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Optimization of a Two-Warehouse Inventory Model for Deteriorating Items under Inflation and Partial Backlogging Using Genetic Algorithm

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ABSTRACT

This paper presents a two-warehouse inventory model for deteriorating items under stock-dependent demand, time-dependent holding cost, shortages, and inflation. Each cycle begins with shortages and ends without them, reflecting real-world supply chain dynamics. The model considers limited capacity in an owned warehouse (OW) and higher costs in a rented warehouse (RW). A Genetic Algorithm (GA) is applied to optimize key decision variables such as order quantity and cycle time, minimizing the total cost, including holding, deterioration, shortage, and transfer costs under inflation. Comparative analysis shows that the GA-based model outperforms the traditional model when inflation is present, while both perform equally in its absence. Numerical examples and sensitivity analysis validate the effectiveness and efficiency of the proposed approach.

Keywords: *Two-warehouse inventory model; Deteriorating items; Stock-dependent demand; Time-dependent holding cost; Shortages; Inflation; Genetic Algorithm (GA)*

1. INTRODUCTION

One of the most critical and longstanding challenges in the domain of inventory management is determining the optimal strategy for the storage and distribution of goods, especially under capacity constraints and fluctuating market dynamics. Traditional inventory models, often rooted in classical economic order quantity (EOQ) frameworks, typically assume a single, infinitely capacitated, owned storage facility and aim to minimize total inventory-related costs such as ordering, holding, and shortage costs. However, this assumption is far from realistic in many practical scenarios, particularly when bulk purchasing or large-scale production becomes economically viable due to quantity discounts, inflationary pressures, or seasonal demand surges.

In such cases, the firm may be compelled to procure or produce a significantly large quantity of goods. This situation frequently exceeds the storage capacity of the firm's primary warehouse, referred to as the Owned Warehouse (OW). Instead of incurring the capital-intensive cost of constructing a new facility, businesses often opt to utilize an externally leased Rented Warehouse (RW) to store the excess inventory. This two-warehouse inventory system introduces a complex decision-making landscape, as the RW typically incurs higher holding and deterioration costs compared to the OW due to additional expenses associated with rental fees, security, climate control, and inventory handling. However, some RW facilities—such as centrally managed public warehousing systems—may offer advanced preservation technologies that reduce the deterioration rate, which introduces an additional layer of trade-off analysis.

In a two-warehouse setup, a common and cost-effective operational strategy is to first utilize the RW inventory and then switch to the OW stock once the former is depleted. The rationale is to reduce high holding and deterioration costs in the RW by minimizing the time goods remain stored there. This transfer of inventory from the RW to the OW is typically modeled using a continuous release policy that aligns with the consumption or demand rate. Despite its practical significance, the two-warehouse inventory problem remains underexplored, especially under real-world complexities such as limited space, time-dependent deterioration, and stock-dependent or price-dependent demand.

To address these multifaceted challenges and to derive the optimal replenishment policies under such complex scenarios, Genetic Algorithm (GA)—a powerful metaheuristic inspired by the principles of natural selection and biological evolution—

has been introduced into the present inventory model. Genetic Algorithm is particularly well-suited for solving large-scale, nonlinear, and multi-constraint optimization problems where classical analytical methods fall short. By encoding decision variables such as replenishment cycle time, order quantity, and transfer rate as genes in a population of chromosomes, GA iteratively evolves the solution space using genetic operators such as selection, crossover, and mutation to converge on the global optimum.

The integration of GA into the proposed two-warehouse model significantly enhances the model's robustness, flexibility, and computational efficiency. It allows the incorporation of complex objective functions, multiple constraints (such as warehouse capacity, cost parameters, and deterioration rates), and nonlinear demand patterns without sacrificing solution quality. Furthermore, the GA-based approach can accommodate stochastic and fuzzy environments, which are increasingly relevant in real-world supply chains.

