Optimization of Stock Management for a Supply Chain Network with Information Sharing

Suh-Wen Chiou　Chun-Yu Yu
Department of Information Management
Tatung University

Abstract

For a supply chain network, it includes the suppliers, warehouses and customers. The value of information sharing in a supply chain network has been discussed over a variety of aspects. In this paper, we present an optimized stock allocation and distribution policy of the stock levels at warehouses and the product flows for customers in a supply chain network with information sharing. The objective for this supply chain network is to pursue total cost minimization. An optimization of mathematical programme for the stock distribution in the supply chain network is proposed. The development of algorithms based on the minimum cost flows is established. Empirical studies for the comparison of the values of information sharing and non-information sharing in a two-level supply chain have been done in terms of the bullwhip effects and order up to inventory by real sales data over consecutive four years, which has been supported by project 89-EC-2-A-14-0314. Experiments for a three-echelon structure have been conducted on two test networks and good results have been found.

Keywords: information sharing, supply chain network、 stock management

資訊流分享下最佳化供應鏈存貨管理

邱素文　游峻宇
大同大學資訊經營研究所

摘要

對於一供應鏈網路而言，它包涵了三個部分：供應商、庫存商及顧客。供應鏈網路下的資訊流分享，在已過的數年間，早已成為多方面探討的主要話題。在本篇文章中，我們將提出一套以最佳化分析為基礎的數學模式，針對在資訊流分享下的存貨分配，進行在庫存商間的最佳化存貨管理及在顧客需求上的最佳化配送。並據此最佳化模式所推導的最佳化條件，發展相關演算方法，同時進行多方面的模擬測試。本文將引用由八十九年度經濟部產業電子化學界研究推廣計畫(89-EC-2-A-14-0314)下，零組件應用實例分析中的雙階層供應鏈，進行當資訊流分享時，其對於供應鏈在存貨管理上所可能產生的影響及衝擊。

關鍵字：資訊流分享、供應鏈網路、存貨管理

1. Introduction

A supply chain can be regarded as a global network of suppliers, distribution centers, warehouses, retailers and customers. In such supply chain network, the nodes can be identified by the supplier nodes, distribution center nodes, warehouse nodes, retailer nodes and customer nodes; and the links can be identified by the connection of the relationships among these nodes. The values of information sharing in a supply chain network can be realized via EDI or advanced development of techniques, e.g. EBXML. The corresponding improving effects brought about by conducting the technique of information sharing even can be quantified in which the bullwhip effects have been demonstrated reduced greatly. Furthermore, for a supply chain network with information sharing, given stationary process of customer demands over consecutive time periods, the product flows and the stock levels at distribution center nodes, the warehouse nodes and the retailer nodes can be determined in an optimized way such that the total cost incurred by the suppliers, distribution centers, warehouses, retailers and customers for the supply chain network can be minimized. Techniques developed in the area of optimization of network flows can be applied in supply chain network for which the cost minimized problem can be formulated as a mathematical programme and the corresponding optimality conditions can be derived.

In this paper, we present a cost minimization framework for the determination of stock distributions for each link and the stock allocations at the warehouse levels in the supply chain network with information sharing. We formulate this minimization problem as a mathematical programme and the corresponding optimality conditions are derived. Empirical studies for the comparison of the values of information sharing and non-information sharing in a two-level supply chain have been done in terms of the bullwhip effects and order up to inventory levels by real sales data over consecutive four years, which has been supported by project 89-EC-2-A-14-0314. Furthermore, experiments on a three-echelon structure of supply chain network that includes one external supplier, multi-warehouses and multi-customers are conducted on two kinds of test networks. Good results have been found.

The structure of this paper can be arranged as follows. In Section 2, a brief literature survey about the values of information sharing and the associated developments in the supply chain network about the management of stock levels are given. Notation for the supply chain network and the corresponding mathematical programme are expressed in Section 3. In Section 4, the optimality conditions for the determination of stock distributions for each link and the stock allocation at the warehouse levels are derived. In Section 5, the solution method for determining the optimized stock distributions and the stock allocation at warehouses is established. The algorithm for solving an optimized stock distributions and stock levels via minimum cost flows is presented in Section 6, with the corresponding results of experiments which conducted on two kinds of test networks. Also in Section 6, the numerical comparisons about the impacts of the information sharing and non-information sharing are made in terms of the variability in order quantities, order-up-to inventory levels and safety stocks from a real case empirical study. Conclusions for this paper and further extensions of this paper are made in Section 7.

2. Literature Review

Lee, Padmanabhan and Whang [7] are the first ones of people who noted the problem of the information impacts on the inventory control and production scheduling in supply chain management. They have found that the transferred information from the downstream sites to the upstream sites, which are usually in terms of the order forms, tends to be distorted and therefore misguides the inventory and production decisions for the upstream members. Particularly, the variability in order quantities appears increasing as one moves up the supply chain, which is also recognized as the “bullwhip effect” phenomenon. Chen, Drezner, Ryan and Simchi-Levi [2] quantified the related effects of bullwhip due to the techniques of forecasting, lead times and use of information types. Consider a simple two-stage supply chain, where a single retailer places an order q_t to a single manufacturer during the time period t when the customer demand D_t occurs. Thus a simple supply chain model and the corresponding inventory policy can be described as follows. Let $?$ be a nonnegative constant, $?_t$ be the error term and $?$ be a correlation parameter. Then the observed customer demand during t time period is

$$D_t ? ? ? ?D_{t?1} ? ?_t \tag{1}$$

If an order-up-to inventory policy $?s, S?$ is adopted, the order-up-to level S can be decided as

$$y_t ? \hat{D}_t^L ? z\hat{?}_t^L \tag{2}$$

where $\hat{D}_t^L, \hat{?}_t^L$ are the estimates of lead time demand and the standard deviation of forecast error, and z is the chosen constant to meet a desired service level. Therefore the order quantity can be described as

$$q_t ? y_t ? y_{t?1} ? D_{t?1} \tag{3}$$

According to Chen et al., the variance of order quantity relative to that of demand can be given as follows.

$$\frac{Var(q_t)}{Var(D)} ? 1 ? ?\frac{2L}{k} ? \frac{2L^2}{k^2}?(1 ? ?^k) \tag{4}$$

where k is the number of observations.

For the correlation parameter $? ? 0$, eqn (4) can be simplified as

$$\frac{Var(q_t)}{Var(D)} ? 1 ? ?\frac{2L}{k} ? \frac{2L^2}{k^2}? \tag{5}$$

On the other hand, Lee and Billington [6] introduced a supply chain model for the material management in decentralized systems. A supply chain network model was built in which the optimal stock level of inventory at multi production sites can be determined such that a specific target for customers satisfaction was met. Lee and Billington mainly dealt with the process of production and materials delivery. They modeled the supply chain as a network of a number of single production sites, where each production site was regarded as an inventory system stocking the finished product to supply the downstream sites or customers. For each stocking site, it was supposed that a periodic order-up-to inventory policy was applied. Demand transmission process was assumed that the demand placed at downstream sites was transmitted to this site via the demand for parts by bill of materials. Demands placed at the most downstream sites were assumed to be normally distributed. Lee and Billington, however, did not develop an optimal model to find the best base stock policy for each production site in their supply chain network.

Ettl, Feigin, Lin and Yao [4] followed the framework of Lee and Billington with the extension of the development of a supply chain network dealing with the base-stock policy and service requirements. A mathematical programme for optimizing the base-stock at each site in the multiechelon supply chain network was established. Using the conjugate gradients of the cost function with respect to the base stock, Ettl at al. proposed the optimal base-stock policy for the supply chain network throughout the overall inventory capital can be minimized. This model finds the base-stock inventory policy at each site for the supply chain network so as to minimize the total inventory capital in the network while the end-customer service levels are satisfied. Regarding the assumptions of Ettl et al model, a distributed inventory control mechanism is used where each stock site in the network operates a one for one replenishment base -stock control policy. For both Ettl et al and Lee and Billington, however, an optimization of determination of stock levels in the supply chain network still confines to the inventory based systems and the relationships for stock distributions between different inventory stock sites are ignored.

Furthermore, Graves and Willems [5] proposed a strategic safety stock policy for a stochastic demand supply chain network. Graves and Willems introduced the service times as decision variables at each stock site in the supply chain network model. The service time decision variables define the relationships for the upstream stock sites and the downstream sites in terms of the estimates of lead time and transmission delay between sites. Therefore the relationships between different sites existing in the supply chain network can be clearly identified in their model. Graves and Willems proposed a solution procedure on the basis of the minimum spanning tree algorithm in solving the total inventory minimization problem and finding the optimal safety stock policy at each stock site.

