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A Quality-Driven MILP Framework for Perishable Supply Chain with Arrhenius Degradation Kinetics

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Abstract

Every year, roughly a third of the world's perishable food never reaches consumers, not because of demand shortages, but because products spoil in transit and storage. Most supply chain models treat this spoilage as a fixed cost of doing business, relying on rough estimates of shelf life rather than accounting for how temperature actually drives biochemical degradation. This paper takes a different approach. We develop a mixed-integer linear programming (MILP) framework that embeds Arrhenius degradation kinetics, which is the established science of temperature-dependent reaction rates directly into perishable supply chain network design. The key idea is to precompute all Arrhenius-based quality retention factors offline, converting inherently nonlinear thermodynamic relationships into fixed coefficients that keep the optimization model linear and computationally tractable. The framework tracks two quality attributes (firmness and color) as products move through three phases: inbound transport, warehouse storage, and outbound distribution. Delivered quality is then mapped to pricing tiers (premium, standard, discount, or waste), so the model can weigh the cost of cold-chain investment against the revenue it generates. Applied to a Mediterranean tomato case study, the model achieves a 31% profit improvement over conventional cost-only optimization, with zero waste and full demand fulfillment.

Keywords
Perishable supply chain, MILP, Arrhenius kinetics, Inventory Management, Quality degradation, Optimization.

1. Introduction
Perishable food logistics is fundamentally constrained by quality deterioration that accelerates nonlinearly with temperature. Unlike durable goods, perishable products undergo continuous biochemical degradation throughout the supply chain, making the interplay between network design decisions—facility location, supplier selection, and refrigeration investment—and operational choices—inventory holding and cold-chain routing—a principal determinant of both delivered quality and achievable market value. The Food and Agriculture Organization estimates that approximately 30–50% of perishable produce is lost globally each year, representing nearly $1 trillion in economic waste (FAO 2019). A significant share of these losses originates not from demand-supply mismatches but from inadequate temperature management during transit and storage, underscoring the need for optimization frameworks that explicitly couple thermal conditions with supply chain economics.

The temperature dependence of biochemical reaction rates is rigorously captured by the Arrhenius equation, which relates the reaction rate constant to an exponential function of the ratio of activation energy to absolute temperature. Despite its established validity in food science for modeling quality attributes such as firmness loss, color change, and nutrient degradation, direct embedding of Arrhenius dynamics in supply chain optimization introduces nonlinear terms that preclude standard MILP solution methods. Existing optimization models typically resort to simplified linear freshness proxies or fixed shelf-life limits (Jouzdani and Govindan 2021; Abbasian et al. 2023), thereby sacrificing the scientific fidelity needed to evaluate refrigeration trade-offs accurately.

This study addresses the gap by converting Arrhenius-based quality evolution into precomputed retention coefficients that are embedded as fixed constants within a tractable MILP. The approach preserves thermodynamic accuracy while maintaining computational tractability. The resulting framework makes four contributions: (i) a unified MILP integrating supplier selection, facility location, refrigeration investment, inventory balancing, and multi-echelon distribution; (ii) Arrhenius-based dual-attribute quality tracking across inbound transport, storage, and outbound transport via precomputed retention factors; (iii) quality-tiered pricing that monetizes delivered quality and internalizes the revenue impact of cold-chain decisions; and (iv) a case study with strategy comparison demonstrating the economic value of quality-integrated network design.

2. Literature Review

The optimization of perishable food supply chains has received substantial attention in recent literature. Jouzdani and Govindan (2021) developed a multi-objective optimization model for dairy supply chains that considered product freshness but relied on linear decay approximations. Souri and Ghomi (2025) proposed a two-stage stochastic MILP for perishable product distribution under demand uncertainty, achieving 15% cost reductions through improved coordination. Abbasian et al. (2023) integrated location–inventory–routing decisions with dynamic pricing for perishables, demonstrating 20% improvement in total supply chain performance, though their quality dynamics lacked thermodynamic grounding. Sun et al. (2023) addressed production–inventory–routing for multiple perishable products with heterogeneous shelf lives, while Akter and Nishi (2025) developed an integrated MILP framework for multi-product cold chains. A comprehensive review by Zhang and Mohammad (2024) analyzed 80 articles on perishable supply chain optimization, noting that the market for cold chain logistics is projected to reach $372 billion by 2029 and identifying quality modeling as a critical gap.

