Decision on risk share to maximize the supply chain expected profit

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Hasan Hosseini nasab[*], Saleh Hatemi[**], Mohammad-Bagher Fakhrzad[***], Hasan Khademi-Zare[***]

[*]Corresponding Author, Professor, IE Department, Yazd University, Yazd, Iran

[**]PhD candidate, IE Department, Yazd University, Yazd, Iran

[***]Professor, IE Department, Yazd University, Yazd, Iran

Abstract

There are many agents in a supply chain, each of which has its uncertainty and risk. A contract between agents could reduce the risk. In this paper, an insurance contract with three parameters; retailer's risk share, supplier's risk share, and the premium transferred between them is considered to maximize the profit for all agents. Three mathematical models were developed for different types of a supply chains, and one thousand initial scenarios were generated in this stochastic programming. A new algorithm was proposed to reduce the number of scenarios. Three models are programmed and solved in MATLAB software. From the numerical examples solved, the results show that when the retailer gives 0.75 of losses from over and under stock, keeping, and salvage costs, the insurance contract has its best performance, and the supply chain has 2.4% extra benefit using it, almost near the maximum profit that is possible.

Keywords: Supply chain management, Insurance contract, Probabilistic programming, Stochastic programming, Scenario

1. Introduction

When agents are matched in decision-making, and all decisions are decided by one central agency (centralized supply chain), there is more profit and less risk for the whole system. On the opposite side, when there is no dependency on agents' decisions, it has been called a decentralized supply chain. There are ways to coordinate the supply chain and match the agents' decisions, but contracting is more common, and one of the very usable contracts is the Insurance contract. In an insurance contract, the upstream ensures that the downstream deals with overstock, understock, and keeping risks, with two parameters. First, the fraction of losses caused by the deviation of demand from its forecasted amount, which the supplier gives to the retailer (β), (retailer's share is 1-β = α). The second one is the side payment or the premium the retailer gives the supplier for sharing these risks (M). This study has justified the insurance contract for the supply chains with two sale periods. To do this, three two-level supply chain models in two periods, decentralized, centralized, and insured supply chains, have been designed. Furthermore, three probabilistic programs have been designed to model the supply chain behavior. This study considers an insurance contract with three parameters, α, ß, and M, to maximize the profit for all agents. Three mathematical models were developed, one thousand initial scenarios were generated in stochastic programming, and an algorithm was proposed to reduce the number of scenarios. We study a supply chain with one supplier and retailer, where the retailer expresses the stochastic independent demand and price. We choose two periods of sale as a base for a solution to n periods problems through induction or any mathematical instrument that can solve the n periods problem.

