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Design and simulation of demand information sharing in a supply chain

Cheng Zhang *, Chenghong Zhang

Department of Information Management and Information Systems, School of Management, Fudan University, #220 Rd. Handan, Shanghai 200433, China

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Abstract

On the premise of discrete simulation technology, the study developed a simulation approach to quantify firms' business operations and performances in a multi-tier supply chain. By careful simulation scenario design and statistical validation, the simulation model was applied to understand one practical business problem, i.e., how to evaluate the business model and its trade-off of implementing demand information sharing strategy. The results showed that with high demand variance, low demand correlation, and/or high demand covariance, the supply chain without the intermediate tier performed better than that with the intermediary. However, bypassing the intermediate tier in the chain might cause companies less responsive to demand variability. The simulation and analytical approaches presented in the paper can help firms make better decision on business model design and inter-organizational collaboration in supply chains.

Keywords: Discrete simulation; Supply chain management; Demand information sharing

1. Introduction

Supply chain management (SCM) is defined as a set of approaches utilized to efficiently integrate suppliers, manufacturers, warehouses, and stores, so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, in order to minimize system-wide costs while satisfying service level requirements [24]. As SCM has drawn much attention in industrial and academic fields, various techniques are developed to model, analyze, and solve complex decision problems in supply chains. Simulation is one of the techniques, which allows the researcher to capture and experiment with the rules in real or proposed systems. Oftentimes, there are some situations in which a problem cannot meet the assumptions set by analytical modeling methods, especially when a problem exhibits significant uncertainty and is quite difficult to be dealt with analytically [7].

Compute-based simulation, with its own strength on evaluating variations and interdependencies in a complex system [33], is one of the promising methods. With simulation, it is possible for decision makers to examine

* Corresponding author.
E-mail address: zhangche@fudan.edu.cn (C. Zhang).

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the changes in the part of the chain and following consequences with less expense than field experiment which is usually difficult to be carried out. For example, Kimbrough et al. [12] developed a multi-agent simulation system and showed that with proper feedback control design, artificial intelligent could help tiers find an optimized inventory policy to mitigate bullwhip effect. Minegishi and Thiel [21] simulated complex logistic behaviors of an integrated food industry and proposed several managerial recommendations from simulation results.

Simulation models are broadly developed for studying supply chains, which generally had two main characteristics to classify. First, they are either discrete or continuous systems to simulate operations in supply chain. A discrete system is one in which the state variables change instantaneously at separated time points, while a continuous system is one in which the state variables change continuously with respect to time [13]. Examples of discrete simulation system in supply chain studies include Wei and Krajewski [32] and Sivakumar [25]. Examples of continuous simulation system include Homem-de-Mello et al. [11] and Tagaras and Vlachos [28]. Since few cases in the real world are solely discrete or continuous system, the system classification largely depends on researchers' analytical perspective. Secondly, the models are either the event orientation, activity scanning orientation or process orientation. These characteristics are helpful for researchers to simulate and to monitor supply chain activities.

To help organizations understand and evaluate cost and benefit of supply chain practices, this study provided a simulation approach to quantify firms' SCM decisions into business operations, including procurement, storage and distribution, and to measure participant firms' performance in multi-tier supply chains. Furthermore, the study applied the simulation model to solve a practical supply chain problem, i.e., what are the suitable business conditions for firms to consider demand information sharing strategy in supply chains and how the market demand patterns and intermediate firms affect the strategy outcome. The simulation and analytical approaches presented in the paper will help firms make better business model design and inter-organizational collaboration decision in supply chains.

2. Problem background in supply chain management

Due to increasing global competition and higher customer expectations, all business enterprises today are seeking to increase their inter-organizational collaboration network and create smooth material, information and financial flows along the supply chain. For example, the Efficient Consumer Response (ECR) report estimated a potential $30 billion opportunity from streamlining the inefficiencies of the grocery supply chain [14]. To manage a supply chain efficiently and economically, matching supply with market demand is mainly concerned in supply chain management [1].

Sharing market information has been recognized as an effective approach to reduce demand distortion and improve supply chain performance [15]. Various studies used simulation to evaluate the value of information sharing in supply chains. From system dynamics perspective, Towill et al. [29] found that supply chain integration with exchange of information was as beneficial as lead time reduction throughout the supply chain via JIT. From a control theoretic approach, Dejonckheere et al. [5] examined the beneficial impact of information sharing in multi-tier supply chains and discovered that information sharing helped to reduce the bullwhip effect in the chains with different inventory policies. Using multi-agent simulation system, Li et al. [18] compared three types of information sharing strategies in supply chain management.

Besides demand variability, lead time also draws much attention in demand-matching research. Researchers argued that lead time and its variability is another potential factor that would affect supply chain members' responsiveness to market demand [14]. On this topic, Chatfield et al. [3] analyzed the influence of lead-time variability on firm's inventory management by a multi-agent simulation system, while Zhang et al. [34] studied how information could reduce the influence of shipment uncertainty during the lead time by a discrete simulation model. Most literature studies on lead time showed that longer lead time (or larger lead time variability) had a negative effect on supply chain performance, implying that firms should reduce lead time between tiers.

Consider a three-tier supply chain where products are delivered from the producer to end-market customers after passing through the distributor and the retailer. With demand information sharing (DIS) in a supply chain, each tier is aware of end market demand for the products and uses such information to forecast the future demand. In addition, the distributor works as the intermediary between the retailer and the supplier in a chain and manages itself as a buffer between the retailer's demand and the supplier's supply. Reducing the intermediate tiers, i.e., the distributor in this case, may benefit to supply chains. First, the total amount of stock along the supply chain can be reduced. Second, based on previous studies on demand distortion, reducing the numbers of tiers in a supply chain tends to be an intuitive solution to counter the bullwhip effect. With less demand distortion along the chain, a more smooth material flow through the chain is expected. One successful example of this business practice is Dell's direct model. Founded on the simple business insight that the company could bypass the dealer channel and build products to order in 1984 [20], Dell developed a US$21.7 billion business worldwide in 1999 [8] and its direct model is now regarded as exemplifying the principle that companies should sell directly to customers and deal directly with suppliers without any unnecessary interference of intermediaries in supply chains.

