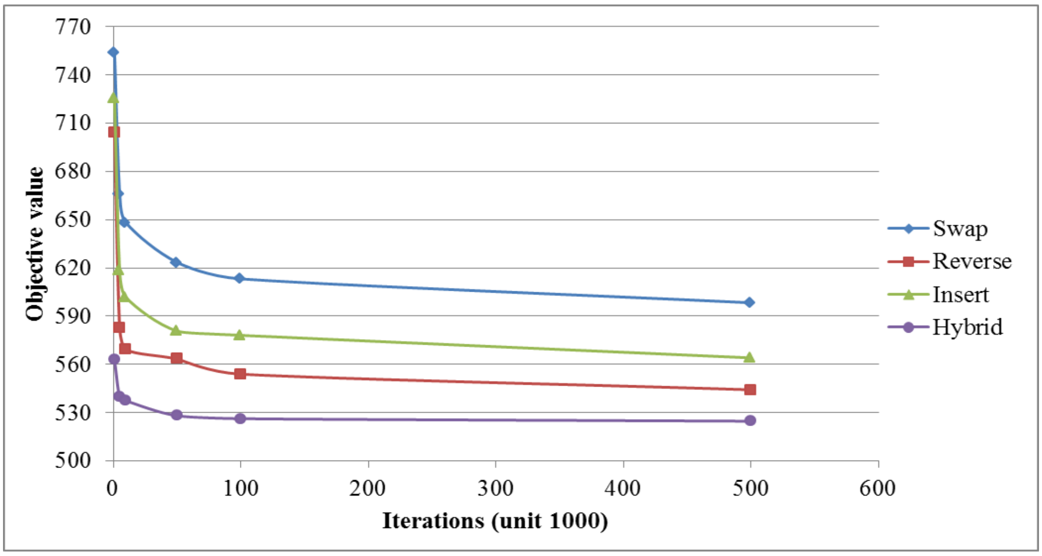


Figure 4.8 The comparison of different operators

In the experiment, the reverse operator performs the best with a 9.9% improvement over the swap operator and a 4.1% improvement over the insert operator. In addition, the insert operator has a 6.0% improvement over the swap operator. The swap operator performs the worst when we adopt a single operator in the neighborhood search procedure. The results demonstrate that the hybrid operator outperforms the other operators. Especially, when the iteration is small, the hybrid operator even outperforms the reverse operator by 20%. With the increase in the number of iterations, the differentiation of performance is gradually decreased. However, the hybrid operator still performs 3% better than reverse operator when the number of iterations reaches 500,000. In addition, the results indicate that a single operator can hardly drive the evolution of solutions to a satisfactory convergent point. Comparatively, the hybrid operator works well due to the better utilization of the existing information and the intensive local search by the crossover operator and the local search operator collaboratively.

4.4.3 Algorithm Performance Analysis

Since the inspiration of the hybrid ABC algorithm is from the original ABC algorithm and the GA, we need to evaluate the performance of the proposed hybrid ABC algorithm through the comparison with the other two. Both the original ABC algorithm and the GA are adapted to solve the same instance, i.e. E-n51-k5. The parameter settings of GA are as follows. The number of population is 10, which is the same as the number of food sources in ABC algorithm. The crossover rate and mutation rate are set as 0.9 and 0.1 respectively. ABC algorithm and GA are implemented in the same computer using same IDE so as to provide convincing comparison, which is illustrated in Figure 4.9. From the result we can see that the performance of GA is like the original ABC algorithm, and the proposed hybrid ABC algorithm outperforms them distinctly. The reason why the hybrid ABC algorithm is over the original ABC algorithm is certainly due to the incorporation of new operators; the crossover operator and the local search operator. As for the difference between the hybrid ABC algorithm and the GA could be explained by their own inherent frameworks. For example, the ABC algorithm comprises four phases, in which the neighborhood search could be conducted twice because of the onlooker bees in one iteration, while in the GA, the generation of new child population could be only once in one loop.

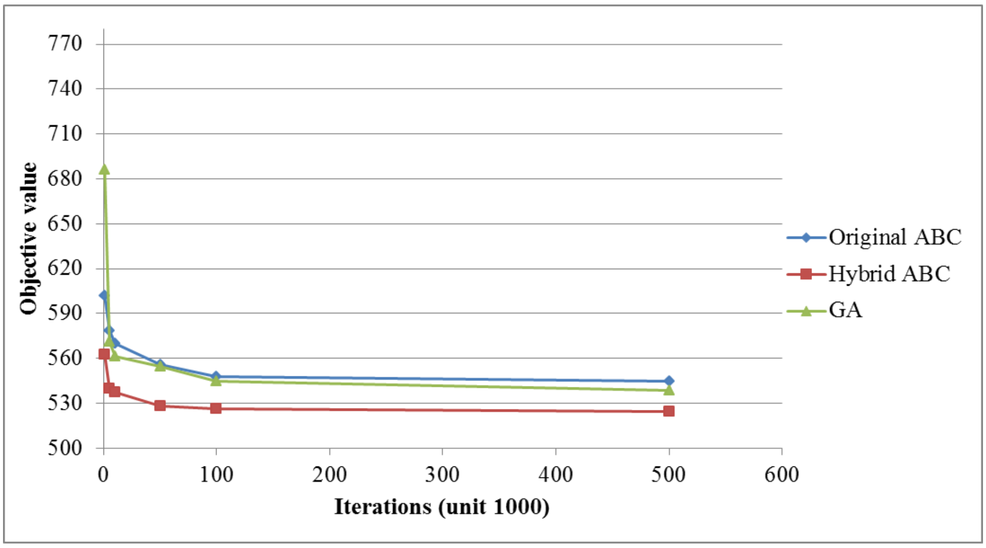


Figure 4.9 The comparison of ABC and GA

4.4.4 Optimal Solution of EVRP

In this section, we conduct our experiments for two situations; situation one with the objective of shortest distance and situation two with the objective of the minimum amount of CO_2 emission. In order to compare the differentiation of the two optimal solutions, we separately calculate the emission of CO_2 along with the optimal solution in situation one and the travelling distance of environmental optimal solution in situation two. Through the analysis of the two situations, it is found that the transformation of the optimal solutions from the shortest travelling distance situation to the minimum CO_2 emission situation is the result of the combination of the two factors, travelling distance and load. Even though in the shortest travelling distance situation, the amount of CO_2 emission varies due to the different travelling direction starting from the depot.

In the formulation of the environmental objective, three parameters should be predetermined; the CO_2 emission rate per liter of fuel, the fuel consumption rate for both empty-load and full-load situations. Numerical experiments indicate that the parameter of the empty-load and full-load affects the weighting of distance and load directly, which further affects the final optimal solution. Referring to a previous case study by Ubeda, Arcelus et al. (2011) *CER* is set as 2.61, empty-load fuel consumption rate $\rho_0 = 0.296$ and full-load fuel consumption rate $\rho^* = 0.390$. The results are illustrated in Table 6. Since the instances are all provided in the symmetric matrix format, for a given route, the amount of CO_2 emission might be different starting from two opposite directions. CO_2_min and CO_2_max are designed to record the minimum and maximum amounts of CO_2 emission separately, along with the optimal solution for the situation of shortest travelling distance by considering the influence of two opposite directions starting from the depot.

From the results, in the situation of the shortest travelling distance, by re-sorting each sub-route within the optimal solution, the amount of CO_2 emission could be reduced by 2.47% on average. The optimal solution in the situation of minimum CO_2 emission could further achieve 0.25% better, on average, which leads to an increase of 0.34% in total travelling distance comparing with its counterpart in the first situation. Such an increase in total travelling distance is reasonable and acceptable, since any solutions with other objectives cannot contain shorter travelling distance than the solution with the objective of the shortest travelling distance. The result from Table 4.7 also indicates that the CO_2 saving from the changes of travelling direction accounts for a large proportion in the transformation of the optimal solutions from situation one to situation two, which meets our expectation that, in reality, the optimal solutions for two situations should not differentiate too much from each other. Actually in practical situations, the factor of the travelling distance is much more crucial than the load factor, which explains the slight changes from the solution of CO_2_min to the environmental optimal solution.

Table 4.7 The computational results of numerical experiments

Instance	Shortest distance solution				Minimum CO_2 solution		CO_2 saving	Distance increase
	Distance	CO_2_min	CO_2_max	CO_2 saving	CO_2	Distance		
A-n32-k5	787.08	685.38	707.46	**3.12%**	682.58	787.81	**0.41%**	**0.09%**
A-n33-k5	662.11	579.98	594.88	**2.50%**	579.20	662.40	**0.13%**	**0.04%**
A-n34-k5	780.94	685.79	698.46	**1.81%**	683.11	790.22	**0.39%**	**1.19%**
A-n36-k5	802.13	704.01	719.68	**2.18%**	702.36	806.17	**0.23%**	**0.50%**
A-n37-k5	672.47	583.00	605.31	**3.69%**	580.69	676.26	**0.40%**	**0.56%**
A-n38-k5	734.18	642.89	665.35	**3.38%**	642.65	735.14	**0.04%**	**0.13%**
A-n39-k5	828.99	730.20	743.16	**1.74%**	727.33	837.07	**0.39%**	**0.98%**
A-n46-k7	917.91	810.73	825.54	**1.79%**	803.73	926.50	**0.86%**	**0.94%**
A-n48-k7	1074.34	944.29	968.14	**2.46%**	944.01	1075.16	**0.03%**	**0.08%**
B-n31-k5	676.09	585.19	588.83	**0.62%**	585.19	676.09	**0.00%**	**0.00%**
B-n35-k5	956.29	839.60	851.16	**1.36%**	838.91	962.24	**0.08%**	**0.62%**
B-n38-k6	808.70	698.50	726.05	**3.79%**	698.50	808.70	**0.00%**	**0.00%**
B-n39-k5	553.16	484.67	495.37	**2.16%**	480.88	553.27	**0.78%**	**0.02%**
B-n43-k6	746.98	652.50	676.07	**3.49%**	651.52	750.41	**0.15%**	**0.46%**
B-n44-k7	914.96	805.66	825.29	**2.38%**	804.94	915.18	**0.09%**	**0.02%**
E-n22-k4	375.28	325.63	340.34	**4.32%**	325.63	375.28	**0.00%**	**0.00%**
E-n23-k3	568.56	481.50	494.29	**2.59%**	479.02	569.75	**0.52%**	**0.21%**
E-n33-k4	837.67	735.69	750.54	**1.98%**	734.88	837.87	**0.11%**	**0.02%**
E-n51-k5	524.61	464.17	471.26	**1.51%**	463.19	527.50	**0.21%**	**0.55%**
Average				**2.47%**			**0.25%**	**0.34%**

The instance of E-n51-k5 exemplifies the specific differentiation of two optimal solutions in corresponding situations. The best known solution for this instance, with the objective of the shortest travelling distance, is 524.61 and contains five sub-routes. Each sub-route is bidirectional since the source data is provided in a symmetric matrix. Thus we need to calculate the maximum and minimum amount of CO_2 emission along with the optimal solution of the shortest travelling distance. After that, we apply our new EVRP model to this instance. All the results are described in Table 4.8. From the results, it is found that the number of routes is the same for both situations. The first, second and forth sub-routes are exactly the same. For the third and fifth sub-routes, the contained nodes are also the same. However, the sequences are quite different, which means even though the overall travelling distance is increased by 0.51%, the construction of the sub-routes could be largely changed. Figure 4.10, 4.11 and 4.12 show the differentiation of the optimal solutions for different situations.

Table 4.8 The optimal results for instance with 50 customer nodes

	Distance	**CO_2**	**Optimal solution**
Situation 1 Shortest distance	524.61	(a) CO_2_max = 471.26	Route #1: {0 46 5 49 10 39 33 45 15 44 37 12 0} Route #2: {0 8 26 31 18 3 36 35 20 22 1 32 0} Route #3: {0 38 9 30 34 50 16 21 29 2 11 0} Route #4: {0 6 14 25 24 43 7 23 48 27 0} Route #5: {0 47 4 17 42 19 40 41 13 18 0}
		(b) CO_2_min = 464.17	Route #1: {0 12 37 44 15 45 33 39 10 49 5 46 0} Route #2: {0 32 1 22 20 35 36 3 28 31 26 8 0} Route #3: {0 11 2 29 21 16 50 34 30 9 38 0} Route #4: {0 27 48 23 7 43 24 25 14 6 0} Route #5: {0 18 13 41 40 19 42 17 4 47 0}
Situation 2 Minimum emission	527.50	(c) CO_2 = 463.17	Route #1: {0 12 37 44 15 45 33 39 10 49 5 46 0} Route #2: {0 32 1 22 20 35 36 3 28 31 26 8 0} Route #3: {0 11 2 29 21 34 30 9 50 16 38 0} Route #4: {0 27 48 23 7 43 24 25 14 6 0} Route #5: {0 47 18 13 41 40 19 42 17 4 0}

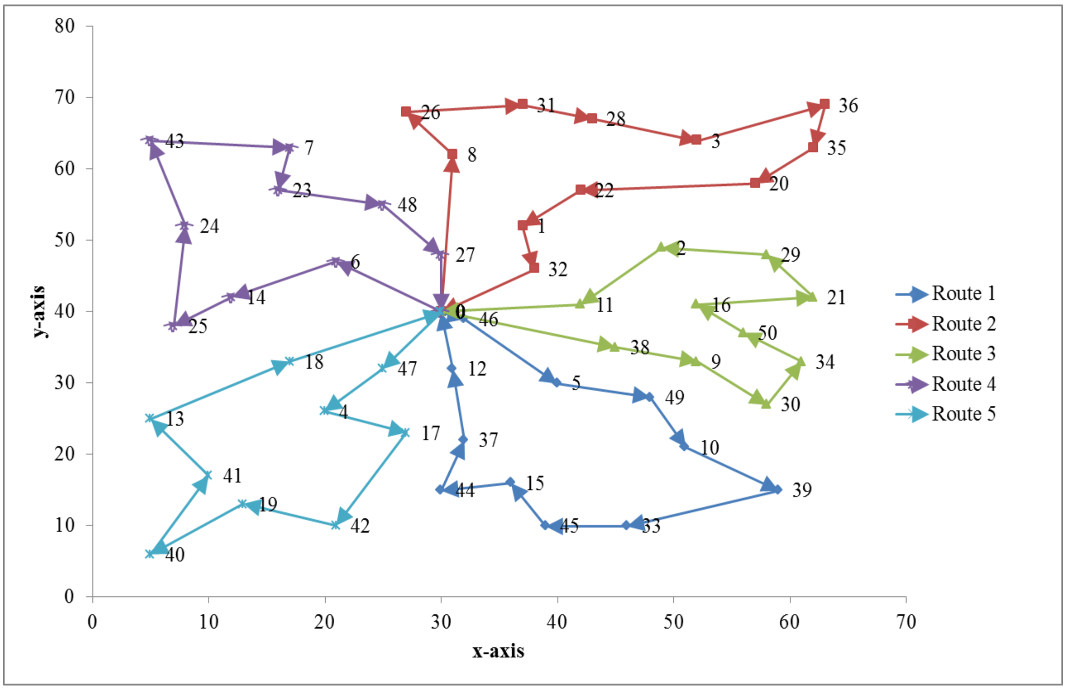


Figure 4.10 The optimal solution of scenario 1 with CO_2_max

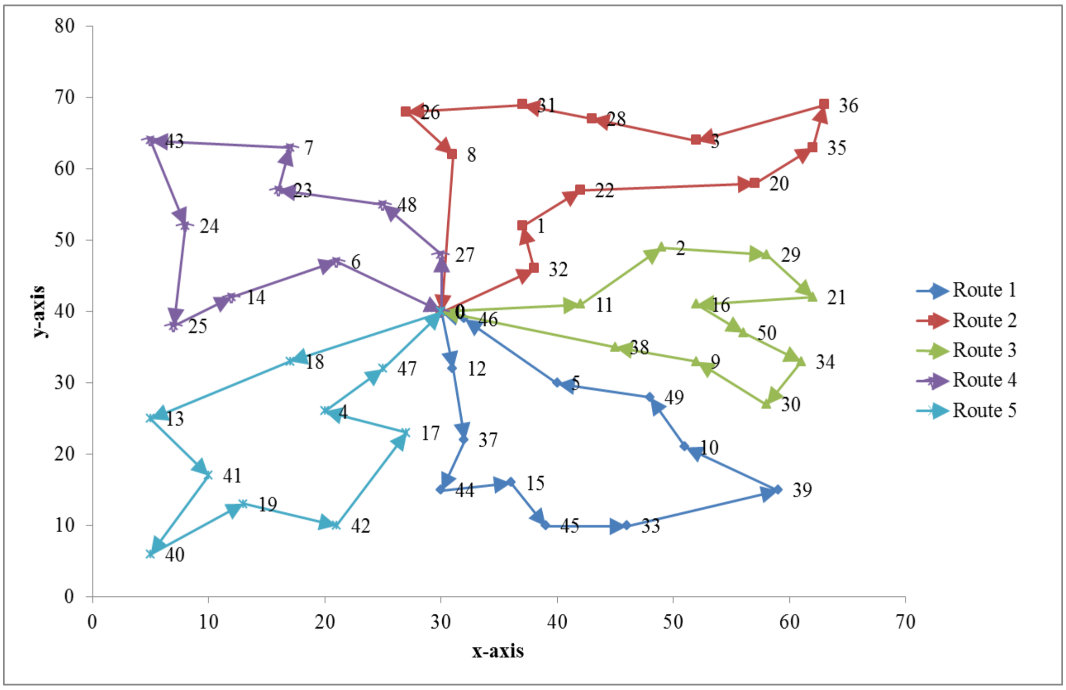


Figure 4.11 The optimal solution of scenario 1 with CO_2_min

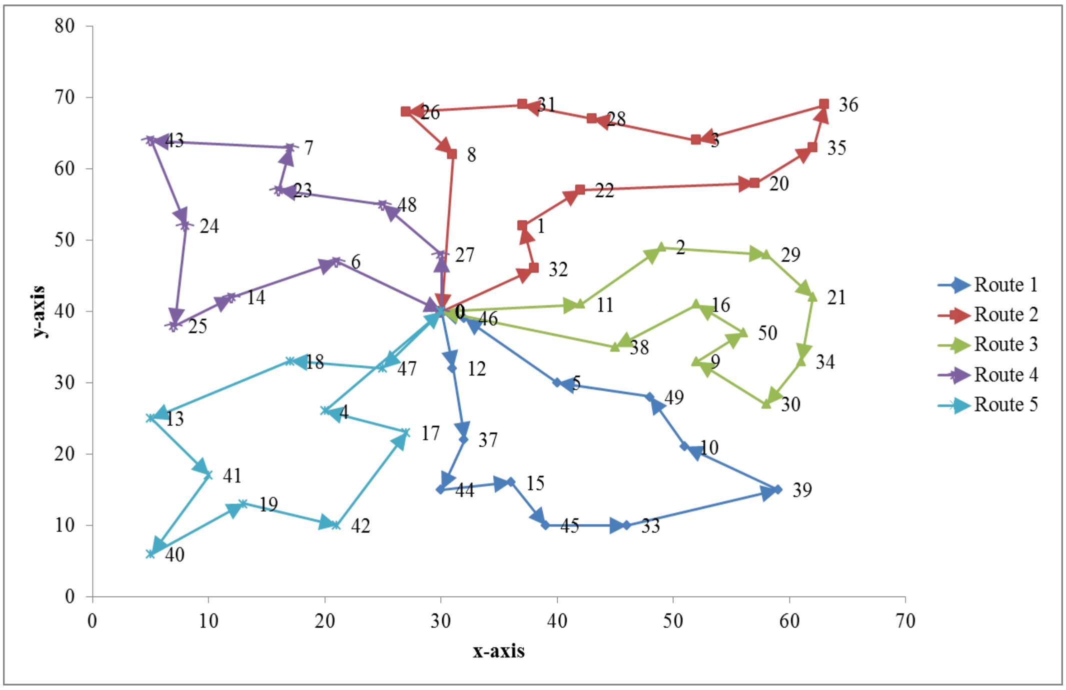


Figure 4.12 The optimal solution of the minimum CO_2 emission

4.5 Summary

This chapter examines the vehicle routing problem (VRP) from an environmental perspective and proposes a new model of environmental vehicle routing problem (EVRP), which meets the latest requirements in practical. The emission of carbon dioxide (CO_2) is used to measure the environmental impact, alongside the vehicle routing. The emission of CO_2 is caused by the consumption of different types of fuel or energy, and may also be affected by various factors. In our research, through a comprehensive analysis of factors involved in practical situations, we find two factors, the load and the travelling distance of vehicles, are the most common and practical factors as opposed to other factors, such as the vehicle speed, road condition, weather and traffic. The other factors are nearly impractical and unreasonable to be measured because the traffic situations in different cities or regions vary significantly from time to time. A new EVRP model was constructed with the objective of minimizing the environmental influence by taking these two factors into account. The computational results in our numerical experiments indicate that the optimal environmental solution is meaningful and could likely be accepted by logistics enterprises, even though the overall travelling distance accompanying this solution is slightly increased, in contrast with the known shortest distance.

