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Modeling Stochastic Closed-Loop Supply Chain for Deteriorating Products under Risk-Averse Criterion

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Abstract

This paper studies the issue of perishable products that are produced and delivered in batches in a closed-loop supply chain. In our problem, the perishable products are placed in returnable containers for safe transport. We assume that the return time of container is random. Under risk-averse criterion, a stochastic mean-standard deviation model is formulated to minimize the total cost and risk. We analyze three scenarios that may encounter in our supply chain problem, and derive the analytical solution of the proposed optimization model. Finally, one numerical example is presented to demonstrate the validity of the proposed optimization model. The computational results demonstrate that the optimal solution to a risk-neutral optimization model is not optimal to our risk-averse optimization model, which coincides with our theoretical analysis.

Keywords: closed-loop supply chain, risk-averse criterion, perishable products, stochastic lead time

1 Introduction

Closed-loop supply chain (CLSC) is a complete cycle of supply chain that from procurement to final sales, which includes the forward supply chain and the reverse supply chain [4, 6]. In the forward supply chain, products are produced in batches, deposited in returnable transport items (RTIs) and flowed to the buyer; while in the reverse supply chain, RTIs are returned to the supplier to ship the next dispatch. Considering the supply and demand risks, He [7] and Zhang [15] discussed sequential price and quantity decisions for a forward supply chain. Wang and Yang [13] discussed a reverse supply chain and proposed two types of uncertain hierarchical facility location models. As the acceleration of the global economy integration process, the competition is not merely among product enterprises, but also among all the enterprises on the supply chain. CLSC aims to derive a balanced production plan to improve the market competitiveness. For centuries, the CLSC system has become an inevitable trend for the future economical structure. In this paper, the RTIs' return time is considered stochastic since delays in returning process may occur. For example, the return time is limited by the transport capacity or the damages of RTIs that need extra time to be repaired. However, delays may result in higher inventory cost, and higher deteriorating rate. To improve the utilization ratio of the containers and reduce the inventory cost of the entire system simultaneously, it is extremely necessary for decision makers to make moderate order quantity of products. Then we can better manage the CLSC and get a higher return.

In the framework of the supply chain, the study on CLSC for deteriorating products is a hot topic in recent years [5, 14]. There are several research branches in this research area. We just review three important directions that are related to our problem. The first direction is about studies on RTIs. Hellström and Johansson [8] presented the impact of controlling the RTIs. In [11], Singh and Saxena presented a closed loop structure with remanufacturing of a single item, and determined the optimal replenishment cycle. Kim et al. [10] considered the return time of RTIs to be stochastic and derived the expected costs of the whole system. Kim and Glock [9] used an RFID system to support the tracking of RTIs positions in the supply chain to get a higher return rate. The second one is the studies on different demand and deterioration

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functions. Skouri et al. [12] analyzed the model with ramp type demand rate, partial backlogging and Weibull deterioration rate. Studies on algorithm designs is the third direction. Devika [1] and Diabat [2] used metaheuristics hybridization techniques and genetic algorithms to obtain the optimal solution. Fahimnia et al. [3] presented a tactical model to minimize the cost of the system by incorporating multiple transport lot sizing and flexible holding capacity of warehouses.

In our CLSC problem, the critical parameter about RTIs' return time is quite uncertain due to various reasons. The significance of uncertainty motivates us to develop a new mean-standard deviation stochastic optimization method for our CLSC problem, in which the standard deviation is suggested to gauge the risk resulted from stochastic uncertainty. What's more, we depict the RTIs' return time as a uniform distribution variable to illustrate its randomness. In the distribution interval, we choose two points, which are the point on which shortage just occurs and the point on which we lose all of the sales opportunities, then the interval is divided into three parts. We obtain the different cost functions in each case. At last, we turn our mean-standard deviation model into an equivalent determinate one. To indicate the effectiveness of our model, we discuss the impact of the risk preference parameter on decision results.

The remainder of the paper is structured as follows. The next section outlines the CLSC problem and proposes a mean-standard deviation model. Section 3 turns the proposed mean-standard deviation model with stochastic return times into an equivalent determinate model. Some numerical experiments are performed to demonstrate the new modeling idea and the effectiveness in Section 4. Section 5 concludes the paper.