In this paper, we present an optimization model for the determination of the stock distributions at different stocking sites, which are in terms of the product flows at each link and the allocation levels at warehouses for the supply chain networkwith information sharing. Following the structure of Graves and Willems, we consider a 3-echelon inventory system, e.g. a single external supplier, a number of warehouses and a number of customers, where the distribution networks are used for the supplier and warehouses and for the warehouses and customers respectively. Since the distribution networks are introduced in our model, the relationships for different sites in the supply chain network are denoted as the product flows on the corresponding links. Adopting the techniques used in the area of the optimization of network flows (Ahuja, Magananti and Orlin [1]), the product flows for the distribution of stocks for the supply chain network with information sharing are regarded as the decision variables, and the objective in a multiechelon supply chain network is to determine the minimization of the total cost incurred for supplier and customers.

3. Problem Formulation

The problem for optimizing the stock distributions at each link and the stock allocations at warehouse levels can be formulated as a mathematical programme in the following way.

Let the supply chain network denoted by $G(N,E)$, where N represents the node set in the supply chain model and E is the link set. In our supply chain network model, the node set N includes the supplier node r, the warehouse node set W, the customer node set D and the transshipment node set T, and the entry in the link set E is denoted as (i, j), where $i, j ? N$. Notation for modeling the supply chain network with information sharing can be described as follows. Let x_{ij} be the product flows for link (i, j) and the corresponding cost can be denoted as $c_{ij}(x_{ij})$, q^{rs} be the demand rate for supplier r to customer s, where

$s ? D$, and f_p^{rs} be the product flows for path p which connecting the demand rate for supplier r to customer s.

The mathematical model for the optimization of the stock distributions at each link and the stock allocation at warehouse levels in the supply chain network can be formulated as

$$\underset{x}{Min} \quad z(x) ? \sum_{(i,j)? E} c_{ij}(x_{ij})x_{ij} ? \sum_{j? W} ?_j \left| y_j ? u_j \right| \tag{6}$$

subject to

$$\sum_{p? P_{rs}} f_p^{rs} ? q_{rs}, ? s ? D$$

$$\sum_{s? D} \sum_{p? P_{rs}} f_p^{rs} ?_{ij}^{p} ? x_{ij}, ? (i,j) ? E$$

$$f_p^{rs} ? 0, ? p ? P_{rs}, s ? D$$

where P_{rs} is the set of path p connecting the demand rate from supplier r to customer node s, $? s ? D$, and $?_{ij}^{p} ? 1$ if path p consists of the link (i, j) or $?_{ij}^{p} ? 0$, otherwise.

In problem (6), the objective function is the sum of the two terms. The first one is the sum of total link flow cost for the supply chain network $G(N, E)$, which describes the resulting stock distributions in terms of the product flows at each link. The second term denotes the inventory costs incurred at the warehouse node set as the sum for the inventory holding and shortage costs.

For any given warehouse policy, let u_j be the specified base-stock level at warehouse j, let the holding cost be h_j for surplus inventory $y_j ? u_j$, and let the penalty cost b_j for the inventory shortage $u_j ? y_j$, where at warehouse j the demand y_j is the resulting product flows for x_{ij} over a given time period with stationary demand process. Thus the second term in the object function can be summarized in detail as follows.

For each node j in the warehouse node set W,

$$?_j ? \begin{cases} h_j, if \quad y_j ? u_j \\ b_j, or \quad y_j ? u_j \end{cases} \tag{7}$$

where $?_j ? 0$ if $j ? W$.

In expression (7), for any $j ? W$, y_j is defined as $y_j ? \sum_{i? N} x_{ij}$.

4. Optimality Conditions

For the mathematical model of optimizing the stock distributions and the stock allocation levels at warehouses, the optimality for problem (6) can be derived in this section. Let $L(f,?) ? z(x(f)) ? \underset{s?D}{?} ?_s \left(q_{rs} ? \underset{p?P_{rs}}{?} f_p^{rs} \right)$ the problem (6) can be reformulated as a Lagrangian of the minimization problem via introducing the Lagrange multipliers $?_s$.

$$\underset{f,?}{Min} \quad L(f,?) ? z(x(f)) ? \underset{s?D}{?} ?_s \left(q_{rs} ? \underset{p?P_{rs}}{?} f_p^{rs} \right) \tag{8}$$

$$\text{subject to} \quad f_p^{rs} ? 0, ? p ? P_{rs}, s ? D$$

In problem (8), at the stationary point of the Lagrangian $L(f,?)$, the first-order condition for finding the local optimum of problem (8) can be given below.

For a given supplier r, for any path $p, p ? P_{rs}$ and any customer s, $? s ? D$

$$f_p^{rs} \frac{?L(f,?)}{?f_p^{rs}} ? 0 \tag{9}$$

$$\frac{?L(f,?)}{?f_p^{rs}} ? 0 \tag{10}$$

$$\frac{?L(f,?)}{??_{rs}} ? 0 \tag{11}$$

Applying equations (9)-(11) to problem (8), for some path l and for some customer m, the derivative for $L(f,?)$ with respect to path flow f_l^{rm} can be expressed as

$$\frac{?L(f,?)}{?f_l^{rm}} ? \frac{?z(x(f))}{?f_l^{rm}} ? \frac{? \left(\underset{s?D}{?} ?_s (q_{rs} ? \underset{p?P_{rs}}{?} f_p^{rs}) \right)}{?f_l^{rm}} \tag{12}$$

In equation (12), the first term can be expressed as

$$\frac{?z(x(f))}{?f_l^{rm}} ? \underset{(i,j)?E}{?} \frac{?z(x)}{?x_{ij}} \frac{?x_{ij}}{?f_l^{rm}} \tag{13}$$

$$? \underset{(i,j)?E}{?} ?_{ij}^{l} ? \left(\frac{? \left(\underset{(i,j)?E}{?} c_{ij}(x_{ij}) x_{ij} ? \underset{j?W}{?} ?_j \left| y_j ? u_j \right| \right)}{?x_{ij}} \right) \qquad ? \underset{(i,j)?E}{?} ?_l^{rm} \left(c_{ij}(x_{ij}) ? x_{ij} \frac{dc_{ij}}{dx_{ij}} ? ?_j \right)$$

$$? \underset{(i,j)? E}{?} ?_l^{rm} \hat{c}_{ij} ? C_l^{rm}$$

(suppose $\hat{c}_{ij} ? c_{ij}(x_{ij}) ? x_{ij} \frac{dc_{ij}}{dx_{ij}} ? ?_j$)

Therefore equation (12) can be rewritten as

$$\frac{?L(f,?)}{?f_l^{rm}} ? C_l^{rm} ? ?_m \quad (14)$$

Applying the first-order conditions for problem (8) in terms of expressions (9)-(11), the optimality conditions for finding the optimal stock distributions in terms of the product flows on each link and the optimal stock allocations at the warehouse levels for the supply chain network can be summarized as follows. For a given supplier r, each customer m in customer node set D and each path flow l in set P_{rm}, we have

$$f_l^{rm}(C_l^{rm} ? ?_m) ? 0 \quad (15)$$

$$C_l^{rm} ? ?_m ? 0 \quad (16)$$

$$\underset{l? P_{rm}}{?} f_l^{rm} ? q_{rm} \quad (17)$$

$$f_l^{rm} ? 0 \quad (18)$$

Where in equation (15) the Lagrange multiplier $?_m$ is the minimum cost for the demand rate from supplier r to customer m and C_l^{rm} is the total cost incurred for the demand rate from supplier r to customer m over a given time period with stationary demand. In the following section, we will develop the optimal stock distribution algorithms on the basis of equations (15)-(18).

5. Optimal Stock Distribution Algorithms for Supply Chain Network with Information Sharing

According to the optimality conditions for problem (8) in equations (15)-(18), optimal stock distribution algorithms for supply chain network are developed in the following steps.

Step 0. (1). Decide the link cost function form c_{ij} for each link (i,j) in the link set E, and decide the inventory cost parameter $?_j$ for each warehouse $j, ? j ? W$.

(2).Set the supply chain network $G(N,E)$ with zero stock distribution for each link and zero stock allocation at warehouses.

Step 1. Compute the cost $\hat{c}_{ij}(x_{ij})$, which is the sum of $c_{ij}(x_{ij}), x_{ij} ? \frac{dc_{ij}}{dx_{ij}}$ and $?_j$ for all links (i,j) in the link set E.

Step 2. For each demand rate from supplier to customer, find the minimum cost flow path which connecting the demand rate from supplier to customer on the basis of *Dijkstra's shortest path algorithm* (see Chiou [6]).

Step 3. For each demand rate, according to *algorithm 1* and *algorithm 2* assign to the shortest path and update the link flows for each link in the link set E.

