ICIC Express Letters
Part B: Applications
Volume **11**, Number **12**, December **2020**

ICIC International ©2020 ISSN 2185-2766
pp. 1173–1180

RESEARCH OF RETAILER REMANUFACTURING PRODUCT INVENTORY OPTIMIZATION MODEL BASED ON AFFINE ADJUSTABLE ROBUST METHOD

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Received March 2020; accepted June 2020

Abstract. *In view of the fact that the market demand for remanufactured products does not obey the probability distribution and does not fluctuate within a certain interval, this paper uses the affine-adjustable robust method to establish a more realistic multi-cycle robust optimization model for retailers of remanufactured products, which effectively circumvents the impact of uncertainty requirements on remanufactured product inventory. An example study was carried out in the ROME environment using Matlab. The results show that the demand information of the first cycle has a great impact on the optimal ordering strategy in each following cycle, most significantly, the second cycle and the last two.*

Keywords: Inventory management, Robust optimization, Affine scalable robust method, Retailer

1. **Introduction.** As the problem of resource shortage and pollution goes on, the recycling of used products has received more and more attention. However, the recycling industry is still in its infancy in China. Consumers' understanding and recognition of recycled products is still fairly low. The market demand for recycled products is very unstable, which makes it difficult for recycled product retailers to effectively determine their inventory levels [1]. In addition, there are uncertainties in the timing, quality and quantity of waste product recycling [2], which makes recycling product inventory management more complicated. To solve problem of the uncertain market demand for current recycled products, this paper describes using robust optimization method to establish an inventory optimization model for retailers of recycled products. The robust optimization inventory model not only solves the problems of the over-reliance on prior knowledge and statistics in the past optimization model, but it also solves all the uncertain parameters.

DOI: 10.24507/icicelb.11.12.1173

The research on the use of robust optimization methods to solve inventory problems mainly focuses on two aspects.

The first aspect is the analysis of demand uncertainty issues. In [3], use robust models to solve the complex question of stable stockings and the network/inventory management problem of pulp production. In [4], the robust optimization generates scenario-based plans by a minimax optimization method to find optimal scenario for the trade-off between target coverage robustness and organ-at-risk (OAR) sparing. In [5], consider a generic class of adaptive optimization problems under uncertainty, and develop a data-driven paradigm of adaptive probabilistic robust optimization (APRO) in a robust and computationally tractable manner. In [6], the general scalar robust optimization problems under the strictly robust counterpart are considered, among which, the uncertainties are included in the objective as well as the constraints. The second aspect is the study of the uncertainty of demand. In [7], address the robust counterpart of a classical single machine scheduling problem by considering a budgeted uncertainty and an ellipsoidal uncertainty. In [8], it introduces a new uncertainty class which is a combination of budgeting uncertainty and ellipsoidal uncertainty. In [9], study the performance of affine policies for two-stage adjustable robust optimization problem with fixed recourse and uncertain right-hand side belonging to a budgeted uncertainty set. In [14], use the affine-adjustable robust method (AARM) to effectively control inventory under the uncertainty of demand. In [11], establish a multi-cycle robust optimization model based on the influencing factors of demand. This model emphasized the requirement to set the next cycle of demand as a function of the previous cycles to solve the inventory problem of the enterprise. In [12], use the affine robust optimization method to solve the inventory coordination and return problems of multi-cycle and multi-products.

The list above provides a lot of decision-making basis for solving the inventory optimization problem, but it also has certain limitations. Based on the limitations, there are two innovations being as follows: one is that it has broken through the disadvantages of too many uncertain parameters in the past optimization models, relying on prior knowledge, and assuming that the demand obeys the probability distribution; the other one is that the model could be used to all uncertain parameters.

2. **Model.**

2.1. **Description of the problem.**

Unlike the supply and sale process of a new product, retailers of remanufactured products face more uncertainties. The change in the quality and quantity of waste products happens, resulting in the final delivery time of remanufactured products is often unstable. At the same time, market demand for remanufactured products is often in an irregular state due to seasonality, government policies, and customer perceptions of remanufactured products. Therefore, retailers need to consider the above-mentioned factors to determine their reasonable inventory levels to achieve the goal of minimizing inventory management costs and maximizing customer satisfaction.

