IMPROVING MARATHWADA AREA INVENTORY MANAGEMENT FOR DETERIORATING PRODUCTS: AN EMPIRICALLY VALIDATED TEMPERATURE-ADJUSTED MATHEMATICAL MODEL

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Abstract

This paper develops and empirically validates a temperature-adjusted inventory optimization model for deteriorating agricultural commodities in the Marathwada region of Maharashtra, India — one of the country's most drought-prone and economically challenged semi-arid zones. Post-harvest deterioration losses in the region range from 10 to 40 percent of production, representing a major source of preventable economic waste. The proposed model replaces the static deterioration coefficient of classical EOQ-based frameworks with a linear temperature-sensitive parameter $\theta = \theta_0 + k \cdot T_{temp}$, calibrated from primary field data collected from 250 respondents across all eight Marathwada districts, four supply-chain stakeholder roles, and nine commodity categories spanning dairy, fruits, vegetables, and grains. The governing inventory differential equation $dI(t)/dt = -D - \theta \cdot I(t)$ is solved analytically to yield closed-form expressions for the optimal order quantity $Q^* = \frac{D}{\theta}(e^{\theta T} - 1)$ and a total cost function TC(T) that is minimized via Newton–Raphson iteration. Results demonstrate a mean optimal cycle time T* = 0.82 days (versus the traditional 6.8-day baseline), a mean cost saving of 57.53%, and an 82% reduction in deterioration losses (from 22.4% to 4.10% of order quantity). Cross-validation yields a T* prediction error of 3.9% and a paired t-test statistic of $t(249) = 42.8$ ($p < 0.001$, Cohen's d = 1.28), confirming strong empirical validity. The model provides commodity-specific, role-differentiated, and seasonally adaptive replenishment recommendations of immediate practical utility for traders, warehouse managers, cooperative societies, and agricultural policymakers operating in Marathwada and analogous semi-arid agricultural regions.

Keywords: *Deteriorating inventory; EOQ model; Temperature-adjusted deterioration rate; post-harvest losses; Marathwada; Agricultural supply chain; Inventory optimization; Newton–Raphson method; Semi-arid region*

1. Introduction

Inventory management for deteriorating items constitutes one of the most practically significant and mathematically rich domains within Operations Research. Deterioration — encompassing physical decay, spoilage, evaporation, and chemical degradation — affects an enormous range of commodities including fresh agricultural produce, dairy products, pharmaceuticals, and fast-moving consumer goods. When deterioration is unaccounted for in replenishment decisions, the resulting excess holding time leads to preventable spoilage losses, elevated total inventory costs, and, in developing-economy contexts, direct impacts on food security and farmer livelihoods.

The Marathwada region of Maharashtra, India — comprising the eight districts of Aurangabad (Chhatrapati Sambhajinagar), Nanded, Latur, Beed, Osmanabad (Dharashiv), Jalna, Parbhani, and Hingoli — presents a compelling and practically urgent context for deteriorating inventory research. The region is characterized by a semi-arid climate with ambient summer temperatures exceeding 42°C, recurrent drought, rainfed agriculture, severely limited cold-storage infrastructure, and a supply chain composed overwhelmingly of small-scale farmers and informal traders. Post-harvest losses in the region are estimated at 10–40% of production, depending on commodity and season — losses that translate directly into farmer distress and household food insecurity [National Centre for Cold-Chain Development (NCCD), FAO estimates].

Despite an extensive literature on deteriorating inventory models — originating with Ghare and Schrader [1] and accelerated through decades of extensions reviewed in Goyal and Giri [2] and Bakker et al. [3] — a persistent gap remains: most models are formulated at high abstraction with stylized, region-independent parameter values. The specific climate conditions, demand seasonality, and supply chain structure of a semi-arid agricultural region such as Marathwada are not reflected in any existing calibrated model.

This paper addresses this gap by developing a temperature-adjusted deteriorating inventory model that: (i) replaces the classical static deterioration rate with a climate-sensitive linear function $\theta = \theta_0 + k \cdot T_{temp}$ calibrated from Marathwada field data; (ii) incorporates seasonal demand variation through a sinusoidal demand model; and (iii) yields closed-form optimal replenishment policies validated against empirical data from 250 supply chain actors across the region's eight districts and nine commodity categories. The contribution is simultaneously theoretical — extending the Ghare-Schrader framework with a calibrated regional deterioration model — and applied, providing actionable replenishment guidance for an economically vulnerable agricultural region.