In this study, a comprehensive two-warehouse inventory model is developed under the assumption of limited capacity in the owned warehouse and the availability of a rented warehouse with differentiated holding and deterioration costs. The objective is to minimize the total inventory cost by determining the optimal values of inventory-related decision variables. The proposed model is then optimized using the Genetic Algorithm, and the results are validated through numerical examples and sensitivity analysis. This hybrid approach provides valuable managerial insights into the strategic allocation of inventory between two warehouses and demonstrates the practical utility of evolutionary algorithms in advanced inventory optimization

2. RELATED WORK

Sarma (1983) proposed a two-warehouse inventory model by assuming the cost of transporting K-unit from RW to OW as constant and called it as K-release rule (KRR). The rate of replenishment was assumed as infinite. **Murdeshwar** and **Sathe (1985)** formulated some aspects of lot size models with two level of storage and derived complete solution for optimum lot size under finite production rates. The authors assumed while deriving the K-release rule that K units were transferred n-times from OW to RW during production stage with constant transportation cost. **Sarma (1987)** developed a deterministic inventory model for a single deteriorating item which was stored in two different warehouses of non deteriorating product. The preserving facilities were better in rented warehouse than own warehouse resulting in a lower rate of deterioration.

Goswami and **Chaudhuri (1992)** developed an economic order quantity model for items with two levels of storage for a linear trend in demand. An inventory model for deteriorating items with two warehouses was formulated by **Pakkala** and **Achary (1992)**. **Pakkala** and **Achary (1994)** proposed an inventory model for deteriorating products when two separate warehouses were used. A deterministic order level inventory model for deteriorating items with two storage facilities was discussed by **Benkherouf (1997)**. **Bhunia** and **Maiti (1998)** developed a deterministic inventory model with two warehouses for deteriorating items taking linearly increasing demand with time, shortages were allowed and excess demand was backlogged as well. **Yang (2004)** developed the two-warehouse inventory models for deteriorating items with constant demand rate under inflation. An inventory model with two warehouses and stock-dependent demand rate was proposed by **Zhou** and **Yang (2005)**. Shortages were not allowed in the model and the transportation cost for transferring items from RW to OW was taken to be dependent on the transported amount. Two-warehouse inventory models with LIFO and FIFO dispatching policies were developed by **Lee (2006)**. **Hsieh et al. (2008)** suggested a deterministic inventory model for deteriorating items with two warehouses by minimizing the net present value of the total cost.

1. ASSUMPTIONS AND NOTATIONS

The following assumptions are used in this study:

1. Lead-time is zero and the initial inventory level is zero.
2. Deterioration is considered only after the inventory is stored in the warehouse.
3. There is no repair or replacement of the deteriorated inventory units.
4. The OW has a fixed capacity of w units and the RW has unlimited capacity.
5. Due to different stocking atmosphere, inventory cost (including carrying cost and deterioration cost) in RW are higher than those in OW.
6. Shortages are allowed and partially backlogged. The fraction of the shortages backordered is a differentiable and decreasing function of time t, denoted by $\delta(t)$ Where t is the waiting time up to the next replenishment, with $0 \leq \delta(t) \leq 1$ and $\delta(0)=1$. Note that if $\delta(t)=1$(or 0) for all t, then shortages are completel backlogged (or lost).
7. When shortages are lost, the cost of lost sale is the sum of the revenue lost and the cost of lost goodwill. Hence the cost of lost sales here is grater than the unit purchase cost.

The notations used in this model are shown as follows:

$f(t) = x + y$ I(t) demand rate.

w fixed capacity level of OW.

α deterioration rate of inventory items in OW with $0 < \alpha < 1$.

β deterioration rate of inventory items in RW with $0 < \beta < 1$. $\beta > \alpha$

r inflation rate.

t_r the time at which the inventory level reaches zero in OW.

t_o the time at which the inventory level reaches zero in RW.

t_s the time at which the shortage level reaches the lowest point in the replenishment cycle.

$I_o(t)$ the inventory level in OW at time t.

$I_r(t)$ the inventory level in RW at time t.

B(t) the backlogged level at time t.

$\delta(t)$ the backlogging rate which is a decreasing function of the waiting time.

C_o the replenishment cost per order.

C_b the backlogging cost per unit per unit time, if the shortages is backlogged.

C_{h1} holding cost per unit per unit time in OW.

C_{h2} holding cost per unit per unit time in RW.

C_s shortage cost per unit per unit time.

C_l the unit opportunity cost due to lost sale, if the shortage is lost.

Note that if the objective is minimizing the total cost, then

$C_l = p + C_g > C_p$, where p is the cost of lost revenue and C_g is the cost of lost goodwill, if the shortage is lost. Otherwise, if it is maximizing the total profit, then $C_l = C_g$.

TC_i the present value of the total relevant cost per unit time for model i, i = 1, 2.