Regarding to the *algorithm 1* and *algorithm 2* in *Step 3*, detailed descriptions are given in Section 6.2

6. Numerical Examples

As far as the value of information sharing in a simple supply chain is concerned, in this Section, we presented numerical comparisons for the supply chain network with information sharing and without information sharing from real sales data, which is supported by project 89-EC-2-A-14-0314. Empirical studies for the comparison of the values of information sharing and non-information sharing in a two-level supply chain are conducted in terms of the bullwhip effects, which are expressed in eqn (5), the order up to inventories and the safety stocks.

6.1. Empirical Studies

Empirical studies are conducted in terms of the effects of bullwhip, the order-up-to inventories and the safety stocks for comparisons of the system performance with information sharing and without information sharing for a well known color picture tubes manufacturer. The consecutive four yearly 1997-2000 sales data have been collected for two major products A & B. Order-up-to inventory policy (s, S) is taken into account, where S can be expressed

$$S = \hat{\mu}_t L + z\sqrt{L}S_t \qquad (19)$$

where $\hat{\mu}_t = \frac{\sum_{i=t-k}^{t-1} D_i}{k}$ and $S_t^2 = \frac{\sum_{i=t-k}^{t-1} (D_i - \hat{\mu}_t)^2}{k-1}$, and L is the lead time and z is a service parameter, which is set as 2.055 representing for 98% service level. (Simichi-Levi, Kaminsky and Simichi-Levi [8]).

The results are expressed in Figs. 1a-1d for bullwhip effects on information sharing and non-information sharing for two products, which are expressed in terms of the variance ratio for the order data and sales data on a variety of values for lead times. As it seen from Figs 1a-1d, the variance ratios for both products A & B with the information sharing are much lower than those without information sharing, where the maximum can be 14.5% for product A and 19.5% for product B. For the comparison in order-up-to inventory level with and without information sharing, for example in 1997, the results are given in Figs. 2a-2b for products A & B. The difference ratio for S is defined as the ratio for the difference between the order-up-to inventory without information sharing and with information sharing. It is clearly found that the order-up-to inventory level is much lower with information sharing than that without information sharing and on average for consecutive four years 1997-2000 for product A they are 0.32, 3.2, 2.88 and 9.77 and 4.90, 1.17, 0.79 and 1.87 for product B. Similarly, the results for comparing the safety stock with and without information sharing, as it shown in Figs 3a-3b, for example 1997 for products A & B, it is clearly observed that the safety stock possessed with information sharing system is much less than that did without information sharing. The safety stock difference between supply chain without and with information sharing for year 1997-2000 on average are 4.73, 97.4,102.19 and 291.86 (in k units) for product A and 30.75, 6.82, 3.92 and 15.28 (in k units) for product B.