2 The Mean-Standard Deviation CLSC Problem

In this section, we consider a closed-loop supply chain consisting of a single supplier and a single buyer. The supplier produces deteriorating products at the rate of P and ships them in batches to the buyer. On account that the RTI has the function of keeping fresh, we assume that product in transit will not go bad. When products arrive, the buyer takes out the goods from RTIs and shelves them. Furthermore, the buyer collects, sorts and cleans these RTIs. Finally RTIs are returned to the supplier. We call this process a lead time (a cycle), in which the buyer decides how many goods to be ordered and the supplier finishes the consignment of goods. We consider the average cost after N orders in one year. In each order, our supply chain will produce setup cost, order cost, inventory cost of the products and the RTIs. In our paper, we calculate these costs in one year and minimize the average cost. Moreover, the cost with higher deviation from the expected average is not expected. In other words, we would better minimize the standard deviation while minimizing the expected cost.

For convenience, we make the following assumptions to simplify our problem:

A1 Both the time the supplier fulls the RTIs and the time the buyer empties the RTIs are not considered;

A2 RTIs with products are not charged, and only those empty RTIs are charged;

A3 When the RTIs' return time is longer than expected time, the products will deteriorate, appropriate discount will be considered;

A4 Products are produced in batch, and half box products are not allowed;

A5 Different order quantity has the same order cost;

A6 The market demand is assumed to be constant.

In addition, we use the following terminology throughout our paper:

Fixed parameters:

S : setup cost at the supplier;

A : order cost, including shipment cost at the buyer;

P_0 : selling price for non-deteriorated products;

L_0 : expected lead time ($L_0 > 0$);

θ : price discount factor;

α : transport capacity of one RTI;

π : shortage cost factor for finished products at the supplier;

D : demand of finished products at the buyer;

P : production at the supplier;

g_b : inventory carrying charge for RTIs at the buyer;

g_s : inventory carrying charge for RTIs at the supplier;
h_b : inventory carrying charge for finished products at the buyer;
h_s : inventory carrying charge for finished products at the supplier;

Decision variables:
Q : the total number of products;
n : return lot size of RTIs ($n = Q/\alpha$);
N : The number of orders every year ($N = D/Q$);

Random variable:
t : a lead time or a cycle time the chain used that follows a uniform distribution on $[L_l, L_r]$;

Related functions:
$p(t, Q)$: selling price after a delay of $(t - L_0)$ units of time $(t \geqslant L_0)$;
$F(\cdot)$: cumulative distribution function of lead time;
$f(\cdot)$: probability density function of lead time.

As for the entire system, we first calculate the total cost of the supply chain system in one order and denote it as $w(Q, t)$. Then the annual cost is $W(Q, t) = Nw(Q, t)$. Furthermore, we denote the expected total cost as $E_t[W(Q, t)]$ and the standard deviation of the total cost as $V_t[W(Q, t)]$. Thus, our target is to minimize $E_t[W(Q, t)]$ and also minimize $V_t[W(Q, t)]$. Therefore we proposed the following model for one year:

$$\begin{cases} \min & \lambda \cdot E_t[W(Q,t)] + (1-\lambda) \cdot V_t[W(Q,t)] \\ \text{s.t.} & Q = n\alpha \\ & n \in N^+ \\ & Q \geqslant 0, \end{cases} \tag{1}$$

where λ expresses the degree of the decision makers' willingness to take risk. $\lambda = 1$ indicates that the decision makers are risk-takers. $\lambda = 0$ indicates that the decision makers are very conservative. The first constraint declares that our products are sold in batches, and the second one illustrates that half box is not allowed.

3 Model Analysis

In this section, we assume the RTIs return time follows a uniform distribution on $[L_l, L_r]$. Two points are selected to divide the interval $[L_l, L_r]$ into three subintervals, which are the point shortages just occur and the point we lose all of the sales opportunities. Our model is analyzed in three cases.

Case I. RTIs are returned before the lot has been completed and no shortages occur at the supplier.

In this case, the return shipment arrives after t units of time with $L_l \leqslant t \leqslant L_0$. The total costs include the setup cost, order cost, inventory carrying charge for RTIs at the buyer, inventory carrying charge for RTIs at the supplier, inventory carrying charge for finished products at the buyer and inventory carrying charge for finished products at the supplier. By calculation, the inventory carrying charge for RTIs at the buyer is $g_b \alpha n (n-1)/2D$, the inventory carrying charge for RTIs at the supplier is $(L_0 - t)\, n g_s$, the inventory carrying charge for finished products at the buyer is $h_b Q^2/2D$, the inventory carrying charge for finished products at the supplier is $h_s Q^2/2P$. As a consequence, the total costs function $w(Q, t)$ for one order is represented as follows:

$$w_a(Q,t) = S + A + \frac{\alpha n (n-1)}{2D} g_b + (L_0 - t)\, n g_s + \frac{Q^2}{2D} h_b + \frac{Q^2}{2P} h_s. \tag{2}$$

Case II. RTIs are returned after the lot has been completed at the supplier, and shortages occur, but there still has sales opportunity.

