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This paper addresses the problem of increasing order variances in multi-tier supply chains. The majority of current approaches for reducing this problem, namely the bullwhip effect, rely on information sharing and/or cooperative planning in inter-organizational systems. Due to multiple barriers in implementing these approaches, we maintain the local autonomy of the participants in the supply chain and provide a multiagent-oriented solution to the problem. In particular, we design an agent-based reverse pricing model for matching supply and demand between independent agents. We adopt reverse pricing for operational procurement decisions and matchmaking that can be automated to a large extent. We evaluate our proposal by conducting a simulation study using a multiagent-based simulation system, and show that the novel approach results in a significant reduction of the bullwhip effect.

Keywords: Bullwhip Effect, JADE, Pricing, Simulation, Software Agents, Supply Chain Management

Introduction

Nowadays, agent technology is utilized in many industrial applications such as production planning, collaborative engineering, and more recently supply chain management. Agent technology and particularly multiagent technology are designed to mitigate the challenges in distributed, complex systems that can not entirely and efficiently be controlled by central mechanisms or plans. This is especially true for inter-organizational systems that are being formed by independent entities which focus on individual economic, often conflicting goals. With regard to supply chains (SC), multiagent technology offers opportunities for supporting these decentralized rather then centralized, emergent rather than planned, and concurrent rather than sequential systems (Chaib-draa and Müller 2006).

An important phenomenon often observed in supply chains is known as the bullwhip effect (BWE), which implies that order variability increases when one moves up the SC towards the manufacturers and the suppliers. To counter this phenomenon, two major approaches can be distinguished: information sharing (such as providing customer demand data to all SC participants) and collaboration (such as cooperation among SC participants and integration of their activities and processes into a holistic SC plan). However, empirical studies indicate that implementing corresponding strategies and systems has to face strong economic, social, political, and technical barriers (Fawcett and Magnan 2002). In contrast to information sharing and collaboration, this paper proposes an approach that maintains local decision making by individual SC participants and integrates demand and supply based on a special form of dynamic pricing called *reverse pricing*. Several authors (Kahn 1987; Naish 1994) have noted that participants in a SC maximize their individual profit without taking into account the effect of their decisions on other participants and the overall performance of the SC. In such a SC without global vision, the price plays a dominating and in many cases an exclusive role for coordinating supply and demand. Therefore, our objective is to design a new coordination mechanism that adopts reverse pricing and specifically addresses multi-tier SCs. This artifact is aimed at reducing the BWE. We address the BWE problem from a procurement perspective: This perspective provides a rich set of concepts, policies, and models for decision making in procurement as well as inventory management. Therefore, we can employ them for describing multi-tier SCs and integrate reverse pricing into these formalisms.

A preliminary study of reverse pricing can be found in (Mujaj et al. 2007). In the current work, we (1) conceptualize the model as a multiagent approach, (2) describe the technical realization of our simulation system, and (3) extend our evaluation significantly by distinguishing order BWE and inventory BWE. Thus, we also consider inventories along the supply chain.

In the next section, we review existing work and relate it to our approach. Then we describe conventional procurement decisions and provide a standard, yet agent-based model that captures these decisions in multi-tier SCs. In the succeeding section, we design a reverse pricing model that integrates concepts of operational procurement. Then, we evaluate this artifact by conducting a comprehensive simulation study. In the final section, we draw conclusions and point out avenues for future research.

Related work

The related work can be grouped into three major areas: using multiagent technology in supply chains, countering the BWE, and adopting dynamic pricing for coordination in supply chains. Each area is briefly discussed below.

Multiagent technology in supply chains

In supply chain management (SCM), multiagent technology is at the brink of being integrated into real-world applications. An example is MASCOT, which is a reconfigurable, multilevel, agent-based architecture for planning and scheduling, aimed at improving SC agility (Sadeh et al. 1999). DragonChain simulates the reduction of the BWE in SCs. The authors base their simulation on two versions of the Beer Game, the MIT Beer Game and the Columbia Beer Game (Kimbrough et al. 2002). NetMan formalizes networked organizations, in order to obtain manufacturing networks in a dynamic environment (Cloutier et al 2001). OCEAN is an agent-based control system with an open, decentralized architecture, which was designed to react to environment dynamics, in order to show that cooperation at the global level may emerge from competition at the local level (Moyaux 2006). Zimmermann et al. (2006) showed that an agent-based approach is suited to reduce negative effects of distributed events in supply chains.

It should be noted that research on multiagent technology in SCM often focuses on optimizing schedules with decentralized mechanisms such as negotiations about resource capacities (e.g., Wagner et al. 2002).

Bullwhip effect

There exists a large body of knowledge on BWE, its causes, and respective countermeasures. Table 1 summarizes the relevant research. Lee et al. (1997a; 1997b) identified the *first four causes* and solutions.

The seminal work by Lee et al. has been extended: With respect to *Cause 5*, Sterman (1989) explained how, in the context of teaching inventory management, the beer distribution game is used to demonstrate the bullwhip effect. In this game, participants have the role of customers, retailers, wholesalers and factories. They are not supposed to communicate with each other and must make decisions based only on the orders received from the next downstream player. Regarding *Cause 6*, it has been noted that SC participants contribute to the BWE, if they maximize their own profit without taking into account the effect of their decision on the rest of the SC. This can happen if SC participants use a specific ordering policy for local optimization (Kahn 1987; Naish 1994).

Table 1. Review of BWE literature according to Moyaux (2006)

#	Cause	Countermeasure	Reference
1	Demand forecast updating	Information sharing (e.g. Vendor-Managed Inventory) and lead-time reduction	Lee et al. 1997a Lee et al. 1997b
2	Order batching	Electronic Data Interchange and Internet technology	Lee et al. 1997a Lee et al. 1997b
3	Price fluctuation	Every Day Low Pricing	Lee et al. 1997a Lee et al. 1997b
4	Rationing and shortage gaming	Allocation based on past sales	Lee et al. 1997a Lee et al. 1997b
5	Misperception of feedbacks	To give a better understanding of the supply chain dynamics to the manager	Sterman 1989 Daganzo 2003
6	Local optimization without global vision	None	Kahn 1987 Naish 1994

Dynamic pricing

Dynamic pricing has been the subject of extensive research in the past. This interest was greatly influenced by commercial implementations of auctions and reverse auctions on the Internet. With regard to SCs, various types of dynamic pricing have been studied for improving procurement, inventory management, and short-term production planning (e.g., Biller et al. 2005; Bertsimas and de Bore 2005). For instance, dynamic pricing for time-limited goods can increase the profits of the supplier by estimating the demand curve and maximizing the gross returns, when the buyer demand curve is unknown (Dasgupta 2005). It has to be noted, however, that the integration of dynamic pricing in SCs is still at an early stage. In particular, the effect on true multi-tier SC has been studied rarely. Most researchers address the direct relation between suppliers and buyers, which is a simple two-tier SC.