2.2. **Model parameters.**

J: the types of products; p_j^t: the fee to buy unit product of j in period t, $j = 1, 2, \ldots, J$; q_j^t: the order quantity of product j in period t, $j = 1, 2, \ldots, J$; d_j^t: the demand of product j in period t, $j = 1, 2, \ldots, J$; h_j^t: the fee of lost-sales of unit product of j in period t, $j = 1, 2, \ldots, J$; c_j^t: storage cost of unit product of j in period t, $j = 1, 2, \ldots, J$; I_j^t: the inventory of product of j at the beginning of period t, $j = 1, 2, \ldots, J$; $I^t(j)$: the total inventory of product of j at the beginning of period t, $j = 1, 2, \ldots, J$; s_j: the maximum inventory of product of j; $q_j^t\left(d_j^{t-1}\right)$: the order of product j in period t, according to d_j^{t-1}.

2.3. **Model establishment.** The inventory cost in period t, includes ordering cost, inventory cost, lost-sale cost. Ordering cost: $\sum_{j=1}^{J} p_j^t q_j^t$; Inventory cost: $\sum_{j=1}^{J} c_j^t \max\left(I_j^t + q_j^t - d_j^t, 0\right)$; Lost-sale cost: $\sum_{j=1}^{J} h_j^t \max\left(d_j^t - I_j^t - q_j^t, 0\right)$. The inventory in period $t+1$: $I_j^{t+1} = I_j^t + q_j^t - d_j^t$, $I^{t+1} = \sum_{j=1}^{J} I_j^{t+1}$.

Let $[x, y]^+ = \max\{x, y, 0\}$, and then the inventory cost and the lost-sale cost in period t can be expressed as: $\sum_{j=1}^{J} c_j^t \left[I_j^t + q_j^t - d_j^t, 0\right]^+$, $\sum_{j=1}^{J} h_j^t \left[d_j^t - I_j^t - q_j^t, 0\right]^+$. When the demand is stochastic, the optimal model for minimized inventory cost can be expressed as:

$$\begin{aligned} \min_{q_j^t}\ & E\left[\sum_{t=1}^{T}\sum_{j=1}^{J} p_j^t q_j^t + \left(c_j^t I_j^{t+1}, -h_j^t I_j^{t+1}\right)^+\right] \\ \text{s.t.}\ & I_j^{t+1} = I_j^t + q_j^t - d_j^t, \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \\ & I_j^t + q_j^t - d_j^t \le s_j, \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \\ & q_j^t\left(d_j^{t-1}\right) \ge 0,\ I_j^1 = 0, \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \end{aligned} \tag{1}$$

The objective function is: minimize the subscription fee plus storage fee or out of stock cost; the first constraint is the relationship between the inventory of the $t+1$ period and the previous t period, the second constraint is the maximum inventory capacity limit, and the third constraint is that the order quantity is greater than zero.

2.4. **Factor-based inventory demand model.** In the factor-based inventory demand model, the demand for product j ($j \in J$) is an affine function of uncertain factor $\overline{z_{jk}}$, ($k = 1, 2, \ldots, K_t$, $1 \le K_1 \le K_2 \le \cdots \le K_T$). As the demand d_j^t occurs, the uncertain factor $\overline{z_{jk}}$ appears. At the beginning of period t, the factor $\overline{z_{jk}}$, ($k = 1, 2, \ldots, K_{t-1}$) appears. Then at the end of period t, the factor $\overline{z_{jk}}$ ($k = K_{t-1}+1, K_{t-1}+2, \ldots, K_t$) appears. Let $K_t = \{1, 2, \ldots, K_t\}$, $K_t^0 = \{0, 1, 2, \ldots, K_t\}$, $\overline{z_j} = (\overline{z_{j1}}, \overline{z_{j2}}, \ldots, \overline{z_{jK_t}})$, $z_j = (z_{j1}, z_{j2}, \ldots, z_{jK_t})$, and then one could get the demand d_j^t for product j in period t is an affine function of $\overline{z_j}$: $d_j^t\left(\overline{z_j}^t\right) = d_j^{t,0} + \sum_{k \in K_t} d_j^{t,k}\overline{z_{jk}}$, $1 \le t \le T$.

