Evolutionary Location and Pricing Strategies in Competitive Hierarchical Distribution Systems: A Spatial Agent-Based Model

Zhou He, T. C. E. Cheng, Jichang Dong, and Shouyang Wang

***Abstract*—Facing horizontal channel competition in a hierarchical distribution system, independent intermediaries such as wholesalers and retailers are keen to find the optimal location and pricing strategies that enable them to adapt to the increasingly competitive business environment. To help market intermediaries to address their challenges, we propose in this paper a spatial agent-based model (SAM), grounded in complex adaptive systems, which comprises four types of agents, namely the world, the manufacturer, firms, and consumers. We derive the firms' optimal behaviors in response to competition by evaluating the evolutionary location and pricing strategies using a genetic algorithm. We observe that a pyramid structure and the bullwhip effect in demand emerge from the evolutionary behavior of the SAM. We also find that buyers' searching ability enhanced by information technology has a significant effect on the degree of competition in a hierarchical distribution system. In addition, we find that firms that distribute elastic goods are likely to lower their prices to attract more buyers and move closer to their suppliers to save transport costs. In the case that the product demand is inelastic, intermediaries will move as close to their buyers as possible because they can maximize their profits in the SAM.**

***Index Terms*—Agent-based modeling, competitive location problem, complex adaptive system, hierarchical distribution system, location and pricing.**

I. Introduction

AFTER PRODUCTS are produced by manufacturers, they must be distributed to the marketplace to reach consumers. Distribution is the process of making products available for consumption by consumers, using either direct means or indirect means with market intermediaries. A common example of an indirect distribution system is one that involves many intermediaries such as wholesalers and retailers. Products are first distributed from manufacturing plants to wholesalers, and then sold to other wholesalers at lower levels if any, and then sold to retailers, which sell the products directly to consumers. Therefore, the structure of an indirect distribution system is basically a multilevel system of facilities [1].

In a hierarchical distribution system, the different objectives of its independent members may create conflicts when one member's actions prevent other members from achieving their goals. Both wholesalers and retailers need to compete against other firms at the same level within the distribution system for the limited demand from buyers at a lower level. In response to horizontal channel competition, profit-maximizing firms may change their pricing strategies in the short term to promote products and attract more buyers, or change their locations in the long term to reduce transport cost and offer more efficient services to customers. As a result, the pricing and location decisions have great importance for firms in free markets. They also result in complex spatial interactions between all the members within a distribution system [2].

Over the past years, competitive location and pricing problems have been mostly studied for single-level systems (i.e., a single facility type). Previous research on the above issues has been predominantly based on the methods of operation research (OR). Under given assumptions, OR-based modeling of a firm's operations has focused on finding the optimal solutions for such issues as competitive location, pricing strategy, and inventory management [3], [4]. However, traditional mathematically-based OR techniques are impractical in today's hierarchical production-distribution context, which is extremely complex (as the problems concerned are often non-linear and non-convex with mixed integer and continuous variables) because such mathematical models require excessive computing time when spatially-interacting cases are considered. Therefore, some researchers propose treating a supply chain as a complex adaptive system (CAS) in order to understand how the supply chain adapts to and co-evolves with the dynamic environment in which it exists [5]. All relevant aspects involved in a specific problem are considered and integrated into a systematic model, and suitable methodologies and tools from the systems engineering discipline are applied to deal with the complexity directly, such as systems architecture analysis [6], system dynamics [7], [8], and system simulation [9]–[11]. Agent-based modeling (ABM), one of

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simulation-based modeling methods, captures many of the challenges facing contemporary supply chain practices by dynamic modeling of the behaviors of firms and other entities in a supply chain [12]. Therefore, spatial and iterative ABMs provide a natural and dynamic representation of hierarchical distribution systems with competitive and complex interaction structures to gain powerful insights into the evolutionary location and pricing problems.

In this paper, we propose a spatial agent-based model (SAM) from the CAS perspective, in which there are only one product and four types of agents for the sake of simplicity, namely the world, the manufacturer, firms (comprising wholesalers, retailers, and other independent intermediaries that perform the distribution function), and consumers. We solve the SAM using a genetic algorithm (GA) to address the following research questions.

1) What are the optimal location strategies for the firms in a competitive hierarchical distribution system when the demand for the product is price inelastic?
2) What are the optimal pricing and location strategies for the firms in the presence of a price-elastic product and price-sensitive consumers?
3) Since transport cost makes up a significant share of the total cost, what is its impact on the performance of the entire system?
4) In a free market, some firms may be eliminated in an increasingly competitive environment over time, which can be considered as evolution, and new firms could enter the market when certain conditions are met. So how does the structure of the distribution system, which is defined as the number of surviving firms at each level in the SAM, change with evolution? We make a contribution by resolving the above challenging research and practical issues.

The remainder of the paper is organized as follows. In Section II, we give a concise review of the related studies in the literature. In Section III, we present the SAM, including the assumptions and technical details. In Section IV, we design a series of experiments to observe the evolution of the SAM under different scenarios. In Section V, we present the data analysis and discuss the results. In Section VI, we conclude the paper and discuss the research and managerial implications of the study. We also acknowledge the research limitations and make suggestions for future research.

II. Literature Review

This paper is closely related to three streams of research, namely location and pricing decisions, supply chain evolution, and agent-based modeling.

A. Location and Pricing Decisions

The field of facility location analysis, coming basically from the fields of operations research, regional science, and geography, deals with the problem of locating new facilities in a spatial market in order to optimize one or several geographical and/or economic criteria, for example, overall distance minimization, and transport and manufacturing cost minimization [13]. Classical facility location problems, such as the p-median problem, the p-center problem, and the maximum cover location problem (MCLP) [14], have been extensively studied in non-competitive situations. However, most situations in practice do not fit such models and there is a need to incorporate competition with other players in the model [13]. Therefore, the competitive location problem that considers the location and pricing decisions of a number of new facilities that are planning to enter a market that may already contain some competitive facilities extends MCLP to the competitive case [15]. Most early competitive location models are based on the maximum capture problem (MAXCAP) [16] under such assumptions as a single facility type, uniform pricing of the product, and static competition [1], [17]. To relax these strict assumptions, the MAXCAP model has been adapted to consider facilities that are hierarchical in nature and where there is competition at each level of the hierarchy [18]. Besides, competition depends not only on location but also on price [19], and game theory is introduced to investigate competitive equilibrium in the problem of two firms competing in a spatial market [20], [21]. Although specific optimal solutions can be obtained from analytical models via mathematical analysis, these models are often limited in their ability to reflect the dynamics of the production-distribution system that is large-scale, non-linear, and complex [22].

B. Supply Chain Evolution

Supply chain evolution treats a supply chain as a continuing evolving dynamic process driven by a number of factors. Common methods to study supply chain evolution include case study, evolutionary game theory, and ABM from a CAS perspective. Examples of works employing the first two methods include the following. Fearne [23] suggests that establishing trust in supply chain partnerships is important by describing the evolution of supply chain partnerships in the British beef industry using a case study. Fujita and Thisse [24] find that the development of new information and communication technologies is one of the major forces that should be accounted for in order to better understand the globalization and evolution of supply chains. Zhu and Dou [25] propose an evolutionary game model between governments and core enterprises in greening supply chains, and find three evolutionary stable strategies in three cases. Jalali Naini *et al.* [26] employ evolutionary game theory and the balanced scorecard (BSC) for environmental supply chain management (ESCM). To understand the complexity of supply chains, CAS theory, proposed by Holland [27], has been applied to model the dynamic and evolutionary behaviors of SCM systems. Choi *et al.* [28] argue that supply chains should be recognized as a CAS for managing supply networks. Li *et al.* [29] provide a complex adaptive supply network (CASN) based on CAS and fitness landscape theory to investigate the evolutionary complexity issues such as emergence, quasi-equilibrium, chaos, and lock-in of CASNs. These works, especially CASN studies, have enriched our understanding of the evolution of supply chains. However, previous research has largely neglected consumers' evolutionary behaviors and often assumes that the consumers exist in a static environment. On the contrary, consumers in fact have the power through their fast-changing behaviors to change the evolution direction of the hierarchical distribution system in today's dynamic and competitive business environment.

