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ORIGINAL ARTICLE

Alok R. Chaturvedi · Shailendra Raj Mehta
Daniel Dolk · Mukul Gupta

Computational experimentations in market and supply-chain co-design: a mixed agent approach

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Abstract The synthetic environment for analysis and simulations (SEAS) is a computational experimentation environment that mimics real life economies, with multiple interlinked markets, multiple goods and services, multiple firms and channels and multiple consumers, all built from the ground up. It is populated with human agents who make strategically complex decisions and artificial agents who make simple but detail intensive decisions. These agents can be calibrated with real data and allowed to make the same decisions in this synthetic economy as their real life counterparts. The resulting outcomes can be surprisingly accurate. This paper discusses the research in this area and goes on to detail the architecture of SEAS. It also presents a detailed case study of market and supply-chain co-design for business-to-business e-commerce in the PC industry.

1 Introduction

The fundamental tenet of business-to-business (B2B) e-commerce is disintermediation in relatively "frictionless" economies. The advent of e-com-

A. R. Chaturvedi (✉) · S. R. Mehta · D. Dolk · M. Gupta
Krannert Graduate School of Management,
Purdue University, West Lafayette, IN 47907, USA
E-mail: alok@purdue.edu
Tel.: +1-765-4949048
Fax: +1-765-4941526
E-mail: mehta@mgmt.purdue.edu
E-mail: drdolk@nps.edu
E-mail: Mukul.Gupta@Business.uconn.edu

merce has shrunk the competitive "time to market" window for new products substantially, particularly in the area of technology products themselves. The pressure to be "first to market" and establish "lock in" is intense for companies in the software, web, and telecommunications industries. With such compressed timelines, the probability of new product success is often more a matter of good fortune than of careful analysis and preparation.

Intuitively, the notion of co-design i.e., integrating all design activities in parallel is an appealing alternative, which a priori one would suspect is superior to the serial approach. Co-design has been used successfully, particularly in designing embedded hardware and software systems.

This paper uses the computational experimentation method to analyze the co-design approach to the problem of designing the supply chain in the PC industry. This is an intensely competitive market marked by rapid change, extremely short product development times, and very short shelf lives. Corporations cannot afford to make very many mistakes in this climate, or they risk losing market share. By adopting a co-design approach, we argue that firms have a higher probability of aligning products with markets, and thus maintaining their competitive edge. The co-design approach that we use to integrate the convergent technology product design processes is a hybrid of microeconomic and OR modeling, namely experimental economics complemented by agent-based simulation (ABS). In an interesting paper which provides an industry perspective on efficiently co-designing the demand and supply chains in an industry, Murphy-Hoye (2002) has said, "Excel spreadsheets and email are no longer sufficient tools for complex collaborative business interaction. Enhanced or new modeling and simulation and techniques will be needed to improve planning capabilities and enable earlier identification of potential problems." This paper is a step in this direction.

Toward this end, we create a synthetic economy to study a computational model of human decision making in the context of B2B e-commerce. There are several important aspects of B2B e-commerce, e-CRM, e-procurement, e-R&D, e-fulfillment, e-service, and e-manufacturing (Swenson et al. 1998; Kaplan and Sawhney 2000; Ramsdell 2000; Timmers 1999; Nagurney 2002; Lucking-Reiley and Spulber 2001; Fensel et al. 2001). We implement agents and simulate different business models to study the decision-making process by creating their computational models.

The remainder of the paper is organized as follows: Sect. 2 presents the importance of the problem and the background research. Section 3 describes the concept of synthetic economies and presents the technical architecture of synthetic environment for analysis and simulations (SEAS). Section 4 presents the case study of application of SEAS to B2B e-commerce in the PC industry. Finally, Sect. 5 concludes the paper.

2 Importance of the problem

Understanding electronic marketplaces is one of the keys for corporations in making the transition from the "old" to the "new" economy. Although many claim that the "old" and the "new" will converge and e-business will become just plain old business as the years unfold, companies still struggle with the rapid changes e-business has wrought on the landscape. The finer granularity of customer relationship management, disintermediation and reintermediation of the supply chain, B2B exchanges, and the evolution of agent technology are just some of the phenomena that have emerged from the electronic marketplace (Bailey and Bakos 1997).

Although these processes will undoubtedly be assimilated into the "business as usual" environment at some point, they require new approaches and tools for analysis and modeling. This is particularly true in the area of economics where the standard neoclassical economic model has proven to be inadequate in capturing the dynamic evolution brought about by technological change.

E-business faces a number of paradoxes. These competing issues, such as the conflict between trading exchanges and customer relationship management, Internet market efficiency, and competitive pricing etc., have to be resolved by every e-business that is to be successful in the market place. A major problem is that decision makers would have to draw upon techniques from various disciplines. In this paper, we discuss the new decision-making technology of ABS and its role in addressing some of the critical problems that arise in electronic marketplaces. Specifically, we look at ABS as an engine for building synthetic economies that can, in turn, be used as the basis of analyses for the e-business phenomena discussed above. The ABS-driven economy, consisting of many thousands of software agents whose emergent behavior defines the marketplace, can be used as a platform with which human players can engage in strategic decision-making simulations. ABS in this context is a hybrid of microeconomic analysis combined with the OR/MS discipline of simulation (although a much different, bottom-up kind of simulation when compared with the typical top-down discrete event simulation). This approach wherein human players can participate concurrently with an agent-based economy offers the following benefits:

- The seamless integration of human and software agents: this allows significantly more complex experiments to be conducted than are currently possible in the field of experimental economics (Kagel and Roth 1995). These experiments can combine depth of decision making (using humans) and breadth (combining artificial agents).
- The consequences of decisions can be measured: this extends the purview of traditional decision support from building models that support human decision making to actually being able to gauge the impacts of decisions as well.
- A laboratory for testing the efficacy of decision support tools: experiments can be devised that measure the effects of various decisions against the support tools used to arrive at those decisions.

For the ABS approach to work effectively, viable virtual economies must be constructed. This requires careful attention to the design and specification of the agents who will populate the economy. This demands that we will be able to access reliable, accurate computational models of human behavior which we can then invoke appropriately upon our population of agents to achieve a marketplace behavior with acceptable verisimilitude. There is a vast repository of such models from disciplines such as experimental economics, artificial intelligence, cognitive science, psychology, and decision theory.

2.1 Shortcomings of classical economics

The standard economic model is that of *homo economicus*. This is basically a constrained optimization exercise. An agent starts with an objective (maximize profit, maximize utility) and a choice set (defined by a budget constraint or an endowment or input prices), and computes the optimal solution. This solution is then implemented in a setting with certain rules (a market, a bilateral negotiation) and those rules then, perhaps after several iterations determine an outcome (an allocation, prices). This standard model (e.g. Kreps 1990; MasColell et al. 1995) forms the basis of much of economics and a significant amount of management modeling.