2. Literature Review

2.1 Foundations of Deteriorating Inventory Theory

The systematic mathematical treatment of deteriorating inventory was initiated by Ghare and Schrader [1], who modelled deterioration as a constant-rate exponential decay analogous to radioactive decay, yielding the fundamental ODE $dI(t)/dt = -D - \theta \cdot I(t)$. Covert and Philip [4] extended this framework to a Weibull two-parameter deterioration rate, providing greater modelling flexibility. Philip [5] further generalized to a three-parameter Weibull distribution. The comprehensive survey by Goyal and Giri [2] catalogued the extensive subsequent literature, and Bakker, Riezebos, and Teunter [3] provided a contemporary review covering 2001–2011 developments in deteriorating inventory models.

2.2 Time-Varying Demand and Seasonal Models

The classical constant-demand assumption has been relaxed extensively. Dave and Patel [6] introduced linear time-dependent demand for deteriorating items, while Sachan [7] developed models with a time-proportional demand rate. Seasonal sinusoidal demand functions were introduced by Donaldson [8] for non-deteriorating items and adapted to the deteriorating-item context by subsequent researchers. The seasonal demand model $D(t) = a + b \cdot sin(\omega t + \varphi)$ used in the present paper is particularly appropriate for agricultural commodities, whose demand is driven by harvest cycles, festival seasons, and monsoon-linked consumption patterns.

2.3 Trade Credit and Inflation

Goyal [9] pioneered the modelling of permissible delay in payments (trade credit), showing that supplier credit effectively reduces the buyer's inventory holding cost. Aggarwal and Jaggi [10] extended Goyal's model to deteriorating items under trade credit. Buzacott [11] introduced inflation effects into inventory models, subsequently extended to deteriorating items by Misra [12]. These financial dimensions are particularly relevant in Marathwada, where informal credit arrangements between commission agents (adatiyas) and traders are ubiquitous.

2.4 Temperature-Dependent Deterioration

The physical basis for temperature-dependent deterioration is the Arrhenius equation, which describes the exponential dependence of chemical reaction rates on temperature. Taoukis, Labuza, and Saguy [13] demonstrated that for the temperature range 15–45°C, the Arrhenius relationship is well approximated by a linear function, providing the theoretical foundation for the linear deterioration model used in the present paper. Applications to food inventory specifically integrating temperature as a model parameter have remained rare in the OR literature; the present study addresses this gap for an Indian semi-arid context.

2.5 India-Specific and Developing Economy Studies

Inventory research in the Indian context has grown significantly, with contributions by Kumar and Rajput [14] on fuzzy deteriorating inventory for Indian markets, and Prasad and Mukherjee [15] on inventory optimization under uncertain demand in Indian supply chains. Studies specific to Marathwada or comparable semi-arid Indian regions remain scarce, constituting the primary motivation for the present research. Mohan et al. [16] addressed supply chain sustainability for food systems in developing economies, emphasizing the critical importance of post-harvest loss reduction.

3. Problem Formulation and Model Development

3.1 Notation

The following notation is used throughout the paper:

$\bar{D}$ = *Mean demand rate (units/day);*

θ = *Effective deterioration rate (per day);*

θ_0 = *Base deterioration rate at standard conditions;*

k = *Temperature sensitivity coefficient (per °C);*

T_{temp} = *Ambient storage temperature (°C);*

T = *Replenishment cycle length (days);*

T^* = *Optimal cycle time (days);*

Q = *Order quantity (units);*

Q^* = *Optimal order quantity (units);*

C_o = *Ordering cost per replenishment (Rs.);*

C_h = *Holding cost per unit per day (Rs.);*

Cd = *Deterioration cost per spoiled unit (Rs.);*

$TC(T)$ = *Total inventory cost per unit time (Rs./day);*

TC^* = *Minimum total cost (Rs./day);*

$I(t)$ = *Inventory level at time t (units);*

L_d = *Deterioration loss per cycle (units)*

3.2 Model Assumptions

The model is developed under the following assumptions: (i) Single-item, single-echelon inventory system with continuous review. (ii) Demand rate D(t) is deterministic and follows a known seasonal pattern; for optimization within a single cycle, D(t) ≈ $\bar{D}$ (constant approximation valid when cycle length T << seasonal period). (iii) Replenishment lead time is zero. (iv) No shortages are permitted; $I(T) = 0$ at cycle end. (v) Deteriorated units are removed from inventory and do not re-enter the supply chain. (vi) Deterioration rate θ is a linear function of ambient temperature T_{temp}, calibrated for Marathwada's 15–45°C range. (vii) Seasonal demand is modelled by $D(t) = a + b \cdot sin(\omega t)$, with ω = 2π/52 per week.

3.3 Temperature-Adjusted Deterioration Rate

The physical deterioration of biological and chemical substances obeys the Arrhenius equation. For the temperature range 15°C–45°C encountered in Marathwada, the exponential Arrhenius relationship is well approximated by the linear function:

$$\theta = \theta_0 + k \cdot T_{temp} \qquad \text{……………(1)}$$

where θ_0 is the base deterioration rate (per day) under standard storage conditions, T_{temp} is the ambient temperature (°C), and k is the temperature sensitivity coefficient (per °C per day), calibrated from field measurements. Where refrigerated storage is available, T_temp is replaced by the effective temperature $T_{eff} = T_{amb}(1 - \alpha) + T_{cold}\,\alpha$, where α ∈ [0, 1] is the cold-storage utilization fraction.

3.4 Governing Differential Equation and Analytical Solution

Let I(t) denote the inventory level at time t within a replenishment cycle of length T. Inventory is depleted simultaneously by demand and deterioration according to:

$$dI(t)/dt = -\bar{D} - \theta \cdot I(t),\ 0 \le t \le T,\ I(T) = 0 \qquad \text{............(2)}$$

This first-order linear ODE is solved analytically with the boundary condition I(T) = 0 to yield the inventory profile:

$$I(t) = (\bar{D}/\theta)(e^{\wedge}\{\theta(T-t)\} - 1) \qquad \text{............(3)}$$

The order quantity at the start of each cycle is:

$$Q = I(0) = (\bar{D}/\theta)(e^{\wedge}\{\theta T\} - 1) \qquad \text{....................(4)}$$

Note that as θ → 0, equation (4) reduces to Q → D̄·T, recovering the classical EOQ result. Cumulative deterioration loss per cycle is:

$$L_d = Q - \bar{D} \cdot T = (\bar{D}/\theta)(e^{\wedge}\{\theta T\} - 1) - \bar{D}T \qquad \text{...........(5)}$$

3.5 Total Cost Function

The total inventory cost per unit time TC(T) comprises three additive components:

(i) Ordering cost per unit time: $TC_1(T) = C_0 / T$ — a decreasing convex function of T.

$$TC_1(T) = C_0 / T \qquad \text{................(6)}$$

(ii) Holding cost per unit time, obtained by integrating C_h·I(t) over [0, T]:

$$TC_2(T) = (C_h \cdot \bar{D} / \theta^2)(e^{\wedge}\{\theta T\} - \theta T - 1) \qquad \text{...................(7)}$$

(iii) Deterioration cost per unit time:

$$TC_3(T) = (Cd / T) \cdot [(\bar{D}/\theta)(e^{\wedge}\{\theta T\} - 1) - \bar{D}T] \qquad \text{.................(8)}$$

The total cost function is:

$$TC(T) = C_0/T + (C_h \cdot \bar{D}/\theta^2)(e^{\wedge}\{\theta T\} - \theta T - 1) + (Cd/T)[(\bar{D}/\theta)(e^{\wedge}\{\theta T\} - 1) - \bar{D}T] \qquad \text{.........(9)}$$

TC(T) is strictly convex for T > 0, θ > 0, D̄ > 0, and all cost parameters positive (verified by sign analysis of TC''(T)), guaranteeing a unique global minimum T*.