2. Literature review

A supply chain contains a set of suppliers, manufacturers, distribution centers, and transfer channels. Each participant plays a separate role in manufacturing final products from raw materials conferring to the customer's needs (Feng et al. 2018). In current years, the globalization of trade, competition, and the integration of supply chains (SCs) have made organizations pay more care to their production plans and the other related members in the SC (Fakhrzad et al. 2019). Similarly, providing a production plan for the SC of an organization is one of the most excellent substantial decisions to make in SC management. Therefore, supply chain management (SCM) should be able to plan all the activities complicated in the chain from the suppliers to the final clients; unsuitable management of SC can lead to the bankruptcy of the members and failure in worldwide competition (Goodarzian et al. 2020). SCM is a critical procedure over which competitive ability in the market is amplified. Also, managers can decrease the costs forced on their organizations by practicing SCM. It provides a balance among the supplier, the manufacturing or service organization, and the consumer(s) and eventually promises the persistence of the organization in the market (Naderi et al. 2020). With new developments, globalization, and random behaviors of customers and opponents, the field of competition has been changed from companies to supply chains. Therefore, Supply Chain Management (SCM) is one of the most wanted topics in logistics. Moreover, Supply Chain Network Design (SCND) is a strategic decision underwriting the supply chain. Mixing several strategic and tactical decisions like determining the locations, number, and capacity of facilities and material flow through the network makes SCND a complex subject in SCM. Formerly, minimizing total cost or maximizing profit was the main objective of the supply chain, and original in the economic measurement was enough to outperform the competitors. But, in current years, supply chains have become in charge of their activities' Environmental Impact (EI) and Social Impact (SI). This concern has led to the progress of a new idea in SCM, namely Sustainable Supply Chain Management (SSCM), which is well-defined as seeing EI and SI of supply chain actions as well as economic routine in the management of physical, data, and money stream. An important task related to SCND problems is to control the way of handling the uncertain nature of some future conditions, which may affect the input parameters of the problem. Uncertainty can be joined with economic, legal, and political issues, affecting parameters like the level of demand, production cost, supply of raw materials, etc. Countless authors have proposed numerous stochastic programming models to deal with this subject in the Sustainable Supply Chain Network Design (SSCND) background. Giarola et al. (2012) and Verma et al. (2013) applied a two-stage stochastic programming method to dealing uncertainties in single-objective environmental supply chain design. Pishvaee et al. (2012) presented Robust Possibilistic Programming (RPP) as a programming method for handling uncertain parameters in their bi-objective model, including minimizing the total cost and maximizing SC Social Responsibility (SR). A computational outline has been proposed to measure the potential role of uncertainty in the environmental damage for the multi-objective optimization of a sustainable supply chain in (Guillén-Gosálbez, Ignacio Grossmann,2010). A multi-objective (economic and environmental features) facility position model, which explores the effect of demand and return uncertainties on the SCND by applying scenario-based stochastic programming, has been introduced by Amin and Zhang (2013). Ruiz-Femenia et al. (2013) presented a stochastic multi-scenario Mixed-Integer Linear Program (MILP) in which demand uncertainty was considered for the multi-objective optimization of the chemical supply chain, and economic and environmental routines were accounted for instantaneously. The element that it is better to consider ambiguity and risk in SSCND research has been highlighted by Eskandarpour et al. (2015). An ideal funding strategy for the supply chain by considering investment limitations is debated in (Wang et al. 2016). Most scholars regularly take into account the financial features, such as financial factors (Ramezani et al. 2014) and financial flows of SC, while few studies address financial decisions in the SCND model as decision variables. Sometimes, it is enough to consider a single-period model to develop an ideal solution to the SCND problem. Nevertheless, financial and capital expenditure-related problems should be planned by implementing multi-period planning models (Melo et al. 2006). Furthermore, developing a multi-period setting of this model and the nature of financial decisions may lead to multi-stage stochastic programming. Financial decision-making contains a sequence of decisions to react to outcomes that evolve over periods, and multi-stage stochastic programming introduces an appropriate strategy to manage the complexity of this subject in the SSCND problem. The method was applied by Nickel et al. (2012) to solve an SCND problem with financial decisions and uncertainty assumptions for demand and interest rate, where a set of scenarios presented uncertainty.

3. Methodology

The basic two-period supply chain model is shown in figure 1.

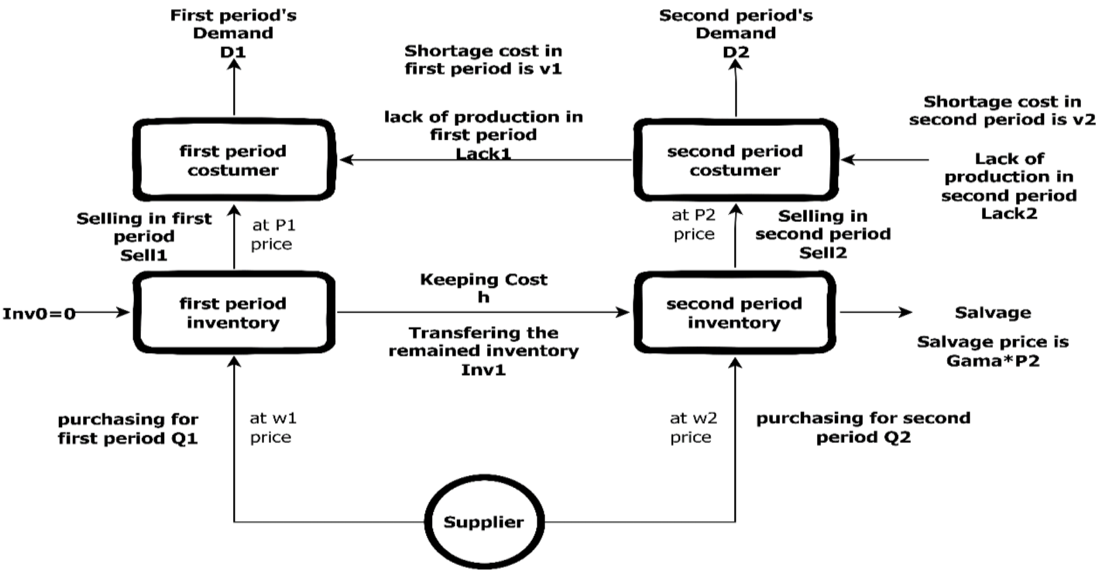

Figure 1. The basic two-period supply chain model (designed for this paper)

