

AI-Based Demand Forecasting and an Intelligent Sustainable Inventory Model for Green Deteriorating Products

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ABSTRACT: The increasing need for green products and the unpredictable nature of the market demands have posed serious challenges in dealing with deteriorating green products. Traditional inventory theories may not consider AI demand prediction, especially where demand varies. To solve this problem, this study formulates an intelligent sustainable inventory model using AI-based demand prediction for deteriorating green products. The model aims to determine optimal inventory policies by evaluating relevant inventory costs, including ordering, holding, and deterioration costs. AI-based forecasting predicts the demand needed for making inventory decisions. The effect of important variables on the efficiency of the model is investigated through numerical experiments and sensitivity analysis. The study also investigates the impact of demand forecasting, inventory, and deterioration losses. The proposed framework establishes an integrated approach to intelligent inventory planning by connecting AI-based demand prediction with sustainable inventory optimization. This is because it allows analysis of how better forecasts can help with replenishment, waste reduction, and efficiency. The current study makes a valuable contribution to green inventory management through integration of artificial intelligence-based forecasting into the optimal design of inventory for deteriorating items.

1. Introduction

In modern supply chain and inventory management, the issue of sustainability has turned out to be of critical importance for scholars and practitioners alike. Increasing awareness about the environment, changing preferences of consumers, and rising sustainability legislation have greatly contributed to the high demand of green

products. In the context of economic development and reduction of the negative effect on the environment, managing inventories has turned into a key element of achieving efficiency and sustainability in the process.

Inventory management of green products is particularly difficult if these products deteriorate. Deterioration refers to the natural process of reducing the quantity and/or the quality of the product during its storage, which results in inventory losses, higher costs, and lower profit margins. This problem becomes particularly significant for products such as organic food, eco-friendly consumer goods, pharmaceutical products, and other environmentally sensitive products. Thus, the development of the appropriate inventory policies for deteriorating green products becomes a topical area for research.

Another significant problem that organizations are facing is that of demand uncertainty. Classical inventory management frameworks assume demand processes to be deterministic in nature or probabilistically determined. However, demand is very dynamic due to changing market conditions and is affected by various economic, social, and technological determinants. Improper forecasts of the demand lead to having excess inventory or lack thereof and results in waste generation and bad customer service experience. Therefore, improvement of demand forecasting is one of the primaries aims for inventory management.

The development of AI and machine learning technology has given rise to new possibilities for enhancing inventory decisions. With the help of advanced AI forecasting mechanisms, it is possible to analyze vast amounts of historical and current data, to detect complicated patterns and to make more accurate forecasts than classical forecasting approaches. Better forecasts allow optimizing replenishment process and reducing deterioration-related costs.

In light of the above-stated issues and opportunities, this study suggests an intelligent sustainable inventory model for green deteriorating products through the introduction of artificial intelligence-based demand forecasting within the inventory management setting. The goal of the suggested model is to incorporate the aspects of sustainability, deterioration of products, and improved demand forecasting to derive optimal inventory policies for fluctuating demands.

The contribution of this research to the existing body of knowledge will be made around sustainable inventory management and is reflected in the combination of the

concepts of green products, their deterioration, and demand forecasting using artificial intelligence.

1.1 Research Objectives

The main objective of this study is to develop an intelligent and sustainable inventory model for green deteriorating products by incorporating AI-driven demand forecasting into the inventory decision-making process.

The specific objectives of this study are:

- I. To develop an AI-driven demand forecasting framework for deteriorating green products and integrate the forecasted demand into inventory decision-making.
- II. To formulate a sustainable inventory optimization model that incorporates product deterioration, forecast-based demand, and relevant inventory costs to determine optimal inventory policies.
- III. To measure the performance of the model by means of numerical experiments, comparison analysis, and sensitivity analysis in various demand situations.

2.1 Literature Review

Inventory management for deteriorating items has gained much attention as the deterioration of items can impact product availability, costs, and efficiency. Current trends in inventory management have seen an increase in the consideration of sustainability, environmental costs, and sophisticated decision-making tools when modeling inventory systems. In their review on developing deteriorating inventory systems, Asghari et al. (2026) pointed out the increasing importance of managing uncertainty, considering sustainability and utilizing inventory management based on data.

