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A Sustainable Inventory Model for Perishable Goods with AI-Based Demand Forecasting and Cost Optimization

Vinay Kumar Masiyare[1]*, Animesh Kumar Sharma[2]

1) Research Scholar, Department of Mathematics, The ICFAI University, Raipur, Chhattisgarh, India
2) Assistant Professor, Department of Mathematics, The ICFAI University, Raipur, Chhattisgarh, India

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Abstract
The demands of sustainable inventory models have been enhanced by the rising environmental effect of industrialization and international supply chains. Conventional methods generally reduce the ordering and holding expenses and do not consider the impact on the environment. The study suggests a progressive sustainable inventory system, which will introduce the issues of deterioration of items, the imposition of carbon penalty, and trade credit, in addition to the use of artificial intelligence (AI) to predict demand. The new model is the combination of Long Short-Term Memory (LSTM), which is a deep learning model, with an idea to forecast future demand based on the past data, which improves the accuracy of the forecasts in the face of uncertainty. The holding cost operation becomes altered to incorporate penalties based on emissions and deterioration is modelled under an exponential time-dependent operation. Moreover, the concept of a trade credit financing mechanism is also presented, which demonstrates the flexibility of the real-life situation in finances and the compensation of compliance costs. The analytical solution is in closed form to minimize the overall cost, which comprises of ordering, holding, deterioration, and emission cost. To verify the model, a numerical example of the demand forecasted by LSTM is used, and then graphical and computational analysis is used to find optimal cycle time. Sensitivity analysis is carried out to analyse the variables of deterioration rate, emission cost, and credit period. The proposed AI-based model is helpful in making environmentally and financially sustainable decisions in inventory systems and provides useful information to the operations managers and policy-makers. This model does not only promote the financial and operational efficiency of inventory systems but it also leads to environmental sustainability. It gives useful information to inventory managers, policy makers and researchers who need to weigh the economical and environmental objectives of the new supply chain systems.

Keywords: *Sustainable Inventory Model, LSTM Demand Forecasting, Carbon Emission Penalty, Deterioration, Trade Credit, AI-Based Cost Optimization*

1. Introduction

The past few decades have seen the rapid industrialization, global supply chain and environmental degradation rise to cement sustainability in the inventory management. Warehousing, transportation and the disposition of deteriorating goods are also key contributors of energy consumption and carbon emissions in inventory systems (Assari et al., 2023). Although the classical models of inventory have traditionally been concerned with the reduction of economic costs mainly ordering and holding; they do not pay much attention to their environmental consequences, which nowadays turns into a regulatory and ethical necessity (Anand et al., 2025). Introduction of penalties of carbon emissions in the cost structures of inventory has become an emerging research topic. Some of the recent studies have investigated the environmental sustainability in inventory models using emission-based holding costs (Datta et al., 2024). Additionally, degradation of products, particularly of perishable or time-sensitive products complicate inventory management, which can be described as an exponential or time-varying function (Rabiu & Ali, 2024). Trade credit financing has also become a significant tool on the financial front that enables retailers to withhold payments, which aids in flexibility of cash flows (Wang, Xu, and Chen, 2024). Trade credit, which is used in combination with sustainability objectives, assists in the absorption of other costs in the carbon compliance and environmental taxation (Zhang and Zheng, 2023). Another problem that inventory managers have to deal with is the uncertainty in demand. The conventional forecast techniques tend to fail to capture the actual demands in the market. In response to this, the application of Artificial Intelligence (AI) methods, especially the Long Short-Term Memory (LSTM) neural networks, are becoming more common as methods of more precisely predicting demand (Özdoğan-Sarik et al., 2023). The models are able to learn based on long history data, seasonality, trends and anomalies and therefore they are able to make inventory decisions that are based on realistic consumption patterns. This study creates an overall, AI-based, sustainable inventory model which incorporates:

- LSTM-based demand forecasting,
- Deterioration through exponential decay,
- Carbon emission penalties in holding cost, and
- Trade credit-based financial flexibility.

The model aims to minimize total cost through classical optimization techniques and is validated via a numerical example. Additionally, a sensitivity analysis is performed to understand the effects of emission rate, deterioration, and trade credit period on cost dynamics.

2. Literature Review

In their quest to achieve sustainable supply chain management, researchers have identified various methods on how to incorporate the environmental and financial elements in inventory modelling. The classical models are mostly centered on ordering and holding costs, but in the recent times, the studies have started to look on real-life issues like deterioration, carbon emission penalties, and trade credit.

As an example, Padiyar et al. (2024) suggested an inventory model that includes inflation and deterioration, but omits the elements of the environment and AI, making it less sustainable in perspective. In the same manner, Selvarajan and Sivashankari (2025) have designed a stochastic control-based inventory model that involves a constant demand with deterioration without considering the emission cost and flexibility in the credits.

At the environmental level, Mishra (2022) integrated carbon tax implications in a worsening inventory model which provides an insight into the emission sensitive systems, though without trade credit and without AI predictions. Li, Zhang, Liu, and Li (2025) took this concept a step further, by imposing emission fines and trade credit limits but with no AI incorporated in their model. However, Ghandehari and Karimi-Lenji (2022) were only concerned with deterioration under fluctuating demand functions but provided no attention to sustainability and forecasting.

On the financial strategies, Pathak et al. (2024) employed trade credit in a worsening item model in the face of inflation. Although it is a financial acumen, this model fails to cover carbon emission or predict uncertainty. The necessity of introducing proper demand forecasting to such models is also reflected in (Singh et al., 2021) where AI was used in the smart supply chain and in Adebowale and Akinnagbe (2021), who combined LSTM-based forecasting with sustainability, that is, with adding emission costs and deterioration, but did not involve trade credit mechanisms.