The brief review of related work points to the fact that: (1) local approaches on demand forecasts can reduce the BWE, but their impact on the BWE is limited, especially in multi-tier SCs, (2) cooperative approaches such as information sharing and coordination have a greater impact on the BWE, though their application is often restricted due to barriers and lack of trust between SC participants, and (3) dynamic pricing provides a rich set of mechanisms for supporting coordination between suppliers and buyers. To our best knowledge, reverse pricing as a special form of dynamic pricing has not been adopted for coordinating supply and demand in SCs. Considering these observations, we propose using reverse pricing for procurement decisions, since it sustains decision making with local information and control.

Procurement decisions

In this section, we describe procurement decisions in SCs with local information. We represent each SC participant by an autonomous software agent. In this model, the agents use a standard (s, S) inventory policy for local optimization. Under such a policy, the agent orders (S – I) units of the good, if the inventory level I falls below s. It has been formally shown that this inventory policy induces the BWE (Daganzo 2003; Chen et al. 2000).

Basic model

Each agent uses a standard model that captures conventional procurement decision making in SCs. Such a decision consists of selecting the supplier agent, calculating the order quantity, and determining the time of order. Figure 1 depicts a SC, consisting of four agents, denoted by j. Considering a multi-tier SC and a full spectrum of goods, the respective decision models get very complex in terms of parameters and variables. Therefore, we simplify the relevant part of the SC and look at a linear one-product SC only (see also Lee et al. 1997a; Chen et al. 2000), in which each participant adds value to the good.

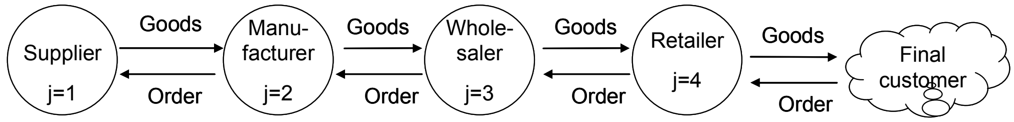

Figure 1. Multi-tier supply chain

In this SC, the lead time L is constant and defined as the duration between receipt of the order by agent j and delivery of the ordered goods to agent $j+1$. The procurement decision consists of forecasting the demand and determining the order quantity based on the inventory policy (Chen et al. 2000). We specify the procurement decision in algorithm 1.

Algorithm 1: Procurement decision
Input:
$D_{t,j}$, $D_{t-1,j}$: Customer demand in time period t and $t-1$.
T : Time periods for the moving average forecast and the standard deviation of the forecast error.
L : Lead time.
z : Service level.
Output:
$y_{t,j}$: Order placed by agent j in t.
Process:
$\hat{D}_{t,j} \leftarrow \frac{1}{T}\sum_{n=1}^{T} D_{t-n,j}$: Agent uses a simple moving average forecast to estimate the demand received by j in t.
$\hat{\sigma}_{t,j} \leftarrow \sqrt{\frac{1}{T-1}\sum_{n=1}^{T}(D_{t-n,j}-\hat{D}_{t-n,j})^2}$: Estimated standard deviation of the forecast error.
$q_{t,j} \leftarrow (L\hat{D}_{t,j} + z\sqrt{L}\hat{\sigma}_{t,j})$: (s, S) inventory policy in t.
$y_{t,j} \leftarrow q_{t,j} - (q_{t-1,j} - D_{t-1,j})$: Order quantity in t.

Bullwhip effect

An agent interacts with other agents by placing orders for goods. An example of this interaction is shown in Figure 2: In each period t, an agent j observes the current inventory level and sends an order (calculated by algorithm 1) to agent $j-1$. After the order is placed, the agent j observes and fills its demand for this period, denoted by D_t. Since our objective is to quantify the BWE, we must determine the variance of placed orders y_t, relative to the variance of D_t, i.e., the variance of the orders placed by agent j to agent $j-1$, relative to the variance of the final customer demand D_C, received by the retailer agent (Chen et al. 2000).

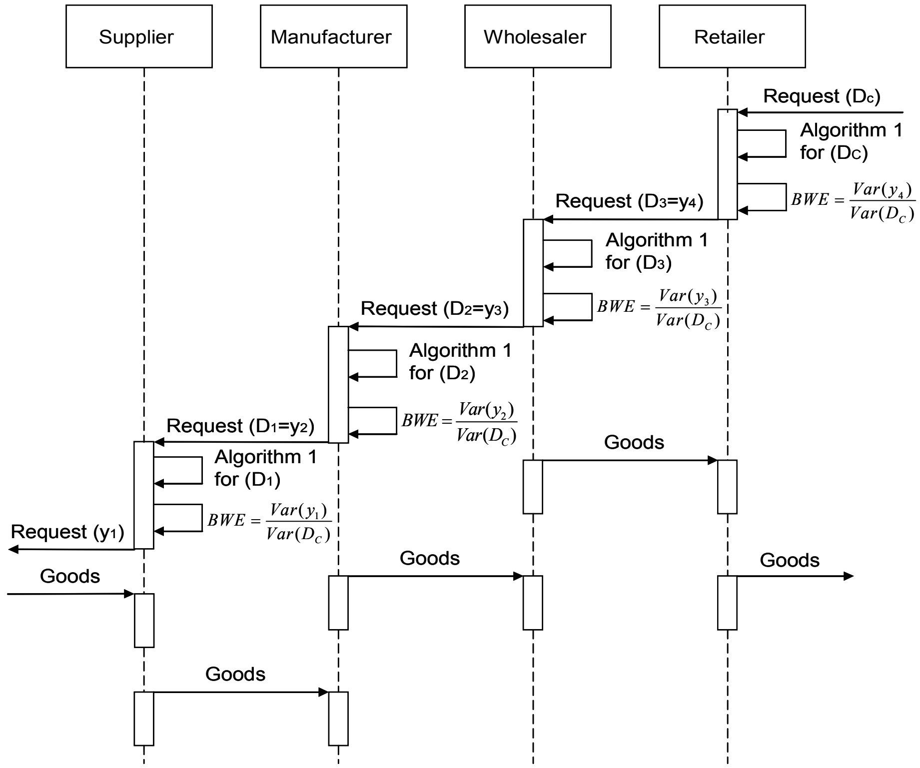

Figure 2. Interaction between agents and quantification of the BWE
(D: demand; y: order quantity)

Adoption of reverse pricing

In this section, we design a reverse pricing model for operational procurement decisions. For a comprehensive discussion about reverse pricing in supply chains from a microeconomics perspective see (Mujaj et al. 2007).