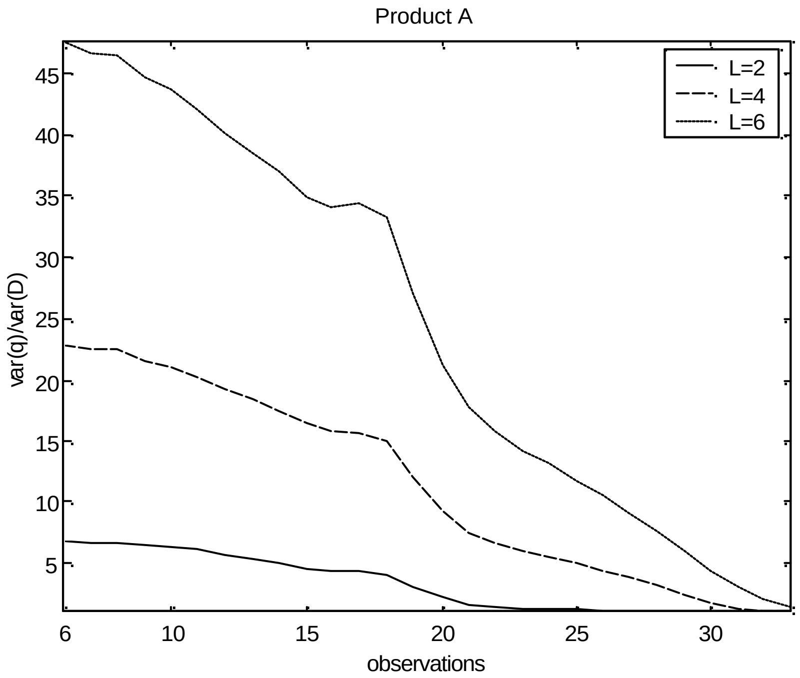


Figure 1a. Bullwhip effects on information sharing

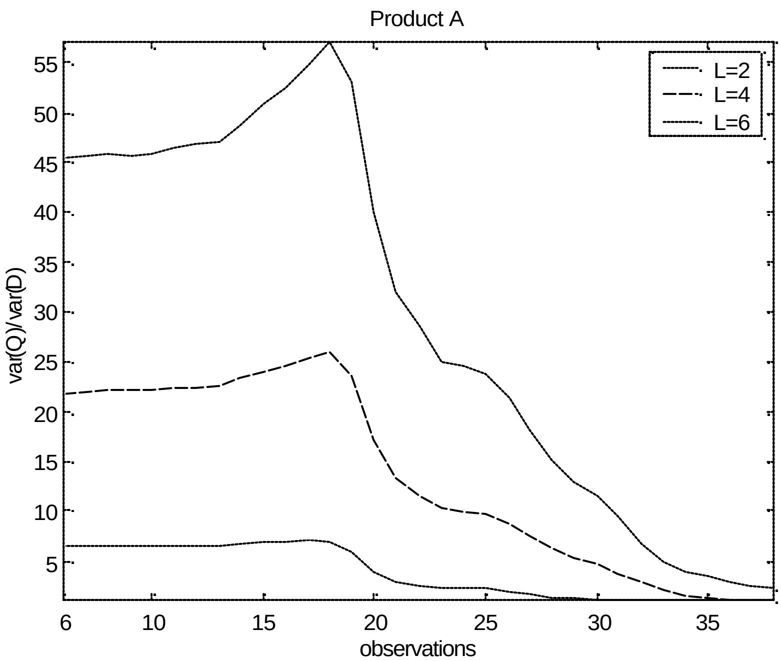


Figure 1b. Bullwhip effects on non-information sharing

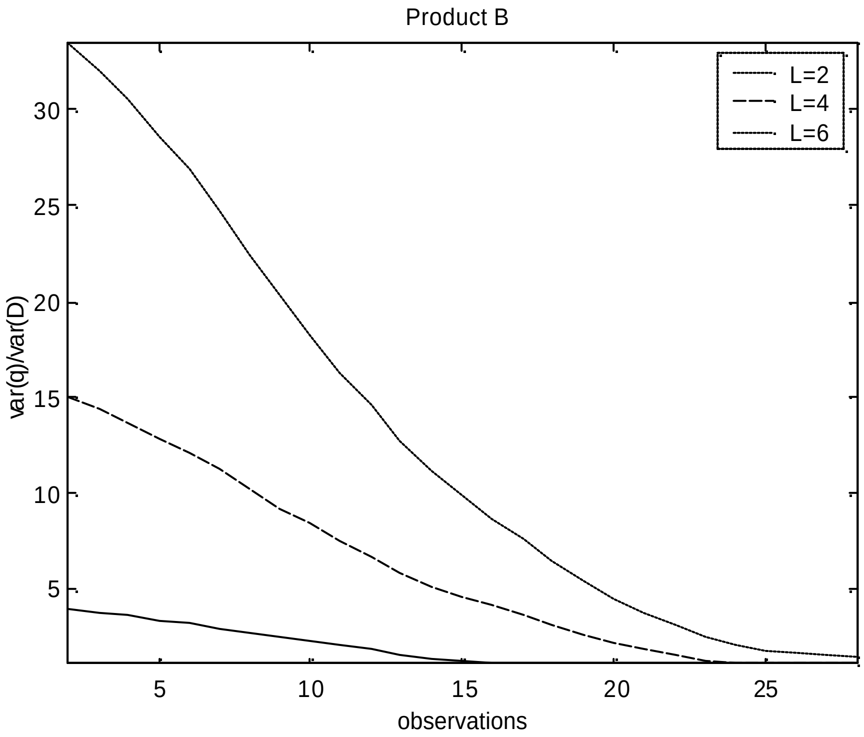


Figure 1c. Bullwhip effects on information sharing

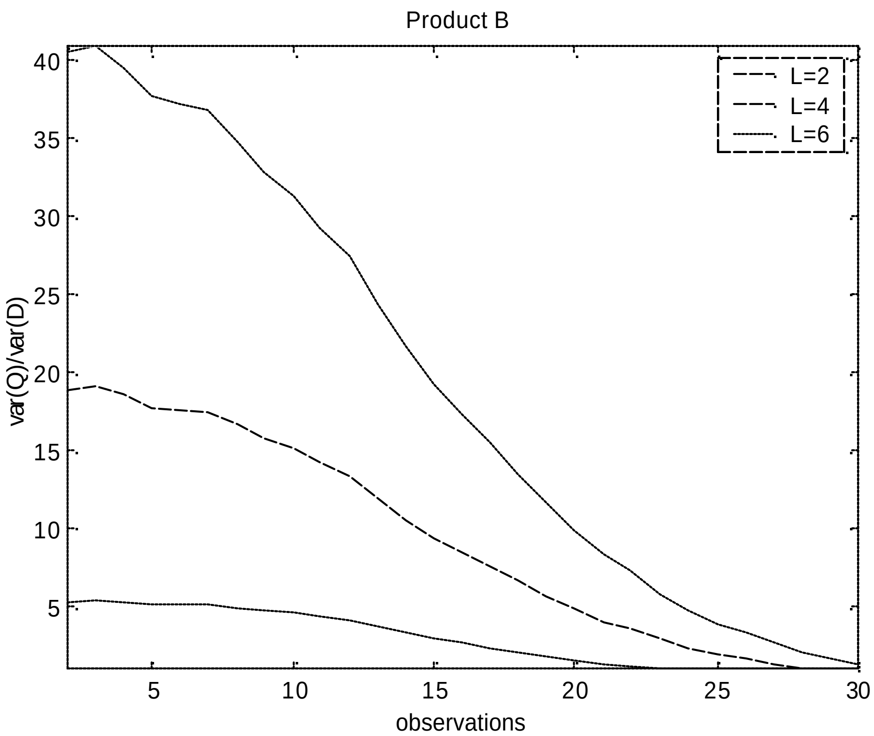


Figure 1d. Bullwhip effects on non-information sharing

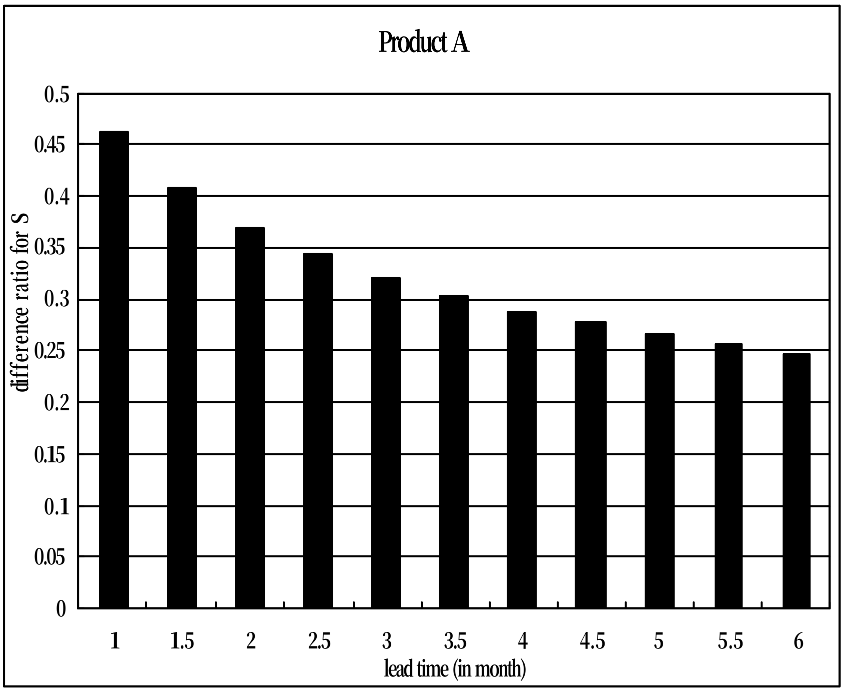


Figure 2a. Information sharing vs non-information sharing for 1997

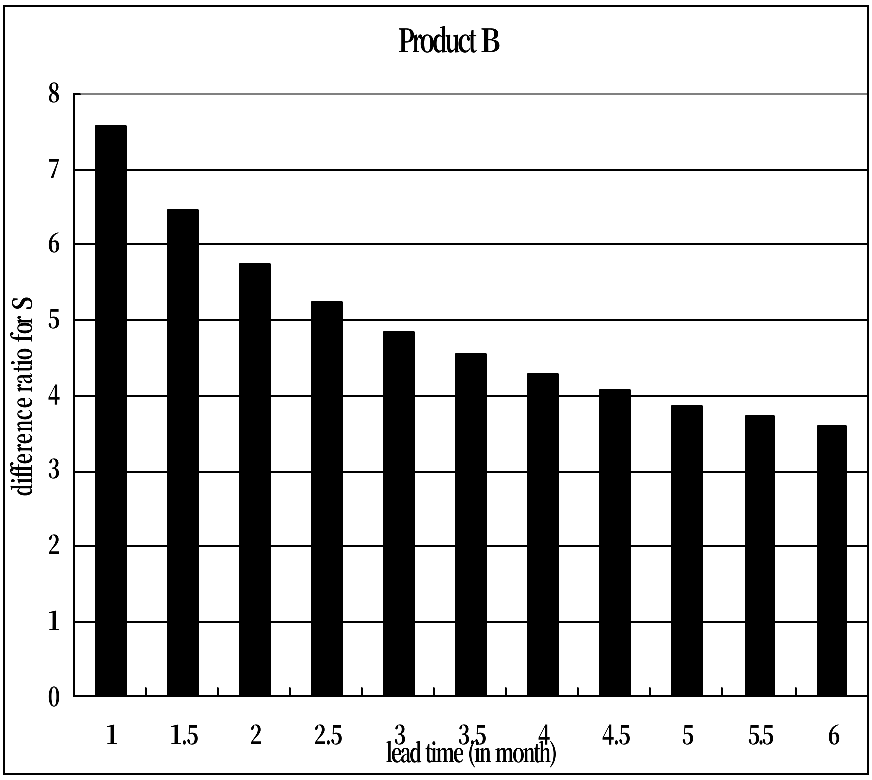


Figure 2b. Information sharing vs non-information sharing for 1997

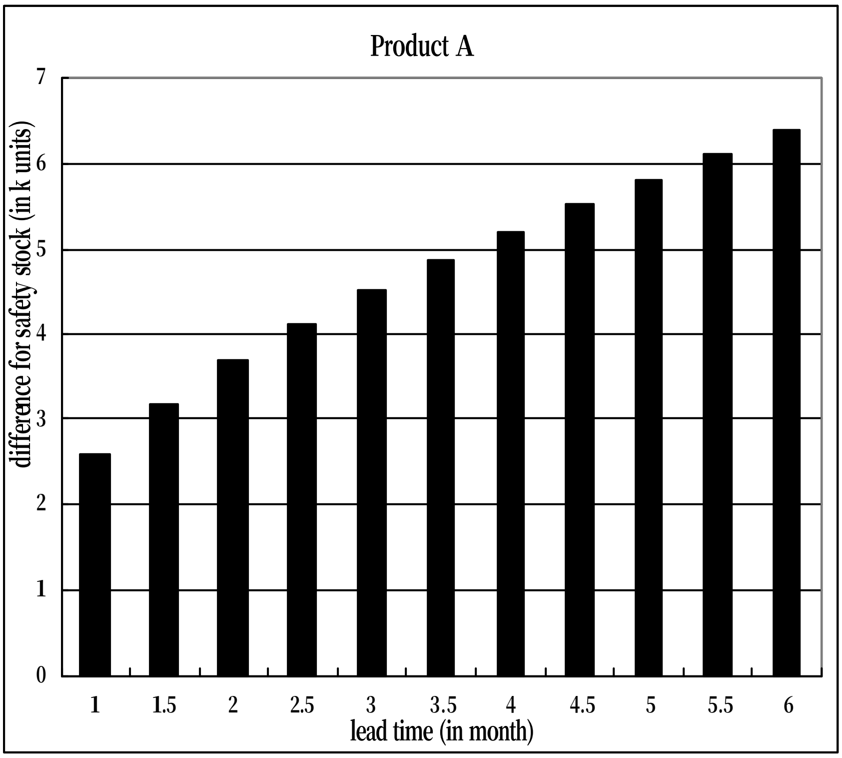


Figure 3a. Information sharing vs non-information sharing for 1997

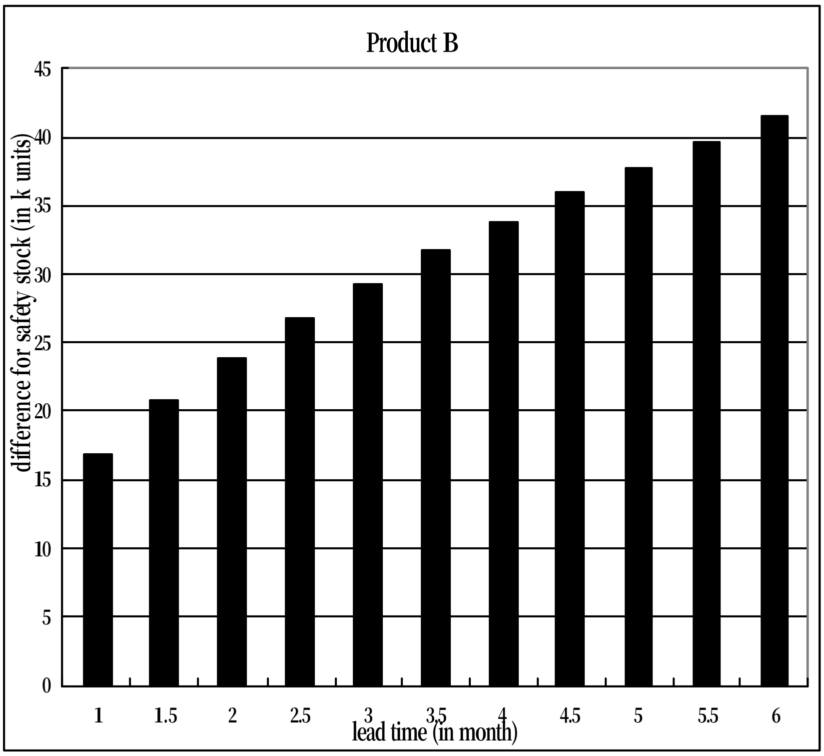


Figure 3b. Information sharing vs non-information sharing for 1997

6.2. Experimental Results

In this subsection we conducted the optimal stock distribution algorithms on test networks. Two algorithms, *algorithm 1 and algorithm 2*, are presented for testing the efficiency of assignment strategies for stock distribution in the supply chain network with information sharing. *Algorithm 1* is conducted for one by one unit assignment for stock distribution with the current minimum cost flow from supplier to customer. On the other hand, *algorithm 2* is conducted for batch assignment on the basis of *all or nothing rule* with the current minimum cost flow from supplier to customer. The test network for supply chain model is designed for small scale, including a single external supplier with unlimited capacity for demand request, three warehouses with given base-stock policy at each level and five dispersed customers with stationary demand rate during a given time period. Two kinds of the test network are illustrated as shown in Fig. 4 and Fig. 5, where the second one is the expansion of the first one with the inclusion of the transshipment nodes and their corresponding links. Information for the data input for the link cost function c_{ij} and the parameters for the base-stock policy at warehouse j are given in Table1. Link cost function can be decided as a BPR (Bureau for Public Road) form as used commonly in transport studies.

$$c_{ij} = 0.15\left[1+\left(\frac{x_{ij}}{cap_{ij}}\right)^4\right] \qquad (20)$$