2. The mathematical formulation of the model starting with no Shortage:

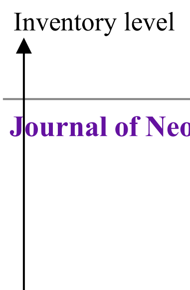
The inventory level, I(t), $0 \le t \le t_s$ satisfies the following differential equations with the corresponding boundary conditions :

$$\frac{dI_r(t)}{dt} + \beta I_r(t) = -(x + yI_r(t)), \quad 0 \le t \le t_r, \quad I_r(t_r) = 0. \tag{1}$$

$$\frac{dI_o(t)}{dt} = -\alpha I_o(t), \quad 0 \le t \le t_r, \quad I_o(0) = w. \tag{2}$$

$$\frac{dI_o(t)}{dt} + \alpha I_o(t) = -(x + yI_o(t)), \quad t_r \le t \le t_o, \quad I_o(t_o) = 0. \tag{3}$$

$$\frac{dB(t)}{dt} = \delta(t_s - t)x, \quad t_o \le t \le t_s, \quad B(t_o) = 0. \tag{4}$$



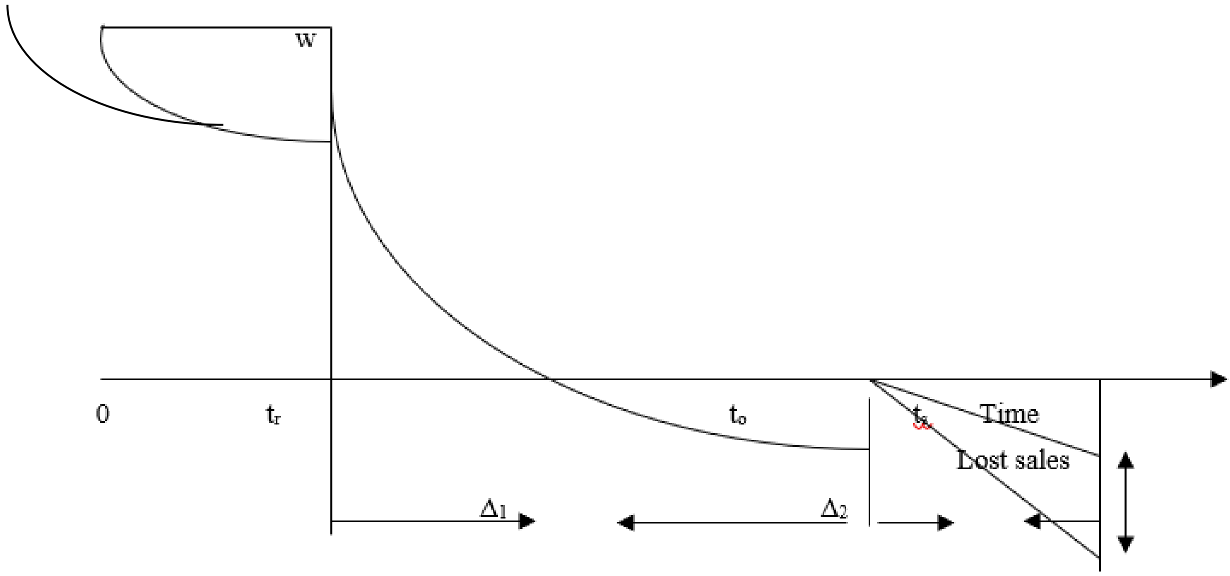


Fig. 1 Graphical representation of a two-warehouse inventory system for Model 1

Solutions of above equations are respectively,

$$I_r(t) = \frac{x}{(\beta + y)}\left[e^{-(\beta+y)(t-t_r)} - 1\right], \quad 0 \le t \le t_r. \tag{5}$$

$$I_o(t) = we^{-\alpha t}, \quad 0 \le t \le t_r. \tag{6}$$

$$I_o(t) = \frac{x}{\alpha + y}[e^{-(\alpha+y)(t-t_o)} - 1], \quad t_r \le t \le t_o. \tag{7}$$

$$B(t) = \int_{t_o}^{t} \delta(t_s - u)x du \quad t_o \le t \le t_s. \tag{8}$$

The number of lost sales at time t is

$$L(t) = \int_{t_o}^{t} \left[1 - \delta(t_s - u)\right]x du, \quad t_o \le t \le t_s. \tag{9}$$