Reverse pricing

Reverse pricing gives the buyers an active role: The price of a transaction is not given by the seller, but mainly determined by the buyer's bid (Hann and Terwiesch 1997; Bernhardt and Hinz 2005). In recent years, reverse pricing as a special form of dynamic pricing and as popularized by marketplaces such as priceline.com, has attracted growing interest in e-commerce. Reverse pricing in business-to-business scenarios has not been studied so far. We will use the *regulative function* of prices when designing our reverse pricing model. It is being reflected in the relation that high prices have a stewing effect on the demand, thus on the buyer's order behavior. If we integrate this effect into the model, then one could expect that it results in a reduction of order variances, thus a reduction of the BWE.

We look at the inter-relationship between order behavior on the buyer's side and supply behavior on the supplier's side. Both can be represented by demand and supply functions (or curves) respectively. These functions describe how demand and supply dictate the price of a good. The intersection of both functions determines the equilibrium price and the equilibrium quantity. The equilibrium price is the price at which the quantity demanded equals the quantity supplied. The equilibrium quantity represents the quantity bought and sold at the equilibrium price.

The adaptation of reverse pricing for procurement decision calls for specifications of the three steps of reverse pricing:

1. *Buyer's bid:* For determining the bid of the buying agent, we refer to the demand function. A commonly used, though simple form is the linear demand curve, thus an increasing price P causes a decreasing demand Q (Besanko and Braeutigam 2005):

$$Q_d = a - bP, \text{ where } a > 0 \text{ and } b > 0 \tag{1}$$

Therefore, the demand function describes the bidding behavior of the buyer.

2. *Seller's minimum price:* For determining the minimum price of the supplying agent, we refer to the supply function. The linear form is (Besanko and Braeutigam 2005):

$$Q_s = c + dP, \text{ where } c < 0 \text{ and } d > 0 \tag{2}$$

3. *Matching:* By comparing bid price and the minimum price, the supplying agent decides on the validity of the bid, thus on the transaction. Due to maintaining the supply of goods, it is necessary to arrive at a transaction in all cases. Thus, the supplying agent will only modify the quantity, if required.

Step 1 and 2 require that equilibrium price P^* and equilibrium quantity Q^* as well as estimates for the price elasticity of demand E_d and the price elasticity of supply E_s are available. The price elasticity measures how much the quantity demanded or supplied changes, when its price changes. Then we can determine a and b from the demand function as well as c and d from the supply function. Figure 3 shows the relationship between demand and supply as described.

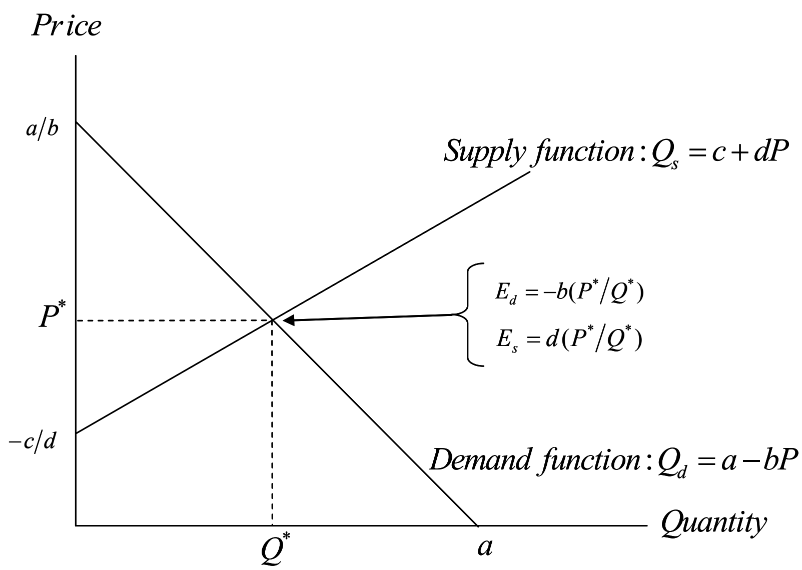

Figure 3. Demand and supply function

Step #1: Buyer's bid

The parameters a and b of the demand function must be calculated for each time period t and for each agent j by using the equilibrium quantity, the equilibrium price, and the price elasticity of demand:

- Let $Q^*_{t,j}$ be the equilibrium quantity and $P^*_{t,j}$ the equilibrium price.
- Let E_d be the price elasticity of demand, which is generally given by $E_d = -b_{t,j}(P^*_{t,j}/Q^*_{t,j})$. Solving this equation for b yields (Besanko and Braeutigam 2005):

$$b_{t,j} = -E_d(Q^*_{t,j}/P^*_{t,j}) \tag{3}$$

- To determine a, we note that Q^* and P^* must be on the demand curve. Thus, $a_{t,j} = Q^*_{t,j} + b_{t,j}P^*_{t,j}$. Substituting the expression in equation (3) for b and by canceling P^* and factoring out Q^*, we get (Besanko and Braeutigam 2005):

$$a_{t,j} = (1 - E_d)Q^*_{t,j} \tag{4}$$

Any demand curve has a corresponding inverse demand curve that expresses the price as a function of quantity. We can find the inverse demand curve by solving the equation for the demand curve, i.e., equation (1), for P in terms of Q_d. The inverse demand curve is:

$$P_{t,j} = (a_{t,j}/b_{t,j}) - (1/b_{t,j})Q_{t,j} \tag{5}$$

Using demand $D_{t,j}$, instead of quantity $Q_{t,j}$ in (5):

$$P_{t,j} = (a_{t,j}/b_{t,j}) - (1/b_{t,j})D_{t,j} \tag{6}$$

we arrive at the price that the buyer is willing to pay for $D_{t,j}$. This price $P_{t,j}$ is regarded as the bid price, denoted by $\mathrm{B}_{t,j}$. In algorithm 2, we summarize the determination of the buyer's bid.

Algorithm 2: Demand curve and buyer's bid
Input:
$D_{t,j}$: Customer demand in t.
E_d : Price elasticity of demand.
$P^*_{t,j}$: Equilibrium price.
$Q^*_{t,j}$: Equilibrium quantity.
Output:
$\mathrm{B}_{t,j}$: Bid price in t.
Process:
$b_{t,j} \leftarrow (-E_d(Q^*_{t,j}/P^*_{t,j}))$: Coefficient b of the demand curve.
$a_{t,j} \leftarrow ((1-E_d)Q^*_{t,j})$: Coefficient a of the demand curve.
$B_{t,j} \leftarrow ((a_{t,j}/b_{t,j}) - (1/b_{t,j})D_{t,j})$: Bid price.