However, if we view intermediate tiers as stock buffers in the chain, bypassing the intermediate tier means the company's supply lead time increases and it may become less responsive to demand variability from the end market. To counter this cost, one key initiative is information sharing between partners in a supply chain. In Dell, it maintained continuous and close electronic links with suppliers, sometimes even on an hourly basis [22]. On the other hand, research has shown that demand distortion cannot be completely eliminated by demand information sharing [4]. As a result, the direct model still takes its cost even with information sharing.

In practice, we have observed different decisions by firms: some firms are actively moving their distribution centers closer to target markets, but some others are centralizing their supply bases, which results in farther supply to markets, while some others are removing intermediary tier in their chain. These conflicting trends also motivate us to re-think the impact of lead time from a new perspective, i.e., the role of intermediate tier in supply chains.

Therefore, it is valuable to discover when reducing an intermediate tier is beneficial and how the system parameters, such as demand patterns and lead time, influence the whole supply chain. By simulation experiments, the study can provide useful managerial insight for companies to choose a suitable business model in their specific business environment.

3. Simulation model

In this paper, we employed a simulation approach to quantify the benefit of demand information sharing in a three-tier supply chain model. The simulation process followed Evans and Olson [7]'s five essential stages.

Our system in this study is a discrete one since tiers' supply chain activities, such as order fulfillment, inventory replenishment and product delivery, are either triggered by customers' orders or arrival shipments from suppliers at points of time. Therefore, these activities can be viewed as discrete events.

There are multi-agent modeling technologies existing in simulation studies, e.g., Yung and Yang [31], Swaminathan et al. [27], Lin and Pai [19] and Chatfield et al. [3]. However, the study' focus is to help organizations understand and evaluate cost–benefit of demand information sharing strategy in supply chain. Therefore, tiers in the research design act in a sequential order along the chain and follow determined inventory policy without intelligent optimizations. Therefore, discrete simulation is suitable to this study.

3.1. Simulation mechanism

We model the entities in a supply chain network consisting of three different roles: retailer, distributor, and supplier. Each of the entities performs tasks including receiving orders, receiving shipment from its supplier, fulfilling orders, calculating inventories and backlogs, forecasting demands, placing orders to its supplier and expecting shipments to arrive in the future. The combination behavior of each entity composed a complex environment.

The mechanism of order fulfillment process in the supply chain can be described as follows:

(a) Customers come to retailer and make their purchases.
(b) Retailer sells goods to its customer and places new order with its distributor based on its inventory management policy and forecast on future demand to ensure continuous selling.

(c) Distributor ships its stock to the retailer after receiving retailer's order and forecasts on retailer's future demand to ensure a continuous fulfillment to retailer, and then it places order on products to its upstream supplier.
(d) After receiving the distributor's order, the supplier will ship out goods to the distributor and place order to its supplier.
(e) At the end of each cycle, every tier summaries its cost and service performances and updates information about demand and shipment for future usage.

Fig. 1 shows a three-tier supply chain activities and the simulation mechanism.

3.2. Simulation tool: GPSS/world

GPSS, the General Purpose Simulation System, is one popular language in computer simulation, firstly developed by Geoffrey Gordon at IBM in the early 1960s. It provides a rich basis for modern simulation environments. Moreover, GPSS deeply influences many other simulation languages that now rely on derivations of GPSS concepts.

GPSS/World, maintained by Minuteman Software, is a direct descendent of GPSS/PC, an early implementation of GPSS for personal computers which was introduced in 1984. GPSS/World is primarily intended to be an extension of simulation environment for GPSS/PC users, enhanced by an embedded programming language PLUS, Programming Language Under Simulation. It brings all the simulation primitives up to the user interface, and makes it easier to visualize and manipulate simulations. As a result, simulations can be developed, tested, and understood more quickly than ever before in GPSS/World environment. All transactions in the simulation can be saved at any time in any state, with detailed descriptive statistics. Its nature allows the internal mechanisms of models to be revealed and captured. Its interactivity allows one to explore and manipulate simulations. Its pre-developed simulation validity technology makes experiment convenient to be warmed-up and repeated. Its built-in data analysis facility can calculate confidence intervals and analysis of variance easily.

3.3. Statistical analysis for model validity

Since GPSS is a stable simulation system that provides detailed transaction reports for post analysis, we focus our internal validation on whether the simulation model correctly represents the supply chain. Considering the three-tier linear supply chain structure which consists of a retailer (R), a distributor (D) and a supplier (S), if we set the safety stock factor at upper tiers, i.e., D and S, extremely high in the chain, say 8, then D can be viewed as an ultimately source to R which has unlimited supplying capability. As a result, R reverts to a basic single-stage case in operations research. It can be calculated that when $z > 7$, the tier's expected stock-out probability, i.e., $1 - \Phi(z)$ where $\Phi(\cdot)$ is the standardized normal cumulative distribution, is below $1E - 12$ which can be safely ignored. Since such inventory management case that has been well studied in operations research, we can compare the simulation result with theoretic values under such situation.

We evaluated the fill rate and the inventory level of each product at retailer's side while varying demand variance and lead-time between the retailer and its supplier. Other indexes, such as inventory cost, can be inferred from these two indexes. The theoretic values are shown in Table 1, where (x, y) indicates the combination of demand standard deviation STD(σ) and lead time value LT(L). For example, $(10, 3)$ stands for the situation: STD as 10% of the mean and lead time in between as 3 periods.

The simulation ran 2000 periods for each condition and the average value of these indexes, shown as X_iY_i, was calculated. If one computer period simulated 1 h (or 1 day) in the real world, the whole 2000 would represent 1-year (or 8-year) activities in a supply chain. Therefore, a 2000-period running should be enough

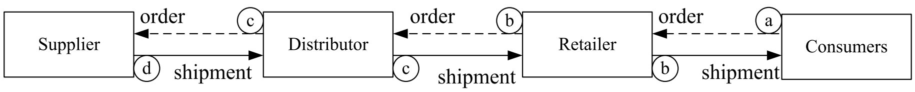


Fig. 1. The diagram of supply chain activities and simulation mechanism.

