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A Multiple-Supplier-Multiple-Buyer Collaborative Supply Chain Model Considering Information Sharing Investment Using Genetic Algorithm Solutions

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In practice, supplier-buyer integration is crucial for business success, and information sharing is a key strategy for achieving integration. Information sharing is closely related to supplier pricing and buyer order quantity. Therefore, this study extends the single-supplier-single-buyer production-inventory model to a multiple-supplier-multiple-buyer inventory model, also known as a multiple-supplier-multiple-buyer collaborative supply chain model, to identify the optimal replenishment policy considering information sharing investments. The decision variables include information sharing investment costs, delivery frequencies, and delivery lot sizes. This study employs genetic algorithms (GAs) to solve problems. We first analyzed the GA parameters to compare the execution time and the solution quality of various population size to determine the population size in the algorithm parameters. Because genetic algorithm crossover and mutation rates affect the solution quality, parameter analysis must pair the crossover rates with mutation rates. Using selected GA parameters for solution, we analyzed the sensitivity of the model parameters to understand how variations in the model parameters affect the related total costs. In the tests, five calculations are performed for each pair. The results of sensitivity analysis show that suppliers must reduce variable costs, including purchase, indirect, and material handling costs, to obtain significantly lower total costs and show that decreases in buyers' fixed transportation costs per delivery also result in significant declines in buyers' costs. This study period is from January to December 2011.

JEL Codes: Q21, G14 and G31

1. Introduction

In recent years, management philosophies and artificial intelligence have been frequently adopted to achieve prompt customer responses. Numerous scholars and industry practitioners have investigated the importation and implementation of the just in time (JIT) strategy, which is a representative of management philosophy (Ahmad, Schroeder & Sinha 2003; White & Prybutok 2001). The integration of suppliers and buyers enables the supply chain system to better obtain cost benefits compared to the traditional individualized system.

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Supply chain management not only considers product logistics, but also information flow. Through information sharing, suppliers can reduce the distortion of information caused by observation of customer demand phenomena. Sharing information is a basic operation of effective supply chain management. Lee, So and Tang (2000) and Raghunathan (2001) examined the value of information sharing in two-step supply chains and found that information sharing enables only the suppliers to benefit from lower costs. Mishra, Raghunathan and Yue (2003) analyzed the value of information sharing in inventory and order production to understand the value of information accuracy in information sharing. Agrell et al. (2004) developed a three-stratum supply chain to explore a model of information sharing in the telephone industry amid demand uncertainty and information asymmetry. Because information sharing is indispensable to the operation of supply chains (Chopra & Meindl 2007), information sharing investments are a significant topic for managers of supply chains.

This study extends the single-supplier-single-buyer production-inventory model into a multiple-supplier-multiple-buyer inventory model, also known as the multiple-supplier-multiple-buyer collaborative supply chain model, to identify the optimal replenishment policy considering information sharing investments. The decision variables of the collaborative supply chain model employed in this study include information sharing investment costs, the number of replenishment deliveries, and delivery lot sizes. We first analyzed the GA parameters, such as group number, to determine the execution time and solution quality of various population size and, thus, identify the optimum group number. We also explored the pairing tests of the crossover rates with the mutation rates to determine their influence on the solution quality. We then selected GA parameters to analyze the sensitivity of the model parameters to the total costs. The remainder of this study is organized as follows: The notations, assumptions, modeling, and analysis methods are introduced in Section 3. In Section 4, we explain the analyses of GA parameters. The sensitivity analysis results of the model parameters are provided in Section 5, followed by the conclusion.

2. Literature Review

Gavirneniet et al. (1999) proposed using a two-stratum model to integrate the application of information flow between a single supplier and single retailer. They employed empirical design methods to examine the relationships among capacity, inventory, and information. Zhao, Xie and Zhang (2002) found that the coordination of information and ordering was influenced significantly by demand patterns and capacity. Mitra and Chatterjee (2004) also explored the effects of using demand information for a supply chain system with a single warehouse and two retailers under periodic review. However, these studies did not consider delivery frequency. Studies such as Lee and Rosenblatt (1986), Goyal and Gupta (1989), Goyal and Gunasekaran (1995), Hill (1997), and Kim and Ha (2003) investigated supply chain problems related to integration and delivery frequency. Cao and Schniederjans (2000) examined inventories and production costs to compare the differing efficiencies of the traditional EPQ model and the revised EPQ/JIT model. These studies do not provide in-depth discussions of the issues related to information sharing.

Lee and Rosenblatt (1987) and Ben-Daya and Hariga (2000) explored the influence of production on damaged items under lot-size strategies. Banker et al. (1998) discussed the relationship between quality and competition. Tkaczyk and Jagla (2001) argued that preventive maintenance costs depend on the quality demanded by buyers.

However, these studies did not address the issues of information sharing and coordination. Shum, Yeh and Chung (2007) proposed a collaborative integrated model for information sharing investments and delivery frequencies that was a single-supplier-single-buyer production inventory model (this represents our previous research work).

In recent years, a number of studies have investigated supply chain and inventory management using GAs. Nachiappan and Jawahar (2007) proposed heuristic GA solutions for the single-supplier-multiple-buyer supply chain model when suppliers manage inventory operations. Altiparmak et al. (2006) used GAs to identify the Pareto-optimal solution for the design of multiple-target supply chain networks. After analyzing average inventory, setup, and transportation costs in each unit of time, Torabi, Fatemi Ghomi and Karimi (2006) proposed hybrid GA solutions for supply chain lot size and delivery scheduling. Applications in inventory include the following: Addressing stock-dependent demands and two storage facilities, Maiti and Maiti (2007) used GAs to solve a multiple-item inventory model. Maiti, Bhunia and Maiti (2006) employed real-coded GAs to solve problems of multiple-item multiple-price-breakpoint structures. Pal et al. (2005) also adopted real-coded GAs for hybrid integer nonlinear programming to identify the optimal strategic analysis of a two-warehouse inventory.