where cap_{ij} is the maximum flow capacity for link (i, j).

Table1: Input parameters for test networks

cap_{ij}	b_j	h_j
10	5	1

Numerical experiments are conducted for the following examples.

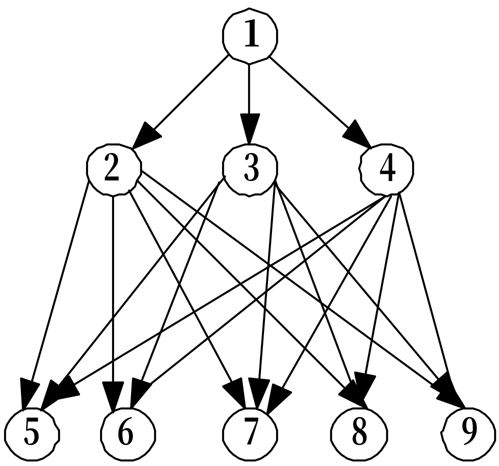


Fig. 4: Test network 1

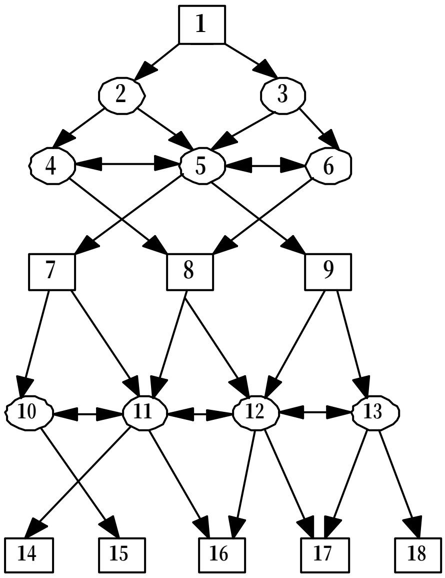


Fig. 5: Test network 2

Table 2: Results for stock allocations and distributions on test network1

Algorithm1		Algorithm2	
warehouse 2	34	warehouse 2	40
warehouse 3	33	warehouse 3	40
warehouse 4	33	warehouse 4	20
link (1,2)	34	link (1,2)	40
link(1,3)	33	link(1,3)	40
link(1,4)	33	link(1,4)	20
link(2,5)	7	link(2,5)	20
link(2,6)	7	link(2,6)	0
link(2,7)	6	link(2,7)	0
link(2,8)	7	link(2,8)	20
link(2,9)	7	link(2,9)	0
link(3,5)	7	link(3,5)	0
link(3,6)	6	link(3,6)	20
link(3,7)	7	link(3,7)	0
link(3,8)	7	link(3,8)	0
link(3,9)	6	link(3,9)	20
link(4,5)	6	link(4,5)	0
link(4,6)	7	link(4,6)	0
link(4,7)	7	link(4,7)	20
link(4,8)	6	link(4,8)	0
link(4,9)	7	link(4,9)	0
Nodes cost	260.0	Nodes cost	260.0
Links cost	46.1	Links cost	104.5
Total cost	306.1	Total coat	364.5

Table 3: Results for stock allocations and distributions on test network2

Algorithm1		Algoritm2	
warehouse7	32	warehouse7	20
warehou se8	35	warehouse8	40
warehouse9	33	warehouse9	40
link(1,2)	50	link(1,2)	60
link(1,3)	50	link(1,3)	40
link(2,4)	25	link(2,4)	20
link(2,5)	25	link(2,5)	40
link(3,5)	26	link(3,5)	20
link(3,6)	24	link(3,6)	20
link(4,5)	8	link(4,5)	0
link(5,4)	0	link(5,4)	0
link(5,6)	0	link(5,6)	0
link(6,5)	6	link(6,5)	0
link(4,8)	17	link(4,8)	20
link(5,7)	32	link(5,7)	20
link(5,9)	33	link(5,9)	40
link(6,8)	18	link(6,8)	20
link(7,10)	14	link(7,10)	0
link(7,11)	18	link(7,11)	20
link(8,11)	15	link(8,11)	20
link(8,12)	20	link(8,12)	20
link(9,12)	13	link(9,12)	20
link(9,13)	20	link(9,13)	20
link(10,11)	7	link(10,11)	0
link(11,10)	13	link(11,10)	20
link(11,12)	14	link(11,12)	0
link(12,11)	13	link(12,11)	0
link(12,13)	19	link(12,13)	0
link(13,12)	9	link(13,12)	0
link(10,15)	20	link(10,15)	20
link(11,14)	20	link(11,14)	20
link(11,16)	6	link(11,16)	0
link(12,16)	14	link(12,16)	20
link(12,17)	10	link(12,17)	20
link(13,17)	10	link(13,17)	0
link(13,18)	20	link(13,18)	20
nodes cost	260.0	nodes cost	260.0
links cost	268. 3	links cost	388.0
total cost	528.3	total cost	648.0