In this chapter, a hybrid ABC algorithm was employed to solve the EVRP problem. In contrast to the original ABC algorithm, the hybrid ABC algorithm was shown to be improved in four aspects; new mechanism of initialization, incorporation of new operators, more suitable adjustment of parameters and continuous improvement. These improvements could either speed up the convergence or promote the diversification of the evolution of solutions. Numerical experiments proved that this hybrid ABC algorithm outperforms the original ABC significantly.

Chapter 5 Network Design

In this chapter, we introduce a new strategic design model for supply chain network with multiple distribution channels (MDCSCN). The MDCSCN can benefit both supply chain enterprises and customers by providing direct sales of products and services from available facilities regardless of the supply chain echelons in contrast with the conventional SCN model, which limits the flow of products and services. The organization of this chapter is described as follows. First, a brief introduction of the SCN design is presented and the motivation of the MDCSCN design is stated. Then, we formulate the MDCSCN model using mathematical expressions. The MDSCN model involves multiple objectives, which corresponds to the consideration of the sustainable development. Afterwards, the solving methods are explained in detail, which integrates the priority-based encoding mechanism, the Pareto optimality criterion and the swarm intelligence. Furthermore, we conduct numerical experiments to examine the effects of the proposed model and the efficiency of the introduced method. Finally, we summarize the findings of this chapter.

5.1 Introduction

Along with the development of green logistics, supply chain enterprises are facing new challenges. On the one hand, an increasing number of customers tend to purchase their products online rather than shopping in the conventional brick-and-mortar stores (Brynjolfsson, Hu et al. 2013). Meanwhile, customers are expecting more flexible delivery services than ever before, such as fast delivery, dynamic delivery and on time delivery. On the other hand, the market competition is forcing the supply chain enterprises either to provide novel value-added services or to optimize the existing operations to fulfill the customer requirements (Chan, He et al. 2012), which helps to maintain or increase their economic profit. In addition, two other aspects which confront the development of supply chain enterprises are the environmental influence and social concerns. Energy and resource consumption, governmental legislation and customer awareness are all compelling supply chain enterprises to conduct practical initiatives so as to keep a good environmental image and shoulder the social responsibility. The economic measurement, environmental influence and social concerns constitute the triple bottom line for the sustainable development of supply chain enterprises (Linton, Klassen et al. 2007).

Aiming to overcome these challenges and meet the latest requirements, supply chain enterprises need to undertake a variety of operations and activities. For instance, to ensure a flexible delivery, a number of central or regional warehouses need to be built in specific areas in order to shorten the distance to customers and adequate product allocation for different warehouses should be realized by considering the preferences of customers from particular regions. Among the various supply chain operations and activities, the design of SCN is the most important and fundamental initiative as a well-designed SCN could be treated as a flexible and scalable platform for further operations and activities. (Sachan and Datta 2005)

The design of the SCN has been drawing ever-growing attention from academic researchers and industrial practitioners and there have been a number of publications concerning the SCN design from different perspectives. One of the popular trends is the design considering reverse logistics, which emphasizes the collection and process of end-of-life or end-of-use products. For example, Wang and Yang (2007) designed a reverse logistics network for recycling electronic waste. Reynaldo and Jürgen (2009) designed a reverse logistics network for collection of end-of-life vehicles. The closed-loop supply chain is another research topic, in which the forward logistics and reverse logistics are integrated. For instance, Kusumastuti, Piplani et al. (2008) designed a closed-loop service network emphasizing the post-sale service. Easwaran and Üster (2010) designed a closed-loop SCN with integrated forward and reverse channels. The integration of the SCN design with other supply chain components is also a promising research area. For example, Hugo and Pistikopoulos (2005) incorporated the life cycle assessment criteria as part of the strategic investment decisions into the SCN design. Amin and Zhang (2012) integrated the closed-loop supply chain configuration with the supplier selection model. Tancrez, Lange et al. (2012) presented a location-inventory model for large three-level SCN. Govindan, Jafarian et al. (2012) introduced a multiple-vehicle location-routing model for the design of SCN for perishable food.

The concept of sustainability could be used to integrate the multifarious objectives for designing SCN (Linton, Klassen et al. 2007). The measurement of the sustainability of the SCN could be categorized into three aspects, i.e., economic consideration, environmental influence and societal concerns (Piplani, Pujawan et al. 2008). The economic consideration is the most common measurement metric when designing any SCNs, which is frequently measured in terms of either minimizing cost (Fledelius and Mayoh 2008) or maximizing profit (Poli 2008). The environmental influence is frequently measured in terms of the carbon emissions, which are associated with the various activities in the supply chain (Sundarakani, Desouza et al. 2010). The sustainable development for designing SCN becomes a popular trend. For instance, Frota, Bloemhof et al. (2008) developed a framework for the design and evaluation of sustainable logistics networks, which balanced the economic profitability and environmental impacts. Karaboga (2005) planned a sustainable reverse logistics system balancing costs with environmental and social concerns, in which the economic objective, environmental objective and social objective are represented as the collection variable costs, carbon emission and working hours respectively.

Eskandarpour, Zegordi et al. (2013) designed a sustainable post-sales network with multiple objectives, among which the first objective consists of fixed and variable cost; the second objective is to measure customer tardiness and the third objective is to compute the number of disposed components. More research concerning the sustainability and supply chain can be found in the literature (Seuring and Müller 2008; Hassini, Surti et al. 2012).

Even though a number of studies concerning the design of the SCN from different perspectives with different objectives have been conducted, few of them are suitable for the latest requirement of customers in which flexible options of sales and deliveries are particularly emphasized and few of them cover the three objectives of sustainable development simultaneously. To provide customers with a flexible delivery service, we propose a novel strategic design of the SCN that considers the feasibility of multiple distribution channels for direct sales, namely multiple distribution channel supply chain network (MDCSCN). In contrast with the conventional SCN, in which the products have to flow through a strict sequence of facilities, the design of MDCSCN presents a much more flexible network for customers. Customers could be served from any available facility in the MDCSCN regardless of their supply chain echelons. For instance, a customer order could be fulfilled by manufacturers, central distribution centers (DCs) or regional distribution centers (DCs). The determination of serving facilities for customers in the MDCSCN is affected by multiple considerations such as the transportation cost, customer service level and the environmental influence, which are designed to initiate sustainable development for the supply chain. The trade-off among the economic, environmental and social objectives could provide more compromised options for decision making. Both the supply chain enterprises and customers could benefit from the MDCSCN model.

The design of the MDCSCN pertains to the category of the facility location problem (FLP), in which the location of a number of facilities and the allocation of customers to particular facilities need to be determined (Melo, Nickel et al. 2009). The MDCSCN model is of high complexity due to the multiple echelon settings, the large number of facilities in each echelon and the multiple distribution channels, which lead to a large scale problem and it is not feasible to be solved by exact algorithms. Therefore, meta-heuristic algorithms become the only practicable choice. In this research, swarm intelligence is employed to solve the MDCSCN problem. Swarm intelligence is inspired by the collective behavior of social insects or animal societies, which forms a new branch of the meta-heuristic approaches in contrast with evolutionary computation (Blum and Li 2008). Swarm intelligence possesses three inherent features, i.e., decentralization, self-organization and collective behavior (Bonabeau, Dorigo et al. 1999). Decentralization means that no central mechanism exists for controlling or managing the behavior of each individual. Self-organization indicates that each individual determines its own behavior. An individual may interact with the other individuals or the environment so as to determine its next move. Such an interaction might follow some simple rules. The behavior of an individual might be non-deterministic or even random. However, the collective behavior of the entire population turns out to be intelligent in regard to achieving certain goals. Ever since the introduction of the concept of swarm intelligence by Beni and Wang (1993), a number of swarm intelligent algorithms have been proposed, such as the Ant System inspired by the operations of ant colonies (Dorigo, Maniezzo et al. 1996) and the Artificial Bee Colony algorithm inspired by the behavior of bee colonies (Karaboga and Basturk 2007). A recent review of swarm intelligence can be found in the literature (Parpinelli and Lopes 2011; Zhang, Lee et al. 2015).

Among the various popular swarm intelligent algorithms, ABC algorithm is a relatively new exemplar. The detailed introduction of ABC algorithm can be found in section 2.4.3. Ever since the introduction, the ABC algorithm has gained much popularity due to its robust yet simple architecture; and more and more researchers try to explore the application of the ABC algorithm for solving practical problems. For example, Baykasoglu, Ozbakir et al. (2007) employed the ABC algorithm to address the generalized assignment problem. Vishwa, Chan et al. (2010) employed the ABC algorithm to solve an environmental closed-loop logistics model. Li, Pan et al. (2011) applied the ABC algorithm to the job shop scheduling problem. Zhang, Lee et al. (2014) introduced a hybrid ABC algorithm for the environmental vehicle routing problem. Moreover, one of the promising trends is to apply the ABC algorithm to the multi-objective problems. For instances, Humphreys, Wong et al. (2003) presented a parallel vector evaluated multi-objective variant of the ABC algorithm (VEABC) for multi-objective design optimization of composite structures. Das, Narasimhan et al. (2006) proposed a hybrid Pareto-based discrete ABC algorithm for solving flexible job shop scheduling problems with multiple objectives. Ho, Xu et al. (2010) introduced a hybrid multi-objective ABC algorithm named HMOABC for burdening optimization of copper strip production.

In this research, a multi-objective artificial bee colony (MOABC) algorithm is introduced for solving the MDCSCN model, which comprises the priority-based encoding mechanism for solution representation, the concept of Pareto optimality for handling multiple objectives, and the swarm intelligence of the bee colony. The priority-based mechanism is used for encoding solutions; the Pareto optimality mechanism is adopted for handling the multiple objectives and the ABC algorithm is applied for solving the distribution problem. To our knowledge, it is the first research in applying the MOABC algorithm to the multi-objective SCN design problem with the consideration of multiple distribution channels. The advantages of the MDCSCN model are not only explained qualitatively, but also measured quantitatively through numerical experimentation, which provides practical managerial insights for industrial practitioners. The successful application of the MOABC for solving the MDCSCN problem demonstrates the potential of the ABC algorithm, which inspires the application of the ABC application for solving other practical multi-objective problems.

5.2 Problem Formulation

In this section, the MDCSCN is formulated as a mixed integer linear programming (MILP) model, in which the location of facilities and allocation of customers to specific facilities need to be determined. In conventional SCN, the flow of products has to go through a relatively strict sequence of facilities, i.e., from manufacturers to central distribution centers (DC), from central DCs to regional DCs, and then from regional DCs to customers. However, in MDCSCN, both the manufacturers and the central DCs could act as serving facilities for customers directly in addition to the regional DCs as illustrated in Figure 5.1.

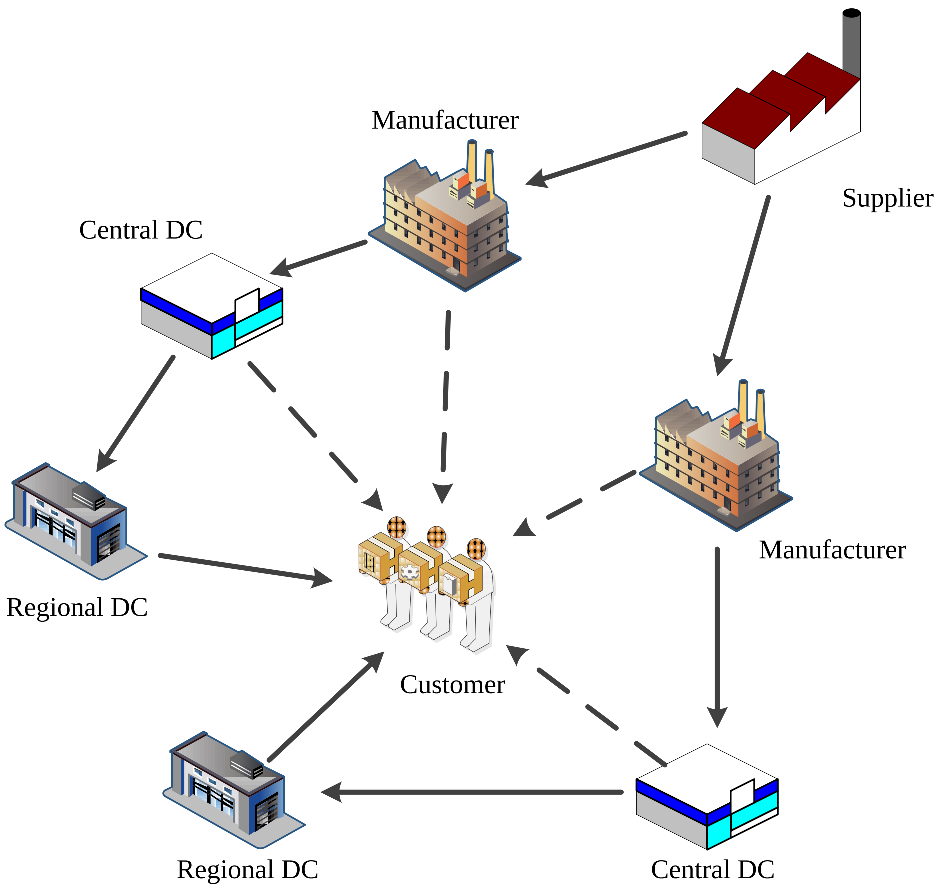


Figure 5.1 The illustration of the MDCSCN

The manufacturers are treated as the core entity of the supply chain network, which purchase raw materials from suppliers and manage the establishment and operation of central DCs and regional DCs. The establishment of suppliers is not considered in this research as they do not act as a distribution channel to customers directly. Therefore, the cost of operating suppliers is not considered except for the transportation cost from suppliers to manufacturers. The other assumptions for designing the MDCSCN model are listed as follows.

(1) The location and capacity of suppliers are known in advance. The operating suppliers have enough capacity to meet the requirements from facilities downstream.

(2) The location and demand of customers are known in advance.

(3) The potential locations of manufacturers, central DCs and regional DCs are known with corresponding determined capacities.

(4) The inventory of manufacturers, central DCs and regional DCs are not considered.

(5) The facilities in the same supply chain echelon share the same settings, e.g., capacity, operating cost and environmental influence.

(6) Each facility can acquire products only from its direct upstream facility except for customers.

(7) Single customer can only purchase products from one facility.

(8) Customer demands have to be satisfied.

The notations and settings employed for designing the MDCSCN model are described in Table 5.1, while the decision variables are described in Table 5.2.

Table 5.1 The notations of the MDCSCN

Notations	**Description**
$s \in S, p \in P, k \in K, l \in L, m \in M$	The set of suppliers, manufacturers, central DCs, regional DCs and customers
s, s_c	The index and capacity of suppliers
p, p_c, p_f, p_e	The index, capacity, fixed cost and environmental influence of manufacturers
k, k_c, k_f, k_e	The index, capacity, fixed cost and environmental influence of central DCs
l, l_c, l_f, l_e	The index, capacity, fixed cost and environmental influence of regional DCs
d_m	The demand of customer
$d_{ij}, i, j \in S \cup P \cup K \cup L \cup M, i \neq j$	The distance between two facilities
$c_{ij}, i, j \in S \cup P \cup K \cup L \cup M, i \neq j$	The unit transportation cost between two facilities
$e_{ij}, i, j \in S \cup P \cup K \cup L \cup M, i \neq j$	The unit environmental influence between two facilities

Table 5.2 The decision variables of the MDCSCN

Decision variables	**Description**
y_p, y_k, y_l	Binary variables denoting the open/close status of manufacturer, central DC and regional DC
$x_{sp}, x_{pk}, x_{kl}, x_{lm}$	Binary variables denoting the product flow from supplier to manufacturer, from manufacturer to central DC, from central DC to regional DC and from regional DC to customers
x_{pm}, x_{km}	Binary variables denoting the product flow from manufacturer and central DC to customers directly
$z_{sp}, z_{pk}, z_{kl}, z_{lm}$	Integer variables denoting the amount of product flow from supplier to manufacturer, from manufacturer to central DC, from central DC to regional DC and from regional DC to customers
z_{pm}, z_{km}	Integer variables denoting the amount of product flow from manufacturer and central DC to customers directly

The design of a sustainable MDCSCN model consists of three objectives, i.e., the economic measurement, the social concern and the environmental influence, which are also known as the triple bottom lines for sustainability. All these three objectives are considered in the formulation of the MDCSCN model. The first objective is to minimize the total cost, which comprises the operating cost for running facilities and the transportation cost for delivering products between any two facilities in different supply chain echelons as shown in equation (5.1). The first three terms denotes the cost of operating manufacturer, central DC and regional DC respectively. The remaining terms denotes the transportation cost from supplier to manufacturer, from manufacturer to central DC, from central DC to regional DC, from regional DC to customer, from manufacturer to customer and from central DC to customer.

$$\min f_1 = \sum_{p \in P} p_f y_p + \sum_{k \in K} k_f y_k + \sum_{l \in L} l_f y_l$$

$$+ \sum_{s \in S} \sum_{p \in P} c_{sp} z_{sp} + \sum_{p \in P} \sum_{k \in K} c_{pk} z_{pk} + \sum_{k \in K} \sum_{l \in L} c_{kl} z_{kl} + \sum_{l \in L} \sum_{m \in M} c_{lm} z_{lm} \tag{5.1}$$

$$+ \sum_{p \in P} \sum_{m \in M} c_{pm} z_{pm} + \sum_{k \in K} \sum_{m \in M} c_{km} z_{km}$$

The second objective is to maximize the customer service level in terms of customer demand coverage. In order to measure the customer demand coverage, some further notations and settings are needed. The maximum coverage distance for each facility is denoted as D_{max}. Customers within this distance range to an open facility are considered well served (Villegas, Palacios et al. 2006). The set of manufacturers, central DCs and regional DCs which could serve customer m within the maximum coverage distance are denoted as $Q_p = \{p \in P: d_{pm} \leq D_{max}\}$, $Q_k = \{k \in K: d_{km} \leq D_{max}\}$ and $Q_l = \{l \in L: d_{lm} \leq D_{max}\}$ respectively. With the above notations and settings, the second objective could be expressed as equation (5.2).

$$\max f_2 = \sum_{m \in M} d_m \left(\sum_{p \in Q_p} x_{pm} + \sum_{k \in Q_k} x_{km} + \sum_{l \in Q_l} x_{lm} \right) \tag{5.2}$$

The third objective is designed to measure the environmental influence of the MDCSCN network as shown in equation (5.3), which derives from the facility operation and vehicle transportation. The first three terms represents the environmental influence from operating the manufacturer, the central DC and the regional DC respectively. The remaining terms represents the environmental influence from the transportation of products.

$$\begin{aligned} \min f_3 = &\sum_{p \in P} p_e y_p + \sum_{k \in K} k_e y_k + \sum_{l \in L} l_e y_l \\ &+ \sum_{s \in S} \sum_{p \in P} e_{sp} z_{sp} + \sum_{p \in P} \sum_{k \in K} e_{pk} z_{pk} + \sum_{k \in K} \sum_{l \in L} e_{kl} z_{kl} + \sum_{l \in L} \sum_{m \in M} e_{lm} z_{lm} \end{aligned} \tag{5.3}$$

$$+\sum_{p\in P}\sum_{m\in M} e_{pm}z_{pm} + \sum_{k\in K}\sum_{m\in M} e_{km}z_{km}$$

The associated constraints for the MDCSCN model are summarized as follows.

$$\sum_{p\in P} x_{pm} + \sum_{k\in K} x_{km} + \sum_{l\in L} x_{lm} = 1; \forall m \in M \tag{5.4}$$

$$\sum_{p\in P} z_{pm} + \sum_{k\in K} z_{km} + \sum_{l\in L} z_{lm} = d_m;\ \forall m \in M \tag{5.5}$$

$$z_{pm} = \{x_{pm} = 1\ ?\ d_m : 0\};\ \forall p \in P, m \in M \tag{5.6}$$

$$z_{km} = \{x_{km} = 1\ ?\ d_m : 0\};\ \forall k \in K, m \in M \tag{5.7}$$

$$z_{lm} = \{x_{lm} = 1\ ?\ d_m : 0\};\ \forall l \in L, m \in M \tag{5.8}$$

$$x_{lm} \leq y_l; \forall m \in M, l \in L \tag{5.9}$$

$$x_{km} \leq y_k;\ \forall m \in M, k \in K \tag{5.10}$$

$$x_{pm} \leq y_p;\ \forall m \in M, p \in P \tag{5.11}$$

$$\sum_{m \in M} z_{lm} = \sum_{k \in K} z_{kl} \leq l_c; \forall l \in L \tag{5.12}$$

$$\sum_{m \in M} z_{km} + \sum_{l \in L} z_{kl} = \sum_{p \in P} z_{pk} \leq k_c;\ \forall k \in K \tag{5.13}$$

$$\sum_{m \in M} z_{pm} + \sum_{k \in K} z_{pk} = \sum_{s \in S} z_{sp} \leq p_c,;\ \forall p \in P \tag{5.14}$$

Constraint (5.4) means that customers can only purchase products from one facility. Constraint (5.5) indicates that customer demands have to be satisfied. The relationship between the flow connectivity and the flow amount between two facilities from different supply chain echelons are denoted in constraints (5.6), (5.7) and (5.8). Once a customer is assigned to purchase products from a particular facility, all its requirements are satisfied by the particular facility, which is consistent with the constraint (5.4) and (5.5). Constraints (5.9), (5.10) and (5.11) suggest that the flow of products can only be associated with open facilities. The capacity and product flow of the regional DC, central DC and manufacturer cannot be violated as illustrated in constraints (5.12), (5.13) and (5.14) respectively.

