RESEARCH PAPER

A Mathematical Inventory Optimization Framework with AI- Based Demand Forecasting for Perishable Agricultural Products

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

[1]Research Scholar, Department of Mathematics, Faculty of Science, The ICFAI University, Raipur, Chhattisgarh, India
[2]Assistant Professor, Department of Mathematics, Faculty of Science, The ICFAI University, Raipur, Chhattisgarh, India
**Corresponding Author's Email: vinaym.phd2024@iuraipur.edu.in*

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ABSTRACT

Managing inventory of perishable products in agricultural supply chains is a difficult affair owing to the uncertainty in demand, short jobs of the products and the deterioration that constantly occurs. Unproductive inventory choices usually lead to high levels of spoilage, cost of operation, and lower level of service. As much as classical models of inventory offer analytical information, their deterministic assumptions of demand restrict their application in the real agricultural settings. Conversely, new developments on artificial intelligence allow predicting demand correctly but do not necessarily directly enter into the inventory analysis decision model. This paper presents a unified concept of AI-based demand forecasts and analytical optimization of inventory with demand uncertainty in the agricultural supply chain of perishable products. The forecast of demand using historic data is done by a Long Short-Term Memory (LSTM) neural network, and the result is the predicted demand that is used to serve as an effective input to the mathematically solvable inventory model. The model takes into account deterioration, shortages with partial backlogging and fixed ordering cost as realistic operational conditions. The goal will be to reduce the total inventory cost which is on average calculated by establishing the best length of the replenishment cycle and order quantity. The relevance of the suggested approach is proven by a numerical example with references to perishable agricultural products. Sensitivity analysis is done to investigate the soundness of the optimal policy about important parameters. The findings suggest that when integrating AI-based demand forecasting with analytical inventory modelling, realistic and cost-effective inventory policies are offered that offer useful managerial information on sustainable management of agricultural supply chain.

Keywords: *AI-based forecasting; Perishable inventory; LSTM; Supply chain optimization; Deterioration; Agriculture logistics*

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1. INTRODUCTION

Vegetables are highly perishable agricultural commodities, and their quality and market value decline rapidly due to biological deterioration during storage and transportation. In agri-food supply chains, this deterioration interacts with uncertain demand, limited cold-storage capacity, and frequent replenishment decisions, making inventory planning both cost-sensitive and risk-sensitive. Recent agri-food network studies highlight that explicitly modelling perishability and quality decay can significantly change inventory–capacity decisions and even the selection of storage technologies (e.g., refrigerated vs non-refrigerated facilities) (Bolívar et al., 2025).

In such contexts, classical deterministic inventory models may be insufficient because demand is rarely stable for vegetables; it is influenced by seasonality, weather shocks, festivals, pricing, and post-harvest losses. Therefore, modern inventory research increasingly incorporates uncertainty, preservation actions, and advanced planning to reduce deterioration losses and improve service levels. For instance, deterioration control through preservation investment under uncertain demand has been modelled to protect profitability and reduce waste (Mahapatra et al., 2022). Similarly, perishable inventory models have been extended to include advanced payment/trade-credit features and time-varying costs to reflect real market practices (Khan et al., 2020).

At the same time, forecasting accuracy has become a major lever for cost reduction in perishable systems. Deep learning methods especially recurrent networks such as LSTM and BiLSTM are increasingly adopted in demand forecasting because they can capture nonlinear temporal patterns and complex dependencies that traditional time-series approaches may miss (Aldahmani et al., 2024; Casolaro et al., 2023). Evidence from supply chain applications also suggests that AI/ML integration improves decision-making across inventory control and demand estimation functions (Khedr & Rani, 2024). Consequently,

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**Author for Correspondence: vinaym.phd2024@iuraipur.edu.in* recent research trends point toward integrated frameworks that combine (i) data-driven demand forecasting and (ii) mathematically derived inventory decisions for perishable goods.

