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Real-time optimization of an integrated production-inventory-distribution problem.

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REAL-TIME OPTIMIZATION OF AN INTEGRATED
PRODUCTION-INVENTORY-DISTRIBUTION PROBLEM

By

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DEDICATION

This dissertation is dedicated to my parents

Mr. Yuchen Yang

and

Mrs. Li Ma

who have given me invaluable educational opportunities and encouragement.

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ABSTRACT

REAL-TIME OPTIMIZATION OF AN INTEGRATED
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Xu Yang

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In today's competitive business environment, companies face enormous pressure and must continuously search for ways to design new products, manufacture and distribute them in an efficient and effective fashion. After years of focusing on reduction in production and operation costs, companies are beginning to look into distribution activities as the last frontier for cost reduction.

In addition, an increasing number of companies, large and small, are focusing their efforts on their core competencies which are critical to survive. This results in a widespread practice in industry that companies outsource one or more than one logistics functions to third party logistics providers. By using such logistics expertise, they can obtain a competitive advantage both in cost and time efficiency, because the third party logistics companies already have the equipment, system and experience and are ready to help to their best efforts.

In this dissertation, we developed an integrated optimization model of production, inventory and distribution with the goal to coordinate important and interrelated decisions related to production schedules, inventory policy and truckload allocation. Because outsourcing logistics functions to third party logistics providers is becoming critical for a

company to remain competitive in the market place; we also included an important decision of selecting carriers with finite truckload and drivers for both inbound and outbound shipments in the model.

The integrated model is solved by modified Benders decomposition which solves the master problem by a genetic algorithm. Computational results on test problems of various sizes are provided to show the effectiveness of the proposed solution methodology. We also apply this proposed algorithm on a real distribution problem faced by a large national manufacturer and distributor. It shows that such a complex distribution network with 22 plants, 7 distribution centers, 8 customer zones, 9 products, 16 inbound and 16 outbound shipment carriers in a 12-month planning period can be redesigned within 33 hours.

In recent years, multi-agent simulation has been a preferred approach to solve logistics and distribution problems, since these problems are autonomous, distributive, complex, heterogeneous and decentralized in nature and they require extensive intelligent decision making. Another important part in this dissertation involved a development of an agent-based simulation model to cooperate with the optimal solution given by the optimization model. More specifically, the solution given by the optimization model can be inputted as the initial condition of the agent-based simulation model. The agent-based simulation model can incorporate many other factors to be considered in the real world, but optimization cannot handle these as needed. The agent-based simulation model can also incorporate some dynamics we may encounter in the real operations, and it can react to these dynamics in real time.

Various types of entities in the entire distribution system can be modeled as intelligent agents, such as suppliers, carriers and customers. In order to build the simulation model more realistic, a sealed bid multiunit auction with an introduction of three parameters α, β and γ is well designed. With the help of these three parameters, each agent makes a better decision in a simple and fast manner, which is the key to realizing real-time decision making.

After building such a multi-agent system with agent-based simulation approach, it supports more flexible and comprehensive modeling capabilities which are difficult to realize in a general optimization model. The simulation model is tested and validated on an industrial-sized problem. Numerical results of the agent-based simulation model suggest that with appropriate setting of three parameters the model can precisely represent the preference and interest of different decision makers.

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CHAPTER 1

INTRODUCTION

Today's business environment has become increasingly competitive. This causes enormous pressure for many companies in many industries. In such an environment, companies need to continuously search for ways to design new products, manufacture them and distribute to end customers in an efficient and effective fashion. After years of focusing on reduction in production and operation costs, companies are beginning to look at distribution, as one of the last frontiers for cost reduction.

Logistics and supply chain design involve all of the efforts associated with upstream and downstream entities and activities in the entire production and distribution system. Entities could be raw material suppliers, manufacturers, distributors, logistics service providers, retailers, and end customers. The activities include production, inventory, distribution as well as other important logistics functions.

The distribution problem is a very active research area in the academic field. All of the entities and activities in the supply chain are highly interrelated to each other by means of material and information flow. As a result, synchronized consideration of production, inventory and distribution is necessary and critical in the study of a distribution problem. An integrated view of the logistics and supply chain design may

lead to an improvement in service level as well as substantial savings in total costs. Our primary intent is to develop optimization models for an integrated production, inventory and distribution problem and apply an efficient algorithm to generate good solutions.

Cooperation with third party logistics (3PL) providers can help reduce transportation and administrative costs, allowing a company to focus on core competencies, improve productivity and upgrade communication capabilities. Building collaborative business relationships with 3PLs also help improve service level and facilitate smooth operations. The production, inventory and transportation functions could be outsourced to 3PLs or performed in-house so that the total costs including production, inventory and distribution in the entire network are minimized.

Complex logistics and distribution problems have been formulated as deterministic mathematical programming models and solved optimally using exact algorithms. However, these models assume that the various parameters such as demand, capacity and transportation cost are known with certainty. Today's logistics and distribution problems are characterized by a high degree of volatility. Decision makers prefer tools that allow them to perform sensitivity analysis. In addition, the entities and their activities are highly interrelated in a supply chain. Each entity can communicate, compete, collaborate and/or coordinate with other entities to achieve its own goals as well as the goals of the system.

Due to the dynamic nature of the supply chain and numerous quantitative as well as qualitative attributes of its various entities, agent-based simulation is a more appropriate approach for modeling the system than general-purpose simulation. In agent-based simulation, each component is modeled as a software agent that is able to communicate

with other agents and act when there is a change in the environment. By reading data from sensors or sending commands to effectors or by interacting with other agents, an agent in the system is able to act in a goal-directed fashion to achieve individual goals as well as system-wide goals.

In our research, we first developed an integrated optimization model by considering production, inventory and distribution simultaneously. By applying some efficient algorithms, the model can be solved optimally or near optimally. Secondly, we developed an agent-based simulation model by setting up the initial condition of the model as the optimal solution given by the optimal model. The agent-based simulation model can incorporate some dynamics and many other factors to be considered in the real-world, but the mathematical programming based optimization approach may not be able to handle these. By keeping the good features of the solution given by the optimization model and formulating dynamics and real-world considerations into the model, the agent-based simulation model can search for a solution quickly and effectively, which is the key to realizing real-time decision making.

The remainder of this dissertation is organized as follows. In the next chapter, we provide a comprehensive literature review of distribution, third party logistics, optimization models and algorithms to solve logistics and supply chain management problems, we also discuss the application of simulation in logistics and supply chain design. Chapter 3 presents an integrated production-inventory-distribution model in a multi-product, multi-period, multi-echelon, multi-inbound and outbound shipments carrier system. A solution algorithm and experimental results are presented in Chapter 4. In Chapter 5, an agent-based simulation model is developed and presented as well as

some numerical results. Conclusion and future research directions are discussed in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

In this chapter, we review definitions and the literature pertaining to distribution and third party logistics. Optimization models and algorithms for logistics and supply chain planning, as well as simulation applications and the methodology of intelligent-agent simulation, are also reviewed.

2.1 Distribution

We give a definition of distribution in this section based on a comprehensive review of the previous literature. We then describe some characteristics of distribution networks. The importance of distribution in a logistics system is also addressed.

2.1.1 Definition of distribution and characteristics of distribution network

Distribution involves a large number of activities over a complex network. Various definitions of distribution are available in the literature. Bowersox (1969) defines distribution as business activities pertaining to the transportation of finished inventory and/or raw materials in a way that they arrive at the designated place, when needed and in usable condition. Bowersox (1969) does not consider the location of origin or destination points. Chopra (2003) defines distribution as the steps taken to store and transport a

product from the supplier stage to the customer stage in the supply chain. Only two stages are considered in this definition: supplier and customer. There could be more than two stages in the distribution network, such as a consolidation, break-bulk, or cross-dock distribution centers (DCs).

In this proposal, we define distribution as a sequence of activities involving the transfer of products directly from supply points to demand points or via transshipment points such as DCs and warehouses. The supply points might be manufacturing facilities, DCs or warehouses, while the demand points might be customers or retail stores.

There are six categories of distribution networks (Chopra, 2003):

(1) Manufacturer storage with direct shipping;

(2) Manufacturer storage with direct shipping and in-transit merge;

(3) Distributor storage with package carrier delivery;

(4) Distributor storage with last mile delivery;

(5) Manufacturer/distributor storage with customer pickup;

(6) Retail storage with customer pickup.

In categories (1) and (2), the supply points are manufacturers and the demand points are customers. The only difference between these two categories is whether there is a transshipment point between the manufacturer and the customer. The supply points in categories (3) and (4) are distributors (these could be intermediate warehouses) and there are no transshipment points. The two categories provide different delivery options

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respectively: carrier delivery or last mile delivery. Categories (5) and (6) are relatively unique compared to other categories, which let customers pick up their order either from a manufacturer/distributor or from a retail store.

Another taxonomy is based on Langevin et al. (1996)'s research. They divide the distribution into six types:

(1) One-to-many distribution without transshipments;

(2) Many-to-one distribution without transshipments;

(3) Many-to-many distribution without transshipments;

(4) One-to-many distribution with transshipments;

(5) Many-to-many distribution with transshipments;

(6) Integrated networks.

We categorize distribution networks by means of supply, demand and transshipment points:

(1) Supply points. Supply points could be manufacturing facilities, intermediate DCs or warehouses, raw material suppliers, retail stores or pickup sites.

- Distribution from a manufacturing facility could centralize inventories at the manufacturer, which provides a higher level of product availability and is typically used for high value, low and unpredictable demand products. Another advantage of this type of distribution network is that handling costs could be reduced significantly since the products could be shipped to

customers directly from the production line. However, there are several disadvantages, such as high transportation costs, multiple shipments, long response times, difficulty in handling products return and so on.

- Distribution from an intermediate distribution center or warehouse allows inventory to be carried in the intermediate facilities. This type of distribution network is good for relatively high demand products. Transportation costs are typically lower and response times shorter. However, since there are additional intermediate facilities rather than manufacturing facilities, facility costs as well as processing and handling costs tend to be high.

- Distribution from a raw material supplier usually occurs at an early stage of the production, and this process is linked to the procurement process. This type of distribution always has a fixed and stable destination, namely the manufacturing plant.

- Distribution from a retail store could reduce distribution costs significantly since retail stores are usually close to customers. This option also provides fast response and return times. However, the cost of opening and operating a retail store could be high especially when many retail stores are needed. Accordingly, inventory carrying costs in retail stores could be high too. It is a better distribution choice when customers value response time more than other factors.

- Distribution from a pickup site provides the largest convenience to customers letting them pick up an order, so the distribution costs could be

lower than other distribution options. However, to build such a distribution network could be expensive because customers may need many pickup sites to coordinate their demands; also, there is a need for an expansive information infrastructure to coordinate between the storage location and pickup location.

(2) Demand points. Demand points could be end customers, retail stores and pickup locations, or even manufacturers and DCs/warehouses. By choosing different distribution destinations, multiple service levels could be obtained and transportation costs could be reduced. We describe some characteristics of distribution networks with different destinations here.

- Shipping directly to end customers could have different distribution costs depending upon the origin and destination points. An advantage here is that after an easy and fast order placement, orders will be delivered directly to end customers.

- Distribution to retail stores could lower transportation costs because the online or telephone orders can be delivered to the stores, from where customers can pick up.

- Distribution to pickup locations could reduce transportation costs significantly. This distribution option allows customers to pick up their orders at their desired time and location.

- Distribution to supply points, e.g., manufacturers.

- Distribution to intermediate transshipment points and warehouses.

(3) Transshipment points. We classify a distribution network based on the existence of a transshipment point. We refer to a distribution network without transshipment points as a two-stage distribution network, and refer to a distribution network with one or multiple transshipment point(s) as a three-stage distribution network or a multi-stage distribution network.

- Two-stage distribution network: There are only origin (supply points) and destination (demand points) in this type of distribution network.

- Three-stage distribution network: Other than supply and demand points, there is also a transshipment point in the distribution network, which is referred to as intermediate facilities. Typically, there are three types of intermediate facilities: consolidation, break-bulk and crossing docking facility.

- Multi-stage distribution network: There may be more than one transshipment facility along the entire distribution network.

2.1.2 The importance of distribution in a logistics system

In 1991, the Council of Logistics Management, a trade organization based in the United States, defined logistics as: "the process of planning, implementing, and controlling the efficient, effective flow and storage of goods, services, and related information from point of origin to point of consumption for the purpose of conforming to customer requirements". In Merriam-Webster, logistics is defined as the aspect of science dealing with the procurement, maintenance, and transportation of materials, facilities, and personnel. This is a frequently used definition and originated in the military. Logistics is a value-added process that supports the primary objective of the companies, which is to

remain competitive in terms of price, quality, customer service level and response to market demand (Slats et al., 1995).

Logistics costs are a large portion of the GDP (gross domestic product) in the United States. The annual State of Logistics Report stated that logistics costs exceeded 10% of the GDP in 2007 for the first time since 2000, and at 10.1% matched a level not seen for a decade. Not surprisingly, logistics costs have risen to 9.9% (to $1.31 trillion) in 2006 from 9.4% of the GDP in 2005. Logistics costs constitute about 30% of the cost of the products sold in the United States (Eskigun et al., 2005). In a logistics system, distribution cost is typically the highest single expense, which is usually greater than warehousing cost, inventory cost and order processing cost (Parthanadee and Logendran, 2006). Distribution has captured management's attention due to rapid wage and freight rate inflation, critical swing of transportation costs and regulation, high cost of carrying inventory, and oil market uncertainties (Geoffrion et al., 1982).

Procurement, manufacturing, distribution, warehousing, inventory and information systems are important logistics functions, among which, distribution is a key function in the entire logistics system and the key link between manufacturers and customers. Accordingly, companies have been taking a variety of approaches to reduce distribution costs in order to reach the goal of reducing overall logistics costs. The research focused on distribution systems and distribution problems has been an active area during the last 30 years. We believe that by focusing our study on the relationship between distribution and other functions in a logistics system, new opportunities can be identified and new results can be proposed.

As previously mentioned, in the entire logistics system, distribution plays an important role. Distribution from one or more origins to one or more destinations is the core of logistics (Langevin, 1996). In addition, distribution is a major driver of profitability in a company, because it has a direct impact on both the logistics cost and the customer experience (Chopra, 2003). Although product features, quality and price are important factors for customers, logistics performance is the key to a company's success (Robinson et al., 1993). A good design of distribution network could achieve a number of logistics goals, ranging from low operational cost to high customer service level.

In this competitive business world, the dimensions of cost, quality, efficiency and customer service level are not trade-offs for a company anymore. They have to be considered simultaneously. To achieve this objective, optimally redesigning the entire distribution network is critical, and most of the time, necessary. As Stewart (1965) mentions in his paper, distribution is described as "the Economy's Dark Continent" and it is possibly the last frontier for cost reduction in the United States. This is even more appropriate in the current business environment, because it is becoming increasingly difficult to reduce costs of raw material and labor.

2.1.3 Difficulties in distribution related research

Accurate and efficient approaches and tools are required to support and enhance the distribution planning process. There are several important factors to consider when designing a distribution network: cost, quality, delivery reliability, service level, lead time, product availability, technical ability, warranties and so on (Mentzer et al., 1989).

Distribution planning must consider these issues:

(1) Global perspective

In today's world, global logistics management has become a new discipline attracting the attention of many researchers. Foreign manufacturers offer highly efficient and less expensive production. Companies in the United States are under enormous pressure to make their operations more efficient and effective while reducing costs dramatically. Many researchers highlight the importance of coordination and cooperation among all international entities in the entire logistics system in order to improve competitiveness; otherwise, it is impossible for a single entity to achieve its overall goals.

Vidal and Goetschalckx (1997) present a comprehensive review on logistics models with a global perspective. These models can choose suppliers and locate plants and warehouses throughout the world. Cash and information flow are difficult nevertheless important to manage in global operations. Global distribution must take into considerations taxes and duties, exchange rates, trade barriers, transfer prices and so forth, which are not easy to include the mathematical models.

(2) Reverse logistics

Guiltinan and Nwokoye (1975) were one of the first researchers in the reverse logistics area. Reverse logistics is the way to deal with used products no longer usable or required by the users. There are four important components of reverse logistics: reduce, substitution, reuse and recycle (Jayaraman et al., 2003).

Fleischmann et al. (1997) present an extensive review on quantitative models in reverse logistics. They divide this field into three main areas: distribution

planning, inventory control and production planning. In each area, they review the mathematical models and point out directions for future research.

Jayaraman et al. (2003) propose a model framework on reverse distribution problems in order to minimize costs to transfer products from origins through collection sites to their destinations and fixed costs of opening the collection and destination sites. They develop a strong and a weak formulation for reverse distribution problems that include product recall, product recycling and reuse, product disposal and hazardous products return.

Ko and Evans (2007) develop a mixed integer nonlinear programming model for an integrated distribution problem that simultaneously considers forward and return network. They apply a genetic algorithm-based heuristic and compare it with an exact algorithm on a set of problems.

Du and Evans (2008) present a bi-objective optimization model, which minimizes the total costs as well as the total tardiness. They develop a solution approach that consists of a combination of three algorithms: scatter search, dual simplex and constraint method.

(3) Logistics collaboration

Many companies prefer cooperative decision making to other operation modes. A single dominant company typically optimizes its own logistics decisions regardless of their impact on other companies in this logistics system. Most of the time, it is only good for the short run, but in the long run, it should build strategic relationships with other companies to form a logistics alliance. To achieve this long-term, win-win relationship, this dominant company plays an important role

in fostering cooperative agreements to jointly optimize the entire supply chain (Erenguc et al., 1999).

As Erenguc et al. (1999) indicate developing a cooperative relationship with other entities (such as suppliers, carriers) in the entire logistical system is critical to achieving system-wide objectives. However, there are no approaches or tools to analyze the integrated system in this emerging collaborative environment in spite of the awareness and understanding of its necessity (Sarmiento and Nagi, 1999).

(4) System dynamics

Dynamics within a logistics system could necessitate a change in the entire distribution network, which in turn could result in an increase in logistics costs including inventory, transportation, facilities and handling, and information changing (Chopra, 2003). At the operational level of distribution planning, variability is observed in scheduling services, empty vehicle distribution or reposition, crew scheduling, allocation of resources and so on (Crainic and Laporte, 1997). Many uncertainties and qualitative factors can be analyzed via a specification of different scenarios and performing sensitivity analysis.

(5) Limited capacity

Limited capacity is a critical problem faced by many companies. Lack of sufficient production machines, warehouse space, trucks, or even drivers could have a large effect on overall logistics performance.

Langevin et al. (1996) point out that backhauls could allow vehicles to make productive use of return trips when finishing line haul distribution to avoid

returning empty to their origins, which needs to better utilization of truckload capacity.

However, for other limited capacity resources, it still remains an open field and requires more research.

(6) Technology revolution

As the supply chain gets longer and goes beyond national boundaries, effective communication and information infrastructures to support such complex processes and systems become essential (Erenguc et al., 1999). Information technology and telematics allow mathematical models to be applied in real-time systems and process controls. Development of telecommunication and information technology has created many opportunities to increase the integration of logistics functions such as raw material purchasing and the distribution of products to customers, which increases the performance in the entire logistics system and helps achieve a win-win solution for all the participants: suppliers, customers and intermediaries (Slats et al., 1995).

(7) Intermodal transportation

Distribution over multiple transportation modes is an important component of transportation science and has attracted many researchers in recent years. However, due to the inherent difficulties and complexities of such problems, the study of intermodal transportation at either the regional or the national level has not yet fully matured (Crainic and Laporte, 1997).

(8) Just-in-time (JIT)

Since the just-in-time concept was first introduced, there have been a wide variety of studies in this area. Small and frequent shipments are required between suppliers and manufacturers in a just-in-time environment, emergency shipments may be necessary for supplying the right volume at the right time in the right place. Emergency shipments are contracted by suppliers whenever there is a sudden increase in customer demand (Sarmiento and Nagi, 1999). How to balance regular shipments and emergency shipments to reach the just in time goal is a fertile research topic.

Supplier performance and relationship with suppliers are two important components in JIT environment. Quality, cost and on-time delivery are the three most important criteria when evaluating supplier performance. Buyers and suppliers have a win-win relationship in a successful JIT implementation (Erenguc et al., 1999).

(9) Customer satisfaction

Satisfying customers' need is becoming increasingly important because only when customers' need is met, can the company's revenues be maximized (Chopra, 2003). Managers in a company must not only consider trade-offs among facilities, inventory and transportation costs, but must also focus on customer service issues (Robinson, et al., 1993). Chopra (2003) also points out that there are many factors influencing customer satisfaction, e.g., response time, product variety, product availability, customer experience, order visibility and return-ability. Increasingly, customers not only expect low price, but also demand a high quality service, which is generally measured in terms of speed, flexibility and

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reliability. Consequently, how to balance between operating costs and service performance is one of the major concerns for companies. An active research area for academicians is to include these factors into the objective function of the associated models (Crainic, 2000).

(10)   Special cases

Distributing special products introduces more complexity.

Bell et al. (1983) apply an optimization model to the gas industry to determine daily production, delivery scheduling, and dispatching. The joint determination achieves cost savings between 6 and 10%.

Federgruen et al. (1986) develop a model to distribute perishable products (e.g. blood, food, medical drugs) from a regional center to many customer locations and allocate available inventory in the regional center.

(11)   Transshipments

There are two major functions of transshipment facilities: consolidation and break-bulk. Consolidate shipments are used to combine shipments from many scattered origins into larger loads. Break-bulk shipments provide an opposite function to split a large load into smaller shipments.

Campbell (1993) uses an analytic model to study a one-to-many distribution problem with transshipments. Transshipments take place in a one-to-many distribution system when vehicles at the origins cannot serve their destinations directly. In other words, the vehicle capacity is limited and the serving area is large. Transshipment facilities are used to transfer loads from line haul vehicles (which serve between origins and transshipment facilities) to local vehicles

(which serve between transshipment facilities and destinations). Research shows that optimal decisions on a distribution system are decided by a ratio of load size of line haul vehicles to local vehicles; moreover, distribution with transshipments could increase inventory and terminal costs but reduce transportation costs because of economies of scale. Campbell (1993) also points out that transshipments are important in many-to-many distribution systems due to efficient loads through consolidation and break-bulk terminals, and sometimes it is necessary to have more than one level of transshipment facilities to further reduce costs.

Distribution systems with transshipment points are often organized hierarchically into separate levels of transshipment facilities (Langevin et al., 1996). In such a distribution network, economies of scale could be achieved by using different sizes of vehicles at different levels.

(12)   Integrated distribution

Current industry trends show that distribution networks are selected by adopting an integrated perspective (Erenguc et al., 1999). Synchronizing the logistics processes cover raw materials supply and production activities to marketing and final distribution choices (Fumero and Vercellis, 1999). However, most previous studies treat each component (such as purchasing, production and scheduling, inventory, warehousing, and transportation) separately ignoring many complex supply chain interactions (Cohen and Lee, 1988; Vidal and Goetschalckx, 1997). Nevertheless, there are a wide variety of recent works that have integrated the multiple logistics functions. On the basis of applications and case studies, many

researchers have proposed potential economic benefits deriving from an integration of the logistics decision process.

Martin et al. (1993) present a large-scale linear programming model to integrate production, distribution and inventory planning decisions, and apply it to a real-world industrial problem with 4 plants, 200 products and 40 demand zones in a 12-month planning horizon.

Mak and Wong (1995) present an integrated production-inventory-distribution approach to determine optimal levels of stocks and quantities of production and transportation in order to minimize total costs.