5.3 Algorithm Design

As mentioned in section 5.1, the MDCSCN model is of high complexity because of its unique features, e.g., the flexible delivery channels, the multi-echelon settings and the large number of facilities in each echelon. Therefore, a modified ABC algorithm is employed to solve the MDCSCN model. Concerning the large number of facilities available in the MDCSCN, which might lead to the solution scheme with large dimension, the priority-based encoding mechanism is adapted. In consideration of the multiple objectives, the concept of Pareto optimality is introduced. The hybridization of the ABC algorithm, the priority-based encoding mechanism and the Pareto optimality results in a multi-objective ABC algorithm (MOABC), which can find a number of Pareto optimal solutions in one execution.

5.3.1 Solution Scheme

The design of the solution scheme is the first consideration before implementing any algorithm. A network can be represented in different schemes. For example, Brynjolfsson, Hu et al. (2013) used a matrix-based scheme to represent a transportation network. Syarif, Yun et al. (2002) converted a transportation network into a spanning tree and encoded the spanning tree with the Prufer number. In this research, we employ two encoding mechanisms to construct the solution. The solution consists of four separate stages, among which the first three stages are the same as the traditional supply chain network, which are the product flow from supplier to manufacturer, from manufacturer to central DC and from central DC to regional DC respectively. The first three stages are encoded with a priority-based encoding mechanism, which takes into consideration both the position and the priority of each element in the solution (Gen, Altiparmak et al. 2006) . For instance, the supply chain network comprises 3 suppliers, 4 manufacturers, 3 central DCs, 4 regional DCs and 6 customers. The position of each element denotes the index of the facility, while the priority of each element is assigned as a random permutation of the set $\{1,2,\cdots,7\}$. A similar encoding mechanism applies to the second and the third stages as well. As for the fourth stage, we adopt a different encoding mechanism since it involves the supply of customer demands from different facilities. Instead of considering only two successive echelons in the first three stages, we locate and assign the facility for customers directly in this stage. The position of each element in stage 4 represents the index of each customer and the value for each element is taken in the set $[1, |P| + |K| + |L|]$. Figure 5.2 illustrates an example of a solution encoding step for each individual stage and the final scheme, with 3 suppliers, 4 manufacturers, 3 central DCs, 4 regional DCs and 6 Customers.

	1st stage						
	Supplier			Plant			
Node	1	2	3	1	2	3	4
Priority	5	1	4	6	2	7	3

	2nd stage						
	Plant				Central DC		
Node	1	2	3	4	1	2	3
Priority	3	4	2	7	1	5	6

	3rd stage						
	Central DC			Regional DC			
Node	1	2	3	1	2	3	4
Priority	4	2	1	7	5	6	3

	4th stage					
	Customers					
Node	1	2	3	4	5	6
Facility	8	11	9	6	5	3

1st stage							2nd stage							3rd stage							4th stage					
5	1	4	6	2	7	3	3	4	2	7	1	5	6	4	2	1	7	5	6	3	5	11	9	8	10	4

Figure 5.2 The solution encoding mechanism

Given the encoded solution, we have to decode it so as to construct the practical supply chain network, which is further measured by considering the multiple objectives. The decoding procedure is conducted backwards, since the first priority is that the customer demands have to be satisfied. The decoding scheme for the first three stages and the last stage is also different with different encoding schemes. The decoding scheme for stage 4 is rather straightforward, as it consists of the direct links between the facilities and customers. The decoding scheme for the first three stages involves three factors, which are the priority of the facility, the capacity of the facility and the unit transportation cost from/to this facility. Suppose we have K sources and L depots with associated capacity and demand a_k and b_l respectively. The unit transportation cost from source k to depot l is denoted as c_{kl}. The encoding scheme with the K

sources and L depots is denoted as $P(K+L)$, which comprise two sections as $P(K)$ and $P(L)$. The amount of products transported from source k to depot l is denoted as g_{kl}. Figure 5.3 shows the decoding algorithm. One of the advantages of this decoding algorithm is that the balance between supply and demand is no longer considered, as we process the solution backwards and focus on the demand side.

While $P(L) \neq 0$

  Find the facility f with highest priority from $P(K+L)$

  If $f \in K$, $k^* \leftarrow f$

    Find the depot l^* with minimum unit transportation cost

  Else if $f \in L$, $l^* \leftarrow f$

    Find the source k^* with minimum unit transportation cost

  Assign the amount $g_{k^*l^*} \leftarrow \min(a_{k^*}, b_{l^*})$

  Update the available amount of source k^* and depot l^*

    $a_{k^*} = a_{k^*} - g_{k^*l^*}$ and $b_{l^*} = b_{l^*} - g_{k^*l^*}$

  If $a_{k^*} = 0$, then $P(k^*) = 0$

  If $b_{l^*} = 0$, then $P(l^*) = 0$

End

Figure 5.3 The solution decoding algorithm

5.3.2 Pareto Optimality

The Pareto-based optimization method is very popular and practical for addressing multi-objective optimization problems. In practice, one solution cannot satisfy all the objectives to a maximum level simultaneously. Some solutions may favor some objectives, while other solutions may approve of other objectives. Therefore, the concept of the Pareto optimal solution is introduced to find solutions which are at least good for one objective. The Pareto optimality can be described as follows. For a multi-objective optimization problem $f = \min\,(f_1(x), f_2(x), \cdots, f_k(x))$, solution s_1 is claimed to dominate solution s_2 denoted as $s_1 \prec s_2$ under the following condition (Collette and Siarry 2005). Solution s_1 is called the Pareto optimal solution provided that there is no other solution that dominates it. The set of Pareto optimal solutions is named the Pareto frontier.

(1) $\forall i \in \{1, \cdots, n\}, f_i(s_1) \le f_i(s_2)$

(2) $\exists j \in \{1, \cdots, n\}, f_j(s_1) < f_j(s_2)$

In addition to the simple comparison between any two solutions, we often need to rank and sort a number of solutions (population) so as to find the Pareto frontier and conduct further analysis (Deb, Pratap et al. 2002). The determination of the non-domination fronts are described as follows. Each solution belongs to a certain non-domination front, denoted as s_{front}, and any two solutions which cannot dominate each other belong to the same non-domination front. In this regard, two more parameters are introduced to determine the non-domination front for one individual solution, namely (1) dominated count n_s (the number of solutions which dominate the solution s) and (2) domination set P_s (the set of solutions which are dominated by the solution s). The non-domination front of solution s can be calculated as shown in Figure 5.4. All the solutions in the first non-domination front F_1 have the same dominated count 0 and the non-domination front F_1 is also called Pareto frontier. For each solution within the first non-domination front F_1, we visit its domination set and reduce the dominated count by one for each member within the domination set. The solutions with dominated count of 0 constitute the second non-domination front F_2. This procedure is continued until all solutions are assigned to a certain non-domination front.

For each $s \in P$ $n_s = 0,\ P_s = \emptyset$ For each $s' \in P, s' \neq s$ If $s \prec s'$ $P_s = P_s \cup \{s'\}$ Else if $s' \prec s$ $n_s = n_s + 1$ End End End	$\boldsymbol{F_1} = \emptyset$ If $n_s = 0$, then $s_{front} = 1$ $F_1 = F_1 \cup \{s\}$ End	$\boldsymbol{F_2} = \emptyset$ For each $s \in F_1$ For each $s' \in P_s$ $n_{s'} = n_{s'} - 1$ End If $n_{s'} = 0$, then $s'_{front} = 2$ $F_2 = F_2 \cup \{s'\}$ End End ...

Figure 5.4 The determination of non-domination fronts

Once the non-domination fronts are determined, we need to further compare the solutions within the same non-domination front. For this purpose, the concept of crowding distance is introduced to measure the density of solutions in a non-domination front. The crowding distance for a given solution is calculated using the Euclidean distance between two nearby solutions in terms of the multiple objectives (Fleischer 2003). The crowding distance can be calculated as follows. Suppose there are N non-dominated solutions with M objectives, we first need to sort the N solutions in terms of the first objective. Then, the crowding distance d_i for solution s_i can be calculated as equation (5.15).

$$d_i = 0.5 * \sqrt{\sum_{j=1}^{M} (f_j(s_{i-1}) - f_j(s_{i+1}))^2} \tag{5.15}$$

5.3.3 Performance Metric

Different Pareto frontiers obtained by different multi-objective algorithms need to be compared through some performance measurement metrics. Different metrics emphasize different features of the Pareto fronts and some of them even conflict with each other (Beamon 1998). Some metrics are used simultaneously to assess the performance of different Pareto fronts. In this research, we use four metrics to evaluate the Pareto frontiers from different algorithms, of which the first three metrics emphasize the inner features of a Pareto frontier and the fourth metric underlines the comparison between different algorithms.

(1) The Pareto ratio (PR) is used to calculate the percentage of the Pareto frontier solutions among the whole population. Suppose the number of Pareto frontier solutions and population are denoted as $|PS|$ and $|S|$ respectively. Then, PR is calculated referring to equation (5.16).

(2) The Pareto crowding space (PCS) is used to calculate the distribution of the Pareto frontier. PCS is implemented using the crowding distance of each individual solution as shown in equations (5.17) and (5.18).

(3) The Average Ideal distance (AID) is the average distance between the practical Pareto solutions and the ideal solution (Govindan, Jafarian et al.

2012). The calculation of the AID and the ideal solution is shown in equations (5.19) and (5.20).

(4) Percentage domination (PD) is to calculate and compare the percentage of different Pareto frontiers obtained from different algorithms. To calculate the PD, we first need to construct a mixed set of solutions containing all the Pareto solutions obtained from different algorithms. Then the dominated solutions are eliminated and the percentage of the remaining solutions belonging to different algorithms is calculated.

$$PR = \frac{|PS|}{|S|} \tag{5.16}$$

$$PCS = (\frac{1}{N}\sum_{i=1}^{N}(1-\frac{d_i}{d^*})^2)^{1/2} \tag{5.17}$$

$$d^* = \frac{\sum_{i=1}^{N} d_i}{N} \tag{5.18}$$

$$AID = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\sum_{j=1}^{M}(f_j(s_i) - f_j(ideal))^2} \tag{5.19}$$

$$f(ideal) = \{\min(f_1), \cdots, \min(f_m)\} \tag{5.20}$$

5.3.4 MOABC Algorithm

The original ABC algorithm was firstly introduced by Karaboga (2005), which simulates the foraging behavior of honey bees. One bee colony consists of three types of bees, i.e., scout bees, employed bees and onlooker bees. Each type of bee performs a specific function and the roles of bees are interchangeable (Karaboga and Basturk 2008). The role of scout bees is to find the initial food sources or to find alternative food source once a food source is abandoned. The role of employed bee is to exploit the food sources, while the role of onlooker bees is to determine promising food sources. The operation of a bee colony is described as follows. At the beginning, a number of scout bees are sent out to find food sources randomly in a certain area. Once the food sources are found, scout bees change their roles to employed bees and start to exploit the food sources. During the exploitation period, employed bees try to find better food sources nearby to replace the current food source. Employed bees share the food source information with onlooker bees waiting in the hive after they return to the hive. Then onlooker bees may determine to explore some preferential food sources, which is mainly determined by the richness of corresponding food sources. The role of onlooker bees is changed to employed bees once they determine to exploit food sources. After a number of exploration and exploitation cycles, some food sources may be exhausted. In this case, the corresponding employed bees would abandon the exhausted food source, and change their role to scout bees so as to find alternative food source. The three types of bees work collaboratively in order to find the best food sources, which is treated as the optimal solution.

The ABC algorithm was originally invented to solve numerical optimization problems, where the problems usually have regular search spaces (Karaboga and Basturk 2007; Karaboga and Basturk 2007). However, industrial problems differ from the numerical optimization problems substantially in terms of the isolated search spaces, the discrete decision variables, the varying constraints, etc. In this research, we introduce an MOABC algorithm based on the modification of the ABC algorithm so as to address the MDCSCN problem. The MOABC algorithm incorporates the features of a network structure with the concept of Pareto optimality. The pseudo code of the MOABC algorithm is illustrated in Figure 5.5.

```
Initialize P = {s_1, s_2, ⋯, s_n} ← GenerateInitialPopulation
Evaluate P
    For each s ∈ P
        Calculate f(s) = {f_1(s), ⋯, f_m(s)}
        Calculate s_front and d_s
    End for
    Rank and sort P
While termination conditions not met
    Employed bee phase
        For each s ∈ P
            s' ← N(s)
            s ← (f(s') ≤ f(s) ? s' : s)
            s_trial ← (f(s') ≤ f(s) ? 0 : s_trial + 1)
        End for
    Onlooker bee phase
        Evaluate P
        For s ∈ P
            s ← TournamentSelection(P)
            s' ← N(s)
            s ← (f(s') ≤ f(s) ? s' : s)
            s_trial ← (f(s') ≤ f(s) ? 0 : s_trial + 1)
        End for
    Scout bee phase
        If s_trial ≥ limit
            s ← Regenerate
            s_trial = 0
        End if
    Evaluate P
End while
```

Figure 5.5 The pseudo code of the MOABC algorithm

Initialization phase

The ABC algorithm is of great popularity and practicability which is partially attributed to the simple parameter settings. Two major parameters need to be tuned before its execution. The first parameter is the number of food sources. One food source is treated as one solution to a specific problem. In the ABC algorithm, the number of employed bees and the number of onlooker bees are commonly set the same as the number of food sources, as one employed bee manages one food source. The number of scout bees is not fixed, because any employed bee can change its role to a scout bee once its associated food source is abandoned. A larger number of food sources indicate better diversified search capability. The second parameter is the abandonment criterion, denoted as $limit$. If a candidate solution cannot be improved through a number of trials $limit$, it would be discarded and replaced by another solution. The setting of $limit$ represents a trade-off consideration between a diversified search and an intensified search.

After the parameter settings, a number of initial solutions could be generated with respect to the priority-based encoding scheme. The first three stages share the same initialization mechanism. Provided that there are m sources and n depots, any random permutation of $\{1,2,\cdots,m+n\}$ can be treated as a solution segment for a single stage. For the fourth stage, since customers can get their products from any available facility, it is possible to assign the facility index to each customer directly. Following the same procedure, a number of initial solutions could be generated. After the initialization phase, we need to evaluate the whole population. Referring to the predefined Pareto optimality, the ranking and sorting of the initial solutions are determined by the non-domination front and the crowding distance, which are calculated using the equation mentioned in the above section. For any two solutions with different non-domination fronts, the one with a lower non-domination front has priority over that with higher non-domination front. If two solutions belong to the same non-domination front, the one with larger crowding distance is preferred.

Employed bee phase

The major role of the employed bee is to exploit the corresponding food source. In addition to the exploitation of the food source, the employed bee also attempts to conduct a neighborhood search around the current food source aiming to find a better food source. In the original ABC algorithm, the neighborhood search for a given solution is realized through the interaction with another randomly found solution. However, such a mechanism is not suitable in this research due to the characteristics of the practical problem. Therefore, we redesign the neighborhood structure referring to the designated encoding mechanism. For the first three solution segments, three neighborhood structures are introduced as swap, reverse and insert. For the fourth solution segment, one more neighborhood structure is introduced due to its unique encoding mechanism as reassign. Figure 5.6 illustrates the mentioned neighborhood structures.

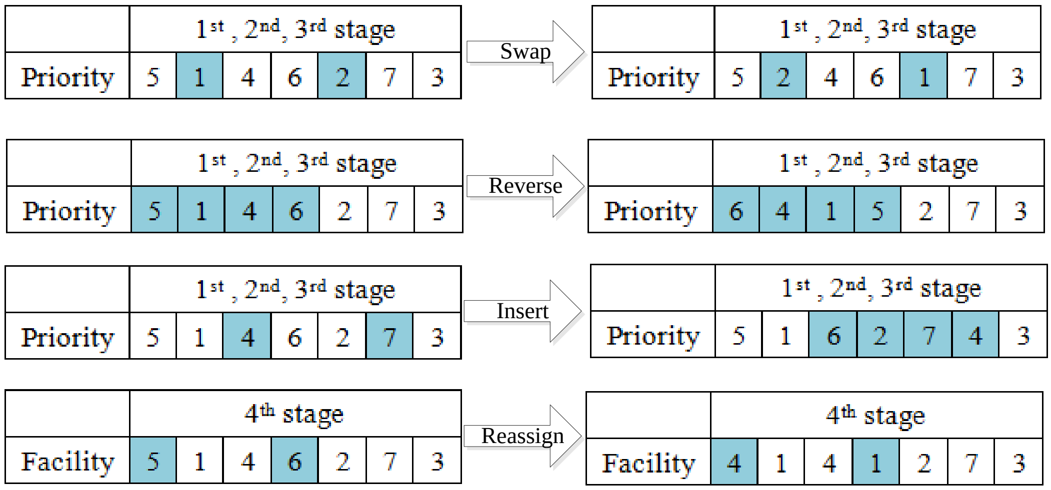


Figure 5.6 The neighborhood structure

Once a neighborhood solution is generated, we need to compare the neighborhood solution with the current solution. For a single objective problem, we could simply compare their associated fitness values. However, for a multi-objective problem, the concept of Pareto optimality is applied herein. If one solution could dominate another, certainly the non-dominated one is preserved. If the two solutions could not dominate each other, the original one is kept for simplicity. In addition, the number of trials to improve the original solution increases by one, which leads to a diversified search once it reaches the abandonment criterion.

Onlooker bee phase

The onlooker bees acquire the information on food sources from the employed bees, which return to the hive after the exploitation phase. The onlooker bees then determine to exploit and explore some food sources as well. The decision-making for onlooker bees is proportional to the richness of the food sources. In the original ABC algorithm, the probability of choosing a solution is calculated using its associated fitness value. However, for multi-objective problems, the fitness calculation is no longer proper. In this regard, the tournament selection mechanism is employed herein after we rank and sort the solutions referring to the non-domination front and crowding distance. A detailed explanation of the tournament selection mechanism can be found in the literature (Hiremath, Sahu et al. 2013).

An onlooker bee changes its role to an employed bee once it determines to exploit and explore a food source. It would repeat the same operations as the employed bee, carrying a neighborhood search for finding better solutions. The same selection rules apply in this phase as in the employed bee phase. The function of the onlooker bee phase is to facilitate the intensified search of the ABC algorithm, as the promising solutions have more chance to be improved due to the more frequent neighborhood search.

Scout bee phase

Whenever a neighborhood search is conducted, we try to improve a given solution. If the given solution can be improved, we reset its associated trial number as zero; otherwise, its trial number is increased by one. Once the trial number exceeds the predetermined setting as $limit$, the given solution is abandoned and substituted by a new solution found by the scout bee. The trial number of the new solution is reset as zero. The purpose of the abandonment mechanism is two-fold. One is to discard the solutions with poor performance, and the other is to avoid trapping in some local optimal points. The abandonment mechanism could facilitate a diversified search of the ABC algorithm. After the scout bee phase, all the solutions would be evaluated one more time. The non-domination front and crowding distance for each solution is recalculated. After a number of iterations, the Pareto frontier from the last population is obtained as the final result for further analysis.

5.4 Experiment and Analysis

In this section, experiments are conducted with two purposes; one is to show the effect of the proposed MDCSCN in comparison with the traditional supply chain network, in order to provide valuable managerial insights for industrial practitioners; the other is to examine the effectiveness and efficiency of the introduced MOABC algorithm, which could be employed to solve other practical problems.