Hypothesis 2.1. *The uncertain factor $\overline{z}$ has an un-known probability distribution, and $\overline{z} \in w$ (support set w is a full-dimensional convex polyhedron containing uncertainties). Let the uncertain factor $\overline{z}$'s mean support set be $\overline{w}$. As the retailer aims to minimize the worst-case inventory management cost in the factor-based demand model, one gets the robust optimization model is:*

$$\begin{aligned} \min \max_{P \in U} & E_P\left[\sum_{t=1}^{T}\sum_{j=1}^{J} p_j^t q_j^t\left(\overline{z^{t-1}}\right) + x_j^t\left(\overline{z^t}\right)\right] \\ \text{s.t.}\ & c_j^t I_j^{t+1}\left(\overline{z^t}\right) \le x_j^t\left(\overline{z^t}\right),\ -h_j^t I_j^{t+1}\left(\overline{z^t}\right) \le x_j^t\left(\overline{z^t}\right) \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \\ & I_j^{t+1}\left(\overline{z_j^{t+1}}\right) = I_j^t\left(\overline{z^t}\right) + q_j^t\left(\overline{z^t}\right) - d_j^t\left(\overline{z^t}\right) \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \\ & I_j^t + q_j^t - d_j^t \le s_j \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \\ & q_j^t\left(z^{t-1}\right) \ge 0,\ I_j^1\left(\overline{z^0}\right) = 0,\ I_j^t, q_j^t \in F_{K_{t-1}} \quad 1 \le t \le T,\ j = 1, 2, \ldots, J \end{aligned} \tag{2}$$

The objective function of the model is: minimize the subscription cost + storage fee or out-of-stock cost; the first constraint is the equilibrium condition of the inventory; the second constraint is the capacity limitation condition of the inventory; the third constraint is the capacity constraint of the inventory; the fourth constraint is the initial conditions of the inventory.

3. **Model Transformation.** Since the model (2) is a nonlinear problem and is not easy to solve, it is transformed into a linear optimization problem that is easy to solve. Under Hypothesis 2.1, the objective function can be transformed into:

$$\max_{P\in U} E_P\left[\sum_{t=1}^{T}\sum_{j=1}^{J} p_j^t q_j^t\left(\overline{z^{t-1}}\right)+x_j^t\left(\overline{z^t}\right)\right]=\max_{z\in\overline{w}}\sum_{t=1}^{T}\sum_{j=1}^{J}\left[p_j^t q_j^t\left(z^{t-1}\right)+x_j^t\left(z^t\right)\right]$$

Equation (2) could be expressed as:

$$\begin{aligned}
&\min\ \max_{z\in\overline{w}}\sum_{t=1}^{T}\sum_{j=1}^{J}\left[p_j^t q_j^t\left(z^{t-1}\right)+x_j^t\left(z^t\right)\right]\\
&\text{s.t.}\quad c_j^t I_j^{t+1}\left(z^t\right)\le x_j^t\left(z^t\right),\ -h_j^t I_j^{t+1}\left(z^t\right)\le x_j^t\left(z^t\right) && 1\le t\le T,\ j=1,2,\dots,J\\
&\qquad I_j^{t+1}\left(z^{t+1}\right)=I_j^t\left(z^t\right)+q_j^t\left(z^t\right)-d_j^t\left(z^t\right) && 1\le t\le T,\ j=1,2,\dots,J\\
&\qquad I_j^t+q_j^t-d_j^t\le s_j && 1\le t\le T,\ j=1,2,\dots,J\\
&\qquad q_j^t\left(z^{t-1}\right)\ge 0,\ I_j^1(z^0)=0,\ I_j^t,q_j^t\in F_{K_{t-1}} && 1\le t\le T,\ j=1,2,\dots,J
\end{aligned}\tag{3}$$

where $\overline{S}=\left\{z\in R^{K_T}|\exists u\in z\in R^{N_b}:\overline{A}z+\overline{B}u\le\overline{q}\right\}$, $\overline{w}=\left\{z\in R^{K_T}:z\in G,z\in\overline{S}\right\}$.

Model (3) is a robust optimization problem that is difficult to solve and needs to be transformed into a linear programming problem that is easy to solve. For the transformation model (3), the duality theory, Lemma 3.1, is introduced.