In this case, the return shipment arrives after t units of time with $L_0 \leqslant t \leqslant L_0 + Q/D$. Due to the lost of sale opportunities, the buyer reduce the order of products at the rate of D. Thus, before the sale opportunities have been completely lost, the buyer order $\widetilde{n}$ units of products, where $\widetilde{n} = (Q - (t - L_0)\, D)/\alpha$. The total costs include the setup cost, order cost, inventory carrying charge for RTIs at the buyer, inventory carrying charge for finished products at the buyer, inventory carrying charge for finished products at the supplier, shortage cost for finished products at the buyer, and the lose caused by deterioration. By calculation, the inventory carrying charge for RTIs at the buyer is $g_b\alpha\widetilde{n}\,(\widetilde{n}-1)/2D$, the inventory carrying charge for finished products at the buyer is $h_b(Q-(t-L_0)\,D)^2 2D$, the inventory carrying charge for finished products at the supplier is $\left(Q^2/2P+(t-L_0)\,Q\right)h_s$, the shortage cost for finished products at the buyer is $(t-L_0)^2\,D\pi/2$, the lose caused by deterioration is $QP_0\left(1-e^{-Q\theta(t-L_0)}\right)$. Then, for one order, we can get the total cost

$$\begin{aligned} w_b\,(Q,t) =& S+A+\frac{\alpha\widetilde{n}\,(\widetilde{n}-1)}{2D}g_b+\left(\frac{Q^2}{2P}+(t-L_0)\,Q\right)h_s+\frac{(t-L_0)^2\,D\pi}{2} \\ &+\frac{(Q-(t-L_0)\,D)^2}{2D}h_b+QP_0\left(1-e^{-Q\theta(t-L_0)}\right). \end{aligned} \tag{3}$$

Case III. RTIs are returned late and shortages occur, and the sales opportunity is lost.

In this case, the return shipment arrives after t units of time with $L_0+Q/D\leqslant t\leqslant L_r$. And the total costs include the setup cost, order cost, inventory carrying charge for finished products at the supplier, shortage cost for finished products at the buyer and the lose caused by deterioration. After calculation, the inventory carrying charge for finished products at the supplier is $\left(Q^2/2P+(t-L_0)\,Q\right)h_s$, the shortage cost for finished products at the buyer is

$$\frac{Q^2}{2D}\pi+\left(t-L_0-\frac{Q}{D}\right)Q\pi,$$

the the lose caused by deterioration is $QP_0\left(1-e^{-Q\theta(t-L_0)}\right)$. The total cost function $w\,(Q,t)$ is

$$w_c\,(Q,t)=S+A+\left(\frac{Q^2}{2P}+(t-L_0)\,Q\right)h_s+\frac{Q^2}{2D}\pi+\left(t-L_0-\frac{Q}{D}\right)Q\pi+QP_0\left(1-e^{-Q\theta(t-L_0)}\right). \tag{4}$$

Based on the above analyses, the expected annual total cost of the supply chain system is obtained as the following formula:

$$\begin{aligned} E_t[W\,(Q,t)] &= \int_{L_l}^{L_0} W_a\,(Q,t)\,f\,(t)\,dt+\int_{L_0}^{L_0+\frac{Q}{D}} W_b\,(Q,t)\,f\,(t)\,dt+\int_{L_0+\frac{Q}{D}}^{L_r} W_c\,(Q,t)\,f\,(t)\,dt \\ &= \int_{L_l}^{L_0} Nw_a\,(Q,t)\,f\,(t)\,dt+\int_{L_0}^{L_0+\frac{Q}{D}} Nw_b\,(Q,t)\,f\,(t)\,dt+\int_{L_0+\frac{Q}{D}}^{L_r} Nw_c\,(Q,t)\,f\,(t)\,dt \\ &= \frac{N}{L_r-L_l}\{A_a(L_0-L_l)+\frac{1}{2}ng_s(L_0-L_l)^2+A_b\frac{Q}{D}+\frac{1}{2}B_b\frac{Q^2}{D^2}+\frac{1}{3}C_b\frac{Q^3}{D^3} \\ &\quad +\frac{P_0}{\theta}(\exp(\frac{-Q^2\theta}{D})-1)+A_c(L_r-L_0-\frac{Q}{D})+\frac{1}{2}B_c((L_r-L_0)^2-\frac{Q^2}{D^2}) \\ &\quad +\frac{P_0}{\theta}(\exp(-Q\theta(L_r-L_0))-\exp(\frac{-Q^2\theta}{D}))\}. \end{aligned} \tag{5}$$