Motivated by these developments, the present work positions a vegetable focused perishable inventory problem within an agriculture supply chain setting and aligns with the conference theme by integrating a mathematical inventory formulation (cost minimization under perishability and operational constraints) with AI-enabled forecasting as an input to replenishment decisions (Aldahmani et al., 2024; Komijani & Sheikh Sajadieh, 2024). This integration is practically important because even moderate forecast errors in vegetables can cause either stockouts (lost sales) or overstocking (spoilage), both of which rapidly increase total cost in a short shelf-life environment (Bolívar et al., 2025; Mahapatra et al., 2022).

2. LITERATURE REVIEW

2.1 Perishable/agricultural inventory and deterioration-aware planning

Perishability has been recognized as a central modelling component for agri-food supply chains because deterioration affects not only holding costs but also selling price (through quality decay) and feasible distribution strategies. A recent agri-food supply chain design study shows that including deterioration/quality explicitly can materially change strategic decisions and profit outcomes, and that cold-chain choices (refrigerated storage) can improve profitability (Bolívar et al., 2025). Complementing network-level models, inventory research has also examined deterioration under operational policies such as preservation investments. Under uncertain demand, preservation strategy can mitigate the negative financial effects of deterioration and improve inventory performance (Mahapatra et al., 2022).

Recent inventory work also reflects real market mechanisms common in food/agriculture trade such as advance payment and credit policies. For example, a perishable inventory model incorporating advanced payment, time-dependent holding cost, and demand drivers (selling price and advertisement) demonstrates how combined operational and market factors reshape optimal policies (Khan et al., 2020). These studies collectively support that vegetable/agri inventory decisions must account for both biophysical deterioration and economic/market conditions (Bolívar et al., 2025; Khan et al., 2020; Mahapatra et al., 2022).

2.2 Stock or price dependent demand and realistic inventory features

To represent practical retail and wholesale behaviour, recent models frequently use stock- and price-dependent demand along with backlogging or shortage structures and trade facilities. For instance, an inventory model with stock- and price-dependent demand and multiple trade facilities (with full backlogging) reflects how payment structures and demand sensitivity influence replenishment decisions and costs (Sarker et al., 2024). Such formulations are relevant to vegetables because demand often responds to displayed freshness/availability (stock effect) and daily price fluctuations (price effect), especially in local markets and short-cycle procurement settings (Sarker et al., 2024).

2.3 Integrated production–inventory–routing for perishables

Beyond classical single-stage inventory, recent research increasingly integrates production, inventory, and routing decisions to reflect real distribution constraints for perishables. An integrated planning model for perishable goods with stochastic lifespan addresses combined decisions across production, inventory, and logistics under uncertainty, reflecting the multi-stage nature of perishable supply chains (Komijani & Sheikh Sajadieh, 2024). These integrated perspectives align strongly with agricultural vegetables, where farm procurement timing, cold storage, and distribution routing jointly determine waste and service level outcomes (Bolívar et al., 2025; Komijani & Sheikh Sajadieh, 2024).

2.4 AI/deep learning for demand forecasting in supply chains

Demand forecasting is now a major research stream in supply chain and inventory management because forecast quality directly affects ordering and spoilage costs. Deep learning forecasting surveys show strong momentum in LSTM-family models and related architectures for time-series prediction due to their ability to represent temporal dependencies and nonlinear patterns (Casolaro et al., 2023). In supply chain forecasting contexts, deep learning models such as BiLSTM and hybrid approaches are increasingly evaluated against classical baselines to improve accuracy and reliability (Aldahmani et al., 2024).

Comprehensive reviews at the supply chain management level also note that nowadays ML/DL approaches are actively used in the area of inventory control, demand estimation, and operational planning, which means that the implementation of AI is no longer a niche, but a general trend (Khedr and Rani, 2024). Moreover, recent applied studies have also identified hybrid learning pipelines (e.g., clustering and LSTM) to enhance demand pattern detection and forecasting performance in an inventory setting (Ji et al., 2024).

2.5 Research Gap

The recent research in the area of perishable inventory management has brought a lot of advancement in terms of accountability of deterioration, preservation, practical operation limits in the agricultural supply chains. Similar studies in the field of artificial intelligence have shown that deep learning-based models, especially LSTM-based systems, can be used to predict demand in intricate and unpredictable conditions. Nevertheless, regardless of these developments, there are a number of key limitations in the literature that exist.