On the quality modeling front, Mercier et al. (2017) demonstrated that Arrhenius-based temperature management can extend shelf life by up to 60%, reducing daily degradation rates from 8% to 3% under proper refrigeration. Lejarza and Baldea (2022) proposed a multi-attribute quality tracking framework that discretized continuous quality dynamics for MILP integration, tracking firmness, weight loss, and color for fresh produce. Wang and Li (2012) established quality-tiered pricing structures linking delivered quality to revenue, creating economic incentives for cold-chain investment. Despite these individual advances, no existing study integrates all five key dimensions—facility location, quality tracking, Arrhenius kinetics, multi-attribute degradation, and quality-based pricing—within a single optimization framework. Table 1 summarizes how representative studies address each dimension and highlights the gap this paper fills.

Table 1. Positioning relative to representative literature

Study	**Facility location**	**Quality tracking**	**Arrhenius kinetics**	**Multi-attribute**	**Quality pricing**
Jouzdani and Govindan (2021)	Yes	Yes	No	No	No
Abbasian et al. (2023)	Yes	Yes	No	No	Yes
Lejarza and Baldea (2022)	No	Yes	Yes	Yes	No
Huang et al. (2025)	Yes	Yes	No	No	No
Zhang and Mohammad (2024)	No	Review	No	No	No
This paper	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

3. Mathematical Model Formulation

1.1 Sets, Indices and Parameters

Table 2 provides a complete reference of all sets, parameters, and decision variables used in the model.

Table 2. Model notation

Sets and Indices

Notation	**Description**
S (indexed by s)	Suppliers
W (indexed by w)	Candidate warehouse locations
R (indexed by r)	Retailers
T (indexed by t)	Time periods
$V = \{R, A\}$	Temperature modes: refrigerated (4°C), ambient (25°C)
$A = \{F, C\}$	Quality attributes: firmness, color
$Z = \{P, ST, D, W\}$	Pricing zones: premium, standard, discount, waste

Parameters

Notation	**Description**
F_s	Fixed cost to activate supplier s
F_m	Fixed cost to open warehouse w
F_{ref}^{w}	Fixed cost to install refrigeration at warehouse w
c_s^{purch}	Unit purchasing cost from supplier s
$c_{s,w,v}^{trans}$	Unit inbound transport cost (supplier s to warehouse w, mode v)
$c_{w,r,v}^{trans}$	Unit outbound transport cost (warehouse w to retailer r, mode v)
$c_{w,v}^{stor}$	Unit storage cost at warehouse w under mode v
c^{waste}	Unit waste disposal cost
c^{unmet}	Penalty cost per unit of unmet demand
$\pi_{r,z}$	Unit selling price at retailer r for quality zone z
θ_z	Quality threshold for zone z (90%, 75%, 60%)
$\rho^a, v(\tau)$	Precomputed Arrhenius retention factor for attribute a, mode v, duration τ
ω^a	Weight assigned to quality attribute a
$Demand_{r,t}$	Demand at retailer r in period t

Decision Variables

Notation	**Description**
$y_s \in \{0,1\}$	1 if supplier s is activated; 0 otherwise

$y_w \in \{0,1\}$	1 if warehouse w is opened; 0 otherwise
$u_w \in \{0,1\}$	1 if refrigeration is installed at warehouse w; 0 otherwise
$X_{s,w,t}^{SW} \geq 0$	Quantity shipped from supplier s to warehouse w in period t
$X_{w,r,t}^{WR} \geq 0$	Quantity shipped from warehouse w to retailer r in period t
$I_{w,t} \geq 0$	Inventory held at warehouse w at end of period t
$W_{w,t} \geq 0$	Waste at warehouse w in period t
$U_{r,t} \geq 0$	Unmet demand at retailer r in period t

