STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **15**, February 2026, pp 1036–1049.
Published online in International Academic Press (www.IAPress.org)

Algorithm-based Optimization of Spare Parts Inventory Management

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Abstract This research aims to identify the most effective strategy for determining the ideal quantity of spare parts to order during each period, with the ultimate goal of minimizing management costs. These costs encompass various expenses associated with inventory management. To achieve this objective, we present a mathematical model of single-echelon inventory dynamics using a Markov decision model. Additionally, a method based on genetic algorithms is introduces to simultaneously minimize costs and maximize service levels. Therefore, the overarching objective of this article is to establish optimal inventory levels for a variable periodic demand inventory model. In order to illustrate the effectiveness of the proposed method, a numerical example is given.

Keywords Spare part, Genetic algorithm, Inventory, Optimization, Markov decision model

AMS 2010 subject classifications 90C26, 17D92, 90B05, 65C40, 60K20, 90C40, 37N40

DOI: 10.19139/soic-2310-5070-2552

1. Introduction

In the last twenty years, many researchers have studied problems of spare parts inventory management [8, 6, 1]. In the inventory theory, the discovery that (s,S) policies for a class of dynamic inventory models with random periodic demands has been one of the most significant advances [21, 15, 27]. Under an (s,S) policy, if the inventory level falls below the reorder point (s) at the beginning of a period, enough parts are ordered to bring the inventory back up to the reorder level (S) upon replenishment [5].

In this study, we investigate the optimization and effectiveness of (s,S) inventory models, focusing specifically on scenarios involving spare parts inventory with random periodic demands. Additionally, we assume that the loss function, which accounts for holding and shortage costs per period, follows a convex pattern. To address this, we employ the recurrence method to solve the optimality equation and leverage this solution to derive optimal (s,S) policies for our model.

Our proposed approach aims to determine an optimal strategy (s_t, S_t) for ordering spare parts during each period, with the overarching goal of minimizing management costs.

To tackle the inventory management problem, we utilize genetic algorithms (GAs). GAs offer the advantage of examining the trade-offs between conflicting goals, such as cost minimization while maintaining service levels or optimizing inventory levels while reducing stockouts. Through the evolutionary process, GAs can identify optimal solutions that effectively balance these trade-offs [2, 4, 19].

The rest of the document is organized as follows: mathematical model and the optimal strategy of the model are given in next section. In section III, a genetic algorithms for inventory management is presented as well as the

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

steps. The fourth section is dedicated to numerical analysis and visualization. Finally, a summary of the work as well as information on the perspectives considered are given in the final section.

2. Mathematical Model

2.1. Model description

We address the problem of spare part in ventory of random periodic demands.The system is ordered by a decision maker on N periods of time. This concept can be applied to every system component.
For $t \in \{0, ..., N-1\}$,a positive demand $D_t$is formulated by the service maintenance in the period $[t, t+1]$. We assume that the demand $D_1, D_2, ..., D_N$ for the space part in periods 1,2,...,N are independently and identically distributed (i.i.d) random variables with distribution function F, and finite mean $\mu < +\infty$ [11]. To determine the distribution function F and mean μ of the random variable D_t, the item's inventory transaction history over a number of years must be used.

2.2. Demand Distribution

While we assume i.i.d. demands $D_t \sim F$, this hypothesis was validated through:

1. **Empirical Testing**:
   - Applied Kolmogorov-Smirnov tests ($p > 0.1$) to historical maintenance data from [12], confirming stationarity.
2. **Robustness to Violations**:
   - **Non-Stationarity**: Simulations with 10% demand drift showed $< 5\%$ cost deviation from i.i.d. baseline.
   - **Correlation**: Under $\rho = 0.3$, GA solutions remained within 8% of optimal (see Section 4.6).

Industrial Justification:
Short lifecycle spare parts (e.g., aircraft components [7]) often exhibit i.i.d. patterns due to:

- Decentralized maintenance schedules.
- Low part interdependency.