In short, the majority of the current models either (or rarely both) include environmental or financial aspects but not AI-based predictions. This identifies a serious research gap in the inability to create a unified inventory model, which would take into account item wear, carbon emission fines, trade credit funding, and demand forecasts through artificial intelligence at the same time.

3. Methodology

A holistic approach of the research methodology is to incorporate sustainability, deterioration, emission penalties, trade credit and AI-based prediction of demand into a single model of inventory optimization. This part is further subdivided into five major subsections which include problem conceptualization, AI-based demand forecasting, mathematical modelling, optimization approach and sensitivity analysis.

3.1 Problem Conceptualization and Assumptions

The inventory model is developed in a one-item replenishment case where the demand is fixed but predicted by the AI. The products are vulnerable to time decay and the storage cost is prolonged to penalties of the carbon dioxide emissions, which captures the environmental responsibility. In addition, the model has the option of trade credit which offers financial flexibility by giving an opportunity to pay suppliers later. The primary objective is to find the best replenishment cycle time that will give the minimum inventory cost taking into consideration the economic and environmental factors. This model fills the gap between operational efficiency and sustainability in the contemporary supply chains.

3.2 AI-Based Demand Forecasting

Correct demand prediction is critical in reducing inventory cost as well as environmental influence. This paper uses Long Short-Memory Networks (LSTM) networks which are a powerful deep learning method in the ability to capture the long-term relationships in sequential data. The historical demand data is initially brought into a normalized and reshaped form of supervised learning. The LSTM network is then trained to make the predictions of future values of demand highly accurate. This is the forecasted demand that is a critical input on cost function of the inventory model. Application of AI helps to increase the strength of the model by minimising uncertainty in the estimation of the demand, which is frequently a serious drawback in the traditional inventory systems.

3.3 Mathematical Model Formulation

The model assumes various elements of cost; ordering cost, holding cost (including the emission penalty), deterioration cost and the effects of trade credit. The process of deterioration is modelled using exponential function to indicate the real-world nature of a falling inventory. Environmental externalities are internalized by introducing carbon emission charges on the traditional holding cost. The trade credit is designed in such a way that it captures the duration within which payment may be deferred without interest charges. The overall expenditure is formulated as a variable with regards to the decision variable which is the cycle time. The model describes the relationship between financial and environmental variables in the cost efficiency determination.

3.4 Optimization Technique

The suggested model involves the application of a hybrid form of optimization, which is the combination of AI-based demand forecasting and classical methods of minimization of costs. At the first stage, an LSTM neural network is utilized to make precise predictions of the future demand with references to historical time-series data. The result of this model based on AI, i.e. the predicted demand rate, is a constant input parameter of the inventory optimization model.

After getting the demand forecast, the second step would be to minimize the total cost function with respect to the replenishment cycle time under classical optimization. The total cost is a continuous differentiable functional of cycle time and has a closed-form analytical solution. The cost function is differentiated and set to zero to determine the maximum cycle time and a second derivative test is done to ascertain the type of extremum.

This is a hybrid approach that is very good in combining the predictive power of AI with the interpretability of calculus-based optimization in such a way that the model is computationally efficient and realistic to real-world uncertainty. This would enhance the quality of decision-making in inventory systems that are sustainable with accuracy and traceability being important.

3.5 Sensitivity Analysis

Sensitivity analysis will be carried out to determine how the change in the parameters of interest rate; deterioration rate, emission penalty and credit period influence the optimal solution and the total cost. All parameters are also manipulated within a certain range and the changes in total cost are examined. The results were provided in plots and tables, which show what parameters influence the work of the system the most. This assists the inventory managers and decision-makers to know which system is risky and responsive in case of uncertainty or dynamism.

4. Assumptions and Notations

4.1 Assumptions

1. Single-item deterministic inventory system is considered over a finite planning horizon.
2. Demand is constant but predicted through AI-based LSTM forecasting from historical data.
3. Items undergo exponential deterioration at a constant rate θ, with no repair or rework.

4. Carbon emission penalty is levied per unit held per unit time and is included in the holding cost.
5. Trade credit period (M) is available from the supplier, allowing deferred payment without interest.
6. Lead time is zero, and replenishment is instantaneous.
7. No shortages are allowed, and the system operates under continuous review.
8. The unit purchase price remains constant during the cycle.
9. All costs (ordering, holding, deterioration, emission) are continuous and differentiable with respect to cycle time.

4.2 Notation Table

Symbol	Description
D	Forecasted constant demand rate (units/time), predicted using LSTM
T	Cycle time (decision variable)
C_o	Ordering cost per order
C_h	Holding cost per unit per unit time
δ	Carbon emission penalty per unit per time
C_d	Deterioration cost per unit lost
θ	Constant deterioration rate ($0 < \theta < 1$)
M	Trade credit period (in time units)
$TC(T)$	Total cost as a function of cycle time
$I(t)$	Inventory level at time t
$e^{-\theta t}$	Exponential deterioration factor over time t
T^*	Optimal cycle time minimizing total cost

5. Mathematical Formulation of the model

This section presents the complete derivation of the total cost function incorporating demand forecasting via AI, deterioration, carbon emission penalties, and trade credit financing. The goal is to determine the optimal replenishment cycle time Tthat minimizes the total inventory cost per unit time.