Lemma 3.1. *The "Necessary and Sufficient Condition" of* $\max_{z\in\overline{w}} z^T y\le r$ *is* $\exists\beta\in R^N$, $\alpha^t\in R^M$ $(t\in T)$*, satisfying:* $\sum_{t=1}^{T}\left(d^{t,0}\right)'\alpha^t+\beta' q\le r$, $\sum_{t=1}^{T}\left(-D^t\right)\alpha^t+A'\beta=y$, $B'\beta=0$, $\beta\ge 0$, $\alpha^t\ge 0$, $t\in T$.

In order to transform the nonlinear robust optimization problem into a linear programming problem that is easy to solve, Theorem 3.1 is proposed in this paper.

Theorem 3.1. *Under the linear ordering strategy, the optimal problem* $\min\phi$ *has a solution and the problem equals the linear programing, which is easy to solve.*

$$\begin{aligned}
&\min\phi\\
&\text{s.t.}\ \sum_{t=1}^{T}\left(d^{t,0}\right)'\alpha^t+\beta' q\le\phi-\varphi_0,\ \sum_{t=1}^{T}\left(-D^t\right)\alpha^t+A'\beta=\varphi,\ B'\beta=0 && \beta\ge 0,\ \alpha^t\ge 0,\ t\in T\\
&\varphi_k=\sum_{t=1}^{T}\sum_{j\in J}\left(q_j^{t,k}+x_j^{t,k}\right),\ m_j^{t,k}=c_j^t I_j^{t+1,k}-x_j^{t,k} && k\in K_T,\ t\in T\\
&m_j^{t,0}+\sum_{k=1}^{K_t} m_j^{t,k}z_k\le 0,\ n_j^{t,k}=-h_j^t I_j^{t+1,k}-x_j^{t,k},\ n_j^{t,0}+\sum_{k=1}^{K_t} n_j^{t,k}z_k\le 0 && j\in J,\ k\in K_T,\ t\in T\\
&\varphi_k=\sum_{t=1}^{T}\sum_{j\in J}\left(q_j^{t,k}+x_j^{t,k}\right),\ m_j^{t,k}=c_j^t I_j^{t+1,k}-x_j^{t,k},\ m_j^{t,0}+\sum_{k=1}^{K_t} m_j^{t,k}z_k\le 0 && j\in J,\ k\in K_T,\ t\in T\\
&H_j^{t,0}+\sum_{k\in K_t} H_j^{t,k}\le s_j,\ q_j^{t,0}+\sum_{k\in K_{t-1}} q_j^{t,k}z_k\ge 0 && j\in J,\ k\in K_T,\ t\in T\\
&I_j^{t+1,k}=x_j^{t,k}=q_j^{t,k}=0 && j\in J,\ k\in K_T\backslash K_t,\ t\in T
\end{aligned}$$

4. **Case Analysis.** Taking Jinnan Fuqiang Power Co., Ltd. WD615.87 remanufactured engine as an example, the impact of uncertainty demand on retailer inventory was analyzed. From [12], consider a 12 period inventory problem.

Let the support set of uncertain factor $(z_1,z_2,\dots,z_{11})$ be $w=\{z:-5\le z_k\le 5,\ k=1,\dots,12\}$, the mean support set is $\overline{w}=\{0\}$. Since $w\subset G$, there is sufficient inventory to meet maximum demand $(z_k=1)$, which is $\sum_{k=1}^{12} z_k y_k\le r\Leftrightarrow\sum_{k=1}^{12}|y_k|\le r$. Therefore, it can be converted into a standard linear constraint. The optimization problem under the above conditions is equivalent to

