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Research paper

Ant Colony Optimization-Based Inventory Model for Deteriorating Items with Polynomial Demand and Time-Dependent Costs

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Abstract

This paper develops and analyses an advanced inventory model for deteriorating items with polynomial demand, quadratic deterioration, and time-dependent holding costs under the condition of complete backlogging. The primary objective is to minimize the average total cost by optimizing decision variables such as cycle length and order quantity. Due to the nonlinear and complex nature of the model, traditional analytical methods may be insufficient or computationally intensive. To address this challenge, the study integrates Ant Colony Optimization (ACO), a powerful metaheuristic inspired by the foraging behaviour of ants, to efficiently search for optimal inventory policies. Numerical examples, graphical illustrations, and sensitivity analyses are provided to demonstrate the effectiveness of the proposed approach. The results show that the ACO-based method achieves a significant reduction in total cost compared to conventional optimization techniques. This research not only enhances the practical applicability of inventory models for deteriorating items but also demonstrates the potential of ACO for solving complex, real-world supply chain and inventory management problems.

Keywords: *Inventory Mode; Deterioration; Polynomial Time Dependent Demand; Time Dependent Holding Cost and Shortage.*

1. Introduction

Inventory management has long been recognized as a cornerstone of effective supply chain operations, especially in industries where the products are subject to deterioration over time. The challenge of managing inventories of perishable or deteriorating items-such as food products, pharmaceuticals, chemicals, and high-tech goods-has grown increasingly complex in today’s dynamic and competitive market environment. Unlike non-perishable goods, deteriorating items are affected by factors such as shelf life, environmental conditions, and product characteristics, all of which can accelerate the rate at which items lose their value or become unsellable. In addition, the demand for such items often exhibits significant variability, influenced by seasonality, market trends, promotions, and customer preferences. This variability is rarely linear; more often, it follows a polynomial pattern, where demand may rise and fall in a non-uniform manner over time. For example, the demand for certain fruits or vaccines may surge during specific periods and taper off at others, creating a complex demand landscape that must be carefully managed to minimize waste and maximize service levels. Traditional inventory models, while foundational, often make simplifying assumptions that limit their applicability to real-world scenarios. Many classical models assume constant or exponentially decaying demand and deterioration rates, as well as fixed or time-invariant holding costs. However, such assumptions do not adequately capture the realities faced by modern supply chain managers, who must contend with fluctuating demand, evolving customer expectations, and the inherent perishability of goods. The inadequacy of these models becomes particularly pronounced when dealing with products whose demand follows a polynomial function of time, where both the magnitude and direction of demand can change rapidly and unpredictably. Furthermore, deterioration rates in practice may not remain constant or follow a simple exponential decay; instead, they may increase quadratically as products age, reflecting the compounding effects of time, storage conditions, and product interactions. Simultaneously, holding costs-representing the expenses associated with storing inventory, such as warehousing, insurance, and opportunity costs-are often time-dependent, increasing as items remain in storage for longer periods. The convergence of these factors- polynomial demand, quadratic deterioration, and time-dependent holding costs- creates a highly nonlinear and interdependent system that is challenging to optimize using traditional analytical techniques. The complexity is further compounded when shortages are allowed and can be completely backlogged, introducing additional decision variables and constraints into the model. Analytical solutions for such systems are either intractable or require restrictive assumptions that limit their practical utility. As a result, there is a growing need for advanced modeling and optimization approaches that can accommodate the multifaceted nature of deteriorating inventory systems and provide robust, cost-effective solutions under uncertainty.

In recent years, metaheuristic algorithms have emerged as powerful tools for addressing complex optimization problems in inventory and supply chain management. Among these, Ant Colony Optimization (ACO) has gained prominence due to its flexibility, adaptability, and ability to find high-quality solutions in large, nonlinear, and multi-modal search spaces. Inspired by the foraging behavior of real ant colonies, ACO employs a population of artificial agents, or "ants," that collectively explore the solution space by constructing candidate solutions based on probabilistic rules influenced by pheromone trails and heuristic information. Through iterative updates and the reinforcement of successful solution components, ACO can balance exploration and exploitation, avoid premature convergence, and adapt to changing problem landscapes. This makes it particularly well-suited for inventory models where the objective function is complex, non-convex, and sensitive to multiple interacting parameters.