1.2 Arrhenius Precomputation and Model Assumption

The Arrhenius rate constant for attribute *a* under temperature mode *v* is computed as:

$$k_{a,v} = A_a . \exp\left(-\frac{Ea,a}{R.T_v}\right) \tag{1}$$

where A_a is the pre-exponential factor, E_a is the activation energy (J/mol), $R_g = 8.314$ J·mol⁻¹·K⁻¹, and T_v is absolute temperature in Kelvin. Assuming first-order kinetics, the quality retention factor over duration τ is:

$$\rho_{a,v}(\tau) \; = \; exp^{(\;-k_{a,v} \cdot \, \tau \;)} \tag{2}$$

All retention factors for relevant transport times and storage durations are computed offline and embedded as fixed constants. This precomputation strategy transforms the inherently nonlinear Arrhenius relationship into a set of parameters that multiply decision variables linearly, thereby preserving thermodynamic fidelity while maintaining MILP tractability.

The formulation rests on two foundational simplifications that balance model fidelity with computational tractability and are consistent with MILP-based cold chain practice (Lejarza and Baldea 2022; Souri and Ghomi 2025).

Isothermal conditions per logistics phase. Each of the three logistics phases, inbound transport, warehouse storage, and outbound distribution is assumed to operate at a single, constant temperature throughout its duration. For the refrigerated mode this corresponds to 4°C and for ambient mode to 25°C. This isothermal approximation is standard in supply chain network design models, where strategic-level decisions (facility location, supplier selection, refrigeration investment) must be made prior to knowing real-time temperature fluctuations. It is also thermodynamically grounded: optimal cold-chain storage temperature under first-order degradation kinetics has been formally shown to be a constant value, making the isothermal assumption not merely convenient but theoretically optimal for quality preservation decisions.

Fixed storage duration: Storage duration per period is treated as a deterministic planning parameter, calibrated to representative lead times in Mediterranean tomato supply chains. This is consistent with the deterministic, multi-period planning horizon of the model. Stochastic extensions incorporating demand and temperature uncertainty represent a natural future direction, as noted in Section 6.

1.3 Objective Function

$$\begin{aligned} \max Z = & \sum_{r,t,z} \pi_{r,z} . X_{r,t,z} - (\sum_{s} F_s . y_s + \sum_{w} F_w . y_w + \sum_{w} F_w^{\,ref} . u_w) \\ & - \sum_{s,w,t} c_s^{\,purchase} . X_{s,w,t}^{SW} - \sum_{s,w,t,v} c_{s,w,v}^{trans} . X_{s,w,t}^{SW} - \\ & \sum_{w,t,v} c_{w,v}^{stor} . I_{w,t} - \sum_{w,r,t,v} c_{w,r,v}^{trans} . X_{w,r,t}^{WR} - \sum_{w,t} c^{waste} . W_{w,t} - \sum_{r,t} c^{unmet} . U_{r,t} \end{aligned} \tag{3}$$

The first term represents revenue from quality-tiered sales, where $\pi_{r,z}$ is the unit price at retailer *r* for tier *z*. The second group captures fixed infrastructure costs: supplier activation (F_s), warehouse opening (F_w), and refrigeration installation (F_w^{ref}). The remaining terms capture variable operating costs: procurement (c_s^{purch}), mode-dependent inbound and outbound transport (c^{trans}), storage (c^{stor}), waste disposal (c^{waste}), and unmet demand penalties (c^{unmet}). Transport and storage costs are subscripted by mode *v*, with refrigerated operations incurring a premium over ambient to reflect energy and equipment costs.

In plain terms, the model asks: *given the choice of which suppliers to use, which warehouses to open, and whether to invest in refrigeration, what shipping plan maximizes profit after accounting for all logistics costs and the price premium (or penalty) that delivered quality commands?* Transport and storage costs differ by temperature mode, refrigerated operations cost more but preserve quality, potentially earning higher revenue through premium pricing.