C. Agent-Based Modeling

Agent-based modeling, which is a new analytical method for computational social science, combines elements of game theory, complex systems, emergence, computational sociology, multiagent systems, and evolutionary programming [30], [31]. The term agent denotes an individual or organization that has the following characteristics: autonomy, social ability, reactivity, and pro-activeness [32]. Therefore, an independent intermediary in a distribution channel, which carries out tasks by itself and interacts with other companies, is fit to be modeled as an agent using computer programs to simulate its behavior and gain insight into supply chain management. Recently, the multiagent system (MAS) approach, a subdomain of ABM that comes from the discipline of distributed artificial intelligence (DAI), has been widely adopted as an intelligent IT support tool to study various SCM issues such as decision making [11], [33], supply chain coordination [34], product design engineering [35], planning and scheduling optimization problems in manufacturing processes [36], [37] etc. In fact, only a few studies have been conducted on the spatial market using ABM. For example, Lombardo *et al.* [38] simulate the dynamics of retailing locations by integrating an MAS into a geographical information system (GIS) in eight macro-zones with few links connecting 80 consumers and 12 retailers. Heppenstall *et al.* [2] design a multiagent model to simulate the petrol retail market, and employ a GIS and GA to explore the parameterization and verification of the model. Chao *et al.* [39] propose a spatial ABM with customer agents, commercial facility agents, and government agents, to simulate commercial facility location choice in an 11*11 grid virtual city. Despite increasing studies of MAS-based SCM, there have been few spatial agent-based models proposed to investigate the location and pricing decisions in hierarchical distribution systems in a bottom-up way.

D. Summary

Motivated by the above observations, we set out to study a hierarchical distribution system consisting of four types of agents and model their behaviors from the CAS perspective. It is worth noting that our model differs fundamentally from previous work (i.e., the classical MAXCAP and its extensions) in the following aspects.

1) The whole distribution system is considered as a hierarchical CAS wherein selected combinations of building blocks at one level become building blocks at a higher level of the organization [40]. For example, in the SAM, the adaptive rules for all firm agents are exactly the same when the firms act as independent individuals. However, when they act as organizations playing the roles of retailers, wholesalers, and top wholesalers at different levels, the optimal location and pricing strategies of different organizations vary significantly in a statistical sense. According to CAS theory, the evolutionary location and pricing strategies of these adaptive agents are emergent phenomena, which help us to understand their complex behaviors in reality. Therefore, we focus on the overall strategies of intermediaries in response to competition throughout the evolution of the proposed SAM, rather than the specific optimal solutions of individuals in static competition in traditional models.
2) From a methodological point of view, we apply spatial ABM and GA, rather than traditional mathematical analysis, to capture heterogeneity across individuals and competitive interactions among them in the distribution system.
3) The relaxed assumptions in the SAM, as well as the reasonable mechanism for firms to enter and exit a free market, enable us to model a hierarchical distribution system in a more realistic way and achieve dynamic equilibrium of the SAM through evolution.

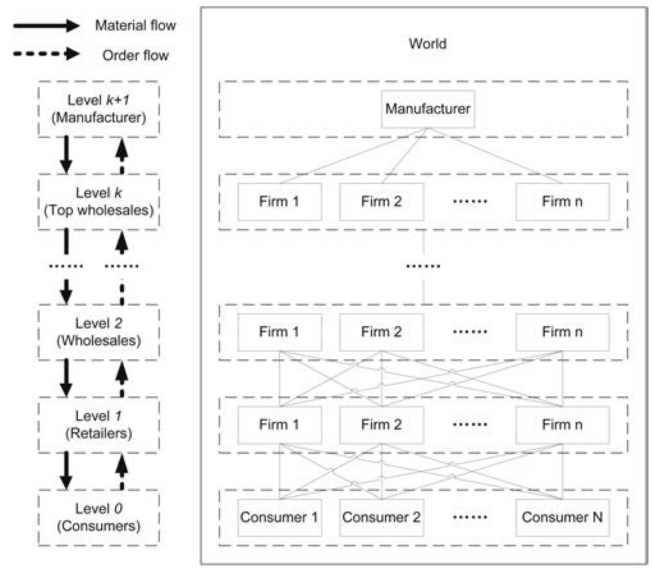

Fig. 1. Market structure of the SAM, which is assumed to be a hierarchical CAS composed of $k + 2$ levels.

III. Model Description

A. Overall Structure

Our SAM explicitly models micro-scale interactions among the world, the manufacturer, firms, and consumers, and macro-scale feedback of market transactions. Fig. 1 shows the overall market structure of our distribution system composed of $k+2$ levels, which consists of one world, one manufacturer at the highest level $k + 1$, a specified number of consumers at the lowest level 0, and competing firms at other k levels ($k > 0$).

Underlying the SAM are the following basic but essential notions.

1) The order flow starts from a lower level and ends at a higher level; while material flow moves in the opposite direction. Therefore, the SAM corresponds to

most supply chain models with a forward flow of goods and a backward flow of information [41].

2) There is only one type of product in the SAM, which is produced by the sole manufacturer and independently priced by each seller. The single or homogeneous product assumption follows the original maximum capture problem with price model (PMAXCAP) [19], but a key difference here is that each intermediary is able to optimize its location and pricing behaviors independently, while in PMAXCAP all the outlets of a given firm charge the same price. The multiple products case, which is not considered in this paper because it will result in exceedingly high complexity,[1] will be taken into account in an extended version of the SAM.
3) Facilities, including wholesalers, retailers, and consumers, get price information about the product from the advertisements of close-by firms at a higher level and choose to obtain the product from one firm only. This assumption, called the single-sourcing policy, also follows PMAXCAP and allows us to study how customers' behaviors influence firms' decisions on location and pricing.
4) The world agent generates new firms to enter the market and removes some firms from the model if certain conditions are met. In other words, we build a free market in the SAM to simulate the natural selection process, which is the driving force of evolution in biology. Therefore, the optimal location and pricing strategies can be derived from observing the evolutionary behaviors of surviving firms.
5) Since most of the facility location models use networks and planes for realistic spatial representations [19], we model the world agent in the SAM as a 2-D grid with $X * Y$ cells for an (x, y) coordinate (all coordinates are integers). Other agents are represented as discrete points and placed in the plane according to their coordinates. Besides, co-location of agents is not permitted, as in [42] and [19].
6) All the delays in production and transport are negligible in the SAM, which means that the lead time of the product is zero, and cargos from upstream entities will be transported to downstream partners as soon as the trade transactions between them are completed in each time step.
7) Horizontal interactions among facilities are not explicitly considered in our SAM. In other words, each agent, which makes decisions independently, only reacts to its upstream or downstream partners, if any. Although the horizontal relations among the agents might exist in real-world competition, such interactions are commonly ignored in many studies [1].

In the following we discuss the various components of the model in detail and explain the behaviors of the four types of agents in a static time step as a snapshot of the SAM. Appendix A summarizes all the parameters and variables used in the SAM.

B. Consumers' Behaviors

In our spatial model, demand for the product is assumed to be concentrated at discrete demand points (consumer agents) in a plane (the world). The position of each consumer is fixed after random distribution upon initializing the SAM. As a result, repeated experiments with random initial positions of the agents yield a distribution of outcomes following the Monte Carlo pattern.

Based on the assumptions of PMAXCAP [19], we divide consumers' behaviors in the SAM into three stages in each time step: search, choose, and trade.