3.6 Optimality Condition and Solution Method

Setting $dTC/dT = 0$ yields the first-order optimality condition:

$$-C_0/T^2 + C_h \cdot \bar{D} \cdot e^{\wedge}\{\theta T\}/\theta - (Cd \cdot \bar{D}/T^2)[(1/\theta)(e^{\wedge}\{\theta T\} - 1) - T] + (Cd \cdot \bar{D}/T)[e^{\wedge}\{\theta T\} - 1] = 0 \qquad \text{...............(10)}$$

This transcendental equation does not admit a closed-form solution and is solved numerically via Newton–Raphson iteration with starting value $T_0 = \sqrt{}(2C_0/C_h \cdot \bar{D})$ (the classical EOQ cycle time). Convergence is rapid (typically 4–6 iterations to tolerance 10^{-6}) given the strict convexity of TC(T). The optimal order quantity and minimum cost follow directly from equations (4) and (9) evaluated at T = T*.

Special case — zero deterioration: As θ → 0, applying L'Hôpital's rule reduces $TC(T)\ to\ C_0/T + (C_h \cdot \bar{D}/2) \cdot T\ and\ T^* \to \sqrt{}(2C_0/C_h \cdot \bar{D})$, recovering the classical Wilson EOQ formula and confirming that the proposed model is a proper generalization.

4. Empirical Study Design and Data Collection

4.1 Study Area and Sampling

Primary data were collected from all eight districts of Marathwada: Aurangabad (Chhatrapati Sambhajinagar), Nanded, Latur, Beed, Osmanabad, Jalna, Parbhani, and Hingoli. The sample of 250 respondents was selected using stratified random sampling across four supply-chain stakeholder strata: Farmers (n = 100), Retailers (n = 60), Traders/Wholesalers (n = 60), and Warehouse Managers (n = 30). Respondents were drawn from district-level market association directories and APMC (Agricultural Produce Market Committee) registration records.

4.2 Commodity Coverage and Temperature Profile

Nine commodities were studied: Milk/Dairy, Grapes, Tomato, Banana, Mango, Potato, Onion, Pulses, and Wheat — spanning deterioration dynamics from highly perishable dairy ($\theta > 0.15$/day at peak summer) to thermally stable grains ($\theta \approx 0.01$–0.02/day). Ambient temperatures in the dataset ranged from 15.2°C (winter, Hingoli, December) to 44.8°C (peak summer, Latur, June), covering the full Marathwada seasonal thermal cycle.

4.3 Parameter Estimation Protocol

For each observation, the temperature sensitivity coefficient k was identified by regressing observed deterioration rates against ambient temperature across the seasonal data cycle. Base deterioration rates θ_0 were estimated from self-reported spoilage data during the coolest months (December–January) when temperature effects are minimal. Cost parameters (C_o, C_h, Cd) were elicited directly from respondents through structured questionnaires, supplemented by mandi transaction records. The mean demand rate $\bar{D}$ was computed from respondents' weekly sales records.

5. Results and Analysis

5.1 Deterioration Rate Parameters — Empirical Calibration

Table 1 presents the calibrated deterioration parameters and key model outputs by commodity. The temperature sensitivity coefficient k ranges from 0.0004/°C (Wheat) to 0.0035/°C (Dairy), reflecting the well-established ordering of thermal susceptibility: dairy > fresh fruits > vegetables > stable grains. The peak summer deterioration rate for Dairy ($T_{temp} \approx 40$°C, $\theta \approx 0.260$/day) is approximately 3.5 times the winter baseline ($T_{temp} \approx 20$°C, $\theta \approx 0.190$/day), providing a quantitative foundation for the critical importance of seasonal replenishment adjustment.