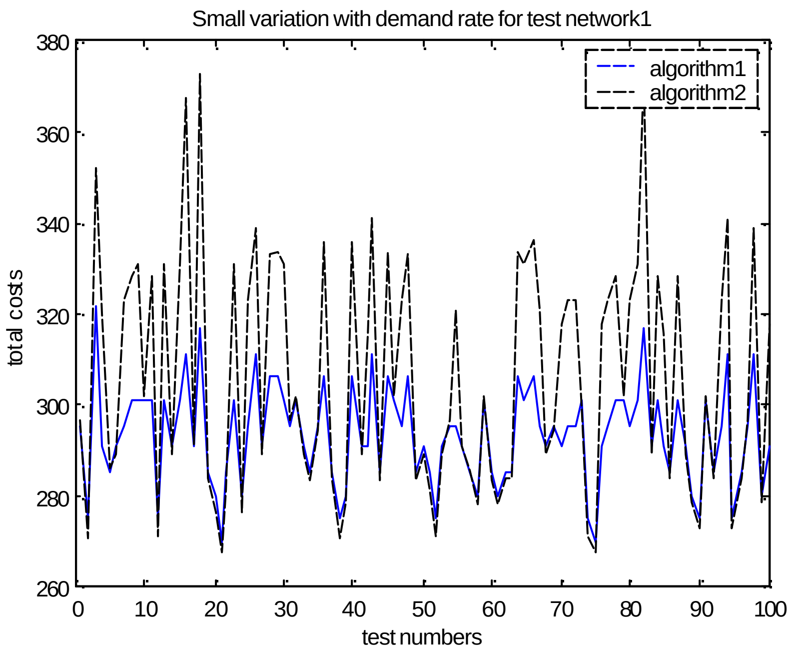


Figure 6: 100 tests for small variation on demand rates with normal distribution N(20,1)

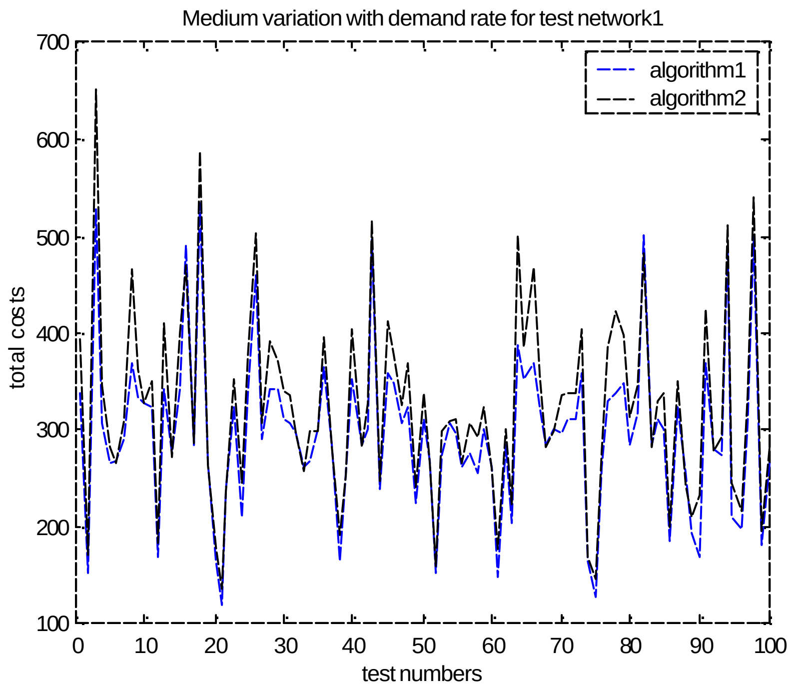


Figure 7: 100 tests for medium variation on demand rates with normal distribution N(20,6)

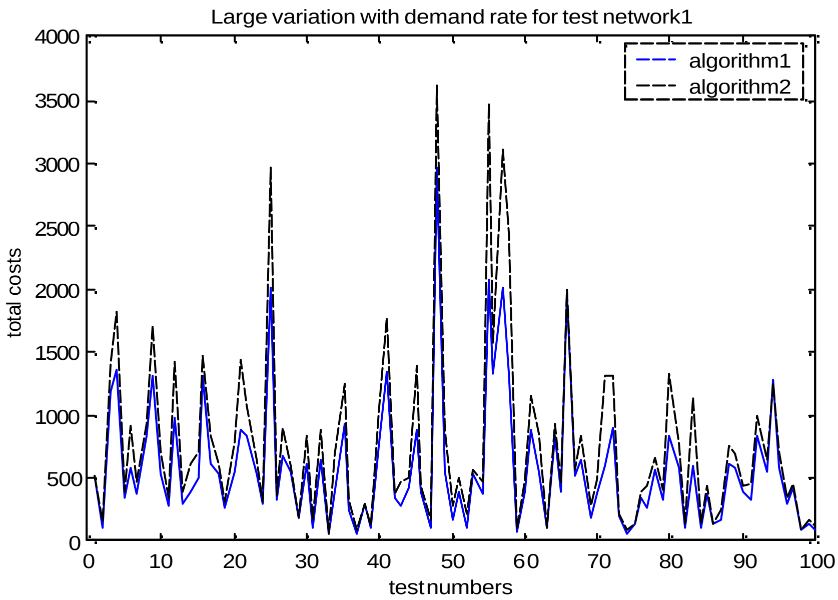


Figure 8: 100 tests for large variation on demand rates with normal distribution N (20,19)

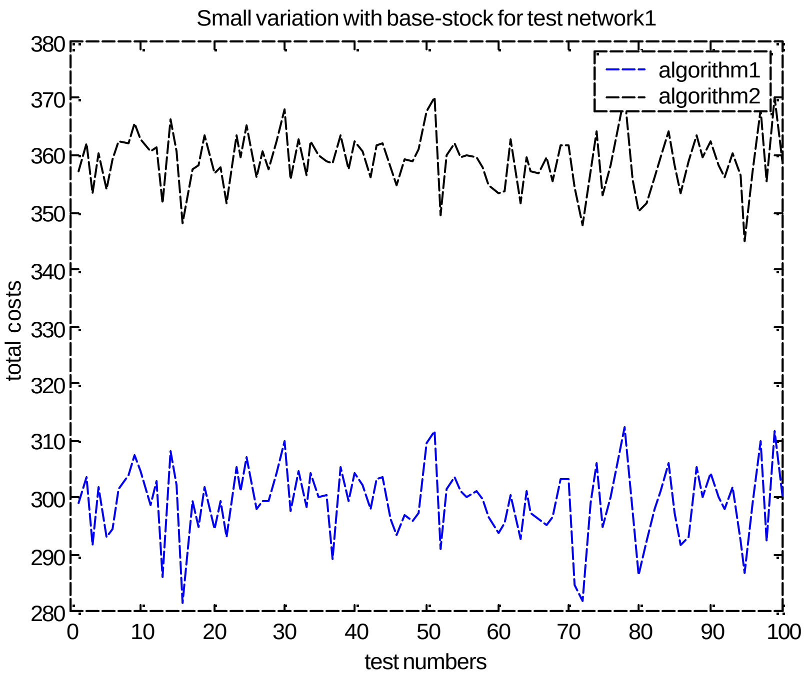


Figure 9: 100 tests for small variations on base-stocks with normal distribution N(20,1).

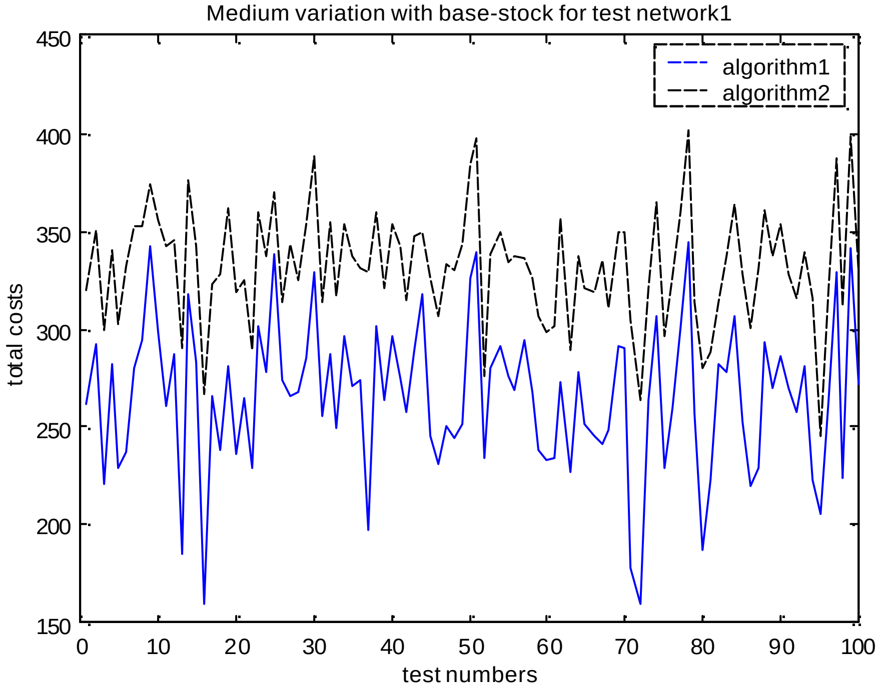


Figure10: 100 tests for medium variations on base-stocks with normal distribution N(20,6).