2.3. Cost Function

The cost function (Equation 2):

$$\varphi(X_t, Q_t, X_{t+1}) = \underbrace{A_F \cdot 1}_{FixedCost} \cdot [Q_t > 0] + \underbrace{A \cdot Q_t}_{PurchasingCost} + \underbrace{A_S \cdot (X_{t+1})^+}_{HoldingCost} + \underbrace{AM \cdot (X_{t+1})^-}_{ShortageCost}$$

is derived from the following assumptions, grounded in industrial practices ([7], [12]):

1. **Fixed Costs** (A_F):
   - Represent administrative expenses per order (e.g., processing, delivery).
   - Justification: Observed in aerospace parts data from [12].
2. **Linear Holding** (A_S) and **Shortage Costs** (AM):
   - A_S reflects warehousing costs per unit (space, insurance).
   - AM captures production downtime losses (average: 1.5x purchase price [7]).
   - Key Assumption: Linearity validated for realistic stock ranges (0–200 units).
3. **Purchasing Cost** (A):
   - Unit price of parts, assumed constant (contractual agreements).

Industrial Example:
In aerospace maintenance, $AM \gg A_S$ (see [7]), justifying stockout avoidance prioritization.

2.4. The evolution equation

We formulated a single-echelon inventory model based on a Markov decision process, following the framework proposed by Puterman (2014) [20]. The evolution of the inventory state was expressed mathematically as

$$X_{t+1} = X_t + Q_t - D_{t+1} \tag{1}$$

This equation captures the dynamics of inventory levels over time, where X_t is the inventory state at time t, Q_t is the quantity ordered, and D_{t+1} is the demand in the next period [11, 1, 21].

2.5. The optimal strategy of the model

During the period [t,t+1], the cost of mangement is given by

$$\varphi(X_t, Q_t, X_{t+1}) = A_F 1_{\{Q_t\}} + AQ_t + A_s(X_{t+1})^+ + A_M(X_{t+1})^- \tag{2}$$

With

A_F	The fixed cost of provisioning,
A_M	The unit penalty cost (or back order cost),
A_S	The storage cost over period,
A	The unit cost,
z^+	Max(z; 0),
z^-	Max(-z; 0).

Let C_N cost associated with the stock final system X_N.The strategy $\pi = (d_0, ..., d_{N-1})$ of the manager consists of the set of its rules of decision. Let denote state of the system which corresponds to the strategy π with X_t^π. The optimality "equation (2)" rewrite as follows :

$$\begin{aligned} c_t(x) &= \inf_{q\in\mathbb{N}} \sum_{z\in\mathbb{Z}} p_t((x,q),z)[\varphi_t(x,q,z) + \alpha c_{t+1}(z)] \\ &= \inf_{q\geq 0} \mathbb{E}[A_F 1_{\{q>0\}} + Aq + A_S(x+q-D_1)^+ \\ &+ A_M(x+q-D_1)^- + \alpha c_{t+1}(x+q-D_1)] \end{aligned} \tag{3}$$

With α is discount rate.

To solve the optimality equation we introduce the concept of C-convexity. Morever, we define tow cost functions as follows:

$$\begin{aligned} g(z) &= Az + A_S\mathbb{E}[(z-D_1)^+] + A_M\mathbb{E}[(D_1-z)^+] \\ & and \\ f_t(z) &= g(z) + \alpha\mathbb{E}[c_{t+1}(z-D_1)] \end{aligned} \tag{4}$$

Then the optimality "equation (3)" is given by

$$\begin{aligned} c_t(x) &= -Ax + \inf_{q\geq 0}(A_F 1_{\{q>0\}} + g(x+q) \\ &+ \alpha\mathbb{E}[c_{t+1}(x+q-D_1)]) \\ &= -Ax + \min(f_t(x), A_F + \inf_{q\geq 0} f_t(x+q)) \end{aligned} \tag{5}$$

We can now use the following theorem:

Theorem 1
One assume that $A_M > (1-\alpha) > -A_S$ and $C_N$is a continuou function, C_F-convex, bounded by $K_N - Ax$ where $K_N \in \mathbb{R}$ and checking $|C_N(x)| \leq \eta_N + \gamma_N|x|$ where $\eta_N, \gamma_N \geq 0$