3. Notation and Assumptions

To ensure the model connotations are understood, we define the notations in Section 3.1; those of the suppliers and buyers are listed separately. The assumptions of this model are described in Section 3.2, defining the scope of this study. In Section 3.3, we explain the modeling and analysis processes.

3.1 Notations

3.1.1 Notations for the Suppliers in the Model

α_j Suppliers' estimated demand variation rate; $0 < \alpha_j < 1$

D_S Suppliers' average annual estimated demands before information sharing; $D_S = \sum_{i=1}^{k} D_i \left(1 + \sum_{j=1}^{l} \alpha_j / l\right)$

D'_S Average annual estimated demands with information sharing; $D'_S = \sum_{i=1}^{k} D_i \left(1 + \sum_{j=1}^{l} \alpha'_j / l\right)$, where $0 < \alpha'_j < \alpha_j$

P_j Suppliers' production rate

Q_j Suppliers' production lot size

$H_{S\,j}$ Suppliers' inventory costs per unit

$C_{P\,j}$ Suppliers' price costs per unit

$C'_{P\,j}$ Suppliers' selling price per unit after investing in information sharing

C_P^{SV} Unit salvage value of suppliers' excess inventory; $C_P^{SV} = \sum_{j=1}^{l} C_{P\,j}(1-\beta)$ or $C_P^{SV} = \sum_{j=1}^{l} C'_{P\,j}(1-\beta)$; $0 < \beta < 1$

β Salvage ratio

C_{mj} Variable costs including suppliers' purchase, indirect, and material handling costs

G_{mj} Suppliers' gross profit goals per unit

K_j Suppliers' capital invested in information sharing

m_j Suppliers' return on investments after reducing demand uncertainty

C_j Suppliers' setup costs per hour

S_j Supplier's setup costs

$C_{insp\,j}$ Inspection costs per unit

$L_{f\,j}$ Suppliers' failure costs per unit

Z_j Total number of defective items produced

y Ratio of defective items in the entire production lot size

$f(\alpha'_j)$ Costs with information sharing, assuming $M = f(\alpha'_j)$ and decreases as investment increases

3.1.2 Notations for the Buyers in the Model

D_i Average buyer demand rates

H_{Bi} Buyers' holding cost rates ($ per product unit)

A_i Buyers' ordering costs per purchase

N_j Delivery quantity per batch cycle

$_iW_{Bsave}$ Cost reduction after implementing JIT delivery

L Lead time for replenishment of order from the supplier to the buyer

F Buyers' fixed transportation costs per delivery

V Variable transportation costs for handling and receipt per unit

p_{Bi} Shortage probability acceptable to buyers

k_{Bi} Buyers' safety factors corresponding to anticipated shortage probability

σ_{Bi} Standard deviation of daily customer demands within lead time

Q_{Bi} Order quantity for each time

3.2 Assumptions When Developing the Production Inventory Model

(1) Production rates exceed demand rates; (2) Production rates are independent of production lot size; (3) Buyers pay for transportation costs; (4) Work-in-progress items are not considered; (5) Defective items in the production process are instantly discarded; (6) Defective items in the production process can be detected; (7) Buyers' numbers of units shipped are limited to integers; (8) Buyers' standard deviations are identical before and after coordination.

3.3 Modelling and Analysis

This study assumes that defective items exist in each production lot and that inspection plans during production cause inspection costs and preventive maintenance costs. It is also assumed that inspection time can be overlooked. As mentioned in the Introduction, products are manufactured and delivered periodically based on contracts. Suppliers set their production strategies and product prices to meet specific profit goals. Because suppliers do not have complete information regarding buyers' order quantity, they can only manufacture products according to buyers' ordering behaviour. By investing in information sharing, suppliers can obtain buyer information for pricing and production planning.

3.3.1 Modelling of Total Costs

Because suppliers only provide buyers with lead time length, and because suppliers do not have complete information of buyers' order quantity, the distribution of lead-time demand is unknown. When the lead time of suppliers delivering products to buyers is L, assuming the distribution of lead-time demand (probability density function, p.d.f.) is f(y), the limited average is dL and the standard deviation is $\sigma_i\sqrt{L}$; thus, the safety inventory required for buyer systems to manage demand uncertainty is $k_i\sigma_i\sqrt{L}$. Therefore, buyers' lead-time demand is $U_i = d_i L + k_i \sigma\sqrt{L}$, where k_i is the safety factor. Furthermore, assuming that $\Im$ is the worst possible distribution of lead-time demand, we use the following lemma to determine the acceptable shortage probability during the lead time:

Lemma 1: For all p.d.f. f(y) $\in \Im$, Y represents the lead-time demand and distribution is p.d.f. f(y). The average Y is dL, and the standard deviation is $\sigma\sqrt{L}$ (>0), where the real number e > 0 (Ouyang & Wu 1997).

$$p_r(Y > e) \le \frac{\sigma^2 L}{\sigma^2 L + (e - dL)^2}. \tag{1}$$

Because lead-time demand $U_i = D_i L + k_i \sigma_i \sqrt{L}$, Inequality (1) shows that the acceptable shortage probability during the lead time is