At first, a consumer (i.e., C_i^0) collects price information from several nearby retailers (i.e., F_j^1), which are sorted in ascending order of the distances between them (d_{ij}) in the SAM, through their advertisements. So the consumer knows the selling prices of the product before deciding on a retailer from whom to buy the product [43]. Besides, the number of retailers from which the consumer gets price information θ is fewer than or equal to the sum of all the available (surviving) retailers at time t. Essentially, θ denotes the degree of the searching ability of consumers enhanced by information technology in the market. If $\theta = 1$, the consumer always chooses the nearest retailer, so the price of the product has no effect in this stage. As θ increases, the competition among the retailers becomes fiercer because consumers have more retailers to choose to shop with, which reflects channel competition in the retail market. In fact, $\theta = 2$ in PMAXCAP because only two firms are studied. Note that the searching cost that may exist in reality is ignored in our model and so is in PMAXCAP.

After searching, we assume that each consumer can only choose to shop with one and only one retailer in each time step with its full demand, that is, the winner gets it all principle, which follows PMAXCAP. In terms of the parameters and variables of the model shown in Appendix A, we formulate the consumer's decision problem, in which the consumer's goal is to maximize his utility at time t, as follows:

Maximize

$$U(q_{ij}) = q_{ij} \tag{1}$$

subject to

$$(P_j + v d_{ij}) * q_{ij} \leq B_i. \tag{2}$$

In the above problem, each consumer seeks to maximize his utility subject to his budget constraint. We can easily derive the optimal quantity of the product that consumer C_i^0 buys from retailer F_j^1 as follows:

$$U_{ij}^* = q_{ij}^* = B_i/(P_j + v d_{ij}). \tag{3}$$

[1]Incorporating more products in the present study could result in exponentially increasing complexity in the SAM. For example, we need to define the interrelationships among the products (are they substitutable, supplementary, or independent of one another?) and examine the impacts of products' interrelationships on the experimental results. We also need to consider the number of product types that any of the firm agents offers. Moreover, given large numbers of product and firm options, it will be difficult to find the optimal consumers' spatial behaviors. The above issues, which exist in the real world, are beyond the scope of this paper to address.

For a consumer C_i^0 at time t, the retailers F_j^1s from which the consumer gets the price information can be sorted in descending order of utility (U_{ij}^*). Then the consumer will choose the retailer that offers him the maximum utility. Note that the price $P_j + vd_{ij}$ faced by consumers in each local market is exactly the same as that in PMAXCAP, so consumers in the SAM always patronize the retailer with the lowest total price, regardless of its ownership, as that in PMAXCAP. Besides, the budget constraint and utility notion, which come from consumer choice theory in classical microeconomics, are employed to model consumers' behaviors in a reasonable way.

In the trade stage, the sum of all the consumers' order quantities (q_{ij}^*) makes up the total demand (Q_j^1) for retailer F_j^1, which we will further discuss in the section on firms' behaviors.

In sum, the consumer agents in the SAM are able to collect price information on products from several nearby retailers, and compute their maximum utilities based on the distance between them and the retail prices offered by the retailers. To maximize his utility, each consumer agent will choose the retailer that offers him the maximum utility to shop with in the current time step.

C. Manufacturer's Behaviors

Only one manufacturer at level $k + 1$ is modeled in the SAM, which is assumed to provide an infinite quantity of the product for consumers. The manufacturer is right in the center of the 2-D lattice, and it never moves like consumers. As the locations of consumers are randomly assigned in simulation, the manufacturer could be far away from its end customers. Therefore, this manufacturer in reality, especially a small- and medium-sized one that cannot build its own distribution channel due to high costs, needs to cooperate with the intermediaries. In the SAM, the manufacturer delivers the product to wholesalers at level k at the wholesale price, which is also fixed and denoted by P^{k+1}. We simplify the manufacturer's behaviors to focus on firms' behaviors.

D. Firms' Behaviors

Similar to consumers, firms are modeled to search, choose, and trade with their sellers at a higher level in each time step. Then, surviving firms are able to optimize their decisions on price and position to adapt to the competitive market.

Take a firm F_i^l at level l for example. It will search θ nearby intermediaries at level l+1 for trade as long as it receives orders from customers at level $l-1$. However, unlike consumers that choose retailers to maximize their utilities, the firm F_i^l attempts to minimize its purchase cost PC_i^l and transport cost TrC_i^l. In the trade stage, F_i^l places an order equal to its aggregate demand Q_i^l to the chosen firm (i.e., F_j^{l+1}). Therefore, firm F_i^l makes a profit PR_{it}^l and accumulates wealth W_i^l at time t. As mentioned in the consumer's trade stage, setting the selling price P_i^l of the product and position (x_i^l, y_i^l) in the 2-D zone are the key decisions of firm F_i^l, which aims to maximize its profit. We express the objective function of firm F_i^l in the SAM as follows:

Maximize

$$PR_i^l(price, position) = R_i^l - PC_i^l - TrC_i^l - FOC_i^l \quad (4)$$

subject to

$$P_i^l \geq P_j^{l+1} \quad (5)$$

where

$$R_i^l = P_i^l \times Q_i^l \quad (6)$$
$$PC_i^l = P_j^{l+1} \times Q_i^l \quad (7)$$
$$TrC_i^l = vd_{ij} \times Q_i^l. \quad (8)$$

Both the fixed cost (FOC_i^l) and marginal cost (PC_i^l) are considered in PMAXCAP. We add the transport cost (TrC_i^l) and pricing constraint (5) in the SAM due to its hierarchy. That is, buyers always bear the transport cost; and the firms will not engage in such a price war regardless of the purchase cost.

Although the above optimization problem is stated in a static time step, it is difficult to directly express the profit function, given P_i^l and (x_i^l, y_i^l) as independent variables, and to maximize the profit in a dynamic context using traditional OR methods for the following two reasons.

1) It is difficult to derive the optimal selling prices to maximize firms' profits because of the uncertainty in the quantity of the product sold. Although the quantity of the product sold is a decreasing function of its selling price according to supply-demand theory in classical microeconomics, which is true for most of the cases of the SAM, buyers at level l are able to compare the prices offered by different firms at level l+1 and choose a single firm to shop with. Other surviving firms' prices are also independent of the firms' sold quantities, and the elasticity of buyer demand is hard to estimate because the demand function is non-linear and imprecise.
2) It is very difficult to find the optimal location to balance creating more demand against reducing transport cost. Distance is an important criterion that buyers use to select their trade partners in the search and choose stages. Therefore, firms are motivated to approach their buyers. However, if suppliers are located far away, such movements could increase the transport cost, which creates complexity in maximizing profit. To sum up, because of the complexity, dynamics, and non-linear feedback in the SAM, OR-based mathematical methods cannot be applied to find the optimal decisions on price and location of the firms in the absence of precisely defined objective functions.

To address this problem, heuristic algorithms have been developed for tackling PMAXCAP and its extensions [44]. Here we apply a genetic algorithm (GA) to produce approximate optimal solutions to maximize profit through heuristically searching possible solution spaces. Compared with other heuristic techniques to tackle optimization problems, GA mimics the natural selection process and the mechanism of population genetics. It uses probabilistic rather than deterministic rules for solving many types of complex problems, and possesses

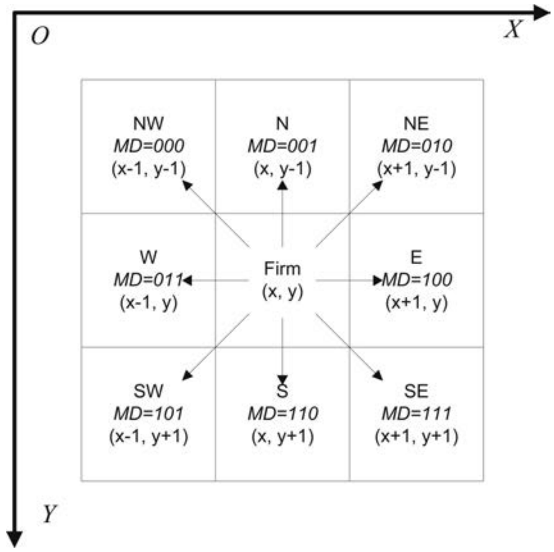

Fig. 2. Firm in the 2-D world is able to move from the current cell to one of eight neighboring cells in each time step.

a remarkable ability to focus on the most promising parts of the entire solution space, which is a direct outcome of its ability to combine strings containing partial solutions [45]. These features make GA a promising technique to find the optimal decisions of the retailers by evaluating the evolutionary behavior of the SAM, given that retailers are selected by consumers and may be eliminated over time in a highly completive environment. Moreover, previous works [46], [47] have demonstrated that GA is a popular and effective machine learning algorithm to assist agents in making decisions, and that GA can be used to address spatial interaction problems with good performance.