Using the continuity of $I_o(t)$ at $t=t_r$, from eq. (6) & (7), we have

$$I_o(t_r) = we^{-\alpha t_r} = \frac{x}{\alpha + y}[e^{-(\alpha+y)(t_r-t_o)} - 1]$$

$$\Rightarrow w = \frac{xe^{\alpha t_r}}{\alpha + y}[e^{-(\alpha+y)(t_r-t_o)} - 1] \tag{10}$$

$$\Rightarrow t_o = t_r + \frac{1}{(\alpha + y)}\ln\left(1 + \frac{(\alpha + y)we^{-\alpha t_r}}{x}\right) \tag{11}$$

Therefore t_o is not a decision variable in model I. Thus, the cumulative inventories in RW during $(0,\ t_r)$ and in OW during $(0,\ t_o)$ are

$$\int_0^{t_r} I_r(t)dt = \int_0^{t_r} \frac{x}{\beta+y}\left[e^{-(\beta+y)\left(t-t_r\right)}-1\right]dt$$

$$=\frac{x}{(\beta+y)}\left[\frac{e^{(\beta+y)t_r}}{(\beta+y)}\left(1-e^{-(\beta+y)t_r}\right)-t_r\right]$$

$$\int_0^{t_r} I_r(t)dt = \frac{x}{\beta+y}\left[\frac{1}{\beta+y}(e^{(\beta+y)t_r}-1)-t_r\right] \tag{12}$$

and

$$\int_0^{t_o} I_o(t)dt = \int_0^{t_r} we^{-\alpha t}dt + \int_{t_r}^{t_o} \frac{x}{\alpha+y}\left[e^{-(\alpha+y)(t-t_o)}-1\right]dt$$

$$=\frac{w}{\alpha}\left(1-e^{-\alpha t_r}\right)+\frac{x}{(\alpha+y)}\left[\frac{e^{(\alpha+y)t_o}}{(\alpha+y)}\left(e^{-(\alpha+y)t_r}-e^{-(\alpha+y)t_o}\right)-\left(t_o-t_r\right)\right]$$

$$=\frac{w}{\alpha}\left(1-e^{-\alpha t_r}\right)+\frac{x}{(\alpha+y)}\left[\frac{1}{(\alpha+y)}\left(e^{-(\alpha+y)\left(t_r-t_o\right)}-1\right)-\left(t_o-t_r\right)\right]$$

$$=\frac{w}{\alpha}-\frac{x}{\alpha(\alpha+y)}\left(e^{-(\alpha+y)\left(t_r-t_o\right)}-1\right)+\frac{x}{(\alpha+y)}\left[\frac{1}{(\alpha+y)}\left(e^{-(\alpha+y)\left(t_r-t_o\right)}-1\right)-\left(t_o-t_r\right)\right]$$

$$=\frac{w}{\alpha}-\frac{x}{\alpha+y}\left(\frac{1}{\alpha}-\frac{1}{\alpha+y}\right)\left(e^{-(\alpha+y)\left(t_r-t_o\right)}-1\right)-\frac{x}{\alpha+y}\left(t_o-t_r\right)$$

$$=\frac{w}{\alpha}-\frac{xy}{\alpha(\alpha+y)^2}\left(e^{-(\alpha+y)\left(t_r-t_o\right)}-1\right)-\frac{x}{(\alpha+y)}\left(t_o-t_r\right) \tag{13}$$

Respectively, and the present value of the inventory holding cost in RW and OW are

$$ch_2\int_0^{t_r} e^{-rt}I_r(t)dt = ch_2\int_0^{t_r} \frac{xe^{-rt}}{\beta+y}\left(e^{-(\beta+y)\left(t-t_r\right)}-1\right)dt$$

$$=ch_2\left[\frac{x}{\beta+y}\left\{e^{(\beta+y)t_r}\int_0^{t_r} e^{-(\beta+y+r)t_r}dt-\int_0^{t_r} e^{-rt}dt\right\}\right]$$

$$=\frac{xch_2}{\beta+y}\left[\frac{e^{(\beta+y)t_r}}{(\beta+y+r)}\left(1-e^{-(\beta+y+r)t_r}\right)-\frac{1}{r}\left(1-e^{-rt_r}\right)\right]$$

$$ch_2\int_0^{t_r} e^{-rt}I_r(t)dt=\frac{x.ch_2}{\beta+y}\left[\frac{1}{(\beta+y+r)}(e^{(\beta+y)t_r}-e^{-rt_r})-\frac{1}{r}(1-e^{-rt_r})\right] \tag{14}$$

and

$$ch_1\int_0^{t_o} e^{-rt}I_o(t)dt=ch_1\left[\int_0^{t_r} we^{-(\alpha+r)t}dt+\int_{t_r}^{t_o}\frac{xe^{-rt}}{\alpha+y}(e^{-(\alpha+y)(t-t_o)}-1)dt\right]$$