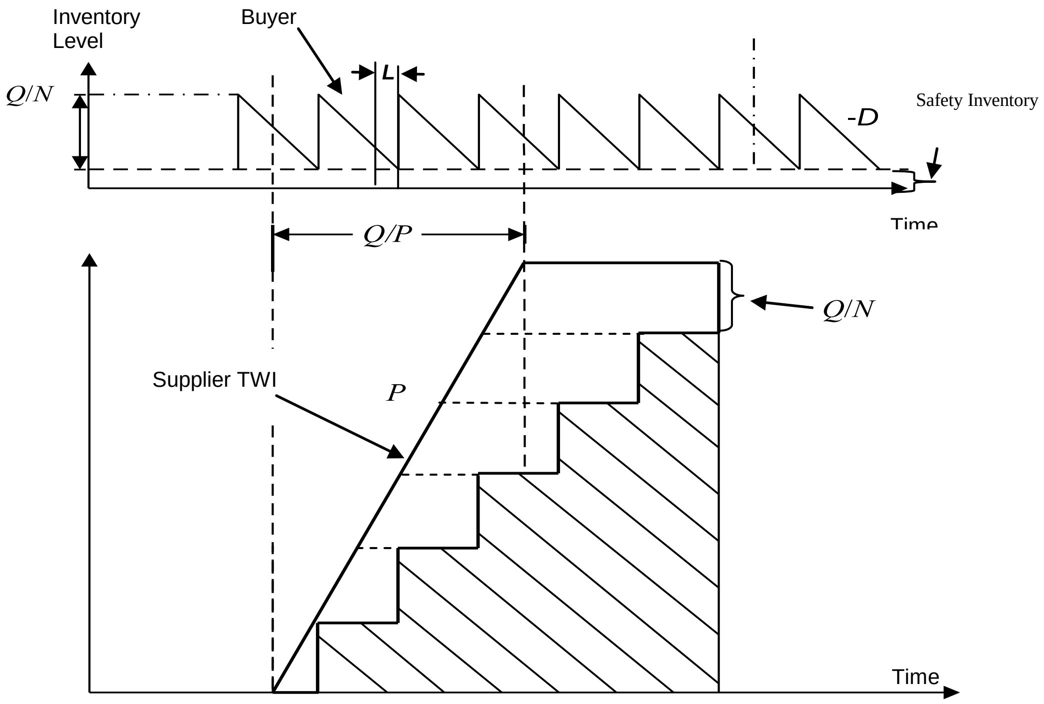
$$p_r(Y > U_i) \le \frac{1}{1 + k_i^{\,2}}. \tag{2}$$

Assuming p_{Bi} is the maximum acceptable shortage probability, the safety factor can be expressed as $k_{Bi} \ge \sqrt{(1 - p_{Bi}) / p_{Bi}}$.

3.3.2 Suppliers' Production Costs and Buyers' Total Costs

Through investments and coordination, suppliers endeavour to obtain additional information from buyers. To reduce buyers' demand uncertainty, suppliers can employ delivery commitments to obtain information. Additionally, information technology, such as electronic data interchange (EDI) and point of sale (POS) information management systems, can be employed to facilitate coordination. When suppliers and buyers adopt collaborative strategies to reduce uncertainty, they can maximize profits. Suppliers' total costs comprise setup costs, storage costs, and quality costs. Assuming that the number of buyers is k and the number of suppliers is one, all k buyers belong to one corporation, and the one supplier belongs to another corporation. Assuming that supplier sales are evenly distributed among buyers, a supplier's average sales is $\sum(Q_{Bi})/l$. Because Z represents the defective items created during production produced, assuming buyers' total order quantity per order is $\sum_{i=1}^{k}(Q_{Bi})/l = \sum_{j=1}^{l} Q / \sum_{j=1}^{l} N$, the supplier's storage costs can be determined using the time-weighted inventory (TWI) concept, as shown in Fig. 1.

Figure 1: **The TWI and Buyer Inventory Level of the Integrated Production Inventory Model**



The supplier's storage costs equal to [trapezoid area-shaded regions]× $\cdot H_{S\,j} C_{m\,j} \big/ \left[N_j \left(\sum Q_{Bi} \right) / \left(l \times D_S \right) \right]$

$$= \sum_{j=1}^{l} \left\{ H_{S\,j} C_{m\,j} \left\{ N_j \left(\sum Q_{Bi} / l \right) \left(\frac{\left(\sum Q_{Bi} / l \right)}{P_j} + \left(N_j - 1 \right) T - \frac{N_j \left(\sum Q_{Bi} / l \right) \left[N_j \left(\sum Q_{Bi} / l \right) / P_j \right]}{2} \right) \right. \right.$$

$$\left. \left. - \frac{\sum Q_{Bi} / l}{D_S} \times \left(\sum \left(Q_{Bi} \right) / l \right) \times \left(1 + 2 + \ldots + \left(N_j - 1 \right) \right) \right\} \cdot \frac{D_S}{N_j \left(\sum Q_{Bi} / l \right)} \right\} = \sum_{j=1}^{l} \left\{ \frac{H_{S\,j} C_{m\,j} \left(\sum Q_{Bi} / l \right)}{2} \cdot \left[\left(N_j - 1 \right) + \frac{D_S \cdot \left(2 - N_j \right)}{P_j} \right] \right\} \tag{3}$$