However, in recent years, at least three strands of literature have converged to upset this neat and somewhat limited view of human behavior. These include experimental economics (Kagel and Roth 1995), learning (Fudenberg and Levine 1999), and behavioral economics (Mullainathan and Thaler 2000). Experimental economics shows that while some parts of economic theory held up reasonably well (such as static markets with bids and asks), others such as individual decision making did not, and were subject to biases, errors, and misperceptions. Behavioral economics complements experimental economics quite nicely by looking for field data as opposed to experimental data and showing that many of the same biases are found in real life. Similarly, learning theory assumes that rational behavior does not emerge fully formed but through a great deal of trial and error.

It is worth quoting in detail an excerpt from a recent survey (Mullainathan and Thaler 2000) to underscore just how radical a departure this is. They confine themselves to the field of finance, but their remarks apply much more generally.

> If economists had been asked, 20 years ago in a poll, to name the domain in which bounded rationality was least likely to find useful applications, the likely winner would have been finance. The limits of arbitrage arguments were not well understood and that time, one leading economist had called efficient markets hypothesis the best-established fact in economics. Times change. Now as we begin the twenty-first century, finance is perhaps the branch of economics where behavioral economics has made the greatest contributions.
>
> Two factors contributed to the surprising success of behavioral finance. First, financial economics in general and the efficient market hypothesis in particular generated sharp testable predictions about observable phenomena. Second, there are great data readily available to test these sharp predictions.

They add:

> The standard economic model of human behavior includes (at least) three unrealistic traits, unbounded rationality, unbounded willpower, and unbounded selfishness. These three traits are good candidates for modification.

With this in mind what sort of modeling approach might supplement the standard economic model? Clearly a broad-based approach is required that incorporates insights from a variety of disciplines, including psychology, management, and economics.

2.2 Agent behavior

Traditionally, economics, and by extension, large sections of management have largely been insulated from the rest of the social sciences. However, if the assumptions of the standard model are modified, then the door is opened for importing significant insights from the sister disciplines, such as psychology, that have had a long history of studying behavior as observed, as opposed to behavior, as deduced from a set of axioms. Clearly then, there is significant motivation for building agents that engage in specific behaviors as opposed to optimization. One can then put them together in increasingly complex environments to see what sort of behavior results emerge (Epstein and Axtell 1996). However, much more sophisticated agents are required. At least four classes of capabilities have to be modeled in detail—including information gathering, information processing, responsiveness, and interaction. For example, Downs-Martin (1997) indicates that the information-processing part might consist of the behaviors as listed in Table 1.

Table 1 Agent behavior verbs

Actions	Simple definitions
Acquire	To gain by one's own efforts, to obtain
Alert	To warn to be ready or watchful
Detect	To discover something hidden, to notice, to observe
Discriminate	To distinguish between things
Extract	To deduce or derive, to take out from
Filter	To strain out unwanted data and so forth
Identify	To fix a person or thing as the one described
Inspect	To look at carefully
Localize	To trace to a particular place, discover the position of
Monitor	To watch, check, regulate performance
Recognize	To identify as known before
Orient	To adjust to a particular situation
Perceive	To become aware of via senses, grasp mentally
Queue	To form up in a line
Read	To get meaning by interpreting characters
Receive	To take or get freely given information
Search	To examine carefully for a thing concealed, survey

It is important to analyze and classify these behaviors with a view to applying them in a broad range of social disciplines, in a collaborative and modular fashion. One sort of modeling paradigm that might work hand in hand with the new departures from the standard model is agent-based modeling techniques.

3 Agent-based economies and SEAS

Agent-based techniques have gained prominence in management and economics (Gode and Sunder 1993, 1997; Duffy 2001; Lopez-Paredes et al. 2002) and this area shows much promise in terms of addressing the three challenges to the standard model, outlined above.

The motivation for agent-based economies is as follows. Rust (1996) argues that researchers are forced to build models which are either stylized enough to be solved analytically or small enough to be solved computationally. Each of these kinds of models is, in Rust's words, a "toy model." Moreover, such models are not modular and cannot be built up cumulatively by large teams of researchers working together, each developing a separate piece of the puzzle. Therefore, Rust suggests that we mimic the intelligence demonstrated in the organization of the market and use decentralized computing along with agents to study these models. Rust's suggestion is quite appealing. He mentions a number of desiderata for such an agent-based environment. Among them is the ability to seamlessly integrate human and artificial agents in the same environment. It would allow experiments of greater complexity and of a larger scale than those possible with existing software such as the pioneering *MUDA* program, developed by Plott and Gray (1990) at Caltech. This would truly enable multidisciplinary research. Computer-based information systems would be integrated with economics to create synthetic economies that could be used as a common meeting ground for techniques from operations research, management science, psychology, and computer science. This, then, is the promise of agent-based research.

Of crucial importance is the ability to put human and artificial agents in the same environment. This allow us to leverage human capabilities to make complex decisions (such as running firms or channels) and to leverage the large numbers of artificial agents that can be deployed to capture fine details of market segments. Moreover such mixed environments allow us to calibrate human and artificial agents against each other. For example, can we mimic a particular human behavior (such as trading) in a narrow domain (such as a simple double auction market) by using artificial agents? Similarly, can we calibrate the complexity of a decision-making task performed by human beings on the basis of the complexity of the artificial agent that might be able to mimic it? In a recent landmark paper, Green (2002) argues that role-playing is extremely valuable in helping predict the outcomes of conflict situations, often doubling the accuracy of prediction and catapulting amateurs ahead of seasoned experts. Similarly Shubik (1975) stated that "an extremely valuable aspect of operational gaming is the perspective gained by viewing a conflict of interests from the other side. Experience gained in playing roles foreign to one's own interests may provide insights hard to obtain in any other manner.” This paper provides a joint environment incorporating ABS techniques and techniques of experimental economics to provide a rich domain in which participants may gain experience.

In the past, machine learning has primarily been used for classification problems. Now, these techniques are increasingly being used in decision support (Chaturvedi et al. 1993), real-time system control, production process control; product design and control knowledge (Chaturvedi and Gulati 1993; Chaturvedi and Nazareth 1998); scheduling and control of flexible manufacturing systems. Now machine-learning techniques are being used to comprehensively model human behavior in markets in the form of shopbots (artificially intelligent agents which help consumers buy goods and services at the best price) (Guttman et al. 1998; Chavez and Maes 1996; Bichler et al. 1998; Hedberg 1996) and pricebots (artificially intelligent agents which help sellers determine the optional price) (Chavez and Maes 1996).

The extraction of human knowledge and behavior requires careful planning. New knowledge has to be reconciled with existing rules. Conflicts must be resolved satisfactorily. Likewise, the potential utility of the new rules also needs to be examined prior to inclusion. Rules that are very specific, and are unlikely to find application, may be discarded. In a similar vein, extremely general rules are unlikely to be included, as they are more prone to generating conflict. This is the balance that needs to be struck and a particular instance of which is described below in the modeling of our consumer artificial agents.