Step #2: Seller's minimum price

Similar to the computation of a and b in step #1, we calculate parameters c and d of the supply function:

– Let E_s be the price elasticity of the supply, which is generally given by: $E_s = d_{t,j}(P^*_{t,j}/Q^*_{t,j})$. Solving this equation for d yields (Besanko and Braeutigam 2005):

$$d_{t,j} = E_s(Q^*_{t,j}/P^*_{t,j}) \tag{7}$$

– The respective transformations yield (Besanko and Braeutigam 2005):

$$c_{t,j} = (1-E_s)Q^*_{t,j} \tag{8}$$

$$P_{t,j} = -(c_{t,j}/d_{t,j}) + (1/d_{t,j})D_{t,j} \tag{9}$$

The latter equation defines the seller's minimum price, which we denote by $\underline{p}_{t,j}$. Algorithm 3 provides the formal specification:

Algorithm 3: Supply curve and seller's minimum price
Input:
$D_{t,j}$: Customer demand in t .
E_s : Price elasticity of supply.
$P^*_{t,j}$: Equilibrium price.
$Q^*_{t,j}$: Equilibrium quantity.
Output:
$\underline{p}_{t,j}$: Seller's minimum price in t .
Process:
$d_{t,j} \leftarrow E_s(Q^*_{t,j} / P^*_{t,j})$: Coefficient d of the supply curve.
$c_{t,j} \leftarrow ((1-E_s)Q^*_{t,j})$: Coefficient c of the supply curve.
$\underline{p}_{t,j} \leftarrow (-(c_{t,j} / d_{t,j}) + (1/d_{t,j})D_{t,j})$: Seller's minimum price.

Step #3: Matching

In our reverse pricing model, the supplier agent receives an incoming bid, including bid price and quantity. The decision whether the demand is valid is solely up to the supplier agent. When matching supply and demand, the supplier agent will not accept arbitrary order quantities, but limit it in terms of its own capabilities. In particular, these capabilities are determined by: (1) the inventory level, (2) the delivery time of its own suppliers, and (3) the service level that needs to be met.

Therefore, the supplier agent applies a *heuristic* that results in a potential reduction of the demanded order quantity. It considers the following two cases:

- The bid price is equal or higher than the seller's minimum price $(B_{t,j} \geq \underline{p}_{t,j})$. In this case, the supplier agent will accept the received order and execute it with the bid price and the requested quantity.
- The bid price is lower than the seller's minimum price $(B_{t,j} < \underline{p}_{t,j})$. The received order quantity (which was calculated by the buyer agent using algorithm 1) will be modified by the supply agent to $y^{new}_{t,j}$. The product of bid price and order quantity is interpreted by the supply agent as the *total willingness to pay* in the current period. It will be divided by the seller's minimum price which leads to the allowed order quantity; hence the proportion of bid price to minimum price expresses the reduction:

$$y^{new}_{t,j} = (B_{t,j} / \underline{p}_{t,j}) y_{t,j} \tag{10}$$

Algorithm 4 summarizes the entire reverse pricing process that begins with determining the order quantity (buyer agent; algorithm 1), followed by determining both the bid price (buyer agent; algorithm 2) and the minimum price (supply agent; algorithm 3), and finally deciding on the transaction (supply agent).

Algorithm 4: Procurement decision with reverse pricing
Input:
$y_{t,j}$: Order quantity from algorithm 1.
$B_{t,j}$: Bid price from algorithm 2.
$\underline{p}_{t,j}$: Seller's minimum price from algorithm 3.
Output:
$y^{new}_{t,j}$: Allowed order quantity in t .
Process:
if $(B_{t,j} \geq \underline{p}_{t,j})$ *then return* $y^{new}_{t,j} \leftarrow y_{t,j}$: No modification.
if $(B_{t,j} < \underline{p}_{t,j})$ *then return* $y^{new}_{t,j} \leftarrow (B_{t,j} / \underline{p}_{t,j}) y_{t,j}$: Modification.

Simulation

In this section, we describe the simulation study, define metrics for evaluating the proposed model, and present the results of our experiments.

Simulation system

We have developed an agent based simulation system called HoPIX (Hohenheimer Process Integrator eXtension), which is specifically designed for simulating multi-tier SCs. In this multiagent-based system, each SC participant is represented by an autonomous software agent.

Figure 4 shows the architecture of HoPIX. It has been implemented using the Java Agent DEvelopment Framework (JADE) that implements the FIPA specification. We selected this platform because JADE, being a standardized open source software, is widely used for developing multiagent systems. The central component of the JADE agent platform is the agent management system, which keeps supervisory control over access and use of the agent platform. The domain facilitator provides white and yellow page services within the platform. All JADE agents implement an agent life cycle and inherit functionality to add certain behaviors, and to be able to exchange messages between agents. HoPIX agents coordinate their ordering behavior by exchanging messages using the JADE message transport system. HoPIX agents are generated using the JADE agent class and by implementing the appropriate agent control behavior on top of it. HoPIX agents can send orders to other agents and receive goods.