Hall (1996) incorporates distribution decisions into production decisions (and vice versa). He provides a substantially different solution than when considering them in isolation, by expressing the magnitude of this difference as regret (a measure of cost penalty without following the optimal policy). Research results show that: (1) considering inventory at both origin and destination could result in a significant difference of batch quantities and cost estimates, but relatively small regret; (2) failure to include consolidation considerations of products that are sent to a common destination could lead to large errors and large regret.

Because there is intense pressure on all companies to minimize transporting and distribution costs, it is important to explore closer coordination along production/transportation and distribution channels (Pirkul and Jayaraman, 1996). They develop a mixed integer programming model to integrate production, transportation and distribution decisions to minimize the total transportation and

distribution costs and the fixed costs of opening and operating plants and warehouses.

By fully understanding the weakness of existing analytical models which focus only on individual components of the supply chain and the simultaneous relationship between facility location, inventory and transportation, Jayaraman (1998) presents an integrated mathematical programming model for minimizing total distribution costs associated with three major decision factors (facility location, inventory planning and alternative transportation selection).

Dogan and Goetschalckx (1999) develop a mixed integer programming formulation of an integrated production and distribution system to minimize total supply, production, transportation, inventory and facility costs. They consider multiple periods, multiple products, multiple suppliers, multiple production and finishing facilities. The results suggest that total costs could be significantly reduced by joint consideration of these factors.

Fumero and Vercellis (1999) propose an integrated optimization model including production and distribution decisions to minimize set up, inventory and transportation costs. In addition, the results show that there is a substantial advantage of a synchronized approach over the decoupled decision process. The system-wide efficiency could be improved by exploiting scale economies due to production/distribution synchronization.

Sarmiento and Nagi (1999) present a comprehensive review on integrated production and distribution systems and conclude that such systems could bring significant benefit to companies that apply them.

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Another review paper on integrated production and distribution systems by Erenguc et al. (1999) indentifies several future research directions: (1) considering all three stages (supplier, plant and distribution) in the entire supply chain; (2) integrated approaches to managing inventory at different stages; (3) utilization of information sharing in a multi-partner supply chain; and (4) analytical and simulation models that integrate the entire logistics system.

Miranda and Garrido (2004) propose a simultaneous approach incorporating inventory decisions into a distribution problem and formulating it as a nonlinear mixed-integer model. Using an application to test the model, they find that costs could be reduced compared to the traditional method when holding costs and demand variability are higher.

2.2 Third party logistics

3PL is third party logistics for short. It was not known in the United States before 1990. We first define it, and then discuss the reasons why business outsources the logistics functions to 3PLs. Next, we review the previous research and attempt to predict the future of 3PL.

2.2.1 Interpreting and defining 3PL

3PL is also referred to as third party logistics, contract logistics, integrated logistics, and outsourced logistics (Sheffi, 1990; Lim, 2000; Knemeyer et al., 2003; Knemeyer and Murphy, 2004; Knemeyer and Murphy, 2005). In the academic realm, there is an unsolved problem regarding the lack of a uniform and standard definition of 3PL.

Although 3PL has many definitions and interpretations, there is no uniform or standard definition that seems to satisfy company managers and academic researchers.

Stank and Maltz (1996) refer to 3PL as any firm that provides a good or service that it does not own.

Sink et al. (1996) define 3PL services as multiple distribution activities provided by a third party, neither the provider nor the customer, who assumes no ownership of inventory. The goal of the 3PL company is to accomplish related functions that the producer does not want to manage.

3PL is a for-hire logistics service provider for the buyer or seller of raw materials, goods in process and finished products (Menon et al., 1998).

Berglund et al. (1999) define 3PL as a logistics service company providing service on behalf of a shipper responsible for the management, transportation and warehousing of goods.

Lim (2000) defines 3PL as an external company responsible for getting the right products to the right place at the right time, and at the right cost.

Some definitions appear to be broad and inclusive in nature, while others have a narrow and more exclusive focus. McGinnis et al. (1995) define 3PL activities as logistical activities that can be provided or required by either a buyer or a seller. Another definition of 3PL characterizes it as an external organization that performs all or part of a producer's or consumer's logistical functions (Coyle et al., 2003). Sink and Langley

(1997) refer to 3PL provider as an external supplier performing some or all of a manufacturer's or customer's logistical functions.

In contrast, Murphy and Poist (1998) give a narrow and exclusive definition of 3PL that is a long-term, mutually beneficial relationship between a shipper and a logistics provider which offers various logistics service functions. Bagchi and Virum (1996) refer to 3PL as a long-term partner that provides all or a considerable number of logistics activities for the shipper.

In this proposal, we consider a 3PL as an external logistics service provider offering single or multiple logistics activities to its customers, which typically is on contract basis. From the provider's point of view, their business covers a great number of relationships involving everything from simple logistical activities to advanced logistical solutions; from the customer's point of view, the degree of outsourcing varies and the outsourced logistics activities differ greatly.

2.2.2 Reasons for outsourcing business to 3PLs

Today outsourcing one or more logistical functions to 3PLs is becoming a widespread practice in industry in the United States and worldwide. An increasing number of companies, large and small, are focusing their efforts on their core competencies which are critical to survival (Skjoett-Larsen, 2000). Moreover, 3PL topics have attracted many researchers, which virtually did not exist prior to 1990, particularly in the United States. See recent comprehensive reviews of Selviaridis and Spring (2007) and Marasco (2008). 3PLs can be used in nearly every industry (retail, service, manufacturing, etc.); moreover, companies can use more than one 3PL.

According to Aghazadeh (2003), during the 1970's, 3PL originally began as a public warehousing provider. Later during the 1980's, due to the need to improve customer service of distribution managers, 3PL expanded to offer throughput besides just selling space. In the 1990's, 3PLs began to consolidate both transportation and warehousing and offered such services to managers who wanted to reduce operation costs and improve customer satisfaction by providing value-added services. The 1990's experienced explosive growth in the 3PL business by offering expanded services and "one-stop" shopping for all companies' needs. Since 1990's, 3PL has grown dramatically.

Today the business of 3PLs is so much more than managing warehouses or picking and delivering customers' orders. In recent years, 3PLs have expanded their service content, which involves more complex activities and significantly more customer service than before. 3PLs initially focused on providing warehousing and transportation; however, nowadays they perform multiple tasks ranging from purchasing raw materials to managing call centers. The market of 3PL is growing by 18% to 22% per year. Aghazadeh (2003) also points out that companies have been outsourcing businesses to 3PLs and relying heavily on 3PLs for warehousing management (56%), transportation (49%) and shipment consolidation (43%).

Previous extensive research indicated a record high rate of 3PL usage among Fortune 500 companies (Boyson et al., 1999; Aghazadeh, 2003; Knemeyer and Murphy, 2004; Vaidyanathan, 2005). Nearly 80% of the Fortune 500 companies are using 3PL (Yeung et al., 2006). In the early 1990's, only 40% of Fortune 500 companies used 3PLs (Knemeyer and Murphy, 2005).

More and more companies adopt complex supply chain management strategies and use logistics expertise to obtain a competitive advantage in cost and time efficiency. Companies are more likely to have a partner who already has the equipment, system and experience and is ready to help. The expansion of 3PL in the supply chain through supplementary services is also the result of customization of product or service offerings to customers. By expanding services, a 3PL is able to respond to specific customer demands and can also provide add-on services (Hoek, 2001).

There are many reasons that encourage companies to outsource "in-house" businesses to 3PL:

(1) Reduce logistics costs such as inventory, transportation, and other costs;

(2) Concentrate on core activities and processes;

(3) Improve customer service level;

(4) Integrate the entire supply chain;

(5) Reduce conflict and reciprocate on mutual goal-related matters;

(6) Increase efficiency, stability and flexibility;

(7) Establish market legitimacy;

(8) Avoid extensive capital expenditures;

(9) Increase productivity;

(10)   Reduce risk, uncertainty and fluctuation;

(11)   Leverage resources;

(12)   Improve expertise, market knowledge and data access;

(13)   Create a competitive advantage either locally or globally;

(14)   Reduce personnel and equipment costs.

3PLs play an important role in the entire logistics process, especially in providing warehousing and transportation services, because their customers expect them to improve lead time, fill rate, and inventory (Ko et al., 2006). They have the resources, scope, scale, and best practice experience in warehousing, distribution and transportation, thus providing services more efficiently and less expensively than what others can do in-house. Accordingly, companies are increasingly leveraging the capabilities of 3PLs to magnify their strengths and benefits. But there are a number of important factors that companies should consider when choosing a 3PL (Table 1):

Table 1

Factors that companies should consider when choosing a 3PL provider

Factors to consider when choosing a 3PL	Cost
	Performance
	Capability
	Responsiveness
	Service range
	Financial stability
	Cultural compatibility
	Customer references
	Operating and pricing flexibility
	Commitment matching

2.2.3 Previous study and future trends of 3PL

Outsourcing logistics functions to 3PL is normally a large, multi-year (one to three years) arrangement and switching 3PL providers could be very costly. Because cost is a primary motivator, 3PL has evolved into a strategic partner (Sink and Langley, 1997; Murphy and Poist, 1998; Lim, 2000; Skjoett-Larsen, 2000; Knemeyer and Murphy, 2005). 3PLs are not merely a means to make the supply chain operation effective and efficient, but also a strategic tool for creating competitive advantage through increased service and flexibility.

Sink and Langley (1997) propose a five-step buying process of 3PL activities: (1) identify the need to outsource logistics; (2) develop feasible alternatives; (3) evaluate candidates and select supplier; (4) implement service; and (5) continuously evaluate.

By considering 3PL from both resource and competence perspectives, Halldorsson and Skjott-Larsen (2004) develop a typology of 3PL with the objective of exploiting competencies and encouraging competence development between 3PLs and their customers.

Aghazadeh (2003) identifies five steps to choose a 3PL: (1) making the decision; (2) developing criteria and objectives; (3) the weeding out process; (4) determining the top prospect; and (5) beginning the new partnership.

Alp et al. (2003) design transportation contracts with 3PLs by means of a bidding mechanism. They define three subproblems within the contract design problem: vehicle dispatching problem, inventory control problem and contract value problem. By solving these three subproblems for an adequate number of contract parameters, the optimal solution with a minimal face value of the contract can be selected.

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Menon et al. (1998) examine what the criteria of 3PL selection are and how the competitiveness of companies as well as the external environment affects these criteria.

Today 3PL providers expand their services significantly, from the traditional services like transportation and warehousing to a class of new activities, services and processes such as cross-docking and export operations. We review previous work and find that outsourcing logistics has a wide range according to different logistics functions (Murphy and Poist, 1998; Murphy and Poist, 2000; Aghazadeh, 2003; Vaidyanathan, 2005) (Table 2):

Table 2

Outsourced logistics functions

Carrier selection	Consulting services	Cross docking
Customer brokerage	Customer clearance	Export operations
Development of distribution strategy/system	Fleet operations	Fulfillment
Freight bill payments and auditing	Help desk	Import operations
Freight consolidation	Freight distribution	Freight forwarding
Information systems	Intermodal services	International telecommunications
Letter of credit review and compliance	Rate negotiation	Replenish inventory
Management and performance reports	Product returns	Inventory management
Order entry and processing	Order management	Overseas distribution
Overseas sourcing	Pickup and delivery	Product assembly/installation
Product marking, labeling and packaging	Product modification	Product repair
Route and network optimization	Traffic management	Shipment planning
Selected manufacturing activities	EDI capability	Warehousing
Transportation (inbound and outbound)	Expedited delivery	Export licensing assistance

Although there is much variance in the growth projection of 3PLs, there is no doubt that this service will continue to grow (Murphy and Poist, 2000). The rate of growth may decrease, but it is reasonable to draw a conclusion that outsourcing logistics functions to 3PLs is still a major trend.

Previously, 3PLs focused mostly on providing single and short-term logistics service, such as warehousing and transportation, which were built on a transaction-by-transaction basis. To become successful in an intense competitive environment, 3PLs still have a long way to go to develop skills, competencies and develop value-added activities. More recently, 3PLs are putting more attention on building a long-term contractual relationship with their customers by providing multiple logistics services. 3PLs have a significant impact on not only the past and the present, but also the future.

Accenture introduced a new concept called the fourth party logistics (4PL). They define a 4PL company as an integrator who puts together the resources, capabilities and technology of all organizations to design, build and run supply chain networks. 4PLs carry out the majority of the administrative activities but leave the physical movement of the goods to other contracted 3PLs. Most 4PLs do not have assets such as warehouse and truck fleet. They just provide services to their customers in the form of knowledge relative to fulfilling the customer requirements (Stefansson, 2006).

2.3 Optimization models and algorithms to solve logistics and supply chain management problems

In this section, we present previous studies on logistics and supply chain management with a focus on distribution problems, since we already have an understanding of the

importance of distribution in a logistics system and supply chain. We provide a review of distribution models as well as efficient algorithms to solve them. Limitations of current research are also pointed out.

2.3.1 Pure distribution problem

The optimal solution of distribution problems is a well-studied research field with a long history. The vehicle routing problem (VRP) as well as its special case, the traveling salesman problem (TSP) both NP-hard problems, have been studied extensively. Our focus is on a class of pure distribution problems that are neither a VRP nor a TSP.

Geoffrion and Graves (1974) present one of the earliest works on distribution problems, which has provided guidance to later researchers (Jayaraman and Pirkul, 2001; Shen, 2005; Eskigun et al., 2005; Elhedhli and Goffin, 2005; Sourirajan et al., 2007; Keskin and Uster, 2007; Elhedhli and Gzara, 2008). The problem is quite basic and it optimally determines the location of distribution centers between plants and customers. The problem is formulated as a single-period, multi-product, mixed integer linear program. The model is successfully solved by Benders decomposition technique and implemented in a major food company.

Burns et al. (1985) study on a one-supplier, multi-customer distribution problem. A comparison between two distribution strategies (direct shipping and peddling) is presented. Formulas for transportation and inventory cost are provided to determine trade-offs between different distribution strategies. Their research indicates that the optimal shipment size is given by economic order quantity (EOQ) model for direct shipping, while for peddling the optimal shipment size is a full truck.

Muckstadt and Roundy (1987) develop a nonlinear, integer programming model to study a multi-product, one warehouse to multiple retailers distribution problem. They propose four important factors that need to be considered: (1) Although such operation is a value-added process, it results in a high inventory holding cost. (2) There are fixed costs in shipping an order. (3) The central warehouse usually has a limited shipping and handling capacity. (4) It is preferable to ship from the warehouse to one particular retailer at equally-spaced points in time. These factors provide good insights to develop distribution models for further study.

An approximate analytic model is developed to solve one-to-many distribution problems with the consideration of transshipment point locations (Campbell, 1993). Rather than only provide mathematical model and solving algorithm, they also explore under what condition transshipment points become necessary. The conclusion is that transshipments points are not desirable when local vehicles can be as large as linehaul vehicles.

Iyogun and Atkins (1993) study a pure distribution problem from multiple facilities to multiple demand points with lot sizing considerations. This problem contains multiple stages which means there may be one or more than one transshipment point. By decomposing the distribution problem into facilities-in-series problems and applying a heuristic to solve the subproblems, a worst case performance of no more than 2% above optimal solution is demonstrated.

Robinson et al. (1993) integrate two independent distribution networks as a whole for Dow Chemical Company. They develop an optimization based decision support tool

to analyze trade-offs among facility, inventory and distribution costs. They also consider customer service related issues. A mixed-integer programming model is formulated for multiple echelons and multiple products. The analytical tool helps managers understand the impact of uncertainties associated with merging distribution networks in terms of cost and customer satisfaction. Robinson et al. (1993) claim that overall costs could be reduced by approximately $ 1.5 million per year.

Pirkul and Jayaraman (1996) develop a mixed-integer programming model for plant and warehouse location problem, which minimizes the total distribution costs as well as fixed facility costs (opening and operating plants and warehouses). By applying a Lagrangian relaxation heuristic, the model obtains feasible solutions for a large health-care manufacturing company.

After an extensive study on the interdependence between facility location, inventory management and transportation policy, Jayaraman (1998) designs an integrated model including these three decisions to minimize distribution design costs. The proposed model supports better understanding of the trade-offs among the three components.

A distribution problem with four stages (suppliers, plants, distribution centers and customers) is formulated as a 0-1 mixed integer linear programming model by Syarif et al. (2002). They minimize the total costs by deciding which plants and distribution centers to open or close and how to distribute items along a distribution network. They propose a spanning tree-based genetic algorithm to solve the model and compare this algorithm to other methods.

Lapierre et al. (2004) present their research work on a distribution problem with transshipment points. They develop a mixed-integer programming model to decide the number and location of transshipment points, as well as transportation modes from less-than-truckload, full-truckload, parcel or own fleet. By combining tabu search and variable neighborhood search, an efficient heuristic is obtained to solve this model and it is validated on several test problems. Comparison with the exact method is also provided, which reveals limitations of the exact method in solving even medium-sized problems and the promising performance of the proposed heuristic algorithm.

To incorporate inventory control decisions (e.g., economic order quantity and safety stock) into a distribution network design problem, Miranda and Garrido (2004) develop a nonlinear, mixed-integer model and apply Lagrangian relaxation and sub-gradient method to solve it. Significant cost reduction is obtained as the holding cost, ordering cost, lead times and service levels increase. Based on this result, real-world decisions could be adjusted by decision makers within the supply chain.

Shen (2005) proposes a nonlinear, integer program to determine the location of potential facilities and the allocation of customers to facilities with minimal costs. Using the Lagrangian relaxation algorithm, this model is solved efficiently. Although it seems that this model is similar to several well-studied distribution models, it represents the first attempt to solve a multi-product, integrated supply chain problem. The model includes the economies of scale costs (e.g., inventory costs) in the objective function.

Eskigun et al. (2005) explicitly incorporate customer satisfaction and consider lead times driven by operational dynamics in a distribution network design model they

propose. The decisions in the proposed model also include the location of distribution centers and the selection of transportation modes. The model is solved by Lagrangian relaxation and the efficiency of the method is demonstrated.

A more recent work by Sourirajan et al. (2007) formulates a location/allocation problem as a nonlinear, integer programming model. In this problem, a production plant produces a single product and replenishes it at multiple retailers. The main decision in the model is the location of distribution centers in the distribution network with the objective to minimize location costs as well as inventory costs of both pipeline and safety stock. A Lagrangian heuristic is applied to solve the model near optimally.

Elhedhli and Gzara (2008) consider a multi-echelon, multi-product supply chain design problem. Given a set of potential plants and warehouses, location, capacity and technology levels of these facilities, the model assigns the products to plants and distributes them to warehouses and customers as required. The problem is formulated as mixed-integer programming and solved by Lagrangean relaxation. A heuristic is used to obtain the lower and upper bounds.

2.3.2 Integrated distribution problem

Many researchers extend pure distribution problems into a whole cluster of integrated distribution problems, which consider a synchronization of other important logistics functions (usually production and inventory). Such new distribution problems include production-distribution, inventory-distribution, as well as production-inventory-distribution problems.

(1) Production-distribution

Cohen and Lee (1988) present an analytical model for an integrated production and distribution problem. Their goal is to predict its impact on the performance of different manufacturing and distributing strategies. The main contribution of their work is the analytical formulation on integration of separate logistics functions. They also develop a software package that supports this analytical structure and provides insights to decision makers.

An application of mathematical programming for solving production and distribution network optimization problem is demonstrated by Roy (1989). Decisions of the problem include location of intermediate facilities, production levels, stock levels, transportation quantities, customer assignment, as well as some particular decisions such as number of trucks and drivers, transportation shifts and schedules. Using an existing general purpose programming software, they implement the model in a petrochemical company, and achieve significant cost reduction.

Chandra and Fisher (1994) develop an integrated model of production and distribution. The model considers producing multiple products in a plant and then distributing them to a number of retail outlets by a fleet of trucks. Such a problem used to be modeled separately as production scheduling and vehicle routing problems. By using a single integrated model, the total production and distribution costs can be reduced from 3% to 20% compared with two separate models. Chandra and Fisher (1994) also provide coordination strategies companies should seek for effective production and distribution.

Dogan and Goetschalckx (1999) present a mixed-integer programming formulation to study a tactical production and distribution problem, which aims to minimize supply, production, transportation, as well as facility costs. The model is solved by Benders decomposition algorithm and applied in the packaging industry. Computational results show that the run time is reduced by a factor of 480 and the total cost is saved by 2% ($ 8.3 million).

An integrated production and distribution model with multiple echelons and multiple products is formulated as a mixed-integer programming model (Jayaraman and Pirkul, 2001). A strategic level decision (location of plants and warehouses) and several operational level decisions (distribution from plants to warehouses and from warehouses to customers) are obtained by solving the model.

Keskin and Uster (2007) present a mixed-integer programming model for an integrated, multi-echelon, multi-product production and distribution problem. A number of distribution centers must be allocated among suppliers and customers so that total costs are minimized. A population-based scatter search with path relinking and trajectory-based local and tabu search are applied to solve the problem. The meta-heuristic approaches are shown to be powerful even for large-size problems. They obtain solutions with smaller than 1% optimality gap within reasonable computational time.

(2) Inventory-distribution

Chandra (1993) integrates inventory and distribution decisions into one model to determine the replenishment quantity and frequency at the warehouse, as well as distribution lots and delivery schedules at the customer level. The problem concerns

multiple products and multiple periods and minimizes overall inventory and distribution costs.

Anily and Federgruen (1993) study a one-warehouse, multi-retailer distribution problem for a single product. They add inventory considerations into the problem and obtain an economical replenishment strategy as well as an efficient routing schedule.

A distribution problem of shipping a family of products from suppliers to plants with inventory constraints is formulated as a nonlinear, integer programming model (Berman and Wang, 2006). By selecting the appropriate distribution strategy, total costs including transportation, plant inventory and pipeline inventory are minimized. Initial solution and upper bound are provided by a greedy heuristic. Based on the Lagrangian relaxation method, a heuristic and branch-and-bound algorithm are applied to solve the nonlinear model. Efficiency of the algorithms are indicated by various computational experiments.

(3) Production-inventory-distribution

An early research on integrated production, inventory and distribution systems was presented by Ishii et al. (1988). The system contains three stages: manufacturer, wholesaler and retailer. By applying a pull ordering policy, the model could provide decisions of base stock levels, lead times for production and distribution.

Haq et al. (1991) develop an integrated model of production, inventory and distribution with a mixed-integer programming formulation. They attempt to minimize the total system-wide costs by optimally determining production and distribution quantities as well as the inventory levels at different production stages and warehouses in a six-month planning horizon. The major contribution of their research is the consideration of various

realistic conditions such as set-up time and cost at various production stages, lead times of the distribution, losses during production and distribution, backlogging and so on. Although this model framework is successfully implemented in a real-world application of a urea manufacturer using existing algorithms, they do not provide new, efficient algorithms to solve the large sized problems.

Another research work presented by Martin et al. (1993) models the production, inventory and distribution operations as an integrated linear programming model. The model is applied in a large glass company for a 12-month planning period and provides a cost saving of more than $2 million annually. But they only code and solve this special application problem using existing software and do not provide a broad solution procedure for the model.

For a similar production-inventory-distribution integrated problem, Mak et al. (1995) formulate it as an integer program and propose a genetic search algorithm to solve this problem. By minimizing the sum of inventory, manufacturing and transportation costs, optimal quantities of production, transportation and levels of stocks can be determined.

Fumero and Vercellis (1999) demonstrate the advantages of synchronized production, inventory and distribution planning over the regular planning strategy where a production plan is first scheduled and then the distribution decisions are obtained. Their research clearly shows the substantial impact of synchronizing planning procedure.