To begin with, most perishable inventory models still use assumed or average demand values even in cases where the uncertainty of demand is explicitly recognized. Demand estimation process aids are mostly seen as a peripheral input, as opposed to a component of the inventory decision frame work. Second, AI-based demand forecasting research mainly aims at making the forecasted demand more accurate and seldom, inserts the forecasted demand into analytically calculated inventory cost functions. Consequently, the correlation between AI-based demand forecasting and the optimal inventory decision-related variables like replacement cycle time and order quantity is loose. Moreover, numerous new hybrid strategies employ a combination of forecasting and inventory control based on simulation or optimization procedures based on heuristics, making them less analytically tractable and less amenable to further theoretical understanding of their cost behaviour and sensitivity analysis. To the best of knowledge, in the scenario of agricultural supply chains involving perishable goods, there is a lack of research that formally combines AI-based demand prediction with mathematically solvable models of inventory optimization under uncertainty of demand. Therefore, a clear research gap exists in developing an analytically solvable inventory framework that directly incorporates AI-predicted demand for perishable products in agricultural supply chains while accounting for deterioration, shortages, and realistic cost structures. The present study addresses this gap by proposing an integrated AI-based demand forecasting and inventory optimization model.

3. ASSUMPTIONS AND NOTATIONS

3.1 Assumptions

1. The product considered is perishable green vegetables.
2. Demand rate is obtained from an LSTM forecasting model and assumed constant within a cycle.
3. Deterioration occurs continuously at a constant rate.
4. Replenishment is instantaneous with zero lead time.
5. Shortages are allowed and partially backlogged.
6. A fixed ordering cost is incurred per replenishment cycle.
7. The planning horizon is infinite with identical cycles.

3.2 Notations

Symbol	Description
(d)	Demand rate (kg/week)
(T)	Cycle length (weeks)
(T_1)	Positive inventory period
(Q)	Order quantity
(θ)	Deterioration rate
(c)	Unit purchase cost
(h)	Holding cost per unit per week
(s)	Shortage cost per unit per week
(π)	Backlogging cost per unit
(A)	Ordering (setup) cost per cycle

4. Mathematical Formulation of the Model

4.1 Inventory Dynamics in $0 \le t \le T_1$

During the positive inventory period $0 \le t \le T_1$, inventory decreases due to demand and deterioration. Let $I(t)$denote the inventory level at time t. Then:

$$\frac{dI(t)}{dt} = -d - \theta I(t), \qquad 0 \le t \le T_1$$

with initial condition:

$$I(0) = I_{\max}$$

Solving the differential equation:

$$\frac{dI}{dt} + \theta I = -d$$

The integrating factor:

$$\mu(t) = e^{\theta t}$$

Multiplying both sides:

$$e^{\theta t}\frac{dI}{dt} + \theta e^{\theta t} I = -d e^{\theta t} \Rightarrow \frac{d}{dt}\left(I(t)e^{\theta t}\right) = -d e^{\theta t}$$

Integrating from 0 to t:

$$I(t)e^{\theta t} - I_{\max} = -\frac{d}{\theta}\left(e^{\theta t} - 1\right)$$

Solving, the inventory level is obtained as:

$$I(t) = I_{\max} e^{-\theta t} - \frac{d}{\theta}\left(1 - e^{-\theta t}\right)$$

At $t = T_1$, inventory becomes zero, yielding:

$$I_{\max} = \frac{d}{\theta}\left(e^{\theta T_1} - 1\right)$$

4.2 Shortages and Backlogging in $T_1 \le t \le T$

During the shortage period $T_1 \le t \le T$, demand is backlogged:

$$B(t) = d(t - T_1)$$

Maximum backlog:

$$B_{\max} = d(T - T_1)$$

Hence, total order quantity per cycle is:

$$Q = I_{\max} + B_{\max}$$

4.3 Cost Components and Optimization

4.3.1 Purchase Cost

$$PC = cQ = c\frac{d}{\theta}\left(e^{\theta T_1} - 1\right)$$

4.3.2 Holding Cost

$$HC = h\int_0^{T_1} I(t)\,dt$$

$$= h\int_0^{T_1}\left[Qe^{-\theta t} - \frac{d}{\theta}\left(1 - e^{-\theta t}\right)\right]dt$$

