REAL-TIME OPTIMIZATION OF A SUPPLIER AND CARRIER SELECTION PROBLEM – AN AGENT-BASED SIMULATION APPROACH

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ABSTRACT

Supplier/carrier selection is a critical issue faced by many companies in today's competitive business environment. In this paper, we apply an agent-based simulation approach combined with an auction mechanism to address a supplier/carrier selection problem. We set the initial condition of the simulation model as the optimal solution given by an optimization model and incorporate any dynamic changes occurring in the actual execution. By introducing three parameters in the design of the auction mechanism, the agent-based simulation model can find a solution in real time, while the optimization model may take up to 32 hours to solve an industrial-sized problem.

Keywords: real-time optimization, agent-based simulation, supplier selection, carrier selection, auction, distribution, supply chain

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.

Complex 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 supply, demand and transportation costs are known with certainty. Today's 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 in a distribution system are highly interrelated. 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 distribution system 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 the distribution process, supplier and carrier selection is very critical to the overall performance of the distribution. Supplier/carrier selection is part of the decision-making process in the distribution that includes choosing the suppliers/carriers, negotiating shipping costs and service levels, and evaluating supplier/carrier performance. An important trend in distribution problems 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 distribution 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 paper, we apply an agent-based simulation approach to model a supplier/carrier selection problem with the initial condition set as an optimal solution (given by an optimization model presented in Yang et al., 2010). 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 rest of the paper is organized as follows. A problem statement is contained in Section 2. A brief review of agent-based simulation methodology in distribution and supply chain management is presented in Section 3. In Section 4, we discuss simulation model development, which includes model assumptions, agents, multi-agent systems, modeling framework, and auction mechanism. Computational results are discussed in Section 5. Conclusions are drawn in Section 6.

2. Problem Statement

We focus our study on the execution phase of the integrated production, inventory and distribution problem proposed by Yang et al. (2010). 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.

We mainly consider the distribution from distribution centers (referred to as suppliers) to customers (Figure 1). 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 that 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 (Yang et al., 2010). We model this partial problem using an agent-based simulation approach to incorporate some dynamics that we may encounter in the real operation.

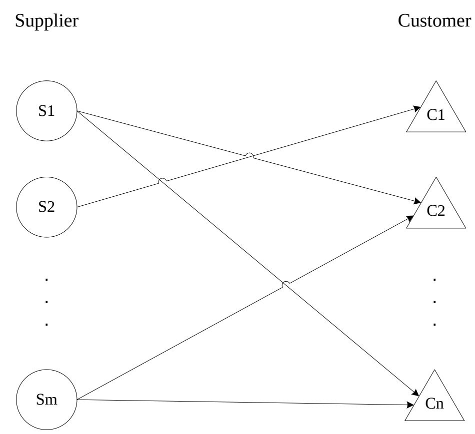

Figure 1: A typical distribution network with *m* suppliers and *n* customers.

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 (Yang et al., 2010). 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 (it takes approximately 32 hours to solve an industrial-sized problem). 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 distribution system. 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 demand 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 simulation approach to determine how to modify the initial plan so it can quickly react to the dynamic changes. Specifically, we model each type of entity in the distribution system 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 problem, 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 example, 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 that 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. Additional details are provided in the flowchart (Figure 2). The auction mechanism (called "RULE") will be explained in the section of Model Development.