Vidyarthi et al. (2007) develop an integrated production, inventory and distribution model for a multi-product distribution problem and formulate the model as a nonlinear mixed-integer program. They introduce the risk-pooling concept into a model that

consolidates safety-stock inventories of the retailers at intermediate distribution centers. The objective of the integrated model is to determine the locations of plants and distribution centers, shipments from plants to distribution centers, safety-stock levels at distribution centers, and the assignment of retailers to distribution centers by minimizing the total fixed facility costs, transportation costs and safety-stock costs. Lagrangean relaxation is applied to decompose the problem into subproblems by echelon, then a heuristic is applied to obtain an overall feasible solution by combining a solution of the subproblems. Computational results show that a solution with an objective function value that is within 5% of that of the optimal solution could be reached.

2.4 Simulation in logistics and supply chain design

We first introduce reasons for applying simulation methodology in logistics and supply chain planning. Then we present the state of the art in the simulation which leads to a discussion on intelligent agent-based framework. We discuss the characteristics and roles of an agent in a multi-agent system. A comprehensive review on various applications of agent-based simulation in logistics and supply chain is also presented.

2.4.1 Why simulation?

Today's dynamic and competitive business environment and the significant potential cost savings of logistics and supply chain process improvement provide an opportunity to apply simulation explore and evaluate various logistics and supply chain improvement policies. Simulation is a very powerful technique to study a logistics system or a supply chain. Mathematical programming techniques often provide a good solution but not always the best solution due to the limitations of this approach. Sometimes it is difficult

to formulate problems as a linear program. Deterministic analytical approaches may not always be useful, because supply chain performance such as fill rate and total cost cannot be obtained due to the presence of uncertainty. Simulation provides an effective approach to analyze and evaluate supply chain design and management alternatives, as well as understand the costs, benefits and risks associated with various alternatives.

Other advantages of simulation include the ability to: (1) understand the entire supply chain process via graphics or animation; (2) compare various operational alternatives without interrupting the real system; (3) compress time so that timely policy decisions can be made; (4) capture system dynamics by using probability distribution for unexpected events; and (5) dramatically minimize the risk of changes dramatically in planning process by testing alternatives before implementing the changes. (Chang and Makatsoris, 2001).

Chang and Makatsoris (2001) point out that a good understanding of the overall logistics and supply chain system is most important when developing a simulation model, and a good understanding of the business characteristics is essential because every industry has unique business characteristics as well as logistics and supply chain process.

Bhaskaran (1998) simulates the upstream information flow in a supply chain and the resulting downstream material flow to analyze supply chain instability and inventory. Research results show that supply chains can be analyzed for continuous improvement opportunities by using simulation.

Petrovic (2001) develops and implements a simulation model to analyze supply chain behavior and performance in an uncertain environment (customer demand, external

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supply of raw materials and lead time to the facilities). The model includes a raw material inventory facility, a number of in-process inventory facilities, an end-product inventory facility, as well as production facilities between them. All the facilities are linked in series. With the help of simulation, supply chain operations could be emulated during a finite planning horizon and the impact of managerial decisions on operational supply chain control parameters can be evaluated.

Based on an object-oriented architecture, Hung et al. (2006) present a new modeling approach for the simulation of supply chain. The model offers a fully dynamic simulation for a multi-national pharmaceutical company's supply chain capturing the system dynamics and characteristics of individual supply chain member. The effect of various uncertainties are evaluated through Monte-Carlo simulation and other sampling techniques. There are three major advantages of the object-oriented approach: (1) modifying supply chain complexity due to the connection of constituent components; (2) integrating various decisions on location, production, inventory and transportation into one model; and (3) creating a set of reusable and generic components. The simulation model can be easily modified to reflect changes in the supply chain and obtain more realistic results.

Using object-oriented simulation, Alfieri and Brandimarte (1997) develop a model of a multi-echelon inventory management system which contains nodes for factory, stock and demand. The simulation model is used to evaluate logistics performance in terms of inventory and transportation costs, as well as service levels expressed by backlog costs. A simple example shows the usefulness of an object modeling approach to evaluate the performance of an integrated supply chain.

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Yung et al. (2006) address a coordinated production-distribution network problem which considers joint decisions in production assignment, lot size, transportation and order quantity for a single product and multiple products with multiple suppliers and multiple destinations. They propose two approaches to solve this problem: a two-layer decomposition (TLD) method and a Lagrangian relaxation decomposition (LRD) method. To compare the results given by these two approaches, a simulation model is developed on different problem sizes and problems with large variances in demand data. Simulation results show that LRD is more effective than TLD in general.

Lin et al. (2000) develop an extended-enterprise supply chain analysis tool called "Asset Management Tool" (AMT) for IBM to achieve the goal that responds quickly to customers with minimal inventory. By using AMT, issues regarding inventory budgets, turnover objectives, customer service targets and new product introductions can be solved easily. AMT is built on six functional modules: data modeling module, graphical user interface, experiment manager, optimization engine, simulation engine and report generator. It integrates graphical process modeling, analytical performance optimization, simulation, activity-based costing, as well as enterprise database connectivity into a system which allows quantitative analysis on extended supply chains. AMT has been shown to generate $750 million in cost savings on material costs and price-protection costs at IBM.

2.4.2 Intelligent agent-based simulation methodology and multi-agent systems

Intelligent agents and multi-agent systems are discussed in this subsection.

(1) Agents

A supply chain is affected by many interacting factors, each of which has its own functions and features. Understanding how these factors influence the supply chain and the logistics process is very critical. Simulation based on agent methodology provides knowledge to support concurrent and distributed decision making. Modeling the logistics system is in effect simulating the individual components and the behavior that emerges through their interactions.

Intelligent agents are autonomous decision-making entities, performing appropriate intelligent actions using their own knowledge in a dynamic environment. Wooldriage and Jennings (1995) point out that an agent could be viewed as any computer system (software or hardware) having four basic properties: autonomy, social ability, reactivity and proactiveness.

Typically, an agent has one or more of the following abilities: the ability to communicate with other software agents, the ability to learn from experience and adapt to changes in the environment, the ability to make plans and the ability to negotiate with other agents. Nissen (1995) summarizes some attributes of an agent: autonomy, communication ability or sociability, capacity for cooperation, capacity for reasoning, adaptive behavior and trustworthiness.

We present several classic definitions of other researchers:

- An agent is an encapsulated computer system in some environment and has the ability to execute flexible and autonomous actions in its environment to obtain its design objectives (Wooldriage and Jennings, 1995).

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- An agent is a system situated within and part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to affect what it senses in the future (Franklin and Graesser, 1996).

- An agent is an autonomous, goal-oriented software process that operates asynchronously, communicating and coordinating with other agents as needed (Fox et al., 2000).

- An agent is a computer system that is either conceptualized or implemented using natural phenomena (Tieju and Yoshiteru, 2005).

(2) Multi-agent system

An MAS is a cluster of individual agents interacting with each other to solve a complex, system-wide problem. Garcia-Flores et al. (2000) point out that MAS should be adaptable to different business processes and allow easy integration of individual components into the system. According to Davidson et al. (2005), a multi-agent system (MAS) is a group of agents that cooperate with each other to fulfill common and individual goals, also agents may compete in some environments. A MAS is "a community of autonomous, intelligent and goal-oriented units efficiently cooperate and coordinate their decisions with other agents to reach a higher level goal (Marik and McFarlane, 2005). There are four main components in an MAS: agent, environment, activity and relationship. An MAS includes cooperation, synergy, negotiation, and competition between agents (Dong et al., 2006).

Agents are autonomous in nature, which means that they could be either cooperatively working towards a common goal or selfishly acting towards achieving their own goals.

Each agent has limited capabilities or incomplete information to solve the problem. Agents have their own models or algorithms to make their decisions, and parameters or indicators to express their status. They perform better than the isolated individual agents due to the cooperation and distribution of tasks between agents in the system. In an MAS, there are communication languages, interaction protocols and agent architectures to facilitate the entire system. An MAS supports more flexible and comprehensive modeling capabilities, and is able to follow the strong evolution ability of the supply chain by adding or removing agents without the need to completely reconstruct the entire supply chain. In other words, such a system is adaptive to changes within the environment in a distributed fashion without necessarily affecting the entire system.

In recent years, MAS has been a preferred approach to solve logistics and supply chain problems, since these problems are autonomous, distributive, complex, heterogeneous, and decentralized in nature and require extensive intelligent decision making. An MAS focused on systems in which various intelligent agents interact with each other could solve more complex problems than systems involving a single agent. Since MAS is applied to solve complex problem, emphasis on coordination and cooperation among agents are required in order to find efficient solution to these problems.

The applications of MAS vary from the lowest level of machine control to management of a distributed enterprise (Marik and McFarlane, 2005). An extensive and very recent review paper by Lee and Kim (2008) present three agent architectures: hierarchical, blackboard and heterarchical and three MAS architectures: functional, blackboard and heterarchical.

There are four main benefits when using agent-based methodology: feasibility, robustness and flexibility, reconfigurability and redeployability, as well as several drawbacks including cost, guarantees on operational performance, scalability, commercial platforms, engineering education, design methodologies, standards, agent system performance and misapplication (Marik and McFarlane, 2005).

2.4.3 Research status on agent-based methodology and various applications in logistics and supply chain

According to Marik and McFarlane (2005), there are several key application areas of agent-based techniques:

- Real-time control of high-volume, high-variety, discrete manufacturing operations;

- Monitoring and control of physically distributed systems;

- Transportation and material-handling systems;

- Management of frequently disrupted operations;

- Coordination of organizations with conflicting goals;

- Frequently reconfigured, automated environments.

Fox et al. (2000) present four important issues when building an agent-based software architecture for the supply chain: (1) decision on how supply chain activities should be distributed across the agents; (2) coordination among components; (3) responsiveness; and (4) availability of knowledge encapsulated in a module. They also propose that the next generation supply chain system should be all of the following:

distributed, dynamic, intelligent, integrated, responsive, reactive, cooperative, interactive, anytime, complete, reconfigurable, general, adaptable and backwards compatible.

Parunak (1999) lists the following characteristics for an ideal application of agent technology:

- Modular. Each entity is defined by many state variables which are distinct from those of the external environment. So the interface to the environment can be clearly identified.

- Decentralized. The application can be decomposed into individual and independent software processes, which are able to perform various tasks without continuous direction from other software processes.

- Changeable. The structure of the application may change quickly and frequently.

- Ill-structured. All information about the application is not available when the system is being designed.

- Complex. The system shows various different behaviors which can interact with each other in sophisticated ways.

Garcia-Flores et al. (2000) model retailers, warehouses, plants and raw material suppliers as a network of cooperative agents, each of them performing one or more supply chain functions. By implementing such model framework in the chemical industry, they identify and understand supply chain dynamics. However, there are still many challenges such as data mining and learning from past performance to develop planning strategies that need to be resolved.

A multi-agent enabled supply chain management support tool is proposed by Fu and Piplani (2000) to map basic supply chain processes. Each agent in the model has his or her own knowledge, interests, status, information, message handlers, process element executors and policies. To validate this model, a simple PC assembling case is presented. Result shows that a real strategic competitive advantage for the entire supply chain could be achieved by using the support model. A framework of collaborative inventory management is then proposed to refine and extend the supply chain management support tool.

Pathak et al. (2000) develop a MAS to support decision making in supply chain management and implement an electronic data interchange (EDI) model in the automobile industry. The proposed model framework could automate the negotiation process between manufacturers and suppliers, which provides agent functions such as floating bids on contracts, gathering and analyzing responses, formulating bid strategies and presenting their results to management.

Gjerdrum et al. (2001) apply multi-agent modeling techniques in a demand-driven supply chain system with the objective of reducing operating costs while maintaining a high level of customer order fulfillment. There are seven types of agents in the supply chain network: customer, external logistics, warehouse, internal logistics, factory, spot market and transportation. Gjerdrum et al. (2001) combine optimization and agent-based simulation to model a supply chain network and measure supply chain performance. The scheduling problem of each production facility is solved by mathematical programming, while the tactical decision-making and control policy problems are formulated using an agent modeling technique.

Reis et al. (2001) model enterprise facilities in a multi-product production/distribution system and manage capacity in these facilities by introducing scheduling agents which perform as enterprise managers making decisions on available capacity. The scheduling problems addressed in the paper are a multi-agent cooperative scheduling problem and a highly dynamic scheduling problem.

To improve the performance of a production system, Virtual Factory Dynamics Configuration System (VFDCS) has been developed (Reaidy et al., 2001). VFDCS is based on MAS which focuses on existing interactions among the resources and is implemented at the product and process level. The intelligent agents have the ability to evaluate available assignments and adjust product and process parameters.

A model framework that integrates various elements of the supply chain including enterprises, production processes and related data and knowledge is proposed by Julka et al. (2002a). A refinery application for the model is also provided in Julka et al. (2002b). The model represents these elements in an intelligent and object-oriented fashion. It considers the entire supply chain structure when making business decisions and manages all important relationships: upstream and downstream in a supply chain. Supply chain elements are classified into entities, flows and relationships and entities are modeled as software agents. There are two major elements in the framework: object modeling of supply chain flows (such as material and information) and agent modeling. Using three types of agents (emulation agents, query agents and project agents) the entire supply chain is modeled.

Davidsson and Wernstedt (2002) implement a MAS to coordinate just-in-time production and distribution of products where the production and/or distribution time is relatively long. With a goal to produce the right amount of products at the right time, each customer is modeled as an agent. The agent makes a prediction about future need and sends that information to production agents. The distribution agents then respond. By using the proposed MAS architecture, it is possible to control trade-offs between quality of service and the degree of excessive production.

By introducing three types of agents (company agent, purchasing agent and internal customer agent), purchasing activities are studied in an organizational environment (Ebben et al., 2002). Such an MAS offers an approach to learn how purchasing performance is affected for non-product related items and services. Preliminary results show the important role of organizational learning in purchasing activities.

Signorile (2002) applies multi-agent simulation technique in order to make flexible and efficient inventory management decisions. After identifying the entities and processes in the system, it becomes a straightforward process to encapsulate the entities in agents. By using such an MAS, the performance of the supply chain is improved.

Xiong and Wu (2003) investigate and evaluate various scheduling algorithms used by suppliers, and implement an MAS to assist suppliers to generate a flexible schedule that can react to unpredicted events. The main idea is that risks and benefits associated with each alternative need to be evaluated.

Wan (2004) studies a joint production and delivery scheduling problem with uncertainty in a two-level supply chain by using distributed agents. Typically, it is

difficult to solve the scheduling problem using traditional analytical approaches due to the uncertainties in demand, lead time and decentralized decision-making process. The proposed approach is experimented on different data sets.

Yin et al. (2004) formulate a discrete resource allocation model based on multiple agents. The model efficiently distributes the scheduled resources under dynamic environment via agent interactions. Yin et al. (2004) study the bidding strategy of both supply and demand agents under independent and dependent production. Better constructions of the decision-making process could lead to efficient resource allocation in the supply chain (Kaihara, 2003).

Ta et al. (2005) develop a new architecture and mechanism for the MAS. They apply it at the operational level in a supply chain management problem. By introducing a combinational auction mechanism, they also present various agents and negotiation protocol between them to facilitate the auction mechanism. A task allocation problem is solved based on the proposed negotiation protocol and agent functionality.

Sarker et al. (2005) propose a MAS model for a manufacturing supply chain network with many stages containing a variety of business entities and complex interactions among them. The model can quantify inventory holding cost, shortage cost, ordering cost, set-up cost and other parameters in the entire supply chain for a selected demand forecast method and batch sizing policy and known lead times.

In order to solve the schedule generation and selection problems, an agent-based information system is developed by Krauth et al. (2005) which focuses on the interaction between the operational and strategic objectives in the company. There are two types of

agents in the system: operational agents and strategic agents. These agents interact with each other based on a bidding coordination mechanism. The information system could support 3PL companies by providing a link between daily operations and strategic goals.

Kong and Wu (2005) develop an intelligent production control model in a dynamic supply chain environment. A number of business entities together form a temporary supply chain for a certain production plan. Every business entity has the ability to choose and adjust its own collaboration attitude for a particular production plan: completely cooperative, completely self-interested or any attitudes between these two extreme cases.

To study the performance of collaborative planning forecasting and replenishment, Caridi et al. (2005) propose a multi-agent model, which uses a collaboration process to optimize negotiation. Results indicate that the agent-driven negotiation process is better than normal process without intelligent agents in terms of costs, sales, inventory level and stock-out level.

Xie and Chen (2005) present a MAS in a one-to-many supply chain network with horizontal cooperation among homogenous retailers. Suppliers and retailers are modeled as intelligent agents so that the cooperation and competition among them are easy to study. Interesting results are obtained: (1) if there are only two retailers, they tend to be cooperative and this relationship is stable; (2) if there are five retailers, no stable cooperation exists, but the alliance with larger number of agents is stable.

Allwood and Lee (2005) introduce a new type of agent to study the supply chain dynamic. These agents have novel features such as ability to choose among competitive vendors, to distribute orders preferentially among customers, to manage production and

inventory scheduling and to determine product price. An individual supply chain process could reach higher profit with a competitive perspective, but the overall profits of the entire supply chain is reduced. Profitability of the supply chain is maximized only when all supply chain processes are operated as a whole.

Sheremetov et al. (2005) apply a multi-agent supply chain simulator in a supply chain design and management problem. The integration of this agent technology and soft-computing technologies such as reinforcement learning, fuzzy rules and perceptual forecasting is shown to be a powerful decision support tool in a supply chain environment characterized by uncertainty.

By modeling a supply chain using flows and agents, an agent-based architecture is developed by Dong et al. (2006). This provides an efficient platform to design and optimize the supply chain. The supply chain described in the paper consists of one retailer, one manufacture, one warehouse, one raw material supplier and many customers. The architecture is used to provide cost savings, improve order processing, shorten lead time and increase customer satisfaction.

Mele et al. (2006) develop a simulation-based optimization model which uses a discrete-event system to model the supply chain in order to overcome the numerical difficulties for solving a large-scale, mixed-integer, nonlinear problem. In the proposed model, each supply chain entity is represented as an agent whose activity is described by states and transitions. Results show that such a model is an attractive alternative in the decision-making process when there is uncertainty.

Zhang et al. (2006) present an approach for manufacturing companies to manage not only their own systems but also supply networks in order to deal with dynamic changes in the global market. The goal is achieved by two manufacturing concepts: agent-based manufacturing system and e-manufacturing (which could generate alternatives dynamically with respect to planning, scheduling, configuration and restructure of both manufacturing system and its supply network).

Living systems/adaptive transportation networks (LS/ATN), a new and successful agent-based optimization system is introduced by Neagu et al. (2006), which has been applied to several real-world problems. The system is applied on a dynamic, multiple pickup and delivery problem with time windows. The development of LS/ATN is motivated largely by the need for highly responsive agents that react locally according to changes in the complex environment. LS/ATN can reduce transportation costs through the route optimization for small and large fleets.

Li and Sun (2007) use a parallel simulation technology to improve the efficiency of the MAS model. The genetic optimization is also applied to provide better planning results in automatic mode. This can overcome the errors from a manual evaluation of the simulation model.

An agent-based approach is applied on the retrofit of a production and distribution network (Mele et al., 2007). Starting with a set of possible design options for the existing supply chain, the multi-agent system provides each design alternative a performance index by searching the best value of operational variables associated with the potential

supply chain network. A genetic algorithm is coupled with the agent-based model to find near-optimal operational variables for each design candidate.

Yang (2007) develops a model for multi-object negotiation in a multi-agent system. In the multi-object negotiation mechanism, interests of all the entities should be considered in order to obtain sharing interests and achieve a win-win objective. The model is applied in a manufacturing enterprise to change the competing type among all manufacturing companies from win-lose to win-win.

Mes et al. (2007) propose an agent-based approach for a real-time dynamic scheduling problem. When full truckload transportation orders with time windows arrive, the model executes scheduling decisions dynamically. Vehicles are modeled as intelligent agents that schedule their own routes. Vehicles agents interact with job agents to minimize transportation costs. The multi-agent model provides fewer empty miles and a higher level of customer service. Moreover, it requires very little information and facilitates an easy-to-adjust schedule whenever information is updated.

Wang and Fang (2007) design an intelligent agent-based simulation model to study supply chain issues such as logistics integration, information sharing, demand forecasting, risk management, automated communication and pricing negotiation. An enterprise or supply chain entity is modeled as intelligent agent. There are six layers in the model: raw material providers, component manufacturers, product assemblers, product holders, retailers and end customers.

A multi-agent simulation for supply chain system with mixed inventory policies in different facilities is developed to study the impact of the factors on the total logistics

costs (Chen et al., 2007). They apply artificial neural network (ANN) as the learning model for the agents in order to obtain the optimal inventory policies. Results indicate that ANN provides good inventory policy to the agents and the supply chain performance and behavior can be precisely estimated.

CHAPTER 3

OPTIMIZATION MODEL DEVELOPMENT

Developing an integrated distribution model can provide a better understanding of distribution problems. Also, outsourcing logistics functions to 3PLs is a trend among all companies in many disciplines. In this chapter, we present a model for a multi-product, multi-period, multi-echelon, multi-inbound and outbound shipments carrier distribution problem faced by many 3PLs.

3.1 Integrated production-inventory-distribution design

Economic benefits can be achieved by integrating the production and inventory functions with distribution. Certain production schedules need to be planned to fulfill each customer's demand. Products must be shipped out as required by the customer. During this process, it might not always be necessary to produce the exact amount as the customers ordered because of the variability in demand, lead times and transportation times.

Furthermore, it may not always be possible to produce goods according to incoming orders due to production capacity. But with DCs, it is possible to meet peak season demand by accumulating inventory. There are three levels of planning in decision making: strategic, tactical and operational. In this proposal, we focus on a tactical planning

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problem in a 12-month time period to synchronize the distribution, production and inventory functions in a supply chain.

The logistics system (see Figure 1) considered in this research consists of several manufacturing plants producing different types of items using a set of resources. When an order is placed by an end customer, the production schedule is planned to ensure fulfillment of the demand. Following production, the products are first shipped to several intermediate warehouses or DCs based on the location of the customers. Then the products are shipped out to the customers based on their seasonal demand and shipping requirement (such as package size). The inbound and outbound transportation could be carried in-house or outsourced to a number of third party trucking companies that own a fleet of homogeneous or nonhomogeneous vehicles with limited capacity. Each trucking company has a limited number of drivers and truckload, which can vary over time. The shipping cost varies based on transported quantities, traveled distance, product type, carrier used and time consumed. For each product type, it is necessary to consider a fixed setup cost, not dependent on the quantity produced. In each manufacturing plant and DC, a particular level (not beyond the maximum capacity) of inventory needs to be kept in case of peak season or emergency shipment. To manage inventory successfully, plants and DCs must balance the risks of obsolescence against those of stockouts. We consider manufacturing plants as private entities. We also consider DCs as privately owned or third party facilities, but all of them have minimal and maximal throughput which can vary by time period.
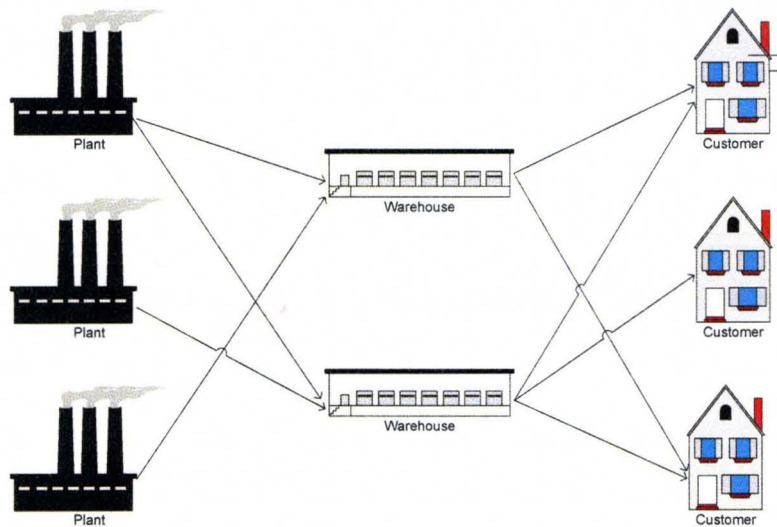
Figure 1. A logistics network including manufacturing plants, warehouses/DCs and end customers.