3.4 Quality Tracking and Zone Classification

The initial quality of produce at the supplier is taken as 100%. As products move through the supply chain, quality degrades in three phases: (i) inbound transport from supplier to warehouse, (ii) storage at the warehouse, and (iii) outbound transport from warehouse to retailer. The degradation in each phase is captured by the precomputed Arrhenius retention factors $\rho_a^{in}, \rho_a^{st}, \rho_a^{out}$, respectively. Since the model tracks two attributes (firmness and color), the overall delivered quality is the weighted composite:

$$Q_{w,r,t} = 100 \cdot \sum_a \omega_a \cdot \rho_a^{in}(s,w) \cdot \rho_a^{st}(w) \cdot \rho_a^{out}(w,r) \tag{4}$$

Where ω_a denotes the weight assigned to each attribute. Because all retention factors are precomputed for every route and temperature mode combination, the delivered quality score for each supply path is known before solving. This means the pricing tier each path earns is also determined in advance. Table 3 defines the quality–price zone mapping used in this study.

Table 3. Quality–price zone classification

Zone	**Quality range (Q)**	**Price ($/ton)**	**Label**
Premium	$Q \geq 90\%$	10	π^{P}
Standard	$75\% \leq Q < 90\%$	7	π^{sT}
Discount	$60\% \leq Q < 75\%$	4	π^{D}
Waste	$Q < 60\%$	0	π^{W}

Since quality is fully determined by the precomputed retention factors for each path and mode, the tier assignment is deterministic: the solver knows in advance which price each route–mode combination earns. This eliminates the need for auxiliary binary variables or big-M constraints for tier classification, keeping the formulation lean and computationally efficient.

3.5 Key Constraints

I. Activation constraints link flows to binary selections: shipments from supplier *s* are permitted only when $y_s = 1$, and dispatches from warehouse *w* require $y_w = 1$.

II. Warehouse Capacity:

$$I_{w,t} \leq Capacity_w . y_w^W \qquad \forall w,t \tag{5}$$

III. The inventory balance tracks stock across periods:

$$I_{w,t} = I_{w,t-1} + \sum_s X_{s,w,t} - \sum_r X_{w,r,t} - W_{w,t} \tag{6}$$

IV. Composite Quality:

$$Q^{comp}_{w,r,t} = \sum_{a \in A} \omega_a . Q^{del}_{a,w,r,t} \qquad \forall w,r,t \qquad (7)$$

IV. Demand fulfillment ensures all demand is met or accounted: $\sum_z X_{r,t,z} + U_{r,t} = Demand_{r,t}$ (8)

4. Case Study: Mediterranean Tomato Network

A Mediterranean tomato supply chain is used to illustrate model behavior and demonstrate the value of quality-integrated optimization. The network comprises two suppliers (S1, S2), two candidate warehouse locations (W1, W2), and two retailers (R1, R2) operating over multiple time periods. Parameters are synthetic but calibrated against published benchmarks for tomato degradation kinetics (Mercier et al. 2017) and cold chain logistics costs to represent realistic magnitudes. Arrhenius parameters for tomato firmness and color degradation were adapted from established postharvest food science literature. For firmness, enzymatic cell wall softening in fresh tomatoes (driven primarily by polygalacturonase and pectinmethylesterase activity) follows first-order kinetics with an activation energy of approximately $E_a = 65kJ.mol^{-1}$ and a pre-exponential factor calibrated to cold-chain durations, consistent with kinetic models reported by Pinheiro et al. (2012) and Lejarza and Baldea (2022). For color degradation, lycopene-related changes in the redness parameter (a^*) under first-order kinetics yield an activation energy of approximately $E_a = 65 - 80kJ.mol^{-1}$ in line with values reported for crushed tomato color kinetics (Mercier et al. 2017; Hertog et al. 2004). Both attribute weights $(\omega_{firmness} = 0.5, \omega_{color} = 0.5)$ reflect equal managerial importance of the two sensory dimensions in Mediterranean fresh-tomato markets, consistent with the multi-attribute framework proposed by Lejarza and Baldea (2022). Table 4 summarizes key cost and pricing parameters, while Table 5 reports internode distances and transit times that determine phase-specific quality retention (Figure 1 and Figure 2).