The problem we will solve is tuning some initial parameters of the insurance contract to maximize the whole supply chain's profit and splitting the extra money the contract earned. The problem is finding the best insurance contract for a two-period supply chain with one thousand scenarios for price and demand. We study a double-period supply chain model with balanced data. At the beginning of the selling period, the retailer orders Q, based on his prediction of market request D. Price and demand are stochastic and behave like a Brownian motion. The supplier products the creation with an item fee c, a wholesale price w, and a retail price p. The lack cost per unit is v, and the salvage value per unit is s. In our model, π means stochastic profit and $\prod$ signifies its expected value. Superscript * indicates optimality; subscripts s, r, and sc represent one-to-one supplier, retailer, and supply chain. Subscripts i mean insurance agreement. The supplier and the retailer settle on an insurance agreement with two parameters earlier than the selling periods. The first parameter ß (ßϵ [0, 1]) is the supplier's part of losses made by differentiating the retailer's order amount from the market request. The retailer's share is α (α=1-ß). The Second parameter is the side payment M, from the retailer to the supplier. When M is adverse, the supplier bounces a side payment to the retailer. This insurance agreement requires that the supplier should share the retailer's losses (Premium or side payment M) while giving money to the supplier; the act of this supply chain is then enhanced. Necessary notations are defined in table 1.

Table 1. Notations

Sets	
S	Scenarios Set with "s" as an Indices
I	Periods Sets, with "i" as an Indices
Parameters	
$D_{i,s}$	Product's Demand for the i_{th} period in s_{th} Scenario
$P_{i,s}$	Retailing Price for the i_{th} period in s_{th} Scenario
K_s	s_{th} Scenario's Happening Probability
w_i	The wholesale price in i_{th} period
c_i	Production cost in the i_{th} period
v_i	Retailer's Shortage cost in the i_{th} period
H	Keeping cost until the second period
γ	Salvage's ratio (a percentage of product's price)
Variables	
Q_i	Quantity of ordered production in the i_{th} period
$Lack_{i,s}$	Shortage amount for i_{th} period in s_{th} Scenario
$Sell_{i,s}$	Retailer's sold amount for i_{th} period in s_{th} Scenario
$Inv_{i,s}$	Retailer's inventory for the i_{th} period in s_{th} Scenario
ß	It is a number between 0 and 1. A percentage of the retailer's loss is caused by mismatching forecasted and the actual amount of demand, which the supplier gives to the retailer.
α	α=1-ß.The retailer's share of the loss is caused by mismatching forecasted and the market's demand.
M	It is premium or the money which the retailer gives to the supplier. It is independent of the volume of orders, and when it is negative, the supplier provides it to the retailer.
Π	Profit
Index	
I	Insurance Contract
C	Centralized
Dc	Decentralized
R	Retailer
S	Supplier
Sc	Supply Chain

4. Model improvements

Three models; a two-level decentralized supply chain for two consecutive periods in which decisions are made are independent, a centralized supply chain that only one agent decides, and a supply chain with an insurance contract discussed.

4.1. Development of a model for decentralized supply chain:

In this case, everyone will maximize their own profit and has no attention to the whole system's profit. The function of the retailer's profit is:

$$\Pi_r = -\sum_{i\in l} w_i Q_i + \sum_{s\in S} k_s \left(\sum_{i\in l} P_{i,s} Sell_{i,s} - \sum_{i\in l} v_i \mathrm{Lack}_{l,s} - \mathrm{In}v_{1,s}\mathrm{h} + \mathrm{In}v_{2,s}\gamma P_{2,s} \right) \quad (1)$$

With algebraic progress, it has been changed to:

$$\Pi_r = -\sum_{i\in l} w_i Q_i + \sum_{s\in S} k_s \left(\sum_{i\in l} P_{i.s} Sell_{i.s} + P_{2.s}\mathrm{In}v_{2.s} \right) \sum_{s\in S} k_s \left(\sum_{i\in I} v_i Lack_{i.s} + Inv_{1.s}h \right.$$
$$\left. + Inv_{2.s}(1-\gamma)P_{2.s} \right) \quad (2)$$

$$\Pi_r = -\sum_{i\in l} w_i Q_i + \sum_{s\in S} k_s \left(\sum_{i\in l} P_{i.s}\mathrm{Sell}_{i.s} + P_{2.s} Inv_{2.s} \right)$$
$$- U(Q_1.Q_2) \quad (3)$$