After evaluation and simplification:

$$HC = h\frac{d}{\theta^2}\left(e^{\theta T_1} - 1 - \theta T_1\right)$$

4.3.3 Shortage Cost

$$SC = s\int_{T_1}^{T} B(t)\,dt = sd\frac{(T - T_1)^2}{2}$$

$$SC = \frac{1}{2}sd(T - T_1)^2$$

4.3.4 Backlogging Cost

$$BC = \pi d(T - T_1)$$

4.3.5 Ordering Cost

$$OC = A$$

4.3.6 Total Cost Function

The total cost per cycle is given by:

$$TC = PC + HC + SC + BC + OC$$

where,

$$PC = cQ$$

$$HC = h\frac{d}{\theta^2}\left(e^{\theta T_1} - 1 - \theta T_1\right)$$

$$SC = \frac{1}{2}sd(T - T_1)^2$$

$$BC = \pi d(T - T_1)$$

$$OC = A$$

The average total cost per unit time is:

$$TAC = \frac{TC}{T}$$

To determine the optimal policy:

$$\frac{\partial TAC}{\partial T_1} = 0, \qquad \frac{\partial TAC}{\partial T} = 0$$

The optimal policy (T_1^*, T^*) is obtained by minimizing TAC numerically.

5. NUMERICAL ILLUSTRATION

Historical weekly demand data for green vegetables are used to train an LSTM network. The trained model predicts next-period demand, which is used as the demand rate in the inventory model. This approach allows the system to adapt to demand uncertainty and seasonal variations commonly observed in agricultural markets.

Historical demand used: [120.0, 135.0, 150.0, 145.0, 160.0, 155.0, 170.0, 180.0, 175.0, 190.0]

Predicted next-period demand = 194.651 kg

Let $\theta = 0.05$, $= 20.0$ (₹$/kg$) , $h = 2.0$(₹$/kg/week$) , $s = 8.0$(₹$/kg/week$),

$pi = 5.0$ ₹$/kg$) , $A = 1200.0$ (₹)

Using these data through Python software with AI based Optimization, optimal values are calculated as:

$$T_1{}^* = 1.9501\ weeks$$

$$T^* = 2.0937\ weeks$$

$$I_{\max}{}^* = 398.7079\ kg$$

$$B_{\max}{}^* = 27.9607\ kg$$

$$Q^* = 426.6686\ kg$$

$$TC^* = ₹\,10654.1239\ per\ cycle$$

$$TAC^* = ₹\,5088.5768\ per\ week$$

Figure 1 compares the historical demand data with the LSTM predicted next period demand.

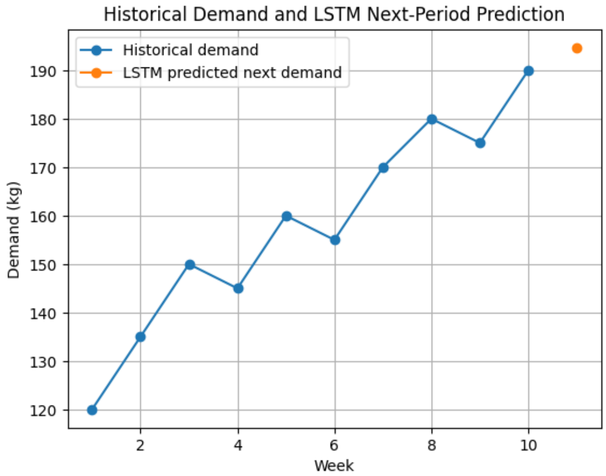

Figure 1: Historical demand data with the LSTM predicted next period demand.

Figure 2 illustrates the variation of the average total cost with respect to the positive inventory time T_1, while keeping the cycle time T fixed at its optimal value.