Some assumptions made in the model development include: (1) Opening or closing a production line happens simultaneously with the plan. There is no time lag between making and realizing the production decision; (2) Demand occurs at the beginning of a period. It is deterministic and known; (3) There are no defectives or losses during the process of production and transportation; (4) Initial inventory is permitted both in the manufacturing plants and DCs.

3.2 Model notation and formulation

Consider the problem of configuring a production-inventory-distribution system, where a set of manufacturing plants need to be established to produce multiple items. The DCs act as intermediate facilities between plants and end customers and facilitate the shipment of products between the two echelons. We develop a mathematical model to assist decision making in an integrated production, inventory and distribution system. The problem

formulated attempts to minimize the total costs by simultaneously considering facility location, production schedule, inventory decision, distribution batch size and so on. To model this problem, we define the following notation.

Indices:

i Index for plants, $i=1, 2, ..., I$.

j Index for DCs, $j=1, 2, ..., J$.

k Index for customers, $k=1, 2, ..., K$.

l Index for products, $l=1, 2, ..., L$.

m Index for inbound-shipment carriers, $m=1, 2, ..., M$.

n Index for outbound-shipment carriers, $n=1, 2, ..., N$.

t Index for time periods, $t=1, 2, ..., T$.

Parameters:

A_{ilt} Fixed production cost for product l at plant i in period t.

B_{ilt} Variable cost for producing a unit of product l at plant i in period t.

C_{ilt} Inventory cost for carrying a unit of product l at plant i in period t.

D_{klt} Demand for product l by customer k in period t.

E_{jlt} Inventory cost for carrying a unit of product l in DC j in period t.

F_{ijlmt} Transportation cost for shipping a unit of product l from plant i to DC j when using carrier m in period t.

G_{jklnt} Transportation cost for shipping a unit of product l from DC j to customer k when using carrier n in period t.

H_{ilt} Production capacity for product l at plant i in period t.

I_{ilt} Inventory capacity for product l at plant i in period t.

J_{jlt} Inventory capacity for product l in DC j in period t.

K_{jt} Upper bound on throughput capacity in DC j in period t.

L_{jt} Lower bound on throughput capacity in DC j in period t.

M_{mt} Truckload capacity of inbound-shipments carrier m in period t.

N_{nt} Truckload capacity of outbound-shipments carrier n in period t.

O_{mt} Driver capacity of inbound-shipments carrier m in period t.

Q_{nt} Driver capacity of outbound-shipments carrier n in period t.

R_{lmt} Average truckload for a standard vehicle shipping product l for inbound-shipments carrier m in period t.

S_{lnt} Average truckload for a standard vehicle shipping product l for outbound-shipments carrier n in period t.

T_{lmt} Average trips a driver of inbound-shipments carrier m can make for product l in period t.

U_{lnt} Average trips a driver of outbound-shipments carrier n can make for product l in period t.

V_{il0} Starting inventory level for product l at plant i.

W_{jl0} Starting inventory level for product l in DC j.

β_{klt} Shipping requirement (the degree of consolidation or break bulk) of customer k

for product l in period t.

Decision Variables:

x_{ijlmt} Amount of product l shipped from plant i to DC j when using inbound-shipments carrier m in period t.

y_{jklnt} Amount of product l shipped from DC j to customer k when using outbound-shipments carrier n in period t.

z_{ilt} 1 if product l is produced at plant i in period t; 0 otherwise.

P_{ilt} Amount of product l produced at plant i in period t.

V_{ilt} Inventory level of product l at plant i in period t.

W_{jlt} Inventory level of product l in DC j in period t.

The objective function in the proposed model is to minimize the total costs including fixed and variable production costs, inventory costs both at plants and in DCs, and inbound and outbound distribution costs:

$$Minimize\ Z = \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{T} A_{ilt} \times z_{ilt} + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{T} B_{ilt} \times P_{ilt} + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{T} C_{ilt} \times V_{ilt}$$

$$+ \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T} E_{jlt} \times W_{jlt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} F_{ijlmt} \times x_{ijlmt}$$

$$+ \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{n=1}^{N}\sum_{t=1}^{T} G_{jklnt} \times y_{jklnt}$$

All the constraints are listed as follows:

$$\sum_{j=1}^{J}\sum_{n=1}^{N} y_{jklnt} = D_{klt}, for\ all\ k,l,t \tag{1}$$

$$P_{ilt} \le H_{ilt} \times z_{ilt}, for\ all\ i,l,t \tag{2}$$

$$V_{ilt} \le I_{ilt}, for\ all\ i,l,t \tag{3}$$

$$W_{jlt} \le J_{jlt}, for\ all\ j,l,t \tag{4}$$

$$L_{jt} \le \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{n=1}^{N} y_{jklnt} \le K_{jt}, for\ all\ j,t \tag{5}$$

$$P_{ilt} + V_{ilt-1} - V_{ilt} = \sum_{j=1}^{J}\sum_{m=1}^{M} x_{ijlmt}, for\ all\ i,l,t \tag{6}$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M} x_{ijlmt} + W_{jlt-1} - \sum_{k=1}^{K}\sum_{n=1}^{N} y_{jklnt} \times \beta_{klt} = W_{jlt}, for\ all\ j,l,t \tag{7}$$

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$$\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} x_{ijlmt} \leq M_{mt}, for\ all\ m, t \qquad (8)$$

$$\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{l=1}^{L} y_{jklnt} \leq N_{nt}, for\ all\ n, t \qquad (9)$$

$$\frac{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} x_{ijlmt}}{\sum_{l=1}^{L} R_{lmt}} \leq \sum_{l=1}^{L} T_{lmt} \times O_{mt}, for\ all\ m, t \qquad (10)$$

$$\frac{\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{l=1}^{L} y_{jklnt}}{\sum_{l=1}^{L} S_{lnt}} \leq \sum_{l=1}^{L} U_{lnt} \times Q_{nt}, for\ all\ n, t \qquad (11)$$

$$x_{ijlmt} \geq 0, for\ all\ i, j, l, m, t \qquad (12)$$

$$y_{jklnt} \geq 0, for\ all\ j, k, l, n, t \qquad (13)$$

$$P_{ilt} \geq 0, for\ all\ i, l, t \qquad (14)$$

$$V_{ilt} \geq 0, for\ all\ i, l, t \qquad (15)$$

$$W_{jlt} \geq 0, for\ all\ j, l, t \qquad (16)$$

$$z_{ilt}\ are\ 0, 1\ variables \qquad (17)$$

In constraint (1), customers place an order containing single or multiple types of products at the beginning of each time period. One customer could receive its entire order from one, or more than one, intermediate DCs. Shipments occurring from DCs to customers are served by company-owned or third party carriers.

Constraint (2) shows that once a decision to produce product l at plant i in period t is made, the amount to produce must be within its production capacity.

In constraints (3) and (4), although both manufacturing plants and DCs are allowed to carry inventory, in each plant and DC there is a predetermined maximum inventory level for each type of product in each planning period, which cannot be exceeded.

The reason to include constraint (5) is because we are using both privately owned and third party DCs, we have to keep the throughput below the upper limit which may vary from one period to the next. On the other hand, it is also necessary to keep the monthly throughput above a lower limit to best utilize available resources.

In constraint (6), production and inventory plans are determined in each plant and month after receiving customer orders. Counting any products left over from last month, each plant produces a particular amount of items to meet customer orders. The shipment is carried out by a number of trucking companies. Products that are not shipped are considered as initial inventory for the next month.

This production, inventory and distribution policy occurs in each DC in each time period. However, the inbound shipment and outbound shipment are different in terms of requirement. It might be necessary to break or consolidate some types of products in the inbound shipments as required by different customers in different seasons in constraint (7).

In constraints (8) and (9), the total shipments carried by each inbound and outbound shipment carriers are different from each other. We need to consider allocating truckloads to each carrier below its maximum capacity even if this carrier could offer the lowest shipping price among all the other carriers.

In many trucking companies, a big issue in operations is that it becomes very difficult to find enough qualified drivers, especially in peak seasons. In constraints (10) and (11), we assume each driver is capable of making the same number of trips and each vehicle is capable of taking the same amount of workload.

Constraints (12) to (17) are the requirements for all the decision variables.

The proposed optimization model is different from the models in the literature in a way that it not only contains three logistics functions (production, inventory and distribution) but also includes an important decision of 3PL selection. The model assumes each 3PL has a limited number of truckloads and drivers. With the successful outsourcing to 3PLs, the total cost in the entire logistics system can be reduced further.

CHAPTER 4

SOLUTION ALGORITHM AND EXPERIMENTAL RESULTS

In this chapter, we solve small-sized and medium-sized instances of the integrated distribution model presented in Chapter 3. All of the small problems can be solved using commercial software.

However, due to the complexity of the model, commercial software fails to solve large-sized problems efficiently. We propose to use Benders decomposition algorithm to solve the model and apply it on a number of problems. Numerical results are provided and discussed.

4.1 Small–medium size problems

We build the model by using LINGO 11.0 and validate the model based on several small-sized problems. All of them can be solved very efficiently. Because LINGO is less efficient when solving medium-sized problems, we apply Benders decomposition to solve them.

4.1.1 Commercial software

In Table 3, I is the total number of plants, J is the total number of distribution centers, K is the total number of customers, L is the total number of products, M is the total number

of inbound-shipment carriers, N is the total number of outbound-shipment carriers and T is the total number of time periods. We also provide the total number of variables and the total number of binary variables in two columns respectively.

As shown in the table, problems 1 to 7 are considered as small-sized problems with less than 1,000 variables and fewer than 1,000 constraints. All of them can be solved within 10 seconds, which demonstrates that the commercial software performs very efficiently on small-sized integrated, production-inventory-distribution problems.

Table 3

Numerical results of test problems

No.	I	J	K	L	M	N	T	Variables	Binary	Constraints	Objective	Time
1	1	2	2	2	2	2	2	68	4	125	858.5	00:00:00
2	2	2	2	1	2	2	2	48	4	93	804	00:00:00
3	2	2	2	2	2	2	1	48	4	81	734.5	00:00:00
4	2	2	2	2	2	2	2	96	8	161	1,022	00:00:00
5	2	2	2	2	2	2	4	192	16	321	2,188	00:00:03
6	2	2	2	2	2	2	8	384	32	641	4,157	00:00:06
7	2	2	2	2	2	2	12	576	48	961	5,959.13	00:00:03
8	4	2	2	4	2	2	12	1,824	192	2,641	6,943.93	00:16:45
9	4	3	2	4	2	2	12	2,448	192	3,385	7,333.43	26:21:53
10	4	3	3	4	2	2	12	2,736	192	3,721	N/A	50 hrs
11	4	3	3	4	3	2	12	3,312	192	4,321	N/A	50 hrs
12	4	3	3	4	3	3	12	3,744	192	4,777	N/A	50 hrs
13	4	4	3	4	3	3	12	4,800	192	5,953	N/A	50 hrs
14	4	4	4	4	3	3	12	5,376	192	6,577	N/A	50 hrs

15	4	4	4	4	4	3	12	6,144	192	7,369	N/A	50 hrs
16	4	4	4	4	4	4	12	6,912	192	8,161	N/A	50 hrs

Note that LINGO is not efficient in solving medium-sized problems. It takes more than 16 minutes to solve problem 8 with 1,824 variables and 2,641 constraints, but more than 26 hours to solve problem 9 with 2,448 variables and 3,385 constraints. Optimal solutions could not be obtained for problems 10–16 even when increasing the computation time to 50 hours.

4.1.2 Benders' decomposition

In order to solve the proposed integrated production-inventory-distribution model, we need to find an alternative approach other than the general purpose branch-and-bound algorithm which is commonly used to solve mixed-integer, programming models. Benders decomposition has been used to solve mixed-integer, programming models in logistics and distribution. We therefore propose to apply Benders decomposition to solve our integrated distribution model.

We use the following notation to explain how Benders decomposition is applied to solve the proposed model. First, we need to transform the model into a standard format as shown below:

$$Minimize \; Bx + Gy \tag{18}$$

$$Subject \; to \; Cx + Dy \leq A$$

$$x \; binary$$

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$$y \geq 0$$

In this transformed model, x are _binary_ variables and y are _general_ (continuous) variables with the restriction of greater than or equal to zero. We fix x to a feasible set of binary values, say x^i. Suppose the original problem (18) is feasible, then it becomes:

$$Bx^i + Minimum\ Gy \tag{19}$$

$$Subject\ to\ Dy \leq A - Cx^i$$

$$y \geq 0$$

Compute its dual as:

$$Bx^i + Maximum\ p(Cx^i - A) \tag{20}$$

$$Subject\ to\ -Dp \leq G$$

$$p \geq 0$$

Based on the duality theorem, the original problem (18) is equivalent to the following problem:

$$Minimize\ Bx + p(Cx - A) \tag{21}$$

$$Subject\ to: x\ is\ a\ feasible\ set\ of\ binary\ variables$$

If the dual problem is infeasible, the objective function in (19) is unbounded for every feasible x, that is, the original problem is infeasible. Since we only consider a feasible original problem, we assume the dual problem is always feasible. The objective

function of the dual problem is unbounded when $q(Cx - A) > 0$, q is an extreme homogeneous solution corresponding to the dual problem.

Let $q^1, \ldots, q^m$ be all the extreme homogeneous solutions of the dual problem. We can conclude that only $q^k(Cx - A) \leq 0$ for all $k = 1, \ldots, m$ can lead us to obtain a feasible solution x. Hence, (21) can be restated as:

$$Minimize\ Bx + p(Cx - A) \tag{22}$$

$$Subject\ to\ q^k(Cx - A) \leq 0\ for\ all\ k = 1\ to\ m$$

$$x\ is\ binary$$

Let $p^1, \ldots, p^n$ be all the basic feasible solutions of the dual problem. Then (21) is equivalent to:

$$Minimize\ z \tag{23}$$

$$Subject\ to\ z \geq Bx + p^l(Cx - A)\ for\ all\ l = 1\ to\ n$$

$$q^k(Cx - A) \leq 0\ for\ all\ k = 1\ to\ m$$

$$x\ is\ binary$$

In (23), z is a continuous variable, which leads to a mixed-integer, programming problem with one continuous variable and the remaining binary variables. If we know an upper bound (UB) on the value of the objective function, z can be written entirely in terms of new binary variables. The objective z then can be expressed as $z = 2^0 z_0 + 2^1 z_1 + 2^2 z_2 + \cdots + 2^j z_j$, where j is the smallest integer satisfying $2^{j+1} - 1 > UB$.

Hence, by substituting a vector z of binary variables for the continuous variable z, (23) can be rewritten as:

$$Minimize\ z \qquad\qquad (24)$$

$$Subject\ to\ z \geq Bx + p^l(Cx - A)\ for\ all\ l = 1\ to\ n$$

$$q^k(Cx - A) \leq 0\ for\ all\ k = 1\ to\ m$$

$$x\ is\ binary$$

$$z\ is\ binary$$

We have noticed that the total number of constraints in (24) is $m + n$, where m and n are the number of extreme homogeneous solutions corresponding to the dual and the number of basic feasible solutions of the dual problem, respectively. It is very likely for both m and n to be large numbers, however, we only need to obtain a small subset of the constraints in (24) in any stage and generate the other constraints only when they are needed. In other words, in each stage, Benders decomposition deals with a restricted problem that is obtained by considering only a subset of the constraints in (24) and neglecting all the others. The restricted problem in a general stage of the algorithm is:

$$Minimize\ z \qquad\qquad (25)$$

$$Subject\ to\ z \geq Bx + p^l(Cx - A)\ for\ all\ l = 1\ to\ s$$

$$q^k(Cx - A) \leq 0\ for\ all\ k = 1\ to\ r$$

$$x\ is\ binary$$

z is binary

Here is a brief description of Benders decomposition algorithm:

Step 1: Set $i = 1$. Fix x^i to a feasible set of binary values. Set lower bound (*LB*) to 0 and upper bound (*UB*) to $+\infty$.

Step 2: Solve the dual problem (20) for the x fixed in Step 1. If we can obtain an optimal solution in this case, let p^l be that optimal solution. If $Bx + p^l(Cx - A) < UB$, set $UB = Bx + p^l(Cx - A)$. If the objective function of the dual problem is unbounded, let q^k be the extreme homogeneous solutions, which force the objective function diverge to $+\infty$.

Step 3: Update (25) by adding either $z \geq Bx + p^l(Cx - A)$ for the optimal solution p^l or $q^k(Cx - A) \leq 0$ for the extreme homogeneous solution q^k. Solve (25) and let x^* be the optimal solution and z be the optimal objective function value. Set $LB = z$. If $LB > UB$, stop. Otherwise, set $i = i + 1$, $x^i = x^*$ and return to Step 1.

The Benders decomposition is coded in MATLAB R2008a. After that, we apply Benders decomposition on some small-sized problems and compare its performance with LINGO (Table 4). For problem 7, we terminate the program after 30 minutes since LINGO only takes 3 seconds to solve it. As shown in the table below, the general Benders decomposition also fails to solve medium-sized and large-sized problems. We need to improve Benders decomposition and apply it on larger size problems.

Table 4

Test problems on Benders decomposition

No.	I	J	K	L	M	N	T	$OBJ_{Benders}$	Time (sec)	OBJ_{LINGO}	Time (sec)
1	1	2	2	2	2	2	2	858.5	3.65	858.5	1.00
2	2	2	2	1	2	2	2	804	0.30	804	1.00
3	2	2	2	2	2	2	1	734.5	0.69	734.5	1.00
4	2	2	2	2	2	2	2	1,022	0.54	1,022	1.00
5	2	2	2	2	2	2	4	2,188	4.97	2,188	3.00
6	2	2	2	2	2	2	8	4,157	67.35	4,157	6.00
7	2	2	2	2	2	2	12	N/A	1,800	5,959.13	3.00

4.2 Experiences with large-sized problems

Benders decomposition exhibits poor performance when solving even small-sized integrated distribution problems. In the following section, we show how it can be improved to solve larger instances of our integrated distribution model.

4.2.1 Modified Benders decomposition

When we take a close examination of each step of Benders decomposition, we find that a branch-and-bound algorithm is applied to solve (25), which is the main cause of the poor performance. That is also the reason why LINGO fails to solve some medium-sized problems, since branch-and-bound is the solver for mixed-integer programming model in LINGO. We need to apply some algorithms which can solve (25) efficiently. Since the main purpose of solving (25) is to provide a candidate solution to feed in the original problem and update the lower bound, we propose to use heuristics to solve it.

Recall (25), which is a pure binary variable model. In the modified version of Benders decomposition, we solve (25) using a genetic algorithm (GA). Poojari and

Beasley (2009) have also applied the similar idea that combines an exact algorithm and a heuristic algorithm to solve the problem more efficiently.

We do not need to use any coding rules to represent a candidate solution of the problem when applying GA to solve (25). In order to apply GA, we first generate the initial population S randomly. Each chromosome represents a candidate solution of the integrated distribution model.

Each candidate solution (or chromosome) has a fitness value based on a given fitness function. This fitness value is the measure of goodness of a solution with respect to the original objective function and the degree of infeasibility. Let F be the sum of coefficient vector of the objective function value of (25), which is $2^0 + 2^1 + 2^2 + \cdots + 2^j$ (where j is the smallest integer satisfying $2^{j+1} - 1 > UB$). Let N^v be the total number of constraints violated by a candidate solution and $\bar{z}$ be the objective function value given by that candidate solution. We define the fitness function as follows:

$$fit\ (x) = (F - \bar{z}) \times 1.01^{-N^v}/F \qquad (26)$$

After developing the fitness function, we need to design genetic operators–cloning, parent selection, crossover and mutation operators.

(1) Cloning operator

First, we list all the chromosomes (candidate solutions) in the initial population by increasing order of their fitness function value; we then determine the proportion of each chromosome to be cloned in order to form a new population, which is P. We compute cloning proportion P_i of

chromosome x_i as $P_i = fit(x_i)/\sum fit(x)$ (hence, $\sum P_i = 1$). According to P_i, we divide (0,1) into S segments, which are $(0, P_1]$, $(P_1, P_2]$, $(P_2, P_3]$, ..., $(P_{S-1}, P_S]$. Next, we randomly generate S numbers distributed in (0,1) and compute how many times those random numbers fall into each segment i, which is the cloning times of chromosome i.

(2) Parent selection operator

The parent selection operator is also an important process that directs GA search toward promising regions in a search space. There are many selection methods, such as random selection, tournament selection and so on. In this research, we use random selection to obtain two parents. Via a crossover operation, two offsprings are generated and entered into a new population.

(3) Crossover operator

We use a single-point crossover operator in this process. The operation of crossover can generate two new offsprings by combining the genes on the chromosomes of two parents so that the new chromosomes could keep the good parts of the parents. However, this operation is only designed for part of the individuals selected for mating, say P_c (usually between 0.6 and 1.0), which provides each chromosome a chance to pass on good genes without the disruption of crossover.

(4) Mutation operator

Mutation is applied to each offspring individually after crossover operation. It randomly inverts each gene with a small probability P_m (usually between 0 and 0.1). Mutation facilitates random research and helps to ensure that no

point in the research space has zero chance to be explored. In other words, the mutation operation prevents solutions from being trapped at a local optimum.

The general procedure of GA to solve (25) is as follows:

(1) Initialization

Generate an initial population based on population size.

(2) Fitness function calculation

Compute fitness function value for each chromosome using equation (26).

(3) New generation

Create a new population by repeating genetic operations (cloning, parent selection, crossover and mutation) until the new generation is completed. Replace new offsprings in the new population.

(4) Termination

Set up a maximum number of generations. Stop the iterations if the end condition is satisfied; otherwise, go to the next generation.

Performance of the improved, but heuristic Benders decomposition is illustrated in Table 5 (*B-GA* represents applying genetic algorithm to solve the master problem (25) in Benders decomposition).