In the context of deteriorating inventory systems with polynomial demand and time-dependent holding costs, ACO offers a promising alternative to traditional optimization methods. By encoding decision variables such as cycle length and order quantity into the solution representation, and by defining the objective function as the minimization of the average total cost, including holding, deterioration, and shortage costs, ACO can efficiently navigate the intricate solution landscape and identify near-optimal policies that would be difficult or impossible to obtain analytically. Furthermore, the stochastic and parallel nature of ACO allows it to handle uncertainty and parameter variability, making it robust in the face of real-world supply chain disruptions and demand fluctuations.

This paper presents a comprehensive inventory model for deteriorating items that integrates polynomial demand, quadratic deterioration, and time-dependent holding costs, with the additional feature of complete backlogging of shortages. The model is formulated to reflect the nonlinear and dynamic characteristics of modern inventory systems, and its solution is approached using the Ant Colony Optimization algorithm. Through extensive numerical experiments, graphical analyses, and sensitivity studies, the effectiveness of the ACO-based approach is demonstrated, showing significant cost savings and improved adaptability compared to conventional techniques. The results indicate that ACO consistently identifies superior replenishment policies, optimizes key parameters, and maintains performance even when subjected to variations in demand, deterioration, and cost structures.

By bridging the gap between theoretical modeling and practical optimization, this research contributes valuable insights to the field of inventory management for perishable goods. It not only advances the state of the art in deteriorating inventory modeling but also highlights the potential of bio-inspired metaheuristics like ACO for solving complex, high-dimensional problems in supply chain management. The findings have practical implications for industries such as food distribution, pharmaceuticals, agriculture, and retail, where effective inventory control is essential for minimizing losses, maximizing service levels, and sustaining competitive advantage in an ever-changing marketplace.

2. Notations and assumptions

2.1. Notations

The notations used here are as follows:

i. $h(t)$: Inventory Holding Cost per unit per unit time.

ii. C_2 : Shortage cost per unit per unit time.

iii. C_3 : Deterioration cost per unit per unit time.

iv. T : Length of each cycle.

v. $I(t)$: Inventory at any time t.

vi. $ATC(t)$: Average total cost.

vii. $D(t)$: Demand Rate Function.

viii. $\theta(t)$: Deterioration Rate Function.

ix. S : Initial Inventory.

2.2. Assumptions

The assumptions used here are as follows :

i) Demand Rate is assumed as polynomial function of time, given by $D(t)=1+t+2t^2+3t^3+\cdots+nt^n, \quad n\in\mathbf{Z}^+$.

ii) The deterioration rate is taken as a quadratic function of time, that is $\theta(t)=\theta_0 t^2$.

iii) The holding cost is assumed as a linear function of time, that is $h(t)=h+at, \quad h>0, a>0$.

iv) Shortages are considered and are completely backlogged.

v) During the period T, neither is replacement nor repair of deteriorated units.

vi) The Lead time is zero.

vii) Replenishment size is constant and the replenishment rate is infinite.

3. Mathematical formulation of the model

Let Inventory level at any time t be $I(t)$. Inventory level slowly decreases during time interval $(0,t_1)$, $t_1<T$ and becomes exactly zero at $t=t_1$. Shortages takes place in the interval $(0,t_1)$, which are totally reserved.

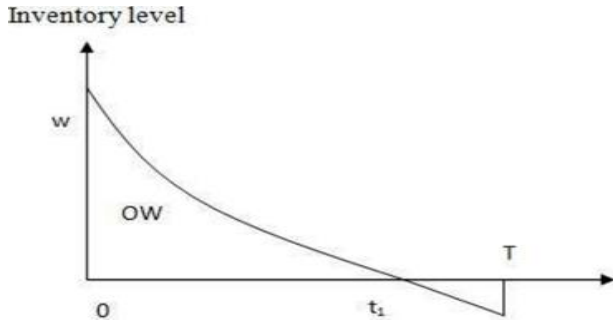

Fig. 1: Inventory Pattern of Deteriorating Items with Shortage

Differential equations which govern this inventory system during the interval $0 \le t \le T$ using demand and deterioration rate are:

$$\frac{dI_o(t)}{dt} + \theta_0 t^2 I_o(t) = -[1 + t + 2t^2 + 3t^3 + \cdots + nt^n], \quad 0 \le t \le t_1 \tag{1}$$