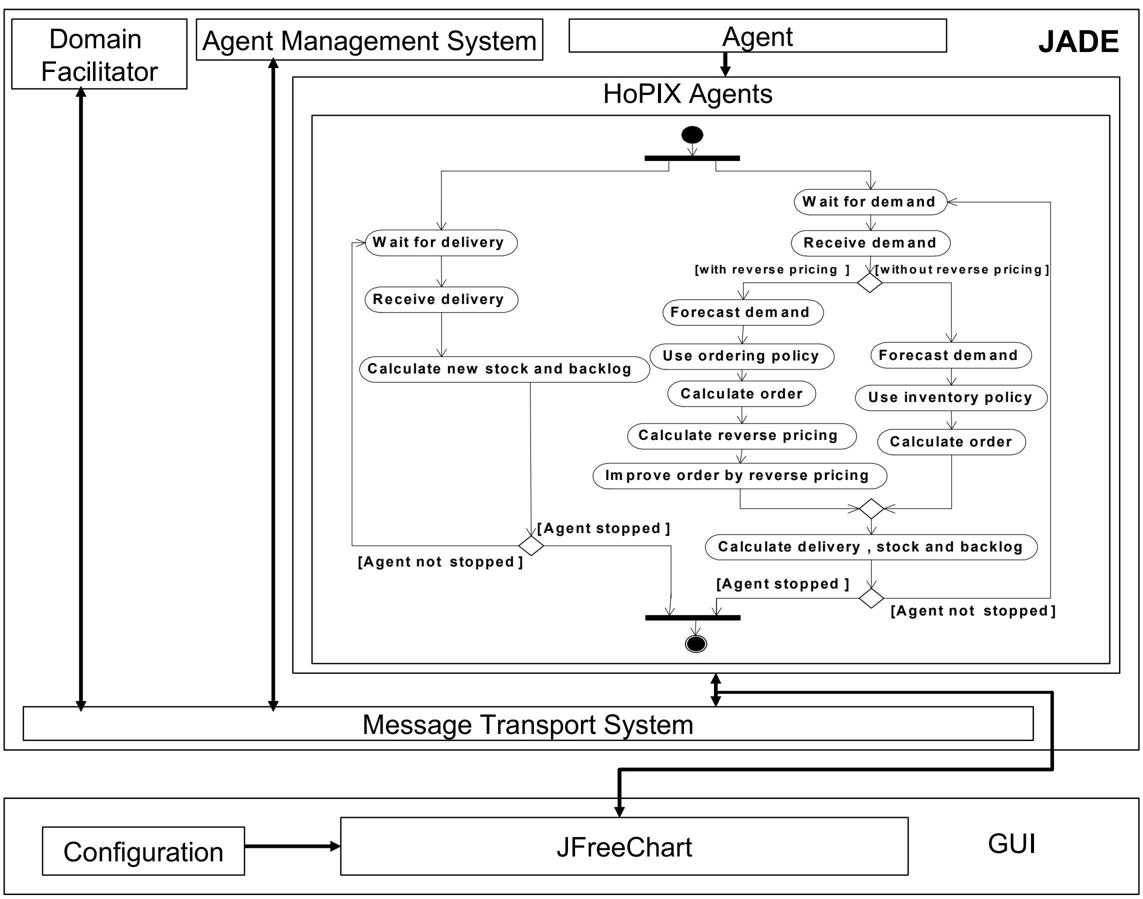

Figure 4. Architecture of the HoPIX system

In this context, we distinguish two types of agents: Agents without reverse pricing determine their orders according to algorithm 1. The procurement decision of those agents consists of three steps: forecast demand, use inventory policy, and calculate order (see the branch 'without reverse pricing' in figure 4). By simulating procurement decisions using this type of agents, we can demonstrate the existence of the BWE.

The second type of agents uses our reverse pricing model in their local decision making. They also calculate the order quantity using algorithm 1 and additionally determine the reverse pricing according to algorithms 2 and 3. The results are used as input for algorithm 4 (see the branch 'with reverse pricing' in figure 4). The distinction of the two agent types allows for comparing the reverse pricing model with the conventional coordination mechanism (i.e., local optimization and no global vision) for the same data set.

The graphical user interface (GUI) enables users to specify simulation settings, such as duration, types of agents to use, and additional parameters. It triggers the generation of the specified number of agents of the respective type, as specified. The GUI is capable of displaying charts of time varying parameters of the simulation. For this purpose, we use JFreeChart, which is an open source Java library. The GUI is divided into three main windows: the agent window (displaying inventories and orders of each agent), the settings window (simulation parameters), and the data window (textual and graphical representations of parameters characterizing global SC behavior). Figure 5 shows a screen of the GUI.

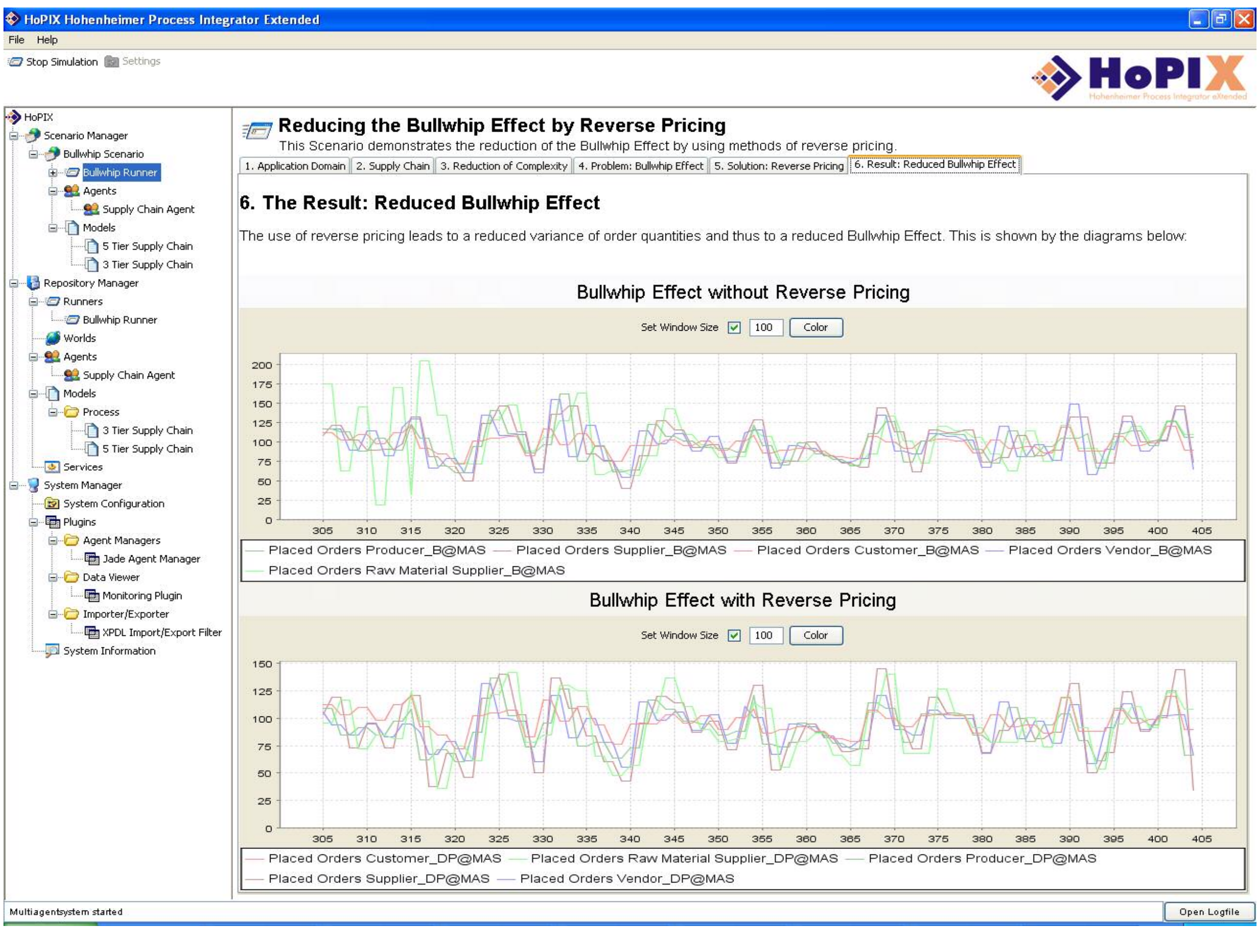

Figure 5. Graphical user interface of HoPIX

Simulation settings

We defined a four-tier SC consisting of four agents (see also figure 1). Only the last agent ($j=4$) knows the final customer demand D_C . We set the following parameters:

- Final customer demand $D_{t,C}$: normally distributed with expected value $\mu=100$ and standard deviation $\sigma=10$.
- Service level: 99%, thus z equals 2.33 (Chen et al. 2000).
- Equilibrium price: we calculate $P^*_{t,j}$ for each agent, based on bid price data $B_{t,j}$ from the preceding $n=52$ periods:

$$P^*_{t,j} = (1/n)\sum_{t=1}^{n} B_{t,j} \tag{11}$$

– Equilibrium quantity: we calculate $Q^*_{t,j}$ for each agent, based on demand data $D_{t,j}$ from the preceding $n = 52$ periods:

$$Q^*_{t,j} = (1/n)\sum_{t=1}^{n} D_{t,j} \tag{12}$$

– Price elasticity[1] for all tiers: $E_d = -0.8$, $E_s = 1.6$ (Besanko and Braeutigam 2005).