Table 1
Theoretical value of service level and inventory level at the retailer's side

Condition (STD, LT)	Fill rate	Average inventory
(10, 3)	0.996	28.5
(10, 6)	0.994	40.4
(10, 9)	0.993	49.5
(30, 3)	0.989	85.7
(30, 6)	0.984	121.2
(30, 9)	0.981	148.5
(50, 3)	0.981	142.8
(50, 6)	0.974	202.0
(50, 9)	0.968	247.5

to provide the stable performance of a supply chain. We got a data set of these indexes: $(X_1 \ldots X_{15})$, $(Y_1 \ldots Y_{15})$ for each condition, with 15 replication, with each replication using a different random seed. The replication here was designed to provide the statistical significance of the simulation results. Then t-test, via SPSS [26] was used to evaluate whether the simulation results fit with theoretic values. The confidence interval was 95% and $H_0: \ E(X_i) = \bar{X}, E(Y_i) = \bar{Y}$. The significances are shown in Table 2.

From the result, we could not find statistical difference between simulation result and theoretic values based on 5% significance test. Meanwhile, 95% confidence intervals of the difference of the data, i.e., the confidence interval of $(E(X_i) - \bar{X})$, all covered zero.

3.4. Statistical analysis for steady-state parameters

To promise a stable simulation result, we designed two simulation processes to examine whether total repeat time and running length of each time would influence the simulation result. Design1 was to repeat the scenario 15, 25, and 35 times, each time the simulation continuously ran 2000 periods with a unique random number seed; Design2 was to vary the running period of each scenario, i.e., the scenario ran for 2000, 3000, and 4000 periods (increasing by 1000 periods each time), respectively, with a unique random number seed and each run repeated 15 times We employed an ANOVA (analysis of variance) test to examine whether these different treatments made system performances different in the simulation given a 95% confidence. If not, we inferred that performance had become steady in the treatment of 15-repeat-of-2000-period and no need to increase simulation length or replication number. In this statistic test, the fill rate and the inventory level of products or components at each tier were chosen as the measurement. The result indicated that neither a longer simulation length nor more replications significantly changed the result from a 2000-period and 15-repeat scenario, shown in Table 3.

We also used the Replication/Deletion approach to improve the estimates of the steady-state mean of the performances. We divided 2000 periods into 20 intervals, each containing 100 periods. The replication time was 15. We calculated the system performances in three ways: calculating the number based on all time periods during the simulation ($d = 0$); deleting the first 100-period simulation data and calculating the number based on the remaining 1900 periods ($d = 1$); and ignoring the first 200-period data in the calculation ($d = 2$) and

Table 2
Significances between the simulation result and theocratic result

Condition (STD, LT)	Sig. test of service level	Sig. test of AVG inventory
(10,3)	0.172	0.260
(10, 6)	0.186	0.346
(10, 9)	0.726	0.611
(30, 3)	0.801	0.706
(30, 6)	0.128	0.265
(30, 9)	0.126	0.233
(50, 3)	0.663	0.801
(50, 6)	0.275	0.086
(50, 9)	0.341	0.296

Table 3
ANOVA test of different simulation scenarios under a 95% confidence

Tier	Design 1		Design 2	
	Fill rate	Inventory level	Fill rate	Inventory level
Retailer	0.254	0.900	0.755	0.588
Distributor	0.172	0.316	0.472	0.947
Supplier	0.966	0.948	0.951	0.914

Service level/inventory level: ANOVA test for comparing the simulated service level/inventory level of product × under different simulation scenario: different replications (Design 1) and cycle length (Design 2).

Table 4
ANOVA test of simulation scenarios with different "warm-up" period under a 95% confidence

Tier	Service level	Inventory level
Retailer	0.920	0.462
Distributor	0.975	0.943
Supplier	0.945	0.973

Service level/inventory level: ANOVA significance of the simulated service level/inventory level of product × under different "warm-up" period.

went on if necessary. ANOVA test was carried out with 95% confidence level in SPSS to examine whether measurements were different significantly under such three treatments. In this way, we could determine whether the "warm-up" period has significant impact to the simulation output. Result, shown in Table 4, indicated that there were no significant difference under different treatments when $d = 0$, $d = 1$, and $d = 2$, which meant that the system quickly became steady. The reason might be that the initial stock setting in simulation was close to the order-up-to level and the running period of simulation was quite long. Therefore the effect of "warm-up" period in this scenario was not significant.

4. Simulation scenario

4.1. Supply chain structure and settings

The simulated supply chain contains three tiers: two retailers that sell same product in distinct regions, a distributor that delivers products to these regional retailers, and a supplier that provides the product to the distributor. In the first design (DIS1) the retailers' order is placed with the distributor and the distributor places its order with the supplier. In the direct model (DIS2), retailers order directly from the supplier, with the distributor acting essentially as an allocation center. As a result, the whole supply chain can be viewed as being two-tier. No information sharing (NIS), where no other information is received by the supplier except for orders from immediately downstream, is used as a benchmark. We do not assume that the retailer knows the exact form of the customer demand process. Instead, the retailer uses a standard forecasting technique to estimate certain parameters of the demand process.

Each tier in the supply chain sets the same service level, $\alpha = 95\%$,[1] i.e., the probability of running out stock in a replenishment cycle, to manage two products. Previous backlogs are prior to fulfill in the future. The ultimate supplier, i.e., the supplier's supplier, has an infinite capacity to supply whatever its customer orders.

The market demand process follows a general auto-correlated AR(1) process without seasonality, i.e., $d_t = u + \rho d_{t-1} + \varepsilon_t$, where $u > 0$, $|\rho| < 1$ and ε_t is normally distributed $(0, \sigma^2)$ (subscript t denotes the variable in period t). Initially we set the demand parameters of two markets both at $u = 100$, $\sigma = 30$, and $\rho = 0$. As a result, two demand processes degenerate to be independent and normally distributed. Later we study the demand trend and covariance using sensitivity analysis. These demands could represent a collection of demands aggregated from numerous individual consumers or from a group of industrial customers.

[1] Please refer to notation table in appendix for details.

Each tier in the supply chain employs the commonly used moving average method [2] to forecast future demand. With demand information available, the formula at each tier can be expressed as $\hat{d}_t = \sum_{j=1}^{n} d_{t-j}/n$, where n is the number of demand observations used as a base. When demand information is not available, upper tiers (i.e., all except the retailer), use $\hat{d}_t = \sum_{j=1}^{n} o_{t-j}/n$ to forecast future demand where o_t is the order placed by the downstream entity with its supplier at period t. Chen et al. [4] argued that the variance of the orders, placed by the downstream to its supplier, satisfies a lower bound as $1 + \left(\frac{2L}{n} + \frac{2L^2}{n^2}\right)(1 - \rho^n)$, where L is the lead time between two tiers. In this study, we assume that each tier set a forecasting window size 10 times greater than the lead time between itself and its customers ($n/L = 10$) to reduce demand distortion to a certain extent. The lead time between tiers is deterministic.