The goal of sustainable inventory management is to combine economic efficiency with environmental responsibility. According to the systematic review carried out by Becerra et al. (2021), quantitative models of green supply chain management involve elements such as inventory costs, order quantity, safety stocks, and environmental effects. It shows that the cost minimization and greenhouse gases reduction are the main goals of sustainable inventory optimization. In addition, Yu et al. (2020) considered deteriorating inventory models with carbon emissions and carbon control strategies, showing how the environmental factors can affect inventory management. San-José et al. (2023) considered another sustainable inventory model that considers time-dependent demand, deterioration, shortages, and taxation on carbon emissions.

Recently, Verma et al. (2026) presented the deteriorating inventory model with preservation investment, carbon emission cost, trade credit, and price-sensitive demand. This research show significant achievements in the field of sustainable inventory optimization, but their focus is different.

Demand forecasting represents another important dimension of inventory management. Forecasting errors can lead to excessive stock, shortages, unnecessary holding costs, and product waste. Artificial intelligence and machine learning offer opportunities to identify complex demand patterns and improve data-driven decision-making. Pournader et al. (2021) systematically reviewed artificial intelligence applications in supply chain management and identified a broad range of applications across supply chain functions. Their review provides a foundation for understanding how AI techniques can support more responsive and informed supply chain decisions.

Machine learning to predict demand in the pharmaceutical industry was investigated by Zhu et al. (2021). This study emphasized the role of relevant information in improving forecasting accuracy under changing demand trends. Preil and Krapp (2022) used Monte Carlo tree search to develop an artificial intelligence-based inventory system. This study demonstrated the applicability of artificial intelligence in managing uncertain demand and lead times. However, both above studies did not deal with sustainable inventory management for deteriorating products.

Recent research has made a significant increase in the application of AI in inventory management. In this regard, Li et al. (2025) carried out research on the application of AI techniques in demand forecasting and inventory management. The authors noted the importance and difficulties in the implementation of these technologies. Yet forecasting alone is not enough for maintaining sustainability in inventory management. Demand forecasts should be embedded in inventory policies considering deterioration costs and economic considerations.

There exist studies on inventory deterioration, sustainable inventory control, and AI-based demand forecast. These studies require further research integration under a unified mathematical structure. In this research, the intelligent sustainable inventory problem for deteriorating green goods is formulated based on AI-based demand forecast. The numerical experiments and sensitivity analysis have been conducted to analyze the proposed model.

Table 1. Related Research Comparisons

Author(s) & Year	Demand Pattern	Demand Depends on	Shortage	Facility	Focus
Ali et al. (2025)	Variable demand	Price and stock	Not specified	Preservation investment	Greening and deterioration control
Amosu et al. (2024)	AI-driven forecasting	Forecasted demand	Not specified	AI-based forecasting	Inventory management and customer satisfaction
Ping et al. (2025)	Data-driven demand	Data-driven forecasting	Not specified	Data-driven optimization	Inventory optimization
Chaudhary et al. (2026)	AI-driven demand	AI forecasting and fuzzy parameters	Not clear from the reference	Fuzzy modeling	AI-driven sustainable inventory optimization
Kaur and Prakash (2026)	Dynamic demand	Deep reinforcement of learning/ state information	Not specified	Hybrid deep reinforcement learning	Dynamic inventory management in pharmaceutical supply chains
Rajawat et al. (2025)	Exponential demand	Time/ forecasting function	Not clear from the reference	Machine learning and carbon constraints	Deteriorating products and emission control
Singh and Mishra (2024)	ML-based forecast demand	Machine learning-based forecasting	Partial backlogging	Carbon-emission control	Imperfect deterioration and sustainable inventory
Verma and Mishra (2024)	Multiple demand patterns	Multiple factors/ policies	Not clear from the reference	Carbon-control, greening and rework policies	Review of deteriorating inventory optimization
Deteriorating Inventory Models: A Comprehensive Review (2026)	Multiple demand patterns	Various factors	Various shortage policies	Various inventory policies	Comprehensive review of deteriorating inventory models
Wadhawan and Rizvi (2025)	Not specified	Not specified	Not specified	Multiobjective reverse logistics	Green inventory and reverse logistics