We conducted the simulation for various configurations of the following parameters:

– T between 5 and 15 (time periods of the moving average forecast)

– L between 1 and 4 (same lead time for all tiers)

Each simulation run started with a warm-up of 200 periods followed by 40 periods, during which we collected data. Due to the stochastic demand, each simulation setting was run twenty times.

Metrics

The evaluation is based on standard metrics that quantify the BWE (see table 2). For each metric we calculated the mean.

Table 2. Metrics

Metric	Definition	Interpretation
Order BWE	Quotient of the variance of the order quantity y in tier j and the variance of the final customer demand D_C (Chen et al. 2000): $O_j^{BWE} = Var(y_j)/Var(D_C),\ where\ j = 1...4$	Values greater than 1 indicate the BWE.
Inventory BWE	Quotient of the variance of the inventory q in tier j and the variance of the final customer demand D_C (Disney and Towill 2003): $I_j^{BWE} = Var(q_j)/Var(D_C),\ where\ j = 1...4$	Values greater than 1 indicate the BWE.

Variation of T

In the first set of experiments, we determined the BWE under variation of T. Table 3 and 4 present the data for $L = 2$ and the order BWE. In general, the BWE decreases with an increasing T (see also figure 6). We calculated the BWE for j=3 (wholesaler) as well as j=1 (supplier). The comparison of the conventional procurement decision and the reverse pricing model yields a reduction in the order BWE of 35.7 % to 49.8 % (wholesaler; mean: 43.4%) and 6.3 % to 16.5 % (supplier; mean: 10.4%).

[1] Price elasticities of demand and supply have been estimated for many products using statistical techniques. Estimations for a variety of goods such as food, transportation services, cars etc. can be found in (Besanko and Braeutigam 2005).

Table 3. Order BWE for j=3 (Wholesaler)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
T	**M**	**SD**	**M**	**SD**	**M**	**SD**
5	7.68	0.69	4.51	0.55	-41.3%	-20.5%
6	6.27	0.60	4.08	0.44	-35.0%	-26.0%
7	6.24	0.53	3.78	0.35	-39.5%	-33.6%
8	6.22	0.50	3.64	0.31	-41.6%	-37.7%
9	5.78	0.49	3.63	0.30	-37.2%	-37.8%
10	5.69	0.48	3.21	0.29	-43.5%	-40.6%
11	5.65	0.41	3.13	0.28	-44.6%	-32.6%
12	5.65	0.40	2.93	0.27	-48.2%	-34.8%
13	5.52	0.35	2.87	0.23	-48.0%	-32.4%
14	5.28	0.31	2.69	0.22	-49.1%	-30.7%
15	5.23	0.30	2.62	0.19	-49.8%	-38.8%
				Mean of Change:	**-43.4%**	**-33.2%**

Table 4. Order BWE for j=1 (Supplier)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
T	**M**	**SD**	**M**	**SD**	**M**	**SD**
5	13.60	1.25	12.17	1.02	-10.5%	-18.3%
6	11.18	1.17	10.48	0.93	-6.3%	-20.7%
7	10.97	1.08	9.95	0.87	-9.3%	-19.6%
8	10.41	1.03	9.55	0.79	-8.3%	-22.7%
9	8.55	0.99	7.81	0.74	-8.7%	-24.8%
10	8.40	0.98	7.12	0.70	-15.3%	-28.4%
11	8.26	0.89	6.89	0.69	-16.5%	-20.3%
12	7.44	0.78	6.69	0.65	-10.1%	-16.6%
13	7.36	0.68	6.49	0.59	-11.8%	-13.0%
14	6.71	0.60	6.08	0.51	-9.3%	-15.6%
15	6.67	0.51	6.08	0.40	-8.8%	-20.9%
				Mean of Change:	**-10.4%**	**-20.1%**

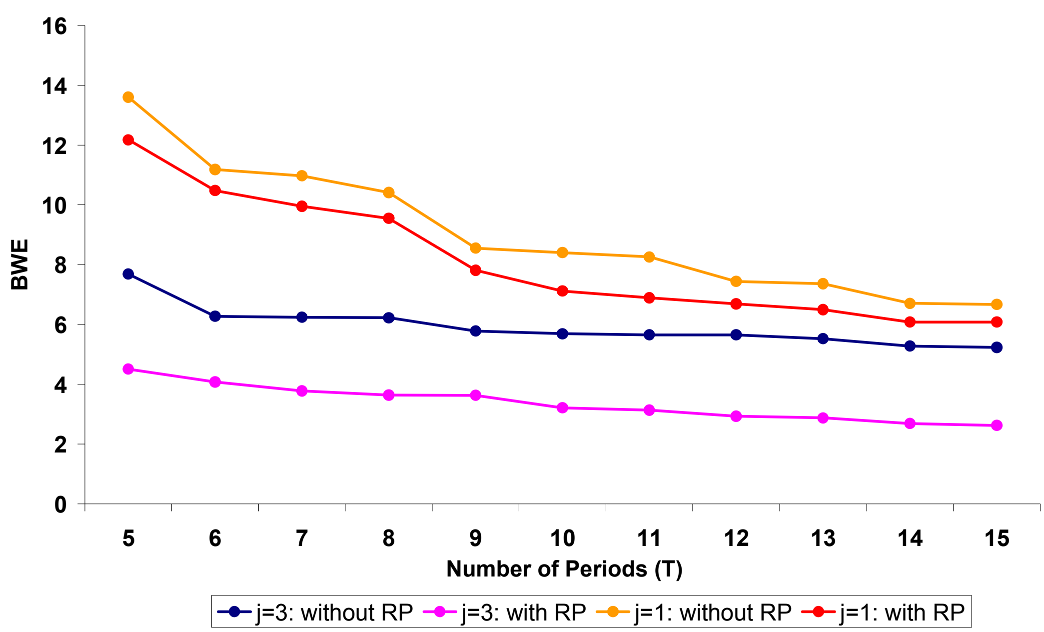

Figure 6. Order BWE and variation of T
(RP: reverse pricing)

In tables 5 and 6, we present the results for the inventory BWE. We observed a reduction of 29.9 % to 43.7 % (wholesaler; mean: 36.8%) and 16.8 % to 24.3 % (supplier; mean: 20.8%) respectively.