We apply a GA that follows the steps shown in Table I. Hanjoul *et al.* [48] note that separating location and price decisions leads to suboptimality because location and pricing decisions depend on each other. To overcome this problem, we combine them in the GA procedure in each time step so the firms are able to derive the optimal location and price decisions at the same time. We introduce the parameter IM^l_{it} to determine whether or not firms move. We encode parameter MD^l_{it} in a three-bit binary variable in the GA, which stands for eight move directions for each firm, as illustrated in Fig. 2. Each movable firm faces a trade-off between moving close to more buyers and moving to sellers in order to find the optimal position in the current time step. Therefore, we introduce MD^l_{it} as an independent variable for all the firm agents to move in a step-by-step way when $IM^l_{it} = 1$. With GA, firms are able to memorize their good pricing strategies and moving behaviors (move or not, move directions) that generated high profits in the past time steps. Moreover, firms are intelligent agents that evolve toward better strategies to optimize their objectives.

E. World's Behaviors

The world agent in the SAM can be viewed as a container that keeps the manufacturer, firms, and consumers in. It performs four important tasks to make the SAM complete. First, the world needs to update the values of all the variables, such as price, position, and other endogenous parameters defined in the SAM. Second, the results are outputted by the world agent for analysis. Third, the world agent is in charge of drawing other agents in order to reflect the evolutionary location behavior of the hierarchical distribution system. Fourth, the world agent is designed to incorporate an entrance and exit mechanism to emulate the evolution of firms over time. A new firm will be added to a certain level of the distribution system when one or both of the following conditions are met:

1) at the level where the profit of each firm increases;
2) at the level where the number of surviving firms is fewer than two.

We attempt to build a perfect competitive market by means of these two conditions. Each new firm is endowed with the same wealth at the beginning of each simulation run and able to make a profit (loss) that accumulates (depletes) wealth. However, the world agent will eliminate the firm agents that meet one or both of the following conditions, which reflect the bankruptcy of under-performing market intermediaries in the real world: 1) the wealth of the firm is negative and 2) the profit of the firm remains negative in the past ten time steps.

These settings help us to examine the best strategies of the firms, especially survivors with high performance reacting to the competitive market, and to gain managerial insights from observations of the evolutionary behavior of the SAM.

TABLE I

GENETIC ALGORITHM PROCEDURE

Step	Detail
1	Generate an initial population of possible solutions randomly by assigning random values to $\{P^l_{it}, IM^l_{it}, MD^l_{it}\}$ as individuals.
2	Compute PR^l_{it} as the fitness of each individual in that population.
3	Select the best-fit (maximal PR^l_{it}) individual $\{P^{l*}_{it}, IM^{l*}_{it}, MD^{l*}_{it}\}$for reproduction at time t.
4	Encode $\{P^{l*}_{it}, IM^{l*}_{it}, MD^{l*}_{it}\}$ in binary as strings of 0s and 1s.
5	Breed new individuals $\{P^{l\prime}_{i(t+1)}, IM^{l\prime}_{i(t+1)}, MD^{l\prime}_{i(t+1)}\}$ through the mutation operations to give birth to offspring.
6	Evaluate the individual fitness $PR^l_{i(t+1)}$ of new individuals $\{P^{l\prime}_{i(t+1)}, IM^{l\prime}_{i(t+1)}, MD^{l\prime}_{i(t+1)}\}$ at time $t+1$.
7	Replace the least-fit population with new individuals.
8	Go to Step 3 until termination.

F. Summary

Fig. 3 summarizes the sequence of events in the SAM in the form of unified modeling language (UML) behavior diagrams. The scheme is quite straightforward and all the components have been discussed above.

In the next section we discuss the simulation experiments we performed to examine the interactions among the world, the manufacturer, firms, and consumers, and derive insights from the simulation results.

IV. SIMULATION

A. Experiment Design

We conducted four experiments using the SAM under different scenarios: fixed price (Scenario A) and variable price (Scenario B). Table II presents the parameter settings of the

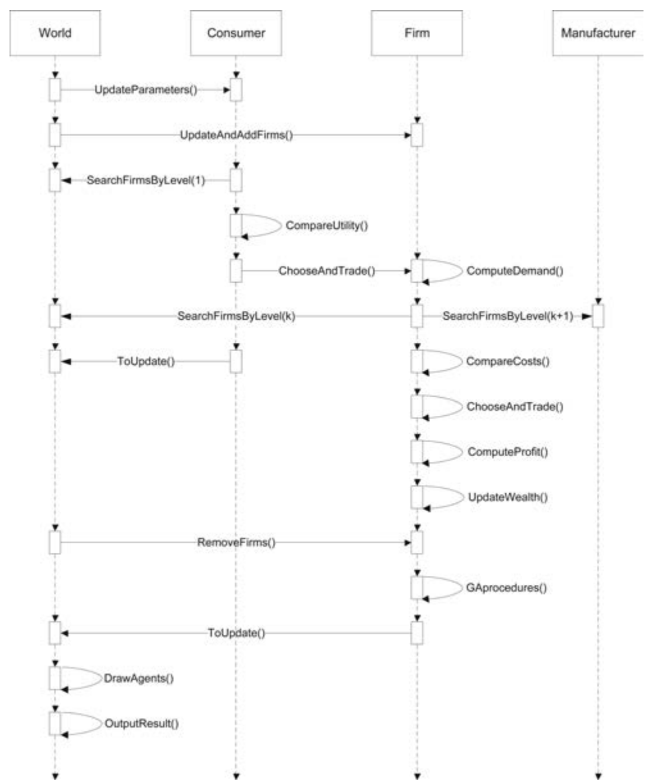

Fig. 3. UML time sequence diagram of the SAM.

four experiments. To the best of our knowledge, there are no appropriate benchmark data that we can use to compare our model with previous ones with regard to the specific problem under study. Hence, the choices of the parameter values (e.g., the scale of the SAM and the initial states of the agents) are arbitrary. We keep most of parameter settings unchanged in all the experiments to reduce system instability and make the experimental results comparable in a statistical sense. This enables us to focus on the differences in the experiment results that are mainly caused by changes in price adjustability and θ. Note that the SAM can be easily scaled by adding or removing agents if necessary without changing the model architecture, which is a considerable advantage over conventional modeling techniques for large and complex problems.

Under Scenario A, the pricing strategies of firms at the same level are uniform and fixed. Therefore, location is the only determinant of success in competition. Note that both consumers and firms always trade with the nearest seller regardless of the value of θ and the price of the product because of the single-sourcing and fixed price assumptions in Exp. A1. The optimal location strategies of firms could help us to explore the regular pattern of the distribution of goods with inelastic demand, such as gasoline.