3.1 Synthetic environment for analysis and simulations

Synthetic environment for analysis and simulations is an interactive synthetic economy that models the critical relationships between economies, markets, product and process innovations, price, and business rules using human and artificial agents. It allows participants to view the economy from different perspectives such as the government, universities, commercial sectors, and households/consumers/tax payers.

The SEAS computational infrastructure allows large number of human players to interact with hundreds of thousands of artificial agents. We briefly describe the architecture in the Appendix.

4 PSEAS: a PC industry case study

These ideas have been implemented in an artificial economy which mimics the behavior of the PC industry. The particular issue that we seek to address is as follows. B2B e-commerce is the new battleground for firms in the PC industry. Dell Computers pioneered the direct-sales business model that every other PC maker is trying to emulate, but with limited success. In this disintermediated model, an original equipment manufacturer (OEM) abandons distributors, wholesalers, and retailers and sells directly to the end customer. There are several advantages of this model. First, by manufacturing computers to order, the company economizes inventory and prevents the depreciation due to technological obsolescence. Second, it allows the OEM to be paid before it manufactures computers and sells to its suppliers. Third, it allows the OEM to capture the lucrative margins on add-on services such as warranties, financing, upgrades, and portal services.

So, what prevents the other PC makers from adopting the direct model? With the traditional business model, OEMs developed a web of relationships with the channel firms, who do the assembly and supply to the final customers. The problem is that the latter "own" the customers, and provide the profitable parts of the computer value chain—the add-ons. By going direct, a traditional computer company runs the risk of alienating the channel. If that happens, the intermediary can set up competing operations by teaming up with generic PC makers. To analyze these questions we set up a synthetic economy as follows:

1. In the SEAS environment, we create a synthetic economy representing the PC industry and populate it with four classes of agents—computer makers, channels and service providers, and business customers.
2. We divide the business customers into three segments—small, medium, and large. Each of these segments has two subsegments—the "self-integrator" segment and "need help" segment. We calibrate the behavior of the artificial agents to closely resemble that of the segment they represent in the "real economy."
3. We allow human agents to play the roles of computer makers and channels while thousands of artificial agents perform the roles of business customers.
4. There are two classes of products sold in the economy—goods and services. The goods sold in the market are the base units and add-on options. Each of these goods has five levels representing five different qualities. There are four classes of services—warranty, implementation, financing, and portal.
5. Firms can make different types of investments to improve their performance—such as ease of doing business, e-branding, sales force, information portal, facilitation, transactions, and integration.

4.1 Business process modeling

PSEAS focuses on how various entities in the value-chain function and interoperate under differing external circumstances. The "Aha!" experiences from playing the game increased the participants' insights and awareness into the following issues:

- Adoption of different e-biz models by the players in response to the changes in environment;
- Interaction among the various entities in the value chain (e.g., manufacturers, traditional channels, e-channels);
- Implications of a manufacturer going "direct" on its channel partners;
- Nature of channel conflicts and their implications;

– Effect of B2B exchanges on manufacturers' and channels' margins, market shares, and profitability;
– The sustainability of these business models?

One of the most important decisions that participants have to make in the exercise is in which market are they going to choose to sell their products. They have to decide if they will take the risk to antagonize the channels, if they segregate products by channels, and how to mark up products according to channels, etc. PSEAS e-business model alternatives are presented in Fig. 1.

4.1.1 Human players' overall choices

Manufacturers have the following choices:

1. Design product class and configuration—should they sell stripped down models or models loaded with options?
2. Should they just sell hardware or bundle the hardware with services?
3. Sell to the channels, whether they are traditional brick and mortar distributors (BM) or e-distributors (ED). A manufacturer makes an offer to a distributor by sending him/her a message with the product type, quantity, and price. The distributor may accept or reject the offer.
4. Sell direct to end customers.
5. Sell through B2B exchange to channels or to customers. Manufacturers can create their own exchange and invite customers and suppliers (suppliers of manufacturers are not included in the model) to join them or they may choose join an existing exchange.
6. Sell through the neutral B2B marketplace.

Figure 2 shows the interface of a PC manufacturer. The cost, quantity, price, and outlet for the goods are shown in the picture. By contrast, Fig. 3 shows the production screen where the product is configured and then

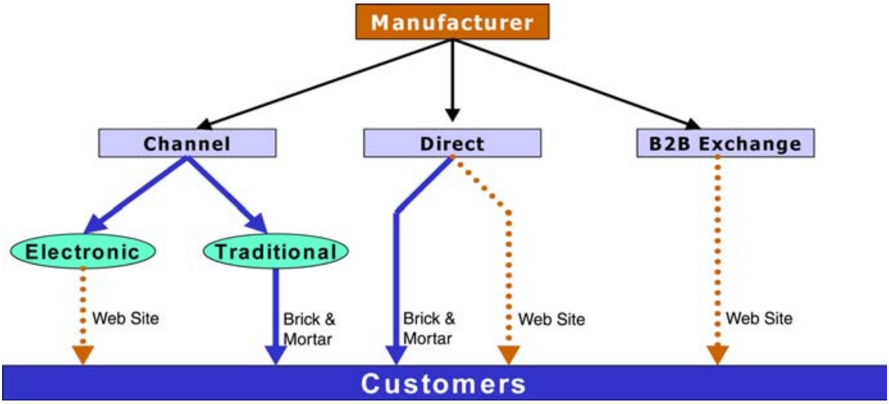

Fig. 1 The business models in PSEAS

priced. It shows the various combinations of processor speed and add-ons that are available.

Traditional distributors have the following choices:

1. Sell direct to customers, whether it is through their web site or their stores,
2. Create a B2B exchange and have their suppliers and manufacturers join it to facilitate transaction (but do not allow the competition to join),
3. Join or create a neutral B2B marketplace (with the competition).

E-distributors can:

1. Create a B2B exchange and have their suppliers join it to facilitate transactions (but do not authorize the competition to join it),
2. Join a neutral B2B marketplace,
3. Create a neutral B2B marketplace and play the role of a neutral agent.

Overall there are four different distribution business model choices for the players:

1. Channel: manufacturers sell to channels.
2. Direct: manufacturers and channels sell directly to customers through the traditional method or via their web sites.
3. B2B exchange: manufacturers or distributors open their own marketplace and allow their suppliers and customers to join or join a supplier/customer B2B marketplace.
4. B2B e-hub (neutral exchange): several competitors in the industry at different positions in the supply chain (manufacturers, distributors, and customers) join a neutral marketplace.