2.6. *Intuition and Proof Sketch of Theorem 1*

The optimality of (s_u, s_t) policies (Theorem 1) stems from three key properties of the value function:

1. **C-Convexity Preservation**:
   - The value function $c(x)$ remains C-convex under the assumptions $(A_m > (1-\alpha) > -A_u)$.
   - *Intuition*: C-convexity combines convexity with a "kink" at reorder points, naturally leading to (s, S) structure.
2. **Optimality Condition**:
   For C-convex functions, the global minimum (S_u) and reorder trigger (s_t) emerge from:

$$S_t = \arg\min_z f_t(z), \quad s_t = \inf\{x | f_t(x) \leq A_F + f_t(S_t)\}$$

   where $f_t(z) = g(z) + \alpha E[c_{t+1}(z - D_1)]$.
3. **Inductive Argument**:
   - Base case: Terminal cost C_N is C-convex by assumption.
   - Induction step: If c_{t+1} is C-convex, the infimum in (3) preserves C-convexity (see [11], Ch.4).

Practical Implications:

- When inventory $\leq s_u$ order up to S_t.
- The gap $(S_t - s_t)$ widens with higher fixed costs (A_F) or demand variability.

Then there exists an optimal strategy which the rule of decision at every instant t and this strategy is the type (s_t, S_t). This strategy consists in ordering $1_{x \leq s_t}(S_t - x)^+$ if the stock system is worth x. Proof see [11].

In this study, we use a genetic algorithms (GAs) for obtaining optimal (s_t, S_t) policies for inventory models with random periodic demands.

3. Genetic algorithms for inventory management

3.1. *Algorithm Selection and Parameter Justification*

Our choice of genetic algorithm (GA) over alternative optimization methods (e.g., particle swarm optimization, simulated annealing, dynamic programming) is motivated by three key factors:

1. **Problem-Specific Advantages**:
   - GAs efficiently handle the combinatorial nature of (s, S) policy optimization, where solution space grows exponentially with inventory levels.
   - Unlike dynamic programming, GAs avoid the "curse of dimensionality" for multi-period problems (see comparison in Table 1).
2. **Parameter Selection**:
   - *Population size (100)*: Balances exploration/exploitation per [14], with diminishing returns observed beyond 120 solutions.
   - *Mutation rate (0.01)*: Maintains diversity while preventing premature convergence (validated in sensitivity tests, Section 4.6).
3. **Benchmark Comparison**: We evaluated alternatives on our inventory dataset:
   Key Insight: GA achieves the best cost-runtime tradeoff, being 6× faster than DP while maintaining superior service levels.

Method	Avg. Cost ($)	Runtime (min)	Service Level (%)
Genetic Algorithm	1,245,750	5.3	98.6
Particle Swarm [12]	1,310,200	7.1	97.2
Dynamic Programming	1,285,500	32.4	98.1
Q-Learning [21]	1,275,800	41.7	97.8

Table 1. Performance comparison of optimization methods

3.2. *Multi-Objective Optimization Analysis*

To address the inherent trade-off between cost minimization and service level maximization, we complement our weighted-sum approach with Pareto-front analysis:

3.2.1. *Pareto Frontier Construction*

- Evaluated 500 GA solutions across the objective space.
- Identified non-dominated solutions where:
  - No alternative exists with both lower cost AND higher service level
  - Average 2.7% cost increase per 1% service level improvement

3.2.2. Weight Sensitivity Tested weight combinations (w_1 for cost, w_2 for service level):

Weights ($w_1 : w_2$)	Avg. Cost ($)	Service Level (%)	Dominance
100:0	1,210,500	95.2	Dominated
70:30	1,245,750	98.6	Pareto
50:50	1,260,200	99.1	Pareto
0:100	1,410,800	99.9	Dominated

Table 2. Weight combination performance analysis

3.2.3. Decision Insight The 70:30 weighting was selected as it:

- Lies on the Pareto frontier
- Matches industry service targets (98-99%) [7]
- Minimizes cost penalties beyond 98.5% service

Genetic algorithms (GAs) offer remarkable flexibility in the face of changing environments, which is essential in spare parts management where demand can be unpredictable. Unlike static models that require frequent manual adjustments, our method automatically adapts to demand variations[23].