Author(s) & Year	Demand Pattern	Demand Depends on	Shortage	Facility	Focus
Sarker et al. (2025)	Learning-dependent, hybrid stochastic–fuzzy	Price and learning effect	Partial backlogging	Single-echelon; carbon-emission cost	Robust sustainable inventory, hybrid uncertainty
Sarker et al. (2026)	Interval demand	Price, stock level, eco-awareness	partial backlogging	Multi-layer warehouses; advance payment	Multi-layer inventory, payment policies, carbon costs
Proposed Study	AI-driven demand forecasting	Time, selling price and green investment	As specified in the proposed model	Green investment, deterioration control and carbon-emission management	Intelligent sustainable inventory optimization for deteriorating green products

2.2 Research gap

While various researchers have worked on inventory deterioration, green inventory management, and AI-based demand prediction in the past, these areas of research have not been combined. The current models fail to consider the relationship between sustainability, inventory deterioration, and dynamic demand. Furthermore, demand forecasting based on AI is hardly ever applied in inventory optimization. Thus, an intelligent sustainable inventory model is proposed for green deteriorating products.

2.3 Research contribution

- The current research formulates an intelligent inventory model incorporating AI-powered demand forecasting and inventory optimization for green items that deteriorate over time.
- The present research incorporates demand forecasting through AI to enhance the process of demand estimation in changing conditions.
- The formulated model considers deterioration of goods, economic factors, and green sustainability in the context of inventory management.
- Sensitivity analysis is performed to analyze the impact of certain parameters on inventory management decisions.

3.1 Assumptions

- i. The inventory system considers only one green deteriorating item within a certain finite planning period.
- ii. Demand is a function of the price of the item, AI demand forecast, and green investment, which can be formulated by $D(t, p, G) = F_{AI}(t)p^{-b}(1 + \gamma G)$,
- iii. It is assumed that the AI demand forecast is known and positive for all t in the planning period.
- iv. Continuous deterioration of the items occurs at a constant rate, and any deteriorated items are discarded.
- v. Green investment leads to better environmental performance and impacts positively on demand.
- vi. Replenishment is instant, there is no lead time, and no shortages are allowed.
- vii. Ordering, purchasing, holding, and carbon emission costs are incorporated in the model.
- viii. The aim of the model is to maximize profit.

3.2 Notation

Symbol	Description
t	Time within a replenishment cycle
T	Replenishment cycle length
$I(t)$	Inventory level at time (t)
Q	Order quantity at the beginning of a cycle
b	price elasticity parameter
p	Selling price per unit
$D_{AI}(t)$	AI-forecast baseline demand
$D(t)$	Effective demand rate
G	Green investment decision
U	Preservation investment decision
θ	Deterioration rate under preservation investment
A	Ordering cost per replenishment
C	Purchase cost per unit
H	Holding cost per unit per unit of time
$C_u(u)$	Preservation expenditure per unit of time
$C_g(g)$	Green investment expenditure per unit of time
e_o	Emissions associated with one order
e_h	Emissions per unit of inventory held per unit of time
e_d	Emissions per unit of deteriorated product
γ	Carbon price per unit of emissions

Symbol	Description
M	Permissible trade-credit period
i_e	Interest-earning rate
i_p	Interest-charging rate
TC	Net trade-credit financing benefit
π	Average profit per unit of time

4.1 Problem Statement

here are various issues with the management of green deteriorating products because of the product deterioration, the environment and the unpredictability of customer demands. Conventional inventory models usually concentrate on minimizing the costs and making the demand forecasts, assuming predictable patterns that may not always be accurate. Inaccurate forecasts lead to an increase of inventory levels, increase in deterioration, shortages and wastages. While the potential of AI in making the forecasts more accurate has been already proved, the use of AI in sustainable inventory models for green deteriorating products is yet to be applied.

4.2 Inventory Dynamics

Let $I(t)$ denote inventory level at time t .

The inventory depletion occurs due to demand and deterioration.

$$\begin{aligned} \text{or,} \quad & dI(t)dt = -\theta I(t) - F_{AI}(t)p^{-b}(1 + \gamma G) \\ \text{with} \quad & dI(t)dt + \theta I(t) = -F_{AI}(t)p^{-b}(1 + \gamma G) \\ & I(0) = Q, \quad I(T) = 0 \end{aligned}$$

where Q is the order quantity.

4.3 Solution of Inventory Level

Using integrating factor $e^{\theta t}$,

$$I(t) = e^{-\theta t} \left[Q - p^{-b}(1 + \gamma G) \int_0^t F_{AI}(x)e^{\theta x} dx \right]$$

Applying $I(T) = 0$,

Ordering Cost: $OC = C_o$ where C_o is ordering cost per cycle.