A player can configure the product by clicking on the base and option levels and can create a bundle by clicking on the service button. He/she can

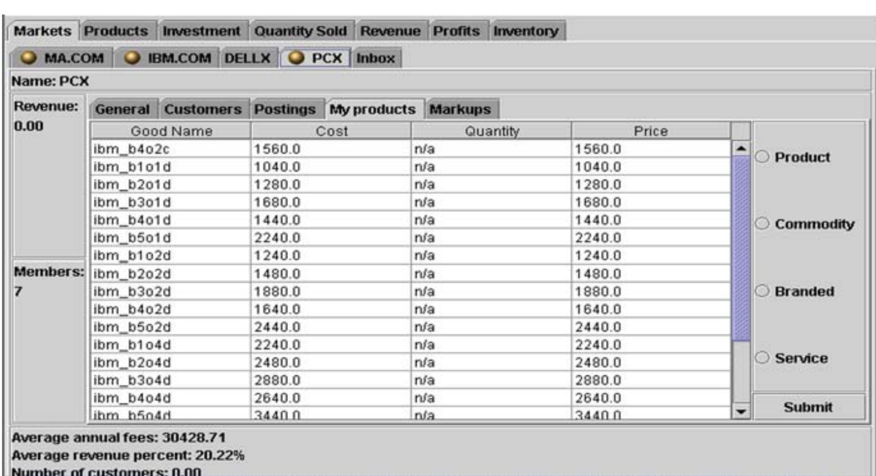

Fig. 2 PSEAS B2B interface

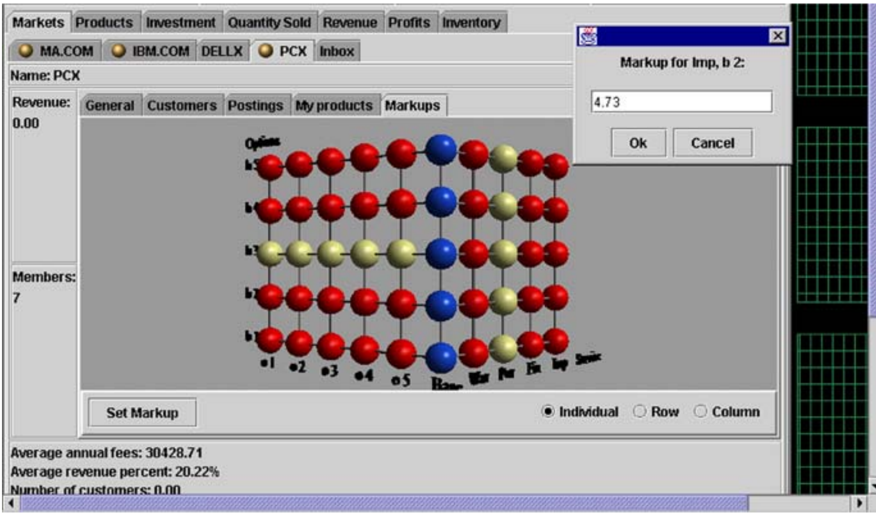

Fig. 3 The production interface

set the markup by clicking on the individual offering or on the entire row or column. The marginal costs of production (which is assumed to be fixed for simplicity) for the various goods and services a firm produces are known to it. It chooses prices by choosing markups over cost. Production levels are chosen by firms for each category of goods and services. Once a particular level of the good is produced, its marginal cost times quantity is deducted from its cash balance. Firms have production capacities beyond which they may not produce. Distribution is defined by product.

If there is a leftover inventory of products not sold by channels or B2B exchange, then by default the inventory is liquidated.

Firms may invest in marketing, logistic support, and customer support to enhance demand for their products. Additional investments, such as investment in infrastructure, lower the transaction costs. Firms can engage in two types of R&D—to increase perceived quality and to decrease the cost of production in the next period. For each investment, there is an obsolescence variable introduced i.e., if the firm does not invest enough in comparison with other firms, sales will be impacted.

4.2 Artificial agent behavior modeling[1]

Consumers make decisions in two steps. First they decide which product to buy and then they determine how much to buy. A product is defined as a combination of attributes. For simplicity, it was assumed that more

[1] Details of the exact functional forms are available upon request. What follows is a highly condensed description.

memory and hard drive go together and thus only two technical attributes were considered—processor speed and memory/storage. The third attribute was considered to be of quality or brand image—i.e., certain brands were considered to be ''premium'' brands and consumers were assumed to pay a premium for them. The valuation attached by different consumers to each of these attributes varied by market segment. In general, high-end consumers value these attributes more than low-end consumers, therefore, other things being equal, end up buying higher-end computers.

Consumer segments have various switching costs. While each consumer segment is attached to a particular firm, a particular channel, and a particular market segment, (which is given by their behavior from the previous period) they can switch upon payment of a switching cost measured in dollars. There are separate switching cost for firms, channels, and products. Thus if a particular consumer segment bought computers of brand x1, from channel y1, in market segment z1 in the previous period but switched to brand x2 while keeping channels and market segments the same, he would incur only a brand switching cost which would be added to the price. If he changed channels as well, the channel switching cost would be added as well.

The consumers evaluate each product on offer in the market based on their valuations of attributes. Then they compare the prices charged by vendors and choose the one product that offers the maximum surplus (value minus price) based on their specific valuation taking into account the switching costs as described above.

Once the product choice is made in this fashion, the quantity is determined by a system of Cobb-Douglas demand equations.

If there are n competing manufacturers selling differentiated goods, and the quantity Q_1 is sold by firm 1 at price P_1 and the quantity Q_n sold by firm n at price P_n then the demand is assumed to be:

$$
\begin{aligned}
Q_1 &= A_1 P_1^{-\alpha_1} P_2^{\beta_{2,1}} P_3^{\beta_{3,1}} P_4^{\beta_{4,1}} \ldots P_n^{\beta_{n,1}} \\
&\vdots \\
Q_n &= A_n P_n^{-\alpha_n} P_1^{\beta_{1,n}} P_2^{\beta_{2,n}} P_3^{\beta_{3,n}} \ldots P_{n-1}^{\beta_{n-1,n}}
\end{aligned}
$$

where α is the own price elasticity of demand and β is the cross price elasticity of demand. In general, there should be a separate α for every commodity and a separate β for every ordered pair of commodities, but for simplicity in this exercise all α's are taken to be equal as are all β's. Firms can invest in advertising. The advertising level chosen by i firm increases its demand by increasing its shift parameter A_i given above in the Cobb-Douglas demand case. It simultaneously causes the demand for the other firms to drop but not by the full amount of the increase in demand of the advertising firm. In other words, if all firms increased advertising simultaneously, total demand would increase, but some firms could suffer a drop in demand on account of the relative effects. Similar argument applies to other investments as well.

4.3 Configuration and calibration

We used data from a variety of sources to populate our synthetic economy. We used the reports by industry analysts, published articles, annual reports, SEC filings, company websites, and other published materials. For elasticity of demand, a major PC manufacturer made available to us the basic marketing data on price responsiveness collected by it. They also gave us data on brand perception, switching costs, and valuation of attributes such as processor speed etc. Marginal cost of production for the various manufacturers were inferred from prices and margin estimates published in the industry press.