Eppen and Scharage [6] showed that when using linear inventory holding and backlog costs and under fairly moderate assumptions, the order-up-to inventory policy had a satisfying performance. Therefore in this study we assumed that all chain members used order-up-to periodic-review inventory policies. The order-up-to level is given by $S_t = L\hat{d}_t + z\hat{\sigma}_t\sqrt{L}$, where $z = \Phi^{-1}[b/(b+h)]$, $\Phi(\cdot)$ is the standardized normal cumulative distribution, b the unit backorder cost per period, and h the unit inventory holding cost per period. Setting $h = 1$ and $b = 19$, we get 95% target service level and $z = 1.65$. Initially the lead time between each tier was the same and we set it as 6 periods which could represent 6 days or 6 weeks of transportation. Since this study focuses on the trend of system change with lead time varying, we believe the number initially set in the simulation will not significantly affect the conclusion. $\hat{d}_t$ and $\hat{\sigma}_t$ is the estimated mean demand and estimated standard deviation of demand, respectively, at period t. Note that under different information circumstances, the optimal inventory policy might not be the same. However, to facilitate comparison and to focus on the impact of "changing a given" [23] rather than on optimizing inventory policy, we fixed the inventory policy to be the same in all cases of this study.

4.2. Scenario design

The scenario consisted of two processes: the initialization stage and the periodic ongoing stage. The initial stage was carried out only once, to set system parameters and to initialize randomness. The periodic running process contained all the activities in a supply chain, including demand forecasting, product ordering, storing and shipping, and performance statistics collecting. In the periodic running stage, system parameters were independently varied from a lower value to a higher value respectively to perform sensitivity analysis. The process ran for 2000 computer-simulated periods to simulate daily (or weekly) operations of each tier in a supply chain. Each 2000-period scenario required 15 replications to gain enough statistical significance.

Recall the supply chain model in this work. It is clear that there are two sets of system parameters that determine supply chain behavior: the first set is the independent parameters of the market demand. There are three parameters influencing the demand process: the demand variance σ, the demand correlation over time ρ, and the demand covariance cov. The second set of parameter is from the supply side. The critical parameter influencing the supply is the lead time L_d, i.e., the distributor location in chain, which influences the order, inventory and shipment quantities. These four parameters are meaningful and important in practical business situations: σ indicates the degree of demand fluctuation, ρ indicates the trend of demand, cov indicates the relation of demand processes, such as the relation of product sales in different regions or different product models in the same product family, while L_d indicates the supply delay from inventory to market. We include these four parameters in the sensitivity analysis, summarized in Table 5.

Table 5
Summary of scenario settings employed in the sensitivity analysis

System parameters	Value in basic case	Values in sensitive scenario	Number of sensitive scenario
σ	30	Low (10), high (50)	2
ρ	0	Negative (−0.5), positive (0.5)	2
Cov	0	Negative (−0.5), positive (0.5)	2
L_d	6–6	Forward (3–9), postponed (9–3)	2

There were actually five factors, including the style of information sharing, being investigated in the simulation. A full factorial study would consist of 243 scenarios. In the study, however, we used partial factorial analytical method, i.e., when analyzing one factor, we kept other factors unchanged. Though the design might limit our observation on the complicated situations, we could simplify the analyses and concentrate on factors' impact compared to the basic case. In this way, the analytical work could still provide plentiful insights to us. Therefore, we only ran 27 scenarios for partial factorial analysis purpose.

Also note that there are three supply lead times for the three tiers in the chain. In this study we were more interested in the lead time changes between the retailer tier and the supply tier, i.e., the location of the distributor in the channel. Initially we placed the distributor midway between the supplier and the retailer, giving a 6–6 units of time away from each one. However the distributor might move closer to the supplier or to the market. In this study, we used $x - y$ to indicate the location of the distributor in the channel.

4.3. Algorithm logic in the simulation

This subsection lists the algorithm describing supply chain activities, including demand forecasting, product ordering, storing and shipping, and performance statistics collecting, in the simulation.

1. Initial stage
   - Importing configuration file of scenario settings.
   - Setting system variables with proper values in the scenario.
   - Initializing random number generators.
   - Warming up the system to store enough historic data for demand forecasting and order-up-to level calculation.
2. Periodic activities in a supply chain.
   - *At each tier from retailer to first tier supplier*
   - Receiving product orders from its customers.
   - Receiving shipments from its supplier.
   - Fulfilling orders and any accumulated backlogs.
   - Forecasting future demand and estimating its demand variance of products.
   - Calculating the order-up-to level.
   - Determining the order quantity and placing the order with its supplier.
   - Summarizing its service and cost performances at this period.

5. Results and analyses

ANOVA tests using a 5% significance level were performed in SPSS to examine significant performance changes among various cases. If such significance was found, i.e., the overall F-test demonstrated that at least one difference existed, a multiple comparison procedure was used to assess which groups' data differed significantly from the others. (Prior to the multiple comparison procedure, Levene's test of homogeneity of variance [17] with a 5% significance level is employed to examine whether the dependent variables, i.e., the performance indices, have the same variance in each group). Tukey's honestly significant difference (HSD) test [30] was used when the assumption of the homogeneity of variance was met and Games–Howell [10] method was used when the assumption was not met.