Purchasing Cost: $PC = C_p Q$

Therefore $PC = C_p p^{-b}(1 + \gamma G) \int_0^T F_{AI}(t)e^{\theta t} dt$

Holding Cost: $HC = h \int_0^T I(t) dt$

Substituting $I(t)$,

$$HC = h \int_0^T e^{-\theta t} [Q - p^{-b}(1 + \gamma G) \int_0^t F_{AI}(x) e^{\theta x} dx] dt$$

Green Investment Cost: A common formulation is $GC = \frac{k}{2} G^2$ where k is the green investment coefficient.

Total Profit Function:

$$TP = SR - OC - PC - HC - GC$$

Hence
$$TP = p^{-b}(1 + \gamma G) \int_0^T F_{AI}(t) dt - C_o - C_p Q - HC - \frac{K}{2} G^2$$

Subject to
$$Q = p^{-b}(1 + \gamma G) \int_0^T F_{AI}(t) e^{\theta t} dt$$

4.4 Optimization Problem

Determine the optimal values (T^*, p^*, G^*)

Such that $\max_{T, p, G} TP(T, p, G)$, with $p > 0, G \geq 0, T > 0$.

Optimization of the Proposed Inventory Model

The objective of the proposed inventory model is to determine the optimal selling price, green investment level, and replenishment cycle length that maximize the total profit of the inventory system. The total profit function is expressed as

$$TP(p, G, T) = p^{-b}(1 + \gamma G)[p^{1-b}A(T) - p^{-b}C(T)] - C_o - \frac{K}{2}G^2$$

Where $A(T) = \int_0^T F_{AI}(t) dt$ and $C(T) = C_p B(T) + C_h H(T)$ and $B(T) = \int_0^T F_{AI}(t) e^{\theta t} dt$ and $H(T) = \int_0^T e^{-\theta t} [\int_t^T F_{AI}(t) e^{\theta s} ds] dt$.

The optimal decision variables are denoted by T^*, p^*, G^* . These variables are determined by maximizing the total profit function subject to the relevant feasibility conditions:

Determination of the Optimal Selling Price

Solving for p , the candidate optimal selling price is obtained as

$$p^* = \frac{bC(T)}{(b-1)A(T)}$$

provided that $b > 1$, $A(T) > 0$, and $C(T) > 0$. The final optimal price is evaluated at the optimal cycle length T^* .

Determination of the Optimal Green Investment

the candidate optimal green investment is

$$G^* = \frac{\gamma}{K} [p^{1-b} A(T) - p^{-b} C(T)]$$

Considering the non-negativity constraint on green investment, the feasible solution is expressed as

$$G^* = \max\{0, \frac{\gamma}{K} [p^{1-b} A(T) - p^{-b} C(T)]\}$$

This equation suggests that the best amount of green investment is dependent on the extra profit made through green investment along with its cost of investment.

Determination of the Optimal Replenishment Cycle Length

The optimal cycle length T^* is determined by solving

$$\frac{b C(T^*)}{(b-1)A(T^*)} = \frac{C'(T^*)}{F_{AI}(T^*)}$$

Since this equation generally cannot be solved explicitly for an arbitrary AI-generated demand forecast, a numerical optimization technique can be employed to determine T^* .

4.5 Mathematical Properties of the Proposed Model

Property 1: Existence and Uniqueness of the Inventory Level

Consider the inventory differential equation

$$\frac{dI(t)}{dt} + \theta I(t) = -F_{AI}(t)p^{-b}(1 + \gamma G),$$

with initial condition $I(0) = Q$, where $\theta > 0$ and $F_{AI}(t)$ is continuous on $[0, T]$.

Since this is a first-order linear differential equation with continuous coefficients and a continuous forcing function, it has a unique continuously differentiable solution on $[0, T]$.

Property 2: Effect of Green Investment on Demand

The demand function is defined as,

Given $D(t, p, G) = F_{AI}(t)p^{-b}(1 + \gamma G)$, with $\gamma > 0, p > 0$ and $F_{AI}(t)p^{-b} > 0$, the partial derivative of demand with respect to green investment is

$$\frac{\partial D}{\partial G} = \gamma F_{AI}(t)p^{-b} > 0$$

Therefore, demand increases with green investment G , provided that the other variables remain constant.