Because the buyer's demand parameters are unknown, the bullwhip effect is likely to occur. The existence of defective items should also be added to this consideration; therefore, suppliers typically expect to manufacture more products than demanded by buyers. In other words, the estimated demand of supplier production plans exceeds that of the buyer's contract. By investing in information sharing, suppliers hope to reduce the demand ratio from α_j to α'_j, meaning the supplier's estimated demand is $\sum_{i=1}^{k} D_i \left(1 + \left(\sum_{j=1}^{l} \alpha'_j \right) / l \right)$, where $\alpha_j > \alpha'_j$. The relationship between the estimated demand ratio α_j, α'_j, and investment costs can be considered exponential, as shown below.

$$\alpha'_j = y + \left[\alpha_j - y \right] \exp(-mK), \text{ where } \left[\alpha_j - y \right] > 0. \tag{4}$$

K is the supplier's information sharing investment, which includes the supplier offering lower prices to buyers as an incentive to improve information sharing. Prices declining from C_{Pj} to C'_{Pj} are shown as $C'_{Pj} = C_{Pj}\left(1-\left\lfloor \alpha_j - \alpha'_j \right\rfloor\right)$. Because of information sharing, the supplier can better understand buyers' demands, thus, reducing the uncertainty of demand and the production lead time. The profit from reduced costs is $D'_S M$, and $M = f(\alpha'_j)$; therefore, $D'_S M = D'_S f(\alpha'_j)$.

Assuming that by the end of each production cycle excessive inventory is sold at salvage value $C_P^{SV} = C_{Pj}(1-\beta)$, the annual salvage value of excessive inventory can be calculated as follows:

$$S_{EX}^{SV} = \left[D'_S - D - Dy\right] C_P^{SV} = \sum_j D\left[\alpha'_j - y\right] C_{Pj}(1-\beta), \text{ where } \left\lfloor \alpha'_j - y \right\rfloor > 0. \tag{5}$$

Therefore, defective items Z is

$$\sum_j Z_j = \sum_j Q_j \cdot y. \tag{6}$$

3.3.3 Total Costs

Because $Q_j = (N_j \sum_{i=1}^{k} Q_{Bi})/l$ and $C'_{Pj} = C_{Pj}\left(1-\alpha_j + \alpha'_j\right)$, we can assume that the buyer's total costs are $TC_B = \sum_{i=1}^{k}\left[TC_{Bi}(Q_{Bi})\right]$, the supplier's total costs are $TC_S(N_1,\ldots,N_l,Q_{B1},\ldots,Q_{Bk},K_1,\ldots,K_l)$, and the system's total costs are $TC(N_1,\ldots,N_l,Q_{B1},\ldots,Q_{Bk},K_1,\ldots,K_l)_{coordinated}$. The system's total costs are the objective function of this study, and there are no restricted conditions. Therefore, various total costs can be obtained as follows:

$$\begin{aligned} TC_B(Q_{B1},\ldots,Q_{Bk}) = & \left\{\sum_{i=1}^{k}\left(\frac{D_i A_i}{Q_{Bi}}\right) + \sum_{i=1}^{k} D_i \times \left(\sum_{j=1}^{l} C_{Pj}\left[1-\alpha_j + \alpha'_j\right]\right)/l \right. \\ & + \sum_{i=1}^{k}\left\{H_{Bi}\left[\sum_{j=1}^{l} C_{Pj}\left(1-\alpha_j+\alpha'_j\right)/l\right] Q_{Bi}\left(\frac{1}{2}+p_{Bi}\right)\right\} \\ & \left. + \sum_{i=1}^{k}\left\{H_{Bi}\left[\sum_{j=1}^{l} C_{Pj}\left(1-\alpha_j+\alpha'_j\right)/l\right]\left(\sqrt{\frac{(1-p_{Bi})L}{p_{Bi}}}\right)\sigma_{Bi}\right\} + \sum_{i=1}^{k}\left\{\frac{D_i}{Q_{Bi}}\left(F+VQ_{Bi}-{}_iW_{Bsave}\right)\right\} + \sum_{i=1}^{k}\left(\pi_{Bi} D_i p_{Bi}\right) \right\} \end{aligned} \tag{7}$$

$$\begin{aligned} TC_S(N_1,\ldots,N_l,Q_{B1},\ldots,Q_{Bk},K_1,\ldots,K_l) = & \left\{\frac{D'_S\left(\sum_{j=1}^{l} C_j S_j\right)}{\sum_{j=1}^{l} N_j\left(\sum_{i=1}^{k} Q_{Bi}\right)}\right\} + D'_S \sum_{j=1}^{l} C_{mj}/l - D'_S \sum_{j=1}^{l} M_j/l + \sum_{j=1}^{l}\left\{\frac{H_{Sj} C_{mj}\left(\sum_{i=1}^{k} Q_{Bi}/l\right)}{2}\cdot\left[\left(N_j-1\right)+\frac{D'_S\cdot\left(2-N_j\right)}{P_j}\right]\right\} \\ & + \sum_{j=1}^{l}\left\{D'_S \cdot C_{insp\,j} + \frac{D'_S y L_{fj}}{\sum_{i=1}^{k} Q_{Bi}/l} + K_j - \left[\left(\sum_{i=1}^{k} D_i\right)/l\right]\left[\alpha'_j - y\right]\times\left[C_{Pj}\left(1-\alpha_j+\alpha'_j\right)\right](1-\beta)\right\} \end{aligned} \tag{8}$$

$$TC(N_1,\ldots,N_l,Q_{B1},\ldots,Q_{Bk},K_1,\ldots,K_l)_{coordinated} = TC_B(Q_{B1},\ldots,Q_{Bk}) + TC_S(N_1,\ldots,N_l,Q_{B1},\ldots,Q_{Bk},K_1,\ldots,K_l) \tag{9}$$

where $\alpha'_j = y + \left\lfloor \alpha_j - y \right\rfloor \exp\left(-m_j K_j\right)$ and $D'_S = \sum_{i=1}^{k} D_i\left(1+\left(\sum_{j=1}^{l}\alpha'_j\right)/l\right)$.