Once the data is gathered, economy was populated with 30,000 artificial agents with 10,000 agents in each of the high, medium and low segments. Their behaviors were calibrated and verified against a few known scenarios to create the SEAS virtual execution environment.

Two small (12–15 participants) and two midsized (40–45 participants) experiments were conducted to validate, verify, and calibrate the synthetic environment. Business executives participated in the small group experiments while MBA students participated in the midsized experiments. The purpose of these experiments was to assess the realism and reasonableness of the synthetic environment as well as test the stability and performance of the model. Based on the recommendations and the results of these experiments, the parameters were adjusted, algorithms were refined, and the environment was tuned for performance. Also, these experiments gave insights into scalability of the SEAS environment.

4.4 Experiment and results

The main experiment was run with 180 students, divided into four parallel sessions. Each session had the full complement of manufacturers, channels, and B2B exchanges. The experiment comprised of several steps—some involved a facilitator and the others used computer-based simulation. The first step involved ideas and insights generation. In this step, participants brought forth their own ideas, insights, and understanding of the issues facing the companies they represented and the industry as a whole. The second step involved testing these ideas and insights against the industry structure pertaining to relative positions of firms on product mix, customer perception, and infrastructure sophistication. In addition to the structure, the ideas and insights were also tested for robustness against economic, cultural, and competitive uncertainties. The fourth step involved the development of different options and business ideas. The fifth step involved testing the business ideas in SEAS' synthetic economy. The sixth and final step involved an after-action review, in which participants discussed their moves, counter-moves, and outcomes.

While the teams devised several strategies during the facilitated idea generation session, the five most commonly used strategies for the manufacturing firms were:

1. Stay a pure manufacturer.
2. Develop a symbiotic relationship with the channel.
3. Go direct aggressively with bundled services.
4. Subscribe to an existing B2B exchange.
5. Collaborate with other manufacturers and channel firm to create a new B2B exchange.

The channel firms, likewise, identified the following five options to explore:

1. Just add value through service.
2. Develop a symbiotic relationship with the manufacturer.
3. Compete aggressively with the name brand firms through white-boxes.
4. Subscribe to an existing B2B exchange.
5. Collaborate with manufacturers and other channel firms to create a new B2B exchange.

Experiments were run in two phases. In the first phase, OEMs' had to decide whether they were going to setup a "dot com" or not and the channels had to react to those decisions. In phase two of the experiment, a neutral exchange was introduced as well as OEMs and channels were given the ability to start their own exchanges. The results of these experiments are given below.

4.4.1 To dot com or not to dot com

Phase I of the experiment—"to dot com or not to dot com" focuses more on the relationship between the manufacturer and the channel partner. When PC manufacturers first considered venturing into "going direct," they did so with much trepidation. They did not want to roil the retailers on whom they so intimately depended. The retailers, carefully watching the rise in the number of manufacturers going direct, kept the pressure on manufacturers to restrict their efforts to bypass their traditional sales channels. The box-makers (OEMs) quickly discovered one of the fundamental sources of channel conflict—where they wanted to send fully loaded boxes while the channel wanted "stripped down" versions of boxes. The channels were quite successful in playing off one manufacturer against the other.

As a result, the box-makers quickly discovered that the only way to move fully loaded boxes was to go direct, (see next section). This preference for going direct was reinforced by the finding that the channels were increasingly turning to the generics (white boxes) to supply them with low-end machines.

Manufacturers found going direct challenging, as they feared channel firms could fight back by concentrating on white boxes. However, indecision proved to be even worse. Gradually many came to the realization that there was no alternative. Regardless of the difficulty of selling direct, manufacturers still found ways to sell direct to customers without offending the distribution channel, e.g.,

(a) Some manufactures negotiated with their channel partners to sell only certain configurations direct and the rest through them. Thus, the channel partners did not find them to be in direct competition.
(b) Successful manufacturers sold low base systems with low option load through the traditional channel and sold high-end systems directly.
(c) Manufacturers who offered a wide range of products through the channel and made no investment in direct sales facility, very quickly lost their bargaining power. Without appropriate infrastructure to sell direct and without a channel firm to sell their products, these manufacturers ended up losing substantial market share, and lost their leverage with the channel. When they finally did decide to go direct, it was too little and too late. Their customers had left them and very few returned.
(d) Going direct with just hardware proved difficult. These firms did not gain enough new customers to justify their move and lost the trust of the channel to boot. Manufacturers bundling services ended up with higher profit margins and market share.

White box play was key for channel firms. As more manufacturers resorted to direct selling, the channel firms came back aggressively with white boxes and bundled them with service. Power play for margins was quite evident in the exercise. Some manufacturing firms used "reward power" to entice channels to cooperate. In this power play, the manufacturing firm allowed the channel to take margins on low-end base systems while they went direct with the high-end configurations. This approach seemed to work in the short run and the channels' bargaining power gradually eroded. Two channel firms were relegated to being rather insignificant pure value-added resellers.

However, when the channel firm was aggressive with the right mix of white boxes and branded products, it wielded significant market power. In certain cases, it was even able to exert "coercive power" on the manufacturer, especially with those brands that found going a bit tough. These manufacturers had to agree to bigger share of the profit on options in order to sell their systems. Figure 4 shows the profits of the firms over time, one of which, named D (representing Dell), managed to stem the trend toward lower profits by aggressively bundling services with hardware and attained industry leadership.

4.4.2 To B2B or not to B2B

In phase II of the experiment, a fictitious, neutral B2B exchange, PCex, was introduced. In a B2B exchange, multiple buyers and sellers come together to trade. PCex was set up as a vendor neutral exchange. In other words, it had no interest in success or failure of the participating members. Every OEM had the choice to subscribe to this exchange. The key strategic issues that the players had to consider were:

1. Status quo.
2. Sell all direct.

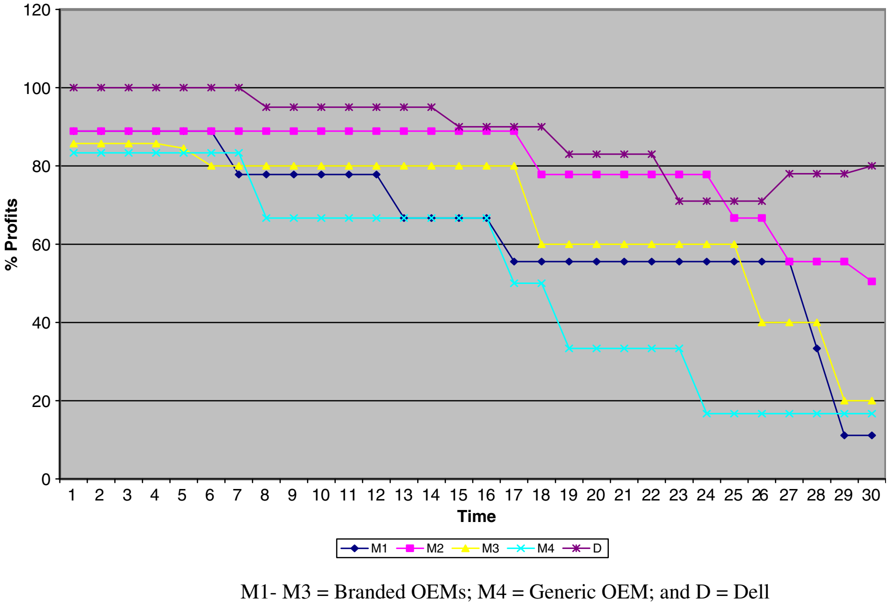

Fig. 4 The profits of the firms over time. *M1–M3* branded OEMS, *M4* generic OEM, *D* dell

3. Sell high-valued products direct.
4. Sell commodity and surplus products through the exchange.
5. Sell direct to value-added resellers.
6. Go all out through B2B exchange.