5.1. Results from basic experiments

The performance changes, including service level (SL), inventory cost (IC), backlog cost (BC), and total cost (TC), in the supply chain were studied, as shown in Table 6. In the basic case, it is clear that the supply chain without the distributor achieved a lower total cost than the other two cases, but it also had the lowest

Table 6
95% confidence of the mean difference of supply chain performance among No-IS and Demand-IS

Supply chain performance			Service level	Inventory cost	Backlog cost	Total cost
Experimental settings						
	Basic case		$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D1 > D2$
Sensitivity analysis						
	Demand variance	Low	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$D2, N > D1$
		High	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D1 > D2$
	Demand correlation over time	Negative	0	$N > D1 > D2$	0	$N > D1 > D2$
		Positive	$N, D1 > D2$	$N > D1 > D2$	$D2 > D1 > N$	$D2 > N > D1$
	Demand covariance	Negative	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D2 > D1$
		Positive	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D1 > D2$
	Location of distributor in Chain	Forward	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D1, D2$
		Postponed	$N, D1 > D2$	$N > D1 > D2$	$D2 > N, D1$	$N > D1 > D2$

N: No-IS; D1: Demand-IS Case 1; D2: demand-IS Case 2 ($D1 > N$ means the performance value under the Demand-IS Case 1 is significantly larger than that under Traditional-IS. $D1 > D2 > N$ implies $D1 > D2$, $D1 > N$ and $D2 > N$, while $D1 > D2, N$ equals $D1 > D2$, and $D1 > N$ only; 0 means no such significant mean difference).

service level. By eliminating the stock at the distributor tier, the two-tier supply chain had 42.4% and 32.1% lower inventory cost than the other two cases respectively. However, as the retailers' supply lead time increased and the buffer stocks held at the intermediary were removed, retailers became less responsive to customer's fluctuating orders. As a result, retailer's service level dropped, causing its backlog cost to increase. However, the benefit from inventory reduction compensated for the cost from increased backlogs. Overall, the two-tier supply chain, i.e., DIS2, performed the best with a 20.1% and 8.0% total cost reduction compared with the other two cases respectively. These improvements could be compared with a 13.2% reduction in total cost when information sharing was included in a three-tier supply chain, i.e., DIS1. When demand correlation was negative, the service level and backlog cost became insignificantly different among three cases.

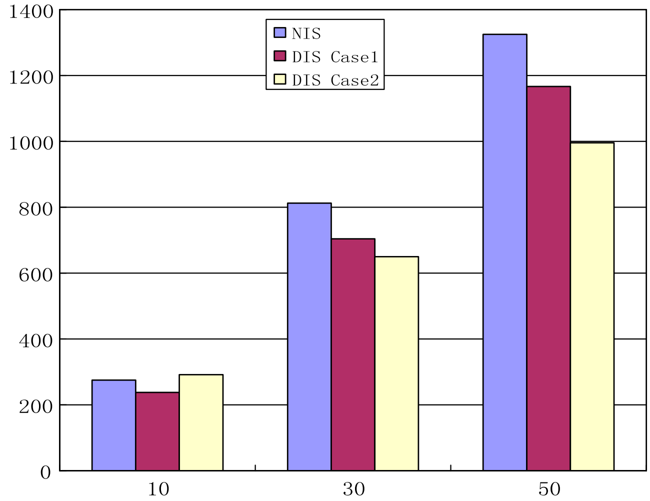
5.2. Analysis of demand variance

We first studied the situation when demand variance fluctuates and found that the significant change in total supply chain cost arose from the inventory cost for all tiers. DIS2 reduced 24.9% of supply chain' total cost in the numerical result, while DIS1 reduced 14.0%, when the demand variance was high. This result is quite natural: as demand fluctuations increase, more forecast error on future demand and demand distortion occurs. Therefore the improvement of forecast accuracy enabled by information sharing, along with subsequent benefits, increases. Our results confirm that cost savings from information sharing can be substantial when demand variance is large [16].

On the other hand, when demand variance was low, the total cost in DIS2 approached the case without information sharing, indicating that the impact of faster response from shorter lead time overcame the impact of information value when demand was stable. As demand fluctuation decreased, less forecasting error and demand distortion was generated in the supply chain. Therefore the value of information sharing declined. In this situation, the benefit from information might become less to cover the loss of responsiveness to customer orders, so the performance of DIS2 in the direct model was less than DIS1. As shown in Fig. 2, with low demand variance, the total cost in DIS1 was 12% and 18.5% significantly less than the other two cases, respectively.

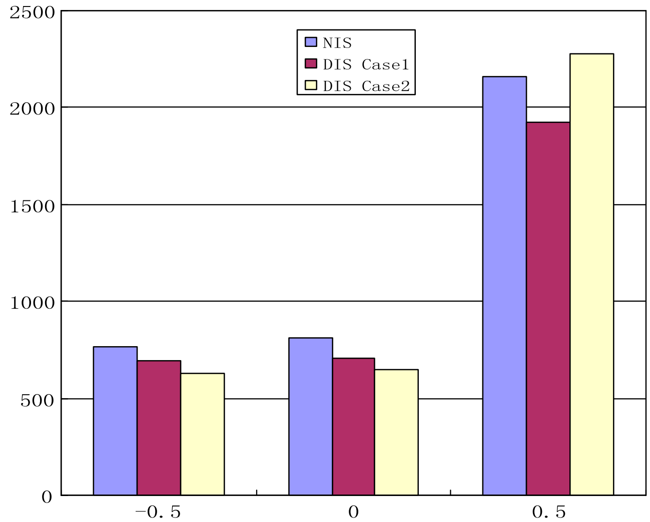
5.3. Analysis of demand trend

Next we studied the impact of demand trend on the supply chain performance. When demand trend changed to negative 0.5 and positive 0.5, the average demand became 67% and 200% of the initial demand, respectively (see Appendix for proof). Fig. 3 shows that when the demand had no such trend, information sharing reduced 13.2% of the supply chain's total cost in DIS1 and 20.1% in DIS2, comparing with that without information sharing. When the demand trend was negative, information sharing reduced 8.7% of the supply chain's



Demand Variance	NIS	DIS Case1	DIS Case2
10	276	238	292
30	813	706	649
50	1324	1165	994

Fig. 2. Supply chain total cost in no information sharing, demand information sharing Case 1 and demand information Case 2 as a function of demand variance.



Demand Correlation	NIS	DIS Case1	DIS Case2
-0.5	763	696	628
0	813	706	649
0.5	2160	1921	2279

Fig. 3. Supply chain total cost in no information sharing, demand information sharing Case 1 and demand information Case 2 as a function of demand correlation over time.

cost in DIS1 and 17.7% in DIS2, which meant that using the direct model was more beneficial to the supply chain.