Under Scenario B, each firm is able to optimize its location and pricing strategies. The only difference among these four experiments is the variable θ, i.e., the number of candidates from which low-level agents are able to get price information. As mentioned in discussing consumers' behaviors, θ denotes the degree of the searching ability of buyers. In reality, various information technologies (IT) including the Internet, TV, mobile APPs, and other telecommunication services that distribute commercial information such as advertisements, pricing information, promotion etc to numerous buyers in a convenient and efficient way lead to fiercer in- and cross-channel competition in hierarchical distribution systems. Therefore, as θ increases, buyers can collect more price information from firms at a higher level, which means the firms face greater competition in the SAM. We are interested to examine changes in firms' evolutionary behaviors that are driven by competition in the IT era.

B. Implementation and Performance Measures

We conducted simulation experiments using the SAM on the SWARM v2.2 platform[2] with Java programming codes. We performed each experiment with the SAM under the two scenarios 30 times to ensure robust outputs. We carried out the steps presented in Fig. 3 over 1000 time steps for each experiment to examine and analyze the evolutionary behavior of the SAM. Specifically, we focused on the dynamic changes of the following variables in order to generate insight:

1) number of surviving firms at level l: SF_t^l;
2) average price offered by surviving firms at level l: $\overline{P}_t^l$;
3) average distance between agents at level i to agents at level j: $\overline{d}_t^{ij}$;
4) average order quantity of agents at level l: $\overline{q}_t^l$;
5) average transport cost between agents at level i to agents at level j: $\overline{TrC}_t^{ij}$.

The index SF_t^l, defined as the structure of the distribution system, reflects the degree of competition in the SAM. $\overline{d}_t^{ij}$ and $\overline{P}_t^l$ can be viewed as location and pricing strategies of the surviving firms at level l from the viewpoint of the entire level. Besides, $\overline{q}_t^l$ and $\overline{TrC}_t^{ij}$ provide information on the evolutionary behaviors in a hierarchical distribution system.

V. Results and Discussion

The means and standard deviations of the indices in all the experiments are presented in Table III. In order to display the running of the SAM in a more vivid and dynamic way, we provide an online video[3] that records the simulation process as sample runs for each experiment. Besides, we take the snapshots of the plane of all the experiments in the final time step in Fig. 4.

First, it can be observed that the number of surviving firms (SF^l) after 1000 time steps is a decreasing function of its level (l) in all the experiments. In other words, although we generated 20 firms at each level initially, the SAM always developed a pyramid structure in the end. The pyramid structure is a classical supplier structure in an appreciable number of industries, for example, automotive industry [49], which have one or a few suppliers and numerous end customers.

[2]SWARM is a kernel and library for the multiagent simulation of complex systems. Technical information of this platform can be accessed at .

[3]The video is uploaded on Youtube. Please visit . For the reader who cannot visit and watch it normally due to technical problems, please e-mail the corresponding author.

TABLE II
PARAMETER SETTINGS OF THE FOUR EXPERIMENTS

Parameters	Remark	Scenario A	Scenario B		
		Exp. A1	Exp. B1	Exp. B2	Exp. B3
IVP	Is Variable Price? 0=No, 1=Yes.	0	1	1	1
θ	Number of candidates for choosing.	2	2	3	4
k	Levels of firms.	$k=3$. Initially, we created 20 firm agents at each level, and 30 consumer agents at level 0.			
(X, Y)	Size of the *world*.	$X=Y=151$.			
(x, y)	Initial position of other agents.	Random initial position for consumers and firms. Fixed position for the manufacturer at (76, 76).			
pm	Probability of mutation in GA.	10%.			
v	Unit transport cost divided by distance.	0.1			
B	The budget of consumers.	1000.			
W_0	Initial wealth of firms.	10000.			
FOC	Fixed operating cost of firms at each time step.	100.			
P^{k+1}	Fixed price offered by the manufacturer.	50.			
P^l	Fixed price offered by the firms.	If l={1, 2, 3}, then P^l={200, 150, 100} in Exp. A1.			

Therefore, the pyramid structure is expected since we model one manufacturer and 30 consumers. Another conjecture is proved to be correct. As θ increases under Scenario B, SF^l drastically declines at each level. These results indicate that consumer choice is a key factor that intensifies horizontal channel competition in hierarchical distribution systems. Moreover, the online video illustrates that the supply-demand relationships between sellers and buyers in the SAM under Scenario A are in a simple and stable condition. Proof in reality can be found at gasoline stations in that rational drivers are likely to purchase gasoline at the nearest stations since gasoline demand is relatively inelastic to price changes, both in the long and short terms [50]. However, under Scenario B, the trade partner of each agent frequently changes due to variable pricing and buyers' enhanced searching ability. As we will see later in this section, these changes from buyers and the nature of the product itself have a profound impact on firms' behaviors.

Second, we turn our attention to firms' pricing ($\overline{P}^l$) and location ($\overline{d}^{ij}$) strategies to examine their evolutionary adaptation. According to common knowledge, price should be lower if competition is fiercer. As we see from Table III, $\overline{P}^1$ keeps in line with our guess; while $\overline{P}^2$ and $\overline{P}^3$ are not in Exp. B3. We provide two reasons to account for this phenomenon. First, note that in Exp. B3, there are high chances that SF^2 and SF^3 are less than θ (96.48% and 94.83%, respectively, according to their distribution). Therefore, comparing with Exp. B2, the competition driven by θ is not intensified in Exp. B3. In other words, these firms need not lower their prices. Second, as transport cost rises sharply in Exp. B3, it is not surprising that the firms raise prices to maximize their profits. In fact, these firms have dominated the upstream distribution system through low-price competition. Hence, price wars at the right time make sense, especially when they will drive undesirable rivals to exit the market [51], [52].

Regarding the location decision, the winning principle in Exp. A1 can be concluded as get as close to your customers as possible as shown in Fig. 4, so $\overline{d}^{ij}$ is small except $\overline{d}^{34}$ because there is only one manufacturer right in the center of the world, and all the top wholesalers at level 3 have to trade with it no matter where it is. However, this principle is discarded under

TABLE III
MEANS AND STANDARD DEVIATIONS OF THE INDICES IN ALL THE EXPERIMENTS

Index	Exp. A1 $IVP=0$ $\theta=2$	Exp. B1 $IVP=1$ $\theta=2$	Exp. B2 $IVP=1$ $\theta=3$	Exp. B3 $IVP=1$ $\theta=4$
SF^1	30.43(1.33)	13.43(2.28)	9.7(2.78)	3.5(1.36)
SF^2	27.17(1.93)	8.43(2.34)	3.73(1.7)	2.77(0.68)
SF^3	23.6(2.46)	4.77(1.5)	2.1(0.4)	2.73(0.78)
$\overline{P}^1$	200(0)	185.46(9.4)	183.4(12.57)	181.17(15.75)
$\overline{P}^2$	150(0)	140.51(6.76)	137.74(10.16)	139.95(10.73)
$\overline{P}^3$	100(0)	90.77(7.24)	88.92(11.73)	93.02(8.56)
$\overline{d}^{01}$	4.39(0.62)	19.79(4.54)	29.31(11.71)	62.66(12.39)
$\overline{d}^{12}$	5.27(0.66)	23.34(10.61)	42.23(13.94)	32.01(18.21)
$\overline{d}^{23}$	6.43(1.03)	27.23(8.69)	37.37(25.74)	15.2(14.88)
$\overline{d}^{34}$	45.12(3.92)	44.11(10.78)	37.04(17.91)	20.07(13.31)
$\overline{q}^0$	4(0)	5.3(1.2)	6.08(1.41)	6.64(2.15)
$\overline{q}^1$	3.95(0.17)	12.32(4.29)	23.18(19.37)	70.13(49.93)
$\overline{q}^2$	4.46(0.32)	21.32(11.31)	59.7(28.98)	78.15(40)
$\overline{q}^3$	5.16(0.55)	38.08(19.03)	88.86(24.78)	80.47(40.67)
$\overline{q}^4$	120.4(2.65)	158.97(35.99)	181.53(43.5)	203.1(76.44)
$\overline{TrC}^{01}$	1.76(0.25)	11.3(5.71)	19.04(9.81)	41.85(17.7)
$\overline{TrC}^{12}$	2.28(0.29)	29.77(10.79)	131.6(139.92)	387.26(252.58)
$\overline{TrC}^{23}$	3.14(0.5)	76.63(60.95)	252.97(167.49)	263.42(271.86)
$\overline{TrC}^{34}$	25.93(3.3)	200.79(171.34)	494.13(275.35)	375.69(262.87)

Scenario B because Table III indicates that $\overline{d}^{ij}$ between low levels is increasing (i.e., $\overline{d}^{01}$) while decreasing between high levels (i.e., $\overline{d}^{34}$). The video also shows that firms frequently adjust their prices but rarely move. In fact, pricing becomes much more important than location to enhancing demand not only in the SAM, but also in the real world. In the IT era, location is relatively irrelevant and competition is intense in the presence of e-business [53].