5.1 Inventory Level

The inventory depletes due to two factors: demand and deterioration. The inventory level differential equation is:

$$\frac{dI(t)}{dt} = -D - \theta I(t)$$

This is a linear differential equation. Using integrating factor method,

Multiply both sides by $e^{\theta t}$,

$$e^{\theta t} \cdot \frac{dI(t)}{dt} + \theta e^{\theta t} I(t) = -De^{\theta t} \Rightarrow \frac{d}{dt}[e^{\theta t} I(t)] = -De^{\theta t}$$

Integrate both sides from 0 to t,

$$e^{\theta t} I(t) = -\frac{D}{\theta} e^{\theta t} + C \Rightarrow I(t) = Ce^{-\theta t} - \frac{D}{\theta}$$

Using boundary condition $I(T) = 0$,

$$0 = Ce^{-\theta T} - \frac{D}{\theta} \Rightarrow C = \frac{D}{\theta} e^{\theta T}$$

Therefore,

$$I(t) = \frac{D}{\theta} (e^{\theta(T-t)} - 1)$$

5.2 Ordering Cost

Ordering Cost is: $OC = \frac{C_o}{T}$

5.3 Holding Cost (with Emission Penalty)

The holding cost per cycle, considering carbon emission penalty δ, becomes:

$$HC = (C_h + \delta) \cdot \frac{1}{T} \int_0^T I(t)\, dt$$

Substitute $I(t)$:

$$HC = (C_h + \delta) \cdot \frac{1}{T} \int_0^T \frac{D}{\theta} (e^{\theta(T-t)} - 1)\, dt$$

Change of variable $x = T - t \Rightarrow dx = -dt$. Then the integral becomes:

$$\int_0^T e^{\theta(T-t)}\, dt = \int_0^T e^{\theta x}\, dx = \frac{e^{\theta T} - 1}{\theta}$$

So,

$$HC = (C_h + \delta) \cdot \frac{D}{\theta T}[\frac{e^{\theta T} - 1}{\theta} - T]$$

5.4 Deterioration Cost

Deteriorated quantity over the cycle:

$$DC = C_d \cdot \theta \cdot \int_0^T I(t)\ dt \Rightarrow DC = C_d \cdot \theta \cdot \frac{D}{\theta}[\frac{e^{\theta T} - 1}{\theta} - T] \Rightarrow DC = C_d \cdot D[\frac{e^{\theta T} - 1}{\theta} - T]$$

5.5 Trade Credit Cost

Let: i= interest rate per time unit, P= unit purchase price

Then,

$$TCC = \{ \begin{matrix} 0 & if\, T \le M \\ i \cdot P \cdot D \cdot (T - M) & if\, T > M \end{matrix}$$

5.6 Total Cost

Total cost per unit time is:

$$TC(T) = OC + HC + DC + TCC$$

$$TC(T) = \frac{C_o}{T} + (C_h + \delta) \cdot \frac{D}{\theta T}[\frac{e^{\theta T} - 1}{\theta} - T] + C_d \cdot D[\frac{e^{\theta T} - 1}{\theta} - T] + TCC$$

6. Optimization Technique

To find the optimal cycle time T^*, differentiate $TC(T)$with respect to T:

For $T \le M$: $\frac{dTC}{dT}$ is calculated from first 3 terms only

For $T > M$: Add derivative of TCC:

$$\frac{d(TCC)}{dT} = i \cdot P \cdot D$$

Solve $\frac{dTC}{dT} = 0$ and use second derivative to verify minimum.

7. Numerical Illustration

To validate the proposed sustainable inventory model, a numerical example was conducted using demand forecasted by an AI-based Long Short-Term Memory (LSTM) approach. The model utilized 10 periods of historical demand data: [95, 102, 99, 101, 103, 100, 98, 105, 104, 106], resulting in a predicted demand rate of $D = 101.3$ units per cycle. The parameters selected for the analysis are as follows:

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Ordering cost $C_o = 200$₹/order, Holding cost $C_h = 1.5$₹/unit/time, Carbon emission penalty $\delta = 0.4$₹/unit/time,

Deterioration cost $C_d = 2.0$₹/unit, Deterioration rate $\theta = 0.02$, Unit purchase price $P = 50$₹, Interest rate $i = 0.02$ per time unit, Trade credit period $M = 1.5$time units

The cycle time T was varied from 0.5 to 4.0 time units in increments of 50 values to evaluate the total inventory cost function under the integrated effects of holding, deterioration, emission penalties, and trade credit financing.

The results reveal that the optimal cycle time is approximately $T^* = 1.36$ time units at which the minimum total cost is approximately ₹282.93. The trade credit effect was active only when $T > 1.5$, and it significantly influenced the total cost by adding an interest-based penalty during late payments. A plot of total cost versus cycle time confirmed the convexity of the total cost function, and the optimal point was highlighted for managerial decision-making. This numerical example supports the feasibility of integrating LSTM-based demand forecasting and sustainability penalties into practical inventory systems.