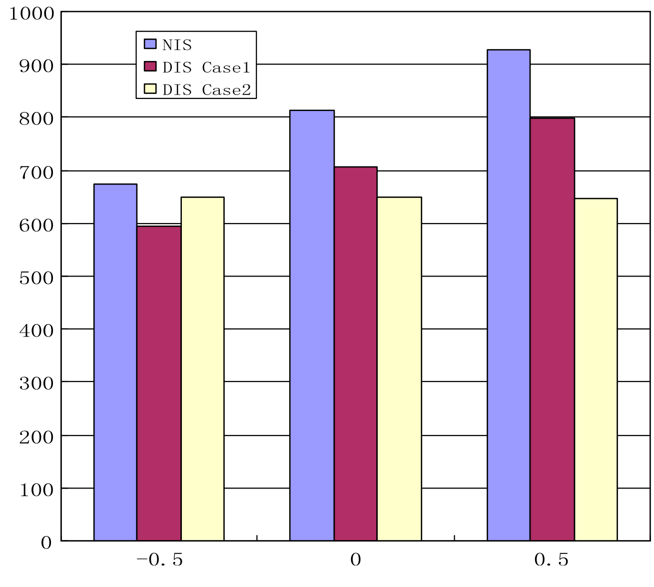
However, when the demand trend was positive, the supply chain cost in DIS2 increased 5.5% while the cost in DIS1 decreased 11.1%, comparing with that without information sharing. As demand increased, higher quantities should be ordered, but the supply lead time delayed the match between demand and supply. Although retailers hold some safety stock to meet demand fluctuations, increased demand accumulated during the lead time might exceed the buffer capability of safety stock. Because the supply chain in DIS2 applied a direct model that bypassed the distributor between the retailers and the supplier, a longer lead time was required for retailers' order fulfillment. Consequently, retailers had less capability to counter the increasing demand. While demand information helped the supply chain to adapt to the changed demand, the benefit was insufficient to counter the slower match between demand and supply during the longer supply lead time. With insufficient stock, the supply chain in DIS2 performed worse than the other two cases. In DIS1 retailers obtained shipments faster from the distributor and were thus more able to meet the changed demand before accumulated demand exceeded their safety stock. With available demand information, upper tiers could respond faster to the changing demand, resulted the lowest total cost in DIS1.

5.4. Analysis of demand correlation

Sometimes the demand processes are correlated. For example, a product being sold well in one region may have its sales promoted in another region, while a better sale of one product model may reduce another model's sales when the total market demand is constant. Studying the impact of demand covariance provides a better understanding of the value of intermediaries in a supply chain with information sharing. As shown in Fig. 4, when demand covariance was negative, the total supply chain cost in DIS1 and DIS2 reduced by 11.8% and 3.7%, respectively, comparing with that without information sharing. In this situation the three-tier structure performed better than the other two cases: when the demand covariance was negative, the sum of two demand processes neutralized the demand variability greatly. Because of demand pooling at the distributor tier, the demand at upper tiers became more stable and demand distortion was reduced. Consequently the supply chain cost reduced. This result also showed that the supply chain's benefit from negative demand covariance reduced the benefit of information sharing: comparing with the situation with zero demand covariance, the cost reduction ratio enabled by information sharing decreased when the covariance was negative. When demand covariance was positive, the cost reduction ratio enabled by information sharing in DIS1 and DIS2 increased to 14.0% and 30.2%, respectively. We also found that the benefit in DIS2 was superior to that in DIS1 when demand covariance became positive, indicating that the direct model was more suitable in the situation when the demand processes were positively correlated.

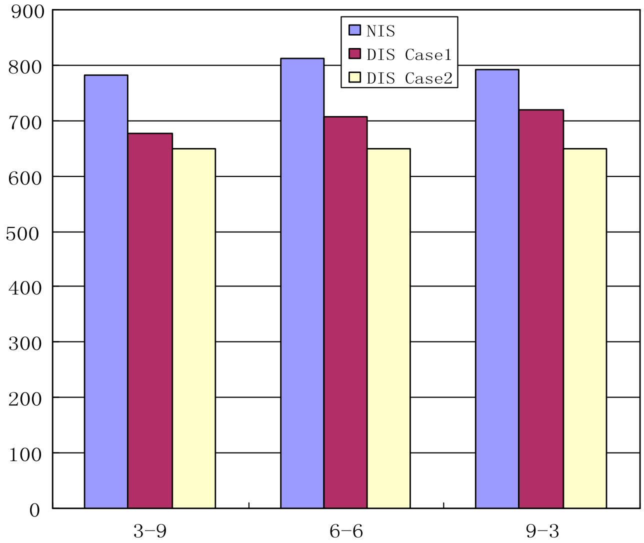
5.5. Analysis of distribution location

The last factor we studied was the location of the distributor in the supply chain: the distributor could be arranged close to the retailers or close to the supplier. This location change would consequently affect a retailer's responsiveness to demand fluctuation and the supply chain's ability to match demand with supply in a three-tier supply chain. However, in DIS2 the distributor's location did not affect the supply chain perfor-



Demand Covariance	NIS	DIS Case1	DIS Case2
-0.5	674	594	649
0	813	706	649
0.5	928	798	647

Fig. 4. Supply chain total cost in no information sharing, demand information sharing Case 1 and demand information Case 2 as a function of demand covariance.



Distributor Location	NIS	DIS Case1	DIS Case2
3-9	782	676	649
6-6	813	706	649
9-3	791	719	649

Fig. 5. Supply chain total cost in no information sharing, demand information sharing Case 1 and demand information Case 2 as a function of the changes of distributor's location.

mance since it did not hold inventory or place orders. As shown in Fig. 5, when the distributor located further down the chain, the total cost reduced. With demand information available, the supply chain's total cost in DIS1 and DIS2 reduced 13.6% and 17.0%, respectively. However, from Table 6, these two reductions did not show a statistical significant difference by ANOVA which meant that the three-tier supply chain performed equally well as two-tier one with information available: as the distributor moved close to the retailers, the supply chain could react more quickly to the market demand with less backlog cost and this benefit became equivalent to the benefit of inventory cost reduction at the distributor in DIS2. However, when the distributor moved towards the supplier, the cost saving in DIS1 and DIS2 was 9.1% and 17.9%, respectively. Such saving became significantly different by ANOVA: the supply chain applying the direct model with information sharing performed better than the other two cases.

In summary, the supply chain applying the direct model performed better with high demand fluctuation, decreasing demand trend, and positive correlation of demand processes. However, when demand variance was low, when the demand tended to increase, and when the correlation of demand processes was negative, the supply chain with an intermediate tier could perform better than the direct model. Furthermore, when the distributor was located close to the market, the supply chain with an intermediary might perform equivalently to the direct model.