Since the variance of the total costs is

$$V_t^2[W\,(Q,t)]=\int_{L_l}^{L_0} W_a^2\,(Q,t)\,f\,(t)\,dt+\int_{L_0}^{L_0+\frac{Q}{D}} W_b^2\,(Q,t)\,f\,(t)\,dt+\int_{L_0+\frac{Q}{D}}^{L_r} W_c^2\,(Q,t)\,f\,(t)\,dt-E_t^2[W\,(Q,t)],$$

the standard deviation of the total costs is

$$\begin{aligned} & V_t[W\,(Q,t)] \\ =& \left(\int_{L_l}^{L_0} W_a^2\,(Q,t)\,f\,(t)\,dt+\int_{L_0}^{L_0+\frac{Q}{D}} W_b^2\,(Q,t)\,f\,(t)\,dt+\int_{L_0+\frac{Q}{D}}^{L_r} W_c^2\,(Q,t)\,f\,(t)\,dt-E_t^2W\,(Q,t)\right)^{\frac{1}{2}}. \end{aligned}$$

For the above three integrals, we have the following calculated results:

$$\int_{L_l}^{L_0} W_a^2\,(Q,t)\,f\,(t)\,dt = \frac{N^2}{L_r-L_l}\{A_a^2(L_0-L_l)+\frac{1}{3}n^2g_s^2(L_0-L_l)^3+A_ang_s(L_0-L_l)^2\}, \tag{6}$$

$$\begin{aligned}\int_{L_0}^{L_0+\frac{Q}{D}} W_b^2\,(Q,t)\,f\,(t)\,dt \quad = \quad & \frac{N^2}{L_r-L_l}\{A_b^2\frac{Q}{D}+A_bB_b\frac{Q^2}{D^2}+\frac{1}{3}(B_b^2+2A_bC_b)\frac{Q^3}{D^3}+\frac{1}{2}B_bC_b\frac{Q^4}{D^4} \\ & +\frac{1}{5}C_b^2\frac{Q^5}{D^5}-\frac{P_0^2Q}{2\theta}(\exp(\frac{-2Q^2\theta}{D})-1)+\frac{2A_bP_0}{\theta}(\exp(\frac{-Q^2\theta}{D})-1) \\ & +\frac{2B_bP_0}{\theta^2Q}[(\frac{Q^2\theta}{D}+1)\exp(\frac{-Q^2\theta}{D})-1] \\ & +\frac{2C_bP_0}{\theta^3Q^2}[(\frac{2Q^2\theta}{D}+\frac{Q^4\theta^2}{D^2}+2)\exp(\frac{-Q^2\theta}{D})-2]\},\end{aligned} \tag{7}$$

$$\begin{aligned}\int_{L_0+\frac{Q}{D}}^{L_r} W_c^2\,(Q,t)\,f\,(t)\,dt \quad = \quad & \frac{N^2}{L_r-L_l}\{A_c^2(L_r-L_0-\frac{Q}{D})+\frac{1}{3}B_c^2[((L_r-L_0)^3-\frac{Q^3}{D^3})] \\ & +A_cB_c[((L_r-L_0)^2-\frac{Q^2}{D^2})]-\frac{P_0^2Q}{2\theta}(\exp(-2Q\theta(L_r-L_0)) \\ & -\exp(\frac{-2Q^2\theta}{D}))+\frac{2A_cP_0}{\theta}(\exp(-Q\theta(L_r-L_0))-\exp(\frac{-Q^2\theta}{D})) \\ & -\frac{2B_bP_0}{\theta^2Q}[\exp(-Q\theta(L_r-L_0))(-Q\theta(L_r-L_0)-1) \\ & +\exp(\frac{-Q^2\theta}{D})(\frac{Q^2\theta}{D}+1)]\},\end{aligned} \tag{8}$$