In the above equation, the term U (Q_1, Q_2) is the projected losses generated by the retailer's order quantity deviation from the market request. Here is the summation of the shortage, keeping, and salvage costs.

$$U(Q_1.Q_2) = \sum_{s\in S} k_s (\sum_{i\in l} v_i \mathrm{Lack}_{i.s} + \mathrm{In}v_{1.s}h + \mathrm{In}v_{2.s}(1-\gamma)P_{2.s}) \quad (5)$$

By adding the constraints to the profit function of the retailer, the complete model has been derived as below:

$$\text{Max}\ \pi_r \quad = -\sum_{i\in l} w_i Q_i + \sum_{s\in S} k_s\left(\sum_{i\in l} P_{i.s}\text{Sell}_{i.s} + P_{2.s} Inv_{2.s}\right) - U(Q_1.Q_2) \tag{6}$$

$$\text{Inv}_{1.s} = \text{Q}_1 - \text{Sell}_{1.s} \qquad \forall \text{s} \in \text{S} \tag{7}$$

$$\text{Inv}_{2.s} = \text{Inv}_{1.s} + Q_2 - \text{Sell}_{2.s} \qquad \forall s \in S \tag{8}$$

$$\text{Sell}_{\ 1.s} + \text{ Lack}_{\ 1.s} = D_{1.s} \qquad \forall s \in S \tag{9}$$

$$\text{Sell}_{2.s} + \text{Lack}_{2.s} = \text{Lack}_{1.s} + D_{2.s} \qquad \forall s \in S \tag{10}$$

$$U(Q_1.Q_2) = \sum_{s\in S} k_s\left(\sum_{i\in l} v_i \text{Lack}_{i.s} + \text{In}v_{1.s}h + \text{In}v_{2.s}(1-\gamma)P_{2.s}\right) \tag{11}$$

$$Q_1.Q_2.\text{Inv}_{1.s}.\text{Inv}_{2.s}.\text{Sell}_{1.s}.\text{Sell}_{2.s}.\text{Lack}_{1.s}.\text{Lack}_{2.s}.U\left(Q_1.Q_2\right) \geq 0 \qquad \forall s \in S \tag{12}$$

The objective function is the expected profit for Q_1 and Q_2 order amounts, which must be maximized. The term U in the objective function (discussed earlier) has been noted as a constraint. The first two constraints (7&8) have been driven by a counterbalance on inventory in two periods. The third and fourth constraints (9&10) are balancing demand with sold and lacking amounts in two periods.

We call the optimum amounts driven from solving the model Q_1* and Q_2* and the maximum profit function π_r^*. The profit function for the supplier is:

$$\pi_s{}^* = \sum_{i\in l} (w_i - c_i)Q_i^* \tag{13}$$

By adding the two amounts driven, the whole system's maximum profit is:

$$\pi_{sc}{}^* = \pi_s{}^* + \pi_r^* \tag{14}$$

4.2. Development of a model for centralized supply chain

In this case, agents decide together, and we have:

$$\pi_{sc} = \pi_s + \pi_r \tag{15}$$

$$= \sum_{i\in l} (w_i - c_i)Q_i - \sum_{i\in l} w_iQ_i + \sum_{s\in S} k_s\left(\sum_{i\in l} P_{i.s}Sell_{i.s} + P_{2.s}\mathrm{Inv}_{2.s}\right) - U(Q_1.Q_2)$$

$$= -\sum_{i\in l} c_iQ_i + \sum_{s\in S} k_s\left(\sum_{i\in I} P_{i.s}Sell_{i.s} + P_{2.s}\mathrm{Inv}_{2.s}\right) - U(Q_1.Q_2) \tag{16}$$

By adding the inventory balancing, and the demand balancing constraints, to the above function, the mathematical model is:

$$Max\pi_{sc} = -\sum_{i\in l} c_iQ_i + \sum_{s\in S} k_s\left(\sum_{i\in I} P_{i.s}Sell_{i.s} + P_{2.s}\mathrm{Inv}_{2.s}\right) - U(Q_1.Q_2) \tag{17}$$