5.6. Bullwhip effect in supply chains

To obtain an insight into demand distortions in the supply chain, we analyzed the Bullwhip effect (BWE), which is also named as dynamic effect [9], occurring in the chain. BWE is defined as the ratio of order variation generated by a member to the demand variation received by the member. In this study, the supply chain's BWE is expressed as: Bullwhip effect $= \frac{\text{supplier's order variance}}{\text{retailer's demand variance from its customer}}$ when BWE > 1, the demand volatility increases as it passes up through the supply chain. As shown in Table 7, demand distortion in the supply chain was significantly reduced by information sharing in most environments. Furthermore, with information available, reducing the intermediary efficiently decreased the demand distortion of the whole supply chain. However, by jointly analyzing the supply chain's behaviour in Table 6, we found that BWE could not be used to directly measure the supply chain's service and cost performance, i.e., although the supply chain performance became better when BWE decreased, a greater reduction in BWE did not promise a better service level or lower costs. Therefore, BWE may not be a suitable independent measurement to evaluate supply chain performance although it is good to demonstrate the demand distortion process along supply chains.

Table 7
Supply chain's dynamics in No-IS and Demand-IS

Supply chain performance			NIS	DIS Case 1	DIS Case 2
Experimental settings					
	Basic case		6.6	6.0	3.3
Sensitivity analysis	Demand variance	Low	7.0	6.1	3.3
		High	7.3	5.8	3.2
	Demand correlation over time	Negative	4.2	3.9	2.9
		Positive	26.1	21.6	7.7
	Demand covariance	Negative	3.3	3.3	1.7
		Positive	10.0	9.4	4.9
	Location of distributor in chain	Forward	6.1	4.8	3.3
		Postponed	6.0	4.8	3.3

6. Conclusion

On the premise of discrete simulation technology, the study developed a simulation approach to quantify firms' SCM decisions into business operations and measure participant firms' performance in multi-tier supply chains. By careful simulation scenario design and statistical validation, the simulation model was applied to understand one practical business problem, i.e., how to evaluate business conditions and trade-offs to implement demand information sharing strategy.

The success of Dell's direct model shows that reducing unnecessary intermediaries benefits supply chains. However, bypassing the intermediate tiers simultaneously loses their buffer functions in the material flow. As a cost of the direct model, the supply lead time between the company and its supplier increases and the company may become less responsive to demand variability in the end market. Such cost exists with demand information sharing because sharing information cannot eliminate but only reduce the demand distortion in the supply chain. Therefore it is valuable to discover when intermediary tiers are beneficial to a supply chain, when they are not, and how system parameters influence the whole supply chain.

In this work, the simulation model systematically examined the impact of demand parameters and lead time on supply chains with and without the intermediate tier. The simulation scenario considered four variable changes in a supply chain selling two products: demand variance, demand correlation, demand covariance, and distributor location in the supply chain. The results showed that when demand variance was high, when the demand trend was low, and when the correlation of demand processes was high, the supply chain that reduced the intermediate tier performed better than that with the intermediary. In those cases that the market demand was growing and that the products' demands were complementary, e.g., demands of products in the same product family, the supply chain with an intermediate tier could perform better than the direct model. When the intermediate tier moved close enough to the market, two types of supply chains performed equivalently well, which gives a theoretic proof of Dell's strategic advantage of requiring manufactories to build stock near its assemble line.

This cost–benefit analysis provides useful implications for companies seeking suitable business models in their supply chains. For example, the result showed that eliminating the intermediary generates a cost as supply lead time increases. Although organizations can anticipate great supply chain benefit from information sharing, there are some situations that the supply chain using direct model cannot perform as well as using other models. Therefore, whether to bypass the intermediate tiers is a critical task for supply chain managers and requires systematic consideration about specific environmental parameters in their own business, such as the expected demand patterns in the market and order cycle time in supply.

The supply chain in this study is decentralized, i.e., the tiers in the chain manage their own inventory and make order decisions separately. However, a multi-tier chain can be managed in another way: centralized control, where the decision on how much and when to produce/deliver is made centrally based on material and demand status of the entire system. Quantifying supply chain behavior with the centralized control and comparing it to that in decentralized control could provide further insights on how to design the channel structure of supply chains.

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Appendix. Notation table

t	subscript t denotes the variable in period t
α	service level
ρ	demand correlation over time
$d_t = u + \rho d_{t-1} + \varepsilon_t$	auto- correlated AR(1) process, where $u > 0$, $\lvert\rho\rvert < 1$ and ε_t is normally distributed $(0, \sigma^2)$
$(\hat{d}_t, \hat{\sigma}_t)$	estimated mean demand and estimated standard deviation of demand, respectively, at period t
o_t	the order placed by the downstream entity with its supplier at period t
L	the lead time between two successive tiers in the chain
$S_t = L\hat{d}_t + z\hat{\sigma}_t\sqrt{L}$	order-up-to inventory level, where z is the safety stock factor
b	unit backorder cost per period,
h	the unit inventory holding cost per period
n	the number of demand observations in forecast
cov	demand covariance
L_d	location of distribution in the supply chain

Proof 1. $E\left(\lim_{t\to\infty}\frac{1}{t}\sum D_t\right) = \frac{1}{1-\rho}u$, where $D_t = u + \rho D_{t-1} + \varepsilon_t$, $u > 0$, $|\rho| < 1$ and ε_t is normally distributed $(0, \sigma^2)$ □

Lemma 1. $\lim_{t\to\infty}x_t = A \Rightarrow \lim_{t\to\infty}\frac{1}{t}\sum x_t = A$.

When $|x_t - A| < \frac{\varepsilon}{2}\forall t > N_1$ (N_1 is a natural number and ε is positive), $\left|\frac{(x_1-A)+\cdots+(x_{N_1}-A)}{t}\right| < \frac{\varepsilon}{2}\forall t > N_2$ (N_2 is a natural number). Let $N = \max\{N_1, N_2\}$, so $\left|\frac{x_1+\cdots+x_t}{t} - A\right| \leqslant \left|\frac{(x_1-A)+\cdots+(x_{N_1}-A)}{t}\right| + \left|\frac{(x_{N_1+1}-A)+\cdots+(x_t-A)}{t}\right| < \frac{\varepsilon}{2} + \frac{t\varepsilon}{2t} = \varepsilon\forall$ $t > N$.