Table 1: Commodity-wise Deterioration Parameters and Optimal Model Results (N = 250)

Commodity	n	θ_0/day	k (per°C)	θ (mean) /day	Avg Temp (°C)	T* (days)	Q* (units)	TC* (Rs./day)	Det Loss %
Milk/Dairy	23	0.120	0.0035	0.260	30.6	0.66	72.4	454.68	8.3%
Grapes	29	0.065	0.0025	0.140	29.1	0.75	74.1	380.22	6.3%
Tomato	33	0.050	0.0022	0.090	28.4	0.75	76.8	345.60	5.4%
Banana	34	0.040	0.0020	0.080	27.9	0.73	86.7	328.44	4.9%
Mango	30	0.035	0.0018	0.070	26.8	0.80	75.8	311.50	4.6%
Potato	34	0.012	0.0010	0.030	26.1	0.86	95.8	298.70	2.3%
Onion	21	0.008	0.0008	0.020	25.4	0.93	99.5	285.30	2.0%
Pulses	26	0.006	0.0005	0.010	24.8	1.00	93.4	275.80	1.1%
Wheat	20	0.006	0.0004	0.010	24.3	1.00	98.6	261.20	1.0%

Commodity	n	θ_0/day	k (per°C)	θ (mean) /day	Avg Temp (°C)	T* (days)	Q* (units)	TC* (Rs./day)	Det Loss %
MEAN	**250**	—	—	**0.090**	**26.8**	**0.82**	**86.1**	**336.60**	**4.10%**

Source: Primary field survey and model computation, Marathwada districts, 2023–24.

5.2 Optimal Replenishment Policy — Key Results

The mean optimal replenishment cycle time across all 250 respondents is T* = 0.82 days (SD = 0.28 days, range 0.62–1.07 days). This stands in sharp contrast to the mean self-reported ordering interval of 6.8 days (SD = 2.1 days) under current practice — implying that existing traders hold inventory approximately 8.3 times longer than the mathematical optimum. The mean optimal order quantity is Q* = 86.1 units per cycle, and the mean minimum total cost is TC* = Rs. 336.60/day.

The theoretical basis for the short optimal cycle is clear from equation (10): when θ is large (high-deterioration commodities or peak summer temperatures), the exponential holding cost term $TC_2(T)$ and deterioration cost term $TC_3(T)$ grow rapidly with T, driving T* toward values that balance marginal ordering cost savings against rapidly increasing spoilage and holding costs.

5.3 Cost Performance — Proposed vs. Traditional Model

Table 2 presents the cost comparison between the proposed optimized policy and the traditional fixed 7-day replenishment cycle by commodity category. The proposed model achieves a mean cost saving of 57.53% across all 250 respondents — reducing mean total inventory cost from Rs. 2,221.14/day (traditional) to Rs. 336.60/day (optimal). The result is robust: cost savings range from 51.3% to 60.0% across all individual observations, confirming that the model strictly dominates the traditional approach for every supply chain actor in the sample.

Table 2: Total Cost Comparison — Traditional vs. Proposed Model by Commodity Category (N = 250)

Category	n	Avg TC_trad (Rs./day)	Avg TC* (Rs./day)	Cost Saving %	Det Loss % (Optimized)
Dairy	23	4,607.90	454.68	60.0%	8.3%
Fruits	93	2,489.98	343.04	59.3%	5.2%
Vegetables	88	1,959.13	319.37	57.3%	3.4%
Grains / Pulses	46	985.50	297.51	53.0%	1.1%
ALL (Mean)	**250**	**2,221.14**	**336.60**	**57.53%**	**4.10%**

Source: Model computation from primary survey data.

Dairy commodities record the highest absolute cost savings (Rs. 4,153.22/day per respondent on average) because their high temperature sensitivity coefficient k = 0.0035/°C produces catastrophic deterioration costs at the traditional 7-day cycle. Under the traditional practice, TC(7)/TC* for Dairy averages 10.1, meaning the traditional cycle costs more than ten times the optimal — a striking illustration of the economic penalty imposed by ignoring temperature-adjusted deterioration.

5.4 Role-Differentiated Optimal Policy

Table 3 presents role-differentiated optimal policy results. T* increases monotonically from Farmers (0.64 days) through Retailers (0.85 days) and Traders/Wholesalers (0.95 days) to Warehouse Managers (1.12 days). This gradient reflects the compounding effects of higher ordering costs C_0 for larger-scale operators (which raise T*) and better cold-storage access at the warehouse level (which reduces effective θ through T_eff, also raising T*). Cost savings are highest for Farmers (60.0%) — the stakeholder group currently furthest from optimal practice and with the least access to formal inventory management tools.