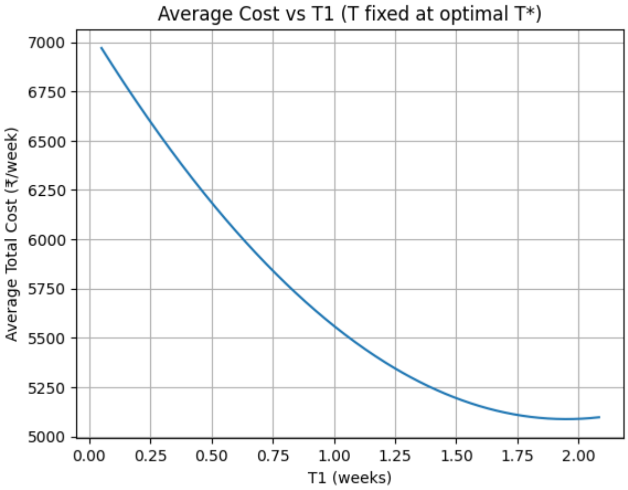

Figure 2: Average total cost versus positive inventory time T_1 with cycle time fixed at its optimal value.

Figure 3 depicts the variation of the average total cost with respect to the replenishment cycle time T, while fixing T_1 at its optimal value.

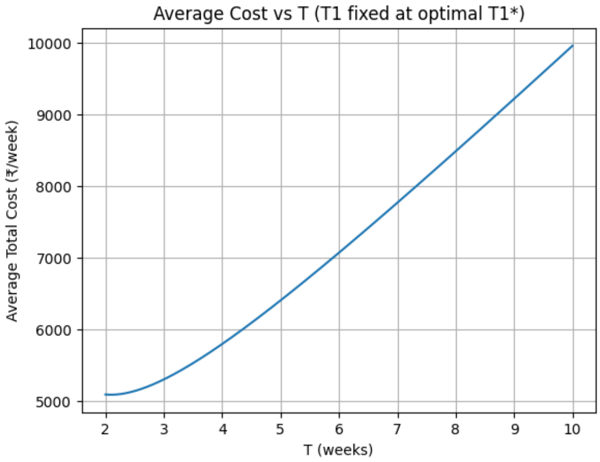

Figure 3: Average total cost versus cycle time T with positive inventory time fixed at its optimal value.

The convex nature of the cost curves in Figures 2 and 3 confirms the existence of a unique optimal solution and validates the numerical optimization procedure employed in the study.

6. SENSITIVITY ANALYSIS

Sensitivity analysis was conducted by varying key parameters by −20%, −10%, 0%, +10%, and +20%, around their base values while keeping all other parameters unchanged. Results are shown in Table 1.

Table – 1: Sensitivity Analysis of the Model

Parameter	-20%	-10%	0%	+10%	+20%
θ(TAC*)	5047.43	5068.26	5088.58	5108.41	5127.78
h(TAC*)	5011.70	5051.12	5088.58	5124.24	5158.25

6.1 Effect of Deterioration Rate (θ)

The effect of variations in the deterioration rate on the optimal inventory policy is presented in Table 1 and illustrated graphically in Figure 4.

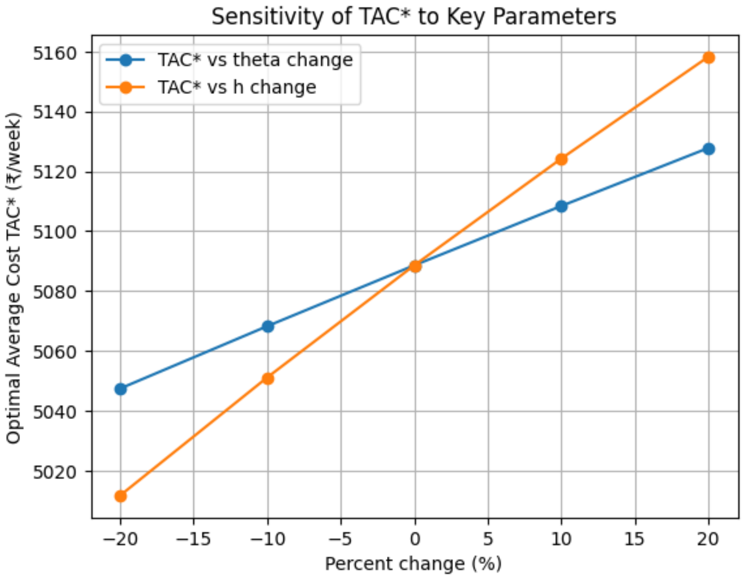

Figure 4: Sensitivity of optimal average total cost to variations in deterioration rate and holding cost.