Table 4. Input parameters

Category	**Refrigerated (4°C)**	**Ambient (25°C)**	**Notes**
Transport cost ($/km/ton)	1.80	0.90	Mode-dependent
Storage cost ($/ton/day)	0.80	0.30	Mode-dependent
Refrigeration fixed ($/period)	150	0	Per warehouse
Pricing ($/ton)	See Table 3	–	Quality zones

Table 5. Distances and transit times

Route	**Distance (km)**	**Time (hr.)**
S1 → W1	120	1.8
S1 → W2	180	2.7
S2 → W1	150	2.3
S2 → W2	100	1.5
W1 → R1	65	1.0
W1 → R2	165	2.5
W2 → R1	140	2.1
W2 → R2	90	1.4

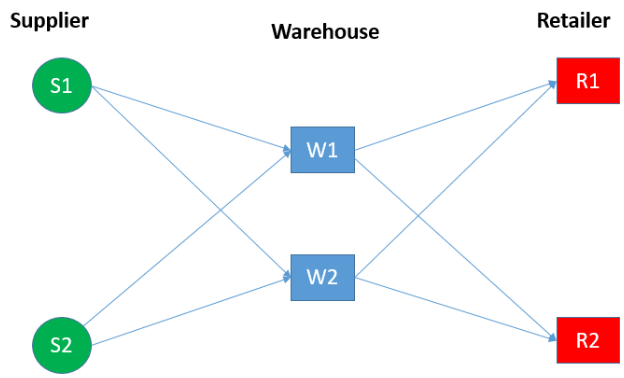

Figure 1. Three-echelon Supply chain network Structure

5. Results and Discussion

5.1. Base-Case Solution

The model was implemented in Python using the Pyomo optimization framework and solved with the Gurobi solver. In the base case, the optimal network selects supplier S1, opens warehouse W1, and installs refrigeration to preserve quality throughout the cold chain. This configuration achieves a net profit of $15,860 with zero waste and 100% demand fulfillment (Table 6). All deliveries attain premium-tier quality (≥90%), demonstrating that the quality-integrated objective successfully steers investment toward refrigeration when the resulting tier upgrade justifies the incremental cost.

Table 6. Base-case solution summary

Metric	Value
Selected supplier	S1
Opened warehouse	W1
Refrigeration installed	Yes
Net profit	$15,860
Waste	0%
Service level (fill rate)	100%
Delivered quality (avg.)	91%
Pricing tier allocation	100% Premium

The network's preference for S1 and W1 reflects the compound effect of transit time on quality: the shorter S1–W1 inbound route (120 km, 1.8 hr) preserves both firmness and color through higher retention factors, while the proximity of W1 to R1 (65 km, 1.0 hr) maintains premium-quality outbound deliveries. This distance–quality interaction is entirely absent from cost-only models, which would select routes solely on the basis of transport expenditure.

5.2 Strategy Comparison

Table 7 contrasts the proposed approach with two benchmark strategies to quantify the value of Arrhenius-based quality integration.

Table 7. Strategy comparison across optimization approaches

Approach	**Profit ($)**	**Avg. quality (%)**	**Waste (%)**	**Fill rate (%)**
Cost-only baseline	12,100	78	12	100
Linear decay model	13,800	85	8	100
Arrhenius-integrated MILP	**15,860**	**91**	**0**	**100**