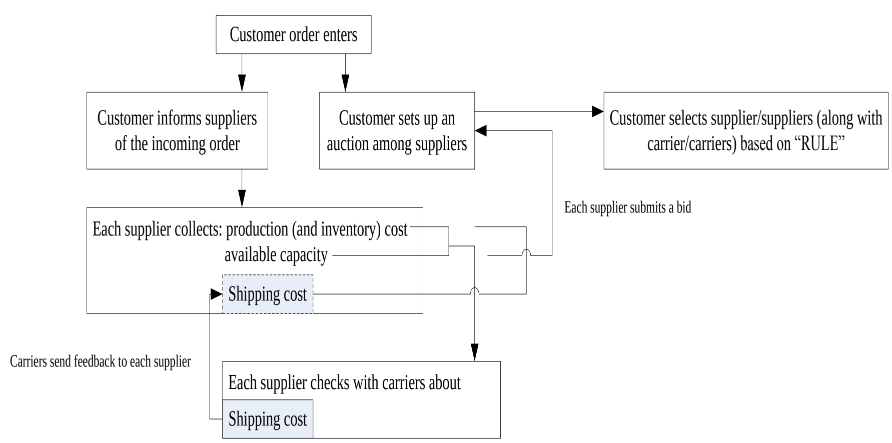

Figure 2: A detailed flowchart of the selection of supplier(s) and carrier(s).

3. Agent-Based Simulation Methodology in Distribution and Supply Chain Management

3.1 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 distribution process is critical to modeling the system. Simulation based on intelligent agent methodology provides knowledge to support concurrent and distributed decision making. Modeling the distribution system within a supply chain 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)."

> "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)."

3.2 Multi-Agent System (MAS)

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), an MAS is a group of agents that cooperate with each other to fulfill common and individual goals, also agents may compete in some environments. An 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 an efficient solution to these problems.

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).

3.3 Agent-Based Simulation and its Applications

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.

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 that 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 that can interact with each other in sophisticated ways.

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 that 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 to 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 an 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 for the best set of values 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 the ANN provides a good inventory policy for the agents and the supply chain performance and behavior can be precisely estimated.

4. Model Development

In this section, we 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.

4.1 Model Assumptions

As described in Section 2, we consider three types of entities in this model: 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 presented by Yang et al. (2010). We assume the good features of the initial planning (optimal/near optimal solution) will be kept, and we only need to respond to the changes in customer demand. The model assumes that 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.

4.2 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 one of 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 of 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" (see Figure 3). 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 of 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 present additional details in the Subsection 4.3 Auction Mechanism. 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 2.

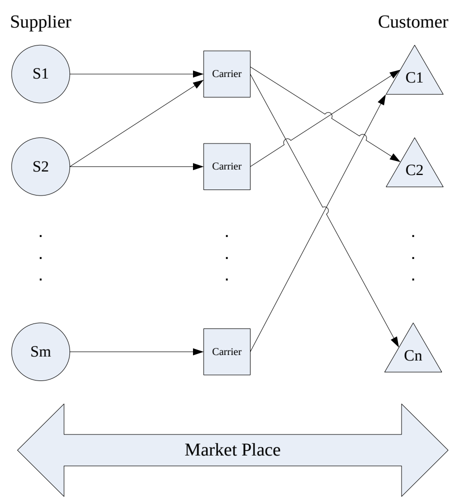

Figure 3: Agent-based simulation modeling framework.

4.3 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 a 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, an auction in which the winning buyer who pays an amount equal to his or her own bid is called a 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 2. 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 ($0 \le \alpha \le 1$) to determine 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 $\left(X \times \left(1 + \frac{Y-P}{Y} \times \alpha\right), P, Z \times \left(1 + \frac{Y-P}{Y} \times \alpha\right)\right)$. 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 × (1+7/10×α). Assume α=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 ($0 \le \beta \le 1$) 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 ($0 \le \gamma \le 1$). By introducing the parameter of γ, the customer is not required to accept a bid if the transaction cannot bring him/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. Results and Discussion

The agent-based simulation model is developed and validated in Microsoft Visual C# development environment. Several problem sizes are tested. In order to maintain consistency with the previous paper (Yang et al., 2010) and to solve industrial-sized problems, we use 7 suppliers, 8 customers and 16 carriers in the modeling setting. 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 process. The results of three cases are provided in Tables 1, 2 and 3 (in the tables, Option 1 is to select one single supplier and Option 2 is to select multiple suppliers).

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 1: Computational result of Case One.

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 2: Computational result of Case Two.

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

Table 3: Computational result of Case Three.

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.

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 4, 5 and 6.