Property 3: Effect of Selling Price on Demand

For $D(t, p, G) = F_{AI}(t)p^{-b}(1 + \gamma G)$,

here $b > 0, 1 + \gamma G > 0, p > 0$ and $F_{AI}(t)p^{-b} > 0$, the partial derivative of demand with respect to selling price is $\frac{\partial D(t, p, G)}{\partial p} = -bF_{AI}(t)p^{-b-1}(1 + \gamma G) < 0$.

Therefore, demand decreases as the selling price increases, with the other variables held constant.

Property 4: Curvature of Demand with Respect to Price

The second derivative of the demand function with respect to price is

$$\frac{\partial^2 D(t, p, G)}{\partial p^2} = b(b + 1)F_{AI}(t)p^{-b-2}(1 + \gamma G) > 0$$

Thus, the demand function is strictly convex with respect to price with $b > 0, 1 + \gamma G > 0, p > 0$ and $F_{AI}(t)p^{-b} > 0$, under the stated assumptions. This indicates that the marginal effect of price on demand varies nonlinearly with the price level.

Property 5: Effect of AI Forecast Improvement on Demand

Suppose two AI forecasting approaches produce forecasts satisfying

$$F_{AI}^{(2)}(t) > F_{AI}^{(1)}(t)$$

for all $t \in [0, T]$.

Then,

$$D^{(2)}(t, p, G) > D^{(1)}(t, p, G)$$

Consequently, a larger demand forecast baseline results in a larger modeled demand rate, assuming all other variables remain constant.

5. Selected parameter values for the numerical example

The following values have been used for illustration purposes only; they have not been obtained through any estimates using actual market data.

Table 2. Values of Darameter

Parameter	Description	Selected Value
θ	Deterioration rate	0.02
b	Price-sensitivity parameter	1.5
γ	Green-investment demand coefficient	0.3
a	Initial baseline demand	1000
s	Linear demand trend	200
C_o	Ordering cost per cycle	30
c	Purchase cost per unit	1.5
h	Holding cost per unit per unit of time	1.5
K	Green-investment cost coefficient	50
λ	Carbon price	0.1
c_d	Disposal cost per deteriorated unit	0.05

The baseline AI forecast is represented by a simple linear benchmark:

$$F_{AI} = 1000 + 200t$$

This is a placeholder for the demand forecast produced by an actual AI model. The linear function allows us to demonstrate inventory optimization calculations before integrating a trained LSTM or other machine-learning model.

5.1 Numerical results

Using the demand function

$$D(t, p, G) = (1000 + 200t)p^{-1.5}(1 + 0.3G)$$

Under the illustrative parameter assumptions, the numerical optimization yields the following results:

Table 3. Optimal Solutions for the Models on the Example Considered

Decision variable	Optimal value
Optimal replenishment quantity, Q^*	85.385 units
Optimal selling price, p^*	6.55 monetary units/unit
Optimal green investment, G^*	1.660
Optimal replenishment cycle, TP^*	0.866 time units
Maximum average profit, TP^*	320.134 monetary units per units time.

These values are only approximate numeric answers and not empirical data. These depend on the chosen parameter values, environmental cost parameters, decision variable constraints, and profit function formulation.

5.2 Sensitivity Analysis

Baseline optimum: $Q^*=84.938$, $p^*=6.546$, $G^*=1.698$, $T^*=0.860$, and $TP^*=320.149$.

Table 5.3: Effect of change of parameters on quantity, Selling Price, Green Investment, Inventory cycle length, Total Profit.

Parameter	Change	Q^*	p^*	G^*	T^*	TP^*
θ	-20%	85.301	6.548	1.698	0.865	320.497
	+20%	84.581	6.545	1.697	0.855	319.802
b	-20%	189.529	15.000	3.311	2.000	810.916
	+20%	67.391	4.786	1.028	0.793	159.906
γ	-20%	78.597	6.747	1.348	0.942	294.394
	+20%	92.269	6.355	2.053	0.782	352.109
a	-20%	79.786	7.556	1.347	1.258	246.045
	+20%	92.796	6.094	2.054	0.677	403.456
s	-20%	79.109	6.356	1.686	0.786	313.947
	+20%	92.399	6.812	1.710	0.964	326.897
C_o	-20%	77.571	6.251	1.718	0.739	327.663
	+20%	91.298	6.838	1.679	0.979	313.616
c	-20%	94.926	5.160	1.878	0.663	355.796
	+20%	79.390	8.042	1.565	1.098	294.792
h	-20%	106.812	6.518	1.731	1.048	334.727
	+20%	71.818	6.640	1.670	0.755	308.205
K	-20%	89.156	6.432	2.132	0.813	338.249
	+20%	82.044	6.633	1.410	0.896	308.177
λ	-20%	84.989	6.546	1.698	0.861	320.197
	+20%	84.888	6.547	1.698	0.860	320.101
C_d	-20%	84.949	6.546	1.698	0.860	320.158
	+20%	84.928	6.546	1.698	0.860	320.140