4. GA Parameter Analysis

Because previous solution methods were complex and the model employed in this study is nonlinear, this study adopts the GA solution and Palisade Corporation's Evolver 4.0 Software (Palisade Corporation, 2004) to examine and solve the multiple-supplier-multiple-buyer collaborative model. The objective function is a fitness function, and the decision variables include information sharing investment costs, delivery frequency, and delivery lot size, which are established as three chromosome types. The structures of these chromosomes are as follows: The information sharing investment costs chromosome comprises a single real-coded gene. The delivery lot size chromosome is composed of five real-coded genes, and the delivery frequency chromosome comprises three real-coded genes. The basic setup of the model parameters is shown in Tables 1 and 2.

Table 1: **Buyer Notations and Values**

Notation	D_1	D_2	D_3	D_4	D_5
Value	1790	1650	2100	1500	2500
Notation	A_1	A_2	A_3	A_4	A_5
Value	25	22	26	13	50
Notation	H_{B1}	H_{B2}	H_{B3}	H_{B4}	H_{B5}
Value	0.4	0.42	0.43	0.11	0.6
Notation	p_{B1}	p_{B2}	p_{B3}	p_{B4}	p_{B5}
Value	0.05	0.045	0.035	0.01	0.07
Notation	σ_{B1}	σ_{B2}	σ_{B3}	σ_{B4}	σ_{B5}
Value	7	6	8	1	15
Notation	πb1	πb2	πb3	πb4	πb5
Value	15	17	13	10	30
Notation	${}^{1}W_{Bsave}$	${}^{2}W_{Bsave}$	${}^{3}W_{Bsave}$	${}^{4}W_{Bsave}$	${}^{5}W_{Bsave}$
Value	150	145	125	100	300
Notation	L	F	V		
Value	27	375	1		

Table 2: **Supplier Notations and Values**

Notation	α_1	α_2	α_3	P_1	P_2	P_3
Value	0.05	0.06	0.07	9650	9655	9660
Notation	H_{S1}	H_{S2}	H_{S3}	C_{P1}	C_{P2}	C_{P3}
Value	0.35	0.3	0.4	12	15	10
Notation	C_{m1}	C_{m2}	C_{m3}	G_{m1}	G_{m2}	G_{m3}
Value	100	120	90	25	22	26
Notation	m_1	m_2	m_3	C_1S_1	C_2S_2	C_3S_3
Value	0.0003	0.0003	0.0003	600	700	500
Notation	C_{insp_1}	C_{insp2}	C_{insp3}	L_{f1}	L_{f2}	L_{f3}
Value	0.5	0.55	0.58	60	65	68
Notation	y	β				
Value	0.01	0.3				

4.1 Population Size Analysis

Excessively large population size affect the solution speed and require longer calculation times, whereas excessively small population size may be trapped easily into obtaining regional optimal solutions, resulting in premature convergence. After the experiments, this study set the population size as 2,000, which should not incur lengthy calculation times or cause regional optimal solutions. During the experiments, we compared population size ranging between 500 and 3,000. Varying population size, increasing by increments of 500 each time, were tested using five experiments for each number. The averages of the five experiments are listed in Table 3. The results show that when the population size is 2,000, the cost of the average better solution is the lowest and the average execution time is 2min48s, which is acceptable.

However, when the population size is 3,000, the execution time is 3min37s. In the next section, this study performs interleaved execution with 25 pairs of crossover rates and mutation rates, and five calculations are executed for each pair, which consumes a significant amount of time. Therefore, for the next section, we adopt a population size of 2,000 to examine the crossover and mutation rates.

Table 3: **Optimal Costs and Execution Time of Various Population Size**

Group Number	*Optimal Average Total Costs*	*Algebraic Average (Trials)*	*Average Execution Time*
500	1240241.541	72386	0:01:34
1000	1240230.879	69656	0:01:56
1500	1240236.453	71345	0:02:24
2000	1240225.387	66115	0:02:48
2500	1240232.675	75800	0:03:41
3000	1240238.935	51289	0:03:37

4.2 Analysis of Crossover Rates and Mutation Rates

The definition of crossover rates and mutation rates is crucial for GAs. Excessively high crossover rates cause radical changes in the genes, preventing the good genes from previous generations from being retained, whereas excessively low crossover rates cause the results to stagnate in regional optimal solutions. Additionally, excessively high mutation rates lead to blind searches, whereas excessively low mutation rates create local optimal solutions. Therefore, appropriate value definitions are essential.

Table 4: **Data Obtained Using Varying Combinations of Crossover Rates and Mutation Rates**

Crossover Rate	*Mutation Rate*	*Optimal Average Total Costs*	*Algebraic Average (Trials)*	*Average Execution Time*
0.1	0.05	1240236.27	52258.8	0:10:35
	0.1	1240232.846	77522.4	0:03:04
	0.15	1240238.971	64747.8	0:02:46
	0.2	1240248.598	54747.4	0:02:31
	0.25	1240264.997	53262	0:02:28
0.3	0.05	1240236.089	46696.2	0:02:15
	0.1	1240232.245	67668.2	0:02:49
	0.15	1240236.984	54699.6	0:02:28
	0.2	1240236.769	62721.6	0:02:48
	0.25	1240241.887	68833.8	0:03:04
0.5	0.05	1240271.451	57670	0:02:32
	0.1	1240225.036	95974	0:03:40
	0.15	1240261.074	56137.6	0:02:30
	0.2	1240228.371	69655.4	0:03:02
	0.25	1240266.718	51498.2	0:02:25
0.7	0.05	1240250.427	70814	0:02:57
	0.1	1240239.67	67250.6	0:02:47
	0.15	1240243.81	58543	0:02:35
	0.2	1240258.631	58385	0:02:41
	0.25	1240251.001	73982	0:03:07
0.9	0.05	1240244.241	45177.8	0:02:20
	0.1	1240234.978	75799.4	0:03:10
	0.15	1240237.166	43158.4	0:02:13
	0.2	1240239.103	59118	0:02:43
	0.25	1240268.262	56936.8	0:02:27