$$
\begin{aligned}
\min \quad & \sum_{t=1}^{12}\sum_{j=1}^{J}\left(x_j^{t,0}+p_j^t q_j^{t,0}\right) \\
\text{s.t.} \quad & -x_j^{t,0}+c_j^t I_j^{t+1,0}+\sum_{k=1}^{6}\left|c_j^t I_j^{t+1,k}-x_j^{t,k}\right| \le 0 && j=1,\ t=1,2,\ldots,12 \\
& -x_j^{t,0}-h_j^t I_j^{t+1,0}+\sum_{k=1}^{6}\left|-h_j^t I_j^{t+1,k}-x_j^{t,k}\right| \le 0 && j=1,\ t=1,2,\ldots,12 \\
& I_j^{t+1,k}=I_j^{t,k}+q_j^{t,k}-d_j^{t,k}, -q_j^{t,0}+\sum_{k=1}^{6}\left|q_j^{t,k}\right| \le 0 && j=1,\ t=1,2,\ldots,12,\ k=1,2,\ldots,6 \\
& I_j^{1,0}+q_j^{t,0}-d_j^{t,0}+\sum_{k=1}^{6}\left|I_j^{t+1,k}+q_j^{t,k}-d_j^{t,k}\right| \le s_j && j=1,\ t=1,2,\ldots,12,\ k=1,2,\ldots,6 \\
& I_j^1\left(\overline{z^0}\right)=0,\ I_j^{t,k}=x_j^{t,k}=q_j^{t,k}=0 && j=1,\ k=2(t-1)+1,\ldots,12,\ t=1,2,\ldots,12
\end{aligned}
$$

4.1. **The impact of demand information in the first cycle on the optimal ordering strategy.** Assuming $p_1^1=p_1^2=p_1^3=8$, $h_1^1=h_1^2=h_1^3=4$, $c_1^1=c_1^2=c_1^3=2$, $s_1^1=s_1^2=s_1^3=45$, the optimal order quantity for different periods is shown in Figure 1. On the whole, the demand information of the first cycle has a greater impact on the optimal order quantity of every following cycle, and the overall change trend is consistent with the change of the demand influence factor. The significant difference is the optimal order quantity for the last two cycles. When the demand trend information for the first cycle is $d_1^1=35$, the optimal order quantity is zero. The main reason is that when the demand information of the first cycle is large, the retailer has a large order quantity in each cycle.

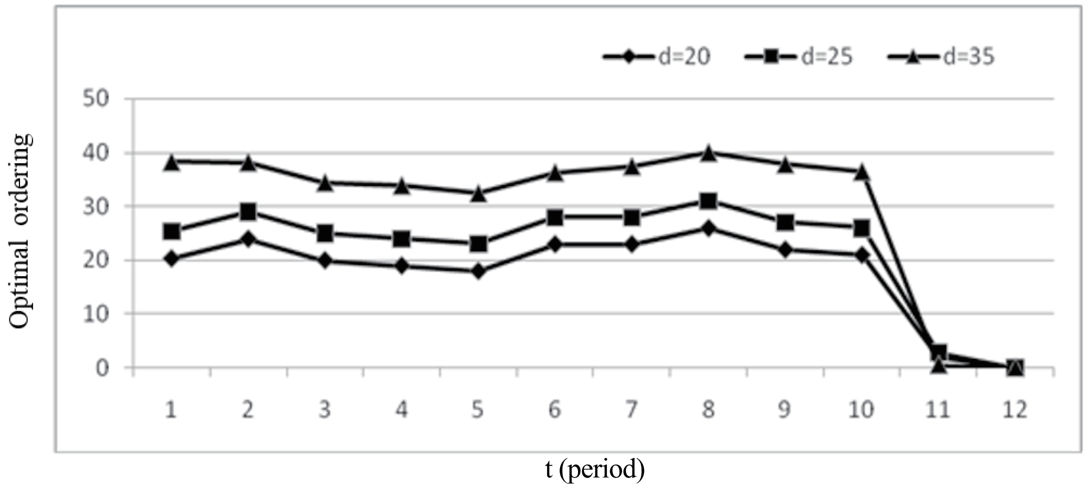

FIGURE 1. The impact of optimal order quantity by first period demand information

4.2. **The impact of out-of-stock costs per unit of product on the optimal ordering strategy.** Assume $p_1^1=p_1^2=p_1^3=8$, $d_1^1=25$, $c_1^1=c_1^2=c_1^3=2$, $s_1^1=s_1^2=s_1^3=40$. As being shown in Figure 2, when the out-of-stock cost per unit product is less than the order cost of the unit product, the order quantity of the first period is slightly larger than the demand information of the first period ($d=25$) and the order quantity for the twelfth cycle is zero. When the out-of-stock cost per unit product is not less than the subscription cost per unit product, the optimal order quantity for the first period is much