5.3 Interpretation of the results

a. Effect of the deterioration rate θ

An increase in the rate of deterioration from 0.02 to 0.024 leads to a reduction in the mean profit from approximately 320.149 to 319.802. There is also a small drop in the optimal time period. This shows that a higher rate of deterioration reduces profitability.

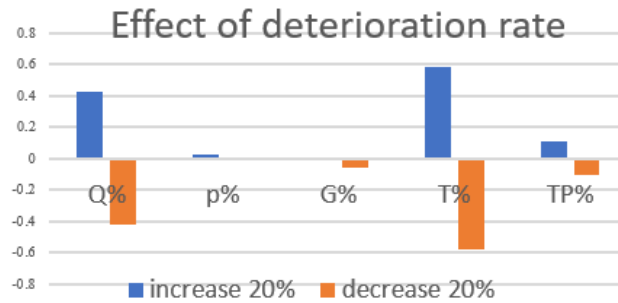


Fig. 1. Effect of deterioration rate

b. Effect of green-investment responsiveness γ

The rise in γ by 20% implies that the amount of green investments becomes equal to 2.053, while profit is increased up to 352.109. The dependence of demand from the change in green investments makes such investments more attractive.

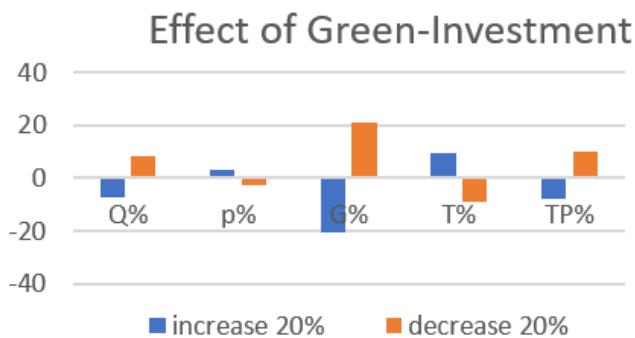


Fig. 2. Effect of green-investment

c. Effect of baseline demand α

An increase of 20% in the initial demand will make the mean profit equal to around 403.456, whereas a decrease of 20% will reduce the profit to 246.045. It is thus clear that the initial demand plays a crucial role in determining the economic viability of the inventory model.

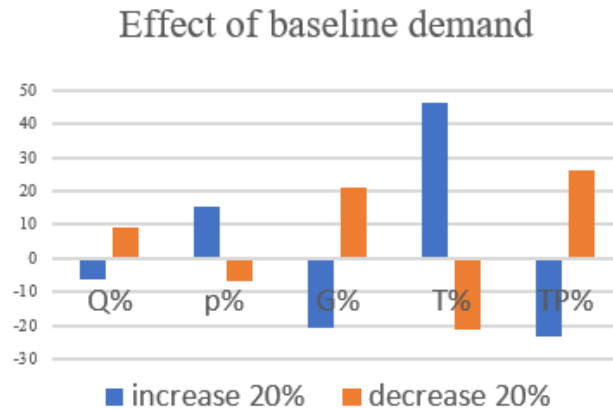


Fig. 3. Effect of demand parameter

d. Effect of price sensitivity b

Price sensitivity impacts the optimal solution significantly. But the case when $b = 1.2$, we attain the highest limit for price and cycle period. This implies that the stated solution will depend on the range within which we have conducted our search and cannot therefore be considered an optimum solution without bounds.