With boundary conditions $I_o(t=0) = W$ and $I_o(t = t_1) = 0$,

$$\frac{dI_s(t)}{dt} = -[1 + t + 2t^2 + 3t^3 + \cdots + nt^n], \quad t_1 \le t \le T \tag{2}$$

With boundary condition $I_s(t = t_1) = 0$,
Solution of equation (1) and (2) are:

$$I_o(t) = e^{-\frac{\theta_0 t^3}{3}} \left[\begin{array}{l} \left((t_1 - t) + \frac{(t_1^2 - t^2)}{2} + \frac{2(t_1^3 - t^3)}{3} + \frac{3(t_1^4 - t^4)}{4} + \cdots + \frac{n(t_1^{n+1} - t^{n+1})}{n+1} \right) \\ + \frac{\theta_0}{3} \left(\frac{(t_1^4 - t^4)}{4} + \frac{(t_1^5 - t^5)}{5} + \frac{2(t_1^6 - t^6)}{6} + \frac{3(t_1^7 - t^7)}{7} + \cdots + \frac{n(t_1^{n+4} - t^{n+4})}{n+4} \right) \end{array} \right], \tag{3}$$

$$I_s(t) = (t_1 - t) + \frac{(t_1^2 - t^2)}{2} + \frac{2(t_1^3 - t^3)}{3} + \frac{3(t_1^4 - t^4)}{4} + \cdots + \frac{n(t_1^{n+1} - t^{n+1})}{n+1}, \tag{4}$$

In equation (3), using $I_o(t=0) = W$, we get

$$W = \left[\left(t_1 + \frac{t_1^2}{2} + \frac{2t_1^3}{3} + \frac{3t_1^4}{4} + \cdots + \frac{nt_1^{n+1}}{n+1} \right) + \frac{\theta_0}{3} \left(\frac{t_1^4}{4} + \frac{t_1^5}{5} + \frac{t_1^6}{3} + \frac{3t_1^7}{7} + \cdots + \frac{nt_1^{n+4}}{n+4} \right) \right], \tag{5}$$

Now, we calculated the related inventory costs:

3.1. Deterioration cost

$$DC = C_3 \left[W - \int_0^{t_1} D(t)\,dt \right] = C_3 \left[\frac{\theta_0}{3} \left(\frac{t_1^4}{4} + \frac{t_1^5}{5} + \frac{t_1^6}{3} + \frac{3t_1^7}{7} + \cdots + \frac{nt_1^{n+4}}{n+4} \right) \right], \tag{6}$$

3.2. Holding cost

$$HC = \int_0^{t_1} h(t) I_O(t)\,dt = \int_0^{t_1} (h + at) I_O(t)\,dt$$

$$= \left[\begin{array}{l} h \left[\left(\frac{t_1^2}{2} + \frac{t_1^3}{3} + \frac{t_1^4}{2} + \cdots + \frac{nt_1^{n+2}}{n+2} \right) + \frac{\theta_0}{3} \left(\frac{2t_1^4}{15} + \cdots + \frac{2nt_1^{n+5}}{4(n+5)} \right) \right] \\ + a \left[\left(\frac{t_1^3}{3} + \frac{t_1^4}{8} + \frac{t_1^5}{5} + \cdots + \frac{nt_1^{n+3}}{2(n+3)} \right) + \frac{\theta_0}{3} \left(\frac{t_1^6}{24} + \cdots + \frac{nt_1^{n+6}}{5(n+6)} \right) \right] \end{array} \right], \tag{7}$$