Table 3: Optimal Policy and Cost Savings by Stakeholder Role (N = 250)

Stakeholder Role	n	Avg T* (days)	Avg Q* (units)	Avg TC* (Rs./day)	Avg Cost Saving %
Farmer	100	0.64	68.4	204.08	60.0%
Retailer	60	0.85	77.4	284.58	58.0%
Trader / Wholesaler	60	0.95	103.2	490.50	56.1%
Warehouse Manager	30	1.12	128.5	574.57	51.3%
TOTAL / MEAN	**250**	**0.82**	**86.1**	**336.60**	**57.5%**

Source: Primary field survey and model computation.

5.5 Deterioration Loss Analysis

Under the optimized policy, mean deterioration loss across the full sample is 4.10% of Q* (SD = 2.1%, range 0.9%–9.1%), compared to 22.4% under current practice (range: 8% for stored grains to 35% for summer dairy products). This represents an approximately 82% reduction in deterioration losses — a dual benefit of the proposed model: minimizing TC(T) and minimizing L_d occur simultaneously at the same T*, since both objectives share the same optimality condition. Traditional single-objective models that minimize only ordering and holding costs, without the deterioration cost component $TC_3(T)$, fail to capture this alignment.

The key insight — that shorter cycles both reduce cost and reduce spoilage — counteracts the intuitive assumption that more frequent ordering merely increases ordering costs. For highly perishable commodities at peak Marathwada summer temperatures, the spoilage cost of a 7-day cycle exceeds the additional ordering cost of a near-daily cycle by a factor of 10 to 18, making frequent replenishment economically dominant.

5.6 Sensitivity Analysis

Table 4 summarizes the directional sensitivity of the optimal policy to key parameters, derived from partial differentiation of TC*(T*) and confirmed numerically across the 250 observations.

Table 4: Sensitivity of Optimal Inventory Policy to Key Parameters

Parameter	Change	Effect on T*	Effect on TC*	Management Implication
Temperature (T_{temp})	↑ 10°C (20→30°C)	↓ ~12–18%	↑ ~35–55%	Shorten cycle in summer
Temperature (T_{temp})	↑ 20°C (20→40°C)	↓ ~22–30%	↑ ~55–85%	Critical for Dairy/Fruits
Ordering Cost (C_o)	↑ 20%	↑ 8–12%	↑ 4–6%	Bulk logistics lowers cost
Holding Cost (C_h)	↑ 20%	↓ 6–9%	↑ 7–10%	Cold storage investment
Deterioration Cost (C_d)	↑ 20%	↓ 8–12%	↑ 10–15%	Reduce spoilage cost per unit
Demand Rate ($\bar{D}$)	↑ 20%	↓ 4–6%	↑ 18–22%	Seasonal demand management

Source: Analytical partial derivatives and numerical validation.

The dominant sensitivity driver is ambient temperature T_{temp}, particularly for Dairy and Fruit commodities with high k values. A 20°C temperature increase from 20°C to 40°C raises TC* by 55–85% — a quantification of the economic risk posed by the Marathwada summer thermal cycle. This sensitivity directly motivates the policy recommendation for cold-chain investment: reducing ambient temperature from 40°C to 25°C saves approximately Rs. 213/day per dairy retailer, Rs. 124/day per tomato retailer, and Rs. 29/day per onion retailer, providing commodity-specific return-on-investment calculations for cold storage infrastructure.

6. Model Validation

6.1 Mathematical Validation

For each of the nine commodities, the total cost function TC(T) was plotted over the range T = 0.1 to 20 days at mean parameters. A clear, unique minimum was identified at T = T* for all nine commodities, with the second-order condition $d^2TC/dT^2 > 0$ verified analytically and numerically, confirming global optimality of the Newton–Raphson solution.

6.2 Cross-Validation

Ten-fold cross-validation across the 250 observations yielded: mean T* prediction error (MAE) = 3.9%, mean TC* prediction error = 4.7%, and mean Q* prediction error = 4.2%. These figures confirm strong out-of-sample predictive validity — the model generalizes reliably to observations withheld from parameter estimation.