B2B exchanges allowed a complex set of strategic alternatives to OEMs. The choices were between three different business models—traditional, direct, and through the exchange.

The evolutions of firms adopting different business models were quite interesting. For example, initially, OEMs successfully segmented the market. They sold commodity PCs through the exchange, used the direct model to serve the high-value accounts with high-end systems, and used value-added resellers to sell to small and midsized customers who had higher needs for service. PCEx that started as an exchange for surplus and commodity product became a full-service vertical market. This resulted in channel companies becoming pure service providers. Prices were lower, the margins were higher with the exchanges as the transaction, and search costs for the customers came down. An interesting hybrid business model that worked was to sign up customers on the exchange and then service them direct.

Once the B2B exchange acquired a critical mass, making profits on a neutral exchange became a real challenge for all manufacturers. Given the transparency of prices, and quantities, prices very quickly converged to the marginal costs of the manufacturers. It is quite evident from the Fig. 5 that

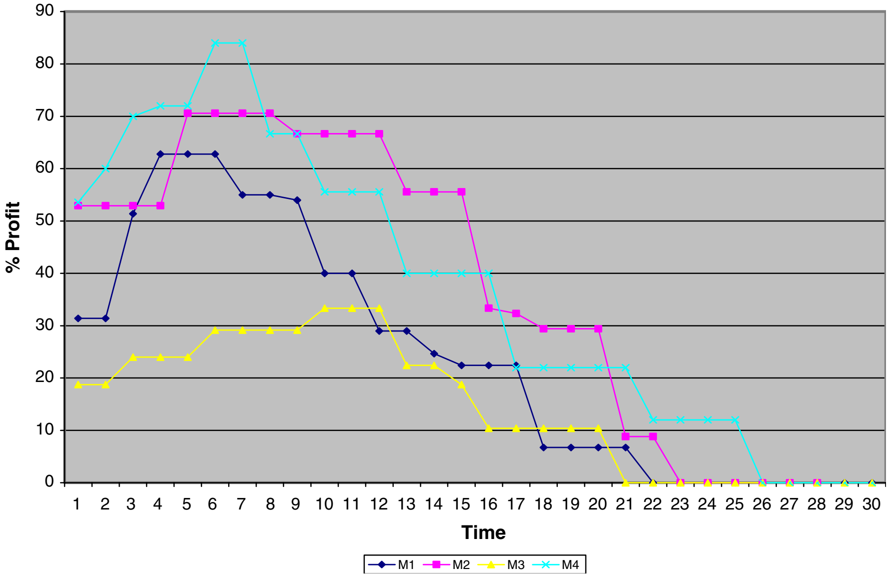

Fig. 5 Profits of firms in a neutral exchange

intense competition between firms led to total erosion of profits. Artificial agents adapted their behaviors to the actions of the manufacturers. They started to hold back their demand in anticipation of prices going down. At each price point, different groups of agents bought computers. This outcome mirrors what happened in the real world as well.

Having multiple B2B exchanges in an industry was disastrous. With four exchanges (B2B1–B2B4), customers were confused and switched rapidly between exchanges and between firms. As a result of this churning, their surplus was much lower, brand loyalty was greatly diminished, and the lack of critical mass on each exchange resulted in poor liquidity for the exchanges.

At this point, the neutral exchange not only lacked loyalty among buyers, but also lacked support from the sellers, as the branded manufacturers created their own exchange. Failing to sustain its business model, the neutral exchange exited the space and the intermediary-oriented exchange reduced its investment in the exchange and chose to become a niche player supporting "branded" surplus and white-boxes. As shown in Fig. 6, all four B2B Exchanges either lost money or barely broke even since at 20% or less they did not cover fixed costs. B2B1 was a neutral exchange, B2B2 was a seller-oriented exchange, B2B3 was a private exchange, and B2B4 was an intermediary-oriented exchange.

Markets became very stable with two prominent exchanges. The prominent "direct" seller continued to have high profits and volumes with its own exchange but the growth in its market share slowed down considerably because customers seeking best price migrated to the sellers' exchange to lower their search costs. Profit margins for branded products were quite high. Each

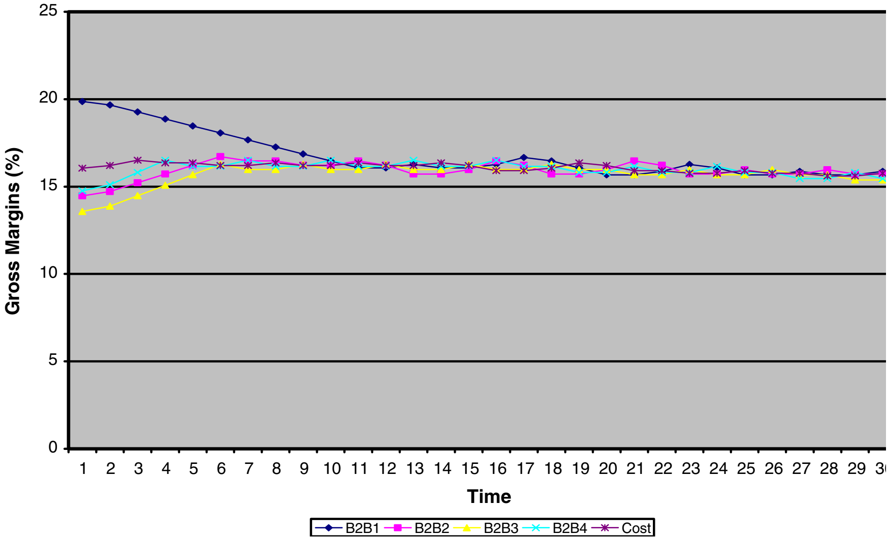

Fig. 6 Profits of B2B exchanges

of these firms was able to maintain its positions quite well and was able to segment its markets quite effectively.