Subject to:

$$\mathrm{Inv}_{1.s} = Q_1 - \mathrm{Sell}_{1.s} \qquad \forall s \in S \tag{18}$$

$$\mathrm{Inv}_{2.s} = \mathrm{Inv}_{1.s} + Q_2 - \mathrm{Sell}_{2.s} \qquad \forall s \in S \tag{19}$$

$$\mathrm{Sell}_{\ 1.s} + \ \mathrm{Lack}_{\ 1.s} = D_{1.s} \qquad \forall s \in S \tag{20}$$

$$\mathrm{Sell}_{2.s} + \mathrm{Lack}_{2.s} = \mathrm{Lack}_{1.s} + D_{2.s} \qquad \forall s \in S \tag{21}$$

$$U(Q_1.Q_2) = \sum_{s\in S} k_s\left(\sum_{i\in l} v_i\mathrm{Lack}_{i.s} + \mathrm{In}v_{1.s}\mathrm{h} + \mathrm{In}v_{2.s}(1-\gamma)P_{2.s}\right) \tag{22}$$

$$Q_1.Q_2.\mathrm{In}v_{1.s}.\mathrm{In}v_{2.s}.\mathrm{Sell}_{1.s}.\mathrm{Sell}_{2.s}.\mathrm{Lack}_{1.s}.\mathrm{Lack}_{2.s}.U(Q_1.Q_2) \geq 0 \quad \forall s \in S \tag{23}$$

4.3. Development of a model for two-period with an insurance contract:

An insurance contract is one of the ways to organize the supply chain. The insurance agreement unifies the supply chain with two parameters ß and M. By adding these parameters to the developed model, we have:

$$max\Pi_r^i = -\sum_{i\in l} w_iQ_i + \sum_{s\in S} k_s\left(\sum_{i\in l} P_{i,s}Sell_{i,s} + P_{2,s}Inv_{2,s}\right) - U(Q_1,Q_2) + \beta U(Q_1,Q_2) - M$$

(24)

Subject to:

$$\mathrm{Inv}_{1,s} = Q_1 - Sell_{1,s} \qquad \forall s \in S \tag{25}$$

$$\mathrm{Inv}_{2,s} = \mathrm{Inv}_{1,s} + Q_2 - \mathrm{Sell}_{2,s} \qquad \forall s \in S \tag{26}$$

$$\mathrm{Sell}_{1,s} + \mathrm{Lack}_{1,s} = D_{1,s} \qquad \forall s \in S \tag{27}$$

$$\mathrm{Sell}_{\,2,s} + \mathrm{Lack}_{2,s} = \mathrm{Lack}_{1,s} + D_{2,s} \ \forall s \in S \tag{28}$$

$$U(Q_1, Q_2) = \sum_{s \in S} k_s \left(\sum_{i \in l} v_i \ \mathrm{Lack}_{\,i,s} + \mathrm{Inv}_{1,s}\mathrm{h} + \mathrm{Inv}_{2,s}(1-\gamma)\,\mathrm{P}_{2,s} \right) \quad \forall s \in S \tag{29}$$

$$\sum_{i \epsilon l} (w_i - c_i)Q_i - \beta U(Q_1, Q_2) \geq \Pi_s^* \qquad \beta \leq 1 \tag{30}$$

$$Q_1, Q_2, \mathrm{ln}v_{1,s}, \mathrm{Inv}_{2,s}, \ \mathrm{Sell}_{\,1,s}, \ \mathrm{Sell}_{\,2,s}, \ \mathrm{Lack}_{\,1,s}, \ \mathrm{Lack}_{\,2,s}, U(Q_1, Q_2), \beta, M \geq 0 \forall s \in S \tag{31}$$

This model's objective function is the expected value for the retailer's profit in the contracted supply chain. The first two constraints (25, 26) show inventory balancing. The third and fourth constraints (27, 28) demonstrate the counterbalance on demand. The fifth constraint (29) is part of the objective function (U). The sixth constraint (30) shows the retailer's warranty to the supplier about not reducing profit after signing the contract. The two final constraints (30, 31) show that ß is a fraction between zero and one. Therefore, the objective function of the supplier's profit is: $\pi_s^i = \sum_{i \in l} (w_i - c_i)Q_i - \beta U(Q_1, Q_2) + M$ (32)

The problem is finding the best ß that maximizes the contract's effect, as there is no reduction in any agent's profit, and then the M would be divided between agents. When M does not appear in constraints, we can eliminate it from calculation until the end. Then it could be split by negotiating between agents.