Table 5. Inventory BWE for j=3 (Wholesaler)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
T	**M**	**SD**	**M**	**SD**	**M**	**SD**
5	2.85	0.37	1.93	0.21	-32,3%	-43,8%
6	2.82	0.32	1.79	0.19	-36,5%	-41,9%
7	2.71	0.27	1.65	0.18	-39,1%	-33,6%
8	2.42	0.27	1.53	0.17	-36,8%	-36,4%
9	2.38	0.24	1.44	0.15	-39,5%	-36,5%
10	2.35	0.20	1.32	0.14	-43,7%	-31,1%
11	2.26	0.18	1.32	0.12	-41,7%	-31,4%
12	2.00	0.18	1.24	0.11	-38,1%	-36,6%
13	1.77	0.15	1.18	0.10	-33,7%	-31,4%
14	1.74	0.14	1.16	0.10	-33,5%	-30,7%
15	1.56	0.11	1.10	0.07	-29,9%	-35,1%
				Mean of Change:	**-36.8%**	**-35.3%**

Table 6. Inventory BWE for j=1 (Supplier)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
T	**M**	**SD**	**M**	**SD**	**M**	**SD**
5	6.73	0.78	5,48	0,63	-18,6%	-19,3%
6	5.74	0.70	4,54	0,57	-20,9%	-19,7%
7	5.62	0.66	4,31	0,53	-23,3%	-20,6%
8	5.34	0.62	4,07	0,49	-23,8%	-21,8%
9	4.75	0.55	3,95	0,42	-16,8%	-23,8%
10	4.56	0.52	3,58	0,38	-21,5%	-27,0%
11	4.20	0.48	3,18	0,36	-24,3%	-24,3%
12	3.88	0.47	3,15	0,34	-18,8%	-27,7%
13	3.80	0.42	3,12	0,29	-17,9%	-32,3%
14	3.53	0.36	2,88	0,25	-18,4%	-32,3%
15	3.00	0.32	2,28	0,23	-24,1%	-29,4%
				Mean of Change:	**-20.8%**	**-25.3%**

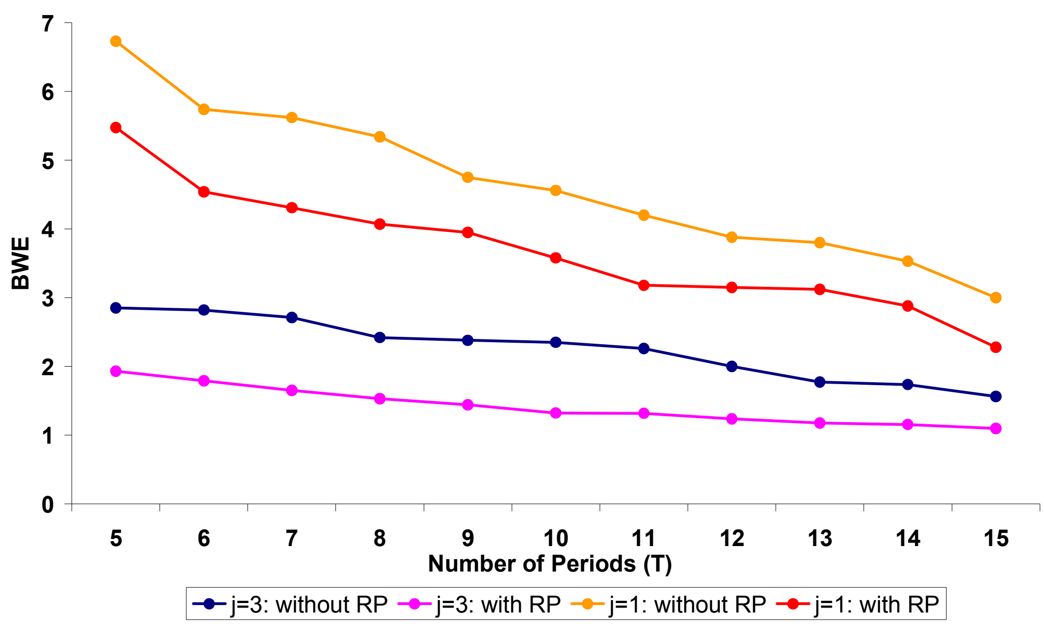

Figure 7. Inventory BWE and variation of T
(RP: reverse pricing)

Variation of L

In the second set of experiments, we studied the influence of L on the BWE. Tables 7 and 8 show the results on the order BWE. We observed a reduction by reverse pricing for j=3 of 37.0% to 48.4% (wholesaler; mean: 44%) and for j=1 of 6.7% to 24.9% (supplier; mean: 14.9%).

Table 7. Order BWE for j=3 (Wholesaler)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
L	**M**	**SD**	**M**	**SD**	**M**	**SD**
1	3.93	0.40	2.10	0.20	-46.5%	-50.0%
2	6.72	0.87	3.47	0.55	-48.4%	-36.7%
3	8.75	2.20	4.90	1.99	-44.0%	-9.7%
4	10.79	4.14	6.80	3.17	-37.0%	-23.4%
				Mean of Change:	**-44.0%**	**-30.0%**

Table 8. Order BWE for j=1 (Supplier)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
L	**M**	**SD**	**M**	**SD**	**M**	**SD**
1	6.81	0.87	5.11	0.71	-24.9%	-18.6%
2	10.37	1.94	8.81	2.44	-15.0%	-17.1%
3	22.18	5.55	19.33	5.27	-12.9%	-5.1%
4	25.10	7.12	23.41	6.58	-6.7%	-7.5%
				Mean of Change:	**-14.9%**	**-12.1%**