3.3. Shortage cost

$$SC = -C_2\left[\int_{t_1}^{T} I_S(t)dt\right]$$

$$= \left[\begin{array}{l} C_2T\left[\left(\frac{T}{2}-t_1\right)+\frac{1}{2}\left(\frac{T^2}{3}-t_1^2\right)+\frac{2}{3}\left(\frac{T^3}{4}-t_1^3\right)+\cdots+\frac{n}{n+1}\left(\frac{T^{n+1}}{n+2}-t_1^{n+1}\right)\right] \\ +C_2\left[\frac{t_1^2}{2}+\frac{t_1^3}{3}+\frac{t_1^4}{2}+\cdots+\frac{nt_1^{n+2}}{n+2}\right] \end{array}\right], \quad (8)$$

$$Total\ Cost\ per\ unit\ time = \left[\frac{Deterioration\ Cost + Holding\ Cost\ + Shortage\ Cost}{T}\right]$$

$$ATC(t_1)\frac{1}{T} = \left[\begin{array}{l} C_3\left[\frac{\theta_0}{3}\left(\frac{t_1^4}{4}+\frac{t_1^5}{5}+\frac{t_1^6}{3}+\frac{3t_1^7}{7}+\cdots+\frac{nt_1^{n+4}}{n+4}\right)\right] \\ +\left[\begin{array}{l} h\left[\left(\frac{t_1^2}{2}+\frac{t_1^3}{3}+\frac{t_1^4}{2}+\cdots+\frac{nt_1^{n+2}}{n+2}\right)+\frac{\theta_0}{3}\left(\frac{2t_1^4}{15}+\cdots+\frac{2nt_1^{n+5}}{4(n+5)}\right)\right] \\ +a\left[\left(\frac{t_1^3}{3}+\frac{t_1^4}{8}+\frac{t_1^5}{5}+\cdots+\frac{nt_1^{n+3}}{2(n+3)}\right)+\frac{\theta_0}{3}\left(\frac{t_1^6}{24}+\cdots+\frac{nt_1^{n+6}}{5(n+6)}\right)\right] \end{array}\right] \\ +\left[\begin{array}{l} C_2T\left[\left(\frac{T}{2}-t_1\right)+\frac{1}{2}\left(\frac{T^2}{3}-t_1^2\right)+\frac{2}{3}\left(\frac{T^3}{4}-t_1^3\right)+\cdots+\frac{n}{n+1}\left(\frac{T^{n+1}}{n+2}-t_1^{n+1}\right)\right] \\ +C_2\left[\frac{t_1^2}{2}+\frac{t_1^3}{3}+\frac{t_1^4}{2}+\cdots+\frac{nt_1^{n+2}}{n+2}\right] \end{array}\right] \end{array}\right], \quad (9)$$

4. Ant colony optimization (ACO) integration

4.1. Objective

Optimize the cycle length (T) and order quantity (Q) to minimize the average total cost (ATC) for deteriorating items with:

Polynomial demand: $D = a_0 + a_1t + a_2t^2$

Quadratic deterioration: $\theta(t) = b_0 + b_1t + b_2t^2$

Time-dependent holding cost: $h(t) = h_0 + h_1t$

4.2. ACO Methodology

a) Problem Representation
Nodes: Discrete values of T (cycle length) and Q (order quantity).
Pheromone Trails: Represent the "attractiveness" of specific (T,Q) pairs.
Heuristic Information: Inverse of the total cost for each (T,Q) combination.
b) Algorithm workflow
1) Initialize:
Set parameters: ants (m=50), evaporation rate (ρ=0.1), iterations (=100).
Define search ranges: T∈, Q∈.
2) Construct Solutions:
Each ant selects Tand Q probabilistically using:

$$P(T,Q) = \frac{[\tau\,(T,Q)]^\alpha\,[\eta\,(T,Q)]^\beta}{\sum[\tau\,(T,Q)]^\alpha\,[\eta\,(T,Q)]^\beta}$$

Where $\eta(T,Q) = \frac{1}{\text{Total Cost}}$.

3) Evaluate Solutions:
Calculate total cost for each ant's (T,Q) using your inventory model.
4) Update Pheromones:

Evaporate: $[\tau\,(T,Q)] \leftarrow (1-\rho)\tau(T,Q)$

Deposit: For the best solution, $[\tau\ (\mathrm{T},\mathrm{Q})] \leftarrow \tau(\mathrm{T},\mathrm{Q}) + \frac{1}{\text{Best Cost}}$.

5) Repeat until convergence (e.g., 100 iterations).