In this section, the initial value of the crossover rate is 0.1, increasing by 0.2 each time, and ending with 0.9; thus, the five groups are 0.1, 0.3, 0.5, 0.7, and 0.9. The initial value for the mutation rate is 0.05, increasing by 0.05 each time, and ending with

0.25; thus, the five groups are 0.05, 0.1, 0.15, 0.2, and 0.25. Interleaved execution is then performed for 25 pairs of crossover rates and mutation rates, and five calculations are performed for each pair. The results are recorded in Table 4. Table 4 shows that in the cross-matches of crossover rates and mutation rates, the combination of the crossover rate at 0.5 and the mutation rate at 0.1 yields the lowest average optimal total costs, that is, NTD$1,240,225.036. Therefore, we employ these GA parameter definitions in the model parameter sensitivity analyses conducted in the next section.

4.3 Model Parameter Sensitivity Analysis

Because of the high number of model parameters, we categorized them into two groups, namely, suppliers' model parameters and buyers' model parameters, and present them in two separate figures to avoid confusion. The suppliers' parameters are α_1, P_1, H_{S1}, C_{P1}, C_{m1}, G_{m1}, m_1, C_1S_1, C_{insp_1}, L_{f1}, y, and β; the buyers' parameters are D_1, A_1, H_{B1}, p_{B1}, σ_{B1}, πb1, ${}_1W_{Bsave}$, L, F, and V. Total cost variations are sensitive to C_{m1}, P_1, and C_{P1} variations. The decreases in variable costs, including suppliers' purchase, indirect, and material handling cost, significantly reduce the total costs; declines in supplier production rates also lead to reductions in total costs. Suppliers must reduce variable costs, including purchase, indirect, and material handling costs, to obtain significantly lower total costs.

Figures 2 and 3 show buyers' total cost variation rates in response to 10% decreases in the model parameters. For the suppliers' parameters, decreases in C_{P1} cause decreases in the buyers' total cost variation rates; decreases in P_1 also cause buyers' total cost variation rates to decrease; and changes in the remaining parameters cause variation rates in buyers' total costs that range between 0.4% and -0.5%. Buyers' total costs variations are sensitive to C_{P1} and P_1 variations. When suppliers' costs per unit decreases, buyers' total costs also decrease; decreases in suppliers' production rate cause decreases in buyers' total costs. When the average demand rates of all buyers decrease, buyers' total cost variations decrease significantly; decreases in buyers' fixed transportation costs per delivery also result in significant declines in buyers' costs.

Figure 2: **Variation Rates of the Buyers' Total Costs in Response to 10% Decreases in the Suppliers' Model Parameters**

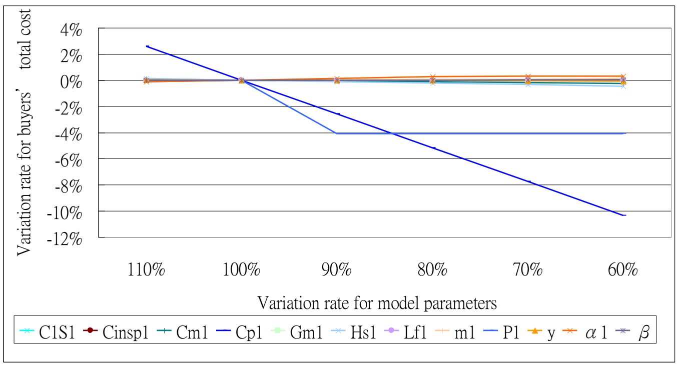
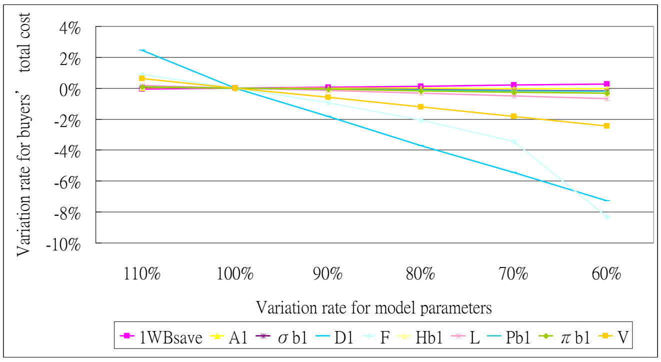


Figure 3: Variation Rates of the Buyers' Total Costs in Response To 10% Decreases in the Buyers' Model Parameters



Figures 4 and 5 show the suppliers' total cost variations in response to 10% declines in the model parameters. Among suppliers' parameters, decreases in C_{m1} cause significant decreases in suppliers' total cost variation rates; decreases in P_1 cause suppliers' total cost variation rates to decline moderately; and changes in the remaining parameters cause variation rates in suppliers' total costs that range between 0.05% and -0.2%. Suppliers' total cost variations are sensitive to C_{m1} and P_1 variations.