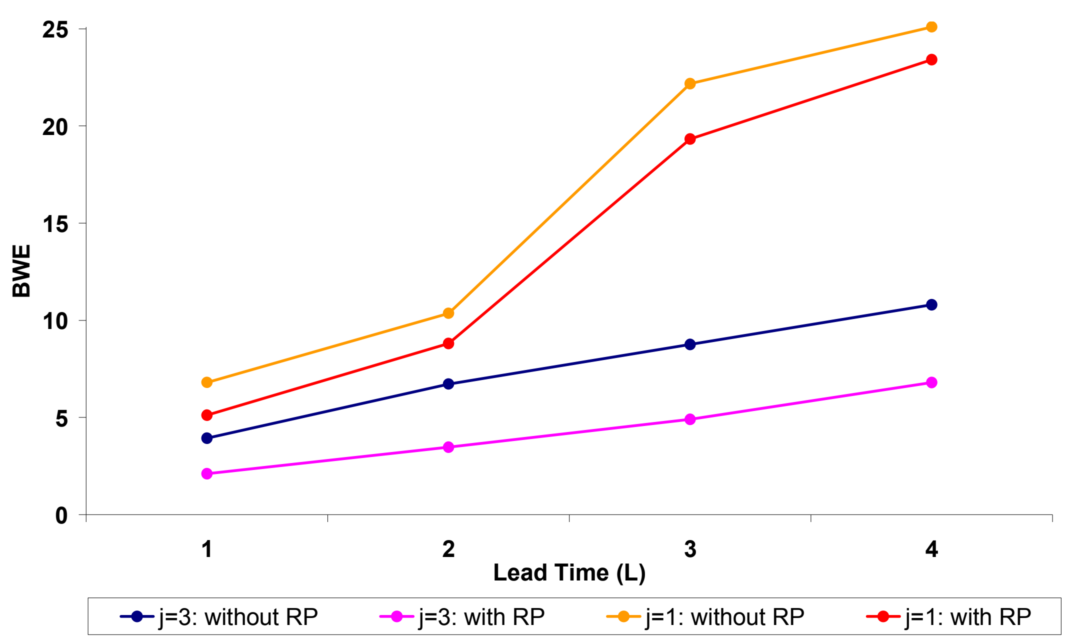

Figure 8. Order BWE and variation of L
(RP: reverse pricing)

The final data set is about the inventory BWE under variation of L (tables 9 and 10, figure 9). We observed a reduction of 13.8 % to 51.7 % (wholesaler; mean: 33.2%) and 10.5% to 39.1% (supplier; mean: 28.5%) respectively.

Table 9. Inventory BWE for j=3 (Wholesaler)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
L	M	SD	M	SD	M	SD
1	2.06	0.28	1.00	0.13	-51.7%	-53.6%
2	2.34	0.38	1.43	0.14	-38.7%	-62.0%
3	4.07	1.20	3.51	1.05	-13.8%	-12.3%
4	8.42	4.20	6.00	4.01	-28.7%	-4.5%
				Mean of Change:	-33.2%	-33.1%

Table 10. Inventory BWE for j=1 (Supplier)
(M: mean; SD: standard deviation; RP: reverse pricing)

	Without RP		With RP		Change	
L	M	SD	M	SD	M	SD
1	2.99	0.43	1,82	0,32	-39,1%	-26,0%
2	4.35	0.71	3,20	0,63	-26,4%	-10,8%
3	9.91	2.02	6,16	1,50	-37,8%	-25,8%
4	14.33	2.56	12,83	2,21	-10,5%	-13,7%
				Mean of Change:	-28.5%	-19.1%

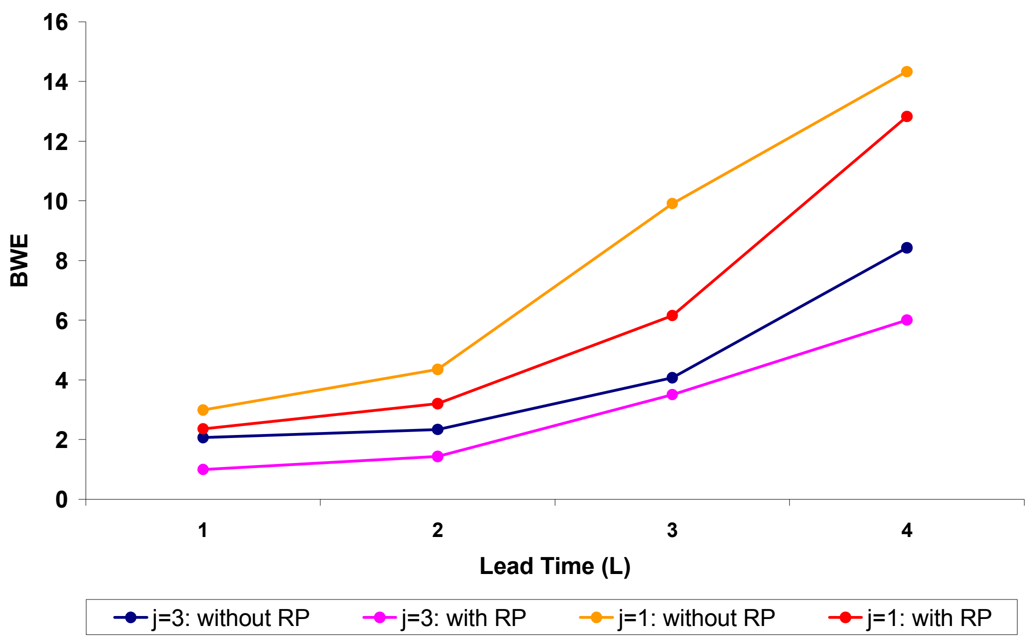

Figure 9. Inventory BWE and variation of L
(RP: reverse pricing)

Conclusions and future work

We aimed at reducing the bullwhip effect in multi-tier SCs by means of reverse pricing. In particular, we studied whether and how reverse pricing can be adopted for supporting procurement decisions in multi-tier SCs. Our methodology included three steps. We have: (1) designed an agent-based coordination mechanism based on reverse pricing concepts and considerations of microeconomics, (2) implemented an agent-based simulation system specifically for SC simulation, (3) evaluated our model by conducting a comprehensive set of simulation experiments, and therefore showed that this approach reduces the BWE with regard to both order variances and inventory variances. Therefore, we have shown that the proposed model actually has a significant impact on the BWE.

Our current reverse pricing model as well as simulation experiments are limited in terms of supply chain complexity. The reason is that modeling multi-tier SCs requires considering and designing a broad range of issues such as local goals, procurement and inventory strategies, and respective cost and revenue functions for each participant respectively agent.

These considerations may result in very complex models which would require additional studies and experiments. Due to limited space and in order to determine the principle contribution of reverse pricing to the problem, we assumed that a number of parameters are equal for all agents, i.e., standard (s, S) inventory policy, lead time, forecast technique, and the type of demand and supply function. Another limitation of the current model is that our inventory policy (algorithm 1) calculates the order quantity independently from costs incurred by ordering and stocking goods.

A major limitation is that we assumed linear supply and demand curves. This assumption is, however, coherent with basic concepts of microeconomics, though other types of functions are more suitable to reflect actual supply and demand behavior. From the perspective of SCM, these functions have a great impact on both supplier's revenues and buyer's costs, since each marginal change in demand leads to a change of the price. This fact is even more important, since in many real-world SCs prices are being settled for a longer period of time. In these cases, reverse pricing can not be used at all. A potential alternative way of implementing our proposed model could be using the mechanism for determining the allowed order quantity only, while all prices remain fixed as defined in a procurement contract between buyer and supplier.

Considering the limitations described, we plan to extend the richness of the agent model and thus the agent behavior in order to prove the validity of our approach for other, more realistic SC models. We also plan to extend the scope of the current simulation by using real-world data from actual supply chains instead of artificially generated data.

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