$$=ch_1\left[\int_0^{t_r}\frac{xe^{\alpha t_r}}{\alpha+y}(e^{-(\alpha+y)(t_r-t_o)}-1)e^{-(\alpha+r)t}dt+\int_{t_r}^{t_o}\frac{x}{\alpha+y}(e^{(\alpha+y)t_o}e^{-(\alpha+y+r)t}-e^{-rt})dt\right]$$

$$=ch_1\left[\frac{xe^{\alpha t_r}}{\alpha+y}(e^{-(\alpha+y)(t_r-t_o)}-1)\left(\frac{1-e^{-(\alpha+r)t_r}}{\alpha+r}\right)\right.$$

$$\left.+\frac{x}{\alpha+y}\left\{e^{(\alpha+y)t_o}\left(\frac{e^{-(\alpha+y+r)t_r}-e^{-(\alpha+y+r)t_o}}{(\alpha+y+r)}\right)-\frac{1}{r}(e^{-rt_r}-e^{-rt_o})\right\}\right]$$

$$=\frac{x.ch_1}{\alpha+y}\left[\frac{e^{\alpha t_r}}{\alpha+r}(e^{-(\alpha+y)(t_r-t_o)}-1)(1-e^{-(\alpha+r)t_r})+\frac{e^{(\alpha+y)t_o}}{(\alpha+y+r)}(e^{-(\alpha+y+r)t_r}-e^{-(\alpha+y+r)t_o})\right.$$

$$\left.-\frac{1}{r}(e^{-rt_r}-e^{-rt_o})\right] \tag{15}$$

Respectively and the present value of the backlogging cost and the opportunity cost due to lost sale are

$$c_b\int_{t_o}^{t_s} e^{-rt}\int_{t_o}^{t}\delta(t_s-u)xdudt=\frac{c_b}{r}\int_{t_o}^{t_s}(e^{-rt}-e^{-rt_s})\delta(t_s-t)xdt \tag{16}$$

And

$$c_1e^{-rt_s}\int_{t_o}^{t_s}\left[1-\delta(t_s-t)\right]xdt$$

In addition, the present value of the cost for the deteriorated items is

$$c_p\left[\beta\int_0^{t_r} e^{-rt}I_r(t)dt+\alpha\int_0^{t_o} e^{-rt}I_o(t)dt\right]$$

$$=c_p\left[\frac{\beta x}{\beta+y}\left\{\frac{1}{\beta+y+r}(e^{(\beta+y)t_r}-e^{-rt_r})-\frac{1}{r}(1-e^{-rt_r})\right\}\right.$$

$$+\frac{\alpha x}{\alpha+y}\left\{\frac{e^{\alpha t_r}}{\alpha+r}(e^{-(\alpha+y)(t_r-t_o)}-1)(1-e^{-(\alpha+r)t_r})+\right.$$

$$+\frac{e^{(\alpha+y)t_o}}{\alpha+y+r}\left(e^{-(\alpha+y+r)t_r}-e^{-(\alpha+y+r)t_o}\right)-\frac{1}{r}\left(e^{-rt_r}-e^{-rt_o}\right)\Bigg\}\Bigg]\Bigg] \quad (17)$$

Consequently, the present value of the total cost per unit time is given by

$$TC_1=\frac{1}{\left(t_r+\Delta_1+\Delta_2\right)}\Bigg[c_o+\frac{(ch_2+\beta c_p)x}{\beta+y}\left\{\frac{e^{(\beta+y)t_r}-e^{-rt_r}}{\beta+y+r}-\frac{1-e^{-rt_r}}{r}\right\}$$

$$-\frac{(ch_1+\alpha c_p)x}{(\alpha+y)}\Bigg\{\frac{e^{-rt_r}}{(\alpha+r)}\left(e^{(\alpha+y)\Delta_1}-1\right)-\frac{e^{-rt_o}}{(\alpha+y+r)}\left(e^{-(\alpha+y+r)\Delta_1}-1\right)$$

$$+\frac{e^{-rt_o}}{r}\left(e^{r\Delta_1}-1\right)\Bigg\}+\frac{(ch_1+\alpha c_p)w}{(\alpha+r)}$$

$$+xe^{-r\left(t_r+\Delta_1+\Delta_2\right)}\int_{t_o}^{t_s}\frac{c_b}{r}\left\{\left(e^{r(t_s-t)}-1\right)\delta(t_s-t)+c_1\left(1-\delta(t_s-t)\right)\right\}dt\Bigg] \quad \ldots \quad (18)$$