The results indicate that an increase in the deterioration rate leads to a noticeable increase in the average total inventory cost. At the same time, the optimal replenishment cycle length and order quantity decrease slightly. This behaviour occurs because higher deterioration accelerates inventory loss, thereby requiring more frequent replenishments to reduce spoilage-related costs.

Conversely, a reduction in the deterioration rate results in a lower average total cost and allows longer replenishment cycles. These findings highlight the strong influence of perishability on inventory decisions and emphasize the importance of effective preservation, cold storage, and handling strategies in agricultural supply chains dealing with perishable products.

6.2 Effect of Holding Cost (*h*)

Table 1 indicated the sensitivity of the optimal inventory policy to the change in holding cost and further explained in Figure 4. It is noted that holding cost increases with a corresponding increase in the average total inventory cost with a decrease in the optimal cycle time and order quantity. Increased holding costs deter long storage and encourage short replenishment periods to reduce the costs of storage.

Conversely, lower holding cost will permit an increase in order quantity and cycle time leading to low total inventory cost. The findings highlight the need to have effective storage control and cost regimes, especially when it comes to perishable agricultural goods like vegetables, where the cost of extended storage is a significant portion of the overall cost.

6.3 Robustness of the Proposed Model

Figure 4 shows that the smooth and monotonic trends can be traced in the given Figure, which indicates that the proposed inventory model does not alter significantly when the parameters are varied moderately. There are no apparent shifts in the set of possible changes in the parameters and no feasible solutions on the considered range of parameters changes, which proves the stability and reliability of the optimal inventory policy.

Altogether, the sensitivity analysis overcomes the fact that the proposed AI based inventory model stands to changes

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**Author for Correspondence: vinaym.phd2024@iuraipur.edu.in* in critical parameters and can be used to make effective decisions in uncertain conditions of dynamic agriculture.

7. RESULTS AND DISCUSSION

The mathematical findings of the suggested AI-based inventory model can give valuable information on inventory decision-making in perishable agricultural products when the demand is uncertain. The paper combines LSTM-based demand prediction and an analytically developed model of inventory cost and this proves a viable framework that can make a good balance between ordering, holding, deterioration and shortage cost.

Application of the LSTM-based demand forecasting makes the inventory model much more realistic. The proposed approach uses data driven demand estimates instead of assumed or deterministic demand values, that is, the actual data regarding consumption of the perishable products. The quantitative example reveals that the LSTM modelled demand results in finite optimal solutions that are stable, thus minimizing the risks of overstocking and stock outs, which are prevalent in the agricultural supply chain.

The numerical output of the best inventory policy shows that there is a unique replenishment cycle and the order quantity, which minimizes the average total inventory cost. The curvature of the cost function against the positive inventory time and the cycle length validates the optimisation process. The above findings indicate that overly long replenishment cycles raise holding and deterioration related costs, whereas the overly short ones raise ordering costs, which underscores the importance of having a balanced replenishment plan.

The sensitivity analysis also provides more support to the findings by showing how strong the proposed model is to parameter change. The findings indicate that the mean total cost is very sensitive to variation in the deterioration rate, thus the importance of perishability in inventory performance is critical. With a growing pace of deterioration, the shortest period of replenishment and least order quantities will be the best solutions to minimize loss of spoilage. This fact is quite consistent with the practice in the vegetable supply chains where high turnover is obligatory to assure the quality of the products.

In the same vein, difference in holding cost also has a great impact on the optimal inventory choice. The increased holding costs translate to the decreasing cycle times as well as the order quantities, meaning that it is not cost effective to have long storage of perishable products. These results suggest that the management of agricultural inventory systems should focus on efficient storage management, cold-chain, and cost reduction.

On the whole, the joint numerical and sensitivity analyses confirm that the given inventory model can be discussed as strong, analytically manageable, and relevant in practice. The combination of AI-based demand forecasting and analytical inventory optimization is a useful decision-support tool to manage perishable agricultural products in case of uncertainty in demand. These findings also indicate that operational efficiency in agricultural supply chain can be significantly enhanced and that the cost of inventories can be significantly lowered by applying both data-driven forecasting and suitable replenishment methods.