Two dominant and stable exchanges and an efficient niche player (2 + 1 model) seemed to be the optimal solution as in Fig. 7. In this case, the customer surplus was quite high, the switching was low, and the search and

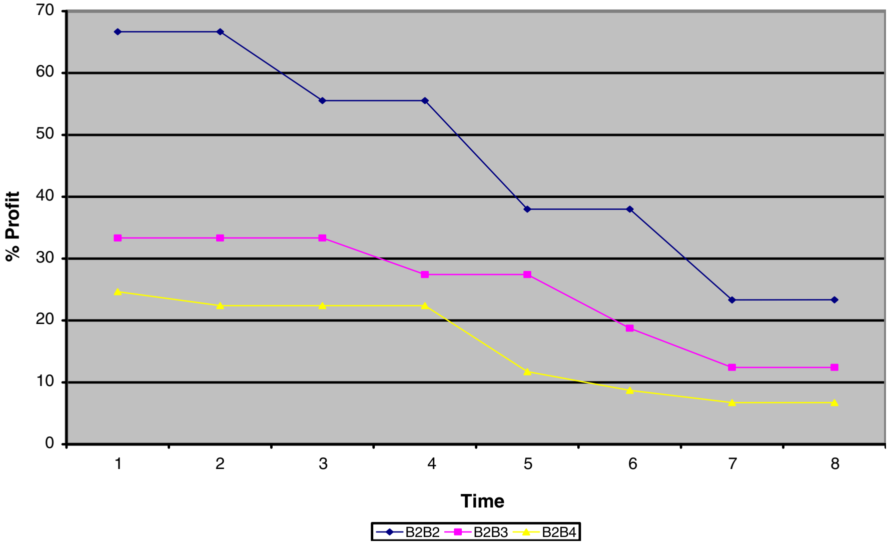

Fig. 7 Sustainable 2 + 1 exchanges

transaction costs were quite low, but towards the end profitability started to erode here as well.

5 Conclusion

This paper describes an agent-based computational experimentation for product and supply-chain co-design. It considers the rationale behind the research in the area of synthetic agents and their use in artificial economies. Past research has shown how analysis of the behavior of artificial agents can lead to valuable insights for businesses. With the growth of the Internet and artificial agents conducting business transactions therein, there is a need to predict possible future scenarios through the use of such synthetic agents interacting with human agents in artificial environments. Rapid growth in computing power and development of sophisticated software engineering methods allow for such modeling.

Specifically, this paper builds a synthetic environment representing the PC industry with brand name manufacturers as well as generic box makers, channels, and business customers. This environment combines simulation with gaming by putting artificial agents and human agents in the same environment. As such, it combines techniques from two different domains, namely ABS and experimental economics. This combination allows us to capture depth of decision making as represented by human players, with breadth of decision making, as represented by thousands of artificial agents. The manufacturers and channels were played by human players while several thousand artificial agents portrayed three segments of customers (small, medium, and large). PC makers were able to sell directly to consumers and to also engage in value-enhancing investments along various dimensions. The model was calibrated based on publicly available data and proprietary data provided by a major PC company. By playing in the simulation, participants, especially those playing manufacturers, were able to co-design the product and the market by choosing the product characteristics as well the outlets jointly. The range and quality of insights obtained by the participants in this mixed setting was striking.

While the model developed here is of interest to both researchers and practitioners, it suffers from several limitations. First, the model did not consider technical change, which is an important aspect of the PC industry. Second, the demand model used Cobb-Douglas demands which implies constant expenditures on the product category. Third, a fringe market (e-Bay or other auction sites) which is becoming quite important in this industry was omitted. Finally, the market segmentation used in this model was quite limited. These are limitations that may be removed in future research.

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6 Appendix

6.1 SEAS virtual execution environment

An Internet-based SEAS virtual execution environment (VEE) is depicted in Fig. 8. In SEAS' VEE, participants from anywhere can take part in an exercise. The VEE consists of three classes of servers: application servers, distributed database servers, and proxy servers. Proxy servers ensure restricted access for the subscribers. There are three different classes of application servers. The agent-processing servers are capable of running hundreds of thousands of different kinds of agents. Economic processing servers are capable of representing different types of markets. Finally, the visualization servers generate advanced 3-D displays of the data generated during the exercise.

There are individual database servers that support each of these application servers. These database servers may run at one or more locations. Thus, the distributed design enables any numbers of participants to take part in an exercise, and many exercises may be available at any given time.

The SEAS software environment is highly reconfigurable. It consists of three classes of active objects called "bots" as depicted in Fig. 9. The ServBots are autonomous agents that perform the business tasks. Examples of ServBots are BuyBot (agents that perform buying function), SellBot, AcquireBot, ProduceBot, etc. These bots also function as application programming interface (API) for third party development.

The second class of bots is SysBots. This class of autonomous agents performs system level tasks such as read, write, update, open, and close connections.

The third class of bots is the data bots. These bots are being developed to interface with enterprise systems so that firms can seamlessly integrate with SEAS to run dynamic exercise to explore new strategy spaces or may use it as a wind tunnel of corporate strategies. These bots interact with the data manager for their data needs using the SEAS middleware.