Figure 4: Variation Rates of the Suppliers' Total Costs in Response to 10% Decreases in the Suppliers' Model Parameters

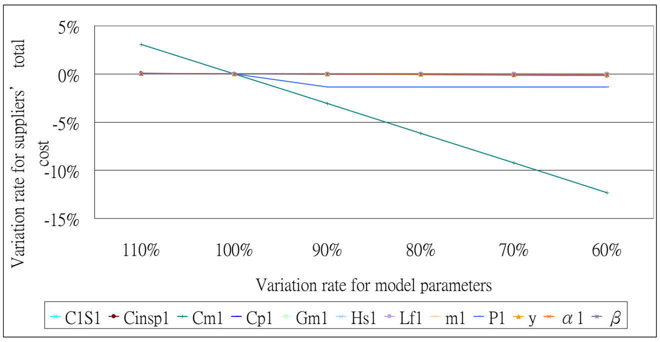
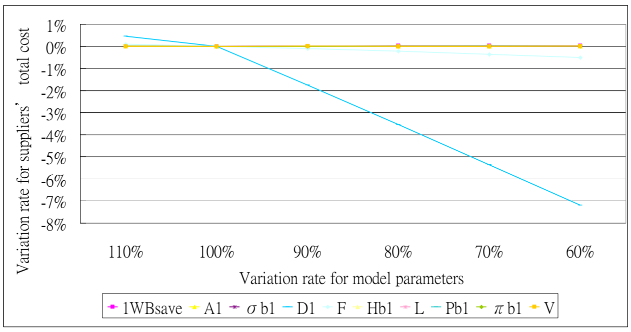


Figure 5: Variation Rates of the Suppliers' Total Costs in Response to 10% Decreases in the Buyers' Model Parameters



The decreases in variable costs, including suppliers' purchase, indirect, and material handling costs, result in suppliers' total costs decreasing significantly. To reduce their total costs, suppliers must first lower their variable costs, including purchase, indirect, and material handling costs. Among the buyers' parameters, decreases in D_1 cause significant decreases in suppliers' total cost variation rates; decreases in F cause moderate decreases in suppliers' total cost variation rates; and changes in the remaining parameters cause variation rates in suppliers' total costs that range between 0.03% and -0.004%. Suppliers' total cost variations are sensitive to D_1 and F variations. When the average demand rates of all buyers declines, suppliers' total cost variations also decline significantly. So buyers must control their fixed transportation costs per delivery to reduce suppliers' total costs significantly.

Figures 6 and 7 show the cost variations of information sharing investments in response to 10% decreases in the model parameters. Information sharing investment costs variations are sensitive to α_1 and C_{m1} variations. For suppliers, variation rates of the suppliers' estimated demands and variable costs, which include suppliers' purchase, indirect, and material handling costs, having a significant influence on the information sharing investment costs. For the buyers' parameters, decreases in D_1 cause significant decreases in the information sharing investment costs; changes in the remaining parameters cause variation rates in information sharing investment costs that range between 2% and -0.8%. D_1 is more sensitive to changes in the information sharing investment costs. The buyers' average demand rates have a significant influence on the costs of information sharing investments.

Figure 6: **Variation Rates of the Information Sharing Investment Costs in Response to 10% Decreases in the Suppliers' Model Parameters**

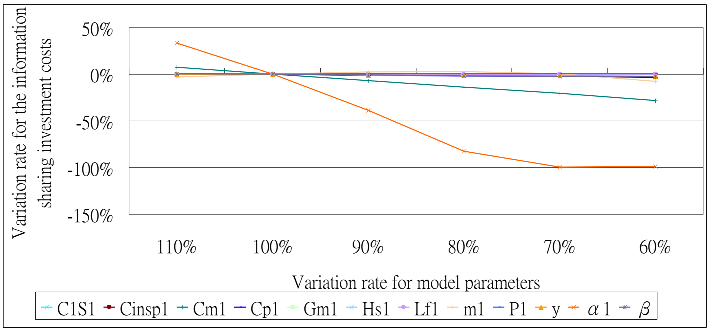
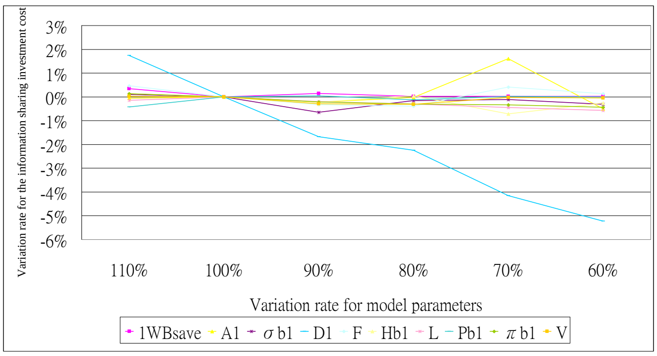


Figure 7: **Variation Rates of the Information Sharing Investment Costs in Response to 10% Decreases in the Buyers' Model Parameters**



Figures 8 and 9 show delivery lot size variations in response to 10% decrease in the model parameters. The decreases in P_1 cause significant increases in delivery lot size; decreases in H_{S1} cause moderate increases in delivery lot size; and changes in the remaining parameters have no significant influence on the delivery lot size. Delivery lot size variations are sensitive to P_1 and H_{S1} variations. When suppliers' production rate and inventory costs per unit decline, the delivery lot size increases. Delivery lot size variations are sensitive to D_1, F, and ${}_1W_{Bsave}$ variations. The decreases in the buyers' average demand rates causes the delivery lot sizes to decrease significantly. When buyers' fixed transportation costs per delivery decrease, the delivery lot size also decreases. Lower costs after implementing JIT delivery cause a slight increase in the delivery lot size.