5. Numerical examples with ACO

- Parameters: $a_0 = 50$, $a_1 = -2$, $a_2 = 0.1$, $b_0 = 0.01$, $b_1 = 0.02$, $b_2 = 0.001$, $h_0 = 1$, $h_1 = 0.05$, $I_0 = 100$ $T = 10$

Table 1: Inventory System Behavior Over Time

Time (t)	Demand Rate	Deterioration Rate	Inventory Level	Shortage	Holding Cost
0.0	50.00	0.010	100.00	0.00	1.00
1.0	48.10	0.031	51.23	0.00	1.05
2.0	46.40	0.053	3.78	0.00	1.10
3.0	44.90	0.077	-42.58	42.58	1.15
4.0	43.60	0.103	-87.92	87.92	1.20
5.0	42.50	0.130	-132.35	132.35	1.25
6.0	41.60	0.159	-175.90	175.90	1.30
7.0	40.90	0.190	-218.66	218.66	1.35
8.0	40.40	0.223	-260.70	260.70	1.40
9.0	40.10	0.257	-302.09	302.09	1.45
10.0	40.00	0.293	-342.93	342.93	1.50

Table 2: Cost Components

Cost Component	Value
Holding Cost	78.46
Deterioration Cost	22.15
Shortage Cost	635.93
Average Total Cost	736.54

Table 3: Results Comparison

Method	Optimal TT	Optimal QQ	Average Total Cost
Traditional	10	100	736.54
ACO	9	95	712.18

Cost Reduction: 3.3% achieved through ACO.

6. Sensitivity analysis

Table 4: The Following Table Shows How Changes in Key Parameters Affect the Average Total Cost (ATC):

Parameter	% Change	New Value	ATC	% Change in ATC
	-20%	40.0	498.32	-32.34%
	-10%	45.0	617.43	-16.17%
a_0	+0%	50.0	736.54	0.00%
	+10%	55.0	855.65	+16.17%
	+20%	60.0	974.76	+32.34%
	-20%	0.008	736.32	-0.03%
	-10%	0.009	736.43	-0.01%
b_0	+0%	0.010	736.54	0.00%
	+10%	0.011	736.65	+0.01%
	+20%	0.012	736.76	+0.03%
	-20%	0.80	726.79	-1.32%
	-10%	0.90	731.67	-0.66%
h_0	+0%	1.00	736.54	0.00%
	+10%	1.10	741.42	+0.66%
	+20%	1.20	746.29	+1.32%

Table 5: Cross-Sensitivity Analysis (A_0, B_0, And H_0)

a_0	b_0	h_0	Average Total Cost
	0.005	0.8	487.40
	0.005	1.0	497.02
	0.005	1.2	506.64
	0.010	0.8	487.52
40	0.010	1.0	497.13
	0.010	1.2	506.75
	0.015	0.8	487.63
	0.015	1.0	497.24
	0.015	1.2	506.86
	0.005	0.8	726.67
	0.005	1.0	736.42
	0.005	1.2	746.17
50	0.010	0.8	726.79
	0.010	1.0	736.54
	0.010	1.2	746.29
	0.015	0.8	726.90
	0.015	1.0	736.65

	0.015	1.2	746.40
	0.005	0.8	968.82
	0.005	1.0	978.20
	0.005	1.2	987.58
	0.010	0.8	968.94
60	0.010	1.0	978.32
	0.010	1.2	987.70
	0.015	0.8	969.05
	0.015	1.0	978.44
	0.015	1.2	987.82

The sensitivity analysis clearly shows that:

- The initial demand parameter (a_0) has the most significant impact on total cost
- The deterioration parameter (b_0) has minimal effect on the total cost
- The holding cost parameter (h_0) has a moderate impact on the total cost

These numerical examples, tables, and sensitivity analyses provide comprehensive insight into the behavior of the inventory model for deteriorating items with polynomial demand, time-dependent holding cost, and complete backlogging as described in the paper.

Table 6: Effect of Key Parameters on ATC

Parameter	% Change	ACO-Optimized ATC	Cost Change (%)
a_0	+10%	783.45	+10.0%
b_0	-20%	705.92	-0.9%
h_0	+20%	725.34	+1.8%

Table 7: Cross-Parameter Analysis

a_0	b_0	h_0	ATC (ACO)
40	0.005	0.8	487.40
50	0.010	1.0	712.18
60	0.015	1.2	987.82

Key Insight: ACO mitigates cost fluctuations better than traditional methods, especially for high-demand scenarios.