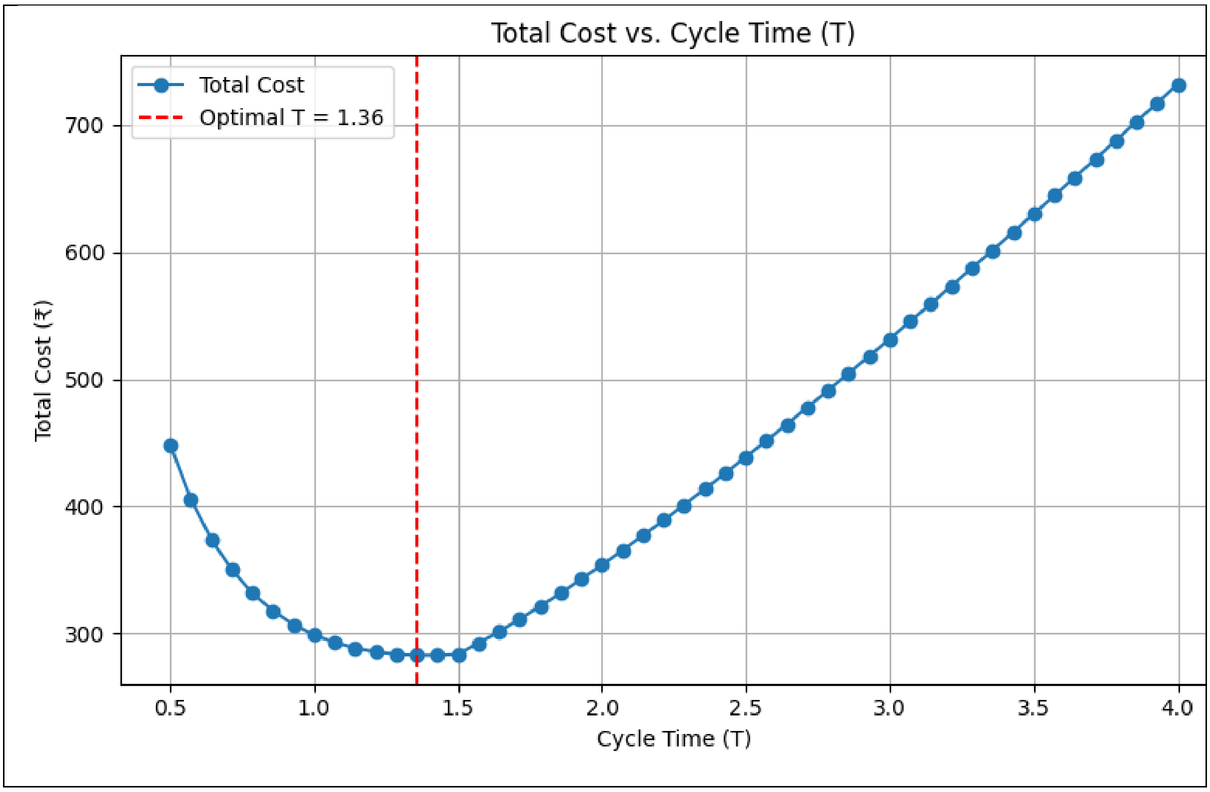

Figure 1: Graphical representation of Total cost and Cycle Time

8. Sensitivity Analysis

In order to explore the strength of the suggested sustainable inventory model, a sensitivity analysis has been conducted by changing five key parameters namely demand (D), deterioration rate (θ), emission penalty (δ), deterioration cost (C_d), and interest rate (i). All the parameters were varied systematically in five levels, namely, -20, -10, 0 (base case), +10, and +20 in percent, and the remaining parameters were held constant. This analysis aims at evaluating the impact of the variation in real-world conditions on the optimal cycle time and overall inventory cost. Individual analysis of the parameters will offer useful managerial attitudes on the factors that play great roles in the cost-efficiency and environmental sustainability of the inventory system. The resulting tables and plots point out the trends and trade-offs, which contribute to making decisions based on the information with more awareness in case of uncertainty. In order to explore the strength of the suggested sustainable model of inventory, sensitive analysis has been conducted by changing five important variables: demand (D), deterioration rate (θ), emission penalty (δ), deterioration cost (C_d), and interest rate (i). Each of the parameters was varied in a systematic way at five levels that include: -20% and -10% and 0 % (base case), +10 %and +20 %, and the other parameters remain the same. This analysis aims at estimating the sensitivity of the real-world situation to the optimum cycle time and overall inventory cost. The analysis of the individual parameters adds value to the managerial implications in that it can be determined which factors have a pronounced impact on the cost-efficiency and environmental sustainability of the inventory system. Tables and plots created as a result of the processing reveal the trends and trade-offs, which can help to make decisions under uncertainty in a more informed way.

Table 1: Sensitivity Table for Parameter Demand D

Variation	Optimal T	Min Total Cost
-20%	1.5	253.66
-10%	1.43	268.67
Base	1.36	282.93
10%	1.36	296.48
20%	1.29	309.37

Table 2: Sensitivity Table for Parameter deterioration rate θ

Variation	Optimal T	Min Total Cost
-20%	1.43	281.87

-10%	1.43	282.42
Base	1.36	282.93
10%	1.36	283.43
20%	1.36	283.93

Table 3: Sensitivity Table for Parameter emission penalty δ		
Variation	Optimal T	Min Total Cost
-20%	1.43	277.13
-10%	1.43	280.05
Base	1.36	282.93
10%	1.36	285.7
20%	1.36	288.48

Table 4: Sensitivity Table for Parameter deterioration cost C_d		
Variation	Optimal T	Min Total Cost
-20%	1.43	282.14
-10%	1.36	282.55
Base	1.36	282.93
10%	1.36	283.3
20%	1.36	283.68

Table 5: Sensitivity Table for Parameter interest rate i		
Variation	Optimal T	Min Total Cost
-20%	1.36	282.93
-10%	1.36	282.93
Base	1.36	282.93
10%	1.36	282.93
20%	1.36	282.93