Figure 8: **Delivery Lot Size Variation Rates in Response to 10% Decreases in the Suppliers' Model Parameters**

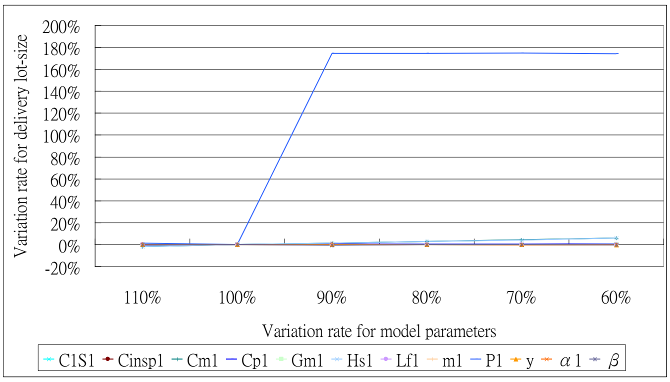
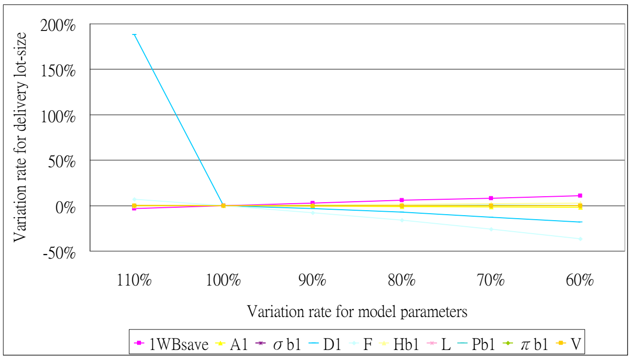


Figure 9: **Delivery Lot Size Variation Rates in Response to 10% Decreases in the Buyers' Model Parameters**



Figures 10 and 11 show the delivery frequency variations in response to 10% decreases in the model parameters. However, this study examined only one delivery frequency (the initial value, N1), overlooking the other two frequencies (N2 and N3). Among the suppliers' parameters, decreases in H_{S1} cause increases in the delivery frequency and changes in the remaining parameters cause the delivery frequency to fluctuate. This indicates that when suppliers' inventory costs per unit decrease, the delivery frequency increases. Among the buyers' parameters, decreases in D_1 cause decreases in the delivery frequency; when F is decreasing, the delivery frequency is also increasing; and changes in the remaining parameters cause the delivery frequency to fluctuate. This indicates that when the buyers' average demand rates decrease, the delivery frequency also decreases. Additionally, when buyers' fixed transportation costs per delivery decrease, delivery frequencies increase.

Figure 10: **Delivery Frequency Variation Rates in Response to 10% Decreases in the Suppliers' Model Parameters**

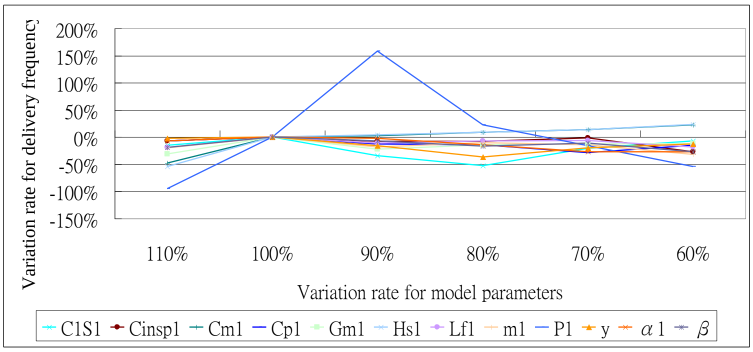
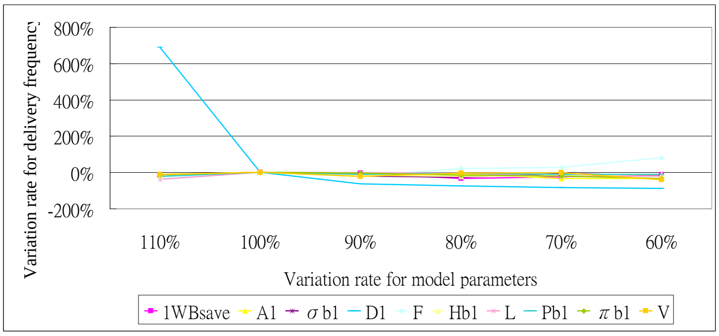


Figure 11: **Delivery Frequency Variation Rates in Response to 10% Decreases in the Buyers' Model Parameters**



5. Conclusions

This study explored the collaborative supply chain model considering delivery strategies and information sharing, and extended the single-supplier-single-buyer model into a multiple-supplier-multiple-buyer supply chain model. Using GAs to obtain more suitable solutions, we analyzed the GA parameters and model sensitivity. The decision variables of the proposed model include information sharing investment costs, delivery frequencies, and delivery lot sizes. We first analyzed the GA parameters to determine the population size for these parameters and the execution time and solution quality of various population size. Based on the results of this study, we conclude that the combination of a 0.5 crossover rate and a 0.1 mutation rate achieves the lowest average optimal total costs. Furthermore, using GA parameters to analyse the sensitivity of the model parameters, we examined the influence of various model parameters on the total costs, buyers' total costs, suppliers' total costs, and information sharing investment costs, delivery lot sizes, and delivery frequencies.

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