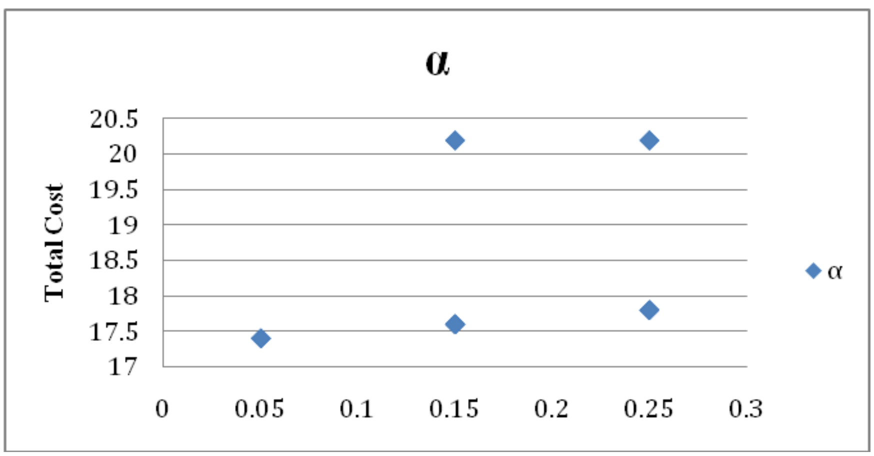

Figure 4: The relationship between α and the total cost in Case One.

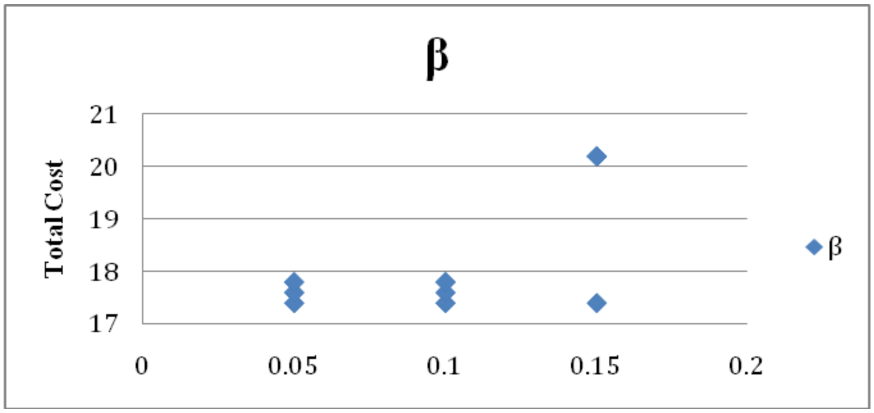

Figure 5: The relationship between β and the total cost in Case One.

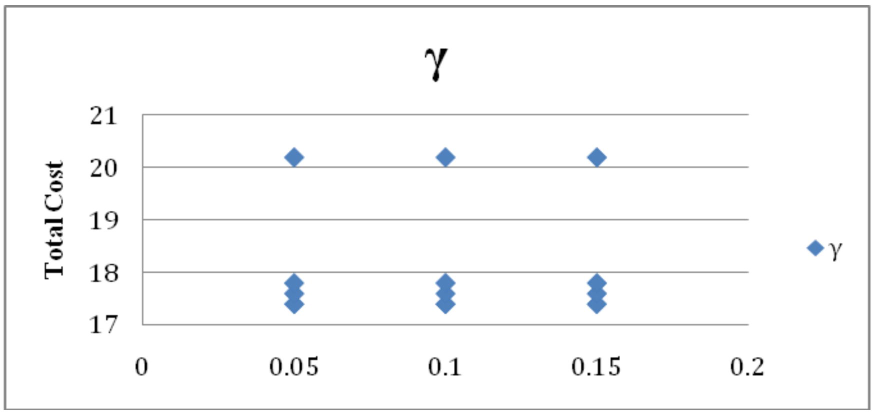

Figure 6: The relationship between γ and the total cost in Case One.

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 7, 8 and 9.