Another reason that firms concentrate under Scenario B is that firms transfer the transport cost to their buyers, which are designed to bear the logistical cost in the SAM. As shown in Table III, $\overline{TrC}_t^{ij}$ generally grows mainly due to increasing order quantities ($\overline{q}_t^l$) of the agents. Although retailers are further away, consumers can buy more goods under the same budget constraint as $\overline{P}^1$ decreases under Scenario B. That is, from the consumer's viewpoint, it seems that they could gain more utility from firms' competition.

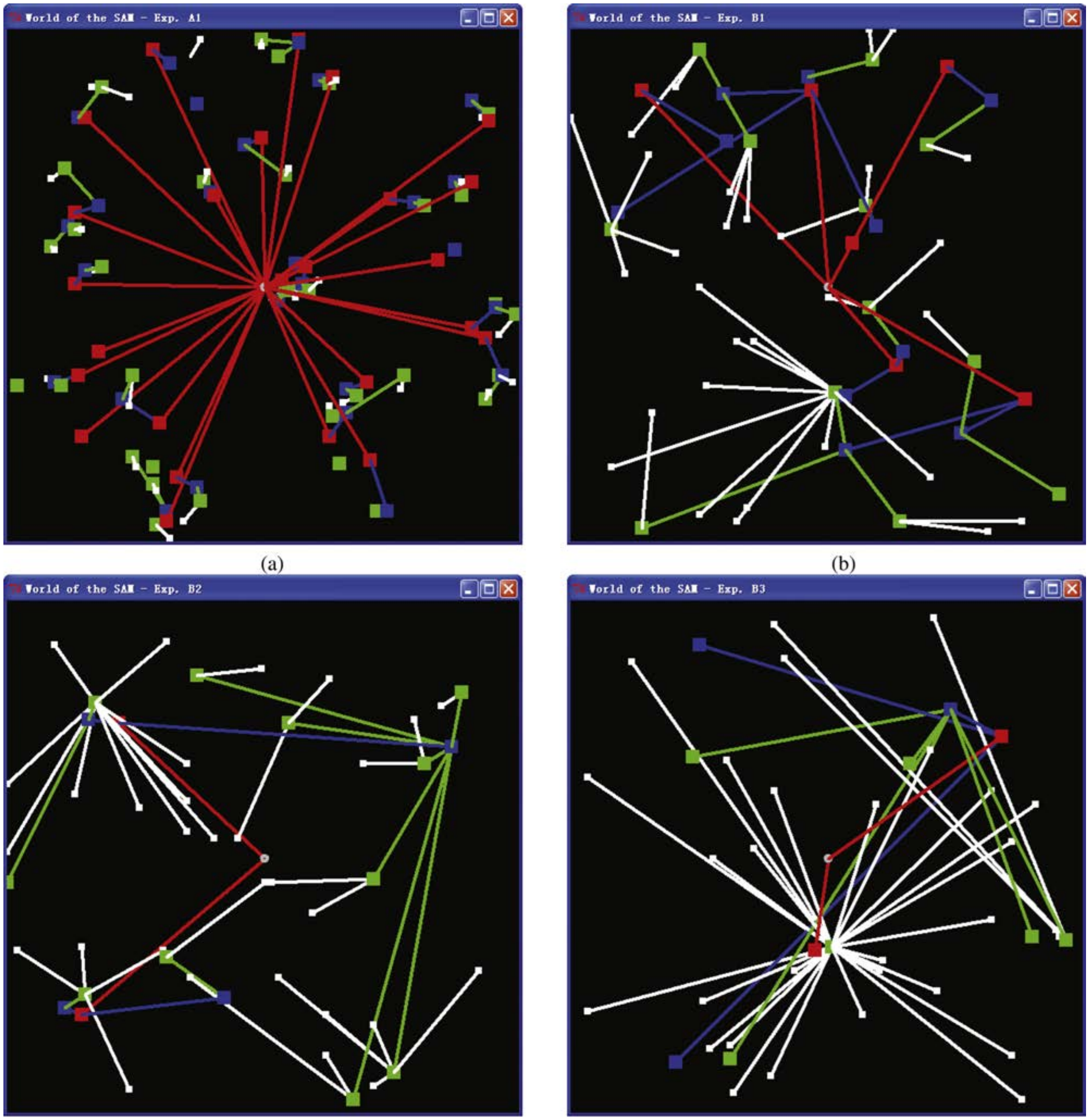

Fig. 4. World agent in the final time step in the four experiments. White nodes represent consumers at level 0, green nodes are retailer firms at level 1, blue nodes are wholesale firms at level 2, and red nodes are top wholesale firms at level 3. The gray node right in the center of the plane is the manufacturer at level 4. Links among agents represent their current supply-demand relationships. (a) Exp. A1. (b) Exp. B1. (c) Exp. B2. (d) Exp. B3.

Moreover, it is worth noting that for the firms under Scenario B, the standard deviation of the demand from buyers is larger as one moves upstream in the SAM (further from the consumers), as shown in Table III. As θ increases under Scenario B, the change in demand significantly increases. In response to uncertain demand, intermediaries often carry an inventory buffer called safety stock in reality. A phenomenon of larger and larger swings in inventory, which is similar to the observed larger demand variations in the SAM, is known as the bullwhip effect. As discussed before, changes from consumers (θ) lead to price variations, which is believed to be a source of the bullwhip effect [54].

Finally, there is more valuable information obtained from the video. For example, under Scenario A, the existing firm agents defend their profits against competition by moving closer to their buyers. They are able to make stable profits, so new firms are attracted to enter the market and SF^l increases. The existing firms then strengthen their location advantages to push their rivals out, as a result SF^l decreases. As the process evolves, SF^l achieves a dynamic equilibrium, and indicators like $\overline{d}^{ij}$ and $\overline{TrC}_t^{ij}$ smoothly decrease in the long run. We can also find that our SAM is in dynamic equilibrium under Scenario B with increasingly larger swings in all the parameters due to intensified competition. These findings may explain why location can be a high barrier to entry into markets with inelastic demand, and it is risky to enter highly competitive markets. Besides, from a methodological point of view, ABM and other system modeling techniques generally outperform mathematical methods not only in examining how the whole system evolves, but also measuring macro-level results that emerge from micro interactions among agents. Therefore, more appropriate tools (e.g., statistical tests, systems engineering methods) can be employed to analyze such results and generate practical insights that help us to discover and explain the complex patterns in real markets.