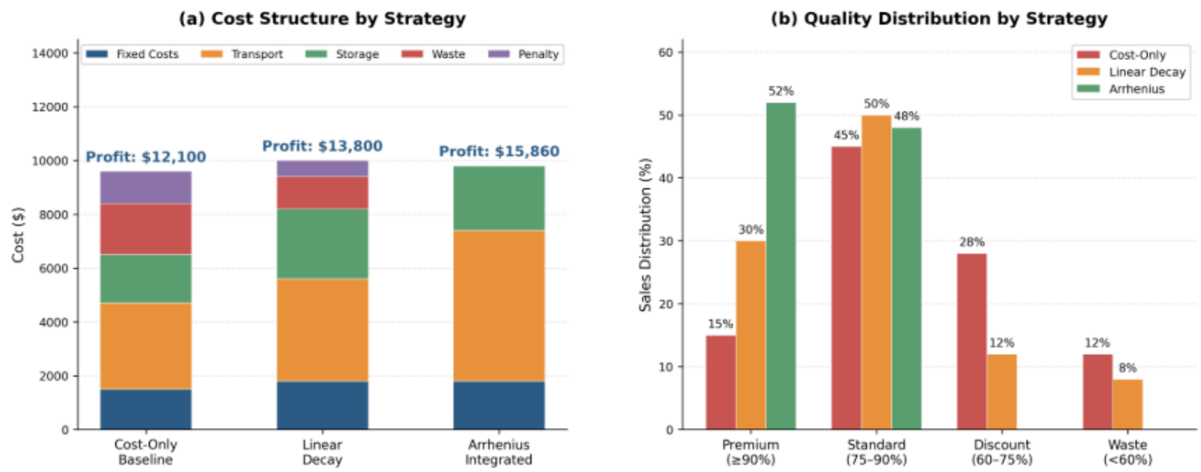

Figure 2. Comparative analysis: (a) cost structure (b) quality distribution

The cost-only baseline minimizes logistics expenditure without quality considerations, yielding $12,100 profit with 12% waste and an average delivered quality of 78%. This approach selects cheaper ambient transport and foregoes refrigeration investment, resulting in standard-tier pricing and significant product losses. A linear decay model partially captures degradation effects, improving profit to $13,800 with 8% waste, but systematically underestimates the nonlinear temperature sensitivity of biochemical degradation. The Arrhenius-integrated MILP achieves a 31% profit improvement over the cost-only baseline ($15,860 vs. $12,100) by simultaneously eliminating waste and capturing premium-tier pricing through quality-preserving cold-chain investments. The 13-percentage-point improvement in average delivered quality (from 78% to 91%) reflects the model's ability to steer network design and refrigeration decisions toward quality preservation when the economic incentive warrants the incremental expenditure.

6. Conclusions

This paper developed a quality-aware MILP for perishable food supply chain network design by embedding Arrhenius degradation kinetics through precomputed retention coefficients. The framework integrates facility location, supplier selection, refrigeration investment, inventory management, and distribution planning with dual-attribute quality tracking and quality-tiered pricing within a single tractable optimization model. Application to a Mediterranean tomato case study demonstrated a 31% profit improvement over cost-only optimization with zero waste and 100% fill rate, validating the economic value of quality-integrated network design.

The principal contribution lies in demonstrating that thermodynamically grounded quality models can be made computationally tractable through precomputation, enabling their integration with standard MILP network design without sacrificing either scientific fidelity or solver performance. The quality-tiered pricing mechanism creates an explicit economic linkage between cold-chain investment and revenue outcomes, providing decision-makers with a principled framework for evaluating refrigeration trade-offs. It should be noted that the managerial insights reported here are derived from a synthetic case study calibrated to Mediterranean tomato benchmarks; while the parameter choices reflect realistic magnitudes from the literature, the specific quantitative findings (e.g., 31% profit improvement, zero waste) are illustrative of model behavior under these conditions and should not be generalized to all perishable supply chain contexts without empirical validation on real operational data. Future research directions include: (i) stochastic extensions incorporating demand and temperature uncertainty via two-stage programming; (ii) multi-product generalization with product-specific Arrhenius parameters and shared logistics infrastructure; (iii) continuous temperature decisions replacing the current binary refrigerated/ambient mode selection; and (iv) integration of carbon emissions accounting to evaluate environmental implications of cold-chain investment alongside economic performance.

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