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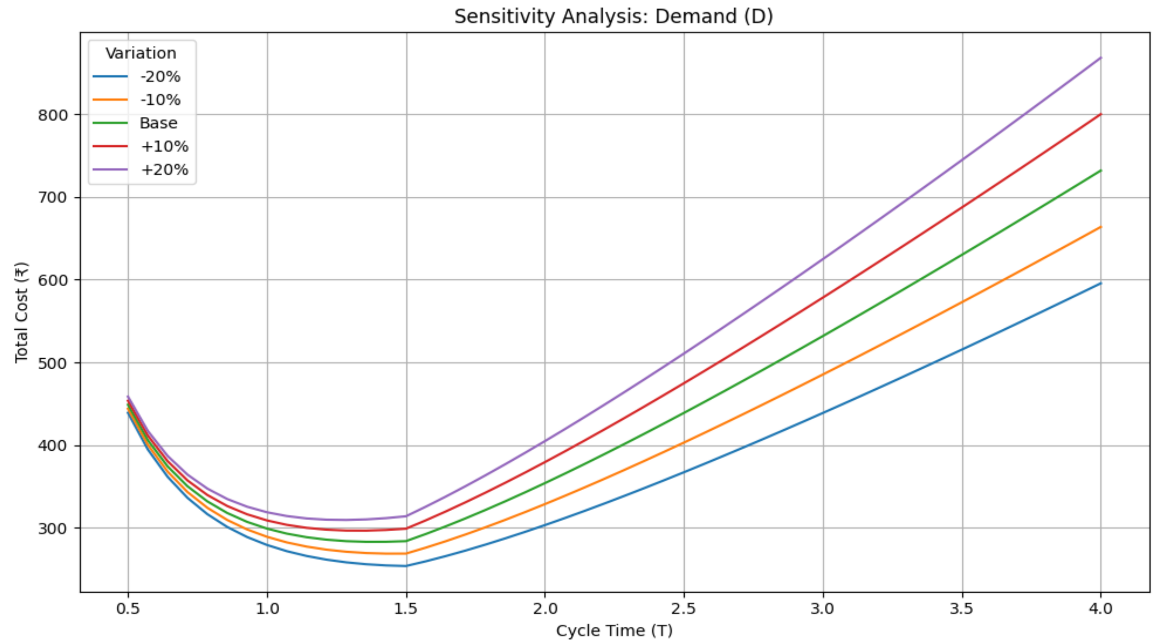