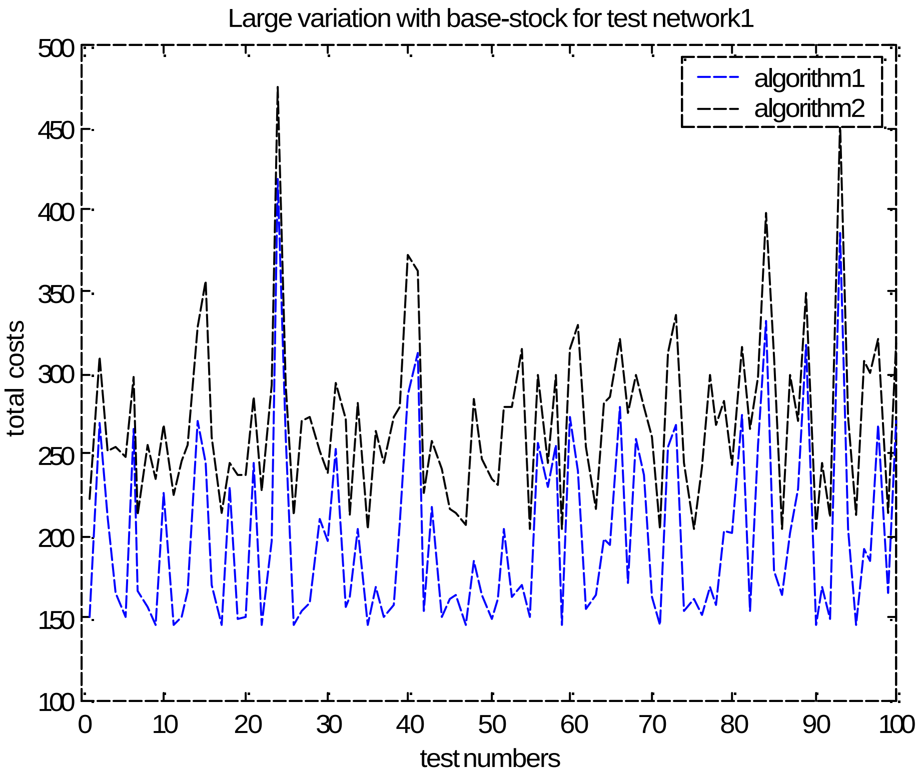


Figure11: 100 tests for large variations on base-stocks with normal distribution N(20,19).

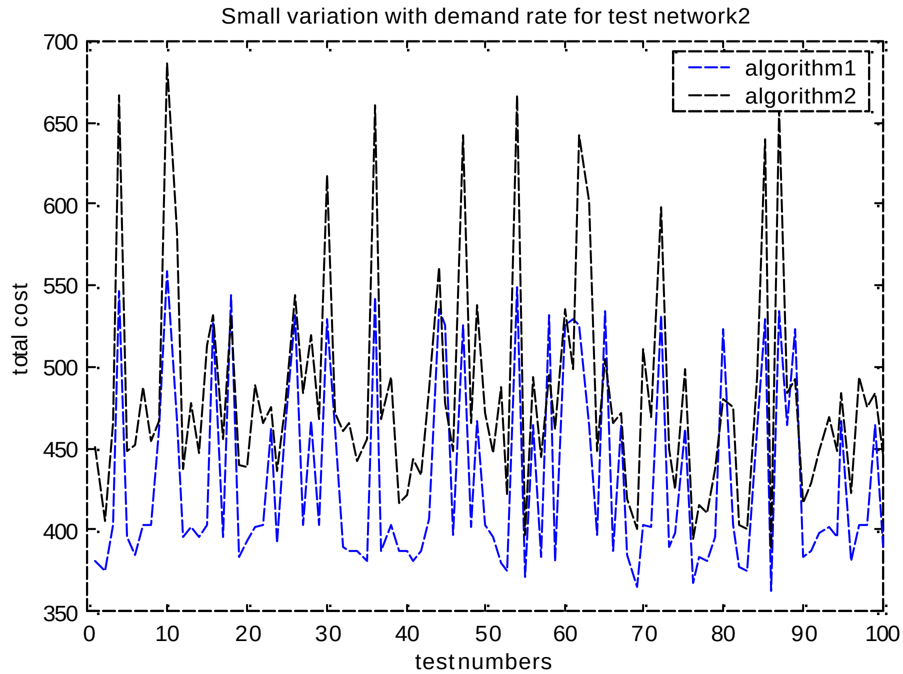


Figure 12: 100 tests for small variations on demand rates with normal distribution N(20,1).

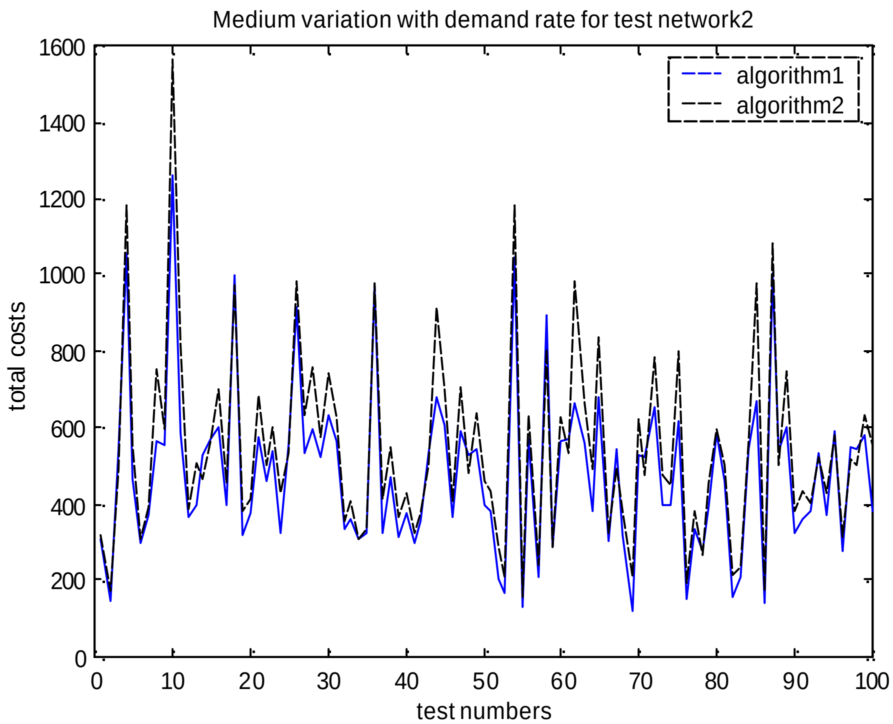
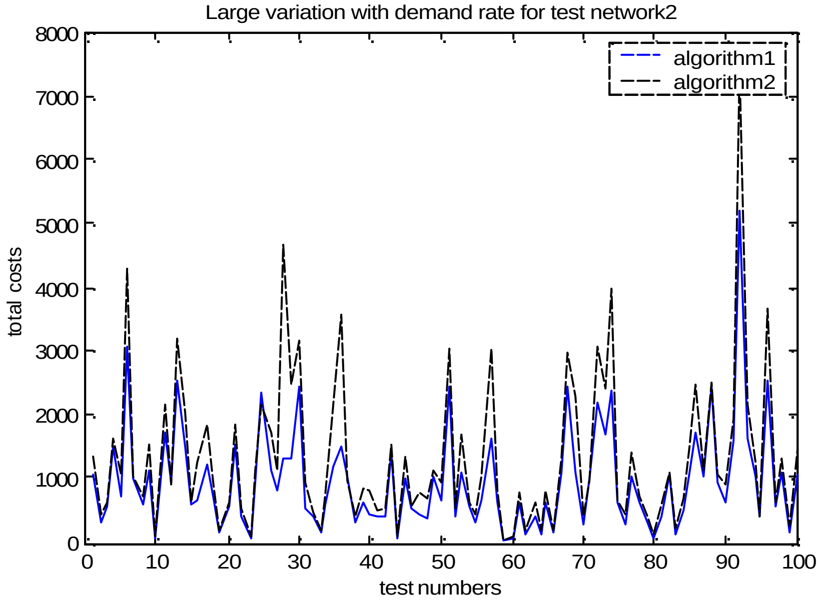


Figure13: 100 tests for medium variations on demand rates with normal distribution N(20,6).



Fre14: 100 tests for large variations on demand rates with normal distribution N(20,19) .