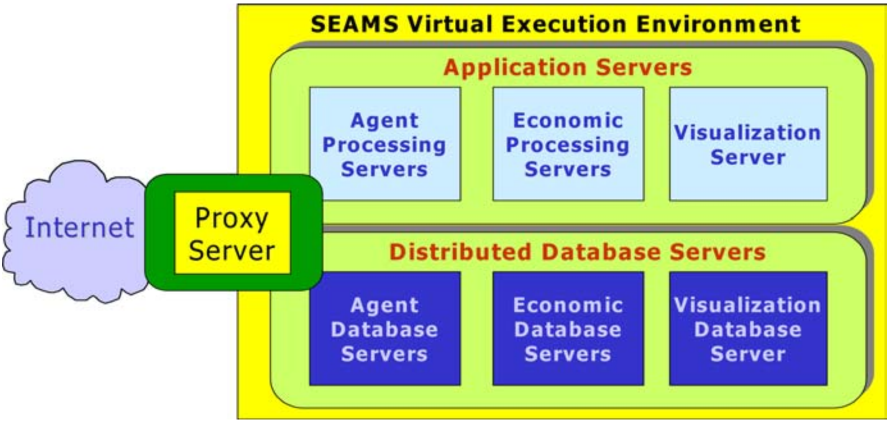

Fig. 8 The SEAS virtual execution environment

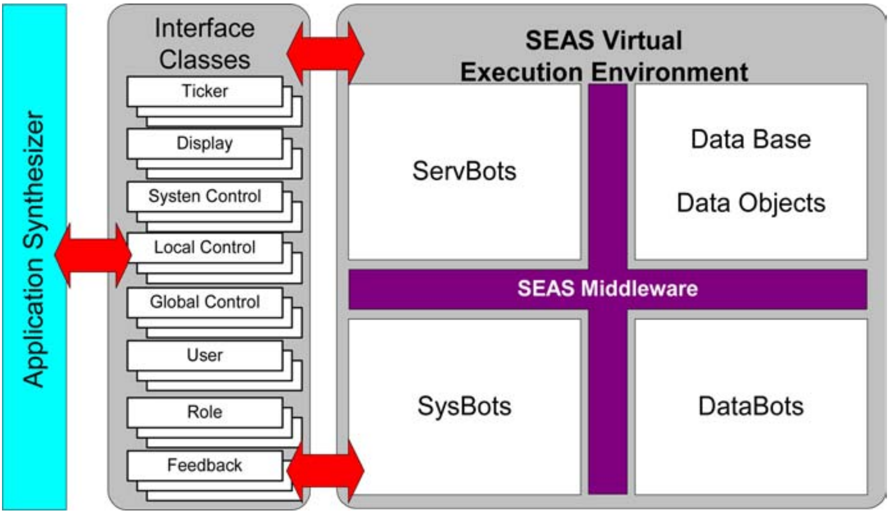

Fig. 9 Anatomy of the SEAS virtual execution environment

The VEE interacts with reconfigurable interface classes. There are eight types of interface classes—ticker, display, system control, local control, global control, user, role, and feedback. ServBots, SysBots, and DataBots are dynamically assembled for each of these interface classes based on the participants profiles or demands by an application synthesizer. This architecture provides the necessary flexibility to adapt SEAS to a wide variety of problem domains.

6.2 SEAS agent architecture

SEAS use intelligent agents (IA) to represent economic realities of electronic markets and hierarchies in a decentralized manner. Intelligent agents in SEAS are autonomous processes that are adaptive and behave like human agents in a narrow domain. In their respective domains, each agent has a well-defined set of responsibilities and authorities so that it can execute its tasks effectively. Examples of *SEAS*' IAs are: economic agents—consumer IAs, producer IAs, and regulator IAs and political agents—government IAs, special interest IAs, etc. An agent in *SEAS* is equipped with reasoning, action, and communication skills required for performing their respective tasks. A SEAS IA is characterized by the knowledge it possesses.

Each agent has a set of seven behavior primitives that enable him or her to perform actions autonomously as shown in Fig. 10. These primitive SysBots are used to initiate, search, decide, execute, update, communicate, and to terminate. Different algorithms for SysBots are used to differentiate between the agents. For example, an agent representing a smart individual will have a

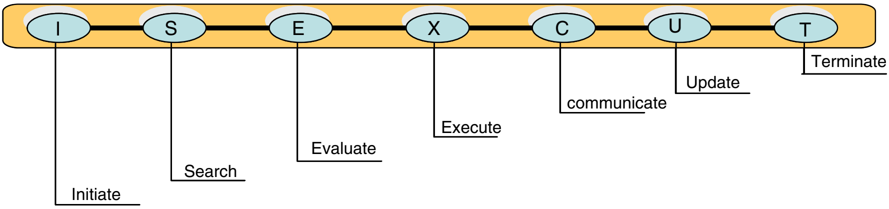

Fig. 10 SysBots are coalesced together to form a ServBot

more sophisticated search and evaluation algorithm than that of a not so smart agent. There can be several instantiations of each SysBot. SysBots that constitute an agent are described below:

- Initiate: these bots are the sensors for a given ServBot. When certain conditions are met then they trigger action from the ServBot.
- Search: these bots provide the ability to search the space for best price, quantity, etc.
- Evaluate: these bots enable the servbot to evaluate different alternatives and select the most appropriate course of action.
- Execute: these bots execute the course of actions needed by the ServBot.
- Communicate: these bots have the knowledge of the workflow and the chain of command. After the action is taken, these bots communicate the appropriate message/information to the appropriate parties.
- Update: these bots update the relevant information/data at the appropriate times. These bots are critical for the system performance.
- Terminate: These are quality assurance bots that make sure that the tasks are completed satisfactorily.

6.3 SEAS market architecture

SEAS markets are implemented in JavaSpace. Javaspace is a descendant of Linda system developed at Yale University (Carriero and Gelertner 1989). Java Space defines the market structure as shown in Fig. 11. The four different types of markets structures supported by SEAS are: posted price, double auction, single auction, and reverse auction. The rules for all the markets are implemented through JavaSpace, which in turn synchronizes the thread between the agents. Agents maintained in the space are updated through their working status. JavaSpace also forms the connectivity between the Enterprise Java Beans (EJB) and the Database, and therefore, after completing the transactions, it updates the database.

JavaSpace supports simultaneous running of multiple games. Every agent created in the EJB has an AgentSpace object. AgentSpace gives every agent partial access to the JavaSpace. This way the agent does not have to worry about the implementation of the space. It gives a clean abstract and encapsulated cover to the implementation of the space.

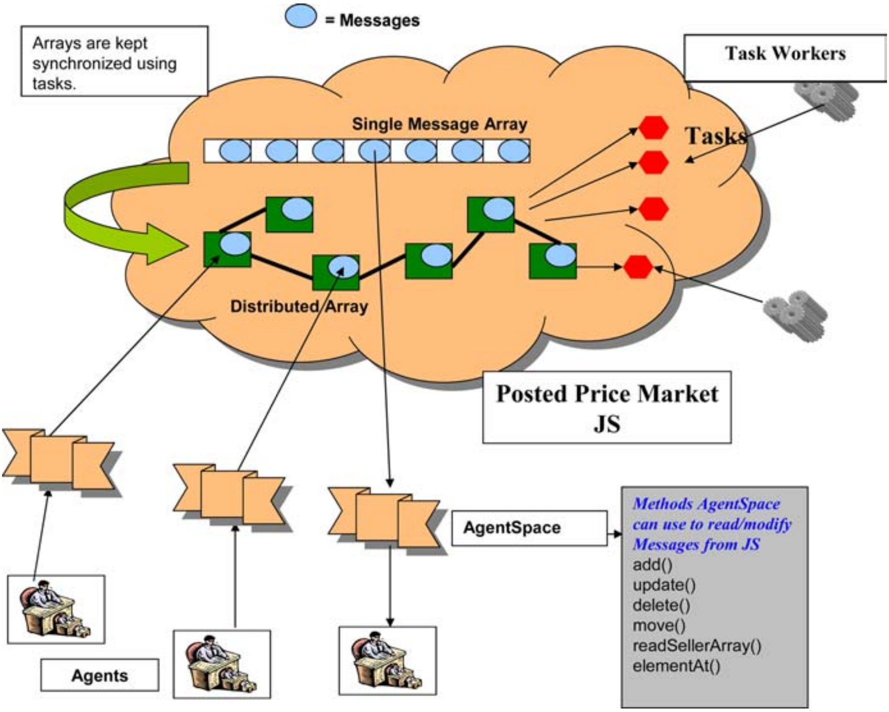

Fig. 11 An example of a posted price implemented in JavaSpace

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