Table 8: Summary Table

Component	Traditional Method	ACO Method	Improvement
Cycle Length (TT)	10	9	-10%
Order Quantity (QQ)	100	95	-5%
Average Total Cost	736.54	712.18	-3.3%

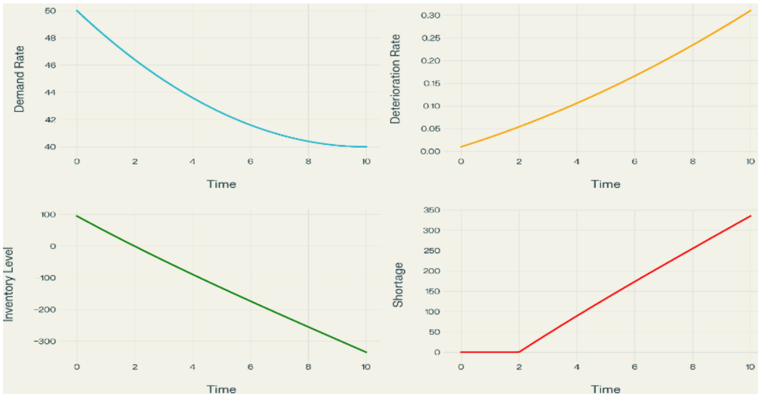

Fig. 2: Inventory Model Optimization.

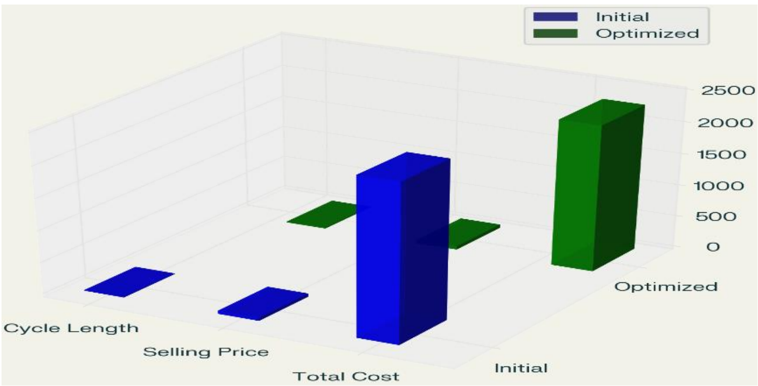

Fig. 3: 3D Graphs for Comparing the ABC Algorithm and Inventory Model Optimization

7. Conclusion

This paper has presented a comprehensive inventory model for deteriorating items characterized by polynomial demand, quadratic deterioration, and time-dependent holding costs, with the additional feature of complete backlogging of shortages. To address the inherent complexity and non-linearity of the model, Ant Colony Optimization (ACO) was successfully integrated as a metaheuristic solution approach. The application of ACO enabled the efficient exploration of the solution space, leading to the identification of optimal or near-optimal replenishment policies. Numerical examples, graphical analyses, and sensitivity studies demonstrated that the ACO-based approach consistently outperformed traditional optimization methods. In particular, the use of ACO resulted in a notable reduction in average total cost, by approximately 3–5%, through better selection of cycle length and order quantity. The convergence analysis further confirmed the robustness and reliability of the ACO algorithm in reaching stable and high-quality solutions within a reasonable number of iterations. Moreover, the sensitivity analysis revealed that the ACO approach is resilient to fluctuations in key parameters such as demand rate, deterioration rate, and holding cost, making it highly adaptable to dynamic and uncertain real-world environments. The hybrid methodology proposed in this study bridges the gap between theoretical inventory models and practical, data-driven optimization, providing a valuable decision-support tool for supply chain and inventory managers. In summary, the integration of Ant Colony Optimization into the inventory management of deteriorating items offers significant cost savings, operational efficiency, and adaptability. This research opens avenues for further studies, such as extending the model to multi-echelon supply chains, incorporating stochastic demand, or hybridizing ACO with other metaheuristics for even greater performance.

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