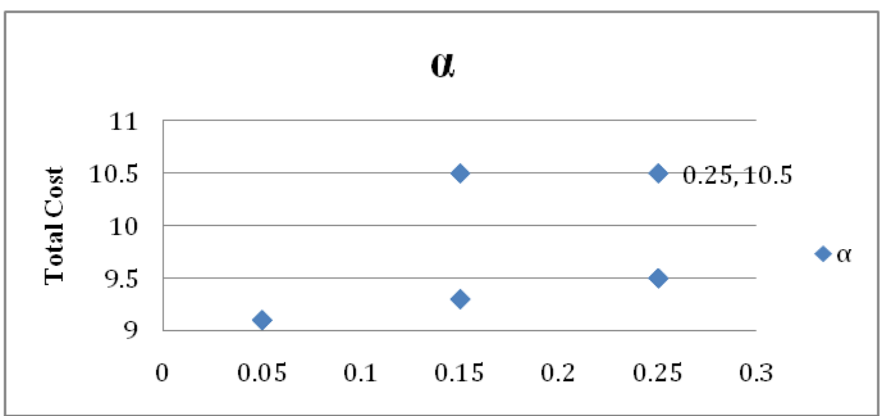

Figure 7: The relationship between α and the total cost in Case Two.

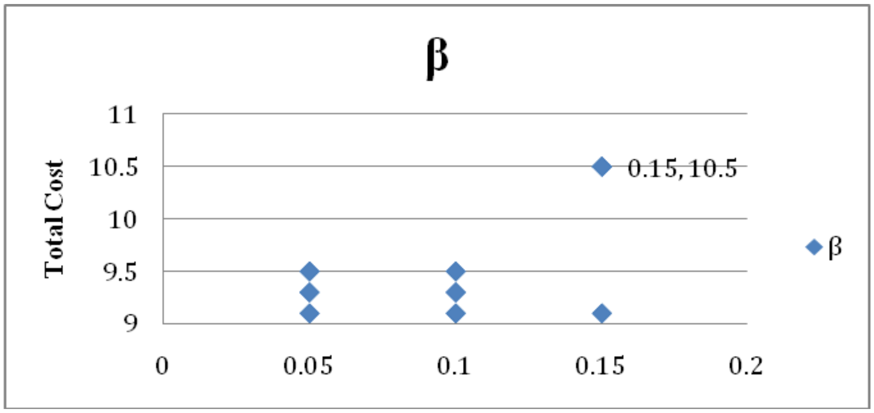

Figure 8: The relationship between β and the total cost in Case Two.

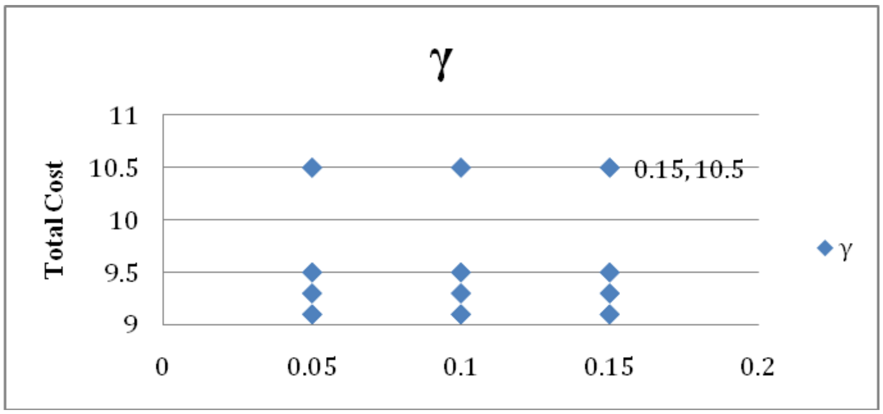

Figure 9: The relationship between γ and the total cost in Case two.

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 10, 11 and 12.