Table 5

Performance of the modified Benders decomposition on test problems

No.	Variables	Constraints	OBJ$_{B-GA}$	Time (sec)	OBJ$_{LINGO}$	Time (sec)	OBJ$_{Benders}$	Time (sec)
1	68	125	858.5	8.44	858.5	1.00	858.5	3.65
2	48	93	854	11.02	804	1.00	804	0.30
3	48	81	760	9.27	734.5	1.00	734.5	0.69
4	96	161	1,342	7.25	1,022	1.00	1,022	0.54
5	192	321	2,603	38.97	2,188	3.00	2,188	4.97
6	384	641	4,864	63.23	4,157	6.00	4,157	67.35
7	576	961	6,166.1	637.50	5,959.13	3.00	N/A	1,800
8	1,824	2,641	11,294	833.94	6,943.93	1,005.00	N/A	1,800
9	2,448	3,385	N/A	N/A	7,333.43	94,913.00	N/A	1,800

It is obvious from Figure 2 that the modified Benders decomposition (B-GA) performs well on test problems 1–7. But on problem 8, the gap between LINGO and the modified Benders decomposition is over 60% (Figure 3), from which we learned that we need to improve some procedures in GA in order to obtain better solutions.
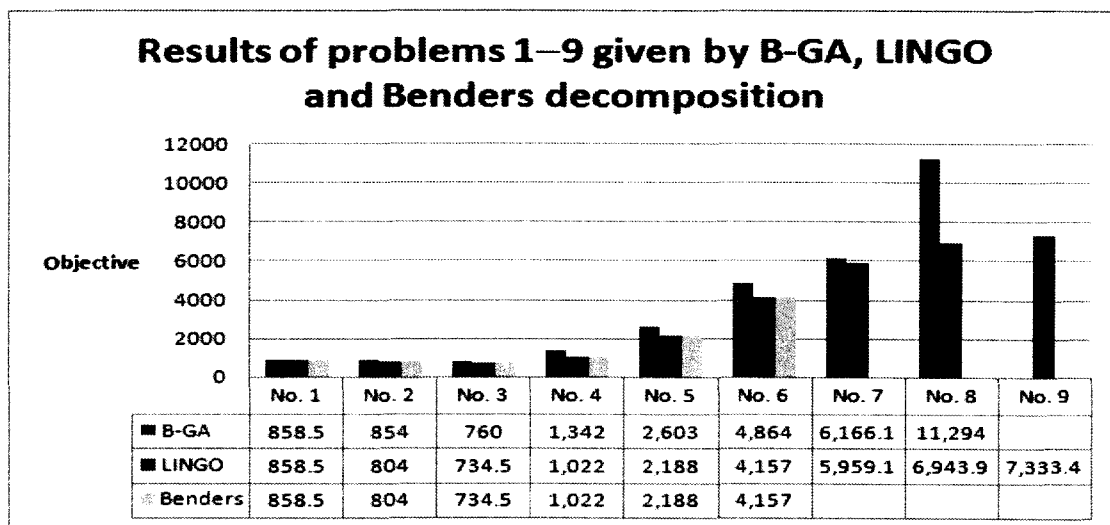
Figure 2. Objective function value of B-GA, LINGO and the general Benders decomposition on test problems.

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Gap between LINGO and the modified Benders decomposition
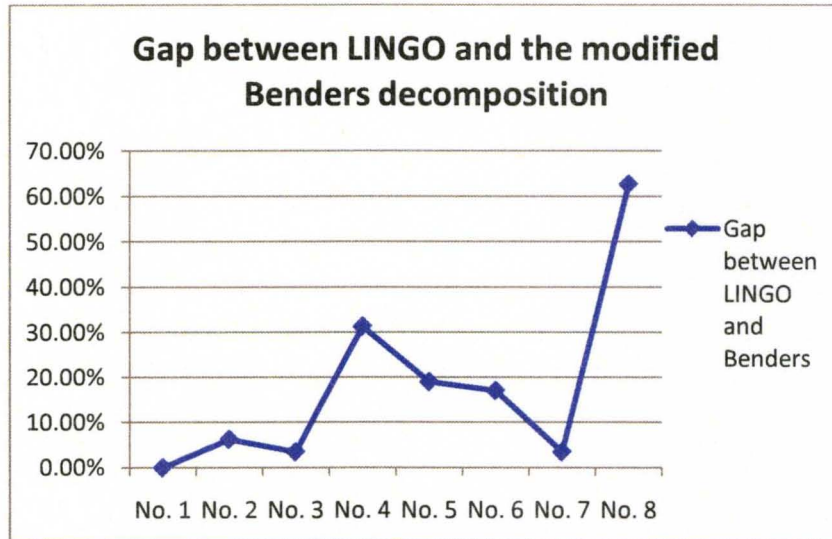
Figure 3. Gap between LINGO and the modified Benders decomposition on test problems.

4.2.2 Improve GA applied in Benders decomposition

There are several efforts we can make to improve GA, such as improving crossover operation, mutation operation, fitness function and so on. When we reexamine the fitness function designed, we find that: (1) the more constraints a candidate solution violates, the lower its fitness value, (2) if two candidate solutions have the same number of constraints violates, the one with better objective function has a higher fitness function value. Such design of fitness function works well on a series of small problems as shown in Figure 2. However, when applying it on larger size problems, where more constraints are violated in candidate solution, its fitness function value becomes zero very quickly. Hence, we lose the diversity of chromosomes in a generation.

In order to improve the fitness function when solving large-sized problems, we define another fitness function as: (N^c is the number of all constraints)

$$fit\ (x) = \frac{(F-\bar{z})}{F} \left(\frac{\pi}{4} - \tan^{-1}\left(\frac{N^v}{N^c}\right)\right) \tag{27}$$

In GA, we want to find a candidate solution which can satisfy all the constraints. Such a solution should have maximum fitness function value. When such a solution cannot satisfy all the constraints, the fitness function value should not have a linear relationship with the number of violated constraints, especially for large-sized problems. The reason that we choose to use inverse tangent function as a part in the fitness function is because it has the similar characteristics as the developing tendency of the growing number of violated constraints. In other words, the change of fitness function value should be maximum when the condition changes from satisfying all constraints to starting violating one constraint. With an increase in the number of violated constraints, the change of fitness function value will slow down. For example, the fitness function value does not have a significant change from violating 1,000 constraints to 1,001 constraints. The inverse tangent function (Figure 4) possesses such characteristics and is used in designing a new fitness function for large-sized problems.

atan
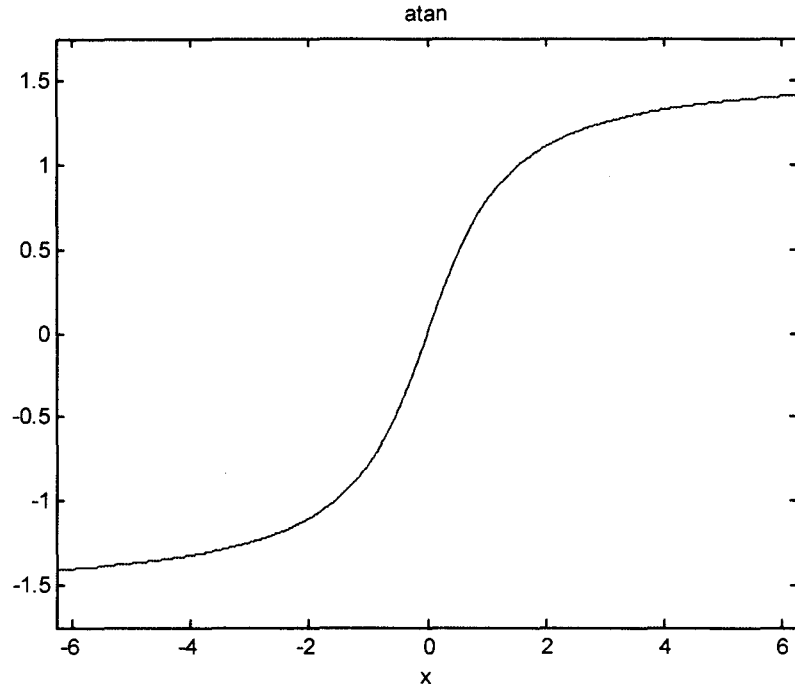
Figure 4. An inverse tangent function.

Since the previous fitness function (26) performs well for small-sized problems, we only test this new fitness function on large-sized problems. Because we do not have the solutions of the test problems beyond problem 10, we only provide results for problems 8 and 9 in Table 6. *Fit 1* is for Benders decomposition which applied GA to solve the master problem using fitness function (26). *Fit 2* is for Benders decomposition that applied GA to solve the master problem using improved fitness function, which is (27).

Table 6

Results on test problems using LINGO, the general Benders decomposition, the modified

Benders decomposition using fit 1 and the modified Benders decomposition using fit 2

No.	OBJ$_{LINGO}$	Time (sec)	OBJ$_{Benders}$	Time (sec)	OBJ$_{fit 1}$	Time (sec)	OBJ$_{fit 2}$	Time (sec)
8	6,943.93	1,005.00	N/A	N/A	11,294	833.94	8,192	209.35
9	7,333.43	94,913.00	N/A	N/A	N/A	N/A	8,253.9	114.88
10	N/A	N/A	N/A	N/A	N/A	N/A	8,526.8	440.29

Before discussing the results in Table 6, we need to clarify two things: (1) The general Benders decomposition fails to provide an optimal solution for these problems in an acceptable time, we cannot compare it with other algorithms; (2) Problem 10 only can be solved by the modified Benders decomposition which uses fitness function (27), we do not compare it with other algorithms on problem 10.

First, we compare LINGO, fit 1 and fit 2 on problem 8 (Figure 5 and 6). The solution given by fit 2 has a 17.97% gap with LINGO, while the gap between fit 1 and LINGO is 62.65%. Moreover, fit 2 significantly reduced run time by 79.17% compared to LINGO (fit 2 only reduced 17.02%).

Objective function value of problem 8
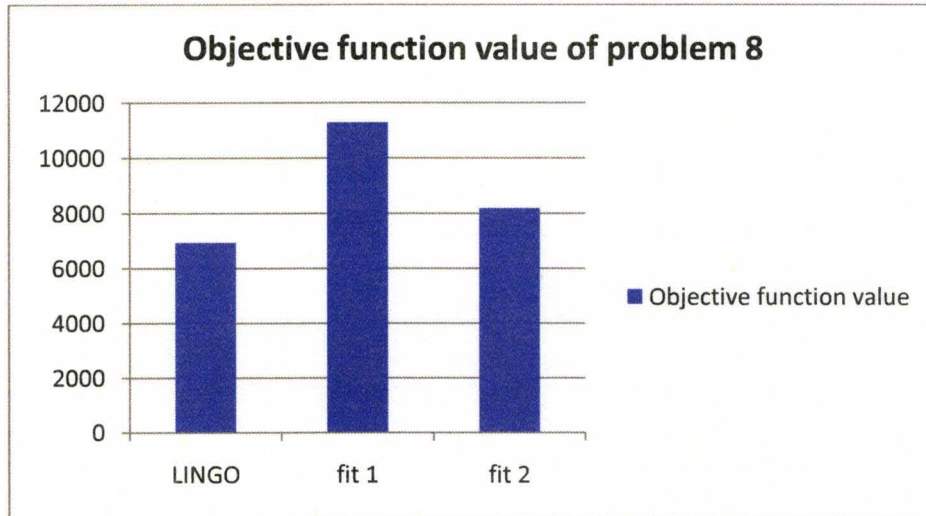
Figure 5. Objective function value obtained by LINGO, fit 1 and fit 2 on problem 8.

Run time to solve problem 8
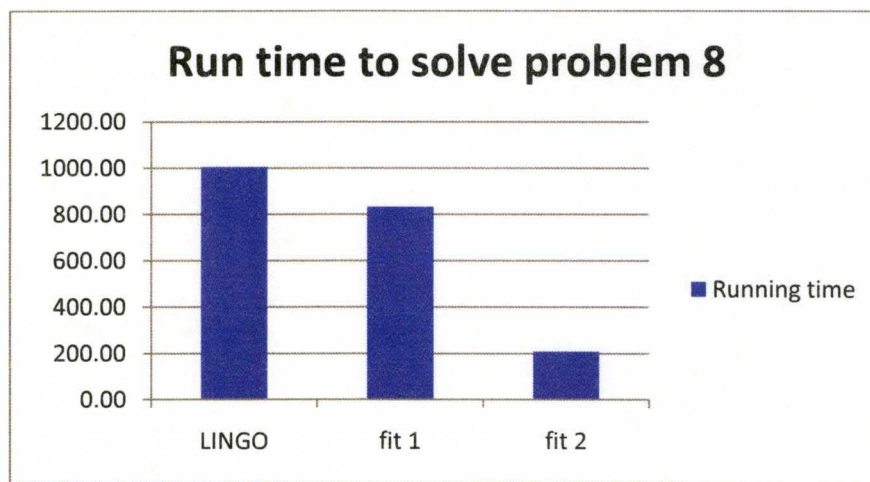
Figure 6. Run time to solve problem 8 using LINGO, fit 1 and fit 2.

Second, we compare LINGO and fit 2 (fit 1 fails to provide a solution in an acceptable time) on problem 9. In Figure 7, the gap between objective function given by LINGO and fit 2 is 12.55%. But the run time when applying fit 2 is reduced by 99.88% compared to LINGO.
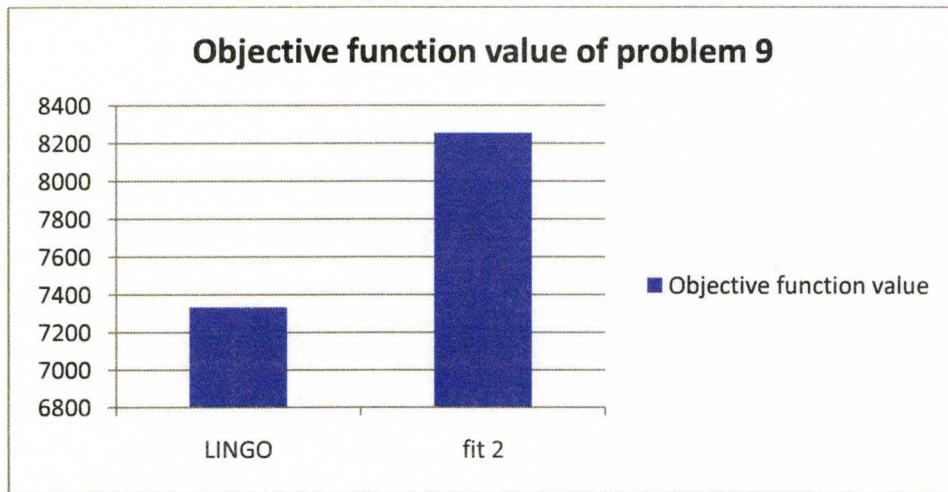
Figure 7. Objective function value obtained by LINGO and fit 2 on problem 9.
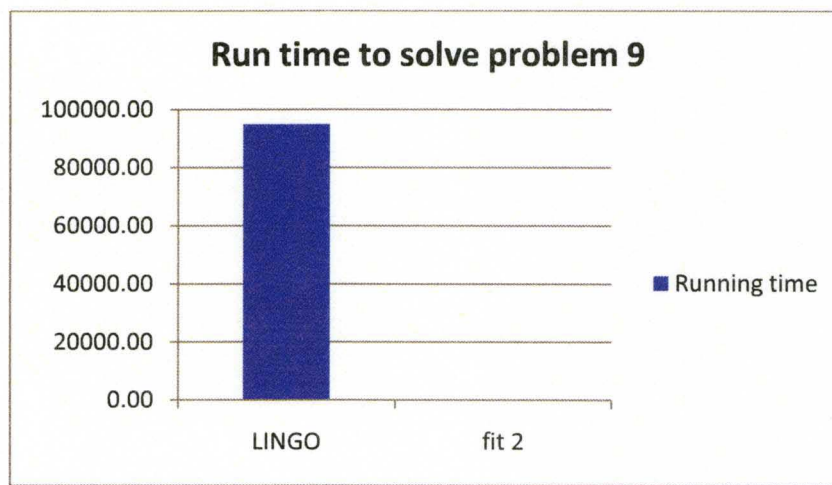
Figure 8. Run time to solve problem 9 using LINGO and fit 2.

We also test the performance of fit 2 on other large-sized problems. All the results are provided as follows:

Table 7

Results of test problems using fit 2

No.	I	J	K	L	M	N	T	Variables	Constraints	OBJ$_{fit\ 2}$	Time (sec)
10	4	3	3	4	2	2	12	2,736	3,721	8,526.8	440.29
11	4	3	3	4	3	2	12	3,312	4,321	7,542.1	463.63
12	4	3	3	4	3	3	12	3,744	4,777	7,273.6	537.20
13	4	4	3	4	3	3	12	4,800	5,953	7,874.8	272.79
14	4	4	4	4	3	3	12	5,376	6,577	11,480	331.45
15	4	4	4	4	4	3	12	6,144	7,369	11,977	286.25
16	4	4	4	4	4	4	12	6,912	8,161	12,285	2,406.88

These large-sized problems cannot be solved by using either LINGO or the general Benders decomposition. Nevertheless, the modified Benders decomposition can solve all of these problems (with total variables ranging from 2,736 to 6,912 and total constraints ranging from 3,721 to 8,161) in an acceptable time.

4.2.3 Numerical result on one industrial-sized problem

A large manufacturer and distributor in the United States has a complex distribution network, which is similar to the distribution network we studied. We collected some related data to form an integrated distribution structure from different sources (website, paper and so on). This results in 22 manufacturing plants and 7 major DCs in its distribution network. We consider shipments to 8 customer zones in all 48 states in a 12-month time period. There are totally 9 types of products this company produces. The inbound and outbound shipments are carried by a number of third party logistics companies as well as in-house carriers. In order to balance between stability and

flexibility, 16 inbound-shipment carriers and 16 outbound-shipment carriers are considered to perform the transportation. All the parameters are provided in Table 8.

Table 8

Parameters in an industrial-sized problem

Plant	DC	Customer	Product	Inbound-shipment Carrier	Outbound-shipment Carrier	Time Period
22	7	8	9	16	16	12

In order to test the performance of the proposed solution methodology (the modified Benders decomposition), another nine test problems are generated with variables ranging from 23,760 to 189,324 and constraints ranging from 27,073 to 197,005. After that, we apply the modified Benders decomposition using fitness function (27) on all ten large-sized problems (Table 9).

Table 9

Results of ten large-sized test problems using fit 2

No.	I	J	K	L	M	N	T	Variables	Binary	Constraints	OBJ$_{fit\,2}$	Time (sec)
17	8	4	4	9	4	4	12	23,760	864	27,073	21,061	1,937.68
18	10	4	4	9	4	4	12	27,864	1,080	31,609	21,900	2,128.64
19	12	4	4	9	4	4	12	31,968	1,296	36,145	22,351	2,690.41
20	14	4	4	9	4	4	12	36,072	1,512	40,681	22,603	6,045.84
21	16	4	4	9	4	4	12	40,176	1,728	45,217	21,574	2,732.48
22	18	4	4	9	4	4	12	44,280	1,944	49,753	23,490	3,097.51
23	20	4	4	9	4	4	12	48,384	2,160	54,289	23,778	4,130.69
24	22	4	4	9	4	4	12	52,488	2,376	58,825	23,605	6,829.23
25	22	7	8	9	8	8	12	189,324	2,376	197,005	39,116	47,866.84
26	22	7	8	9	16	16	12	370,764	2,376	378,829	33,502	118,455.02

Except problems 25 and 26, all the test problems can be solved within two hours. And even for the industrial-sized problem 26 (with 370,764 variables and 378,829 constraints), it can be solved in about 32 hours. Recall when we use LINGO as the solver, it takes 26 hours to solve problem 9 with 2,448 variables and 2,285 constraints. And it takes more than 50 hours but still does not solve problem 10 with 2,736 variables and 3,721 constraints.

Since problems 17–24 can be solved within 2 hours, we compare their solutions with the best and current solutions LINGO and the general Benders decomposition can obtain in 2 hours (Table 10).

Table 10

Comparison between solutions given by LINGO and the general Benders decomposition (in 2 hours) and the modified Benders decomposition (fit 2) on problems 17 to 24

No.	OBJ_{LINGO} (Best/Current) in 2 hours	$OBJ_{Benders}$ in 2 hours	$OBJ_{fit 2}$	Time
17	22,398/23,170.9	N/A	21,061	0.54 hr
18	22,145.86/22,980.93	N/A	21,900	0.59 hr
19	22,458.7/23,245.7	N/A	22,351	0.75 hr
20	22,848.2/23,800.9	N/A	22,603	1.68 hr
21	23,109.5/24,197.6	N/A	21,574	0.76 hr
22	23,449.1/24,600.9	N/A	23,490	0.86 hr
23	24,141.1/25,236.2	N/A	23,778	1.15 hr
24	24,865.9/25,993.4	N/A	23,605	1.90 hr

The general Benders decomposition presents poor performance in solving any of these test problems. Nevertheless, the modified Benders decomposition is a better alternative algorithm than the general Benders decomposition with respect to both solution quality and computation time.

We can clearly find in Figure 9 that for each test problem (except problem 22), the modified Benders decomposition provides better solution than the best objective function value given by LINGO which runs even longer than the actual run time of the modified Benders decomposition. For problem 22, although the modified Benders decomposition does not provide a better solution than the best objective function value given by LINGO (the gap is only 0.17%), the run time is significantly reduced by 57%.
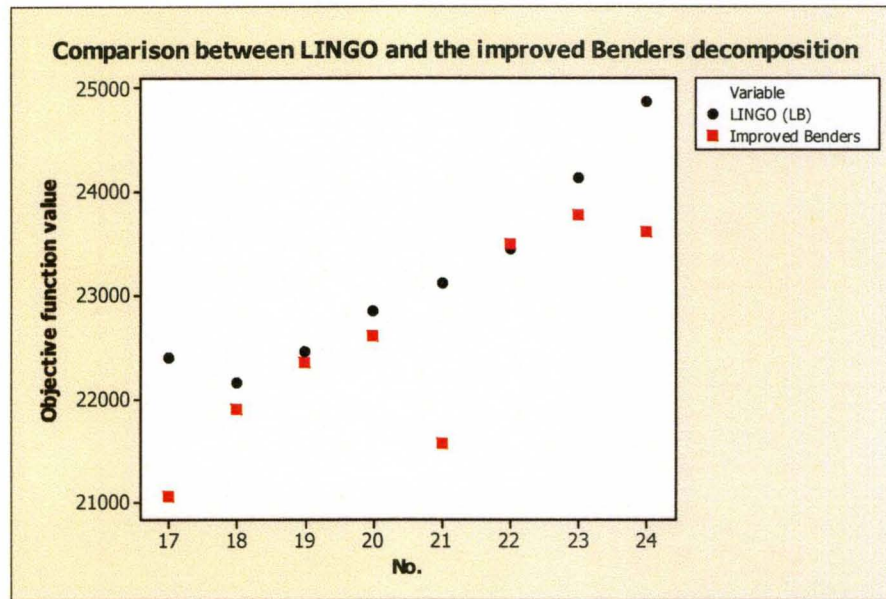
Figure 9. Comparison between the best solution given by LINGO and the solution given by the modified Benders decomposition.

In order to prove the quality of the solutions given by the modified Benders decomposition, we also provide the solutions of the LP relaxation to the original model and compare them with the results given by the modified Benders decomposition (Table 11 and Figure 10).