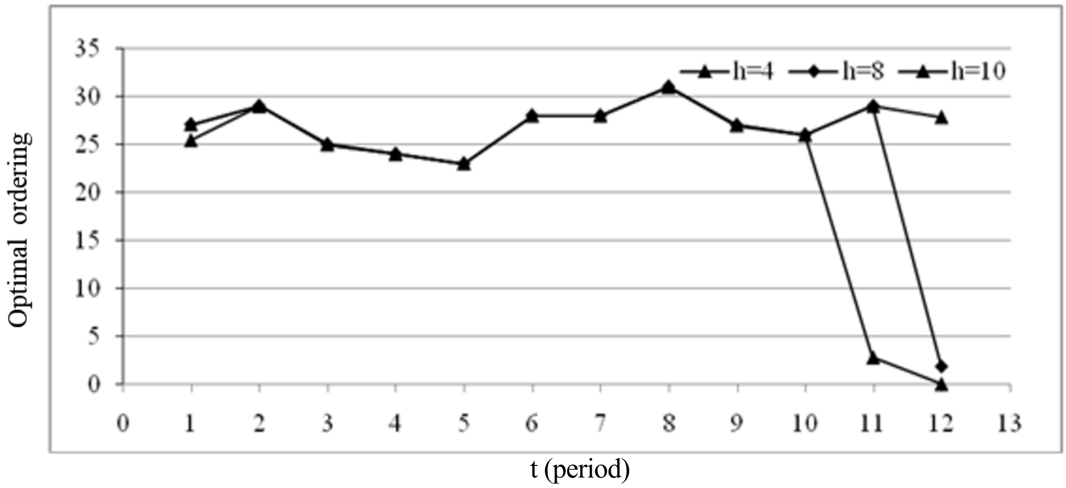

FIGURE 2. The impact of optimal order quantity by unit shortage cost

larger than the demand information for the first period. The difference in order quantity in the twelfth cycle is obvious: when the out-of-stock cost is equal to the ordering cost, the optimal order quantity is much smaller than the inventory capacity; when the out-of-stock cost is greater than the ordering cost, the optimal order quantity is slightly smaller than the actual number of the eleventh cycle. No matter how the out-of-stock cost changes, there is no significant change in the order quantity from the second period to the tenth period. It can be seen that the impact of unit out-of-stock cost on the optimal order quantity is mainly reflected in the first period and the last two periods. The main reason is that when the out-of-stock cost per unit product is less than the subscription fee, the retailer will consider the subscription fee, so the order quantity in the first cycle will be relatively small; when the unit out-of-stock cost is greater than the order cost, the retailer will be in the last two cycles and will choose to order more products.

4.3. **The impact of inventory capacity on the optimal ordering strategy.** Assuming $p_1^1 = p_1^2 = p_1^3 = 8$, $h_1^1 = h_1^2 = h_1^3 = 4$, $c_1^1 = c_1^2 = c_1^3 = 2$, $d_1^1 = 25$, the order quantity for different cycles is shown in Figure 3. Overall, the inventory size has a large impact on the optimal order quantity for each cycle. The overall trend of the optimal order quantity is consistent with the trend of demand factors. When the stock is small, the retailer's optimal order quantity is full stock to order; when the stock quantity is greater than the demand information of the first period, except for the order quantity of the last period,