VI. Conclusion

In this paper we propose a spatial agent-based model (SAM) to model a hierarchical distribution system with four types of agents in a 2-D zone: 1) the world agent that creates and eliminates firms to build a perfect competitive market; 2) the manufacturer agent that provides an infinite quantity of the product for consumers; 3) changing number of profit-maximizing firm agents at different levels that perform the distribution function, and pursue suitable and evolutionary location and pricing strategies; and 4) many consumer agents that are able to collect price information on products from several nearby retailers to maximize their utility by choosing one retailer to shop with in each time step. We derive the agents' optimal behaviors in response to intensified competition by evaluating the evolutionary behavior of the SAM using a genetic algorithm.

Our findings from the simulation outputs of four experiments under two scenarios can be concluded as follows.

1) A pyramid structure always emerges in a hierarchical distribution system composed of one or a few suppliers and numerous end customers. The relationships between buyers and sellers are relatively stable when the demand function of the product is inelastic.
2) Buyers' searching ability enhanced by IT has a significant effect on the degree of competition in a hierarchical distribution system. From the consumer's standpoint, they benefit from the competition.
3) Pricing strategies become much more important than location decisions to enhancing demand in the presence of e-business and intensified competition. Firms that distribute elastic goods are likely to lower their prices to attract more buyers and move closer to their suppliers to save transport cost. In the case that the product has an inelastic demand function, intermediaries will move as close to their buyers as possible to maximize their profits.
4) The bullwhip effect in demand emerges from the evolutionary behavior of the SAM, which is fundamentally caused by buyers' searching behaviors that lead to price variations.

Our SAM adopts the complex adaptive systems perspective to model the optimal responses of agents in competition in a bottom-up way, and identifies that the evolutionary and optimal behaviors of agents are the driving force of the emergence of the SAM. Our approach provides a promising framework and a viable methodology to study other complex issues in supply chain management from an academic standpoint. Our findings generate valuable practical insights for practitioners based on realistic modeling of their optimal behaviors in today's fast-changing, increasingly competitive, and complex business environment.

We suggest several future directions for this model. First, it is worth modeling the manufacturer's optimal behaviors. Each firm in the SAM has its individual objective, so we could model the manufacturer as an intelligent agent in detail to simulate its adaptation and evolutionary behaviors. Second, delays in production and transport, and other elements ignored in our model for simplicity reasons can be taken into account in an extended version of the SAM, which would make agents' behaviors much more realistic. Finally, it is desirable to improve the structure of the SAM by, e.g., incorporating the inventory management of the intermediaries in the market.

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Appendix A
Definitions of Variables and Parameters Used

See Table IV. W, M, F, and C in the "Owner" column are the abbreviations for the world, manufacturer, firm, and consumer agents, respectively. Superscripts of variables associated with firms stand for their levels in the SAM.

TABLE IV
VARIABLES AND PARAMETERS IN THE SAM AT TIME t

Parameter	Owner	Remark
(x, y)	M, F and C	The place that agent located in the spatial market which is a 2D coordinate system.
q_t	F and C	Order quantity of the product from lower-level agents to higher-level agents.
Q_t	F	Total demand from lower-level agents. For example, $Q_t^k = \sum q_t^{k-1}$
d_{ij}	F and C	Euclidean distance between agents. $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
θ_t	F and C	Number of higher-level agents from which lower-level agents get price information.
B	C	The budget of consumers.
P_t	M and F	Price of product offered by agents.
IM_t	F	One-bit binary variable to control movement. The firm will not move unless it equals 1.
MD_t	F	Three-bit binary variable strands for eight move directions of firms, e.g., cardinal directions and intermediate directions.
R_t	F	Revenue of firms.
FOC	F	Fixed operating cost of firms.
TrC_t	F and C	Transport cost of agents.
PC_t	F	Purchase cost of firms.
PR_t	F	Profit of firms.
W_t	F	Wealth of firms.
k	W	Levels of firms.
SF_t^k	W	Number of surviving firms at level k.
pm	W	Probability of mutation in GA.
(X, Y)	W	Size of world.
v	W	Unit transport cost divided by distance.

REFERENCES

[1] G. Şahin and H. Süral, "A review of hierarchical facility location models," *Comput. Oper. Res.*, vol. 34, no. 8, pp. 2310–2331, Aug. 2007.

[2] A. Heppenstall, A. Evans, and M. Birkin, "Using hybrid agent-based systems to model spatially-influenced retail markets," *JASSS-J. Artif. Soc. S.*, vol. 9, no. 3, Jun. 2006.

[3] O. Kwon, G. P. Im, and K. C. Lee, "MACE-SCM: A multiagent and case-based reasoning collaboration mechanism for supply chain management under supply and demand uncertainties," *Expert Syst. Appl.*, vol. 33, no. 3, pp. 690–705, Oct. 2007.

[4] S. Wang, J. Watada, and W. Pedrycz, "Recourse-based facility-location problems in hybrid uncertain environment," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 40, no. 4, pp. 1176–1187, Aug. 2010.

[5] A. Surana, S. Kumara, M. Greaves, and U. N. Raghavan, "Supply-chain networks: A complex adaptive systems perspective," *Int. J. Prod. Res.*, vol. 43, no. 20, pp. 4235–4265, May 2005.

[6] L. D. Xu, "Information architecture for supply chain quality management," *Int. J. Prod. Res.*, vol. 49, no. 1, pp. 183–198, 2011.

[7] B. Janamanchi, "Inventory policies for supply chains a system dynamics model based study," in *Proc. IEEE Int. Conf. SMC*, 2009, pp. 4353–4359.

[8] M. Huang, M. Yang, Y. Zhang, and B. Liu, "System dynamics modeling-based study of contingent sourcing under supply disruptions," *Syst. Eng. Procedia*, vol. 4, no. 0, pp. 290–297, 2012.

[9] D. Huang, H. S. Sarjoughian, W. Wang, G. Godding, D. E. Rivera, K. G. Kempf, *et al.*, "Simulation of semiconductor manufacturing supply-chain systems with DEVS, MPC, and KIB," *IEEE Trans. Semiconduct. Manuf.*, vol. 22, no. 1, pp. 164–174, Feb. 2009.

[10] A. Nikolopoulou and M. G. Ierapetritou, "Hybrid simulation based optimization approach for supply chain management," *Comput. Chem. Eng.*, vol. 47, no. 0, pp. 183–193, Dec. 2012.

[11] E. Elghoneimy and W. Gruver, "Agent-based decision support and simulation for wood products manufacturing," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 1656–1668, Nov. 2012.

[12] B. Chaib-draa, *Multiagent Based Supply Chain Management*, J. Müller, Ed. Berlin, Germany: Springer, 2006.

[13] M. J. Karimifar, M. K. Sikarudi, E. Moradi, and M. Bidkhori, *Competitive Location Problem*. Berlin, Germany: Springer, 2009, ch. 12, pp. 271–294.

[14] M. Nakanishi and L. G. Cooper, "Parameter estimation for a multiplicative competitive interaction model: Least squares approach," *J. Market. Res.*, vol. 11, no. 3, pp. 303–311, Aug. 1974.

[15] N. Saidani, F. Chu, and H. Chen, "Competitive facility location and design with reactions of competitors already in the market," *Eur. J. Oper. Res.*, vol. 219, no. 1, pp. 9–17, May. 2012.

[16] C. Revelle, "The maximum capture or sphere of influence location problem: Hotelling revisited on a network," *J. Reg. Sci.*, vol. 26, no. 2, pp. 343–358, May 1986.

[17] R. Aboolian, O. Berman, and D. Krass, "Optimizing pricing and location decisions for competitive service facilities charging uniform price," *J. Oper. Res. Soc.*, vol. 59, no. 11, pp. 1506–1519, 2007.

[18] D. Serra, V. Marianov, and C. ReVelle, "The maximum-capture hierarchical location problem," *Eur. J. Oper. Res.*, vol. 62, no. 3, pp. 363–371, Nov. 1992.

[19] D. Serra and C. ReVelle, "Competitive location and pricing on networks," *Geogr. Anal.*, vol. 31, no. 2, pp. 109–129, Apr. 1999.