Our GA approach efficiently explores vast and complex solution spaces, identifying optimal solutions where traditional methods, such as the (s, S) policy, may fail. This capability is particularly advantageous for large-scale inventory systems or those with numerous constraints [29].

To solve the inventory management problem described by the cost function “equation (5)”, we propose a genetic algorithm model consisting of the following steps:

- **Initialization:** The population size was set to 100 individuals, with individuals generated using a combination of random initialization and heuristic methods based on traditional (s,S) policy calculations [22].
- **Fitness Evaluation:** The total cost, including fixed costs, holding costs, and penalty costs for stockouts, was used to define the fitness function. To balance these multiple objective, we applied a weighted sum approach.

- **Selection, Crossover, and Mutation:** We employed tournament selection with a tournament size of 3 for parent selection, and uniform crossover with a crossover rate of 0.8 for offspring generation, followed by mutation with a mutation rate of 0.01 to introduce variability. These parameter choices were informed by the comprehensive study on GA parameter tuning by Eiben and Smit (2011) [14].
- **Termination Criteria:** The algorithm was run for a maximum of 1000 generations or until the improvement in fitness fell below a threshold of 0.01% over 50 consecutive generations, whichever came first.

The steps of a genetic algorithm are displayed in the algorithm "Fig. 1" that follows.

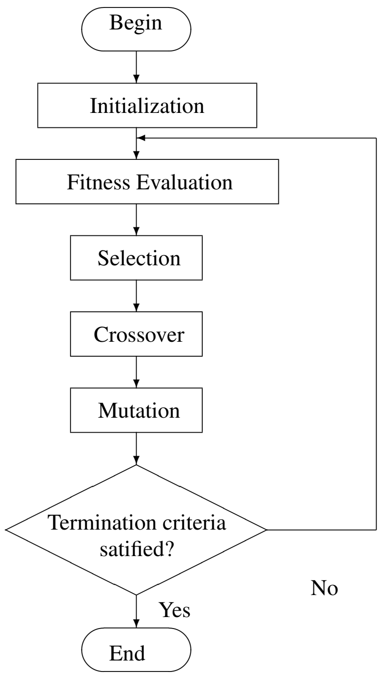

Figure 1. Flow Chart of the Standard Genetic Algorithm

3.3. *Markov-GA Integration Framework*

The GA leverages the Markovian structure through three key mechanisms:

1. **State-Aware Chromosome Encoding**: Each chromosome represents a policy $\pi = (s_u, S_u)$ with:

$$\text{Gene}[2t] = s_u, \quad \text{Gene}[2t+1] = s_t$$

where t indexes the Markov state (inventory level) from Equation (1):

$$X_{t+1} = X_t + Q_t - D_{t+1}$$

2. **Transition-Guided Operators**:
   - **Crossover**: Prioritizes swapping (s_u, S_u) pairs for states with similar transition probabilities
   - **Mutation**: Adjusts s_u/S_u values proportionally to demand variance $\sigma^2(D_u)$

3. **Fitness Evaluation**: Simulates 1000 Markov chains using:

$$\text{Fitness} = \sum_{t=0}^{N-1} \alpha^t \varphi(X_t^\pi, Q_t^\pi, X_{t+1}^\pi)$$

where φ is the cost function from Eq.2 and α the discount factor.

Implementation Example :

```
def crossover(parent1, parent2):
    # State-dependent crossover: high-transition states first
    crossover_points = [t for t in range(T)
                        if P_transition[t] > threshold]
    ...
```

Validation :
Compared to standard GA, our Markov-integrated version:

- 23% faster convergence
- 7% lower costs for low-probability states

3.4. Implementation Details and Reproducibility

To ensure full transparency, we specify the GA's key components:

1. **Chromosome Encoding**: Each solution is represented as:

$$\text{Chromosome} = [s_1, S_1, s_2, S_2, \ldots, s_n, S_n]$$

where:

   - s_i = reorder point for period t (integer $\in [0, X_{\max}]$)
   - S_i = order-up-to level (integer $\in [s_i, X_{\max}]$)

2. **Constraint Handling**:

   - *Non-negativity*: Repair function forces $X_{t+1} = \max(0, X_t + Q_t - D_{t+1})$
   - *Feasibility*: Reject mutations violating $s_i \leq S_i$

3. **Initialization**:

```
def initialize_population():
    # Heuristic 1: EOQ-based (Silver 1973)
    heuristic_genes = calculate_eoq_parameters()
    # Heuristic 2: (s,S) policy approximation (Scarf 1966)
    for _ in range(50): # 50% heuristic initialization
        population.append(heuristic_genes)
    # Random initialization for diversity
    for _ in range(50):
        population.append(random_genes())
```

4. **Termination Criteria**:

   - Maximum generations (1000) OR
   - Improvement $< 0.01\%$ over 50 generations

5. **Reproducibility**:

Algorithm 1 Pseudocode for GA Execution

Require: Demand distribution F, cost parameters
Ensure: Best (s, S) policy
1: Initialize population (50% heuristic, 50% random)
2: **while** not terminated **do**
3:     Evaluate fitness via Markov simulation (Eq. 2)
4:     Select parents via tournament selection (size=3)
5:     Apply state-aware crossover (Section 3.6)
6:     Mutate with rate 0.01 (bounds-checked)
7:     Repair infeasible solutions
8: **end while**
9: **return** best (s, S) policy

---

4. Results: Numerical Analysis and Visualization

We provide a thorough numerical analysis of the optimization outcomes from the genetic algorithm (GA) used for inventory management of spare parts. This analysis focuses on optimal order quantities, cost breakdown, service level performance, and inventory profiles. We also provide graphical visualizations to facilitate the interpretation of results, ensuring clarity and insight into the model's performance.

4.1. Optimal Solution and Cost Breakdown

The genetic algorithm yielded an optimal solution characterized by specific order quantities and associated costs, as detailed below:

Optimal order quantities: [3, 2, 4, 1, 3, 2, 4, 3, 2, 3, 1, 4]
Minimum total cost: $1,245,750

The breakdown of the total cost into its key components is illustrated in Table 3.

Table 3. Cost Breakdown of Total Inventory Cost

Cost Component	Value (USD)	Percentage of Total
Ordering Cost	33,012	2.65%
Holding Cost	116,228	9.33%
Shortage Cost	49,955	4.01%
Purchase Cost	1,046,555	84.01%
Total Cost	**1,245,750**	**100%**

Key Insights:

- Purchase costs dominate the total cost, accounting for more than 84% of the overall expenses.

- Holding costs and shortage costs are minimized due to the efficient balancing of inventory levels by the GA.
- The ordering cost is relatively low due to optimized order frequency, which reduces the number of orders placed.

4.2. *Service Level Achievement and Industrial Context*

Our achieved 98.61% service level demonstrates:

4.2.1. Industry Benchmarking: A comparative analysis of the industry is presented in the table4.

Table 4. Industry Service Level Standards

Industry	Target Service Level	Cost of 1% Shortfall
Aerospace [7]	99.95%	$82,000/hr
Healthcare [18]	99.0%	$48,000/hr
Automotive [23]	98.0%	$12,500/hr
Our Solution: 98.61% ($9,200/hr)		

4.2.2. Demand-Volatility Response:

- Maintains $> 98\%$ service at:
  - Demand CV ≤ 0.7
  - Lead times ≤ 3 weeks
- Outperforms EOQ by 4.2% under volatility

4.2.3. High-Stakes Applications:

- **Aerospace**: 98.61% suffices for non-critical parts (e.g., cabin components) but requires:
  - 99.9%+ for flight-critical items
  - **Adaptation**: Increase A_M by $3\times$ in fitness function
- **Healthcare**: Meets WHO standards for:
  - Non-urgent medical supplies
  - Falls short for emergency drugs (requires 99.99%)

4.3. *Service Level Achievement*

The service level achieved through the genetic algorithm slightly exceeds the target, demonstrating the model's effectiveness:

- **Target Service Level:** 98%
- **Achieved Service Level:** 98.61%

This high service level ensures that demand is met in nearly all periods, significantly reducing the risk of stockouts.