5.4.1 Test Data and Settings

The location of customers, regional DCs, central DCs, manufacturers and suppliers are randomly generated using a coordinate scheme within a square with 200*200. We assume that all the facilities in the same echelon share the same capacity and operating cost, and all customers have the same demand. Various problem instances are generated in different scales, which possess a different number of facilities in each echelon. The customer demand follows a uniform distribution as $\mathrm{U}(10,20)$. The criterion of setting customer demand is that the cumulative customer demand can be served by any facility. The capacities of regional DC, central DC, manufacturer and supplier are set referring to the following inequality (5.21). The transportation cost between any two facilities is expressed using the Euclidian distance between any two facilities. The operational costs for regional DC, central DC and manufacturer follow uniform distributions of $\mathrm{U}(300,400)$, $\mathrm{U}(400,500)$ and $\mathrm{U}(500,600)$

respectively. Indeed, the setting of operational cost for different facilities can be different as long as it follows the principle (5.21).

$$\sum_{s\in S} cap_s > \sum_{p\in p} cap_p * y_p > \sum_{k\in K} cap_k * y_k > \sum_{l\in L} cap_l * y_l > \sum_{m\in M} d_m \qquad (5.21)$$

The first objective is to construct the network with minimum transportation cost and operational cost. The second objective is to design the network with maximum coverage so as to provide efficient service to customers. In this research, the second objective is converted to find the minimum cumulative distance between customers and their corresponding facilities so as to avoid the extra setting of the maximum coverage distance. The serving facilities for customers can only be regional DCs in the traditional supply chain. However, in the MDCSCN, the manufacturers, central DCs and regional DCs all can be the serving facilities. The third objective is to measure the environmental influence. The environmental influences associated with the operation of facilities are set as 100, 200 and 300 for regional DC, central DC and manufacturer respectively. The environmental influence associated with the transportation is proportional to the travelling distance, denoted as $e_{ij} = \alpha * d_{ij}$.

With respect to the parameter setting for the MOABC algorithm, the number of solutions (SN) is set as 40, the limit setting for abandonment is set as $limit = SN * Dim$, in which Dim is the dimension of an individual solution.

The maximum number of iterations is set as 1000. Each problem instance is run 10 times and the mean result is recorded so as to provide a convincing result. The performance of the MOABC algorithm is compared with another popular multi-objective meta-heuristic algorithm, the MOGA (Konak, Coit et al. 2006). The crossover rate and mutation rate of the MOGA are set as 0.9 and 0.1 respectively. The population of chromosomes is set as 40, which is equal to the number of solutions for the MOABC algorithm so as to provide a comparable result. Both the MOABC algorithm and the MOGA are coded in Java Language with Eclipse IDE, and all tests are performed on a PC with a 3.60GHz processor.

5.4.2 Model Comparison

In order to get a better understanding about the differences between the traditional supply chain network and the MDCSCN, we first compare the results of these two networks in terms of a single objective. Twelve instances are classified into three scales, i.e., small, medium and large scales. The major differences among the different scales are in the number of regional DCs and the number of customers. Even though for the small instance, the number of decision variables and constraints can be a large number due to the multi-echelon settings of SCN. For example, instance 1, which comprise 3 potential suppliers, 2 potential manufacturers, 2 potential central DCs, 4 potential regional DCs and 8 customers, have 8 integer variables to denote the open or close status of facilities, 82 binary variables to denote the interconnection between facilities and 82 integer variables to denote the amount of products transported between facilities. Moreover, the settings of multiple objectives certainly increase the complexity of problems. Therefore, it is not appropriate to use exact approaches as it either consumes too much time to search the entire search space or be incapable to handle the large scale instances. Table 5.3 summarizes the whole results for this comparison. From the results, it can be noticed that the largest saving in terms of three objectives occurs in the small scale instances, which reach 24.83%, 14.05% and 17.97% for objective 1, 2 and 3 respectively, on average. However, the advantages of the MDCSCN decrease gradually with the increase of the complexity of problem instances. Such a phenomenon may be attributed to the limitation of the square size for designing the SCN. The large number of facilities and customers in a crowded area weakens the effect the MDCSCN.

Table 5.3 The comparison of conventional SCN and MDCSCN

	Instances	Conventional SCN			MDCSCN			Saving		
	$\{\boldsymbol{S}, \boldsymbol{P}, \boldsymbol{K}, \boldsymbol{L}, \boldsymbol{M}\}$	**Obj1**	**Obj2**	**Obj3**	**Obj1**	**Obj2**	**Obj3**	**Obj1**	**Obj2**	**Obj3**
small case	$\{3, 2, 2, 4, 8\}$	34267.3	482.2	4024.7	25064.8	412.9	3210.3	26.8%	14.3%	20.2%
	$\{4, 3, 3, 6, 12\}$	45082.8	635.3	5589.1	33344.0	537.3	4460.8	26.0%	15.4%	20.1%
	$\{5, 4, 4, 8, 16\}$	55225.2	712.7	6730.2	41670.1	613.5	5634.2	24.5%	13.9%	16.2%
	$\{6, 5, 5, 10, 20\}$	62400.9	847.3	7967.7	49876.0	741.5	6757.5	20.0%	12.5%	15.1%
Average								**24.3%**	**14.0%**	**17.9%**
medium case	$\{6, 6, 6, 12, 40\}$	115082.8	1573.2	13405.6	96127.3	1334.6	12034.8	16.4%	15.1%	10.2%
	$\{7, 7, 7, 14, 60\}$	175093.5	2327.4	20431.0	142107.8	1971.6	17539.7	18.8%	15.2%	14.1%
	$\{8, 8, 8, 16, 80\}$	236593.9	3037.4	27084.1	195420.2	2687.2	23410.0	17.4%	11.5%	13.5%
	$\{9, 9, 9, 20, 100\}$	296598.2	3677.4	33908.3	242346.1	3226.2	28782.1	18.2%	12.2%	15.1%
Average								**17.7%**	**13.5%**	**13.2%**
large case	$\{8, 6, 10, 20, 120\}$	319817.5	4505.5	34978.9	284441.1	4111.6	32353.8	11.0%	8.7%	7.5%
	$\{9, 8, 15, 30, 160\}$	425812.4	5997.1	46511.8	382634.8	5758.9	43923.8	10.1%	3.9%	5.5%
	$\{10, 10, 20, 40, 200\}$	523993.7	8107.4	57884.7	481968.4	7685.8	55435.9	8.0%	5.2%	4.2%
	$\{12, 10, 20, 40, 240\}$	633696.6	10128.8	69379.0	583367.2	9987.8	65545.2	7.9%	1.3%	5.5%
Average								**9.2%**	**4.8%**	**5.7%**

The detailed network design of instance 1 is illustrated in Figure 5.7 with objective 1, which aims at minimizing the operational cost and transportation cost. From the results, it could be seen that two suppliers (S1 and S3), two manufacturers (P1 and P2), two central DCs (K1 and K2) and four regional DCs (L1, L2, L3 and L4) compose the conventional SCN. However, MDCSCN consists of two suppliers (S1 and S3), two manufacturers (P1 and P2), two central DCs (K1 and K2) and one regional DC (L2). The major difference is that all the regional DCs are used in the conventional SCN, however, only 1 regional DC is used in MDCSCN as 2 central DCs and 2 manufacturers could supply products for customers immediately, which leads to a 26.85% cost reduction in objective 1. Figure 5.8 illustrates the results for objective 2, which focuses solely on the customer coverage. In contrast with the conventional SCN in which customers can only be served by regional DCs, the MDCSCN is much more flexible. The products for customers may come from any available facility. Such a change would certainly reduce the aggregate distance between customers and facilities. In this case, the aggregate distance saved is 14.37% on average. Figure 5.9 shows the results comparison for the two networks in terms of the objective 3, which is designed to measure the environmental influence. The major differences concerning the utilization of facilities still occurs in the regional DC and the reduction of environmental influence reaches 20.24%. In a conventional SCN, three regional DCs (L1, L2 and L3) are used. However, in

MDCSCN, only the regional DC with label L4 is used, which means the manufacturer and central DC alleviate the role of regional DC.

The performance of the proposed MDCSCN exceeds the conventional SCN substantially in terms of all three objectives, which can be attributed to the utilization of less number of facilities and their better operational efficiency. Both the manufacturers and central DC can handle the product distribution to customers directly if assigned. Moreover, the design of MDCSCN can help enterprise managers realize the potential of different facilities when they design the supply chain system. A more intelligent supply chain system can be designed, which can handle the information from customer, product inventory and transportation integrally and simultaneously.