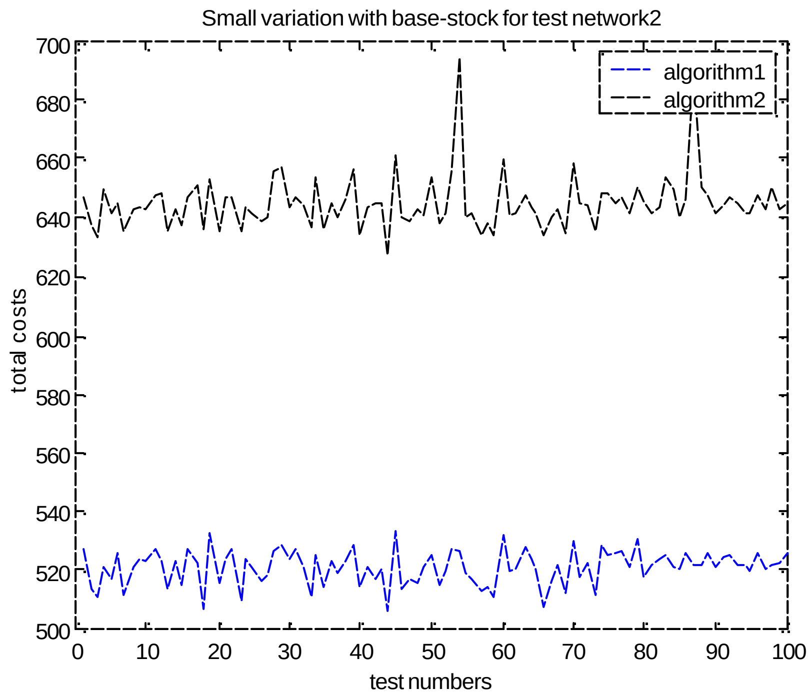


Figure15: 100 tests for small variations on base-stocks with normal distribution N(20,1).

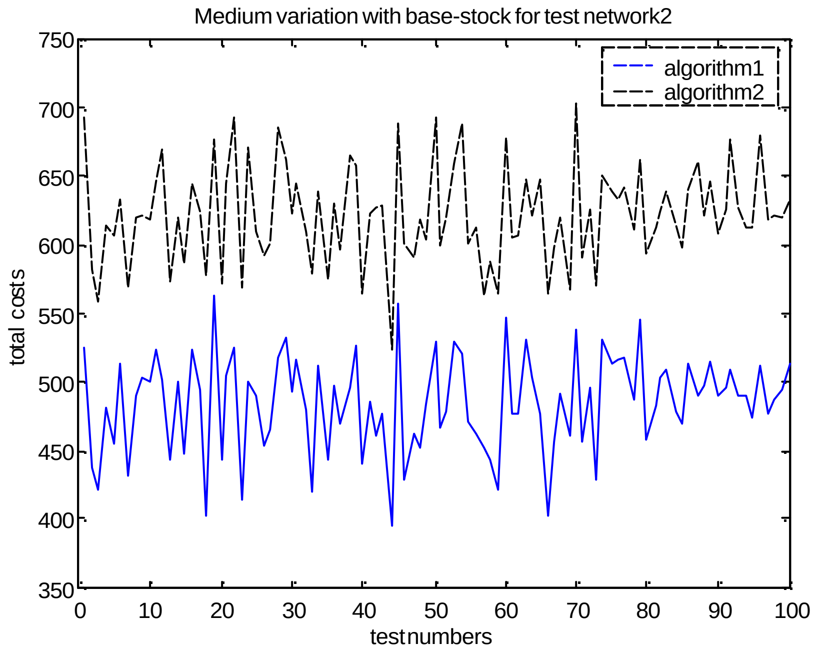


Figure16: 100 tests for medium variations on base-stocks with normal distribution N(20,6).

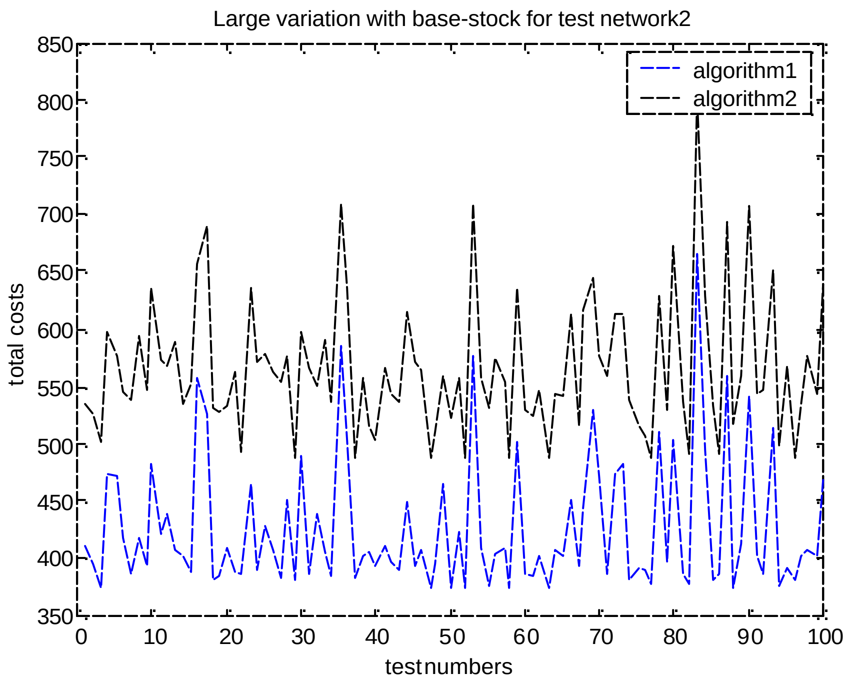


Figure17: 100 tests for large variations on base-stocks with normal distribution N(20,19).

Example 1. For given input data information as shown in Table 1, results for the stock distribution in terms of product flows and allocation at warehouse levels for conducting *algorithm 1* and *algorithm 2* on two test networks are given in Tables 2-3. The rates q for each customer demand are assumed to be identical with value 20. The base-stock policy u for each warehouse is assumed to be identical with value 20.

Example 2. For given base-stock policy at warehouses with identical value 20, 100 numbers of test results conducted on the variation with normal distributed demand $N(?,?)$ for small variation (20,1), medium variation (20,6) and large variation (20,19) are shown in Figs.6-8 for test network 1 and in Fig. 9-11 for test network 2.

Example 3. For given customer demand rates with identical value 20, 100 numbers of test results conducted on the variation with normal distributed base stocks $N(?,?)$ for small variation (20,1), medium variation (20,6) and large variation (20,19) are shown in Figs.12-14 for test network 1 and in Fig. 15-17 for test network 2.

As it shown from example1, the stock allocation at warehouse levels and the stock distributions in terms of product flows on each link for supply chain test network varies greatly for algorithm 1 and algorithm 2, both of which pursue the total cost minimization. As results shown in Tables 2-3, for test network 1 the algorithm 1 achieves better performance than that of algorithm 2 approximately by 16%, and 18.5% for test network 2. Consider the variations of demand rates, which may cause various effects on the total costs when conducted by algorithm 1 and algorithm 2, as it shown from Figs. 6-8 for test network 1 and Figs. 12-14 for test network 2. Experimental results for the performance did by algorithm 1 are far better than those did by algorithm 2 by 10.3%, 8.8% and 10.2% respectively on test network 1 and respectively by 17.2%, 23.4% and 23% on test network 2 for 100 tests on small, medium and large variations for normal distributed demand rates. Similarly, consider the variations on base stock at warehouse levels, which may cause various effects on the total costs when conducted by algorithm 1 and algorithm 2, as it shown from Figs. 9-11 for test network 1 and Figs. 15-17 for test network 2. Experimental results for the performance did by algorithm1 are more robust than those did by algorithm 2 by 16.2%, 15% and 18% respectively on test network 1 and respectively by 21%, 19.1% and 17.8% on test network 2 for 100 tests on small, medium and large variations for normal distributed base stocks.

Furthermore, the differences of the performance did by algorithm 1 and algorithm 2 for variations on base-stock are greater than those did for variations on demand rates. This issue points out an interesting direction where the changeable effects caused by base stocks at warehouse levels may be greater than those did by the rates for customers demands over a stationary process within a given time period for different stock distribution algorithms.

7. Conclusions and Discussions

In this paper, we presented a new approach for solving an optimized stock distribution problem and finding the optimal stock allocations at warehouses in a supply chain network with information sharing. Empirical studies for comparing the values of information sharing and non-information sharing in a two-level supply chain have been done in terms of the bullwhip effects and order up to inventory by real sales data over years 1997-2000, which has been supported by project 89-EC-2-A-14-0314. Also from the experimental results we found different base-stock policy cause great effects on system performance than did by those of demand rates of customers, which needs further discussions on the optimization of the stock distributions over the supply chain network with information sharing in the near future.

8. Acknowledgement

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