Table 11

Comparison between the modified Benders decomposition and the LP relaxation to the

model

No.	I	J	K	L	M	N	T	Variables	Binary	Constraints	OBJ$_{fit\,2}$	Time	OBJ$_{LPR}$	Time
17	8	4	4	9	4	4	12	23,760	864	27,073	21,061	0.54 hr	20,915.7	41 sec
18	10	4	4	9	4	4	12	27,864	1,080	31,609	21,900	0.59 hr	20,783	157 sec
19	12	4	4	9	4	4	12	31,968	1,296	36,145	22,351	0.75 hr	21,211.2	69 sec
20	14	4	4	9	4	4	12	36,072	1,512	40,681	22,603	1.68 hr	21,700.5	253 sec
21	16	4	4	9	4	4	12	40,176	1,728	45,217	21,574	0.76 hr	21,210.2	106 sec
22	18	4	4	9	4	4	12	44,280	1,944	49,753	23,490	0.86 hr	22,506.3	127 sec
23	20	4	4	9	4	4	12	48,384	2,160	54,289	23,778	1.15 hr	23,240.4	151 sec
24	22	4	4	9	4	4	12	52,488	2,376	58,825	23,605	1.90 hr	23,000.5	178 sec

Gap between the modifieded Benders decomposition and the LP relaxation to the original model

	No. 17	No. 18	No. 19	No. 20	No. 21	No. 22	No. 23	No. 24
Improved Benders	21,061	21,900	22,351	22,603	21,574	23,490	23,778	23,605
LP Relaxation	20,916	20,783	21,211	21,701	21,210	22,506	23,240	23,001
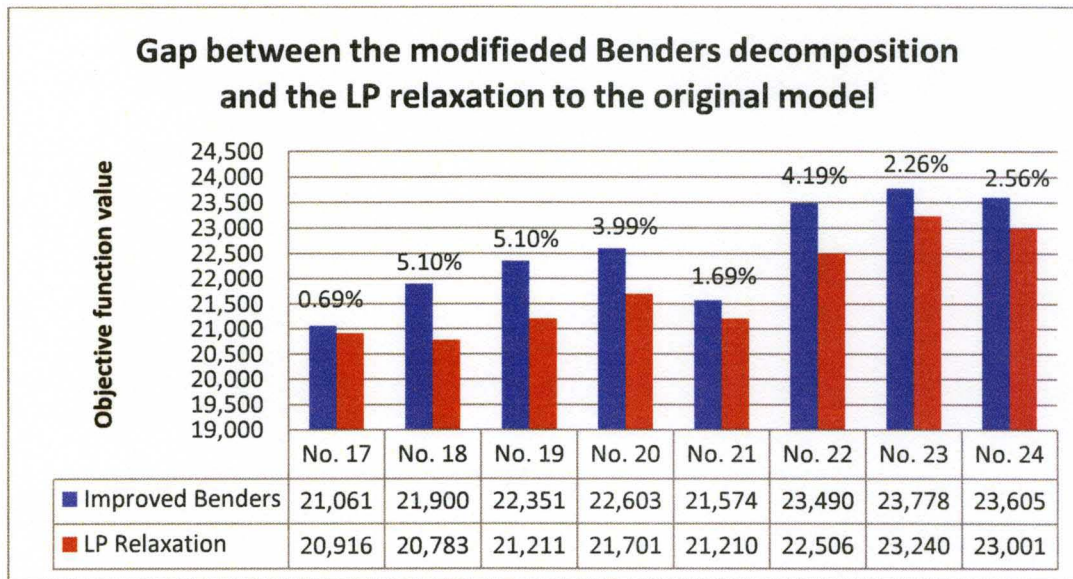
Figure 10. Gap between the modified Benders decomposition and the LP relaxation to the

original model.

Figure 10 shows that all gaps between the modified Benders decomposition and the

LP relaxation to the original model are less than 5.1% and the average gap is 3.2%. We

can also compare these gaps with the gaps between the lower bounds given by LINGO (in 2 hours) and the LP relaxation solutions (Figure 11). Again, except problem 22, the modified Benders decomposition performs well on these large-sized problems.
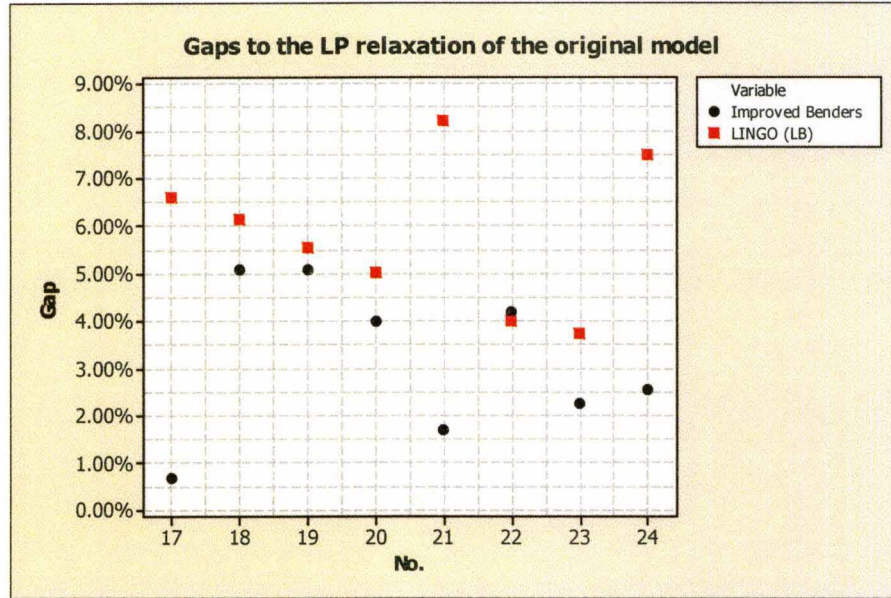
Figure 11. Gaps to the LP relaxation of the original model.

After a careful examination, we conclude that the modified Benders decomposition is an efficient algorithm to solve the integrated distribution model. Especially when solving large-sized problems, this proposed algorithm has more advantages than any other algorithms (branch-and bound, the general Benders decomposition) we compared with.

CHAPTER 5

REAL-TIME OPTIMIZATION REALIZATION IN A MULTI-AGENT SYSTEM

An important trend in logistics and supply chain management is the increased focus on real-time decision making as a result of continuing developments in telecommunication and information technologies such as radio-frequency identification (RFID) and global positioning system (GPS). These technologies can enhance the capability in logistics and supply chain planning and provide necessary information to perform real-time decision making. In order to realize real-time optimization, we need to apply new operations research (OR) techniques in addition to traditional OR-based approaches. In recent years, agent-based simulation has been a preferred approach to facilitate real-time decision making/optimization. In this chapter, we apply agent-based simulation approach to perform real-time optimization in the distribution execution problem. We first define the problem on which we apply real-time optimization. Next, we present the agent-based simulation model, and finally we provide numerical results.

5.1 Problem statement

We focus our study on the execution phase of the integrated production, inventory and distribution problem proposed in Chapter 3. The solution of this integrated model provides us a good starting point for the actual planning; however, we still need to deal

with the dynamic changes occurring in the execution phase. Our objective is to keep the good features of the optimal/near optimal solution given by the optimization model and apply a multi-agent simulation technique to search for a fast and good solution responding to the dynamic changes.

5.1.1 Motivation

In the previous chapters, we presented an optimization model of the integrated production, inventory and distribution problem. We also solved the model using both exact and heuristic algorithms. This optimization model plays an important role in the tactical planning phase. The solution of this model provides us an initial solution or starting point for the real-time decision making approach for the integrated production, inventory and distribution planning. However, the static solution provided by the mathematical programming based optimization approach may not be appropriate when changes in the environment take place dynamically. We want to keep the good features of the initial solution given by the optimization model and respond to unforeseen events that often occur and may deteriorate the effectiveness of the predetermined and static decision.

In the optimization model proposed in Chapter 3, we consider several important functions in the logistics and supply chain planning (such as production, inventory and distribution), which can provide us a high-level planning schema. This plan helps us better understand how to set up a production schedule, manage inventory, allocate limited capacity, assign shipments to carriers and so on in a 12-month tactical planning horizon. The algorithms we applied to solve this model can provide us an optimal or near optimal solution within an acceptable computational time even for industrial-sized problems.

However, when we execute this initial planning schema, the entire system is expected to change dynamically from many perspectives such as supply and demand. In order to maintain a required level of service, we focus our study on real-time re-planning with response to customer demand change in particular. We also focus on the outbound shipments from intermediate distribution centers to end customers.

5.1.2 Defining the problem

We mainly consider the distribution from distribution centers (referred to as suppliers) to customers (Figure 12). The shipments are completed by a number of carriers that own a fleet of homogeneous or non-homogeneous vehicles. In this particular setting, we consider customer orders containing only one type of product. We also consider this problem as an operational-level planning problem which is in a single-period (one month) planning horizon. Thus, this problem contains multiple suppliers (Ss), multiple customers (Cs) and multiple carriers (CAs) and it is an important component of the original integrated distribution problem in Chapter 3. We model this partial problem using an agent-based simulation approach to incorporate some dynamics that we may encounter in the real operation.
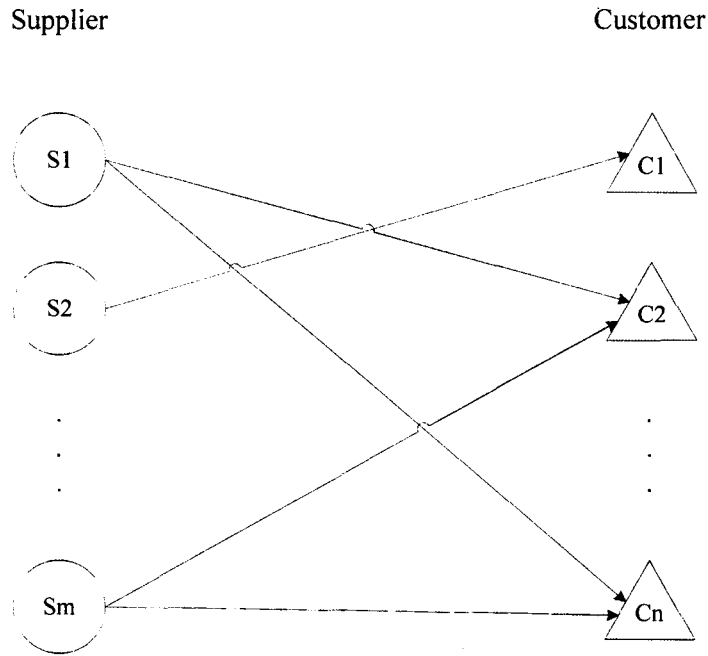
Supplier   Customer

Figure 12: A typical distribution network with *m* suppliers and *n* customers.

The initial solution to this problem (the shipment from supplier S to customer C using carrier CA) can be obtained from the solution of the optimization model. It is expected that customer demand can change dynamically when executing this initial plan. If changes occur, resolving the optimization model is not the best option, because it may take significant computational time. Moreover, dynamic changes are more difficult to formulate in a closed form. Therefore, we keep and utilize the good features of the initial solution and only adapt to the changes occurring in the environment. This can be done in real-time by applying some well-designed rules/algorithms.

There are two categories of customer demand change: demand increases and decreases. If one customer's demand decreases, we will just decrease the amount in its predetermined shipment according to the demand change and update the supply capacity of its supplier. In other words, this portion of the shipment is cancelled and will not be

considered in the system anymore; the supplier that provided this order has his supply capacity increased by the same amount as in the cancelled order. If a customer's demand increases, we will apply an agent-based approach to model determine to modify the initial plan so it can quickly react to the dynamic changes. Specifically, we model each type of entity in the distribution network as an intelligent agent. Each agent has various attributes assigned to it, such as bidding for incoming order, updating current capacity, learning from historical records and so on.

After modeling the entities as agents in the distribution network, we apply an auction mechanism on the selection of suppliers and carriers when facing increased customer demand. In order to keep the good features of the solution given by the optimization model, we only deal with the increased portion of customer demand and follow the initial solution of the unchanged part in the customer order. For instance, if one customer wants to order 10 more items, we only consider these 10 items as an inserted order and separate it from previously placed orders (we still execute the planning schema of the previously placed orders as given by the optimization model). This is how we keep the good features of the optimal/near optimal solution and tackle the unexpected changes. We consider that the selection of suppliers and carriers can be done simultaneously. After the increased customer demand information is presented to the system, each supplier is informed of this change. Then, each supplier determines whether it has additional capacity or inventory to meet the demand in full or in part. Subsequently, suppliers who can meet the increased demand announce a possible shipment schedule which contains information on the shipment quantity, origin and destination to a set of carriers. Each carrier calculates its shipping cost based on its current situation and

provides this information to the supplier. At the same time, an auction mechanism is set up between suppliers and customers to determine which set of suppliers should fulfill this order, as well as the set of carriers to be selected to perform the shipping of this order. More details are provided in the flowchart (Figure 13). The auction mechanism (called "RULE") will be explained in the next section of this chapter.
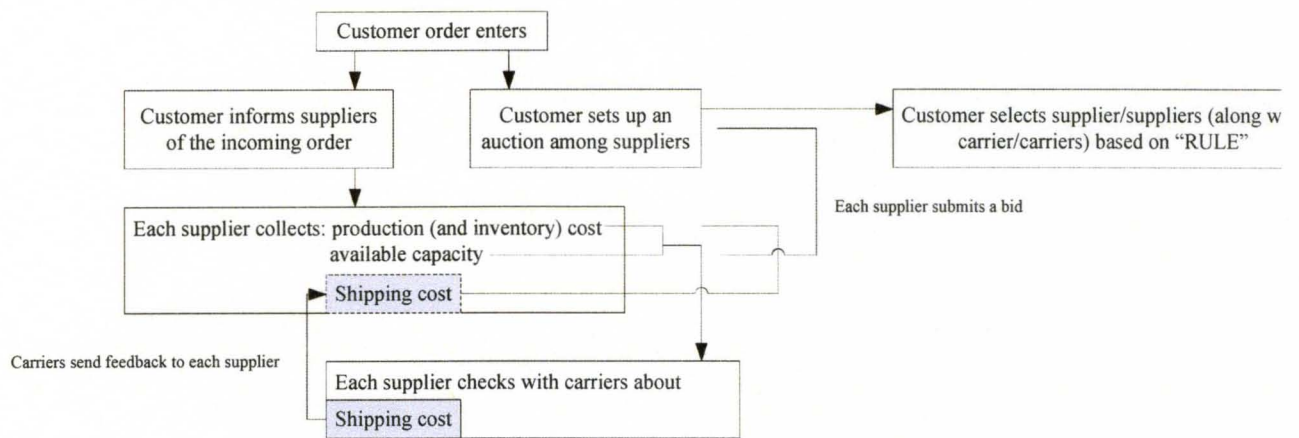
Figure 13: A detailed flowchart of the selection of supplier(s) and carrier(s).

5.2 An agent-based simulation model

We now specify the assumptions associated with the intelligent agent based simulation, define the agents and a multi-agent system, build a modeling framework, and finally design an auction mechanism.

5.2.1 Model assumptions

As described in the previous section, we consider three types of entities in the problem: suppliers, carriers and customers. We also consider that customer orders contain only one type of product. The entire problem is an operational-level re-planning problem. The

initial condition of this problem is provided by the optimization model described in Chapter 3. We assume the good features of the initial planning will be kept, and we only need to respond to the changes in customer demand. We consider the carriers have sufficient shipping capacity in a one-month period but may ship at higher costs in some extreme cases. All information of each type of entity (such as demand, capacity) will be updated in real-time and the re-planning process will occur in real-time as well. A well-designed auction mechanism is the core and essence of the real-time re-planning/decision making.

5.2.2 Agents, multi-agent system and modeling framework

We define three types of agents in the multi-agent system: supplier agents, carrier agents and customer agents. We also assign intelligent attributes to various agents. These attributes can change dynamically during the running of the simulation model. Different types of agents can communicate with each other in order to share information.

The relationships among these agents can be defined as three types: competitive, collaborative and neutral. For example, suppliers are competitors because they are competing with each other to fulfill customer orders. Carriers are also competitors because they are competing with each other to carry shipments from suppliers to customers. The relationship between suppliers and carriers can be defined as a collaborative partnership because carriers support the transportation of goods from suppliers to their customers. Suppliers and customers are also business partners because suppliers want to ensure customer demand is satisfied while making a reasonable profit

from fulfilling orders. The relationship between customers and carriers can be viewed as neutral since there is no direct connection between customers and carriers.

All the interactions (such as placing an order, selecting a carrier and so on) among agents occur in a market-like multi-agent system, which we name "market place" (Figure 14). In such a multi-agent system, each agent has its own goal. For example, customers want their orders to be fulfilled as soon as they place them and delivered at the lowest cost. Other than individual goals, there is also a system-wide/global goal that needs to be achieved. In our case, this global goal is to fulfill customer orders at the lowest accepted price, which cannot be done without coordinating the interests from all agents. Each agent has the ability to diagnose the changes occurring in the system and react to the changes accordingly. Agents may compete against each other in order to reach their selfish individual goals. However, they also cooperate with each other in order to achieve the global goal, which means that when there is a conflict between local goals and the global goal, agents have to give up their individual goals and attempt to achieve the global goal. We will discuss more details in the auction mechanism subsection. When a customer places an order and announces this piece of information to suppliers, an auction is set up for the customer to select the set of suppliers along with the set of carriers. We refer to the auction mechanism as "RULE" in Figure 13.
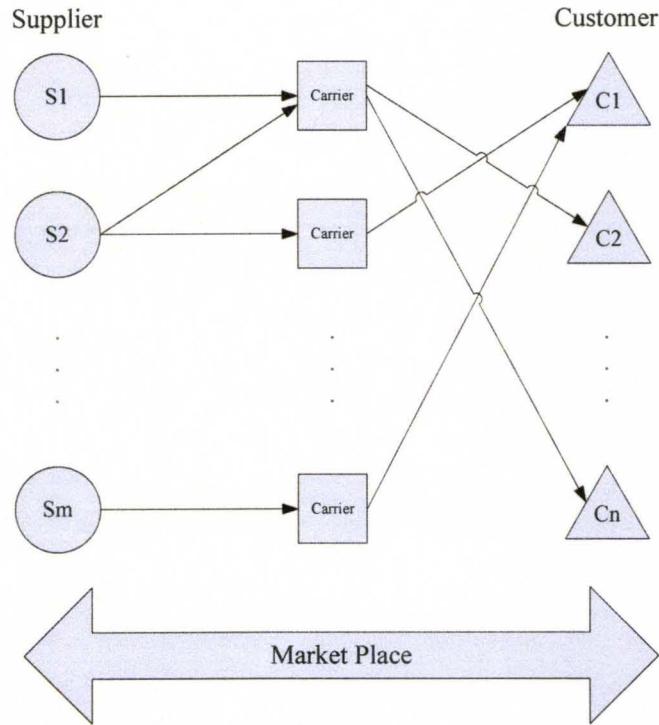
Figure 14: Agent-based simulation modeling framework.

5.2.3 Auction mechanism

Auctions are mechanisms for allocating goods. There are a large number of auction types. In the auction literature, there are typically three commonly used auction mechanisms: single-good auction, multi-unit auction and combinational auction. In the single-good auction, there is one good for sale, one seller and multiple buyers. Each buyer offers a different price to buy the goods based on his or her own evaluation of the goods, and the buyer wants to purchase the good at the lowest possible price. In the real world, sometimes there will be more than a single good to sell, and often different goods are purchased by different buyers. This type of auction is called a multi-unit auction. In particular, a multi-unit auction still considers only one good, but there are multiple identical copies of that good.

If we want to explore auction mechanisms more broadly, there is the combinational auction. In the combinational auction, there are a number of goods available on the market, and the buyers' valuations depend strongly on which set of goods they receive.

Since we consider one type of product but various quantities in our simulation setting, we employ the multi-unit auction mechanism. There are a variety of multi-unit auction mechanisms in the literature. Open-outcry and sealed-bid auctions are two major multi-unit auction types. Because in real-world operations, the production, inventory and shipping costs are not known by the customer (referred to as the buyer in an auction), we choose to apply sealed-bid auction in the agent-based simulation.

But before we discuss sealed-bid multi-unit auctions, let us first look at sealed-bid, single-good auctions. A sealed-bid auction is different from an open-outcry auction in a way that the bids are submitted to the seller as a secret sealed bid and not open to the public. In a sealed-bid single-good auction, the buyer with the highest bid must purchase the good, but the price at which he does so depends on the type of sealed-bid auction. For example, auction in which the winning buyer who pays an amount equal to his or her own bid is called first-price auction. The second-price auction is also called a Vickrey auction.

In our agent-based simulation model, we apply the sealed-bid multi-unit auction mechanism to select a set of suppliers along with the set of carriers. However, there are some issues when implementing the sealed-bid multi-unit auction. First of all, determining the payment rules becomes tricky. If there are three items for sale, and each

of the top three bids requests a single item, then each bid will win one item. In general, these bids will offer different payments; then the question is what each bidder should pay. Under the pay-your-bid rule, each of the top three bidders pays a different amount. This rule therefore generalizes the first-price auction. Under the uniform pricing rule, all winners pay the same amount; this is usually either the highest among the losing bids or the lowest among the winning bids. Another question is how to deal with the bid with a price offer for every number of items. If a bidder simply names one number of items and is unwilling to accept any fewer, we call it an all-or-nothing bid. If a bidder names one number of items but will accept any smaller number at the same price-per-unit, we call the bid divisible. Finally, the tie-breaking rule can also be tricky when bidders place all-or-nothing bids. For instance, consider an auction for 10 units in which the highest bids are as follows, all of them all-or-nothing: 5 units for $20/unit, 3 units for $15/unit and 5 units for $15/unit. There is no doubt that the first bid should be satisfied, but how to determine the tie-breaking rule can be done in various ways, such as by quantity (larger bids win over smaller ones) and by time (earlier bids win over later bids).

Therefore, we design new rules in the sealed-bid multi-unit auction for our particular problem setting by introducing three parameters: α, β and γ. Refer back to Figure 13. An auction occurs between one customer and a number of suppliers. There are three components in each bid: production (and inventory) cost X, available capacity Y and shipping cost Z. Production (and inventory) cost is calculated by the supplier. At the same time, the supplier needs to gather information about its available capacity (how many items he or she wishes to bid). Then the supplier checks with all carriers to choose one with the least shipping cost to transport this shipment. After that, the supplier submits

a bid containing the information about production (inventory) cost, available capacity and shipping cost to the customer who sets up the auction. For example, this is a typical bid (X, Y, Z) = ($10/item, 10 items, $1/item).

We assume all bids are divisible, which means that the supplier is willing to accept any smaller amounts compared to the total number of items he or she bids. However, the supplier charges an amount of penalty as the result of dividing his or her bid. This penalty is proportional to the number of items the supplier cannot supply, so we introduce α ($0 \leq \alpha \leq 1$) to d etermine the penalty. Supplier S is willing to bid for Y items (available capacity), but it only can be satisfied by P items, so the final bid is $\Big(X \times$ $\Big(1 + \frac{Y-P}{Y} \times \alpha\Big), P, Z \times \Big(1 + \frac{Y-P}{Y} \times \alpha\Big)\Big)$. In the previous example, the production (and inventory) cost is $10/item. If its bid can only be accepted by 3 items, then the final production (and inventory) cost is $10 \times (1+7/10 \times \alpha)$. Assume $\alpha=10\%$, the production and inventory cost will be $10.7/item.

The assumption of divisible bids may cause shipments from more than one single supplier, which in reality may increase the chance of shipping delay or mistaken order. In a competitive business environment, customer satisfaction/customer service level is critical to suppliers; therefore, we introduce another parameter β ($0 \leq \beta \leq 1$) to control the preference of the number of suppliers. In the ideal case, the winning supplier is the one with the least cost. At the same time, it also has sufficient capacity to provide the exact amount that the customer ordered. However, it might be necessary to consider divisible bids because (1) there is no single supplier who has sufficient capacity as in the placed order, or (2) ordering from more than one supplier might offer a cheaper price. In our

problem setting, we assume one single supplier is preferable to multiple suppliers if the cost is not significantly higher. In other words, if the cost difference of ordering from one supplier and ordering from multiple suppliers is within β, we prefer ordering from a single supplier. The control of parameter β depends on the weight assigned to customer satisfaction.

After each supplier submits a bid and the winning set of suppliers is chosen, the customer needs to decide whether or not to accept the bid. Each customer keeps the order history and knows the average price paid on each item or unit. The customer may want to accept a bid if the price is lower than or equal to the historical average price. If the bid is at a higher price than the historical average price, we assume the customer is still willing to accept the bid if the percentage difference is less than γ ($0 \leq \gamma \leq 1$). By introducing the parameter of γ, the customer is not required to accept a bid if the transaction cannot bring him or her an anticipated profit. Also, γ makes the market place fair and flexible, and adequately presents the degrees of freedom on the market.

With the control of these three parameters, our auction mechanism is more realistic and insightful in the selection of the set of suppliers and the set of carriers. In particular, these negotiation rules explicitly represent the local goals and the global goal. With the help of α, β and γ, each agent makes a better decision in a simple and fast manner, which is the key to realizing real-time decision making.