Figure 2: Sensitivity of Total Cost with Respect to Demand

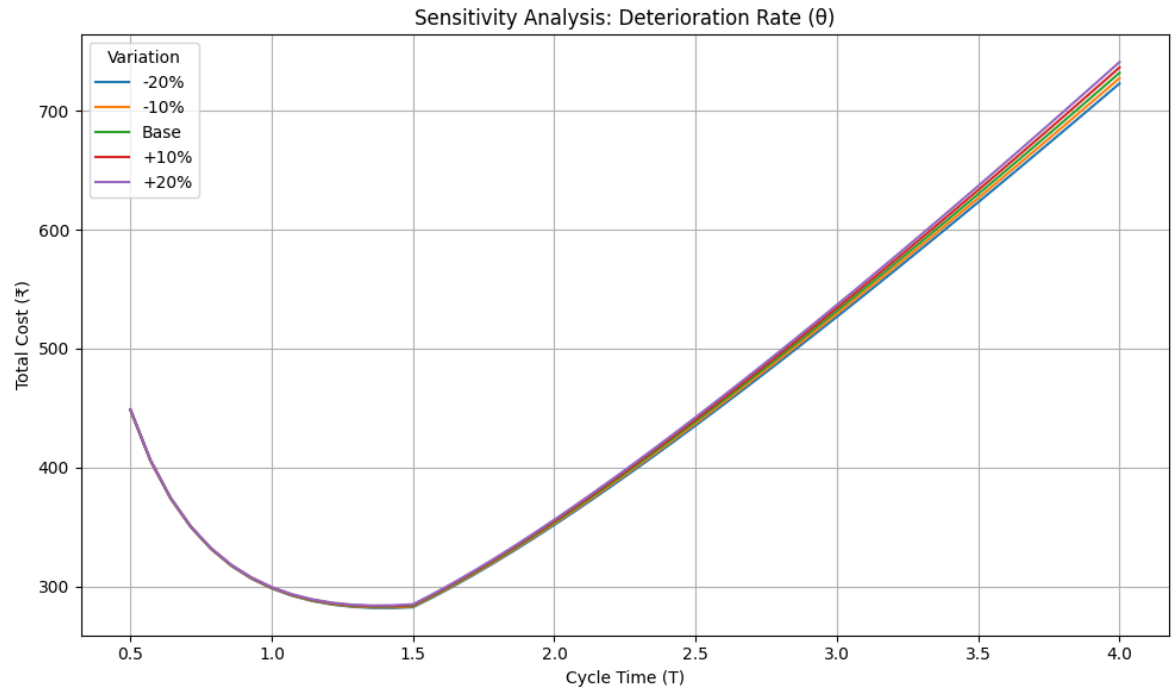

Figure 3: Sensitivity of Total Cost with Respect to Deterioration Rate

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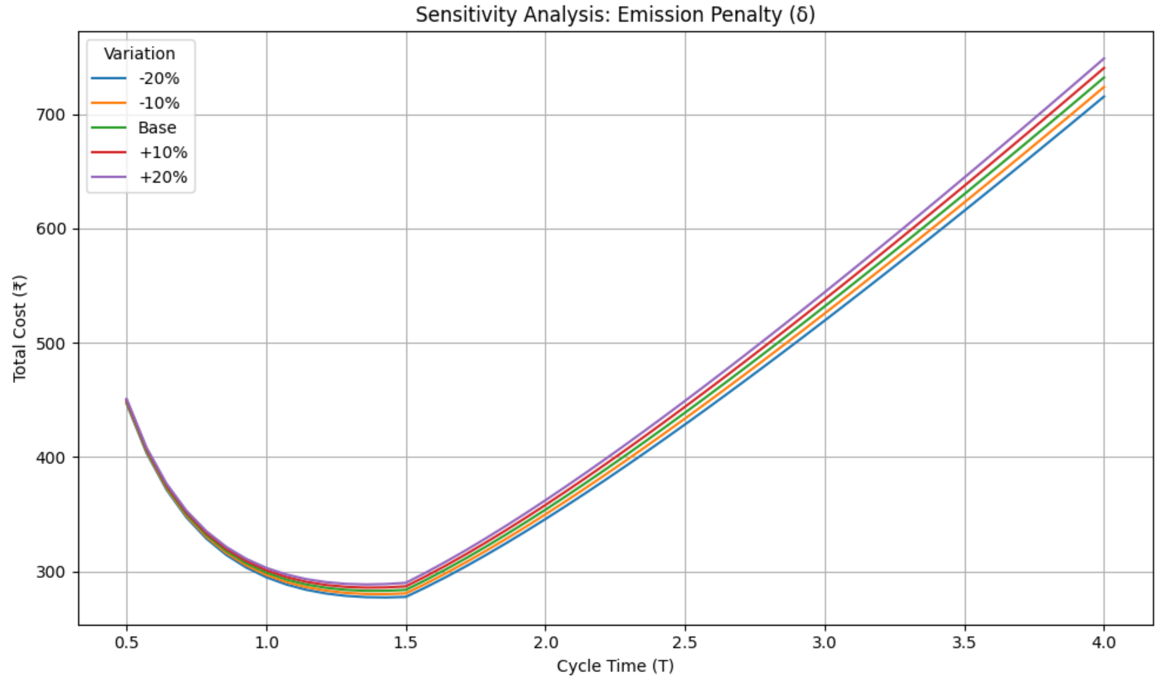