Where from **fig.1**, $\Delta_1=t_o-t_r$, $\Delta_2=t_s-t_o$ and $w=\frac{xe^{\alpha t_r}}{\alpha+y}\left[e^{-(\alpha+y)(t_r-t_o)}-1\right]$

3. Genetic Algorithm Optimization

Step 1: Problem Complexity

The two-warehouse inventory model includes nonlinear costs (holding, deterioration, ordering, transfer) and real-life constraints (limited capacity, time-based transfer), making it difficult to solve analytically.

Step 2: Why Genetic Algorithm (GA)?

GA is a metaheuristic inspired by natural selection. It is ideal for solving complex, nonlinear problems with multiple variables and constraints where classical methods struggle.

Step 3: Chromosome Design

Each possible solution is represented as a chromosome that includes variables like:

- Order quantity (Q)
- Cycle time (T)
- Transfer timing from RW to OW

These variables are encoded for optimization.

Step 4: Fitness Function

The fitness function is defined as the inverse of the total inventory cost:

Fitness=1/Total Cost

Step 5: Selection Process

GA selects the best solutions (chromosomes) using methods like roulette wheel or tournament selection to ensure better individuals are more likely to pass on their traits.

Step 6: Crossover and Mutation

- Crossover: Combines parts of two parent solutions to create better offspring.

- Mutation: Randomly changes small parts of a solution to explore new possibilities and avoid local optima.

Step 7: Iteration and Termination

The process continues for several generations until:

- A maximum number of generations is reached, or
- There is no significant improvement in the solution.

Step 8: Final Outcome

GA provides an approximate global optimal solution for the total cost. It efficiently handles constraints, deterioration, transfer logic, and dual-warehouse complexity

4. NUMERICAL EXAMPLES:

Let D = 350, c0 = 80, ch1 = 1.5, ch2 = 2.5, cs = 0.2, cp = 10, w = 70, α=0.02, β = 0.04, and r=0.06,

The computational results for the two models are shown below:

Model I
t_r =0.0291
Δ_1=0.3177
Δ_2=2.1374
TC_1 =423.5732
GA=445.58

3. CONCLUSION

In this chapter, a comprehensive two-warehouse inventory model has been developed under the combined effects of inflation, constant deterioration, and shortage allowance. The proposed model is an improvement over traditional inventory systems, as it incorporates practical constraints such as limited storage capacity, higher holding costs in rented warehouses, and time-sensitive inventory decay. To address the nonlinear, multi-constraint nature of this problem, a **Genetic Algorithm (GA)**-based optimization technique has been employed for determining the optimal replenishment cycle and associated decision variables. The application of GA significantly enhances the model's capability by effectively navigating complex search spaces and avoiding local optima that often hinder classical analytical methods. By encoding key decision parameters such as order quantity, cycle time, and transfer schedules between the rented warehouse (RW) and the owned warehouse (OW) into a population of solutions, the GA iteratively evolves toward an optimal strategy that minimizes total inventory cost. This cost includes purchasing, holding, deterioration, shortage, and transfer costs—all dynamically influenced by inflationary trends and warehouse limitations. The results show that when the inflation rate is greater than zero, the GA-optimized two-warehouse model yields a lower total relevant cost per unit time compared to the traditional single-warehouse model. However, when the inflation rate is zero, the cost performance of both models becomes comparable. Thus, the proposed approach not only accounts for inflationary economic conditions but also ensures cost-efficiency and resource optimization through intelligent decision-making facilitated by evolutionary computation. In practice, the model is particularly applicable in modern retail and distribution systems, where space constraints, competitive pressures, and customer experience requirements compel businesses to maintain minimal in-store inventory. As market expansion and real estate limitations continue to restrict on-site storage capacity, external rented warehouses serve as essential components of a decentralized storage strategy. The integration of GA enables decision-makers to dynamically and efficiently balance stock levels between warehouses, minimize unnecessary costs, and maintain uninterrupted supply. In conclusion, the combination of a realistic two-warehouse structure with **Genetic Algorithm-based optimization** offers a powerful and adaptive framework for inventory management in complex, inflation-sensitive, and deterioration-prone environments. This model not only addresses the limitations of traditional methods but also aligns with the operational needs of contemporary supply chains, making it a valuable tool for strategic inventory planning and cost minimization.

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