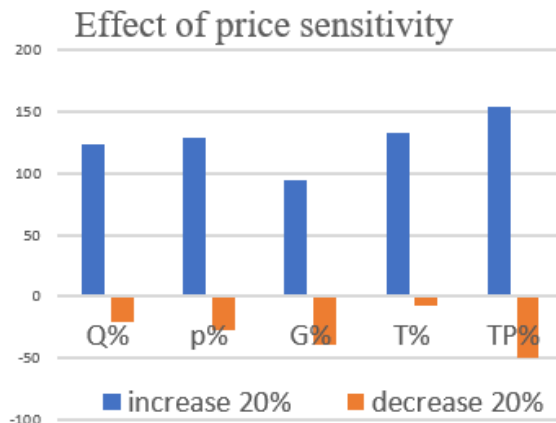


Fig. 4. Effect of price sensitivity

e. Effect of the green-investment cost coefficient K

When K increases by 20%, the best level of green investment is reduced to 1.410 and average profit to 308.177. As green investment gets costly, the model prefers less investment.

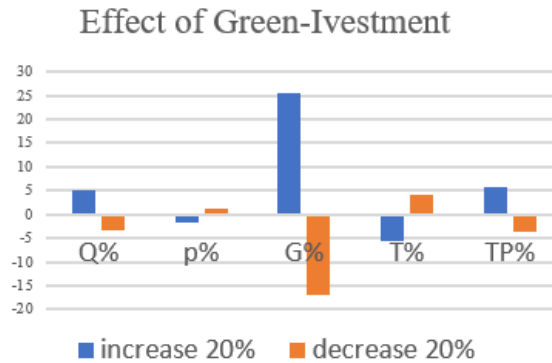


Fig. 5. Effect of Green Investment

f. Effect of holding cost h

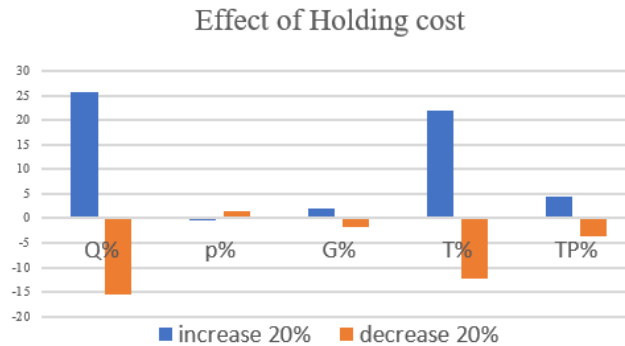


Fig. 6. Effect of holding cost

g. Effect of carbon price λ

The changes in the modeled carbon price have little impact on the profit as well as optimal solution. This is due to the relatively low importance of the emission cost considered in the objective function. This does not mean that carbon pricing is not important in general.

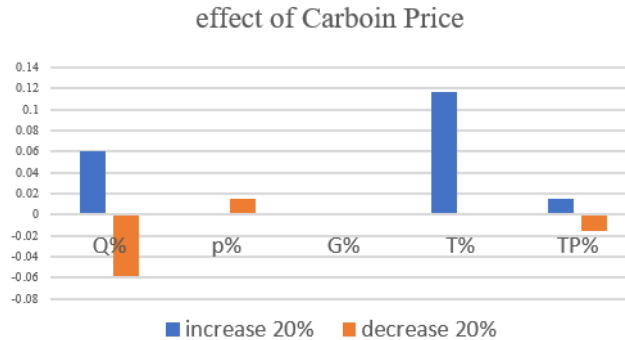


Fig. 7. Effect of carbon price

6. Managerial Implications

- i. Demand Planning: Managers should focus on making correct demand estimations since the variation in baseline demand has a significant influence on profit levels. AI-based forecasting will assist in modifying inventory decision making according to the changes in the environment.
- ii. Managers should think about investing in green practices if the investments could raise the level of demand and profits. However, the level of such investments should be proportional to their costs.
- iii. Managers should keep track of product deterioration and implement appropriate storing and replenishment policies to decrease the number of losses in products and ensure profitability.
- iv. Managers should manage costs related to inventory holding and green investments. In the case of increased costs, total profit may be negatively affected.
- v. Managers should evaluate the decision regarding the selling price of products and consider carbon price when formulating sustainable inventory policy. The significance of carbon price is limited in the current case; however, it may become greater due to stricter environmental regulations.

7. Conclusion

This paper presents an intelligent sustainable inventory system for deteriorating green products incorporating demand forecasting based on AI, green investments, and inventory optimization. From the numerical results, it can be observed that the impact of the baseline demand, responsiveness of the green investment, holding cost, and cost of investment affects the optimal solution and average profit obtained. The

sensitivity analysis also reveals the importance of the deterioration rate and the cost of carbon emissions for the given parameters.

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