5.3 Numerical results

The agent-based simulation model is developed and validated in Microsoft Visual C# developing environment. Several problem sizes are tested. In order to maintain

consistency with the previous chapter and to solve industrial-sized problems, we use 7

suppliers, 8 customers and 16 carriers in the modeling setting (Table 8). The values of α

are set at 5%, 15% and 25%; the values of β and γ are set at 5%, 10% and 15%. We are

particularly interested in finding out how the parameters α, β and γ affect the decision

making. The results of three cases are provided in Tables 12, 13 and 14 (Option 1 is to

select one single supplier and Option 2 is to select multiple suppliers).

Table 12

Computational result of Case One

α	β	γ	Option	Total Cost
0.05	0.05	0.05	2	17.4
0.05	0.05	0.1	2	17.4
0.05	0.05	0.15	2	17.4
0.05	0.1	0.05	2	17.4
0.05	0.1	0.1	2	17.4
0.05	0.1	0.15	2	17.4
0.05	0.15	0.05	2	17.4
0.05	0.15	0.1	2	17.4
0.05	0.15	0.15	2	17.4
0.15	0.05	0.05	2	17.6
0.15	0.05	0.1	2	17.6
0.15	0.05	0.15	2	17.6
0.15	0.1	0.05	2	17.6
0.15	0.1	0.1	2	17.6
0.15	0.1	0.15	2	17.6
0.15	0.15	0.05	1	20.2
0.15	0.15	0.1	1	20.2
0.15	0.15	0.15	1	20.2
0.25	0.05	0.05	2	17.8
0.25	0.05	0.1	2	17.8
0.25	0.05	0.15	2	17.8
0.25	0.1	0.05	2	17.8
0.25	0.1	0.1	2	17.8
0.25	0.1	0.15	2	17.8

0.25	0.15	0.05	1	20.2
0.25	0.15	0.1	1	20.2
0.25	0.15	0.15	1	20.2

Table 13

Computational result of Case Two

α	β	γ	Option	Total Cost
0.05	0.05	0.05	2	9.1
0.05	0.05	0.1	2	9.1
0.05	0.05	0.15	2	9.1
0.05	0.1	0.05	2	9.1
0.05	0.1	0.1	2	9.1
0.05	0.1	0.15	2	9.1
0.05	0.15	0.05	2	9.1
0.05	0.15	0.1	2	9.1
0.05	0.15	0.15	2	9.1
0.15	0.05	0.05	2	9.3
0.15	0.05	0.1	2	9.3
0.15	0.05	0.15	2	9.3
0.15	0.1	0.05	2	9.3
0.15	0.1	0.1	2	9.3
0.15	0.1	0.15	2	9.3
0.15	0.15	0.05	1	10.5
0.15	0.15	0.1	1	10.5
0.15	0.15	0.15	1	10.5
0.25	0.05	0.05	2	9.5
0.25	0.05	0.1	2	9.5
0.25	0.05	0.15	2	9.5
0.25	0.1	0.05	2	9.5
0.25	0.1	0.1	2	9.5
0.25	0.1	0.15	2	9.5
0.25	0.15	0.05	1	10.5
0.25	0.15	0.1	1	10.5
0.25	0.15	0.15	1	10.5

Table 14

Computational result of Case Three

α	β	γ	Option	Total Cost
0.05	0.05	0.05	2	13.65
0.05	0.05	0.1	2	13.65
0.05	0.05	0.15	2	13.65
0.05	0.1	0.05	2	13.65
0.05	0.1	0.1	2	13.65
0.05	0.1	0.15	2	13.65
0.05	0.15	0.05	2	13.65
0.05	0.15	0.1	2	13.65
0.05	0.15	0.15	2	13.65
0.15	0.05	0.05	2	13.95
0.15	0.05	0.1	2	13.95
0.15	0.05	0.15	2	13.95
0.15	0.1	0.05	2	13.95
0.15	0.1	0.1	2	13.95
0.15	0.1	0.15	2	13.95
0.15	0.15	0.05	1	15.9
0.15	0.15	0.1	1	15.9
0.15	0.15	0.15	1	15.9
0.25	0.05	0.05	2	14.1
0.25	0.05	0.1	2	14.1
0.25	0.05	0.15	2	14.1
0.25	0.1	0.05	2	14.1
0.25	0.1	0.1	2	14.1
0.25	0.1	0.15	2	14.1
0.25	0.15	0.05	1	15.9
0.25	0.15	0.1	1	15.9
0.25	0.15	0.15	1	15.9

As shown in the tables and as expected, the combination of three parameters α, β and γ has an effect on the final solution in terms of the total cost. By assigning different values to the three parameters, the preference of the decision makers (third party logistics companies, suppliers, customers and so on) can be represented well.

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Before we examine the results of the three cases, a summary of assumptions and functions of three parameters α, β and γ are provided below:

(1) α is based on the assumption that each supplier is willing to accept any smaller amount compared to the total number of items he or she bids, but he or she charges a penalty.

(2) β represents the preference of ordering from one single supplier or ordering from multiple suppliers based on the cost difference.

(3) γ is assigned to ensure the customer has the flexibility to decide whether or not to accept a bid compared to his or her historical average cost.

For Case One, the relationship between each parameter and the total cost is illustrated in Figures 15, 16 and 17.

Figure 15: The relationship between α and the total cost in Case One.

Figure 16: The relationship between β and the total cost in Case One.

Figure 17: The relationship between γ and the total cost in Case One.

The highest total cost is $20.2 and the lowest total cost is $17.4. The difference is 13.86%.

For Case Two, the relationship between each parameter and the total cost is illustrated in Figures 18, 19 and 20.

Figure 18: The relationship between α and the total cost in Case Two.

Figure 19: The relationship between β and the total cost in Case Two.

Figure 20: The relationship between γ and the total cost in Case two.

The highest total cost is $10.5 and the lowest total cost is $9.1. The difference is 13.33%.

For Case Three, the relationship between each parameter and the total cost is illustrated in Figures 21, 22 and 23.
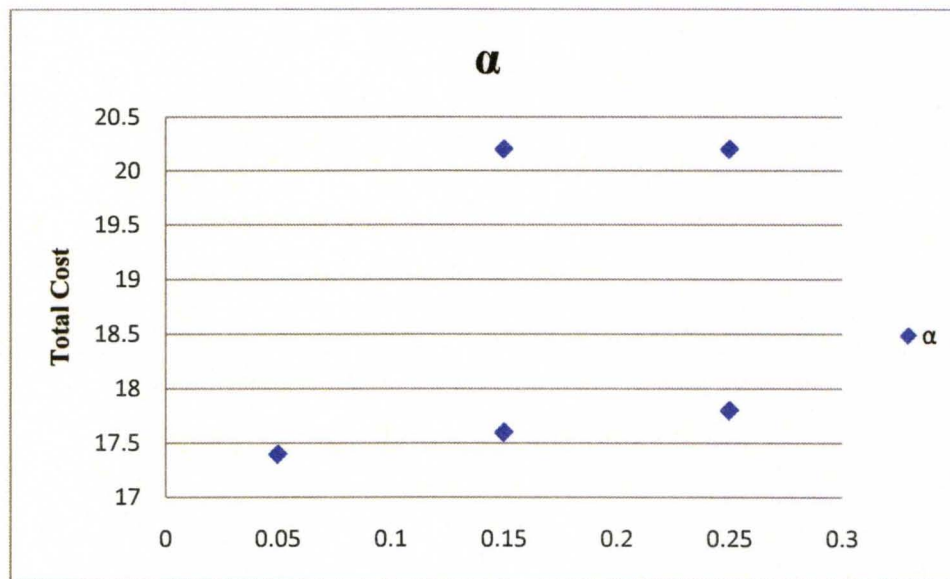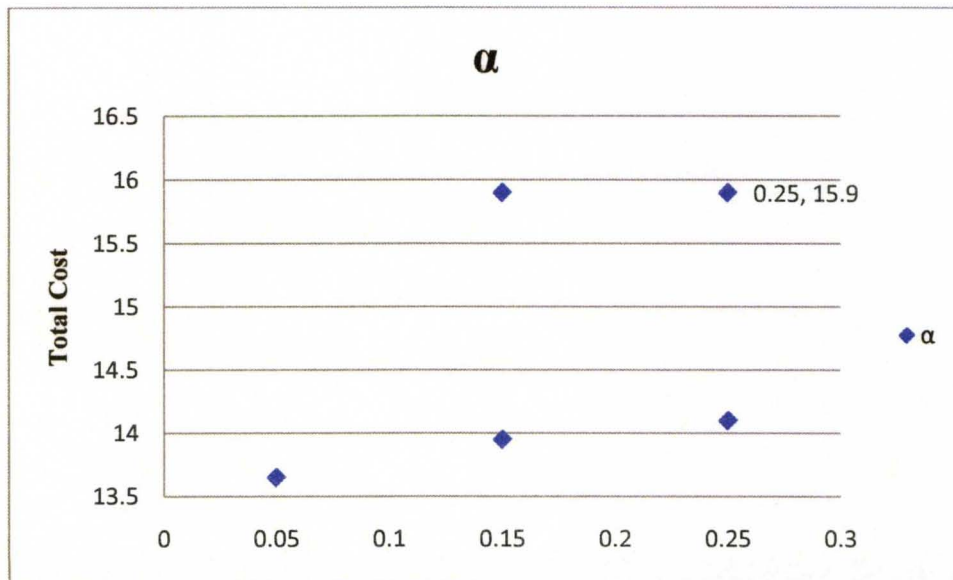
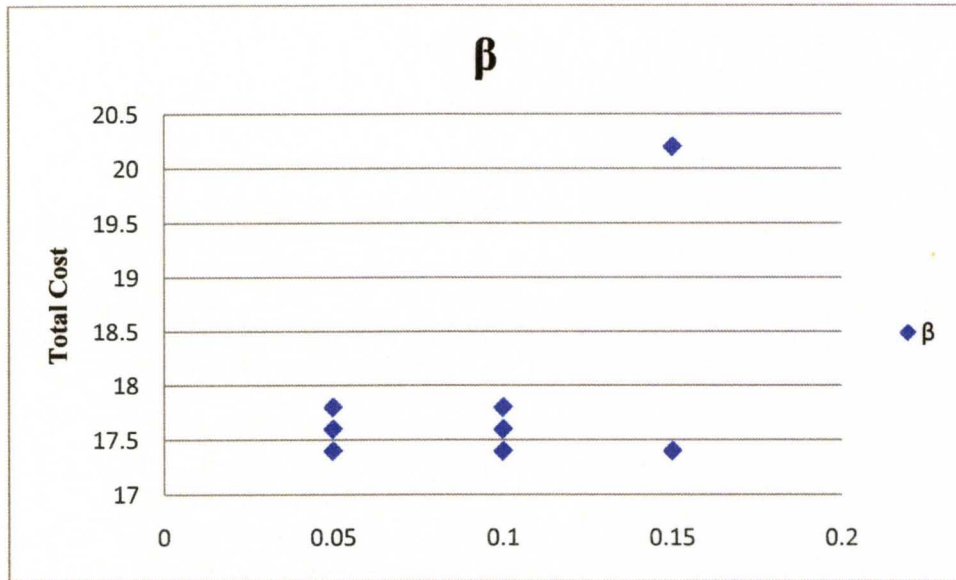Figure 21: The relationship between α and the total cost in Case Three.

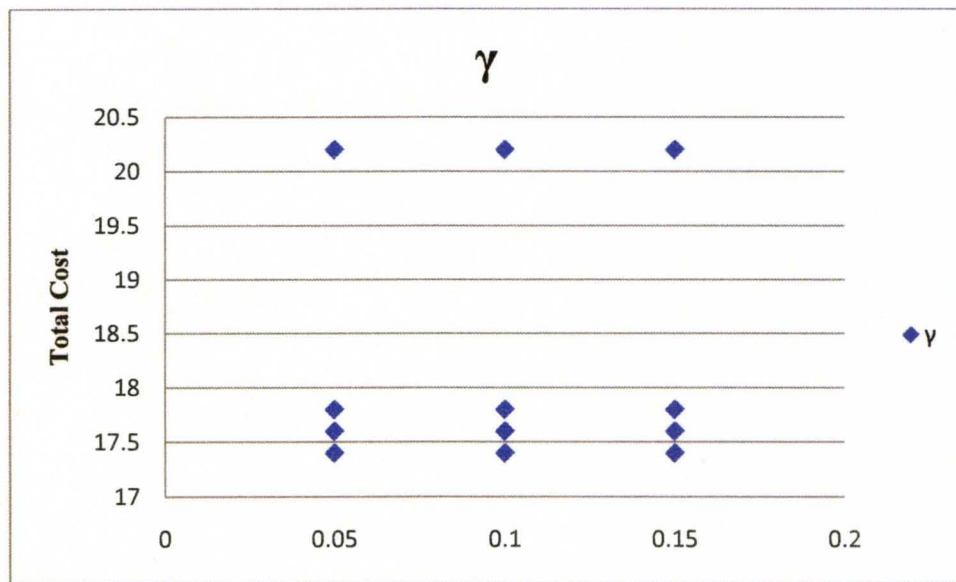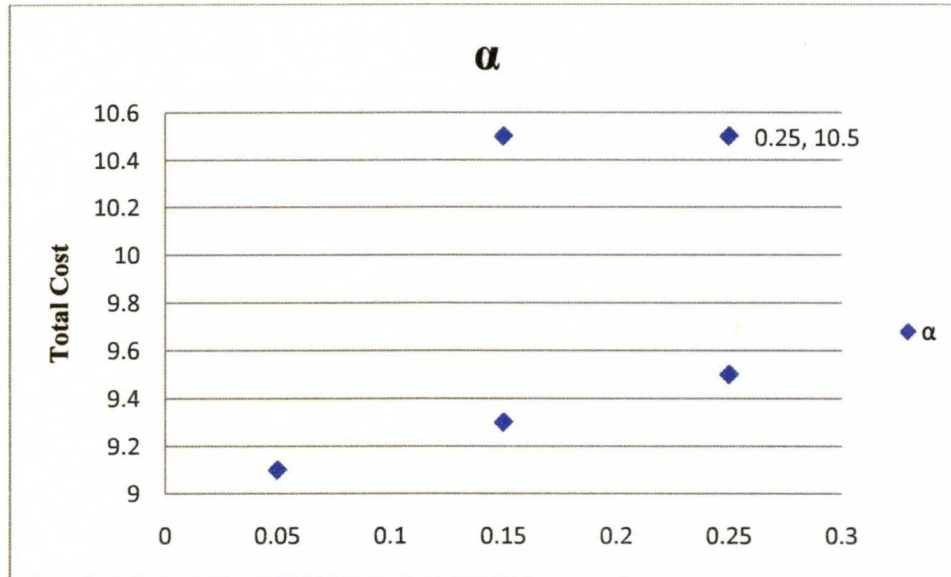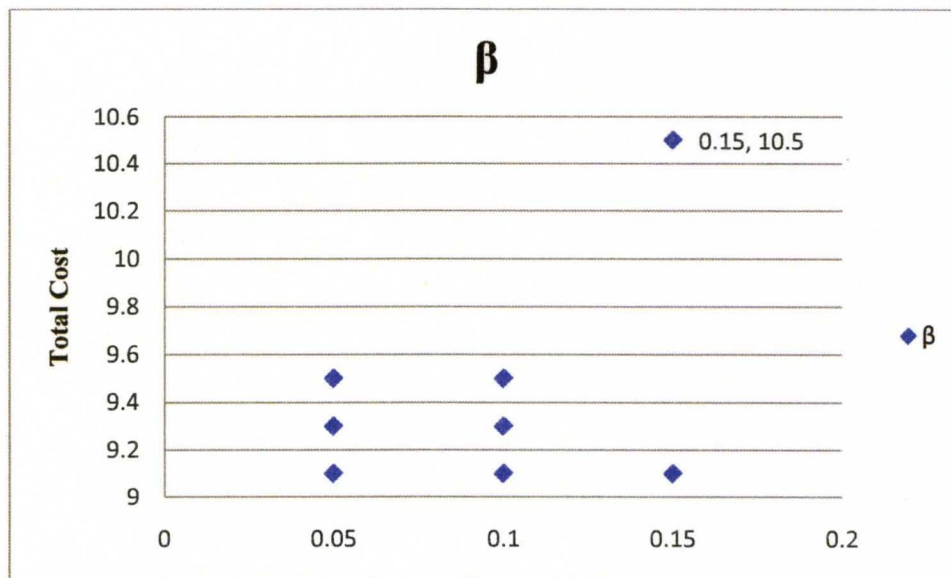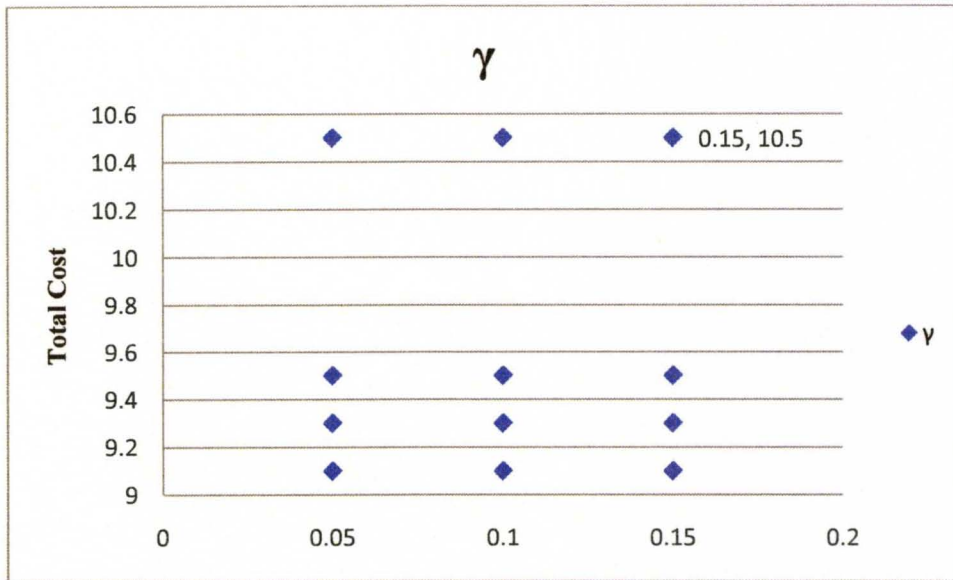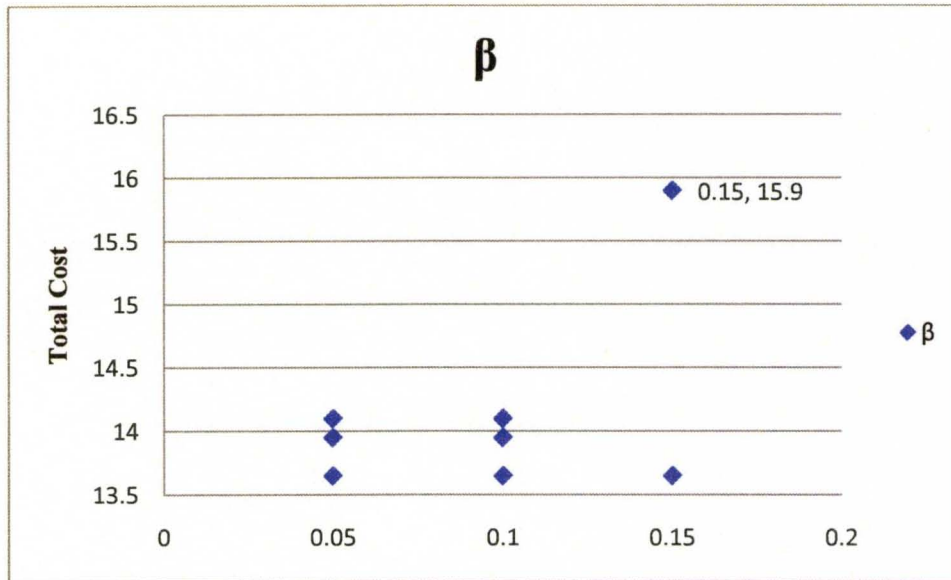Figure 22: The relationship between β and the total cost in Case Three.
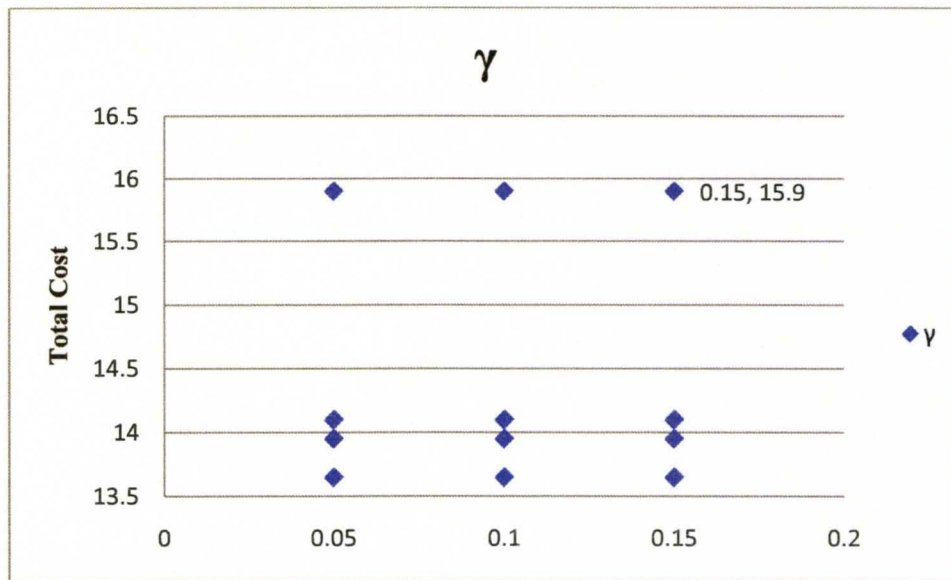
Figure 23: The relationship between γ and the total cost in Case Three.

The highest total cost is $15.9 and the lowest total cost is $13.65. The difference is 14.15%.

From Figures 15 to 23, we can conclude that (1) the different combinations of three parameters α, β and γ lead to different final solutions; (2) the lower the three parameters, the lower the total cost is; (3) the combination of the highest three values of three parameters gives the most expensive total cost; and (4) although different combination of three parameters provides different total cost, the difference between the highest and the lowest cost is within 13%-15%.

Based on the numerical results given by the agent-based simulation model, we can gain some insights on how to incorporate the dynamics seen in the real world and how to set up three parameters in order to react to these dynamics in a simple and fast way. The agent-based simulation model can be used to satisfy the needs of different decision makers, such as suppliers, third party logistics providers and customers. By setting up the values of three parameters α, β and γ, each decision maker is able to finalize its decision based on its own preference. The most important conclusion is that the whole process can be realized in real time.

CHAPTER 6

CONCLUSION AND FUTURE DIRECTION

Today's competitive business environment has resulted in increasing pressure for many companies in almost every industry. In such an environment, companies must fill customer orders, accurately, quickly and efficiently. At the same time, they must reduce inventory, implement reverse logistics and consider other important logistical factors. A company's supply chain constitutes several interactive processes, which are important to the integrated logistics system. In order to reduce costs for every single component of a supply chain, companies may have to redesign their supply chain network and consider every operation as part of a whole. After years of focusing on reduction in production and operation costs, companies are beginning to look into distribution activities as one of the last frontier for cost reduction.

In this dissertation, we developed a distribution optimization model by simultaneously considering production, inventory and distribution in an integrated fashion. Because outsourcing logistics functions to third party logistics providers is becoming critical for a company to remain competitive in the market place, we also include an important decision of selecting carriers with finite truckload and drivers for both inbound and outbound shipments in the model.

Due to the complexity of the model structure, commercial software fails to provide an optimal or near optimal solution to the problem. We propose to apply Benders decomposition as the solution methodology and test it on a number of problems. With the growth of variables and constraints in the test problems, Benders decomposition begins to present poor performance.