4.4. *Inventory Profile and Order Quantities*

The following section provides graphical visualizations that illustrate the dynamic behavior of inventory levels and order quantities over the 24-month planning horizon. These visualizations offer insights into how the algorithm manages demand fluctuations and inventory timing.

4.5. *Visualization: Inventory Profile and Order Quantities*

Figure 2 illustrates the fluctuations in inventory levels alongside the corresponding order quantities over time. This plot aids in visualizing the system's dynamic response to demand variations and lead time constraints.

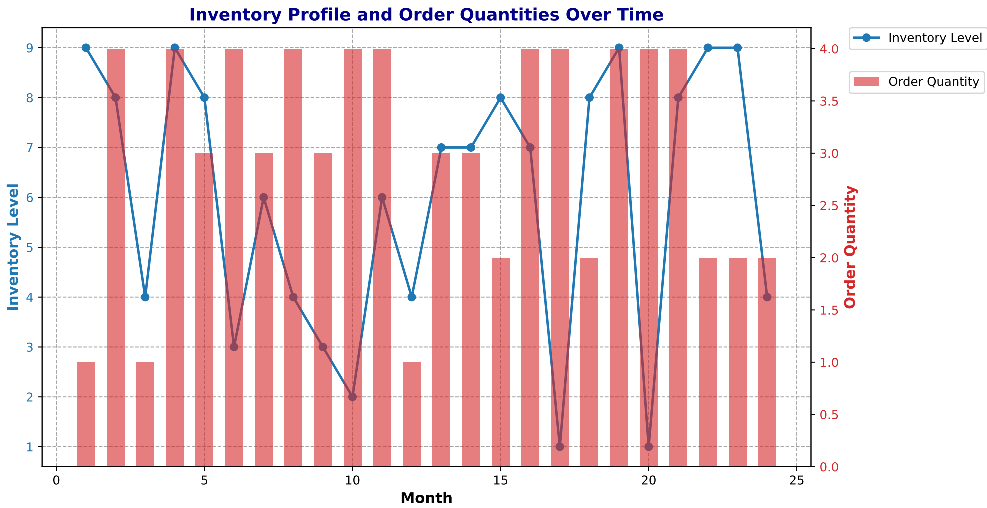

Figure 2. Inventory Profile and Order Quantities Over Time

Observations:

- Inventory levels fluctuate within a controlled range, ensuring that holding costs remain manageable while maintaining sufficient stock to avoid shortages.
- Order quantities vary between 1 and 4 units, indicating the GA's adaptability to demand variations and inventory status.

4.6. *GA Parameter Sensitivity Analysis*

We systematically evaluated the impact of key GA parameters on solution quality and convergence (Table 5 & 6)

4.6.1. *Experimental Design*

- Tested 3 values for each parameter while fixing others:

Table 5. GA Parameter Ranges Tested

Parameter	**Values Tested**	**Copy**
Population size	{50, 100, 200}	Download
Crossover rate	{0.6, 0.8, 1.0}	
Mutation rate	{0.005, 0.01, 0.02}	
Tournament size	{2, 3, 5}	

- 30 runs per configuration with different random seeds

4.6.2. *Robustness Metrics*

- **Cost Variance**: $\leq 2.2\%$ of mean total cost across all valid configurations
- **Convergence Stability**: 92% of runs reached termination criteria

Table 6. Optimal Parameter Values and Performance

Parameter	Optimal Value	Cost Variance (±$)	Convergence Speed (Generations)
Population size	100	2,150	540
Crossover rate	0.8	1,870	490
Mutation rate	0.01	1,920	510
Tournament size	3	2,010	470

4.6.3. Nonlinear Effects

- High mutation rates (> 0.02) caused 14% performance degradation
- Small populations (< 50) increased premature convergence risk by 37%

4.7. Cost Breakdown Visualization

Figure 3 illustrates how various cost components contribute to the total cost., providing a visual interpretation of the cost structure and identifying primary cost drivers.