where

$$\begin{aligned} A_a &= S+A+\frac{\alpha n\,(n-1)}{2D}g_b+\frac{Q^2}{2D}h_b+\frac{Q^2}{2P}h_s, \\ A_b &= S+A+\frac{Q^2}{2D}(\frac{g_b}{\alpha}+h_b)-\frac{Q}{2D}g_b+\frac{Q^2}{2P}h_s+QP_0, \\ B_b &= (\frac{1}{2}-\frac{Q}{\alpha})g_b, \\ C_b &= \frac{D}{2}(\frac{g_b}{\alpha}+h_b+\pi), \\ A_c &= S+A+\frac{Q^2}{2P}h_s-\frac{Q^2}{2D}\pi+QP_0, \\ B_c &= Q(h_s+\pi). \end{aligned}$$

As a consequence, model (1) can be turned into the following equivalent determinate programming model:

$$\begin{cases} \min & \lambda\cdot E_t[W\,(Q,t)]+(1-\lambda)\cdot(\int_{L_l}^{L_0} W_a^2\,(Q,t)\,f\,(t)\,dt+\int_{L_0}^{L_0+\frac{Q}{D}} W_b^2\,(Q,t)\,f\,(t)\,dt \\ & +\int_{L_0+\frac{Q}{D}}^{L_r} W_c^2\,(Q,t)\,f\,(t)\,dt-E_t^2[W\,(Q,t)])^{\frac{1}{2}}. \\ \text{s.t.} & Q=n\alpha \\ & n\in N^+ \\ & Q\geqslant 0. \end{cases} \tag{9}$$

where $E_t[W\,(Q,t)]$ is calculated by equation (5), three integrals $\int_{L_l}^{L_0} W_a^2\,(Q,t)\,f\,(t)\,dt$, $\int_{L_0}^{L_0+\frac{Q}{D}} W_b^2\,(Q,t)\,f\,(t)\,dt$ and $\int_{L_0+\frac{Q}{D}}^{L_r} W_c^2\,(Q,t)\,f\,(t)\,dt$ are calculated by equations (6), (7) and (8), respectively.

Model (9) is a mixed-integer programming problem, which can be solved directly by general purpose software such as MATLAB and LINDO.

4 Numerical Experiment

We assume that the supplier produce products in batches, and each RTI contains 200 kilograms of products. The supplier must pay 20000 dollars for per setup cost while the buyer pay 10000 dollars for per order. If

RTIs are returned before the lot has been completed, they will be charged for 36000 dollars per container per year. For the supplier, there is no inventory cost of the products in this case. For the buyer, 11 dollars per kilogram per year and 36000 dollars per emptied container per year will be charged for inventory cost. However, if shortages occur, the supplier will be charged 11 dollars per kilogram per year and the buyer will be charged 238 dollars per unit per unit shortage per year. What's more, the products begin to deteriorate, the price discount factor is $\theta = 1.5$. We assume that the RTIs' returned time follows a uniform distribution on [0.013,0.063]. So the expected return time is 0.038 year. All the parameters are given annually in Table 1.

Table 1: The values of parameters in the CLSC problem (9)

parameters	S	A	α	p_0	$g_s = g_b$	θ
reference data	20 $k\$/order$	10 $k\$/order$	0.2 kkg	10 $\$/kg$	36 $k\$/container$	1.5
parameters	$h_s = h_b$	D	P	π	$[L_l, L_r]$	
reference data	11 $\$/kg$	4800 kkg	5400 kkg	238 $\$/unit$	$[0.013, 0.063]$ $(year)$	

If we take $\lambda = 1$, the objective function is to minimize the expected value, that is to say, the impact of the risk is not considered. In this case, we have

$$W_a(Q,t) = \frac{4800}{0.2\times n} \times (20 + 10 + \frac{0.2\times n(n-1)}{2\times 4800} \times 36 + (0.038 - t)\, n \times 36 + \frac{(0.2\times n)^2}{2\times 4800} \times 11 + \frac{(0.2\times n)^2}{2\times 5400} \times 11);$$

$$W_b\,(Q,t) = \frac{4800}{0.2\times n} \times (20 + 10 + \frac{0.2\tilde{n}(\tilde{n}-1)}{2\times 4800} \times 36 + \Big(\frac{(0.2\times n)^2}{2\times 5400} + (t-0.38) \times (0.2\times n)\Big) \times 11$$
$$+ \frac{(t-0.38)^2 \times 4800 \times 238}{2} + \frac{((0.2\times n) - (t-0.38)\times 4800)^2}{2\times 4800} \times 11 + 0.2 \times n \times 10\left(1 - e^{-0.2\times n\times 1.5\times (t-0.38)}\right));$$