Therefore, $E\left(\lim_{t\to\infty}\frac{1}{t}\sum D_t\right) = E(\lim_{t\to\infty}D_t) = E\left[\lim_{t\to\infty}\left(\sum_{t=1}^{\infty}\rho^{t-1}\right)\cdot u\right] = \frac{u}{1-\rho}$.

References

[1] S.P. Bradley, R. Nolan, Sense and Respond: Capturing Value in the Network Era, Harvard Business School Press, Boston, MA, 1998.
[2] R.B. Chase, N.J. Aquilano, F.R. Jacobs, Production and Operations Management: Manufacturing and Services, eighth ed., Irwin/McGraw-Hill, Boston, MA, 1998.
[3] D.C. Chatfield, J.G. Kim, T.P. Harrison, J.C. Hayya, The Bullwhip effect – impact of stochastic lead times, information quality, and information sharing: a simulation study, Production and Operations Management 13 (4) (2004) 340–353.
[4] F. Chen, Z. Drezner, J.K. Ryan, D. Simchi-Levi, Quantifying the Bullwhip effect in a simple supply chain: the impact of forecasting, lead times and information, Management Science 46 (3) (2000) 436–443.
[5] J. Dejonckheere, S.M. Disney, M.R. Lambrecht, D.R. Towill, The impact of information enrichment on the Bullwhip effect in supply chains: a control theoretic approach, European Journal of Operations Research 153 (3) (2004) 727–750.
[6] G.D. Eppen, L. Schrage, Centralized ordering policies in a multi-warehouse system with lead times and random demand, in: L.B. Schwarz (Ed.), Multi-level Production/Inventory Systems: Theory and Practice, North-Holland, Amsterdam, 1981.

[7] J.R. Evans, D.L. Olson, Introduction to SimulationChapter 1, Introduction to Simulation and Risk Analysis, Prentice-Hall, Upper Saddle River, NJ, 1998, pp. 1–18.
[8] A.F. Farhoomand, P. Lovelock, P. Ng, Dell: Selling Directly, Globally, Case of University of Hong Kong, 2000.
[9] Y.H. Fu, R. Piplani, Supply-side collaboration and its value in supply chains, European Journal of Operational Research 152 (2004) 281–288.
[10] P.A. Games, J.F. Howell, Pairwise multiple comparison procedures with unequal *N*'s and/or variances: a Monte Carlo study, Journal of Educational Statistics (1976) 113–125.
[11] T. Homem-de-Mello, A. Shapiro, M.L. Spearman, Finding optimal material release times using simulation-based optimization, Management Science 45 (1) (1999) 86–102.
[12] S.O. Kimbrough, D.J. Wu, F. Zhong, Computers play the Beer Game: can artificial agents manage supply chains? Decision Support Systems 33 (2002) 323–333.
[13] A.M. Law, W.D. Kelton, Simulation Modeling and Analysis, second ed., McGraw-Hill, New York, 1991.
[14] H.L. Lee, P. Padmanabhan, S. Whang, The Bullwhip Effect in a Supply Chain, Sloan Management Review 38 (3) (1997) 93–102.
[15] H.L. Lee, P. Padmanabhan, S. Whang, Information distortion in a supply chain: the Bullwhip effect, Management Science 43 (4) (1997) 546–559.
[16] H.L. Lee, K.C. So, C.S. Tang, The value of information sharing in a two-level supply chain, Management Science 46 (5) (2000) 626–643.
[17] H. Levene, Robust Tests for Equality of VariancesContributions to Probability and Statistics, Stanford University Press, Palo Alto, CA, 1960, pp. 278–292.
[18] J. Li, M.J. Shaw, G.W. Tan, Evaluating Information Sharing Strategies in Supply Chains, in: Proceedings of the eighth ECIS, Vienna, Austria, 2000, pp. 437–444.
[19] F.R. Lin, Y.H. Pai, Using multi-agent simulation and learning to design new business processes, IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans 30 (3) (2000) 380–384.
[20] J. Magretta, The power of virtual integration: an interview with Dell Computer's Michael Dell, Harvard Business Review (March/April) (1998) 73–84.
[21] S. Minegishi, D. Thiel, System dynamics modeling and simulation of a particular food supply chain, Simulation Practice and Theory 8 (2000) 321–339.
[22] J.W. Rivkin, M.E. Porter, Matching Dell, Case9-799-158 of Harvard Business School, June 1999.
[23] E.A. Silver, Changing the givens in modeling inventory problems: the example of just-in-time systems, International Journal of Production Economics 26 (1992) 347–351.
[24] D. Simchi-levi, P. Kaminsky, E. Simchi-levi, Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies, Irwin/McGraw-Hill, Boston, 2000.
[25] A.I. Sivakumar, Multi-objective dynamic scheduling using discrete event simulation, International Journal of Computer Integrated Manufacturing 14 (2) (2001) 154–167.
[26] SPSS (Statistical Package for the Social Sciences) for Windows R10.0, SPSS Inc. Available from: <http://www.spss.com>.
[27] J.M. Swaminathan, S.F. Smith, N.M. Sadeh, Modeling supply chain dynamics: a multiagent approach, Decision Sciences 29 (3) (1998) 607–632.
[28] G. Tagaras, D. Vlachos, A periodic review inventory system with emergency replenishments, Management Science 47 (3) (2001) 415–429.
[29] D.R. Towill, N.M. Naim, J. Wikner, Industrial dynamics simulation models in the design of supply chains, International Journal of Physical Distribution and Logistics Management 22 (5) (1992) 3–13.
[30] J.W. Tukey, The Collected Works of John W. Tukey, in: H.I. Braun (Ed.), Multiple Comparisons 1948–1983, vol. 8, Chapman & Hall, New York, NY, 1993.
[31] S.K. Yung, C.C. Yang, A new approach to solve supply chain management problem by integrating multi-agent technology and constraint network, in: Proceedings of the Thirty-second Annual Hawaii International Conference on System Sciences, 1999, Maui, Hawaii.
[32] J. Wei, L. Krajewski, A model for comparing supply chain schedule integration approaches, International Journal of Production Research 38 (9) (2000) 2099–2123.
[33] B. Wyland, Simulating the supply chain, IIE Solutions 32 (1) (2000) 37–42.
[34] C. Zhang, G.W. Tan, D.J. Robb, X. Zheng, Sharing shipping quantity information in the supply chain, Omega: International Journal of Management Science 34 (5) (2006) 427–438.