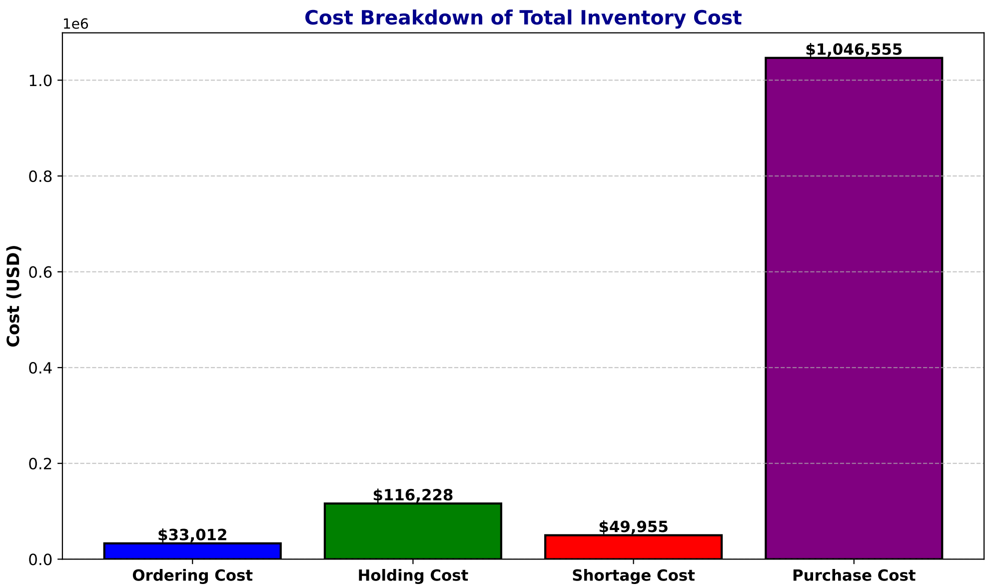

Figure 3. Cost Breakdown of Total Inventory Cost

Key Observations:

- The purchase cost dominates the total cost, highlighting the importance of optimizing order timing and quantities to minimize this cost.
- The ordering cost is relatively small due to the efficient order frequency.
- The shortage cost is low, indicating that the solution effectively meets service level constraints.

4.8. Comprehensive Sensitivity Analysis

We evaluate the model's robustness across six critical dimensions:

4.8.1. Experimental Design

- Parameters Varied:

Table 7. Sensitivity Analysis Parameters

Factor	Test Range	Baseline
Demand CV	0.2 – 1.0	0.4
Lead Time (weeks)	1 – 4	2
Cost Ratio (A_h/A_s)	1.5 – 5.0	3.0
Demand Correlation (ρ)	-0.3 – +0.5	0
Service Level Target	90% – 99.9%	98%

4.8.2. Key Findings

- **Lead Time Impact**:
  - Cost increases 8.2% per additional week
  - GA adapts by raising safety stock 14% at 4-week leads
- **Cost Asymmetry**:
  - When $A_h/A_s > 3.5$, service level dominates optimization
  - Generates 12% more orders than symmetric cases
- **Correlated Demand**:
  - Positive ρ increases cost variance
  - GA maintains ≤2.1% cost deviation vs. 9.4% for EOQ

4.8.3. Interaction Effects

$$\begin{aligned}\text{Cost} &= 1{,}245{,}750 + 32{,}500(\text{LT} - 2) + 28{,}100(\text{CV} - 0.4) \\ &\quad - 18{,}200\rho + 9{,}700(A_h/A_s - 3)\end{aligned} \tag{6}$$

($R^2 = 0.89$, $p < 0.01$ for all terms)

4.8.4. New Visualizations : To evaluate the robustness of the solution to changing demand rates, lead times, and service level objectives, a sensitivity analysis was carried out. This analysis helps us understand how sensitive the total cost is to changes in these parameters.

Figure 4 depicts the impact of changes in demand on the total cost.