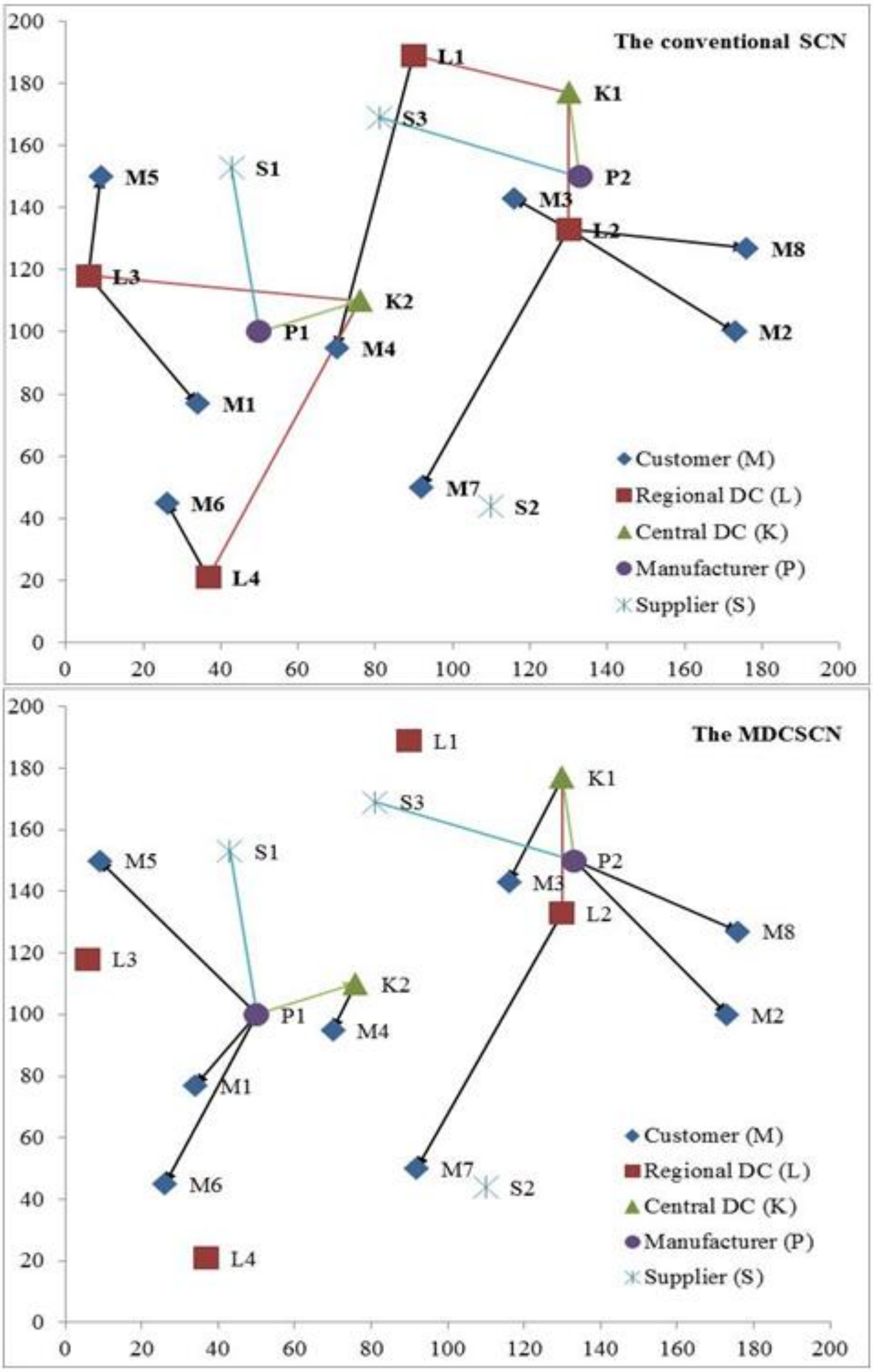


Figure 5.7 Network comparison in terms of the first objective

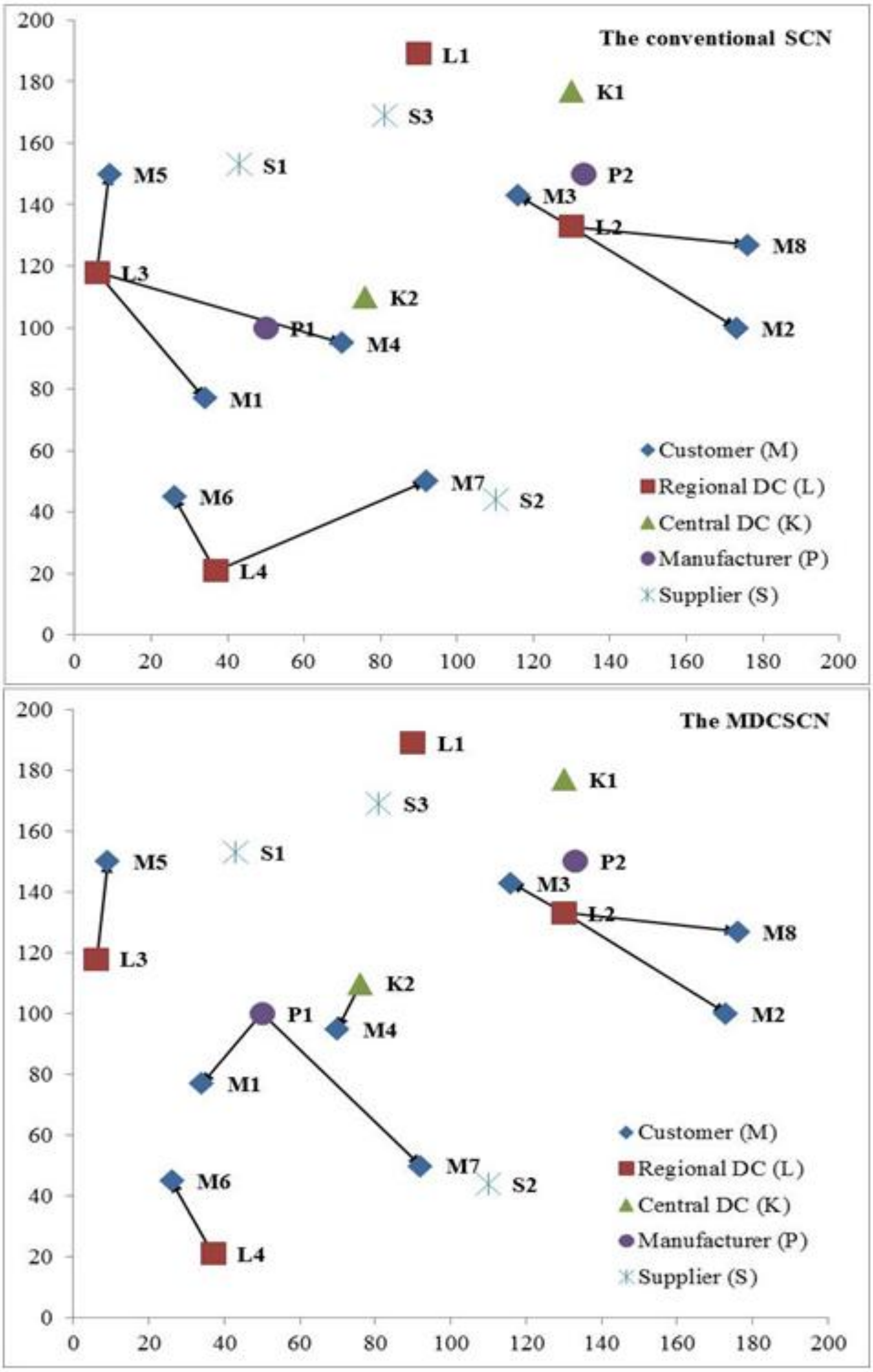


Figure 5.8 Network comparison in terms of the second objective

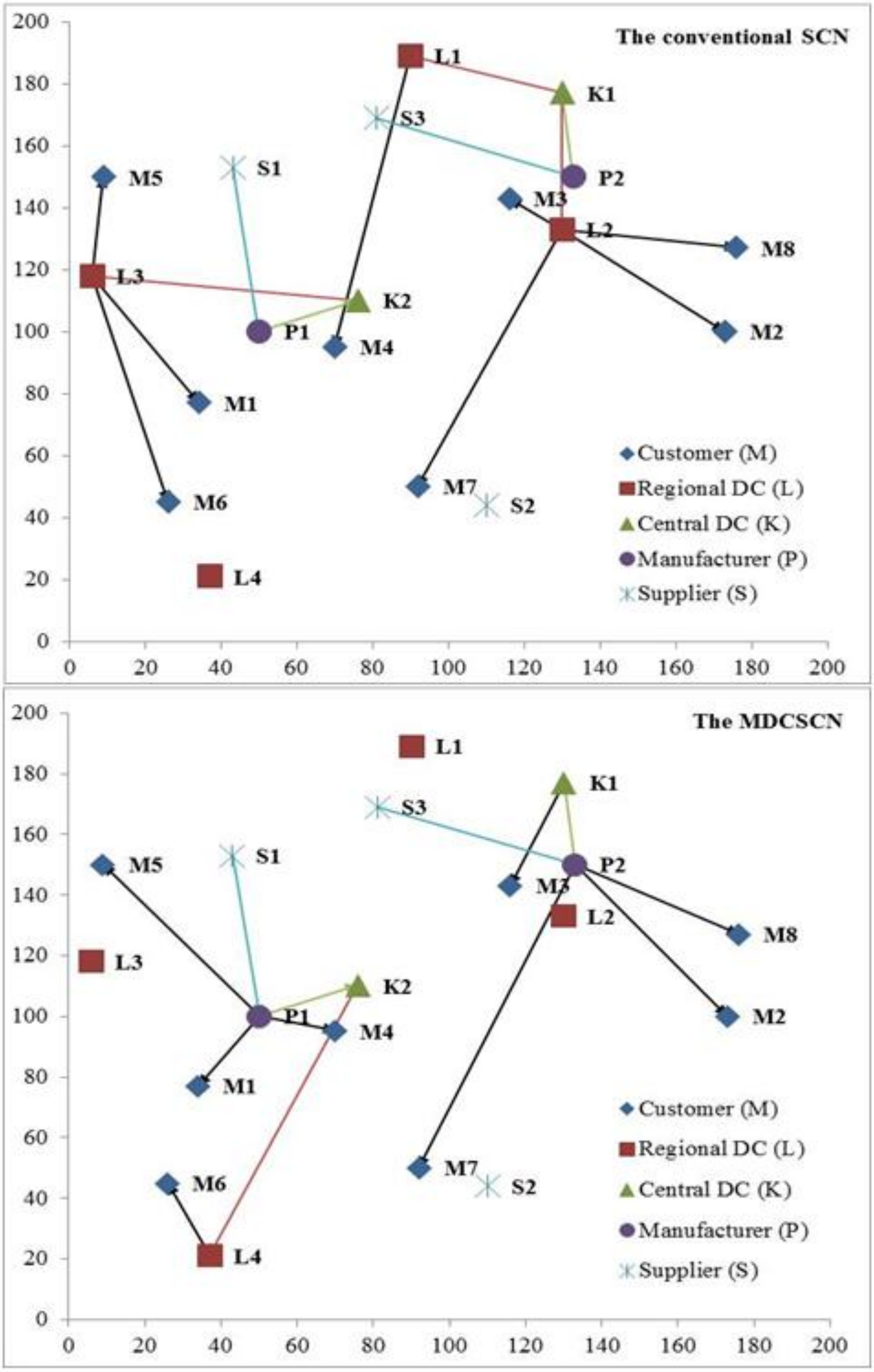


Figure 5.9 Network comparison in terms of the third objective

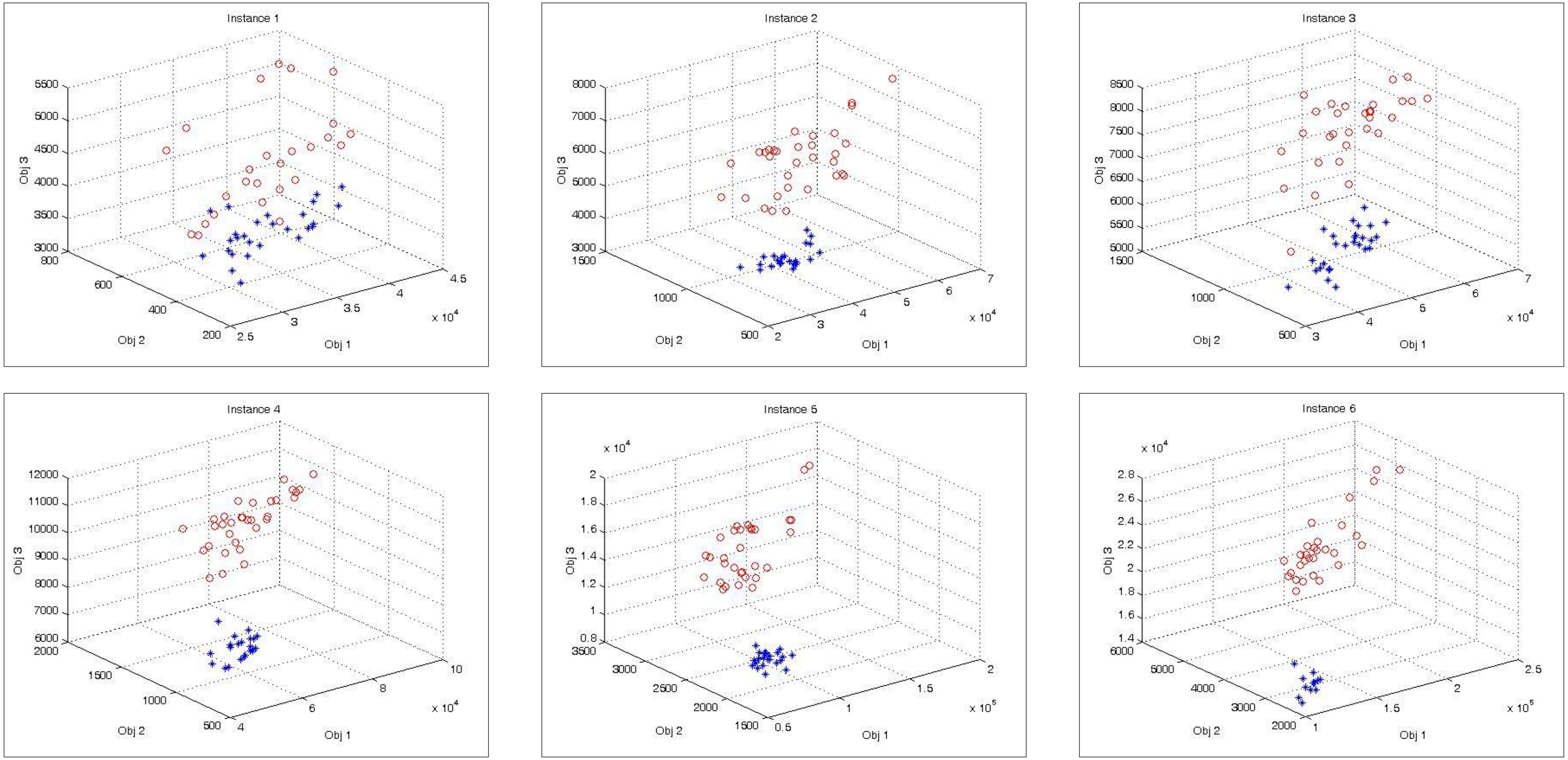
5.4.3 Algorithm Performance Analysis

The above section dealt with the comparison between the traditional SCN and the MDCSCN in terms of each single objective. In this section, the multi-objective MDCSCN model is solved using the MOABC algorithm and the MOGA. According to the performance metrics introduced in the above section, the overall results of the MOABC and the MOGA are summarized in Table 5.4. It can be noted that the Pareto optimal solutions generated by the MOABC dominate the Pareto optimal solutions generated by the MOGA for almost all the problem instances, except for the first and third instances, with small scale, as denoted by the performance metric PD. According to the PCS, AID and PR, the Pareto optimal solutions generated by the MOGA are much more diversified than the ones from MOABC. Regarding the computational time, CPU time is employed for reference. For example, with the same configuration, the MOABC algorithm takes 222 milliseconds to solve the instance 4, while the MOGA uses 118 milliseconds to solve that. The MOABC algorithm takes almost two times computational time in contrast to the MOGA algorithm for solving all the instances, which partially attributes the unique design of four phases in the MOABC algorithm, especially the employed bee phase and onlooker bee phase. Such a design enables the MOABC algorithm to search the solution space intensively. Even though the MOABC algorithm consumes more time than the MOGA algorithm, the results from the MOABC algorithm can outperform the ones from the MOGA substantially. Therefore, we can draw the conclusion that with the same configuration, MOGA could generate more diversified Pareto optimal solutions in contrast to the MOABC. However, the Pareto optimal solutions generated by the MOGA are worse than the ones from the MOABC.

Table 5.4 The performance of the MOABC and the MOGA

	Instances	**MOABC**				**MOGA**				**MOABC**	**MOGA**
	$\{S,P,K,L,M\}$	PCS	AID	PR	$Time$	PCS	AID	PR	$Time$	PD	PD
small case	{3,2,2,4,8}	36114.3	4863.5	0.27	78	38293.7	8009.4	0.26	48	0.78	0.22
	{4,3,3,6,12}	34740.0	4596.1	0.23	114	48163.5	11117.8	0.32	65	1.00	0.00
	{5,4,4,8,16}	48344.7	7617.9	0.27	165	57492.8	14560.5	0.31	88	0.95	0.05
	{6,5,5,10,20}	63141.9	6008.2	0.24	222	85024.8	4077.5	0.33	118	1.00	0.00
medium case	{6,6,6,12,40}	89698.6	7148.4	0.23	370	127786.1	20183.6	0.31	194	1.00	0.00
	{7,7,7,14,60}	144239.1	9384.2	0.13	556	207918.8	25993.4	0.29	287	1.00	0.00
	{8,8,8,16,80}	300608.7	10174.1	0.13	776	379442.5	28181.8	0.31	399	1.00	0.00
	{9,9,9,20,100}	315692.8	12036.8	0.15	1074	417876.1	22280.1	0.28	555	1.00	0.00
large case	{8,6,10,20,120}	351391.2	19151.4	0.11	1171	456677.2	70533.7	0.38	604	1.00	0.00
	{9,8,15,30,160}	470514.9	26162.7	0.11	2173	644766.2	66211.4	0.31	1107	1.00	0.00
	{10,10,20,40,200}	493298.7	29811.7	0.13	3563	675272.1	94666.4	0.38	1762	1.00	0.00
	{12,10,20,40,240}	675624.0	19068.2	0.11	4072	841849.2	97838.4	0.34	2067	1.00	0.00

In order to get a clear understanding of the performance difference from these two algorithms, we accumulate the Pareto optimal solutions acquired from several executions of one instance. Even though the accumulated solutions may not dominate each other, they can be used to illustrate the average performance of the corresponding algorithm. Figure 5.10 illustrates the distribution of Pareto optimal solutions for each instance (o indicates the MOGA solutions; * indicates the MOABC solutions). The results are consistent with the findings of Table 5.2. For instances, 1 and 3, the distribution of solutions from the two algorithms have some overlapping space. However, for other instances, the average performance of the MOABC exceeds the MOGA significantly.


Instance 1
Obj 1
Obj 2
Obj 3
Instance 2
Obj 1
Obj 2
Obj 3
Instance 3
Obj 1
Obj 2
Obj 3
Instance 4
Obj 1
Obj 2
Obj 3
Instance 5
Obj 1
Obj 2
Obj 3
Instance 6
Obj 1
Obj 2
Obj 3

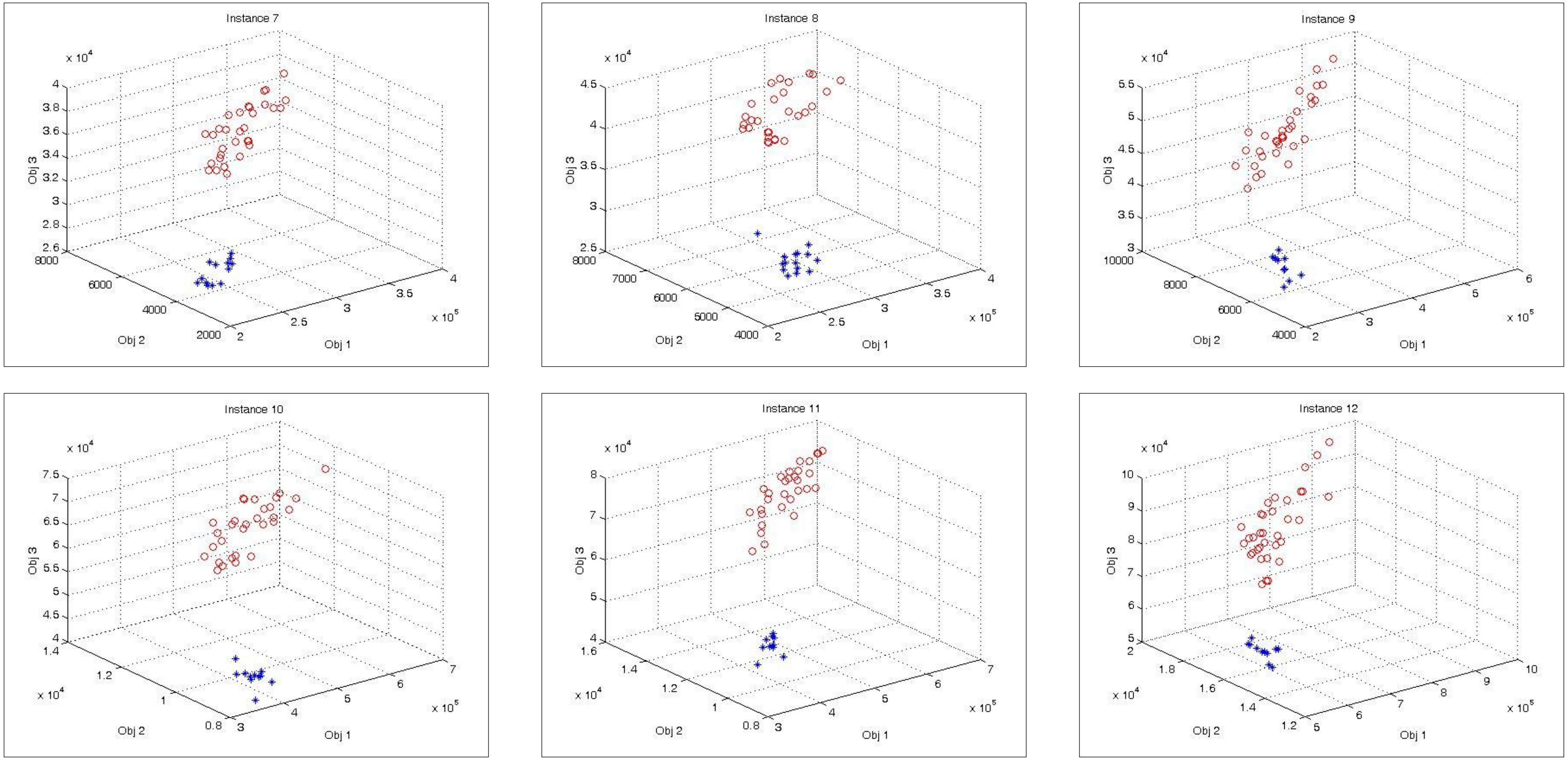


Figure 5.10 The distribution of solutions for MOABC and MOGA

5.5 Summary

This chapter proposes a novel strategic model for designing supply chain networks with multiple distribution channels, which embraces the latest requirements of customers. The concept of sustainable development is considered when designing the MDCSCN model, which can reduce the economic cost for supply chain enterprises, enlarge the flexibility of order fulfillment for customers and diminish the environmental influences. A priority-based solution scheme is employed to encode the network structure, which can reduce the computational complexity significantly. The concept of Pareto optimality is utilized to handle the multiple objectives of the MDCSCN model. A swarm intelligent algorithm named MOABC is designed to solve the MDCSCN problem, which is based on modification of the ABC algorithm and incorporates the concept of Pareto optimality.

Chapter 6 Discussion

In this chapter, the potential issues concerning the modeling of optimization problems and algorithm design are generally discussed. Different problems possess different features; however, they also share some common considerations during the modeling procedures. Some practical guidance is provided concerning the relationship among problem, model and algorithm. In addition, regarding the proposed unified algorithm framework and operational strategies, we further discuss the balance of algorithm performance by take into consideration the effects of intensification and diversification for each strategy.

6.1 Relation among Problem, Model and Algorithm

The relationship among optimization problems, mathematical models and SI algorithms can be illustrated in Figure 6.1. Optimization problems have to be abstracted into mathematical models, considering their specific features, in order to be further processed by SI algorithms. In practice, two aspects that need to be considered from optimization problems to SI algorithms are the required solution convergence and the affordable computational cost. Due to the complicated features of optimization problems, almost no SI algorithm can be guaranteed to find the best solution using the shortest time. In addition, different optimization problems may have different additional requirements during problem solving. Thus, the balance between the required solution quality and the affordable computational cost has to be considered when solving an optimization problem using a certain SI algorithm. Another aspect affecting the performance of SI algorithms is the formulation of mathematical models. The features of the mathematical model, such as single or multiple objectives, linear or non-linear constraints and discrete or continuous variables, influence the algorithm implementation (Majhi and Panda 2010). For example, the features of the decision variables could determine the encoding mechanism of the candidate solutions, and the constraints can be processed or avoided through either an encoding mechanism or a penalty mechanism.

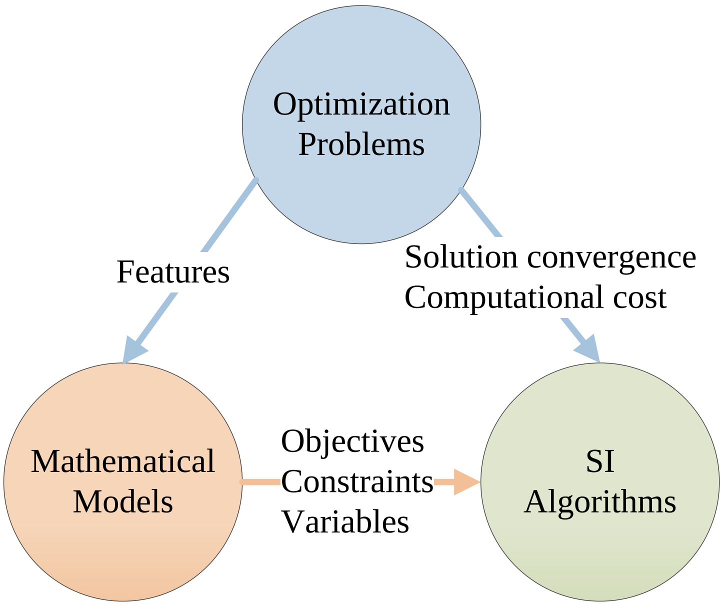


Figure 6.1 The relationship among problem, model and algorithm

The detailed component analogy between the problem, model and SI is listed in Table 6.1. The matching between model and SI is relatively standardized. For example, the objective function is normally replaced by a fitness function in terms of maximization or minimization. Decision variables are commonly encoded using a single-dimensional string with real numbers or binary numbers. As for the constraints, they could be either refrained at the beginning using some initialization mechanisms or be filtered after each iteration to exclude infeasible solutions. Another way to handle the constraints is to use a penalty function, which measures the violation of the constraints. The employment of penalty functions allows the existence of both feasible and infeasible solutions, which can increase the diversity of solutions and promote the searching capability. With regard to the matching between the optimization problems and SI algorithms, the static counterparts are the solution quality and computational cost, which includes the solution representation using SI entities and the measurement of computational costs of the SI algorithms. The dynamic solving process with the SI algorithm is presented in the next section.

Table 6.1 The component analogy among problem, model and algorithm

	Algorithm		
Problem	**ACO**	**PSO**	**ABC**
Solution representation	Pheromone traces	Particles' positions	Food sources
Optimal solution	Candidate solutions with best fitness		
Computational cost	Number of iterations, CPU time, etc.		
Solving process	Ants foraging	Particles aggregating	Bees foraging
Model			
Objectives	Fitness function		
Constraints	Initialization mechanism, Updating strategies, Penalty mechanism, etc.		
Variables	Encoding mechanism		

6.2 Balance between Intensification and Diversification

The performance of SI algorithms can be measured in terms of two criteria: the solution convergence and the computational cost. One is to measure the solutions of the SI algorithm, while the other is to measure the required cost of employing the SI algorithm. The solution convergence can be further divided into two aspects: the convergent value and the convergent speed. The convergent value indicates the best solution that can be found by a certain algorithm, while the convergent speed is to measure the efficiency of the algorithm. Moreover, the convergent speed is commonly measured using the number of iterations or the CPU time, which is indirectly related to the computational cost. The computational cost consists of two aspects, which are time complexity and space complexity. One typical example of the time complexity is the sorting operation in the algorithm so as to find suitable references. The space complexity is commonly represented in terms of memory utilization, which substantially can accumulate search experience and save time complexity. In this regard, the time complexity and space complexity compensate each other. The analysis of computational complexity is another promising research topic, which is not further detailed in this research.

The search mechanism, intensification and diversification (I&D) provide most of the core driving force that leads to the changes of the algorithm performance (Blum and Roli 2003). Intensification indicates the exploitation of the accumulated search experience, while diversification means the wide exploration of the search space. The effects of intensification and diversification can be illustrated as follows. When the search process starts, it generates and computes a set of random solutions in the search space so as to find promising areas diversely. The algorithm then investigates the previously found promising areas to find the local optimum intensively. The driving forces of intensification and diversification mutually interact. Even within one search step, some actions may act as a diversified search, while others may intensively search the designated area. The I&D effects of an action is determined by its intrinsic influence from three considerations: objective guidance (OG) and non-objective guidance (NOG) and randomness (R). OG indicates that an action is influenced or determined by the objective function, which means that an action is commonly conducted towards a better objective value. The more weighting of an OG, the more intensification a strategy possesses. In contrast to OG, R suggests that an action is conducted with a stochastic feature. Such a decision is frequently used for the purpose of escaping from some local trap or restarting the process. The more weighting of R advocates a more diversified effect. NOG means that an action is affected by some considerations which are unrelated to the objective value and the randomness, such as the pheromone update in the ACO algorithm and the setting of different weightings of the inertia, local optimum and global optimum of a particle in the PSO algorithm. NOG affects the search process either intensively or diversely on a case by case basis. Figure 6.2 illustrates the considerations for algorithm performance and balance.

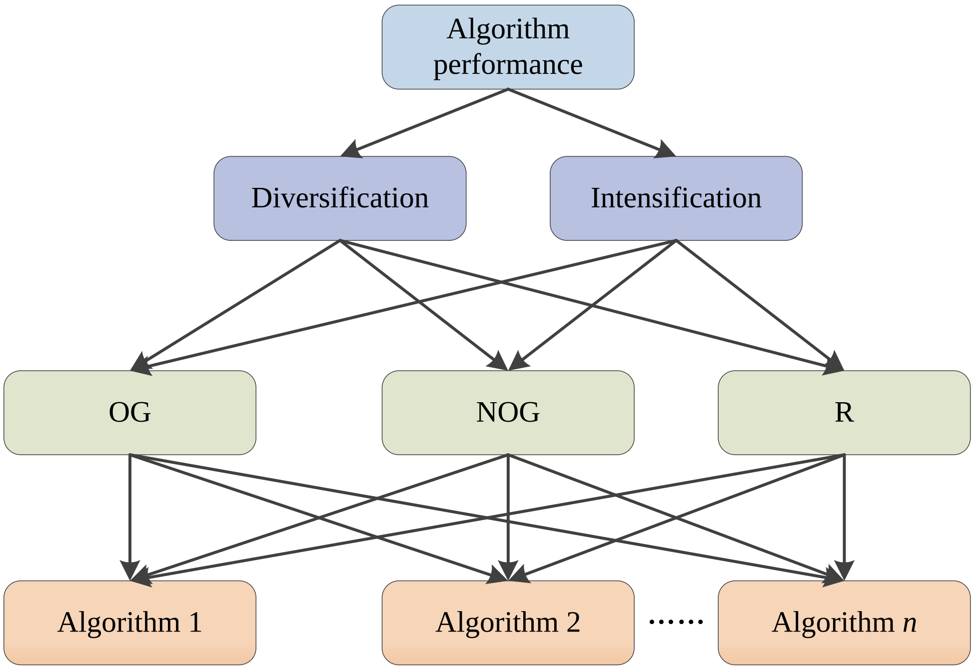


Figure 6.2 The considerations for algorithm measurement

In accordance with the strategies mentioned in the unified framework, Figure 6.3 summarizes the estimated I&D effects of the strategies. Among the initial parameters, the size of population can be treated as a straightforward sign of diversification, while the number of iterations can be regarded as a symbol of intensification. In other words, a larger population indicates a more diversified search in parallel, and more iteration suggests a more intensified search in one area.