[20] H. A. Eiselt, G. Laporte, and J.-F. Thisse, "Competitive location models: A framework and bibliography," *Transport. Sci.*, vol. 27, no. 1, pp. 44–54, Feb. 1993.

[21] D. Konur and J. Geunes, "Competitive multifacility location games with non-identical firms and convex traffic congestion costs," *Transport. Res. E-log.*, vol. 48, no. 1, pp. 373–385, Jan. 2012.

[22] S. D. Pathak, J. M. Day, A. Nair, W. J. Sawaya, and M. M. Kristal, "Complexity and adaptivity in supply networks: Building supply network theory using a complex adaptive systems perspective," *Decision Sci.*, vol. 38, no. 4, pp. 547–580, Nov. 2007.

[23] A. Fearne, "The evolution of partnerships in the meat supply chain: Insights from the British beef industry," *Supply Chain Manag.*, vol. 3, no. 4, pp. 214–231, 1998.

[24] M. Fujita and J.-F. Thisse, "Globalization and the evolution of the supply chain: Who gains and who loses?" *Int. Econ. Rev.*, vol. 47, no. 3, pp. 811–836, Aug. 2006.

[25] Q. H. Zhu and Y. J. Dou, "Evolutionary game model between governments and core enterprises in greening supply chains," *Syst. Eng. Theory Practice*, vol. 27, no. 12, pp. 85–89, Dec. 2007.

[26] S. G. Jalali Naini, A. R. Aliahmadi, and M. Jafari-Eskandari, "Designing a mixed performance measurement system for environmental supply chain management using evolutionary game theory and balanced scorecard: A case study of an auto industry supply chain," *Resour. Conserv. Recycl.*, vol. 55, no. 6, pp. 593–603, Apr. 2011.

[27] J. Holland, *Hidden Order: How Adaptation Builds Complexity*. Reading, MA, USA: Addison-Wesley, 1996.

[28] T. Y. Choi, K. J. Dooley, and M. Rungtusanatham, "Supply networks and complex adaptive systems: Control versus emergence," *J. Oper. Manage.*, vol. 19, no. 3, pp. 351–366, May 2001.

[29] G. Li, H. Yang, L. Sun, P. Ji, and L. Feng, "The evolutionary complexity of complex adaptive supply networks: A simulation and case study," *Int. J. Prod. Econ.*, vol. 124, no. 2, pp. 310–330, Apr. 2010.

[30] G. Briscoe, "Complex adaptive digital ecosystems," in *Proc. Int. Conf. Manage. Emergent Digit. Ecosyst.*, 2010, pp. 39–46.

[31] H. Hattori, Y. Nakajima, and T. Ishida, "Learning from humans: Agent modeling with individual human behaviors," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 41, no. 1, pp. 1–9, Jan. 2011.

[32] M. Wooldridge and N. R. Jennings, "Intelligent agents: Theory and practice," *Knowl. Eng. Rev.*, vol. 10, no. 2, pp. 115–152, Jun. 1995.

[33] R. Garcia-Flores and X. Z. Wang, "A multiagent system for chemical supply chain simulation and management support," *OR Spectrum*, vol. 24, no. 3, pp. 343–370, Aug. 2002.

[34] Arshinder, A. Kanda, and S. Deshmukh, "Supply chain coordination: Perspectives, empirical studies and research directions," *Int. J. Prod. Econ.*, vol. 115, no. 2, pp. 316–335, Oct. 2008.

[35] A. Kusiak and F. Salustri, "Computational intelligence in product design engineering: Review and trends," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 37, no. 5, pp. 766–778, Sep. 2007.

[36] S. S. Heragu, R. J. Graves, B.-I. Kim, and A. St Onge, "Intelligent agent based framework for manufacturing systems control," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 32, no. 5, pp. 560–573, Sep. 2002.

[37] J. Lau, G. Huang, K. Mak, and L. Liang, "Agent-based modeling of supply chains for distributed scheduling," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 36, no. 5, pp. 847–861, Sep. 2006.

[38] S. Lombardo, M. Petri, and D. Zotta, "Intelligent GIS and retail location dynamics: A multiagent system integrated with ArcGIS," *LNCS*, vol. 3044, pp. 1046–1056, May. 2004.

[39] Y. Chao, J. Guo, Q. Wang, and Y. Yue, "Agent-based location choice simulation," in *Proc. 17th Int. Conf. Geoinform.*, 2009, pp. 1–4.

[40] J. Holland, "Complex adaptive systems and spontaneous emergence," in *Complexity and Industrial Clusters* (ser. Contributions to Economics), A. Curzio and M. Fortis, Eds. Heidelberg, Germany: Physica-Verlag, 2002, pp. 25–34.

[41] H. Min and G. Zhou, "Supply chain modeling: Past, present and future," *Comput. Ind. Eng.*, vol. 43, no. 1–2, pp. 231–249, Jul. 2002.

[42] S. Hakimi, "p-median theorems for competitive locations," *Ann. Oper. Res.*, vol. 6, no. 4, pp. 75–98, Apr. 1986.

[43] N. Kumar and R. Rao, "Using basket composition data for intelligent supermarket pricing," *Market. Sci.*, vol. 25, no. 2, pp. 188–199, Mar. 2006.

[44] G. Hua, T.C.E. Cheng, and S. Wang, "The maximum capture per unit cost location problem," *Int. J. Prod. Econ.*, vol. 131, no. 2, pp. 568–574, Jun. 2011.

[45] J. Holland, "Genetic algorithms," *Sci. Am.*, vol. 267, no. 1, pp. 66–72, Jul. 1992.

[46] G. Diplock and S. Openshaw, "Using simple genetic algorithms to calibrate spatial interaction models," *Geogr. Anal.*, vol. 28, no. 3, pp. 262–279, Jul. 1996.

[47] A. J. Heppenstall, A. J. Evans, and M. H. Birkin, "Genetic algorithm optimisation of an agent-based model for simulating a retail market," *Environ. Plann. Plann. Des.*, vol. 34, no. 6, pp. 1051–1070, Mar. 2007.

[48] P. Hanjoul, P. Hansen, D. Peeters, and J.-F. Thisse, "Uncapacitated plant location under alternative spatial price policies," *Manage. Sci.*, vol. 36, no. 1, pp. 41–57, Jan. 1990.

[49] K. Demeter, A. Gelei, and I. Jenei, "The effect of strategy on supply chain configuration and management practices on the basis of two supply chains in the hungarian automotive industry," *Int. J. Prod. Econ.*, vol. 104, no. 2, pp. 555–570, Dec. 2006.

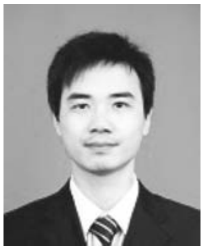
[50] M. Eltony and N. Al-Mutairi, "Demand for gasoline in Kuwait: An empirical analysis using cointegration techniques," *Energ. Econ.*, vol. 17, no. 3, pp. 249–253, Jul. 1995.

[51] A. R. Rao, M. E. Bergen, and S. Davis, "How to fight a price war," *Harvard Bus. Rev.*, vol. 78, no. 2, pp. 107–120, Mar. 2000.

[52] C.-H. Chiu, T.-M. Choi, and D. Li, "Price wall or war: The pricing strategies for retailers," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 39, no. 2, pp. 331–343, Mar. 2009.

[53] J. A. Cazier, B. B. Shao, and R. D. S. Louis, "E-business differentiation through value-based trust," *Inform. Manage-Amster.*, vol. 43, no. 6, pp. 718–727, Sep. 2006.

[54] H. L. Lee, V. Padmanabhan, and S. Whang, "Information distortion in a supply chain: The bullwhip effect," *Manage. Sci.*, vol. 43, no. 4, pp. 546–558, Apr. 1997.



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