As a result, we keep following the general steps in Benders decomposition, but apply a genetic algorithm to solve the master problem instead of a branch-and-bound algorithm. Although this modified Benders decomposition can solve small-sized problems efficiently, it results in poor performance for larger size problems. We design another fitness function especially for large-sized problems for the genetic algorithm. Promising results are provided by this version of the modified Benders decomposition algorithm.

Several large-sized test problems are generated, all of which can be solved in an acceptable time. An industrial-sized problem (22 manufacturing plants, 7 distribution centers, 8 customer zones, 9 product types, 16 inbound-shipment carriers, 16 outbound-shipment carriers and 12 time periods-a total of 370,764 variables and 378,829 constraints) is also tested by the modified Benders decomposition with a run time less than 33 hours. For several test problems, the modified Benders decomposition has been demonstrated to perform well with the respect to both run time and solution quality. Moreover, it can be applied to solve real distribution problems in industry.

An agent-based simulation model is also developed to keep the good features of the optimization model and incorporate some dynamics in the real world. The agent-

based simulation approach appears to be a good decision support tool to reexamine the entire system in a new way. A multi-agent system contains a cluster of individual agents that interact with each other to solve a complex, system-wide problem. In recent years, multi-agent systems have been preferred to solve logistics and distribution problems, since these problems are autonomous, distributive, complex, heterogeneous and decentralized in nature and they require extensive intelligent decision making. Applying multi-agent system to solve complex problems, the coordination and cooperation among agents are required in order to find efficient solution to these problems.

The purpose of the agent-based simulation model we developed is to assist decision makers adjusting from optimal solutions given by the mathematical model. Each entity in the entire distribution network can be considered as an agent. For instance, there are supplier agents, carrier agents, customer agents and so on. In the agent-based simulation model, we set the initial condition to be the solution given by the optimization model. We also assign intelligent attributes to each agent, such as the ability to choose among competitive suppliers, to distribute orders preferentially among customers, to determine order frequency and cancellation. After building such a multi-agent system, it supports more flexible and comprehensive modeling capabilities that are difficult to realize in a general optimization model.

The agent-based simulation model gives us an insightful and thoughtful understanding of how to make a decision from different interest perspectives. In particular, we find that (1) different combinations of three parameters α, β and γ lead to different final solutions; (2) the lower the three parameters, the lower the total cost is; (3)

the combination of the highest three values of three parameters gives the most expensive total cost.

There are several directions we can explore in the future.

(1) Get feedback from real companies regarding the assumptions and constraints in the optimization model. There might be other important factors we need to consider and include in the optimization model.

(2) In order to continuously examine the performance of the proposed modified Benders decomposition algorithm, more test problems need to be generated and tested, especially on large-sized problems.

(3) A more sophisticated negotiation mechanism with game theory can be designed in the agent-based simulation model to assist in real-time decision making. Another extension of the dissertation is to incorporate adaptive learning in agent behaviors.

(4) Currently we focus on modeling a partial distribution problem using an agent-based approach. We can include other logistics function into the simulation model, such as production and inventory. We can also look at a multi-echelon distribution problem in multiple time periods.

(5) The agent-based simulation model can be evolved to a decision support tool with interface to let the decision makers choose the values of three parameters α, β and γ. Different decision makers may have different interests and preferences when making a decision, so this tool really makes the optimization and simulation models applicable.

(6) It would be helpful to obtain real data to test the application of our research findings. We could then apply the models on a real-world problem to demonstrate the effectiveness of this research.

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APPENDICES

1. LINGO code:

```
Data:
III=3;
JJJ=3;
KKK=2;
LLL=2;
MMM=2;
NNN=2;
Enddata

Sets:
Plant/1..III/;
DC/1..JJJ/;
Customer/1..KKK/;
Product/1..LLL/;
Inbound_Carrier/1..MMM/;
Outbound_Carrier/1..NNN/;
Period/1..12/;
!A=fixed production cost for product l at plant i in period t;
!B=variable cost for producing a unit of product l at plant i in period
t;
!C=inventory cost for carrying a unit of product l at plant i in period
t;
!H=production capacity for product l at plant i in period t;
!II=inventory capacity for product l at plant i in period t;
!z=1 if product l is produced at plant i in period t, =0 otherwise;
!P=amount of product l produced at plant i in period t;
!V=inventory level of product l at plant i in period t;
LinkILT(Plant, Product, Period): A,B,C,H,II,z,P,V;
!E=inventory cost for carrying a unit of product l in DC j in period t;
!JJ=inventory capacity for product l in DC j in period t;
!W=inventory level of product l in DC j in period t;
LinkJLT(DC, Product, Period): E,JJ,W;
!F=distribution cost for shipping a unit of product l from plant i to
DC j when using carrier m in period t;
!x=amount of product l shipped from plant i to DC j when using inbound
shipments carrier m in period t;
LinkIJLMT(Plant, DC, Product, Inbound_Carrier, Period): F,x;
!G=distribution cost for shipping a unit of product l from DC j to
customer k when using carrier n in period t;
!y=amount of product l shipped from DC j to customer k when using
outbound shipments carrier n in period t;
LinkJKLNT(DC, Customer, Product, Outbound_Carrier, Period): G,y;
!KK=upper bound of throughput capacity in DC j in period t;
!LL=lower bound of throughput capacity in DC j in period t;
LinkJT(DC, Period): KK,LL;
```

```
!MM=truckload capacity of inbound shipments carrier m in period t;
!O=driver capacity of inbound shipments carrier m in period t;
LinkMT(Inbound_Carrier, Period): MM,O;
!NN=truckload capacity of outbound shipments carrier n in period t;
!Q=driver capacity of outbound shipments carrier n in period t;
LinkNT(Outbound_Carrier, Period): NN,Q;
!D=demand for product l at customer k in period t;
!Beta=shipping requirement of customer k for product l in period t;
LinkKLT(Customer, Product, Period): D,Beta;
!R=average truck load for a standard vehicle shipping product l for
inbound shipments carrier m in period t;
!TT=average trips a driver of inbound shipments carrier m can make for
product l in period t;
LinkLMT(Product, Inbound_Carrier, Period): R,TT;
!S=average truck load for a standard vehicle shipping product l for
outbound shipments carrier n in period t;
!U=average trips a driver of outbound shipments carrier n can make for
product l in period t;
LinkLNT(Product, Outbound_Carrier, Period): S,U;
!V0=starting inventory level for product l at plant i;
LinkIL(Plant, Product): V0;
!W0=starting inventory level for product l in DC j;
LinkJL(DC, Product): W0;
Endsets
```

```
Data:
A=@OLE('V2.XLS','A');
B=@OLE('V2.XLS','B');
C=@OLE('V2.XLS','CC');
E=@OLE('V2.XLS','E');
F=@OLE('V2.XLS','F');
G=@OLE('V2.XLS','G');
H=@OLE('V2.XLS','H');
II=@OLE('V2.XLS','I');
JJ=@OLE('V2.XLS','J');
KK=@OLE('V2.XLS','K');
LL=@OLE('V2.XLS','L');
MM=@OLE('V2.XLS','M');
NN=@OLE('V2.XLS','N');
O=@OLE('V2.XLS','O');
Q=@OLE('V2.XLS','Q');
D=@OLE('V2.XLS','D');
R=@OLE('V2.XLS','RR');
S=@OLE('V2.XLS','S');
TT=@OLE('V2.XLS','T');
U=@OLE('V2.XLS','U');
Beta=@OLE('V2.XLS','Beta');
V0=@OLE('V2.XLS','V0');
W0=@OLE('V2.XLS','W0');
@OLE('V2.XLS','x')=x;
@OLE('V2.XLS','y')=y;
@OLE('V2.XLS','z')=z;
@OLE('V2.XLS','P')=P;
@OLE('V2.XLS','V')=V;
@OLE('V2.XLS','W')=W;
Enddata

!Objective function: minimize total production, inventory and
distribution costs;
MIN=@SUM(LinkILT(i,l,t):A(i,l,t)*z(i,l,t))+@SUM(LinkILT(i,l,t):B(i,l,t)
*P(i,l,t))
      +@SUM(LinkILT(i,l,t):C(i,l,t)*V(i,l,t))+@SUM(LinkJLT(j,l,t):E(j,l
,t)*W(j,l,t))
      +@SUM(LinkIJLMT(i,j,l,m,t):F(i,j,l,m,t)*x(i,j,l,m,t))+@SUM(LinkJK
LNT(j,k,l,n,t):G(j,k,l,n,t)*y(j,k,l,n,t));

!Constraints;
!(1) meet the demand for product l at customer k in period t;
@FOR(LinkKLT(k,l,t):
      @SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t))>=D(k,l,t)
      );
!(2) production capacity for product l at plant i in period t;
@FOR(LinkILT(i,l,t):P(i,l,t)<=H(i,l,t)*z(i,l,t));
!(3) inventory level for product l at plant i in period t;
@FOR(LinkILT(i,l,t)|t #EQ# 1: P(i,l,t)+V0(i,l)-
V(i,l,t)=@SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t)));
@FOR(LinkILT(i,l,t)|t #GE# 2: P(i,l,t)+V(i,l,t-1)-
V(i,l,t)=@SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t)));
!(4) inventory level for product l at DC j in period t;
@FOR(LinkJLT(j,l,t)|t #EQ# 1:
      @SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t))+W0(j,l)-
@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t)*Beta(k,l,t))=W(j,l,t)
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        );
@FOR(LinkJLT(j,l,t)|t #GE# 2:
        @SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t))+W(j,l,t-1)-
@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t)*Beta(k,l,t))=W(j,l,t)
        );
!(5) lower and upper bound of throughput in DC j in period t;
@FOR(LinkJT(j,t):LL(j,t)<=@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t)));
@FOR(LinkJT(j,t):KK(j,t)>=@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t)));
!(6) inventory level for product l at plant i in period t;
@FOR(LinkILT(i,l,t):V(i,l,t)<=II(i,l,t));
!(7) inventory level for product l in DC j in period t;
@FOR(LinkJLT(j,l,t):W(j,l,t)<=JJ(j,l,t));
!(8) truckload capacity for inbound shipments carrier m in period t;
@FOR(LinkMT(m,t):@SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t))<=MM(m,t));
!(9) truckload capacity for outbound shipments carrier n in period t;
@FOR(LinkNT(n,t):@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t))<=NN(n,t));
!(10) driver capacity for inbound shipments carrier m in period t;
@FOR(LinkMT(m,t):@SUM(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t))/@SUM(Product(l
):R(l,m,t))<=@SUM(Product(l):TT(l,m,t))*O(m,t));
!(11) driver capacity for outbound shipments carrier n in period t;
@FOR(LinkNT(n,t):@SUM(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t))/@SUM(Product(l
):S(l,n,t))<=@SUM(Product(l):U(l,n,t))*Q(n,t));
!(12) other constraints;
@FOR(LinkIJLMT(i,j,l,m,t):x(i,j,l,m,t)>=0);
@FOR(LinkJKLNT(j,k,l,n,t):y(j,k,l,n,t)>=0);
@FOR(LinkILT(i,l,t):@BIN(z(i,l,t)));
@FOR(LinkILT(i,l,t):P(i,l,t)>=0);
@FOR(LinkILT(i,l,t):V(i,l,t)>=0);
@FOR(LinkJLT(j,l,t):W(j,l,t)>=0);

!@FOR(LinkILT(i,l,t):z(i,l,t)>=0);
!@FOR(LinkILT(i,l,t):z(i,l,t)<=1);

@FOR(LinkIJLMT(i,j,l,m,t):@GIN(x(i,j,l,m,t)));
@FOR(LinkJKLNT(j,k,l,n,t):@GIN(y(j,k,l,n,t)));
@FOR(LinkILT(i,l,t):@GIN(P(i,l,t)));
@FOR(LinkILT(i,l,t):@GIN(V(i,l,t)));
@FOR(LinkJLT(j,l,t):@GIN(W(j,l,t)));
```

2. Input of Problem No. 1

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S	T	U	V0	W0	Beta
50	1	1	10	3	8	4	0	8	0	100	20	112	145	45	19	5	2	10	20	20	30	1
60	2	2	20	2	9	2	120	14	40	136	10	24	150	56	60	5	3	23	15	10	45	1
40	3	2	20	1	2	5	230	12	40	100	5	90	195	25	42	5	5	25	15		6	2
50	1	3	40	3	3	7	50	4	30	27	5	116	185	56	50	5	6	12	15		8	2
			30	1	3	8			64							5	3	20	15			1
			2	2	4	8			68							5	4	20	20			1
			0	3	4	8			10							5	7	15	20			3
			0	1	2	3			10							5	8	15	20			4
					5	2																
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						6																
						7																

CURRICULUM VITAE

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Education

Ph.D. Department of Industrial Engineering, University of Louisville, Louisville, KY, 2007-2010

- Dissertation: Real-Time Optimization of an Integrated Production-Inventory-Distribution Problem
- Advisors:
  Sunderesh S. Heragu and Gerald W. Evans, Department of Industrial Engineering, University of Louisville
- Committee members:
  Suraj M. Alexander and John S. Usher, Department of Industrial Engineering, University of Louisville
  Richard N. Germain, Department of Marketing, University of Louisville

M.S. Department of Industrial Engineering, University of Louisville, Louisville, KY, 2006-2007

- Thesis: Optimal Allocation of Trucking Workload at GE Consumer and Industrial
- Committee: Gerald W. Evans (co-chair), Richard N. Germain, Sunderesh S. Heragu (co-chair)

B.S. Department of Traffic and Transportation, Beijing Jiaotong University, Beijing, China, 2002- 2006

Research Experience

Research Assistant Logistics and Distribution Institute (LoDI), University of Louisville, Louisville, KY, 2006-Present

- Creating a Sustainable Aluminum Industry Through Transportation Efficiencies, $50,000, September 2007-September 2008, Center for Sustainable Aluminum Industry (CSAI–A Sloan Foundation Center), principal investigator: Richard N. Germain
- Analysis of Trucking Strategies at General Electric, $50,000, September 2006-Janunary 2008, General Electric Corporation, principal investigators: Sunderesh S. Heragu and Gerald W. Evans

Undergraduate Department of Traffic and Transportation, Beijing Jiaotong University, Beijing, Research Student China, 2005-2006

- Strategic Planning for Beijing Daxing Distribution Parks

Teaching Experience

IE 360: Probability and Statistics for Engineers (taught undergraduate students, Summer 2010)

IE 525: Project Management (taught graduate students, Spring 2010)

IE 370: Engineering Economic Analysis (instructor, Fall 2009)

IE 657: Models for Design and Analysis of Logistical Systems

- Taught graduate students four lectures both in the classroom and laboratory, Spring 2009
- Taught laboratory lecture to graduate students, Spring 2008

IE 421: Facility Location and Layout (taught laboratory lecture to senior undergraduate students, Fall 2008)

Publications

Yang, X. and Moghaddam, K.S. 2010. Design and Analysis of a Multi-Product Assembly Line. *Proceedings of 2010 Decision Sciences Institute Annual Meeting*, San Diego, CA, USA.

Lu, Y., **Yang, X.** and Peng, Z. 2010. An Agent-Based Simulation Application on a Multi-Agent Firefighting and Rescue System. *Proceedings of the 8th International Supply Chain Management and Information Systems Conference*, Hong Kong, China, 6-8 October.

Yang, X. and Moghaddam, K.S. 2010. Applications of Multi-Objective Programming in Supply Chain Management. *IMA Journal of Management Mathematics* (under review).

Lu, Y. and **Yang, X.** 2010. An Agent-Based Approach to Study the Relationship between the Distribution of Authority and Team Performance. *Current Topics in Management* (under review).

Yang, X., Evans, G.W., and Heragu, S.S. 2009. Integrated Production-Inventory-Distribution Optimization in a Multi-Echelon, Multi-Product, Multi-Carrier, Multi-Period System. *International Journal of Value Chain Management* 4(3), pp. 267-287.

Yang, X., Heragu, S.S., and Evans, G.W. 2009. The Way to Real-Time Optimization: A Preliminary Study on an Integrated Distribution Problem. *Proceedings of the International Conference on Value Chain Sustainability*. Louisville, KY, USA, 19-21 October.

Yang, X., Evans, G.W., and Heragu, S.S. 2009. A Review of Models and Algorithms for Distribution Problems in Logistics and Supply Chain Research. *European Journal of Operational Research* (under review).

Yang, X., Heragu, S.S., and Evans, G.W. 2009. The General Electric Company Uses Linear Programming to Allocates Funds to Trucking Companies. *Interfaces* (under review).

Yang, X., Evans, G.W., and Heragu, S.S. 2008. Integrated Production-Inventory-Distribution Optimization in a Multi-Echelon, Multi-Carrier System. *Proceedings of the 6th International Supply Chain Management and Information Systems Conference*, Tiruchirappalli, India, 8-10 December.

Yang, X., Evans, G.W., and Heragu, S.S. 2007. Analysis of Trucking Strategies at a Major Consumer Goods Manufacturer and Distributor. *Proceedings of the 5th International Supply Chain Management and Information Systems Conference*, Melbourne, Australia, 9-12 December.

Yang, X. and Xiong, Y. 2005. Global Supply Chain Management Influence on the Transformation of Business Pattern. *China Science and Technology Information* 22(1), pp. 37.

Conference Abstracts and Presentations

Yang, X., Heragu, S.S., and Evans, G.W. How to Select Your Suppliers? An Agent-Based Simulation Application. INFORMS Annual Meeting, Austin, TX, November 7-10, 2010.

Yang, X. Real-time Optimization of an Outbound Distribution Problem. The Fourth Annual University of Kentucky Graduate Student Interdisciplinary Conference, Lexington, KY, April 9, 2010.

Yang, X. Optimal Allocation of Truckload Capacity at a Large Consumer and Industrial Company. American Society for Quality (ASQ) Section 912 Monthly Meeting, Louisville, KY, April 8, 2010.

Yang, X. Real-time Optimization in an Integrated Distribution Problem. The Second Annual Graduate Research Symposium, Louisville, KY, March 5, 2010.

Lu, Y. and **Yang, X.** A Nonlinear Relationship between the Distribution of Authority and Team Performance: an Agent-Based Simulation Model for Firefighting and Rescue Artificial Team. Winter Simulation Conference, Austin, TX, December 13-16, 2009.

Yang, X. The Thoughtful and Effective Classroom. INFORMS Annual Meeting, San Diego, CA, October 11-14, 2009.

Yang, X., Heragu, S.S., and Evans, G.W. Real-Time Optimization in a Multi-Echelon, Multi-Product, Multi-Carrier, Multi-Period System. INFORMS Annual Meeting, San Diego, CA, October 11-14, 2009.

Yang, X., Heragu, S.S., and Evans, G.W. Solution of a Complex, Integrated Production, Inventory and Distribution Model. IIE Annual Conference and EXPO, Miami, FL, May 30-June 3, 2009.

Yang, X., Evans, G.W., and Heragu, S.S. Using Spreadsheet to Optimize Transportation Problem in a Large Consumer and Industrial Company. INFORMS Annual Meeting, Washington, DC, October 12-15, 2008.

Yang, X., Evans, G.W., and Heragu, S.S. A Review of Integrated Optimization-Simulation Approaches to Solve Distribution Problems. INFORMS Annual Meeting, Washington, DC, October 12-15, 2008.

Yang, X., Evans, G.W., and Heragu, S.S. Allocation of Trucking Requirements to Carriers. INFORMS Annual Meeting, Seattle, WA, November 4-7, 2007.

Selected Poster Presentations

- Engineering EXPO, University of Louisville, Louisville, KY, March 6, 2010.
- Engineering EXPO, University of Louisville, Louisville, KY, March 7, 2009.
- Logistics and Distribution Institute Fall Reception, Louisville, KY, November 20, 2008.
- Speed School Homecoming Reunions and Awards Dinner, Louisville, KY, October 17, 2008.
- The 14th Annual Kentucky Experimental Program to Stimulate Competitive Research Conference: Cyberinfrastructure–Connecting with the Future, Louisville, KY, October 3, 2008.
- Engineering EXPO, University of Louisville, Louisville, KY, March 1, 2008.
- Logistics and Distribution Institute Fall Reception, Louisville, KY, November 16, 2007.

Honors and Awards

- National Science Foundation (NSF) Student Travel Grant for NSF Civil, Mechanical and Manufacturing Innovation Grantees and Research Conference, Honolulu, HI, June 2009
- University of Louisville Graduate Student Council Travel Award for IIE Annual Conference and EXPO, Miami, FL, May 2009
- National Science Foundation Student Travel Grant for INFORMS Southwest Regional Conference, College Station, TX, April 2008
- Outstanding Student Leader with Dean's Honor, Beijing, China, April 2005
- Gold Award for China Open Volunteer, Beijing, China, October 2004
- Best Service Award for China Open Volunteer, Beijing, China, October 2004
- Excellent Student Award, Beijing, China, September 2004
- Outstanding Student Leader with Dean's Honor, Beijing, China, June 2004

Scholarships and Fellowships

- American Society for Quality (ASQ) Section 912 Scholarship, Louisville, KY, USA, April 2010
- Scholarship from Greater Louisville Logistics Network, Louisville, KY, USA, October 2008
- Fellowship from Logistics and Distribution Institute of University of Louisville, Louisville, KY, USA, August 2006-May 2010
- Scholarship from Beijing Jiaotong University, Beijing, China, September 2005, December 2004

Professional Memberships

- Academy of Management (AOM)
- Advancing Productivity, Innovation, and Competitive Success (APICS)
- American Society of Transportation and Logistics (ASTL)
- Decision Sciences Institute (DSI)
- European Operations Management Association (EurOMA)
- Institute for Operations Research and the Management Sciences (INFORMS)
- Institute of Industrial Engineers (IIE)
- Production and Operations Management Society (POMS)
- Society of Women Engineers (SWE)

Professional Service

Reviewer	The 44th Hawaiian International Conference on System Sciences, Koloa, Kauai, HI, 2010
Reviewer	The 6th Annual IEEE Conference on Automation Science and Engineering, Toronto, Canada, 2010
Judge	Engineering EXPO at the University of Louisville, Louisville, KY, 2010
Reviewer	Journal of Manufacturing Systems, 2009
Reviewer	The 5th Annual IEEE Conference on Automation Science and Engineering, Bangalore, India, 2009
Reviewer	The 39th International Conference on Computers and Industrial Engineering, Troyes, France, 2009
Reviewer	The 43rd Hawaiian International Conference on System Sciences, Koloa, Kauai, HI, 2009
Reviewer	The 17th European Conference on Information Systems, Verona, Italy, 2009

President	INFORMS Student Chapter of the University of Louisville, Louisville, KY, 2009
Vice President	INFORMS Student Chapter of the University of Louisville, Louisville. KY, 2008
Secretary	INFORMS Student Chapter of the University of Louisville, Louisville, KY, 2007
Co-Founder	Youth Volunteer Organization of Beijing Jiaotong University, Beijing, China, 2004
Volunteer	The Ancient Bell Museum in Dazhong Temple, Beijing, China, 2002-2006

Other Professional Development

- AOM Operations Management (OM) Division Doctoral Consortium, Chicago, IL, 2009
- Future Faculty Program, University of Louisville, Louisville, KY, 2008
- INFORMS Future Academician Colloquium, Washington, DC, 2008
- Intensive English as a Second Language Program Certification, University of Louisville, Louisville, KY, 2008
- Completion of ELFH 683-75 College Teaching, University of Louisville, Louisville, KY, 2008
- Who's Who in LoDI, Graduate Research Assistant Spotlight, Logistics and Distribution Institute Newsletter, Louisville, KY, 2008
- ESRI Certificate of Introduction to ArcGIS I, University of Louisville, Louisville, KY, 2007

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