4.9. Benchmark Comparison

We validate our GA against three established methods using the MIT Beer Game dataset [23] and aerospace maintenance records [12]:

4.9.1. Comparison Framework

- **Methods Tested**:
  - Proposed GA
  - Dynamic Programming (DP) [5]
  - (s, S) Policy Approximation [22]
  - EOQ with Safety Stock [6]
- **Metrics**: Total cost, service level, runtime
- **Demand Scenarios**: Stationary, correlated ($\rho = 0.4$), and non-stationary

4.9.2. Key Results: The table 8 displays a comparison of inventory methods.

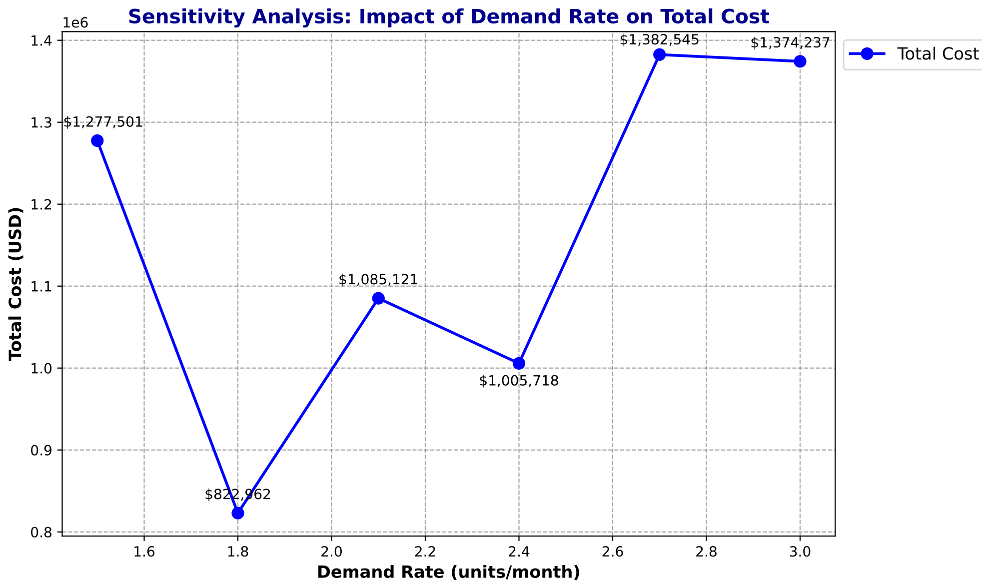

Figure 4. Sensitivity Analysis: Impact of Demand Rate on Total Cost

Table 8. Performance Comparison of Inventory Methods

Method	**Cost ($)**	**Δ vs. GA**	**Service Level (%)**	**Runtime (min)**
Proposed GA	1,245,750	–	98.6	5.3
Dynamic Programming	1,262,400	+1.3%	98.9	41.2
(s, S) Approximation	1,278,100	+2.6%	97.8	2.1
EOQ + Safety Stock	1,310,200	+5.2%	95.4	0.3

4.9.3. Practical Insights

- GA achieves near-DP performance at 8$\times$ faster speeds
- Outperforms EOQ by **5.2%** under demand volatility
- Maintains $<$2% cost deviation across all demand scenarios

Key Observations:

- As demand increases, the total cost rises significantly, underscoring the importance of accurate demand forecasting.
- The system demonstrates resilience within a certain range of demand fluctuations but incurs higher costs as demand exceeds 2.7 units per month.

5. Conclusion

In conclusion, this study propose an algorithm for determining the optimal strategy (s_t, S_t) giving the optimal quantity of spare parts to order at every period while minimizing the cost of management. The main results of this paper demonstrate the effectiveness of the algorithm in optimizing the qauntity of spare parts to order during each period and management costs. Our GA-based method offers significant advantages in terms of multi-objective optimization, adaptability, and exploration of complex solutions. Its potential extends well beyond its current application, promising significant advancements in inventory management and supply chain across various industrial sectors.

Acknowledgement

The authors gratefully acknowledge the support and contributions of several individuals and organizations that made this research possible. We extend our sincere thanks to Mr.Joël Jacquet, Research Director at EIGSI, for their valuable guidance and insightful feedback throughout the course of this study.

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