5. Numerical analysis

5.1. Scenario making

The probabilistic model (33) is used to make necessary scenarios. Demand and price are random parameters that are assumed to be independent, and both follow the random process of Geometric Brownian Motion (GBM).

$$S_t = S_o e^{\left(\mu - \frac{\sigma^2}{2}\right)t - \sigma W_t} \qquad t = 1,2 \ldots N \tag{33}$$

In this equation, S is a parameter that we want to estimate its value in periods one to N. As can be seen, its value in each period is determined based on its predicted value in the previous period. We have to have S_0 to estimate the value of S in periods 1 through N.

μ and σ are the mean and standard deviation of the growth rate, respectively, which affect the predicted parameter value during the planning period, and W_t is a random process that follows the Brownian motion. We generate one thousand initial scenarios based on Brownian distribution for demand and price. The initial demand (D_0) equals 50, and the average and standard deviation of demand growth in each period (μ_D and σ_D), respectively. We considered it equal to 0.6 and 0.15. In the same way, we assumed the initial price value (P_0) to be 30,000$ and the average and standard deviation of price growth in each period (μ_P and σ_P) to be 0 and 0.2, respectively.

5.2. Development of a model for scenario reduction

Since working with many scenarios is very difficult and takes much time, it is necessary to reduce the generated scenarios. The number of decreasing scenarios depends on the type and nature of the optimization problem and should be less than a quarter of the generated scenarios (Heitsch and Römisch, 2000). Reducing the scenario's primary idea is to eliminate low-probability and close-up scenarios. Therefore, scenario reduction algorithms identify a subset of scenarios and calculate the probabilities for the new scenarios so that the probabilities of the reduced scenarios are added to the nearest Scenario in terms of probability distance. The scenario reduction algorithm reduces the batch scenarios using the Kantrovich distance matrix. The Kantrovich distance is the probability distance between two different sets of scenarios, and the small space between the two scenarios indicates two identical possible processes. The Kantrovich distance reduces the maximum probability scenarios without tolerable error. The probability of all deleted scenarios is considered zero. The preserved scenario's new probability equals the sum of the prior probabilities and the probabilities of the closest scenarios. The systematic algorithm for reducing the scenario is described below:

- Collect the generated scenarios.
- Calculate the Kantrovich distance matrix
- Scenario selection. Find the scenario with the lowest Kantrovich
- Delete Scenario. Select the scenario with the least Kantrovich distance
- Update the probability matrix.

Table 2 summarizes the results of the scenario-making and reducing process.

Table 2. Final scenarios configuration

SCENARIO'S NUMBER	FIRST PERIOD'S PRICE	SECOND PERIOD'S PRICE	FIRST PERIOD'S DEMAND	SECOND PERIOD'S DEMAND	SCENARIO'S PROBABILITY
1	37000	37000	71	92	0.070
2	32000	33000	61	73	0.054
3	27000	24000	67	83	0.034
4	26000	25000	72	103	0.052
5	26000	26000	62	73	0.071
6	24000	22000	72	95	0.038
.					
.					
20	34000	44000	60	83	0.028

6. Solving the model and comparing the results

After arranging the supply chain, retailers, and the whole system's profit increase by the insurance contract, comparing different models is shown in table 10.

Table 10 - Comparing result

Description	Decentralized	Centralized	Insured at Betta = 0.25
The optimal order quantity for the first period	71	71	71
The optimal order quantity for the second period	94	121	123
Retailer's optimal profit	2188400	-	2277738
Supplier's optimal profit	1485000	-	1485000
Whole System's profit	3673400	3763700	3762738

7. Managerial insight

The study shows that the supplier's expected profit rises using insurance contract. Before the insurance contract, the retailer faced all three risks (keeping, shortage, and salvage) but with insurance the risks are shared with the suppliers. So, the model can help managers to obtain a proper decision on risk share to maximize the supply chain expected profit.

8. Conclusion and future works

While the insurance contract effectively organizes the supply chain, it also has some limitations. The most severe limitation is that the supplier experiences a managerial cost in monitoring the retailer's sales condition. The second limitation is that the insurance contract may decrease the interest of retailers. Under the insurance contract, the retailer only shares a slice of the risk. This condition may decrease the retailer's sales energies. So, it is one of the possible future research directions. The reduced enthusiasm of retailers is similarly echoed in data updates. Compared with the supplier, the retailer faces the market directly; thus, it is easier for him to gather data on market demands. In conclusion, using an insurance contract, the supply chain's expected profit function is a concave function concerning α. The study shows that the supplier's expected profit rises as α grows, while the retailer's expected profit declines as α grows. This vision agrees with our insight: a higher α denotes a higher risk and a higher likelihood of losses for the retailer. This makes the retailer order less and collects a lesser expected profit.

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