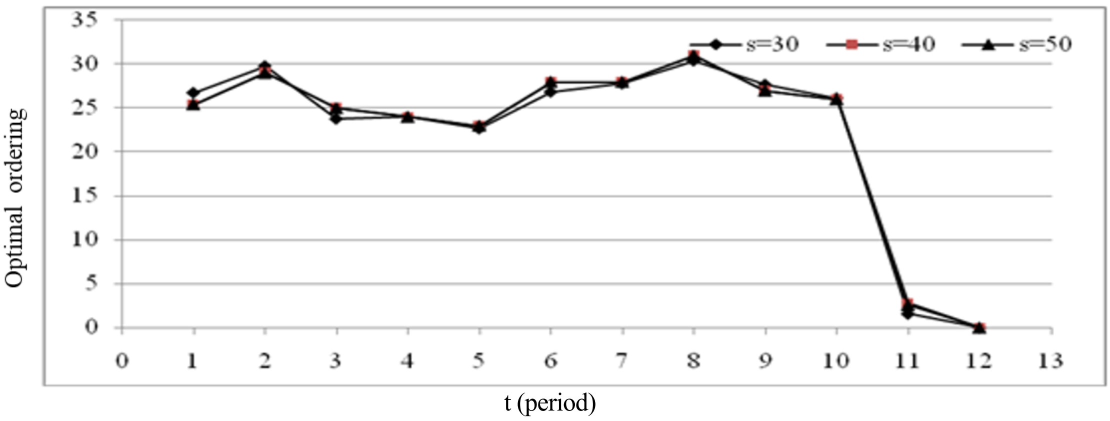

FIGURE 3. The impact of optimal order quantity by inventory capacity

the order quantity of the previous period is less than the order quantity of the previous period. The amount is slightly larger than the actual demand of the previous cycle.

4.4. **The impact of inventory costs per unit of product on the optimal ordering strategy.** Assume $p_1^1 = p_1^2 = p_1^3 = 8$, $h_1^1 = h_1^2 = h_1^3 = 4$, $d_1^1 = 25$, $s_1^1 = s_1^2 = s_1^3 = 45$. When the inventory cost per unit product changes, the optimal order quantity is shown in Figure 4. Overall, the impact of unit inventory costs on the most ordered quantities is not very large.

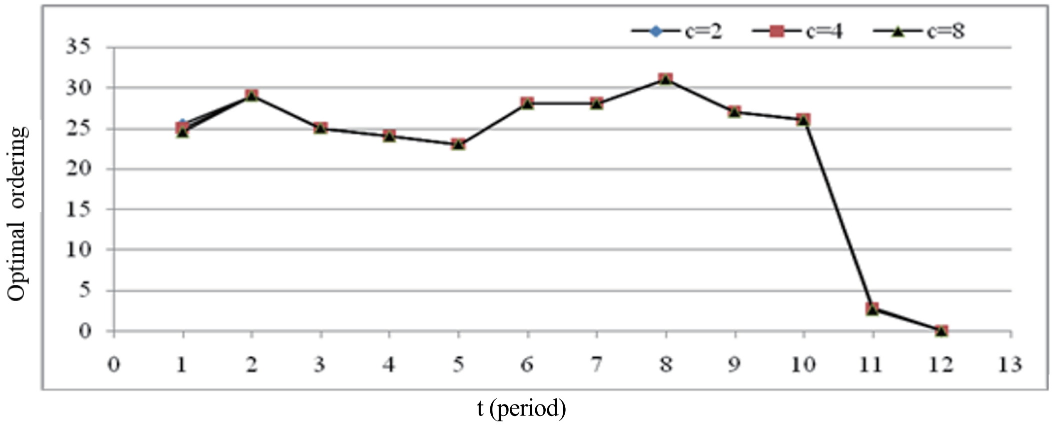

FIGURE 4. The impact of optimal order quantity by unit inventory cost

5. **Conclusion.** The contents of this paper covered how a multi-period robust optimization model is established by using affine-adjustable robust method, and simulated by Matlab in ROME environment. The impact of the first cycle demand information, out-of-stock cost, inventory capacity and inventory cost on the optimal ordering strategy is studied. The trend of demand changes is consistent; when the out-of-stock cost per unit product is less than the order cost of the unit product, the order quantity of the first period is much larger than the demand information of the first period, and when the out-of-stock cost is equal to the order cost, the optimal order quantity is much smaller than the inventory capacity; when the out-of-stock cost is greater than the order cost, the optimal order quantity is slightly smaller than the actual demand quantity of the eleventh period; overall, the stock size has a larger optimal order quantity per cycle. For the impact, however, the overall trend of the optimal order quantity is consistent with the trend of demand factors; the impact of unit inventory cost on the optimal order quantity is not very large.

However, there are many factors that affect market demand. This paper only studies the inventory management based on the previous cycle demand. There must be deficiencies in the inventory management. For example, market position and marketing strategy should be considered comprehensively.

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