$$W_c\,(Q,t) = \frac{4800}{0.2\times n} \times (20 + 10 + \Big(\frac{(0.2\times n)^2}{2\times 5400} + (t-0.038) \times 0.2 \times n\Big) \times 11 + \frac{(0.2\times n)^2}{2\times 4800} \times 238$$
$$+ \left(t - 0.038 - \frac{0.2\times n}{4800}\right) \times 0.2 \times n \times 238 + 0.2 \times n \times 10\left(1 - e^{-0.2\times n\times 1.5\times (t-0.038)}\right)).$$

It is difficult to prove that the programming problem is convex, but as shown in Figure 1, the objective function is convex when $\lambda = 1$. Since the number of RTIs is integer, we derive the optimal solution is $n = 117$, $Q = 23400$ kilograms, and the minimum cost $E_t[W(Q,t)]$=27039 thousand dollars. Furthermore, we illustrate the impact of different risk preference degrees on the optimal solution Q in Table 2 and Figure 2.

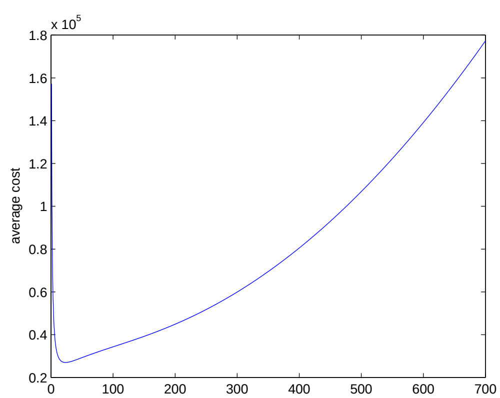

Figure 1: Average cost when $\lambda = 1$

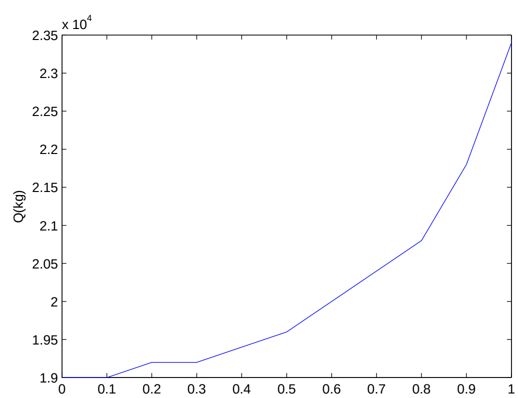

Figure 2: Optimal solutions of Q under different λ

From Table 2 and Figure 2, we can obtain the following observations: (i) If we only minimize the annual cost, we should produce 23.4 thousand kilograms products. The expected annual cost is 27039 thousand dollars accordingly. But the standard deviation is 134470 thousand dollars, which is very high. That is to say, there is a high risk that may probably bankrupt our entire enterprises in the closed-loop supply chain. (ii) As λ increases, the optimal quantity of products and the minimum cost also increase. In other words, standard deviation can be another index considered by decision makers as the lot size increases.

Table 2: Optimal solutions and minimum costs with various values of λ

λ	1	0.9	0.8	0.7	0.6	0.5
$Q(kkg)$	23400	21800	20800	20400	20000	19600
n	117	109	76	104	100	98
min cost ($k\$$)	27039	27062	27105	27129	27158	27191
λ	0.4	0.3	0.2	0.1	0	
$Q(kkg)$	19400	19200	19200	19000	19000	
n	97	96	96	95	95	
min cost ($k\$$)	27210	27230	27230	27252	27252	

5 Conclusions

On the basis of risk-averse criterion, we studied the issue about stochastic closed-loop supply chain for deteriorating items and obtained the following major results.

Firstly, a mean-standard deviation model was developed for a CLSC problem with deteriorating products, in which the return time of container is random.

Secondly, when the return time follows uniform distribution, we analyzed the proposed optimization model in three different cases. The mean and standard deviation of the stochastic total cost can be turned into its equivalent deterministic analytical expressions. The obtained equivalent optimization models can be solved by conventional optimization softwares.

Finally, we conducted several numerical experiments to analyze the impact of the risk preference parameter on the optimal quantity of products and the total costs. From the computational results, we observed that when the scale of production increases, the risk increases too. For our risk-averse optimization model, the optimal solution to risk-neutral optimization model is not optimal.

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