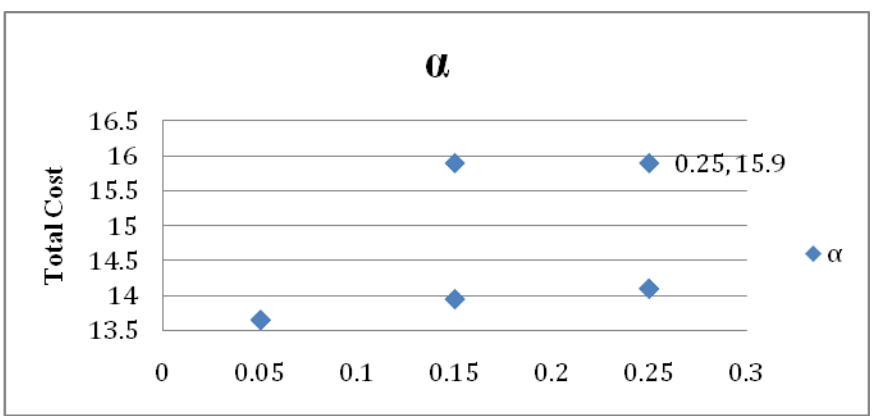

Figure 10: The relationship between α and the total cost in Case Three.

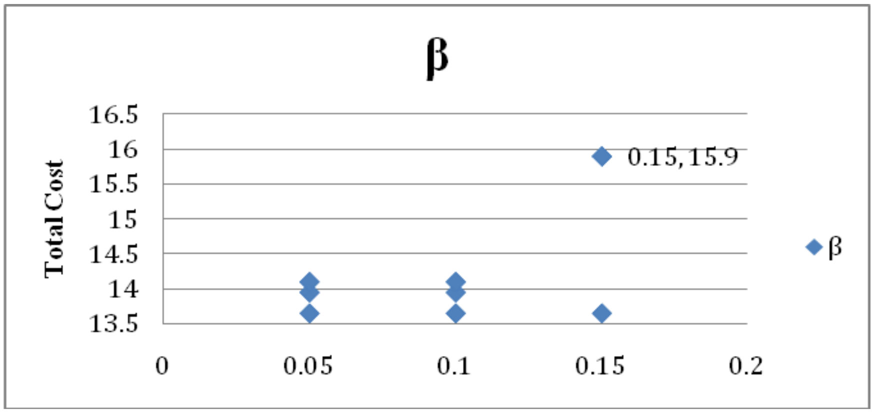

Figure 11: The relationship between β and the total cost in Case Three.

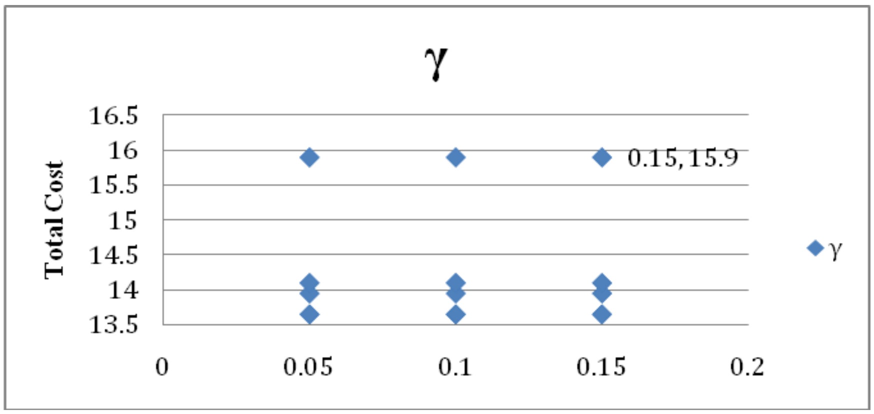

Figure 12: The relationship between γ and the total cost in Case Three.

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

From Figures 4 to 12, 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.

6. Conclusions and Future Research

This paper is an extension of the integrated optimization model presented by Yang et al. (2010). We develop an agent-based simulation model 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 supply chain 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) 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 is to incorporate adaptive learning in agent behaviors.

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

(3) 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.

(4) 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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