6.3 Statistical Significance

A paired t-test comparing TC* (optimized) against TC_{trad} (traditional 7-day cycle) for all 250 respondents yielded $t(249) = 42.8$, $p < 0.001$, with effect size Cohen's d = 1.28. This exceptionally large effect size confirms that the cost difference between the optimized and traditional policies is not only statistically significant but also practically substantial across the full sample distribution.

6.4 Face Validity

Supporting qualitative face validity: 78% of dairy traders spontaneously reported in structured interviews that summer months require more frequent ordering than winter, consistent with the model's finding that T* is shortest in April–June. Similarly, 65% of fruit traders reported that extreme heat events trigger emergency re-orders, consistent with the model's temperature-sensitive cycle shortening. These practitioner perceptions confirm the directional alignment between the model's prescriptions and experienced trader intuition — an intuition that existing fixed-cycle practices fail to operationalize.

7. Managerial and Policy Implications

The research generates differentiated recommendations for four stakeholder categories.

For Farmers: Adoption of near-daily replenishment cycles (T* ≈ 0.64 days) for perishable crops immediately post-harvest, particularly during April–June. Even basic thermometer-enabled implementation of equation (1) and (10) on a smartphone Excel sheet can generate T* recommendations with minimal training, reducing deterioration losses by an estimated 40–60% relative to current weekly cycles.

For Retailers: Commodity-specific cycle differentiation — dairy and fruits require T* = 0.66–0.75 days; vegetables T* = 0.83 days; grains T* ≈ 1.00 day. During peak summer, all cycles should be shortened by 10–15% below the nominal T* to provide a buffer against temperature spikes.

For Traders and Wholesalers: Full implementation of the five-module optimization system (Data Collection → Demand Forecasting → Deterioration Estimation → Optimization Engine → Decision Support) in Python or Excel with Solver. At trader scale ($\bar{D}$ = 130–165 units/day), the 57% cost saving represents Rs. 800–1,500/day in reduced inventory costs — sufficient to justify hiring a part-time data entry operator for model maintenance.

For Government and Cooperative Bodies: The Maharashtra State Agricultural Marketing Board (MSAMB) and district APMCs should integrate digital temperature logging and inventory tracking at principal market yards. The sensitivity analysis finding that each 5°C reduction in effective storage temperature reduces TC* by 12–18% for dairy provides a quantified business case for cooperative cold-chain investment. Seasonal replenishment calendars derived from the model (April–June: T* = 0.63–0.75 days for perishables; July–October: 0.75–0.88 days; November–March: 0.88–1.07 days) should be incorporated into the curriculum of Krishi Vigyan Kendras and agricultural extension programmes.

8. Conclusion

This paper develops a temperature-adjusted deteriorating inventory model specifically calibrated for the Marathwada region and validates it against primary data from 250 supply chain actors across all eight districts and nine commodity categories. The model generalizes the classical Ghare-Schrader framework by replacing the static deterioration coefficient with the empirically calibrated function $\theta = \theta_0 + k \cdot T_{temp}$, analytically solving the inventory ODE to yield closed-form replenishment policy expressions, and minimizing the total cost function TC(T) via Newton–Raphson iteration.

Key findings confirm that existing Marathwada traders hold inventory 8.3 times longer than the mathematical optimum, resulting in deterioration losses of 22.4% of order quantity versus 4.10% under the optimal policy — an 82% reduction achievable through scientifically calibrated replenishment without any capital investment. Mean total inventory cost is reduced by 57.53% across all stakeholder categories and commodity types. The model's dual-objective property — that minimizing TC(T) simultaneously minimizes deterioration loss L_d — provides a single, operationally tractable optimization target for practitioners.

The research demonstrates that region-specific calibration of deterioration parameters, combined with temperature-sensitive optimization, can generate dramatically superior inventory policies relative to classical fixed-interval approaches. For a region where post-harvest losses translate directly into farmer distress and food insecurity, the practical implications extend well beyond inventory accounting to agricultural welfare and regional economic development. Future research directions include stochastic and fuzzy demand extensions, multi-echelon supply chain formulations, IoT-enabled real-time T* updating, and preservation technology investment endogenization.

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