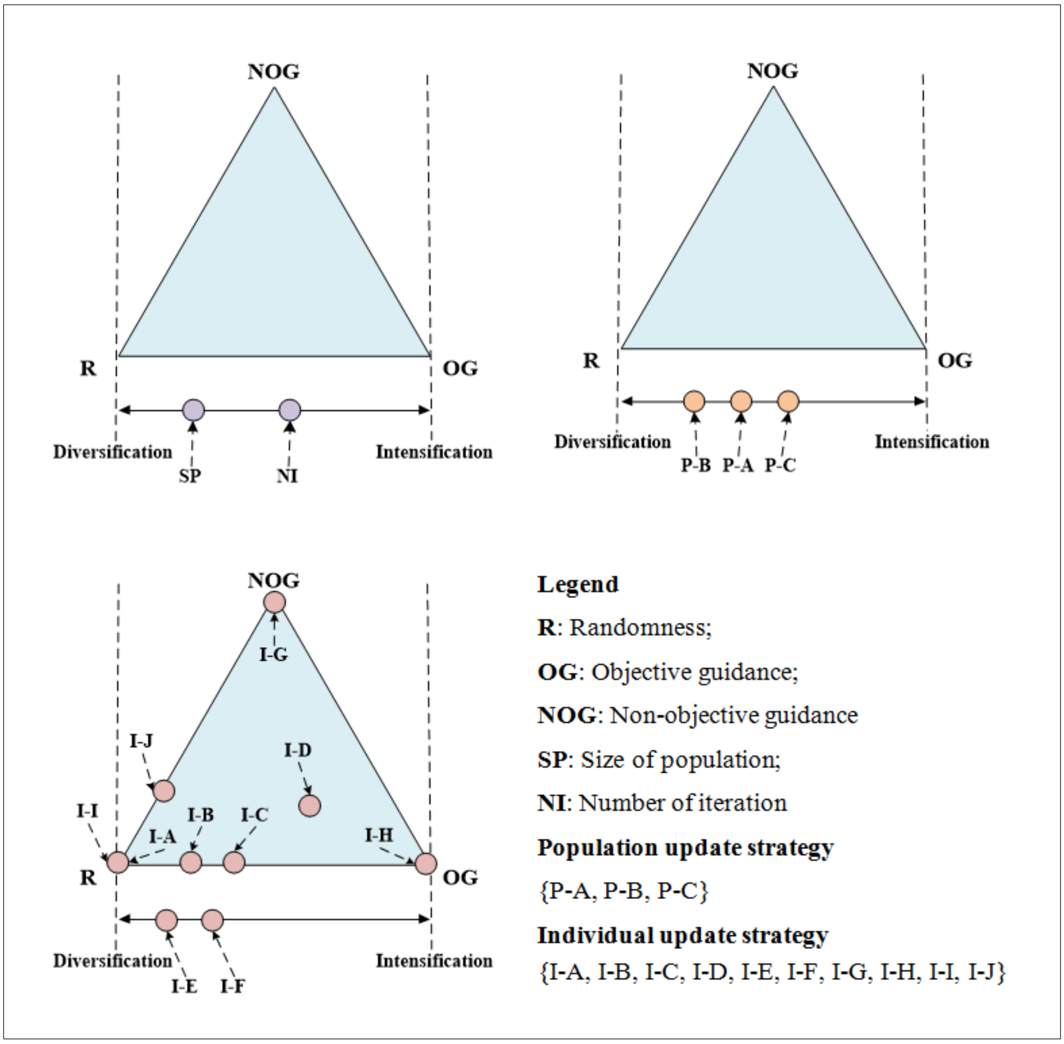


Figure 6.3 The estimated I&D effect of strategies

For the population update strategies, comparatively, strategy *P-B* is more diversified than strategy *P-A*, as the candidate solutions fluctuate significantly with strategy *P-B*, which is further proven in the experimental section. Strategy *P-C* acts as a filter to improve the overall performance of the population based on the fitness ranking, therefore, strategy *P-C* is mainly objective-guided with a selective probability derived from randomness. Concerning the individual update strategies, in step 1, the strategy *I-A* is merely determined by the randomness. The strategy *I-B* is used to find the reference after the sorting of other solutions, which means the objective function takes effect. The strategy *I-C* is a further enhancement of the strategy *I-B* as the reference has to have better fitness value than the current solution. The strategy *I-D* is derived from the PSO algorithm, in which two references are the global optimal solution and the local optimal solution. As the local optimal solution involves the cumulative experience, the strategy *I-D* is also non-objective guided. The ranking of strategies in step 1 from diversification to intensification is *I-A*, *I-B*, *I-C* and *I-D*. As for step 2, even though the strategies *I-E* and *I-F* are both determined randomly, the strategy *I-F* is more diversified than the strategy *I-E* because of the interaction between multiple dimensions. The strategies in step 3 are self-explanatory, as the greedy selection strategy *I-H* is managed by the objective function, while the strategy *I-G* is not. The last two strategies in step 4 are mainly determined by the randomness. Only the regeneration strategy (*I-J*) needs to avoid a repeat of used solution, therefore the non-objective guidance takes effect as well. Among all the strategies listed herein, the criteria to find a suitable combination is the trade-off between the intensification and diversification search, so that the algorithm can find a satisfactory result within an affordable time period, instead of either consuming too much computational time as a result of an excessive diversified search, or converging prematurely towards a local optimum due to an over intensified search.

6.3 Summary

The modeling of practical problems and the design of algorithms vary case by case; however, they share some common operations as well. The analysis of the relationship among problem, model and algorithm can provide general guidance towards the problem modeling and algorithm design. Moreover, the effects of the potential strategies used in the unified framework are analyzed from the perspective of algorithm performance balance. An algorithm can be improved through the adoption of different strategies, which have different effects on the algorithm performance, considering their inherent I&D effects. The trade-off between intensification and diversification is another key issue when adapting any SI algorithm, as a well-balanced I&D design can either avoid wasting too much time in unpromising search areas or evading the premature convergence.

Chapter 7 Conclusions

In this chapter, the conclusions have been drawn, which contain the summary of this research by recapitulating the critical contents in previous chapters. After that, the contribution of this research is explicitly enumerated. Also, we acknowledge that some limitations exist in this research, which might restrict the application and spread of the model and methodology. Therefore, suggestions for future research are provided as well in order to extend the current research and encourage new promising research.

7.1 Summary of the Research

Because of environmental deterioration, and finite and diminishing energy sources, green logistics is receiving an increasing attention from both academic researchers and industrial practitioners. Economic performance is no longer the only objective in logistics activities, and two other aspects, environmental and social performance, are becoming more important than ever before concerning the sustainable development. The operational level logistics activities are fundamental for any upper management strategies, thus the modeling and solving of green logistics activities are of great importance.

The major works concerning the modeling of green logistics activities and the application of swarm intelligence are investigated and identified by a comprehensive and extensive literature review. The classification scheme of operational-level activities in green logistics provides an intuitive description and understanding that helps to identify potentially fruitful research areas in green logistics, which achieves the first objective.

Regarding the second research objective, the review of swarm intelligence algorithms illustrates typical examples of swarm intelligence algorithms and investigates their inner driving force. Moreover, a unified swarm intelligence algorithm framework is proposed in consideration of the common procedures and operators from different swarm intelligence algorithms and a number of strategies are provided as well, for the implementation of this unified algorithm framework.

To fulfill the requirements of the third objective, two typical green logistics activities are selected to exemplify the consideration of sustainable development and the application of swarm intelligence. The first activity is to model an environmental vehicle routing problem, in which carbon dioxide emission is measured as an environmental objective in addition to the conventional economic objective. The computational results indicate that the optimal EVRP solution can save 2.72% carbon dioxide emission at the cost of increasing 0.34% travelling distance in contrast to the shortest distance solution. Such a result indicates that EVRP solution is valuable and practical. The adaption of ABC algorithm demonstrates the effect of parameter tune and operator selection, which can be referred by other research; and the performance of the proposed hybrid ABC algorithm exceeds the performance of GA significantly.

The second activity is to design a supply chain network with multiple distribution channels. Three objectives, i.e., minimizing the transportation cost, maximizing the customer service and minimizing the environmental influence, are designed for this network design towards sustainable development. In comparison with the conventional supply chain network, the proposed MDCSCN can improve 24.3%, 14.0% and 17.9% for the above three objectives respectively in small case problems. In case of medium case problems, the improvements in terms of three objectives are 17.7%. 13.5% and 13.2%, while in large case, they become 9.2%, 4.8% and 5.7%. The results suggest that supply chain network with multiple distribution channels is beneficial for enterprises in terms of all three objectives. Moreover, the proposed MOABC algorithm, which incorporates the priority-based encoding mechanism for solution scheme design and the Pareto optimality mechanism for handling multiple objectives. Such an integration is pioneering and its performance exceeds the performance of MOGA to a large extent.

7.2 Contribution of the Research

The contribution of this research can be described in the following aspects.

First, a comprehensive and extensive literature review regarding the integration of green logistics and swarm intelligence can help to understand the current research status. Both green logistics and swarm intelligence are at the initial development stage and more and more researchers are devoting effort to these areas. The classification scheme of activities in green logistics provides an intuitive description that helps to identify potentially fruitful research areas. Some green logistics categories have been accumulated in a number of studies, while others are still at the starting stage. Apart from the green logistics, this research also presents a straightforward description of the application of swarm intelligent algorithms. Readers can identify future potential research areas by referring to the results of the literature review.

Second, two successful exemplars concerning the modeling of green logistics activities are provided. An environmental vehicle routing model is proposed by considering the emission of carbon dioxide, which suggests a new perspective to schedule product transportation. A new design of a supply chain network with multiple distribution channels is presented aiming to satisfy the latest requirements in e-commerce. Environmental influence can be reduced in this new network while customer satisfaction levels can be improved. The successful applications of swarm intelligence in green logistics provide practical insights regarding the modification and improvement of swarm intelligence.

Third, in consideration of the numerous swarm intelligence algorithms, we provide a useful algorithm analysis mechanism by introducing the intensification and diversification frame. The balance between the intensification and diversification is critical during the search process in swarm intelligence algorithms. More importantly, we propose a unified algorithm framework, which integrates the common procedures and operations of swarm intelligence algorithms. A number of strategies are provided as well for the implementation of this unified algorithm framework. Such a unified algorithm framework allows readers to understand the intrinsic features of swarm intelligence, implement a certain swarm intelligence algorithm, improve its performance, and inspire researchers about the invention of new swam intelligence.

7.3 Limitations of the Research

Even though we have specified the problem context and assumptions when modeling the green logistics activities, there are still some other aspects which can be improved. For example, the modeling of vehicle routing in this research involves two individual objectives, which are minimizing the vehicle travelling distance and minimizing the emission of carbon dioxide. However, these two objectives are processed separately. More insights can be generated if these two objectives are processed simultaneously. Moreover, the calculation of the carbon dioxide emission is affected by the travelling distance and vehicle load in this research. However, in practice, other elements need to be considered, such as vehicle speed and road conditions. For the network design problem, one of the major limitations is that the experiments we conducted to demonstrate the advantages of the proposed multi-distribution channel supply chain network are still limited to numerical experiments. It would be more convincing if practical data can be used from real cases to validate the advantage of the proposed network design.

7.4 Suggestions for Future Research

Concerning the limitations mentioned in the previous section, future research is suggested in the following aspects.

For the modeling of the vehicle scheduling problem, the social consideration can be added by collecting and analyzing customer data. For example, customers may have their preferred time windows for delivery and hope to have the option of product returns. For the implementation of supply chain network with multiple distribution channels, customers can be play a more important roles. For instance, instead of system determination, customers may have their preferred facility or would like to pick up products from certain facility. Another promising future research direction is to design an integrated e-commerce platform where different supply chain entities can participate, and intelligent system can automatically determine the optimal facility for each order considering the availability of different facilities and the variety of customers' requirements.

References

Abbass, H. A. (2001). MBO: Marriage in honey bees optimization-A haplometrosis polygynous swarming approach. Evolutionary Computation, 2001. Proceedings of the 2001 Congress on, IEEE.

Adiba, E. B. E. I., M. Elhassania, et al. (2013). "A Hybrid Ant Colony System for Green capacitated vehicle routing problem in sustainbale transport." Journal of Theoretical and Applied Information Technology **54**(2): 198-208.

Agarwal, G., S. Barari, et al. (2012). "A PSO-based optimum consumer incentive policy for WEEE incorporating reliability of components." International Journal of Production Research **50**(16): 4372-4380.

Agrawal, S. and M. K. Tiwari (2007). "A collaborative ant colony algorithm to stochastic mixed-model U-shaped disassembly line balancing and sequencing problem." International Journal of Production Research **46**(6): 1405-1429.

Akay, B. and D. Karaboga (2012). "Artificial bee colony algorithm for large-scale problems and engineering design optimization." Journal of Intelligent Manufacturing **23**(4): 1001-1014.

Alvarado, I. A., A. J. L. Garcia, et al. (2013). "Optimization of the material flow in a manufacturing plant by use of artificial bee colony algorithm." Expert Systems with Applications **40**(12): 4785-4790.

Amaeshi, K. M., O. K. Osuji, et al. (2008). "Corporate Social Responsibility in Supply Chains of Global Brands: A Boundaryless Responsibility? Clarifications, Exceptions and Implications." Journal of Business Ethics **81**(1): 223-234.

Amin, S. H. and G. Zhang (2012). "An integrated model for closed-loop supply chain configuration and supplier selection: Multi-objective approach." Expert Systems with Applications **39**(8): 6782-6791.

Amiri, A. (2006). "Designing a distribution network in a supply chain system: Formulation and efficient solution procedure." European Journal of Operational Research **171**(2): 567-576.

Asef, V. A., M. Kazemi, et al. (2010). "An ant colony system for enhanced loop-based aisle-network design." European Journal of Operational Research **207**(1): 110-120.

Askarzadeh, A. and A. Rezazadeh (2013). "A new heuristic optimization algorithm for modeling of proton exchange membrane fuel cell: bird mating optimizer." International Journal of Energy Research **37**(10): 1196-1204.

Asl, N. J., B. Zahiri, et al. (2015). "A dynamic closed-loop location-inventory problem under disruption risk." Computers & Industrial Engineering **90**: 414-428.

Augerat, P., J. Belenguer, et al. (1995). "Computational results with a branch and cut code for the capacitated vehicle routing problem." Rapport de recherche- IMAG.

Büyüközkan, G. and G. Çifçi (2013). "An integrated QFD framework with multiple formatted and incomplete preferences: A sustainable supply chain application." Applied Soft Computing **13**(9): 3931-3941.

Bai, C. and J. Sarkis (2010). "Green supplier development: analytical evaluation using rough set theory." Journal of Cleaner Production **18**(12): 1200-1210.

Baker, B. M. and M. Ayechew (2003). "A genetic algorithm for the vehicle routing problem." Computers & Operations Research **30**(5): 787-800.

Balseiro, S. R., I. Loiseau, et al. (2011). "An Ant Colony algorithm hybridized with insertion heuristics for the Time Dependent Vehicle Routing Problem with Time Windows." Computers & Operations Research **38**(6): 954-966.

Bautista, J., E. Fernández, et al. (2008). "Solving an urban waste collection problem using ants heuristics." Computers & Operations Research **35**(9): 3020-3033.

Bautista, J. and J. Pereira (2006). "Modeling the problem of locating collection areas for urban waste management. An application to the metropolitan area of Barcelona." Omega **34**(6): 617-629.

Baykasoglu, A., L. Ozbakir, et al. (2007). "Artificial bee colony algorithm and its application to generalized assignment problem." Swarm Intelligence: Focus on Ant and particle swarm optimization: 113-144.

Beamon, B. M. (1998). "Supply chain design and analysis:: Models and methods." International Journal of Production Economics **55**(3): 281-294.

Bell, J. E. and S. E. Griffis (2010). "SWARM INTELLIGENCE: APPLICATION OF THE ANT COLONY OPTIMIZATION ALGORITHM TO LOGISTICS-ORIENTED VEHICLE ROUTING PROBLEMS." Journal of Business Logistics **31**(2): 157-175.

Bell, J. E. and P. R. McMullen (2004). "Ant colony optimization techniques for the vehicle routing problem." Advanced Engineering Informatics **18**(1): 41-48.

Beni, G. and J. Wang (1993). Swarm intelligence in cellular robotic systems. Robots and Biological Systems: Towards a New Bionics?, Springer**:** 703-712.

Blum, C. and X. Li (2008). Swarm Intelligence in Optimization. Swarm Intelligence. C. Blum and D. Merkle, Springer Berlin Heidelberg**:** 43-85.

Blum, C. and D. Merkle (2008). Swarm intelligence: introduction and applications, Springer.

Blum, C. and A. Roli (2003). "Metaheuristics in combinatorial optimization: Overview and conceptual comparison." ACM Computing Surveys (CSUR) **35**(3): 268-308.

Bochtis, D. D. and C. G. Sørensen (2010). "The vehicle routing problem in field logistics: Part II." Biosystems Engineering **105**(2): 180-188.

Bonabeau, E., M. Dorigo, et al. (1999). Swarm intelligence: from natural to artificial systems, Oxford university press New York.

Boyer, K. K., A. M. Prud'homme, et al. (2009). "THE LAST MILE CHALLENGE: EVALUATING THE EFFECTS OF CUSTOMER DENSITY AND DELIVERY WINDOW PATTERNS." Journal of Business Logistics **30**(1): 185-201.

Brewerton, P. M. and L. J. Millward (2001). Organizational research methods: A guide for students and researchers, Sage.

Brynjolfsson, E., Y. J. Hu, et al. (2013). "Competing in the age of omnichannel retailing." MIT Sloan Management Review **54**(4): 23-29.

Bullnheimer, B., R. F. Hartl, et al. (1999). "An improved ant System algorithm for the vehicle Routing Problem." Annals of Operations Research **89**: 319-328.

Cárdenas, B. L. E. and G. G. Treviño (2014). "An optimal solution to a three echelon supply chain network with multi-product and multi-period." Applied Mathematical Modelling **38**(5–6): 1911-1918.

Carter, C. R. and D. S. Rogers (2008). "A framework of sustainable supply chain management: moving toward new theory." International Journal of Physical Distribution & Logistics Management **38**(5): 360-387.

Castka, P. and M. A. Balzarova (2008). "Social responsibility standardization: Guidance or reinforcement through certification?" Human systems management **27**(3): 231.

Çatay, B. (2010). "A new saving-based ant algorithm for the Vehicle Routing Problem with Simultaneous Pickup and Delivery." Expert Systems with Applications **37**(10): 6809-6817.

Chan, H. K., H. He, et al. (2012). "Green marketing and its impact on supply chain management in industrial markets." Industrial Marketing Management **41**(4): 557-562.

Chandra, M. B. and R. Baskaran (2012). "A survey: Ant Colony Optimization based recent research and implementation on several engineering domain." Expert Systems with Applications **39**(4): 4618-4627.

Che, Z., T. Chiang, et al. (2010). "A SUPPLIER SELECTION MODEL FOR PRODUCT DESIGN CHANGES." International Journal of Electronic Business Management **8**(1): 20-30.

Che, Z. H. (2009). "Using fuzzy analytic hierarchy process and particle swarm optimisation for balanced and defective supply chain problems considering WEEE/RoHS directives." International Journal of Production Research **48**(11): 3355-3381.

Che, Z. H. (2012). "A particle swarm optimization algorithm for solving unbalanced supply chain planning problems." Applied Soft Computing **12**(4): 1279-1287.

Che, Z. H., T. A. Chiang, et al. (2012). "Multi-echelon reverse supply chain network design with specified returns using particle swarm optimization." International Journal of Innovative Computing, Information and Control **8**(10 A): 6719-6731.

Chen, C.-H. and C.-J. Ting (2006). "AN IMPROVED ANT COLONY SYSTEM ALGORITHM FOR THE VEHICLE ROUTING PROBLEM." Journal of the Chinese Institute of Industrial Engineers **23**(2): 115-126.

Chen, C.-H. and C.-J. Ting (2008). "Combining Lagrangian heuristic and Ant Colony System to solve the Single Source Capacitated Facility Location Problem." Transportation Research Part E: Logistics and Transportation Review **44**(6): 1099-1122.

Chen, T. g. and C. h. Ju (2013). "A novel artificial bee colony algorithm for solving the supply chain network design under disruption scenarios." International Journal of Computer Applications in Technology **47**(2): 289-296.