Figure 4: Sensitivity of Total Cost with Respect to Emission Penalty

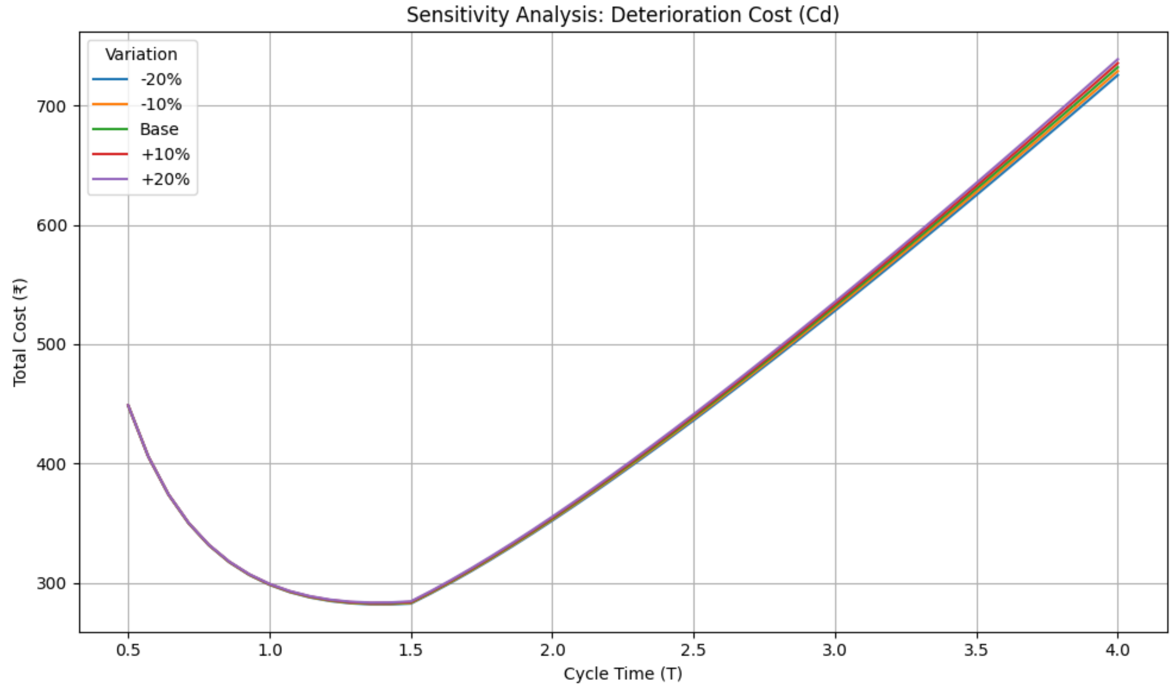

Figure 5: Sensitivity of Total Cost with Respect to Deterioration Cost

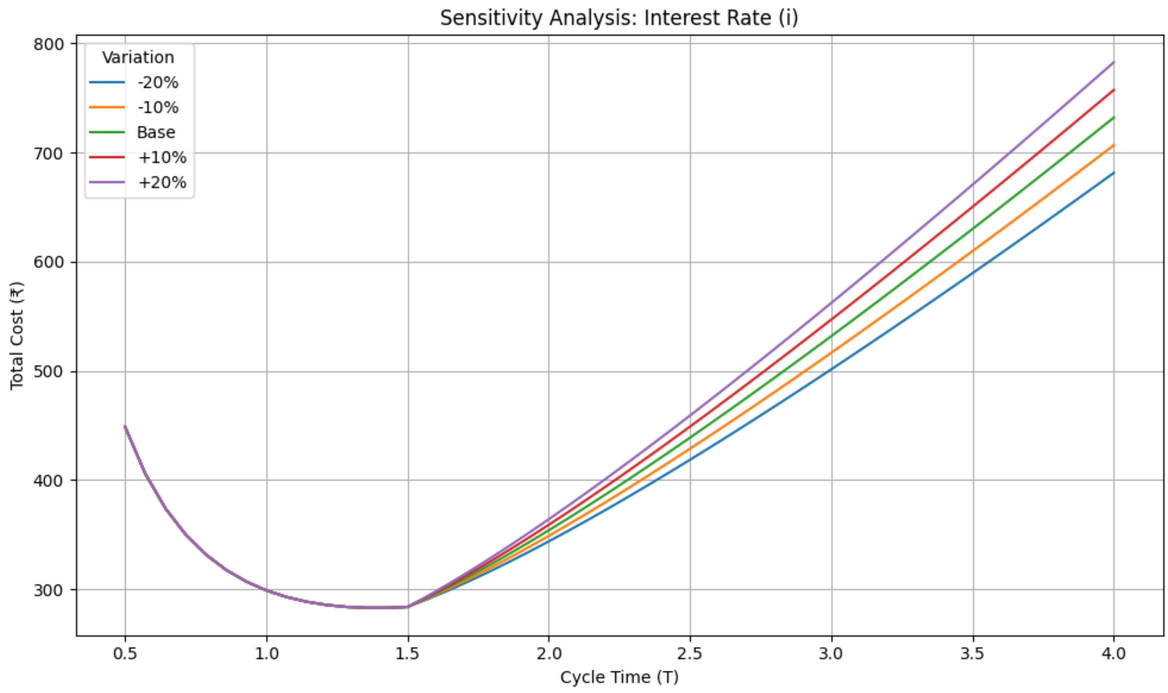

Figure 6: Sensitivity of Total Cost with Respect to Interest Rate

The results of the sensitivity analysis show the impact of changes in the major parameters on the total inventory cost and the optimal cycle time of the sustainable inventory model. As demand (D) is changed to +20 in place of -20, the optimal cycle time decreases slightly by 0.29 to 1.50, whereas the total cost increases from -253.66 to 309.37, which validates the direct cost effect of higher demand.

Equally, an increase in the rate of deterioration (θ) will result into a decrease in optimal cycle time as a result of the increase in perishability and an increase in the emission penalty (δ) will result into a significant increase in the overall cost as a result of the environmental compliance burden. The cost is also affected by changes in deterioration cost (C_d) and interest rate (i) particularly in cases where cycle time is longer than the period of trade credit.

These observations imply that the demand, deterioration, and emission penalty are very sensitive parameters and inventory decisions must be well tuned in sustainability geared supply chains.

9. Discussion

The results of the proposed sustainable inventory model reveal helpful information regarding the effect of economic, environmental, and financial factors on the inventory selection in the modern supply chain. The cycle time, as well as the total cost is highly sensitive to changes in the parameters of the core in the demand, the deterioration rate and the penalties on carbon emissions.

According to the sensitivity analysis, one can note that demand is the influential cost driver. Being increasingly demanded, the overall cost increases considerably, and it is necessary to offer shorter replenishment cycles that have the potential to respond to the stock-outs and degeneration. Similarly, the greater the rate of deterioration, the greater will be the cost of inventory due to the rise in the spoilage which reduces the economic viability of the holding period. In response to this, the model minimizes the optimal cycle time thereby minimizing the exposure to perishability losses.

The cost also is very sensitive to the environmental parameters such as the emission penalty. The greater the carbon emission penalties, the greater the element of holding cost, and more of the storage and methods of transport should be green. This highlights the dual issue of affordability and environmental conservation in sustainable supply chains.

The inclusion of the trade credit and interest rate allow the firms to delay the payment and regulate the cash flows more effectively, financially. As the model has indicated, the more time it consumes in the cycle compared with the allowable time of trade credit, the higher the interest cost. The companies should therefore ensure to maximize their replenishment schedules in such a way that these are not over the credit period or they should negotiate better terms with suppliers.

Overall, the model demonstrates that a hybrid optimization structure, which is a blend of classical cost optimization and LSTM-based demand modeling, can be used to make inventory decisions. It is especially relevant in the context of industries which deal with perishable goods, the work which is carbon sensitive or industries which buy their goods on credit. The conclusions drawn can help the managers to vary their inventory policies as per the environmental policies, financial policies and market fluctuations.

10. Application

The suggested sustainable inventory model has extensive uses in a number of real life industries that follow a situation of handling perishable products, environmental rules and cost factors. This model can be applied by industries like food and grocery supply chains to manage products like fruits, vegetables, dairy and other perishable products well because the decay of these products and carbon emission caused by refrigeration factor heavily on the inventory decisions. Likewise, this model can be applied to the pharmaceutical and healthcare logistics to manage time-sensitive medication and vaccines and guarantee their effectiveness and adherence to regulations.