8. APPLICATION

The suggested AI-based model of inventory optimization is very applicable in the practice of agricultural and perishable products supply chains. The framework has the potential to leverage LSTM-based demand forecasting with analytical inventory modelling to make informed and cost-efficient decisions in high uncertainty in demand and high product deterioration environments.

To begin with, the model can be well implemented in the wholesale markets of vegetables and fruits where demand changes drastically on daily and weekly basis because of seasonal changes and consumer choices. Proper demand forecasting makes the wholesalers know the best replenishment times and orders and hence spoilage is minimized and the service level is improved.

Second, the system suggested is appropriate in cold storage and warehouse operations of perishable farm goods. Managers can also use the model to determine suitable storage periods and replenishment rate based on holding cost and deterioration impacts on inventory resulting in an improvement in the use of storage equipment and less loss of inventory.

Third, the model can be used in retail distribution centers and supply chains of supermarkets with fresh produce. The combination of AI-based demand prediction and inventory optimization assists retailers in matching the procurement decision with the anticipated demand to reduce surplus inventory and stock-outs.

Fourth, the suggested framework can be applied to the farmer-producer organizations (FPOs) and agricultural cooperatives, in which coordinated inventory planning is critical to minimizing the losses in post-harvest conditions. The model facilitates the making of collective decisions since it provides analytically calculated inventory policies using forecasted demand.

Lastly, the suggested model has potential to be expanded into a decision-support system (DSS) to be used by policy-makers and agri-logistics planners that would enhance supply chain efficiency and decrease food waste. The model is practical to apply in everyday analysis due to its ability to be easily adjusted to various perishable products and operation environments.

8. CONCLUSION

This paper has created a holistic AI-based inventory optimization system to handle perishable food products in the case of demand uncertainty. The proposed solution overcomes the major shortcomings of the traditional inventory models that are largely deterministic where demand forecasting is performed using LSTMs and an analytically built inventory model. The model clearly uses deterioration, shortages and partial backlog interventions, thus capturing the realistic operation environment that is mostly evident in agricultural supply chain.

The proposed model is practically applicable as it is proven by the numerical example with the help of perishable vegetables. The findings affirm the presence of an optimal inventory policy, which is finite and unique and minimizes the average total inventory cost. The fact that the cost function has a convex behavior with the decision variables justifies the usefulness of the optimization framework. Besides, sensitivity analysis reveals that deterioration rate and holding cost play a major role in making inventory decisions and effective storage management and high turnover of inventory is important when dealing with perishable goods.

Incorporating the use of AI in forecasting demand boosts the strength and authenticity of the inventory model, as it embraces the dynamic trends of demand detection using past data. Such data-driven strategy minimizes the risk of overstocking and stock-outs, and consequently elevates the level of service and losses on spoilage are minimized as well. In general, the suggested framework is a convenient decision-support system that can help farmers, wholesalers, retailers, and logistics managers of perishable agricultural supply chains.

Finally, the paper illustrates that a combination of artificial intelligence and analytical model of inventory is an opportune approach in dealing with perishable goods in the face of uncertainty. The proposed model adds to the theory and practice by filling the gap between the demand forecasting and inventory optimization and contributing to the costs-effective and sustainable agricultural supply chain operations.

9. DECLARATIONS

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9.2 Funding

No specific funding was received for this research work.

9.3. Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

9.4. Declaration of Artificial Intelligence (AI) Assistance Process

No AI tool was used for generating original ideas, mathematical derivations, results, or conclusions. The authors take full responsibility for the content of this manuscript.

9.5. Author Contributions

Vinay Kumar Masiyare: Conceptualization, model development, mathematical formulation, numerical analysis, writing original draft preparation, and revision.

Animesh Kumar Sharma: Review, editing, validation, and supervision.

All authors have read and approved the final version of the manuscript.

9.6 Ethics Approval

This research does not involve human participants or animals. Hence, ethics approval is not required.

9.7 Data Availability

All data generated or used in this study consist of model-derived numerical values and parameter assumptions, which are fully presented within the manuscript. No external or real-world dataset was used.

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