Chen, Y.-W., L.-C. Wang, et al. (2015). "A particle swarm approach for optimizing a multi-stage closed loop supply chain for the solar cell industry." Robotics and Computer-Integrated Manufacturing.

Christofides, N. and S. Eilon (1969). "An Algorithm for the Vehicle-Dispatching Problem." OR **20**(3): 309-318.

Collette, Y. and P. Siarry (2005). "Three new metrics to measure the convergence of metaheuristics towards the Pareto frontier and the aesthetic of a set of solutions in biobjective optimization." Computers & Operations Research **32**(4): 773-792.

Colorni, A., M. Dorigo, et al. (1991). Distributed optimization by ant colonies. Proceedings of the first European conference on artificial life, Paris, France.

Consoli, S. and D. K. Darby (2007). "Combinatorial optimization and metaheuristics."

Cordon, O., F. Herrera, et al. (2002). A review on the ant colony optimization metaheuristic: basis, models and new trends. Mathware & Soft Computing, Citeseer.

Das, A., R. Narasimhan, et al. (2006). "Supplier integration—finding an optimal configuration." Journal of Operations Management **24**(5): 563-582.

Deb, K., A. Pratap, et al. (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II." Evolutionary Computation, IEEE Transactions on **6**(2): 182-197.

Dobers, K., R. Röhrig, et al. (2013). Green Logistics: Comparability of the Environmental Effects of Logistics Services. Efficiency and Logistics. U. Clausen, M. Hompel and M. Klumpp, Springer Berlin Heidelberg: 135-148.

Donati, A. V., R. Montemanni, et al. (2008). "Time dependent vehicle routing problem with a multi ant colony system." European Journal of Operational Research **185**(3): 1174-1191.

Dorigo, M. and L. M. Gambardella (1997). "Ant colonies for the travelling salesman problem." BioSystems **43**(2): 73-81.

Dorigo, M., V. Maniezzo, et al. (1996). "Ant system: optimization by a colony of cooperating agents." Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on **26**(1): 29-41.

Dyllick, T. and K. Hockerts (2002). "Beyond the business case for corporate sustainability." Business Strategy and the Environment **11**(2): 130-141.

Easwaran, G. and H. Üster (2010). "A closed-loop supply chain network design problem with integrated forward and reverse channel decisions." IIE Transactions **42**(11): 779-792.

Eberhart, R. and J. Kennedy (1995). A new optimizer using particle swarm theory. Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on, IEEE.

Efendigil, T., S. Önüt, et al. (2008). "A holistic approach for selecting a third-party reverse logistics provider in the presence of vagueness." Computers & Industrial Engineering **54**(2): 269-287.

Ehmke, J. F. and A. M. Campbell (2014). "Customer acceptance mechanisms for home deliveries in metropolitan areas." European Journal of Operational Research **233**(1): 193-207.

El-Sherbiny, M. M. and R. M. Alhamali (2013). "A hybrid particle swarm algorithm with artificial immune learning for solving the fixed charge transportation problem." Computers & Industrial Engineering **64**(2): 610-620.

Elhedhli, S. and R. Merrick (2012). "Green supply chain network design to reduce carbon emissions." Transportation Research Part D: Transport and Environment **17**(5): 370-379.

Elkington, J. (1998). "Partnerships from cannibals with forks: The triple bottom line of 21st-century business." Environmental Quality Management **8**(1): 37-51.

Eskandarpour, M., S. H. Zegordi, et al. (2013). "A parallel variable neighborhood search for the multi-objective sustainable post-sales network design problem." International Journal of Production Economics **145**(1): 117-131.

Esmat, R., N.-p. Hossein, et al. (2009). "GSA: A Gravitational Search Algorithm." Information Sciences **179**(13): 2232-2248.

Farahani, R. Z. and M. Elahipanah (2008). "A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain." International Journal of Production Economics **111**(2): 229-243.

Favaretto, D., E. Moretti, et al. (2007). "Ant colony system for a VRP with multiple time windows and multiple visits." Journal of Interdisciplinary Mathematics **10**(2): 263-284.

Fisher, M. (1995). "Vehicle routing." Handbooks in operations research and management science **8**: 1-33.

Fledelius, W. and B. Mayoh (2008). Toward a Unified Framework for Swarm Based Image Analysis. AISB 2008 Convention Communication, Interaction and Social Intelligence.

Fleischer, M. (2003). The Measure of Pareto Optima Applications to Multi-objective Metaheuristics. Evolutionary Multi-Criterion Optimization. C. Fonseca, P. Fleming, E. Zitzler, L. Thiele and K. Deb, Springer Berlin Heidelberg. **2632:** 519-533.

Fleischmann, M., R. J. M. Bloemhof, et al. (1997). "Quantitative models for reverse logistics: A review." European Journal of Operational Research **103**(1): 1-17.

Frota, N. J. Q., R. J. M. Bloemhof, et al. (2008). "Designing and evaluating sustainable logistics networks." International Journal of Production Economics **111**(2): 195-208.

Fuellerer, G., K. F. Doerner, et al. (2009). "Ant colony optimization for the two-dimensional loading vehicle routing problem." Computers & Operations Research **36**(3): 655-673.

Gómez S, C. G., R. L. Cruz, et al. (2014). "Ant colony system with characterization-based heuristics for a bottled-products distribution logistics system." Journal of Computational and Applied Mathematics **259, Part B**: 965-977.

Gajpal, Y. and P. Abad (2009). "An ant colony system (ACS) for vehicle routing problem with simultaneous delivery and pickup." Computers & Operations Research **36**(12): 3215-3223.

Gajpal, Y. and P. L. Abad (2009). "Multi-ant colony system (MACS) for a vehicle routing problem with backhauls." European Journal of Operational Research **196**(1): 102-117.

Gandomi, A. H. and A. H. Alavi (2012). "Krill herd: a new bio-inspired optimization algorithm." Communications in Nonlinear Science and Numerical Simulation **17**(12): 4831-4845.

Gang, J., Y. Tu, et al. (2015). "A multi-objective bi-level location planning problem for stone industrial parks." Computers & Operations Research **56**: 8-21.

Garcia, F. J. M. and J. A. M. Perez (2008). "Jumping frogs optimization: a new swarm method for discrete optimization." Documentos de Trabajo del DEIOC(3).

Gen, M., F. Altiparmak, et al. (2006). "A genetic algorithm for two-stage transportation problem using priority-based encoding." OR Spectrum **28**(3): 337-354.

Genovese, A., K. S. C. Lenny, et al. (2013). "Greener supplier selection: state of the art and some empirical evidence." International Journal of Production Research **51**(10): 2868-2886.

Ghasemy, Y. R., G. S. M. T. Fatemi, et al. (2014). "A hybrid credibility-based fuzzy multiple objective optimisation to differential pricing and inventory policies with arbitrage consideration." International Journal of Systems Science: 1-12.

Giannakis, M. (2008). "Facilitating learning and knowledge transfer through supplier development." Supply chain management: an international journal **13**(1): 62-72.

Goksal, F. P., I. Karaoglan, et al. (2013). "A hybrid discrete particle swarm optimization for vehicle routing problem with simultaneous pickup and delivery." Computers & Industrial Engineering **65**(1): 39-53.

Golden, B. L., S. Raghavan, et al. (2008). The vehicle routing problem: latest advances and new challenges, Springer.

Gong, W., D. Li, et al. (2007). "Improved two-grade delayed particle swarm optimisation (TGDPSO) for inventory facility location for perishable food distribution centres in Beijing." New Zealand Journal of Agricultural Research **50**(5): 771-779.

Gong, Y. and D. Huang (2012). "Optimization of closed-loop supply Chain under uncertainty using hybrid algorithm." Advanced Science Letters **7**: 271-276.

Gong, Y. J., J. Zhang, et al. (2012). "Optimizing the Vehicle Routing Problem With Time Windows: A Discrete Particle Swarm Optimization Approach." Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on **42**(2): 254-267.

Govindan, K., A. Jafarian, et al. (2012). "Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food." International Journal of Production Economics(0).

Govindan, K., A. Jafarian, et al. (2014). "Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food." International Journal of Production Economics **152**: 9-28.

Govindan, K., A. Jafarian, et al. (2015). "Bi-objective integrating sustainable order allocation and sustainable supply chain network strategic design with stochastic demand using a novel robust hybrid multi-objective metaheuristic." Computers & Operations Research **62**: 112-130.

Guide, J. V. D. R. (2000). "Production planning and control for remanufacturing: industry practice and research needs." Journal of Operations Management **18**(4): 467-483.

Guide, V. D. R. and W. L. N. Van (2001). "MANAGING PRODUCT RETURNS FOR REMANUFACTURING." Production and Operations Management **10**(2): 142-155.

Guillermo, C. G., C. Enrique, et al. (2012). "A Hybrid Approach Using an Artificial Bee Algorithm with Mixed Integer Programming Applied to a Large-Scale Capacitated Facility Location Problem." Mathematical Problems in Engineering **2012**: 14.

Hassini, E., C. Surti, et al. (2012). "A literature review and a case study of sustainable supply chains with a focus on metrics." International Journal of Production Economics **140**(1): 69-82.

Havens, T. C., C. J. Spain, et al. (2008). Roach Infestation Optimization. Swarm

Intelligence Symposium, 2008. SIS 2008. IEEE.
He, J., Y. Huang, et al. (2015). "Simulation-based heuristic method for container supply chain network optimization." Advanced Engineering Informatics **29**(3): 339-354.
Hiremath, N. C., S. Sahu, et al. (2013). "Multi objective outbound logistics network design for a manufacturing supply chain." Journal of Intelligent Manufacturing **24**(6): 1071-1084.
Ho, W., X. Xu, et al. (2010). "Multi-criteria decision making approaches for supplier evaluation and selection: A literature review." European Journal of Operational Research **202**(1): 16-24.
Hoff, A., H. Andersson, et al. (2010). "Industrial aspects and literature survey: Fleet composition and routing." Computers & Operations Research **37**(12): 2041-2061.
Holland, J. H. (1975). Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence, U Michigan Press.
Hu, T. J. and W. K. Cheng (2010). "Modeling of vehicle routing problems with backhauls of reverse logistics and ant colony algorithm." Journal of Transportation Systems Engineering and Information Technology **10**(3): 110-114.
Huang, P. C., L. I. Tong, et al. (2011). "A two-phase algorithm for product part change utilizing AHP and PSO." Expert Systems with Applications **38**(7): 8458-8465.
Huang, S.-H. and P.-C. Lin (2010). "A modified ant colony optimization algorithm for multi-item inventory routing problems with demand uncertainty." Transportation Research Part E: Logistics and Transportation Review **46**(5): 598-611.
Hugo, A. and E. N. Pistikopoulos (2005). "Environmentally conscious long-range planning and design of supply chain networks." Journal of Cleaner Production **13**(15): 1471-1491.
Humphreys, P., Y. Wong, et al. (2003). "Integrating environmental criteria into the supplier selection process." Journal of Materials Processing Technology **138**(1): 349-356.
Jabir, E., V. V. Panicker, et al. (2015). "Multi-objective Optimization Model for a Green Vehicle Routing Problem." Procedia - Social and Behavioral Sciences **189**: 33-39.
Jeanne, R. (1986). "The evolution of the organization of work in social insects." Monitore zoologico italiano **20**(2): 119-133.
Jones, D. F., S. K. Mirrazavi, et al. (2002). "Multi-objective meta-heuristics: An overview of the current state-of-the-art." European Journal of Operational Research **137**(1): 1-9.
Kämäräinen, V., J. Saranen, et al. (2001). "The reception box impact on home delivery efficiency in the e-grocery business." International Journal of Physical Distribution & Logistics Management **31**(6): 414-426.

Kadadevaramath, R. S., J. C. H. Chen, et al. (2012). "Application of particle swarm intelligence algorithms in supply chain network architecture optimization." Expert Systems with Applications **39**(11): 10160-10176.

Kamarainen, V. and M. Punakivi (2004). "Unattended reception–a business opportunity?" International Journal of Services Technology and Management **5**(2): 206-220.

Kannan, G., H. A. Noorul, et al. (2009). "Analysis of closed loop supply chain using genetic algorithm and particle swarm optimisation." International Journal of Production Research **47**(5): 1175-1200.

Kanthavel, K., P. S. S. Prasad, et al. (2012). "Optimization of vehicle routing problem with simultaneous delivery and pickup using nested particle swarm optimization." European Journal of Scientific Research **73**(3): 331-337.

Kara, İ., B. Kara, et al. (2007). Energy Minimizing Vehicle Routing Problem. Combinatorial Optimization and Applications. A. Dress, Y. Xu and B. Zhu, Springer Berlin Heidelberg. **4616:** 62-71.

Karaboga, D. (2005). "An idea based on honey bee swarm for numerical optimization."

Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization, Technical report-tr06, Erciyes university, engineering faculty, computer engineering department.

Karaboga, D. and B. Akay (2009). "A survey: algorithms simulating bee swarm intelligence." Artif. Intell. Rev. **31**(1-4): 61-85.

Karaboga, D. and B. Basturk (2007). Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems. Foundations of Fuzzy Logic and Soft Computing. P. Melin, O. Castillo, L. Aguilar, J. Kacprzyk and W. Pedrycz, Springer Berlin Heidelberg. **4529:** 789-798.

Karaboga, D. and B. Basturk (2007). "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." Journal of Global Optimization **39**(3): 459-471.

Karaboga, D. and B. Basturk (2008). "On the performance of artificial bee colony (ABC) algorithm." Applied Soft Computing **8**(1): 687-697.

Karaboga, D., C. Ozturk, et al. (2012). "Artificial bee colony programming for symbolic regression." Information Sciences **209**(0): 1-15.

Karadimas, N., N. Doukas, et al. (2008). "Routing Optimization Heuristic Algorithms for Urban Solid Waste Transportation Management." WSEAS Transaction on Computers **7**(12): 2022-2031.

Karadimas, N. V., K. Papatzelou, et al. (2007). "Optimal solid waste collection routes identified by the ant colony system algorithm." WSEAS Transaction on Computers **25**(2): 139-147.

Kenné, J.-P., P. Dejax, et al. (2012). "Production planning of a hybrid manufacturing–remanufacturing system under uncertainty within a closed-loop supply chain." International Journal of Production Economics **135**(1): 81-93.

Kennedy, J. (2010). Particle swarm optimization. Encyclopedia of Machine Learning, Springer**:** 760-766.

Kennedy, J. and R. Eberhart (1995). Particle swarm optimization. Proceedings of IEEE international conference on neural networks, Perth, Australia.

Khalifehzadeh, S., M. Seifbarghy, et al. (2015). "A four-echelon supply chain network design with shortage: Mathematical modeling and solution methods." Journal of Manufacturing Systems **35**: 164-175.

Kiesmüller, G. P. (2003). "A new approach for controlling a hybrid stochastic manufacturing/remanufacturing system with inventories and different leadtimes." European Journal of Operational Research **147**(1): 62-71.

Kim, B.-I., S. Kim, et al. (2006). "Waste collection vehicle routing problem with time windows." Computers & Operations Research **33**(12): 3624-3642.

Ko, H. J. and G. W. Evans (2007). "A genetic algorithm-based heuristic for the dynamic integrated forward/reverse logistics network for 3PLs." Computers & Operations Research **34**(2): 346-366.

Konak, A., D. W. Coit, et al. (2006). "Multi-objective optimization using genetic algorithms: A tutorial." Reliability Engineering & System Safety **91**(9): 992-1007.

Krishnanand, K. and D. Ghose (2005). Detection of multiple source locations using a glowworm metaphor with applications to collective robotics. Swarm Intelligence Symposium, 2005. SIS 2005. Proceedings 2005 IEEE, IEEE.

Kumanan, S., S. Prasanna Venkatesan, et al. (2007). "Optimisation of supply chain logistics network using random search techniques." International Journal of Logistics Systems and Management **3**(2): 252-266.

Kumar, R. S., K. Kondapaneni, et al. (2015). "Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach." Computers & Industrial Engineering.

Kumar, S. K., M. K. Tiwari, et al. (2009). "Minimisation of supply chain cost with embedded risk using computational intelligence approaches." International Journal of Production Research **48**(13): 3717-3739.

Kumar, V., F. W. Liou, et al. (2013). "Economical impact of RFID implementation in remanufacturing: a Chaos-based Interactive Artificial Bee Colony approach." Journal of Intelligent Manufacturing: 1-16.

Kuo, R. J., S. Y. Hong, et al. (2010). "Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection." Applied Mathematical Modelling **34**(12): 3976-3990.

Kusumastuti, R. D., R. Piplani, et al. (2008). "Redesigning closed-loop service network at a computer manufacturer: A case study." International Journal of Production Economics **111**(2): 244-260.

Laporte, G. (1992). "The vehicle routing problem: An overview of exact and approximate algorithms." European Journal of Operational Research

59(3): 345-358.

Latha, S. B., S. Basavarajappa, et al. (2013). "A bi-objective optimization of supply chain design and distribution operations using non-dominated sorting algorithm: A case study." Expert Systems with Applications **40**(14): 5730-5739.

Lee, C.-Y., Z.-J. Lee, et al. (2010). "An enhanced ant colony optimization (EACO) applied to capacitated vehicle routing problem." Applied Intelligence **32**(1): 88-95.

Lee, C. K. M., W. Ho, et al. (2011). "Design and development of logistics workflow systems for demand management with RFID." Expert Systems with Applications **38**(5): 5428-5437.

Lee, C. K. M. and J. S. L. Lam (2012). "Managing reverse logistics to enhance sustainability of industrial marketing." Industrial Marketing Management **41**(4): 589-598.

Lenstra, J. K. and A. Kan (1981). "Complexity of vehicle routing and scheduling problems." Networks **11**(2): 221-227.

Li, J., Q. Pan, et al. (2011). Flexible job shop scheduling problems by a hybrid artificial bee colony algorithm. Evolutionary Computation (CEC), 2011 IEEE Congress on.

Li, X.-l., F. Lu, et al. (2004). "Applications of artificial fish school algorithm in combinatorial optimization problems." Journal of Shandong University (Engineering Science) **34**(5): 64-67.

Li, X. and M. Yin (2012). "A discrete artificial bee colony algorithm with composite mutation strategies for permutation flow shop scheduling problem." Scientia Iranica **19**(6): 1921-1935.

Lin, C.-W. and Y.-L. Chen (2013). "Optimal Green Facility Planning-Implementation of Organic Rankine Cycle System for Factory Waste Heat Recovery." International Journal of Environmental, Earth Science and Engineering.

Lin, C., K. L. Choy, et al. (2013). "Survey of Green Vehicle Routing Problem: Past and future trends." Expert Systems with Applications(0).

Lin, P., M. A. Contreras, et al. (2016). "A multilevel ACO approach for solving forest transportation planning problems with environmental constraints." Swarm and Evolutionary Computation.

Lin, R. H. (2009). "An integrated FANP-MOLP for supplier evaluation and order allocation." Applied Mathematical Modelling **33**(6): 2730-2736.

Linton, J. D., R. Klassen, et al. (2007). "Sustainable supply chains: An introduction." Journal of Operations Management **25**(6): 1075-1082.

Liu, X., G. Peng, et al. (2012). "Disassembly sequence planning approach for product virtual maintenance based on improved max–min ant system." The International Journal of Advanced Manufacturing Technology **59**(5-8): 829-839.

Liu, Y.-F. and S.-Y. Liu (2013). "A hybrid discrete artificial bee colony algorithm for permutation flowshop scheduling problem." Applied Soft

Computing **13**(3): 1459-1463.

Lu, X. and Y. Zhou (2008). A novel global convergence algorithm: bee collecting pollen algorithm. Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence, Springer**:** 518-525.

Lucic, P. and D. Teodorovic (2002). Transportation modeling: an artificial life approach. Tools with Artificial Intelligence, 2002.(ICTAI 2002). Proceedings. 14th IEEE International Conference on, IEEE.

Majhi, B. and G. Panda (2010). "Development of efficient identification scheme for nonlinear dynamic systems using swarm intelligence techniques." Expert Systems with Applications **37**(1): 556-566.

Marinakis, Y., M. Marinaki, et al. (2010). "Honey Bees Mating Optimization algorithm for large scale vehicle routing problems." Natural Computing **9**(1): 5-27.

Marsillac, E. L. (2008). "Environmental impacts on reverse logistics and green supply chains: similarities and integration." International Journal of Logistics Systems and Management **4**(4): 411-422.

Mastrocinque, E., B. Yuce, et al. (2013). "A multi-objective optimisation for supply chain network using the bees algorithm." Int. J. Eng. Bus. Manage **5**: 1-11.

Mayring, P. (2004). "Qualitative content analysis." A companion to qualitative research: 266-269.