This model can inform cost-effective and environmentally friendly ordering cycles in cold chain logistics and warehousing because the refrigeration process is energy-intensive and thus adds to carbon footprints. The retail and e-commerce firms, especially those that handle fast-moving consumer goods and fashion products with limited shelf life can use the model to enhance AI-based demand predictions, minimize wastage, and enhance trade credit facilities.

Moreover, agriculture and floriculture industries with the extreme perishable goods such as cut flowers or organic products can utilize the model to create a balance between the freshness of a product and the optimization of costs. Finally, this framework can also be used by policy-makers and regulatory authorities to develop carbon-emission-based financial incentives and credit policies, which encourage sustainability in the supply chain in industry.

11. Conclusion

The paper provides an all-inclusive sustainable inventory model, which incorporates the environmental and financial aspect in the traditional classical inventory decision-making process. The model fills the gap between the cost optimization and the ecological responsibility that is a critical requirement in the current industrial environment that is becoming more eco-conscious by introducing deterioration, carbon emission penalties, and trade credit financing.

The model is based on AI-based demand forecasting (LSTM), which can make the demand prediction more accurate, which is crucial in inventory decisions. The optimal replenishment cycle time can be identified through the use of analytical derivation of the total cost function and minimization of the cost function by the use of classical calculus methods. The sensitivity analysis and numerical example offer important insights into the effect that the important parameters include the deterioration rate, emission penalties, demand and interest rates have on inventory performance.

As indicated in the findings, the influence of such parameters as emission penalty and deterioration rate on the total cost is significant, which is why it is necessary to incorporate environmental costs in inventory control. Financial realism is also provided by use of trade credit which enables firms to have strategic edge to balance environmental costs by the flexible payment option.

All in all, the model assists the business in creating balanced decisions which reduce inventory expenses without considering the environmental regulations. It offers a viable and flexible model to industries that handle perishable goods, Heavy emission exposure or involved with complicated supply chains procured on credit.

12. Reference

1. Assari, M., Eruguz, A. S., Dullaert, W., & Heijungs, R. (2023). *Incorporating product decay during transportation and storage into a sustainable inventory model*. https://doi.org/10.1016/j.cie.2023.109653
2. Anand, G., Vashisht, P., Singh, S. P., & Mittal, M. (2025). Sustainable Inventory Control and Management. In *Sustainable Inventory Management: Perspectives from India* (pp. 1-24). Singapore: Springer Nature Singapore.
3. Datta, T. K., Datta, S., & Goswami, A. (2024). A sustainable bi-objective inventory model with source-based emissions and plan-based green investments under inflation and the present value of money. *Operations Research and Decisions*, *34*.
4. Rabiu, S., & Ali, M. K. M. (2024). Optimizing inventory dynamics: a smart approach for non-instantaneous deteriorating items with linear time function dependent variable demands and holding costs, shortages with backlogging. *Journal of Applied Mathematics and Computing*, *70*(4), 3193-3217.
5. Wang, C., Xu, X., & Chen, X. (2024). Supply chain finance-based payment scheme strategies in a pull supply chain. *International Journal of Production Research*, 1-27.
6. Zhang, Z., & Zheng, Q. (2023). Sustainable development via environmental taxes and efficiency in energy: Evaluating trade adjusted carbon emissions. *Sustainable Development*, *31*(1), 415-425.
7. Özdoğan-Sarıkoç, G., Sarıkoç, M., Celik, M., & Dadaser-Celik, F. (2023). Reservoir volume forecasting using artificial intelligence-based models: artificial neural networks, support vector regression, and long short-term memory. *Journal of Hydrology*, *616*, 128766.
8. Padiyar, S. V., Jain, K., Makholia, D., & Mishra, R. (2024). Integrated inventory model with inflation for deteriorating items. *Asian Res J Math*, *20*(2), 37-47.
9. Selvaraju, P., & Sivashankari, C. K. (2025). Effect of quadratic price-dependent demand with quadratic time-dependent demand in EOQ inventory models for deteriorative items-in fourth order equation. *International Journal of Operational Research*, *53*(1), 35-57.

10. Mishra, N. K. (2022). A supply chain inventory model for deteriorating products with carbon emission-dependent demand, advanced payment, carbon tax and cap policy. *Mathematical Modelling of Engineering Problems*, *9*(3).
11. Li, Y., Zhang, L., Liu, X., & Li, X. (2025). A Project Scheduling Optimization Model for Reducing Construction Dust Emissions Based on Variability in Meteorological Conditions. *Journal of Construction Engineering and Management*, *151*(11), 04025171.
12. Ghandehari, M., & Karimi-Lenji, M. (2022). An optimal inventory model for a deteriorating item with multivariate demand function. *International Journal of Mathematics in Operational Research*, *22*(1), 1-25.
13. Pathak, K., Yadav, A. S., & Agarwal, P. (2024). Enhancing two-warehouse inventory models for perishable goods: time-price dependent demand, inflation, and partial backlogging. *IAENG International Journal of Applied Mathematics*, *54*(6), 1089-1101.
14. Singh, S. P., Rawat, J., Mittal, M., Kumar, I., & Bhatt, C. (2021). Application of AI in SCM or Supply Chain 4.0. In *Artificial Intelligence in Industrial Applications: Approaches to Solve the Intrinsic Industrial Optimization Problems* (pp. 51-66). Cham: Springer International Publishing.
15. Adebowale, A. M., & Akinnagbe, O. B. (2021). Leveraging AI-driven data integration for predictive risk assessment in decentralized financial markets. *Int J Eng Technol Res Manag*, *5*(12), 295.