Mazzeo, S. and I. Loiseau (2004). "An Ant Colony Algorithm for the Capacitated Vehicle Routing." Electronic Notes in Discrete Mathematics **18**(0): 181-186.

McWilliams, A. (2000). "Corporate Social Responsibility." Wiley Encyclopedia of Management.

Meiyi, W., L. Xiang, et al. (2015). "Time-dependent fuzzy random location-scheduling programming for hazardous materials transportation." Transportation Research Part C: Emerging Technologies **57**: 146-165.

Melo, M. T., S. Nickel, et al. (2009). "Facility location and supply chain management – A review." European Journal of Operational Research **196**(2): 401-412.

Meredith, J. (1993). "Theory building through conceptual methods." International Journal of Operations & Production Management **13**(5): 3-11.

Miandoabchi, E., F. Daneshzand, et al. (2013). "Multi-objective discrete urban road network design." Computers & Operations Research **40**(10): 2429-2449.

Min, H. and W. P. Galle (1997). "Green Purchasing Strategies: Trends and Implications." International Journal of Purchasing and Materials Management **33**(2): 10-17.

Mirjalili, S., S. M. Mirjalili, et al. (2014). "Grey Wolf Optimizer." Advances in

Engineering Software **69**(0): 46-61.

Mittal, V. and W. A. Kamakura (2001). "Satisfaction, repurchase intent, and repurchase behavior: Investigating the moderating effect of customer characteristics." Journal of marketing research **38**(1): 131-142.

Moghaddam, B. F., R. Ruiz, et al. (2012). "Vehicle routing problem with uncertain demands: An advanced particle swarm algorithm." Computers & Industrial Engineering **62**(1): 306-317.

Mohtashami, A., M. Tavana, et al. (2015). "A novel multi-objective meta-heuristic model for solving cross-docking scheduling problems." Applied Soft Computing **31**: 30-47.

Moncayo Mart ńez, L. A. and D. Z. Zhang (2011). "Multi-objective ant colony optimisation: A meta-heuristic approach to supply chain design." International Journal of Production Economics **131**(1): 407-420.

Montemanni, R., L. M. Gambardella, et al. (2005). "Ant Colony System for a Dynamic Vehicle Routing Problem." Journal of Combinatorial Optimization **10**(4): 327-343.

Mostafavi, S. A. and A. Afshar (2011). "Waste load allocation using non-dominated archiving multi-colony ant algorithm." Procedia Computer Science **3**: 64-69.

Mucherino, A. and O. Seref (2007). Monkey search: a novel metaheuristic search for global optimization. Data Mining, Systems Analysis and Optimization in Biomedicine, American Institute of Physics.

Murphy, P. R., R. F. Poist, et al. (1996). "GREEN LOGISTICS--COMPARATIVE VIEWS OF ENVIRONMENTAL PROGRESSIVES, MODERATES AND CONSERVATIVES." Journal of Business Logistics.

Murphy, P. R. P. R. F. (2000). "Green Logistics Strategies: An Analysis of Usage Patterns." Transportation Journal (American Society of Transportation & Logistics Inc) **40**(2): 5-16.

Musa, R., J.-P. Arnaout, et al. (2010). "Ant colony optimization algorithm to solve for the transportation problem of cross-docking network." Computers & Industrial Engineering **59**(1): 85-92.

Nag, B., B. L. Golden, et al. (1988). "Vehicle routing with site dependencies." Vehicle routing: Methods and studies: 149-159.

Nikolić, M. and D. Teodorović (2013). "Transit network design by Bee Colony Optimization." Expert Systems with Applications **40**(15): 5945-5955.

Noorul, H. A. and G. Kannan (2006). "Effect of forecasting on the multi-echelon distribution inventory supply chain cost using neural network, genetic algorithm and particle swarm optimisation." International Journal of Services Operations and Informatics **1**(1): 1-22.

Pal, A., F. T. S. Chan, et al. (2010). "Aggregate procurement, production, and shipment planning decision problem for a three-echelon supply chain using swarm-based heuristics." International Journal of Production Research **49**(10): 2873-2905.

Pan, W.-T. (2012). "A new fruit fly optimization algorithm: taking the financial distress model as an example." Knowledge-Based Systems **26**: 69-74.

Pandey, S. and S. Kumar (2013). "Enhanced Artificial Bee Colony Algorithm and It's Application to Travelling Salesman Problem." HCTL Open International Journal of Technology Innovations and Research **2**: 137-146.

Parpinelli, R. S. and H. S. Lopes (2011). "New inspirations in swarm intelligence: a survey." International Journal of Bio-Inspired Computation **3**(1): 1-16.

Passino, K. M. (2010). "Bacterial foraging optimization." International Journal of Swarm Intelligence Research (IJSIR) **1**(1): 1-16.

Pham, D., A. Ghanbarzadeh, et al. (2006). The bees algorithm-a novel tool for complex optimisation problems. Proceedings of the 2nd Virtual International Conference on Intelligent Production Machines and Systems (IPROMS 2006).

Pinto, P. C., T. A. Runkler, et al. (2007). Wasp swarm algorithm for dynamic MAX-SAT problems. Adaptive and Natural Computing Algorithms, Springer**:** 350-357.

Piplani, R., N. Pujawan, et al. (2008). "Sustainable supply chain management." International Journal of Production Economics **111**(2): 193-194.

Pishvaee, M. S., R. Z. Farahani, et al. (2010). "A memetic algorithm for bi-objective integrated forward/reverse logistics network design." Computers & Operations Research **37**(6): 1100-1112.

Poli, R. (2008). "Analysis of the publications on the applications of particle swarm optimisation." Journal of Artificial Evolution and Applications **2008**: 3.

Poole, A. and A. Kotsialos (2016). "Swarm intelligence algorithms for macroscopic traffic flow model validation with automatic assignment of fundamental diagrams." Applied Soft Computing **38**: 134-150.

Poorzahedy, H. and O. M. Rouhani (2007). "Hybrid meta-heuristic algorithms for solving network design problem." European Journal of Operational Research **182**(2): 578-596.

Pradhananga, R., E. Taniguchi, et al. (2010). "Ant colony system based routing and scheduling for hazardous material transportation." Procedia - Social and Behavioral Sciences **2**(3): 6097-6108.

Prakash, A., M. K. Tiwari, et al. (2008). "Optimal job sequence determination and operation machine allocation in flexible manufacturing systems: an approach using adaptive hierarchical ant colony algorithm." Journal of Intelligent Manufacturing **19**(2): 161-173.

Pramanik, S., D. K. Jana, et al. (2015). "A fixed-charge transportation problem in two-stage supply chain network in Gaussian type-2 fuzzy environments." Information Sciences **325**: 190-214.

Prins, C. (2004). "A simple and effective evolutionary algorithm for the vehicle routing problem." Computers & Operations Research **31**(12): 1985-2002.

Qi, C. (2011). "Application of Improved Discrete Particle Swarm Optimization in Logistics Distribution Routing Problem." Procedia Engineering **15**(0): 3673-3677.

Qian, T., H. Zhexue, et al. (2013). Optimization of green agri-food supply chain network using chaotic PSO algorithm. Service Operations and Logistics, and Informatics (SOLI), 2013 IEEE International Conference on.

Qu, X. H., W. F. Song, et al. (2011). Research on the triangle distribution model based on third-party logistics alliance, Changchun.

Rajabalipour, C. H., M. Desa, et al. (2013). "A flexible three-level logistic network design considering cost and time criteria with a multi-objective evolutionary algorithm." Journal of Intelligent Manufacturing **24**(2): 277-293.

Rajesh, R., S. Pugazhendhi, et al. (2011). "Genetic Algorithm and Particle Swarm Optimization for Solving Balanced Allocation Problem of Third Party Logistics Providers." International Journal of Information Systems and Supply Chain Management (IJISSCM) **4**(1): 24-44.

Reed, M., A. Yiannakou, et al. (2014). "An ant colony algorithm for the multi-compartment vehicle routing problem." Applied Soft Computing **15**: 169-176.

Reynaldo, C.-R. and E. Jürgen (2009). "Reverse logistics network design for the collection of End-of-Life Vehicles in Mexico." European Journal of Operational Research **196**(3): 930-939.

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. ACM SIGGRAPH Computer Graphics, ACM.

Rizzoli, A. E., R. Montemanni, et al. (2007). "Ant colony optimization for real-world vehicle routing problems." Swarm Intelligence **1**(2): 135-151.

Rogers, D. S. and T. L. Ronald (2001). "AN EXAMINATION OF REVERSE LOGISTICS PRACTICES." Journal of Business Logistics **22**(2): 129-148.

Rondinelli, D. and M. Berry (2000). "Multimodal transportation, logistics, and the environment: managing interactions in a global economy." European Management Journal **18**(4): 398-410.

Roth, M. (2005). Termite: A swarm intelligent routing algorithm for mobile wireless ad-hoc networks.

Ruan, Q., Z. Zhang, et al. (2013). "A hybrid approach for the vehicle routing problem with three-dimensional loading constraints." Computers & Operations Research **40**(6): 1579-1589.

Rusinko, C. A. (2007). "Green Manufacturing: An Evaluation of Environmentally Sustainable Manufacturing Practices and Their Impact on Competitive Outcomes." Engineering Management, IEEE Transactions on **54**(3): 445-454.

Rust, R. T. and A. J. Zahorik (1993). "Customer satisfaction, customer retention, and market share." Journal of retailing **69**(2): 193-215.

Sachan, A. and S. Datta (2005). "Review of supply chain management and logistics research." International Journal of Physical Distribution & Logistics Management **35**(9): 664-705.

Salimifard, K., H. Shahbandarzadeh, et al. (2012). Green Transportation and the Role of Operation Research. 2012 International Conference on Traffic and Transportation Engineering.

Santos, L., R. J. Coutinho, et al. (2010). "An improved ant colony optimization based algorithm for the capacitated arc routing problem." Transportation Research Part B: Methodological **44**(2): 246-266.

Sbihi, A. and R. Eglese (2007). "Combinatorial optimization and Green Logistics." 4OR **5**(2): 99-116.

Šelmić, M., D. Teodorović, et al. (2010). "Locating inspection facilities in traffic networks: an artificial intelligence approach." Transportation Planning and Technology **33**(6): 481-493.

Seuring, S. and M. Müller (2008). "From a literature review to a conceptual framework for sustainable supply chain management." Journal of Cleaner Production **16**(15): 1699-1710.

Shahin, M. S., G. S. M. T. Fatemi, et al. (2014). "Vehicle routing scheduling problem with cross docking and split deliveries." Computers & Chemical Engineering **69**: 98-107.

Shankar, B. L., S. Basavarajappa, et al. (2012). "Bi-objective optimization of distribution scheduling using MOPSO optimizer." Journal of Modelling in Management **7**(3): 304-327.

Shi, Y. J., F. W. Meng, et al. (2012). "A Modified Artificial Bee Colony Algorithm for Vehicle Routing Problems with Time Windows." Information Technology Journal **11**(10): 1490-1495.

Shiqin, Y., J. Jianjun, et al. (2009). A Dolphin Partner Optimization. Intelligent Systems, 2009. GCIS'09. WRI Global Congress on, IEEE.

Sicilia, J.-A., B. Royo, et al. (2014). "A Decision Support System for a Long-distance Routing Problem based on the Ant Colony Optimization Metaheuristic." Procedia - Social and Behavioral Sciences **111**: 1035-1044.

Silva, C. A., J. M. C. Sousa, et al. (2009). "Distributed supply chain management using ant colony optimization." European Journal of Operational Research **199**(2): 349-358.

Soleimani, H. and G. Kannan (2015). "A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks." Applied Mathematical Modelling **39**(14): 3990-4012.

Sprenger, R. and L. Mönch (2012). "A methodology to solve large-scale cooperative transportation planning problems." European Journal of Operational Research **223**(3): 626-636.

Stützle, T. and H. H. Hoos (2000). "MAX–MIN ant system." Future generation computer systems **16**(8): 889-914.

Su, W., S. X. Huang, et al. (2015). "Integrated partner selection and production–distribution planning for manufacturing chains." Computers & Industrial Engineering **84**: 32-42.

Subramanian, P., N. Ramkumar, et al. (2012). "A technical note on Analysis of closed loop supply chain using genetic algorithm and particle swarm optimisation." International Journal of Production Research **50**(2): 593-602.

Sundarakani, B., R. Desouza, et al. (2010). "Modeling carbon footprints across the supply chain." International Journal of Production Economics **128**(1): 43-50.

Suzuki, Y. (2011). "A new truck-routing approach for reducing fuel consumption and pollutants emission." Transportation Research Part D: Transport and Environment **16**(1): 73-77.

Syarif, A., Y. Yun, et al. (2002). "Study on multi-stage logistic chain network: a spanning tree-based genetic algorithm approach." Computers & Industrial Engineering **43**(1–2): 299-314.

Szeto, W. Y., Y. Wu, et al. (2011). "An artificial bee colony algorithm for the capacitated vehicle routing problem." European Journal of Operational Research **215**(1): 126-135.

Taleizadeh, A., S. Niaki, et al. (2010). "A particle swarm optimization approach for constraint joint single buyer-single vendor inventory problem with changeable lead time and (r,Q) policy in supply chain." The International Journal of Advanced Manufacturing Technology **51**(9-12): 1209-1223.

Tancrez, J.-S., J.-C. Lange, et al. (2012). "A location-inventory model for large three-level supply chains." Transportation Research Part E: Logistics and Transportation Review **48**(2): 485-502.

Tang, J., Y. Ma, et al. (2013). "A Max–Min Ant System for the split delivery weighted vehicle routing problem." Expert Systems with Applications **40**(18): 7468-7477.

Tlili, T., S. Faiz, et al. (2014). "A Hybrid Metaheuristic for the Distance-constrained Capacitated Vehicle Routing Problem." Procedia - Social and Behavioral Sciences **109**: 779-783.

Toth, P. and D. Vigo (2002). "Models, relaxations and exact approaches for the capacitated vehicle routing problem." Discrete Applied Mathematics **123**(1): 487-512.

Toth, P. and D. Vigo (2002). "An overview of vehicle routing problems." The vehicle routing problem **9**: 1-26.

Tsai, Y. L., Y. J. Yang, et al. (2010). "A dynamic decision approach for supplier selection using ant colony system." Expert Systems with Applications **37**(12): 8313-8321.

Ubeda, S., F. J. Arcelus, et al. (2011). "Green logistics at Eroski: A case study." International Journal of Production Economics **131**(1): 44-51.

Validi, S., A. Bhattacharya, et al. (2013). "Integrated low-carbon distribution system for the demand side of a product distribution supply chain: a DoE-guided MOPSO optimiser-based solution approach." International

Journal of Production Research.

Veluscek, M., T. Kalganova, et al. (2015). "Composite goal methods for transportation network optimization." Expert Systems with Applications **42**(8): 3852-3867.

Venkatesan, S. P. and S. Kumanan (2012). "A Multi–Objective Discrete Particle Swarm Optimisation Algorithm for supply chain network design." International Journal of Logistics Systems and Management **11**(3): 375-406.

Villegas, J., F. Palacios, et al. (2006). "Solution methods for the bi-objective (cost-coverage) unconstrained facility location problem with an illustrative example." Annals of Operations Research **147**(1): 109-141.

Vishwa, V. K., F. T. S. Chan, et al. (2010). Environmental integrated closed loop logistics model: An artificial bee colony approach. Supply Chain Management and Information Systems (SCMIS), 2010 8th International Conference on.

Wagner, S. M. (2006). "Supplier development practices: an exploratory study." European Journal of Marketing **40**(5/6): 554-571.

Wang, H. S. (2009). "A two-phase ant colony algorithm for multi-echelon defective supply chain network design." European Journal of Operational Research **192**(1): 243-252.

Wang, I. L. and W. C. Yang (2007). "Fast Heuristics for Designing Integrated E-Waste Reverse Logistics Networks." Electronics Packaging Manufacturing, IEEE Transactions on **30**(2): 147-154.

Wang, K.-J. and C. H. Lee (2015). "A revised ant algorithm for solving location–allocation problem with risky demand in a multi-echelon supply chain network." Applied Soft Computing **32**: 311-321.

Wang, Y.-P. (2013). "Adaptive Ant Colony Algorithm for the VRP Solution of Logistics Distribution." Research Journal of Applied Sciences, Engineering and Technology **6**(5): 807-811.

Wang, Y. and J. H. Liu (2010). "Chaotic particle swarm optimization for assembly sequence planning." Robotics and Computer-Integrated Manufacturing **26**(2): 212-222.

Wu, H.-J. and S. C. Dunn (1995). "Environmentally responsible logistics systems." International Journal of Physical Distribution & Logistics Management **25**(2): 20-38.

Xiao, Y., Q. Zhao, et al. (2012). "Development of a fuel consumption optimization model for the capacitated vehicle routing problem." Computers & Operations Research **39**(7): 1419-1431.

Xiao, Z., W. Chen, et al. (2012). "An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation." Applied Mathematical Modelling **36**(4): 1444-1454.

Yamada, T. and Z. Febri (2015). "Freight transport network design using particle swarm optimisation in supply chain–transport supernetwork equilibrium." Transportation Research Part E: Logistics and

Transportation Review **75**: 164-187.

Yang, X.-S. (2008). Firefly algorithm. Nature-inspired Metaheuristic Algorithms. Bristol, UK, Luniver Press.

Yang, X.-S. (2010). A new metaheuristic bat-inspired algorithm. Nature inspired cooperative strategies for optimization (NICSO 2010), Springer**:** 65-74.

Yang, X.-S. and S. Deb (2009). Cuckoo search via Lévy flights. Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on, IEEE.

Yao, B., P. Hu, et al. (2013). "Artificial bee colony algorithm with scanning strategy for the periodic vehicle routing problem." SIMULATION **89**(6): 762-770.

Yapicioglu, H., A. E. Smith, et al. (2007). "Solving the semi-desirable facility location problem using bi-objective particle swarm." European Journal of Operational Research **177**(2): 733-749.

Ye, L., C. Ye, et al. (2011). "Location set covering for waste resource recycling centers in Taiwan." Resources, Conservation and Recycling **55**(11): 979-985.

Yi, W. and A. Kumar (2007). "Ant colony optimization for disaster relief operations." Transportation Research Part E: Logistics and Transportation Review **43**(6): 660-672.

Yu, B., Z.-Z. Yang, et al. (2009). "An improved ant colony optimization for vehicle routing problem." European Journal of Operational Research **196**(1): 171-176.

Yu, B. and Z. Z. Yang (2011). "An ant colony optimization model: The period vehicle routing problem with time windows." Transportation Research Part E: Logistics and Transportation Review **47**(2): 166-181.

Yuce, B., E. Mastrocinque, et al. (2014). "A multi-objective supply chain optimisation using enhanced Bees Algorithm with adaptive neighbourhood search and site abandonment strategy." Swarm and Evolutionary Computation **18**: 71-82.

Zhang, L. L., C. Lee, et al. (2016). "An integrated model for strategic supply chain design: Formulation and ABC-based solution approach." Expert Systems with Applications **52**: 39-49.

Zhang, Q. S. and K. Guo (2014). "A DISCRETE ARTIFICIAL BEE COLONY ALGORITHM FOR THE REVERSE LOGISTICS LOCATION AND ROUTING PROBLEM." International Journal of Information Technology & Decision Making **0**(0): 1-19.

Zhang, R., S. Song, et al. (2013). "A hybrid artificial bee colony algorithm for the job shop scheduling problem." International Journal of Production Economics **141**(1): 167-178.

Zhang, S., C. K. M. Lee, et al. (2015). "Swarm intelligence applied in green logistics: A literature review." Engineering Applications of Artificial Intelligence **37**(0): 154-169.

Zhang, S., C. K. M. Lee, et al. (2014). "Design and development of a hybrid artificial bee colony algorithm for the environmental vehicle routing problem." Transportation Research Part D: Transport and Environment **31**: 85-99.

Zhang, T., W.-x. Tian, et al. (2008). "Improved Ant Colony System for VRPSPD with Maximum Distance Constraint." Systems Engineering - Theory & Practice **28**(1): 132-140.

Zhou, X. C., Z. X. Zhao, et al. (2012). "Remanufacturing closed-loop SUPPLY chain network design based on genetic particle swarm optimization algorithm." Journal of Central South University of Technology (English Edition) **19**(2): 482-487.

Zhou, Z., S. Cheng, et al. (2000). "Supply chain optimization of continuous process industries with sustainability considerations." Computers & Chemical Engineering **24**(2–7): 1151-1158.

Zhu, Q. and J. Zhang (2010). "Ant colony optimisation with elitist ant for sequencing problem in a mixed model assembly line." International Journal of Production Research **49**(15): 4605-4626.